Methods for Predicting Inventory Levels in a Segmented Retail Supply Chain

by

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B.S. Mechanical Engineering,
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Submitted to the MIT Sloan School of Management and the Mechanical Engineering Department in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration and
Master of Science in Mechanical Engineering

In conjunction with the Leaders for Global Operations Program at the Massachusetts Institute of Technology

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Abstract

Inventory is the largest asset on Nike's balance sheet—$3.9 Billion on May 31st, 2014—and a key indicator of supply chain health. With new markets, products, and channels being added to Nike's sales portfolio each year, the environment in which Nike's supply chain must operate is becoming increasingly complex. Nike has responded to this complexity by splintering their supply chain into smaller segments, tailoring each segment to specific market and consumer needs. As a result of these market developments and Nike's organizational response, the task of understanding and predicting inventory movements has become increasingly challenging for Nike's business planning teams.

This project creates an analytical method by which Nike can combine historical supply chain performance with sales forecasts to accurately predict future changes to company inventory levels. To achieve this goal and facilitate simple and flexible inventory predictions, a model was developed around the key segmentation dimensions that define Nike's supply chain. Use of this model enables Nike's senior management team to accurately predict movements in inventory due to product mix changes in the baseline sales forecasts. Additionally, the model provides Nike with a mechanism to evaluate sensitivity to forecast errors and the inventory costs associated with key strategic decisions to grow or shrink segments of their business.

Preliminary results from the model over the time period FY15 – FY18 show a 2% increase in baseline inventory by the end of FY18 due both to growth in Apparel relative to Footwear and to growth in Direct-to-Consumer relative to Wholesale. This upward pressure on inventory leaves Nike in a precarious spot with Wall Street analysts who associate inventory growth relative to sales with poor marketplace performance. By carefully segmenting inventory, applying segment specific forecasts, and analyzing aggregated results through the use of the model, Nike can more accurately predict and explain movements in inventory to shareholders.

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1 Introduction

This section gives the reader an overview of the problem studied by the student in conjunction with the MIT Leaders for Global Operations Program and Nike Inc. First, this section describes the business rationale behind undertaking this project and presents the problem in general terms. Second, this section gives the reader an overview of Nike's corporate history, organizational structure, and supply chain. Finally, this section provides an overview of the remaining sections of the thesis.

1.1 Problem Overview

Nike became the world's largest seller of athletic footwear and athletic apparel in the world through consistent growth over the past 40 years. To maintain their year-over-year sales growth, Nike has pursued a wide variety of markets, channels, and products. From what started as a direct sales business from the back of a Volkswagen van at Track meets, Nike rapidly added nodes to what was becoming an increasingly complex and opaque supply chain network. While Nike was able to adequately manage their business at lower unit throughput, continued growth in top-line revenue and the number of units produced (see Figure 1) has rapidly enhanced the difficulty of their task.

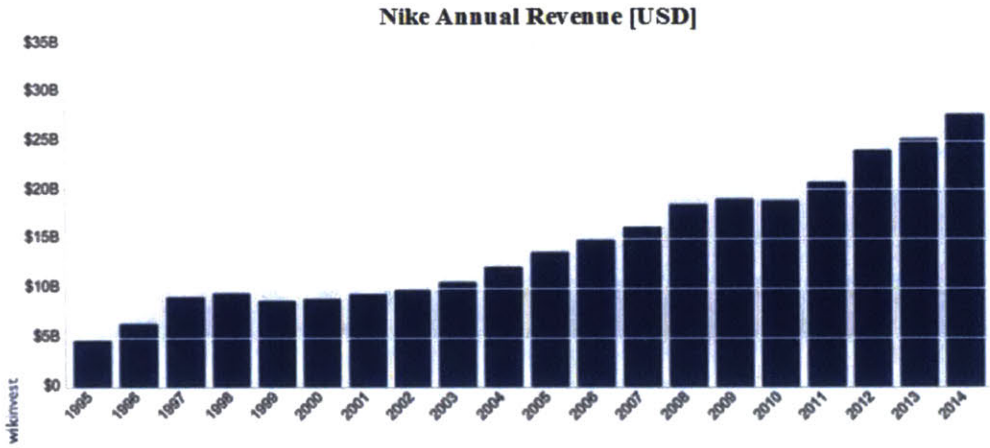

Figure 1: Nike Annual Revenue Growth (1995-2014)[1]

This project analyzes one key aspect of Nike's business model: the strategic use of inventory throughout the supply chain. As the largest asset on the balance sheet and a key Wall Street indicator of business health, Nike must maintain an intimate understanding of why inventory levels change and how they will change in the future. The model described within this paper gives Nike a new tool to both understand historical inventory movement and predict future inventory changes.

Nike commissioned this project at this point in time for three main reasons:

(1) New developments in the retail marketplace are creating an increasingly complex, fragmented landscape for Nike
(2) Nike is responding to the market by segmenting their supply chain, thereby making it increasingly difficult to forecast business metrics like inventory across a multitude of small, dissimilar supply chains

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[1] http://www.wikinvest.com/stock/Nike_(NKE)/Data/Revenue

(3) The ability to accurately predict and control inventory is of paramount importance to Nike's ability to return shareholder value on Wall Street

The subsequent sections discuss each of these points in further detail.

1.1.1 New Developments in the Retail Marketplace

The onset of new major developments in the retail marketplace has driven Nike's supply chain to become increasingly complex. The combination of new ordering models, new distribution channels, new geographic markets, and new consumer trends has resulted in drastic changes within Nike's supply chain.

While Nike has historically utilized a Futures (i.e, make-to-order) ordering model and leveraged wholesale partners to distribute product to a customer base that was largely based in the United States, Nike now utilizes multiple ordering models, employs four distinct direct-to-consumer channels, and derives less than 46% of their revenue from the US. To further complicate the marketplace for athletic footwear and apparel, Nike has had to contend with rising consumer expectations for product personalization and service level. These changes require new business processes at Nike in areas where expertise did not previously exist.

These new developments in the retail marketplace have created a business environment that changes rapidly and is increasingly difficult to forecast. As a result, Nike is actively seeking tools to help them address these marketplace challenges. The project presented in this paper addresses the question of predicting inventory movements as it relates to these marketplace developments.

1.1.2 Supply Chain Segmentation

As a response to the increasing complexity of the marketplace and the rapid rise in unit sales, Nike has slowly adopted a supply chain segmentation strategy over the last decade. Although Nike's business is still largely composed of Futures orders from wholesale partners, Nike has actively experimented with make-to-stock inventory and direct-to-consumer channels. Currently, Futures orders constitute 87% of footwear revenue and 71% of apparel revenue in the US while the direct-to-consumer channel constitutes 21% of global revenue.[2]

The further adoption of segmentation will allow Nike to match specific supply chain models to customer and consumer demands. However, to responsibly and intelligently segment their supply chain to match the expanding set of products and markets, Nike must understand how each granular segment behaves. As depicted by , not all inventory in Nike's supply chain is equivalent—certain segments require strategic or planned inventory while other segments view inventory as waste. As a starting point, this project seeks to understand the impact on inventory due to the adoption of segmentation.

[2] http://investors.nike.com/files/doc_financials/2014/docs/nike-2014-form-10K.pdf

Figure 2: Inventory Segmentation – Not All Inventory Units are Equivalent

1.1.3 Inventory on the Balance Sheet

The overarching rationale for this project stems from a need to understand why inventory levels change and how they will change in the future. This need is derived from the inherent importance of inventory to retail business performance and the emphasis put on inventory by Wall Street.

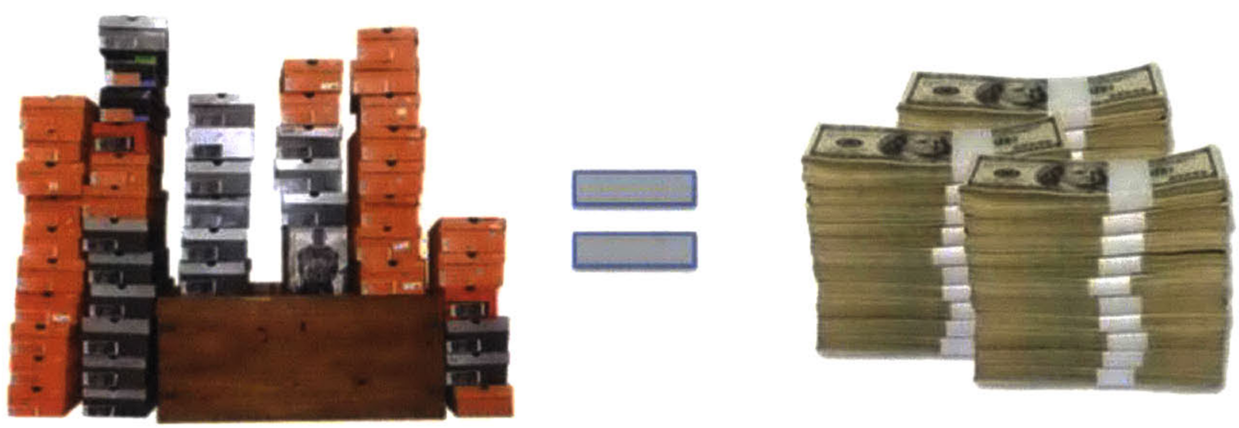

Figure 3: The Importance of Inventory on the Balance Sheet

At the close of Nike's 2014 Fiscal Year on May 31st, 2014, Nike owned $3.9 Billion USD[3] in mostly finished goods inventory—this represented the largest asset on the balance sheet. Figure 4 details the historical balance of inventory Fiscal Year (FY) 2010 to Fiscal Year 2014 based on Nike's 2014 10K filing.

ITEM 6. Selected Financial Data

Unless otherwise indicated, the following disclosures reflect the Company's continuing operations; refer to Note 15 — Discontinued Operations in the accompanying Notes to the Consolidated Financial Statements for additional information regarding discontinued operations. All per share amounts are reflective of the two-for-one stock split that began trading at the split-adjusted price on December 26, 2012.

	Financial History				
(Dollars in millions, except per share data and financial ratios)	2014	2013(1)	2012(1)	2011(1)	2010(1)
Year Ended May 31,					
Inventories	3,947	3,484	3,251	2,630	1,953

Figure 4: Nike Fiscal Year Close Inventory [$USD] (2010-2014)[4]

Included with the 10K filing from FY14, Nike describes the potential risks to their business associated with inventory:

> *"There is a risk we may be unable to sell excess products ordered from manufacturers. Inventory levels in excess of customer demand may result in inventory write-downs, and the sale of excess inventory at discounted prices could significantly impair our brand image and have an adverse effect on our operating results and financial condition. Conversely, if we underestimate consumer demand for our products or if our manufacturers fail to supply products we require at the time we need them, we may*

[3] http://investors.nike.com/files/doc_financials/2014/docs/nike-2014-form-10K.pdf

experience inventory shortages. Inventory shortages might delay shipments to customers, negatively impact retailer and distributor relationships, and diminish brand loyalty."[4]

As a result of the described risks, Wall Street attributes significant weight to Nike's ability to forecast inventory levels and then hit those forecasts [1]. This project attempts to refine Nike's ability to forecast high-level annual changes to inventory levels while providing an understanding of why changes are occurring.

1.2 Nike Overview

Nike is the world's largest seller of athletic footwear and apparel. With over 56,000 employees globally, Nike's products and athletes reach into almost every country in the world. Nike faces strong competition from adidas, V.F. Corp., Puma, Li Ning, Under Armour, lululemon athletica and Uniqlo. In the face of this competition, Nike seeks to differentiate themselves through superior product design and branding.

Nike designs the majority of their products at their World Headquarters in Beaverton, Oregon but uses a network of over 750 suppliers located mainly in South and East Asia to manufacture the products. Nike's products reach the consumer through a combination of wholesale partner stores and direct-to-consumer channels. While Nike designs are specifically crafted for athletic use, a large percentage of consumers wear Nike products for casual or lifestyle purposes.

Nike focuses on eight athletic categories: Running, Basketball, Football (Soccer), Men's Training, Women's Training, Action Sports, Sportswear, and Golf. In addition, Nike owns the Jordan, Converse, and Hurley brands expanding their reach further into Basketball, Lifestyle, and Action Sports respectively.

[4] http://investors.nike.com/files/doc_financials/2014/docs/nike-2014-form-10K.pdf

1.2.1 Company Background

Phil Knight and Bill Bowerman originally founded the company in 1964 under the name Blue Ribbon Sports. As the track coach at the University of Oregon, Bill Bowerman had access to an elite group of runners on which he routinely experimented with shoe design improvements. A prior student of Bowerman's on the Oregon track team, Phil Knight had since left to attend Stanford's Graduate School of Business. In 1964, the two reunited and begun selling Japanese running shoes as a distributor for Onitsuka Tiger. Finally in 1971, Blue Ribbon Sports rebranded to Nike and started selling shoes with the now widely recognized Swoosh logo (see Figure 5).

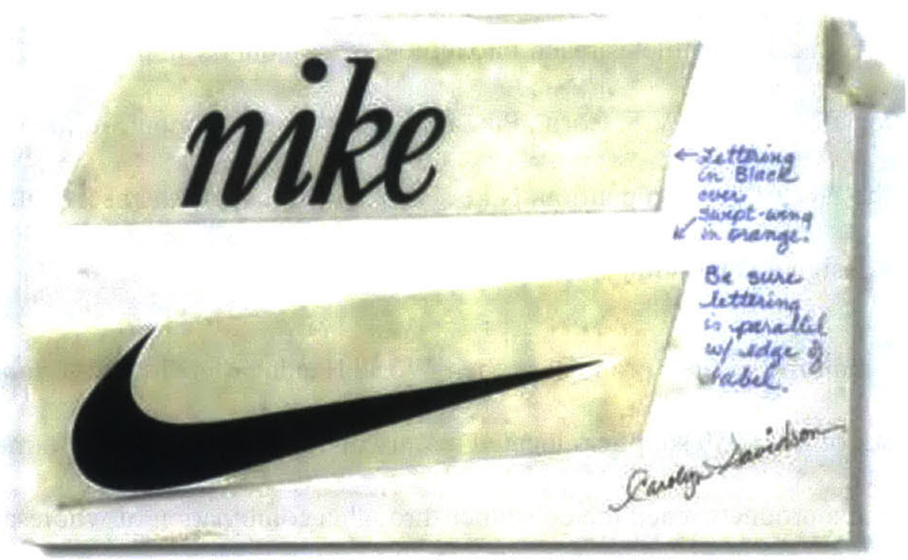

Figure 5: Original Nike Swoosh Design by Carolyn Davidson[5]

Although Nike started off by selling running shoes out of the back of a Volkswagen van at local Track meets, by 1980 Nike had claimed 50% of the market for athletic shoes in the U.S[6]. During the 1980's Nike had become a sports and marketing powerhouse with slogans like "Bo Knows"

[5] http://www.printmag.com/wp-content/uploads/2011/08/swoosh002.jpg
[6] http://news.nike.com/company_overview/history/1980s.html

and "Just Do It" and the signing of signature athletes like Michael Jordan. Throughout the 1990's and 2000's, Nike expanded into new sports and new geographies reaching a total market capitalization of $79.7 Billion USD as of February 2015.

1.2.2 Nike Organizational Structure

Nike operates with a matrix organizational structure sliced along the following dimensions: Brand, Geography, Product Engine, Product Category, Replenishment Model, and Channel. While broadly split by Brand, Geography, and Product Engine, the remaining layers represent new and growing components of Nike's business. A single employee at Nike may work in multiple layers of this matrix simultaneously making the administrative hierarchy a maze of dotted line and hard line relationships. While confusing to outsiders, the lack of direct authority fosters a culture with the freedom to explore new concepts.

For the purposes of this project, an understanding of the matrix structure is key to understanding the selection of inputs, outputs, and levers for the inventory model. Because of the high number of matrix dimensions, the model must obtain data at the most granular level such that it can be re-aggregated along any one particular dimension. For those with an understanding of data structures, this can be thought of as an OLAP Cube[7]. An example of the relationship between the organizational structure and the inventory model would be the following:

> ***Example:*** Nike is experiencing growth in North America in Women's Training in Factory Stores and wants to understand how this growth impacts overall Nike Brand inventory. To perform this assessment, one must have sales and inventory data split by

[7] http://en.wikipedia.org/wiki/OLAP_cube

Geography → North America, Product Category → Women's Training, and Channel → Factory Stores but grouped by Product Engine → All and Replenishment Model → All.

The number of possible permutations of data as a result of this organizational structure is exceedingly large and makes creation of a one-size-fits-all analysis challenging. Further discussion of this complexity and the eventual rationale used to select a dataset takes place in later sections.

1.2.3 Nike Supply Chain

As of 2003, Nike created a corporate focus on supply chain, placing it alongside brand and product in their corporate priorities. This shift in mentality came directly from Phil Knight and the senior leadership team. By focusing on delivering the right product to the right place at the right time, the Nike supply chain enabled the business to please existing customers and reach new customers. Nike's continued focus on improving their supply chain capabilities is evident in their corporate investments into supply chain infrastructure, research, and recruiting.

The term supply chain within the Nike organization can be thought of as the physical transfer of all products from a consolidator located near the manufacturing network to either a wholesale partner or a consumer in the Geography of final sale. Nike takes ownership of their products generally through a consolidator who receives the product at a foreign port location. Nike maintains ownership of the products until the product is either received by a wholesale partner or delivered to an end consumer. The diagram in Figure 6 shows the entire value chain and clarifies the distinction made for supply chain. Note that the value chain includes the retail outlet only for direct-to-consumer stores and not with wholesale partner stores.

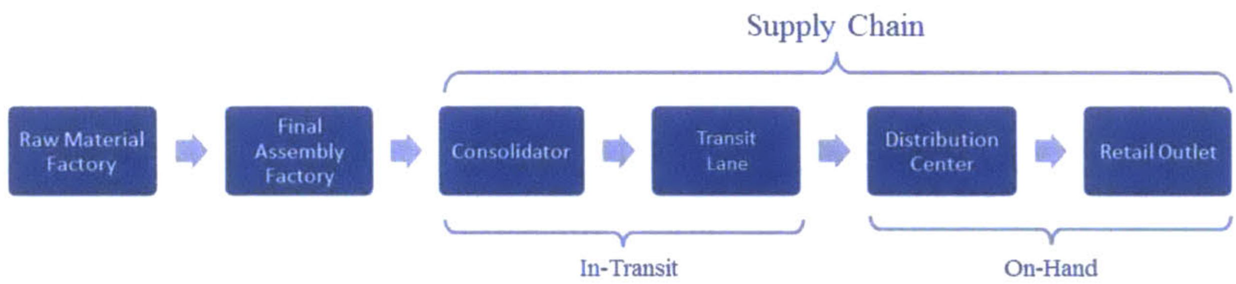

Figure 6: Nike Value Chain and Supply Chain Structure

With a manufacturing network of over 750 suppliers and a globally distributed consumer base, the Nike supply chain resembles a multi-input, multi-output network with hundreds of intermediate nodes and arcs. However, for the purposes of this model, all inventory is classified as either in-transit or on-hand with the changeover occurring when the product is received into a geography-specific Nike warehouse. Within this two-category structure of inventory, the model takes into account different paths for moving inventory through the supply chain. Specifically, inventory is classified as taking one of three transit lanes (e.g. Ocean, Air, or Truck) and one of three delivery modes (e.g. Via a Nike DC, Direct to a wholesale DC, and Via a 3rd Party DC).

Another important distinction within the Nike supply chain is the ordering mechanism used by customers to purchase Nike products. Historically, Nike has employed a futures business model but in the last decade has developed a series of responsive business models. These are discussed in the sections below.

Futures Model

A description of Nike's current futures business model comes from the Nike 2014 10K Filing:

"We make substantial use of our futures ordering program, which allows retailers to order five to six months in advance of delivery with the commitment that their orders will be delivered within a set time period at a fixed price. In fiscal 2014, 86% of our U.S. wholesale footwear shipments (excluding NIKE Golf, Hurley, and Converse) were made under the futures program, compared to 87% in fiscal 2013 and 86% in fiscal 2012. In fiscal 2014, 71% of our U.S. wholesale apparel shipments (excluding NIKE Golf, Hurley, and Converse) were made under the futures program, compared to 67% in fiscal 2013 and 64% in fiscal 2012"[8]

This model resembles a standard make-to-order strategy and allows Nike to eliminate significant risk and uncertainty when manufacturing products. Furthermore, the long lead time allows Nike to batch the manufacturing of products, thereby lowering production costs. At the close of fiscal year 2014, Nike had $13.3 Billion USD in futures orders on their books.

One significant downside to the futures ordering model is the inability to react to short-term fluctuations in market demand. The segmentation of Nike's supply chain to include responsive, make-to-stock models has allowed Nike to maintain many of the benefits of the futures model while better reacting to market pull.

Responsive Models

Nike employs a number of different responsive business models. The majority of the items sold through these responsive models consist of staple products such as base layers, socks, and sandals. These items typically sell across multiple seasons and have low-variability in demand. Because customers expect these Nike products to be available at all times, Nike ensures that

[8] http://investors.nike.com/files/doc_financials/2014/docs/nike-2014-form-10K.pdf

retailers have access to these products with a two-week replenishment turnaround. This model exists mainly within North America and Europe because it requires tighter integration with retail outlets.

Additional responsive models also exist for the purposes of product postponement. For example, NFL jerseys in the U.S. are stored locally with everything but the player's name finished. Depending on the performance of players throughout the season, Nike will quickly finish these jerseys with the appropriate player names and get them quickly to market. Further discussion of these responsive business models can be found in Robert Giacomantonio's thesis [2] from 2013 and Benjamin Polak's thesis [5] from 2014.

The adoption of new responsive business models at Nike means that the supply chain team along with the other Sales and Operations Planning teams must understand the intricate differences across each model to properly forecast business metrics such as inventory. The proliferation in responsive business models is one key reason why Nike undertook this project to understand inventory as it pertains to the futures and responsive business models.

1.3 Thesis Overview

This document contains seven sections. Section 2 provides a review of relevant supply chain literature on inventory management. Section 3 succinctly defines the problem being studied. Section 4 outlines the methodology of this project and walks the reader through the rationale behind the decisions made to create, validate, and automate the inventory model. Section 5 explains the step-by-step actions necessary to use the model for analysis purposes. Section 6 presents the results of the model using Nike's Fiscal Year 2016 – 2018 sales forecasts (i.e. Baseline Case) and explains the result of two sensitivity analyses conducted to demonstrate model use cases. Finally, Section 7 provides conclusions based on this project and outlines short and long-term recommendations for future improvements.

2 Literature Review

Throughout this paper the topic of predictive inventory analytics is discussed at length; however, the details of the presented solution are specific to Nike's business and of a high-level strategic nature. As a result, it is difficult to find exact comparative literature. By expanding the scope of the literature review to the topics of inventory management and inventory strategy as they relate to retail supply chains, a large amount of prior research is available and relevant.

An article in the California Management Review at University of California Berkeley entitled "Retail Inventory: Managing the Canary in the Coal Mine" by Gaur, Kesavan, and Raman [1] explains the importance of controlled inventory growth in the retail industry stating that "investors punish retailers that have unexpected inventory growth". The article proceeds to substantiate this statement with a study that analyzed the stock prices of retailers in the nine-month period following an earnings announcement which fell short of analyst expects. While the average retailer's stock dropped 8% in those nine months, retailers that missed earnings and had unexpected growth in inventory experienced a 13% decline in stock price over the same period while retailers that missed earnings but met inventory forecasts only saw a 2.6% decline. This study shows the immense significance of correctly forecasting inventory levels and lends perspective to why Nike selected this topic of study.

Gaur, Kesavan, and Raman provide further discussion of the relationship between inventory turns and gross margin, finding a 1% increase in gross margin leads to a 1.48% average decrease in inventory turns in U.S. retailers. They hypothesize that, "An increase in gross margin is associated with improved product availability or fill rate, increased variety, a reduction in markdowns, or a shift towards higher-quality, slower-moving products." Finally, an alternative "adjusted inventory turns (AIT)" metric is proposed as a means for both retailers and investors to account for the impact of gross margin variability on inventory performance.

In their Supply Chain Management Review article "The Tip of the (Inventory) Iceberg", Gupta and Iyengar [3] argue that retailers commonly miss the complete picture when managing inventory within their business and do not take into account all of the hidden costs associated with inventory. Gupta and Iyengar lay out three reasons behind the unhealthy build-up of inventory: (1) lack of ownership around inventory metrics, (2) absence of an enterprise-wide perspective, and (3) multiple interventions in the replenishment decision-making process. To combat these causes of excess inventory, Gupta and Iyengar conclude with a recommendation to implement a formal inventory management framework that cuts across functions and departments to provide an enterprise-wide view while tying in key performance indicators (KPIs).

With an understanding of the importance of predicting inventory and a formal inventory management framework, the next step in refining the retail supply chain is through segmentation. In a McKinsey Quarterly article from January 2011, Malik, Niemeyer, and Ruwadi suggest, "splintering monolithic supply chains into smaller, nimbler ones can help tame complexity, save money, and serve customers better" [4]. To arrive at a segmented supply chain, they suggest profiling SKUs by volume and demand volatility. An example SKU segmentation analysis for a consumer-durables company is shown in . By adapting separate supply chain models to each SKU segment, retailers can more judiciously optimize supply chain metrics like inventory holding cost, logistics cost, and on-time delivery.

[4]

3 Problem Definition

The prior two sections provided background information to general questions such as:

- Why study inventory?
- Why do we need to understand and predict inventory levels?
- What retail trends make this relevant to Nike today?
- How is Nike's organization structured?
- How does Nike currently manage supply chain operations?
- What prior research has been conducted in this area?

With an understanding of these topics in place, the specific problem definition can now be developed.

Problem:

Nike seeks to understand the impact to inventory units and inventory dollars based on the relative growth differences of nine key levers related to the sales of product and the movement of product to meet sales. In addition to the baseline forecast of these metrics, Nike also seeks to understand the sensitivity to forecast errors and to evaluate the cost and benefit of specific strategic initiatives.

An understanding of the underlying drivers in the movement of inventory levels will provide Nike with a competitive advantage in the marketplace through two mechanisms:

- By allowing for improved accuracy related to financial inventory forecasts
- By giving supply chain executives a means to quantify and measure the relative cost and benefit of specific strategic initiatives

4 Methodology

To address the problem outlined in the previous section, a series of actions were taken. This section walks the reader through each action, providing context behind the project methodology. First, a current state analysis is provided to discuss tools in place at the start of this research at Nike to partially address this problem. Second, the relevant inputs, outputs, and levers are identified with supporting rationale given. Third, the model framework is developed. Fourth, the steps taken to validate and calibrate the model are discussed. Lastly, an explanation of the tools and processes instituted to automate components of the model are explained.

4.1 Current State Analysis

Before building any new tools, a thorough research process into the set of existing tools at Nike was conducted. Prior work in this area existed at both the global and the geography levels.

4.1.1 Existing Global Models

Looking first at the historical work down at the global level (i.e. spanning across all geographies) the basis for much of the work comes from Marie Wolbert's 2013 LGO Thesis "Predictive Analytics for Inventory in a Sporting Goods Organization" [7]. This model used a bottoms-up approach to aggregate granular inventory data across each individual geography. Inventory data was entered based on Product Engine, Business Model, Transit Lane, and Product Status. To forecast future inventory levels, Wolbert's model accepted expected relative growth rates in each of the inventory segments as well as expected year-over-year inventory efficiency improvement percentages by segment. This model provided an excellent foundation for later work but was limited in two specific ways: (1) Results were difficult to update (2) Failed to include segments that are now growing in importance such as Channel (e.g. Direct-To-Consumer In-Store Inventory).

4.1.2 Existing Geography Models

Although the intention of this project is to develop a model that covers all geographies, a review of the existing single-geography models is beneficial for understanding unmet needs with the existing global models. In the process of researching prior work, two geography level models were identified: (1) North America and (2) Emerging Markets.

In the North America model a simple roll-up of inventory segments was provided with particular adjustments to off-price inventory. This difference prompted the inclusion of Product Status as one of the levers in the latest model.

In the Emerging Markets model a breakout of inventory by Territory provided a deeper segmentation of the geography-level numbers used elsewhere. This was important to the Emerging Markets team because of stark differences between the supply chains in each Territory; however, the data was not readily available to integrate this level of detail into the model later developed in this section.

4.2 Defining Inputs, Outputs, and Levers

Before a model can be developed, it is critical to understand the data available (i.e. inputs), the data desired (i.e. outputs), and the analyses desired (i.e. levers needed). In the case of this inventory model, these three pieces of information were set in advance of any development and were an important factor in shaping what data was collected, how it was processed, and what questions were able to be answered.

4.2.1 Inputs and Assumptions

Data within the Nike supply chain organization is fragmented across a multitude of sources depending on the purpose and the source. For this reason, it was necessary to split the model inputs into those based on historical or actualized data and those based on forecast data.

Historical Data Inputs and Calculations

In order to have consistent data across all inventory segments, especially across Geographies, the Sales, Receipts, and Inventory (SRI) system was utilized as the system of record for all historical data with the exception of data not available in SRI. Specifically, Direct-to-Consumer (DTC) inventory data was not available in-full in SRI and was instead sourced from the Global DTC group.

The SRI system along with the supplementary data from the DTC group, provided a dataset containing monthly shipments (units) and monthly closing inventory (units) in a host of inventory segments. However, the dataset lacked all of the required segmentation splits. To compensate for the lack of granularity a series of assumptions were necessary. These assumptions include:

- *Unknown split between Digital and Inline shipments:* Use historical data from Global DTC to calculate the percentage of Digital shipments and the percentage of Inline shipments then assume these percentages are constant going forward.
- *Unknown DTC inventory in Emerging Markets Geography*: The Global DTC dataset did not contain inventory values for the Emerging Markets Geography. The Emerging Markets shipment values from SRI were used and inventory was then calculated using an

assumed Inventory Turn value for each DTC channel and storage location (DC vs. In-Store) combination.

- *Unknown split between Product Engines in DTC inventory*: Use historical data from Global DTC to calculate the percentage of inventory associated with each Product Engine based on August 2013 and August 2014 only, assume no changes to these ratios going forward.

Dataset Structure

With these assumptions in place, it is possible to generate a complete dataset for shipments and on-hand inventory; however, an additional source is required for in-transit data. Currently, APL Logistics has been contracted by Nike to aggregate and maintain all in-transit data globally. Thus, all transit lane and transit time information was extracted from the APL Logistics data dashboards and then combined with the existing shipments and inventory dataset.

A complete picture of this dataset is provided in Figure 7 and Table 1with key distinctions made between dimensions and measures. An understanding of the data warehousing differences between dimensions and measures is essential to the remainder of this project so definitions and examples are provided below:

Dimensions: Unchanging, descriptive strings. Used to create the segmentation boundaries. A single dimension contains mutually exclusive and completely exhaustive data elements.

Examples:

```
Product Engine = ('Footwear', 'Apparel',    'Equipment')
```

```
Transit Lane = ('Air Freight', 'Truck Freight', 'Ocean
Vessel')
```

***Measure*:** Numeric values collected each month by segment. Can be combined or broken apart across every dimension.

Examples:

```
DC Inventory = Integer [units]

Transit Time = Decimal Value [days]
```

By carefully collecting and categorizing the historical inventory data at Nike into the data warehousing template shown in Figure 7, all calculations performed on this dataset are done in a structured and understandable fashion. An example dataset entry is provided in Figure 8.

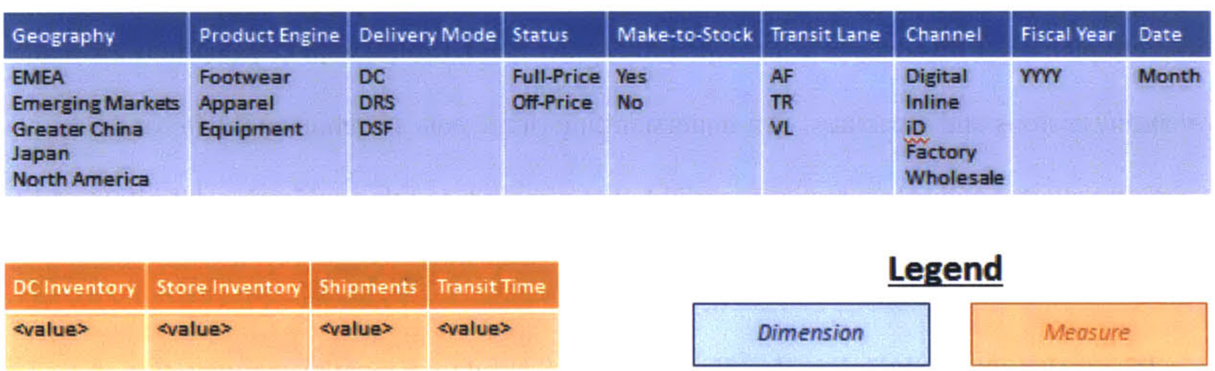

Figure 7: Visual Depiction of Dimensions and Measures

Table 1: Definitions of Dimensions and Measures

Name	Data Type	Explanation
Geography	Dimension	Region of intended sales for the product.
Product Engine	Dimension	Describes the type of product at a high level. This is

		internally important because the three groupings of product are generally designed, manufactured, and reviewed separately.
Delivery Mode	Dimension	Represents the path by which a product travels to an eventual wholesale partner or Nike DTC sales channel. Products can either be shipped directly to wholesalers (i.e. DRS), be brought into a Nike owned distribution center and then shipped (i.e. DC), or be brought into a 3rd party facility and then shipped (i.e. DSF).
Status	Dimension	Qualifies a product as either full-price or off-price which indicates if a product has been marked down.
Make-to-Stock	Dimension	Products at Nike can be classified as either Make-to-Stock or Make-to-Order, this dimension tracks which type of fulfillment model is used for each product.
Transit Lane	Dimension	Method by which the product was moved from the country of origin to the destination country. Includes Air Freight (i.e. AF), Truck Freight (i.e. TR), and Ocean Vessel (i.e. VL).
Channel	Dimension	Represents the intended sales channel. Includes Wholesale, Digital (i.e. online shopping), Inline (i.e. full-price premium), Factory (i.e. outlet discounted) and iD (i.e. personalized user-designed products) channels.
Fiscal Year	Dimension	Nike's Fiscal Year for the given Date
Date (Month)	Dimension	Calendar month
DC Inventory	Measure	Closing month number of units stored in Nike owned distribution center
Store Inventory	Measure	Closing month number of units stored in Nike owned retail stores. Includes Digital (i.e. online shopping), Inline (i.e. full-price premium), and Factory (i.e. outlet discounted) channels.
Shipments	Measure	Shipments represent the number of units shipped from Nike to either wholesaler customers or end consumers during the month.
Transit Time	Measure	Number of days spent in transit from when Nike took ownership of the product until it is either received into a Nike DC or if shipped direct to a wholesale partner, received into a wholesaler's DC

Geography	Product Engine	Delivery Mode	Status	Make-to-Stock	Transit Lane	Channel	Fiscal Year	Date
North America	Footwear	Via Nike DC	Full-Price	Yes	Ocean Vessel	Digital	2014	July

DC Inventory	Store Inventory	Shipments	Transit Time
1,000 units	100 units	500 units	40 days

Legend

Dimension

Measure

Figure 8: Example Entry in Dataset

Dataset Calculations

Dimensions and measures describe the structure of the dataset from a static lens. In order to perform dynamic calculations it is necessary to explicitly define segments and explore the calculations performed with respect to segments.

Segment: A set of measures described by a unique and specific combination of dimensions. Segments can be described by the presence or lack of dimensional constraints.

Examples:

`North America -> Footwear -> 2014 -> July:` This segment describes all measures (DC Inventory, Store Inventory, Shipments, and Transit Times) for the North American geography with respect to footwear in fiscal year 2014 during the month of July. The measures are filtered for the listed dimensions and summed across the remaining unspecified dimensions.

`North America -> 2014 -> July:` This segment is the same as above except the product engine constraint has been removed. Whereas in the prior case the measures represent only Footwear products, the measures now represent the sum of Footwear, Apparel, and Equipment products.

`North America -> Footwear -> Ocean Vessel -> 2014 -> July:` This segment is the same as the first example except that it adds a dimensional constraint around Transit Lane. This added constraint means that only those products employing Ocean Freight as a means of transport from the supplier location to the product destination will be included in the measures.

In order to calculate a measure's value for a given segment, a series of general form equations were developed. Equation 1 below demonstrates the general form for inventory measures. This equation applies to DC Inventory and Store Inventory and will produce an average end-of-month inventory when multiple dates are specified.

$$Inventory_{segment} = \sum_{Geography} \sum_{Product\ Engine} \sum_{Delivery\ Mode} \sum_{Status} \sum_{Make-to-Stock} \cdots$$

$$\cdots \sum_{Transit\ Lane} \sum_{Channel} \sum_{Fiscal\ Year} \sum_{Month} \frac{Inventory_{a,b,c,d,e,f,g,h,i}}{\sum_{Month} 1}$$

where dimensions with prescribed filters are summed only over those included qualifiers (e.g. North America -> 2014 -> July will only include North America in the Geography set, 2014 in the Fiscal year set, and July in the Month set) and a,b,c,d,e,f,g,h, and i represent the respective dimensions listed in the summations (e.g. a = Geography, b = Product Engine, etc.).

Equation 1: General Form Equation for a Segment of Inventory

For the Shipments measure, the general form equation mimics that of inventory but is additive over multiple time periods. This yields a total units shipped measure for the specified segment.

$$Shipments_{segment} = \sum_{Geography} \sum_{Product\,Engine} \sum_{Delivery\,Mode} \sum_{Status} \sum_{Make-to-Stock} \cdots$$

$$\cdots \sum_{Transit\,Lane} \sum_{Channel} \sum_{Fiscal\,Year} \sum_{Month} Shipments_{a,b,c,d,e,f,g,h,i}$$

where dimensions with prescribed filters are summed only over those included qualifiers (e.g. North America -> 2014 -> July will only include North America in the Geography set, 2014 in the Fiscal year set, and July in the Month set) and a,b,c,d,e,f,g,h, and i represent the respective dimensions listed in the summations (e.g. a = Geography, b = Product Engine, etc.).

Equation 2: General Form Equation for a Segment of Shipments

Calculation of Transit Time for a given segment requires the use of a weighted average to balance out the transit time with the volume of units through each transit lane. This is demonstrated in Equation 3. Additionally, the same level of data granularity was not available in transit times so Product Engine, Status, Make-to-Stock, Channel, and Fiscal Year dimensions were removed. This means that when data is later analyzed at a segmentation level that includes one of these unavailable dimensions, an assumption is made that the transit time is homogeneous across the subdivisions of the dimension.

$$Tranist\ Time_{segment}$$
$$= \frac{\sum_{Geography}\sum_{Delivery\ Mode}\sum_{Transit\ Lane}\sum_{Fiscal\ Year} Transit\ Time_{a,b,c,d} * Shipments_{a,b,c,d}}{\sum_{Geography}\sum_{Delivery\ Mode}\sum_{Transit\ Lane}\sum_{Fiscal\ Year} Shipments_{a,b,c,d}}$$

where dimensions with prescribed filters are summed only over those included qualifiers (e.g. North America -> 2014 will only include North America in the Geography set and 2014 in the Fiscal year set and a,b,c,and d represent the respective dimensions listed in the summations (e.g. a = Geography, b = Delivery Mode, etc.).

Equation 3: General Form Equation for a Segment of Transit Time

Forecast Data Inputs and Calculations

While the underlying data structure from Figure 7 provides the basis for collecting forecast inputs, the measures collected differ due to business process differences. Whereas supply chain groups are responsible for maintaining historical data, Nike assigns forecasting responsibility to a network of business planning groups. As a result of this distinction in group responsibility, forecasts are calculated in sales dollars rather than inventory units. Additionally, the forecasted sales plan is high-level and does not include all segments outlined by the set of dimensions above.

To create the necessary inventory dataset from the sales plan inputs, two key conversion factors are required. First, the sales dollars are converted into sales units through the Price Per Unit (PPU) measure also included in the sales forecast. Then, the total sales units are converted into inventory units through the Inventory Turns measure which is taken from the most current historical data. These conversions are done using Equation 4 below.

$$Inventory\ [Units] = Sales\ [USD] * \frac{1}{Inventory\ Turns} * \frac{1}{Price\ Per\ Unit\ \left[\frac{USD}{Unit}\right]}$$

Equation 4: Converting Sales to Inventory

Before this equation can be utilized, an explicit definition of Inventory Turns is required. For the purposes of this model Inventory Turns are calculated using the units shipped over a trailing twelve month time period divided by an end of period inventory as described by Equation 5 below. In general, Nike uses the June-May fiscal year as the time period for this calculation.

$$Inventory\ Turns = \frac{Trailing\ Twleve\ Month\ Shipments\ [units]}{End\ of\ Period\ Inventory\ [units]}$$

Equation 5: Inventory Turns Definition

Combining Equation 4 and Equation 5 allows for the conversion of sales plan data to inventory units. However, in the case of the predictive model, the trailing twelve month shipments and end of period inventory are not yet known. The predictive model assumes that inventory turns for a given segment are constant in the future. This assumption allows an inventory turns value to be calculated using historical data via Equation 5 and then combined with sales plan data via Equation 4 to generate forecasted inventory values. This assumption is validated in Section 4.4. Additionally, the inventory turns values can be edited by the user of the model to study input sensitivity and incorporate future expected increases or decreases in inventory turns.

This conversion from sales plan to inventory is essential to the usefulness of this model. Previous inventory models did not use the sales plan as a baseline and were thus not aligned with other planning activities at Nike.

4.2.2 Outputs

The outputs of the model come directly from Section 3 in which the problem was defined. Specifically, there were two key measures outlined by Nike: inventory units and inventory dollars. As a project deliverable, these measures were required for every inventory segment outlined by the data dimensionsin Figure 7.

Besides these essential measures, Nike also defined secondary metrics. First, the model required the ability to output inventory levels in terms of Days of Sales in Inventory (DSI). This is a more commonly utilized characterization of inventory at Nike and is defined by Equation 6. As mentioned previously, the typical time period utilized by Nike is the June-May fiscal calendar.

$$Inventory\ [DSI] = \frac{365\ Days * End\ of\ Period\ Inventory\ [Units]}{Trailing\ Twelve\ Month\ Shipments\ [Units]}$$

Equation 6: Converting Inventory Units to DSI

Second, Nike sought to understand the sensitivity to all of the aforementioned measures due to deviations from the original sales plan inputs. These are referred to as sensitivity studies and are conducted by manipulating the model's levers discussed in Section 4.2.3.

4.2.3 Levers

With the inputs and outputs defined, the dynamic aspect of the model can be created by giving the users levers with which they can manipulate the inputs. Without levers, the model would serve only as a one-time analysis for the baseline case. With the levers, the model can be repeatedly re-run for new scenarios that Nike wants to test. This capability makes the model able to adapt to the inevitability of forecast error. Additionally, the levers allow Nike to evaluate the impact to inventory measures based on user-created scenarios. Two such scenarios are discussed in Section 6.2.

An overview of the levers provided to the user is shown in Figure 9 below. As shown in the data schema in Figure 7 previously, many of these levers have segments within them. These dimensions and measures became model levers because Nike wanted the ability to either (a) change the mix within the dimension or (b) change the absolute value of the measure. For example, the Geography lever allows the user to re-adjust the sales projections for one Geography relative to the other Geographies and assess the impact of this change on inventory measures (e.g. How does global inventory change if China growth increases 5% faster than anticipated?). This is referred to as Geography Mix. In the case of measures such as Transit Time, the user can change the value directly and assess the impact on inventory measures (e.g. How does In-Transit inventory change if the transit time from Vietnam to Los Angeles by Ocean Freight increases by two days?).

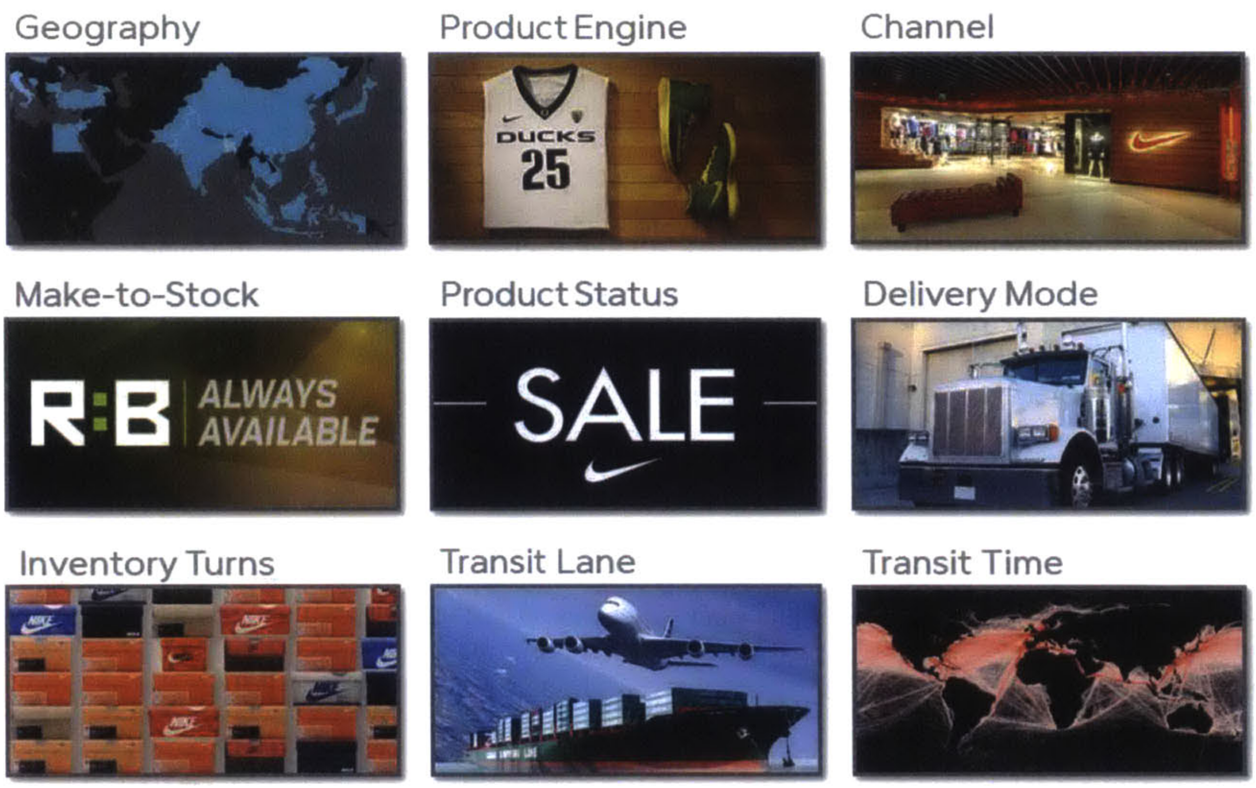

Figure 9: Representation of Model Levers

4.3 Model Development

With the inputs, outputs, and levers adequately defined, the model was then built around these fixtures. As previously discussed with regard to the inputs, there exists a stark contrast between historical inputs and forecast inputs. As such, the model development was also separated along the same boundary with one historical model developed to pull and process actualized SRI data and one predictive model developed to accept sales forecasts and generate future inventory values.

4.3.1 Historical Model

The historical model relies on data taken from SRI via the Teradata data warehouse and on data taken from the APL Logistics dashboards. Once data is extracted from these sources, it is broken apart to the most granular inventory segments, slicing it across each and every dimension. Occasionally assumptions are applied to the data to achieve this granularity as documented in Section 4.2.1. This data processing work occurs in a software program called Alteryx[10] which provides a graphical interface to clean and parse raw data. The step-by-step layout of the historical model is depicted in Figure 10 with Alteryx modules represented in the diagram. The model was specifically design to contain many modules so that each piece was self-contained and could be replaced at a later date if data systems or data architecture changed.

The historical model's main purpose is to generate a dataset that provides a set of baseline inputs for the predictive model. Currently there is no automation linking the historical to the predictive model; however, in many instances the baseline inputs for the predictive model were extracted manually from the historical model's output dataset. The historical model can be updated at most on a monthly basis as new values are loaded into the SRI system. As such, the historical model only needs to be run once for a group of predictive analyses.

The final result of the historical model is a complete historical inventory dataset with all segments represented. Although interesting takeaways are possible to derive from this dataset, no analysis was done with this backward-looking data; all analyses were conducted on the results of the predictive model. The historical model now resides on the shared drive in the Global Supply Chain Innovation group and is maintained by members of this team.

[10] Date Processing Automation Tool (http://www.alteryx.com)

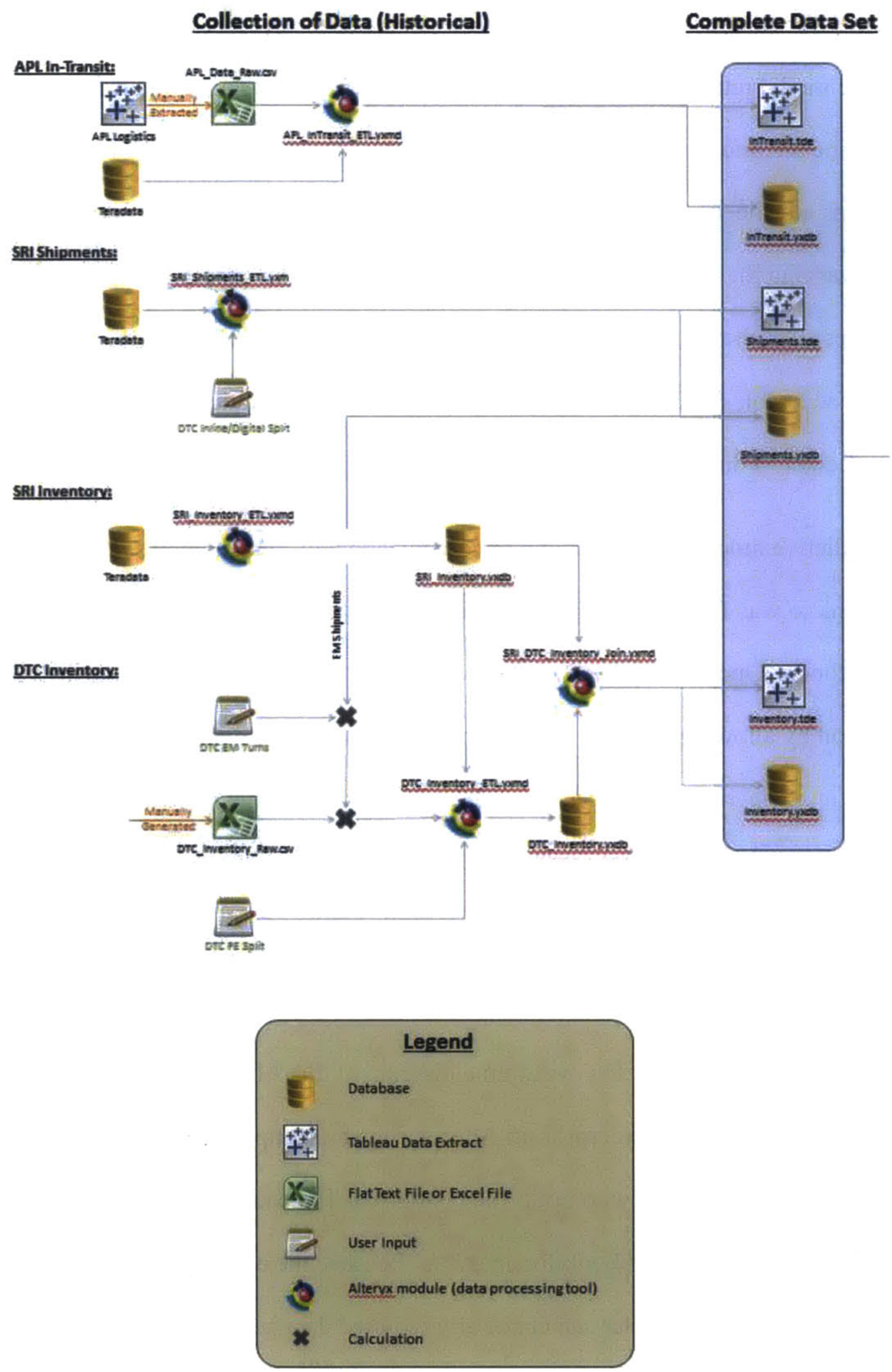

Figure 10: Historical Model Architecture

4.3.2 Predictive Model

The predictive model returns inventory forecasts in units and dollars based on the combined input of baseline historical measures and forecasted sales measures. The framework of the model serves as advanced calculation engine, allowing the user to create new future state scenarios by varying the sales plan and a host of levers that impact supply chain wide inventory. The model uses a combination of inputs and assumptions to break sales and inventory into the most granular segments (e.g. Japan → Apparel → Wholesale → Futures → Full-Price → Distribution Center → Inventory Turns = N →Ocean Freight → N Days In-Transit).

Using the predictive model framework and the organizationally agreed upon sales plan numbers, a baseline scenario was first created and validated—see Section 4.4 for discussion of model validation methods. Once the baseline scenario was put in place, the model lends itself to experimentation by allowing the user to create new scenarios that deviate in a specific dimension from the baseline scenario. These scenarios are created by overwriting one or many of the user input fields shown in Figure 11 that feed the predictive model.

While the user interacts with the model inputs via an Excel template shown in Figure 13 through Figure 17, the calculation engine, which manipulates this data and contains the majority of the model's logic, exists in Alteryx. The wireframe diagram of this Alteryx model is shown in Figure 11 with a more detailed excerpt from Alteryx shown in Appendix A.1. Once the calculations are completed, Alteryx outputs the results to a Tableau data extract which is then linked to a standard Tableau workbook for analysis. Because the data is kept in the most granular segments possible the user can create any required data tables, charts, or analyses after the running the model. New scenarios do however require new instances of the model be run.

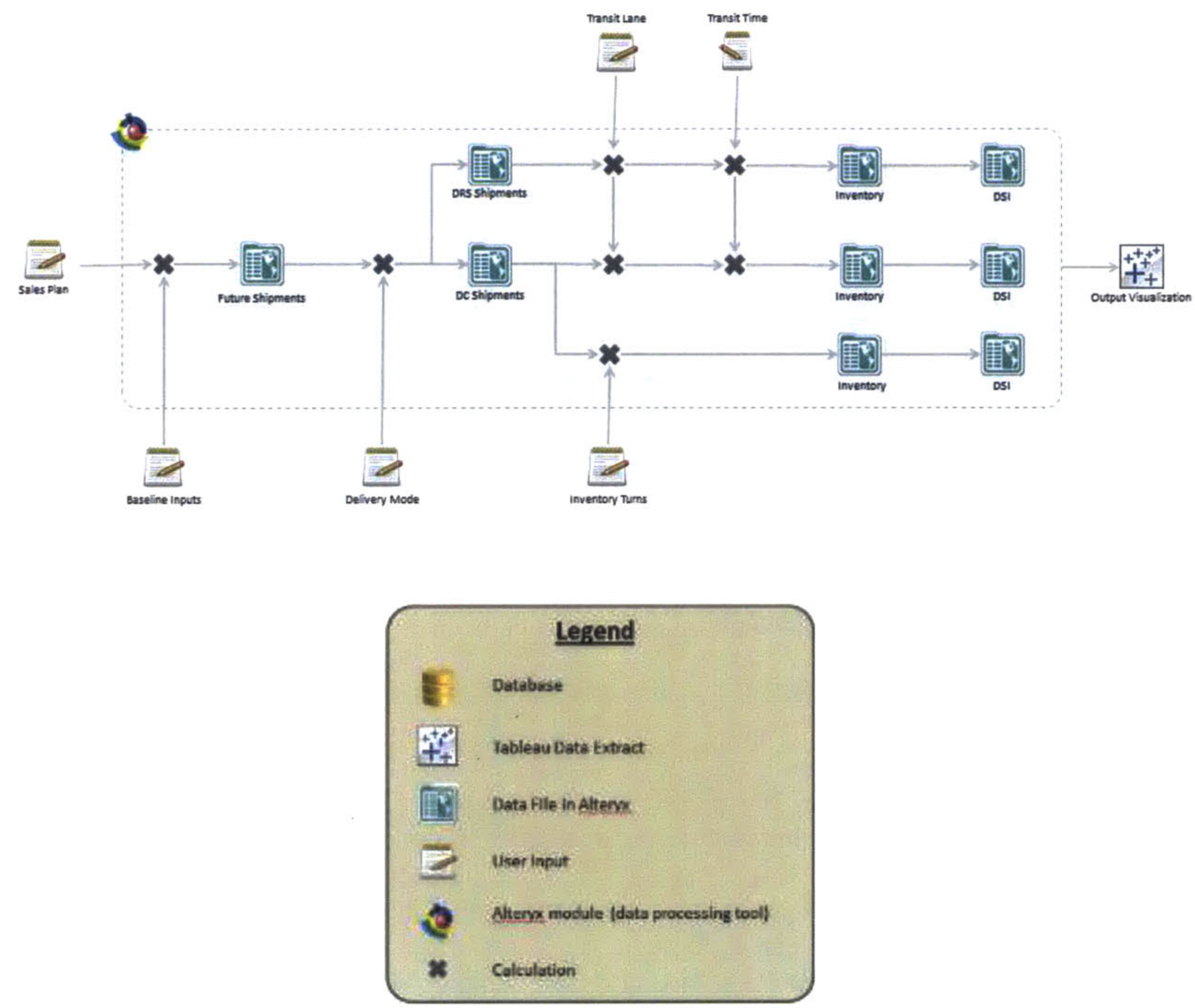

Figure 11: Predictive Model Architecture

4.4 Model Validation and Calibration

After developing the structure of the model in a combination of Alteryx, Excel, and Tableau, a meticulous process of validation was undertaken to ensure the accuracy of the calculations within the model and guard against both logic errors and typos.

Historical Model Validation

The validation process for the historical model consisted of cross-checking model results for the years of 2013 and 2014 against the actual values in these two years. By checking the output of each individual module within Alteryx in a sequential fashion, it was possible to verify each inventory segment in a step-by-step, logical manner. The following iterative process was used to establish the correct baseline values during model validation:

1) Compare DSI values at high-level segments (e.g North America)
2) Identify any segments in which the DSI values do not match
3) Select only those segments with large percentage error values and inspect more granular segments to identify what caused the discrepancies (e.g North America -> Footwear)
4) Repeat this process going into deeper segments until the offending DSI metrics are all discovered (e.g. North America -> Footwear -> Full-Price -> 2013 -> June)
5) Split DSI into Shipments and Inventory and compare these underlying measures to identify what caused DSI to be incorrect.
6) Once the offending measure is confirmed, identify the Alteryx module which performs the corresponding calculation and adjust the assumptions in the model to set the measure to be in-line with the expected value.
7) Repeat all steps until all segments of inventory are close to their real values (the more granular the segment the more the value is allowed to drift from the real value).

By comparing a distributed selection of inventory segments to the correct historical values, a number of errors were identified and corrected.

For the historical model, this validation process proved that the actual historical values observed by Nike very closely matched with the model's calculation for the same measures. Table 2 below shows a high-level comparison of the DSI by geography for FY13 and FY14 between the calculated and the real values. In the case of the historical model, the real values represent what is stored in the Nike data warehouse. The calculated values represent the DSI values generated by the historical model after applying segmentation assumptions to the data and then re-aggregating the values. These assumptions are stated in section 4.2.1 and are necessary to create the complete set of segments for the model.

Table 2: Percent Difference in DSI by Geography (Historical)

	Geography					
Fiscal_Year	North America	EMEA	Emerging Markets	Greater China	Japan	Grand Total
2013	-0.14%	0.00%	-0.03%	0.00%	0.00%	-0.06%
2014	0.00%	0.00%	0.77%	0.00%	0.00%	0.02%

These calculations were performed using Equation 7.

$$Percent\ Difference = \frac{(Real\ DSI_{segment} - Model\ DSI_{segment})}{Real\ DSI_{segment}}$$

Equation 7: Calculation of Percent Difference for Validation of DSI by Segment

Similar comparisons to those shown in Table 2 were performed for more granular inventory segments as needed when high error percentages were identified.

Predictive Model Validation

The validation process for the predictive model utilized a similar process-driven approach of verifying individual inventory segments at more and more granular levels. However, validation for the predictive model differed from the historical model due to the forecasted nature of the inputs. This issue was addressed in three ways:

(1) Using the Predictive Model architecture to simulate 2013 and 2014 data and cross-checking the results with real values
(2) Ensuring data integrity of the results
(3) Validating the methodology used to forecast inventory

The first part of these three validation steps to simulate 2013 and 2014 data enable the use of the same validation steps utilized on the historical model. As such, Table 2's comparison between calculated and real DSI was regenerated using predicted model DSI values and real DSI values in Table 3. Because of the use of additional assumptions, the predictive model showed slightly larger differences to the actual DSI values. However, these differences cancelled out when re-aggregating the segments as shown by the Grand Total column below. This helps give us confidence that the differences are due to variation introduced by using assumptions to split the data apart into segments and not issues with the sales plan data itself or the model architecture. Again, Equation 7 was used for the calculations.

Table 3: Percent Difference in DSI by Geography (Predictive)

	Geography					
Fiscal_Year	North America	EMEA	Emerging Markets	Greater China	Japan	Grand Total
2013	-0.64%	0.41%	-0.02%	-0.44%	-0.72%	0.23%
2014	0.30%	-0.24%	-3.29%	-0.28%	-4.42%	-0.15%

Second, the validation process wanted to ensure data integrity of the sales plan numbers. This meant that if the sales plans specified a number of units sold for a particular segment, when that segment was broken into more granular segments and then re-aggregated into a single segment, the numbers should be almost exactly the same.

Third, the use of Equation 4 to predict inventory required the assumption that inventory turns for particular segment were relatively constant year-to-year and could be assumed constant into future years. While inventory turns is never exactly consistent year-to-year, it does appear to be a good approximation as shown by Table 4. Furthermore, the data shows that the inventory turns number is relative to the prior year. Because inventory turns in the prior year is simply a baseline and can be adjusted by the user of the model, it generates a wonderful picture of what will happen to total inventory if inventory performance does not change year-to-year. Then, if desired, the user can manipulate the inventory turns value to reflect changes to inventory performance based on company specific knowledge.

Table 4: Inventory Turns by Geography by Fiscal Year

	Geography					
Fiscal_Year	North America	EMEA	Emerging Markets	Greater China	Japan	Grand Total
2013	8.8	6.8	6.0	7.5	5.9	7.5
2014	8.6	7.7	5.7	8.5	6.2	7.7
2015	8.8	8.2	5.7	9.1	6.3	8.0

4.5 Model Automation

One of Nike's requirements for success on this project required that the models be re-usable and sustainably by non-LGO Nike employees after the internship ended. To achieve this goal, a focus on reusable data sources and tools was made during the design and development of both the historical and predictive models.

The choice of data sources for the model was not simple. Nike has many overlapping reporting systems. SRI was identified internally as the best representative across all Geographies but the ability to pull data from SRI was significantly inhibited by the interface. As such, the interface was circumvented by directly querying the underlying Teradata database with custom SQL code. While this process was now repeatable, it was not sustainable because most people involved with the project did not possess the knowledge or permissions to execute these queries. To ensure sustainability, the SQL queries were brought into Alteryx modules where they could be run automatically with the rest of the data processing. This selection of Teradata, SQL, and Alteryx means that future iterations of the model can update in seconds rather than weeks.

In addition to the selection of data sources, the choice of tools was a key determinant in the ability to find the right balance of automation and usability in the model. Excel was chosen as the primary data entry tool due to its familiarity within the Nike community. However, the majority of the calculations were not performed in Excel because of concerns about maintaining the model going forward. Instead, all of the data processing steps were completed in Alteryx where they could be graphically laid out and more easily maintained. This combination of tools attempts to bring pieces of the model where user interaction is required into familiar software tools while abstracting the mechanics of the calculations behind highly automated software tools.

5 Model Walkthrough

This section provides a walkthrough of how the historical and predictive models are used in practice. Using the sequence diagrammed in Figure 12 as a framework for visualizing the model workflow, this section will describe each of the five steps in detail.

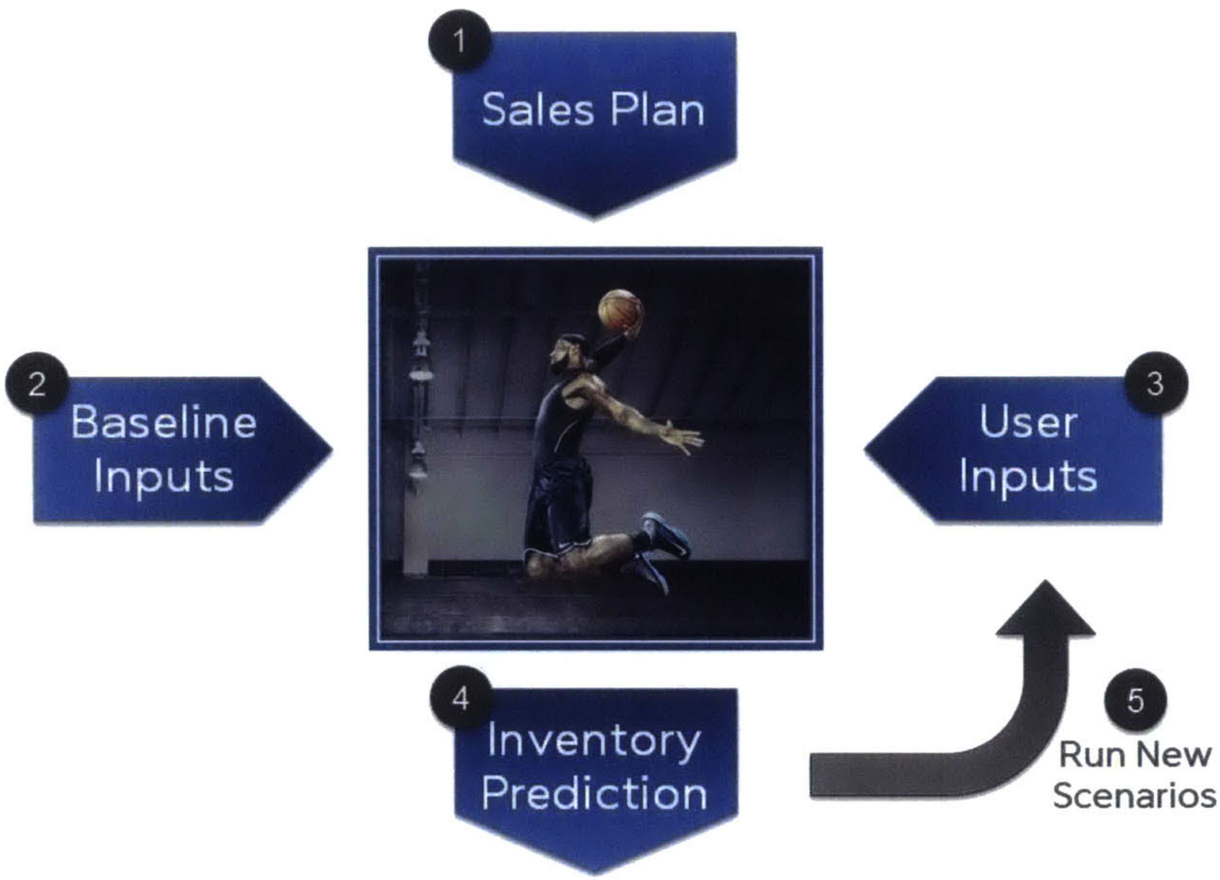

Figure 12: Inventory Model High-Level Overview

5.1 Step 1: Entering Sales Plan

The sales plan is generated on a yearly cycle through a combined effort of many groups. At this point in time, the sales plan data utilized was a combination of data from the Global Business

Planning group, the Global DTC group, and the Global Supply Chain group. Once this data is collected, it needs to be entered into an Excel template. This template should be named after the scenario being analyzed (e.g. "Baseline", "5percent_Shorter_Transit_Times"). An example template for the North America Geography for the Wholesale channel is shown in Figure 13. This data entry needs to be repeated for each Geography->Channel combination.

Geography:	North America					
Revenue (000s)	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Footwear	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Apparel	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Equipment	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Total	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Product Cost (000s)	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Footwear	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Apparel	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Equipment	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Total	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Shipment Units	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Footwear	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Apparel	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Equipment	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Total	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 13: Sales Plan Template

The sales plan data is entered into this template for each cell indicated in this template. This breaks down to the following:

Measures:

Revenue – [USD Total]

Product Cost – [USD Total]

Shipments – [Units Total]

Dimensions:

Geography – 5 Segments

Product Engine – 3 Segments

Fiscal Year – 6 Segments

This means that for each input measure, there are 90 inputs (5x3x6) taken from the sales plan. With three total input measures, this means the sales plan must provide 270 data points.

5.2 Step 2: Baseline Inputs

Once the sales plan data is entered, a host of secondary input fields need to be filled out. These fields are necessary because the sales plan data is not available for all segments. In Step 2, the user fills out the baseline values for each remaining input. Note that these values can later be overwritten for the purposes of analysis during Step 3; however, the baseline inputs are taken from actual values for 2013 and 2014 as a starting point. This is where the dataset generated by the historical model is very helpful. Each necessary baseline value is taken from the historical model at the correct segmentation depth.

Then, for 2015 onward, the baseline model simply carries the 2014 numbers forward. Thus, the baseline model assumes that nothing changes except for the sales plan. With that in mind, it is important to understand that the sales plan does not hold Geography mix, Product Engine mix, or Channel mix constant as these are inherent components of the sales plan.

A quick walkthrough below explains the inputs necessary for splitting sales plan data by Status, Make-to-Stock, Delivery Mode, and Transit Lane. Additionally, Inventory Turns is a necessary input as it is the driver of future inventory predictions. Example baseline input fields are given in Figure 14 through Figure 17Figure 16 below. Each of these baseline inputs applies as a different level of granularity as the segments are broken apart one-by-one.

First, the split by Status, between Full-Price and Off-Price, applies at the Geography->Product Engine->Fiscal Year level. The template for this is shown in Figure 14: Data Input Fields for Percentage Offprice (i.e. Status) Baseline values are taken from the historical model for 2013 and 2014 and then assumed constant through 2018.

Split by Status (FP/OP)

Percent Offprice (Units)	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Footwear	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Apparel	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Equipment	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Total	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 14: Data Input Fields for Percentage Offprice (i.e. Status)

Second, the split between Made-to-Stock and Make-to-Order, applies at the Geography->Channel->Fiscal Year because of the strong correlation between this dimension and the channel dimension. The template for this is shown in Figure **15**. Baseline values are taken from the historical model for 2013 and 2014 and then assumed constant through 2018.

% Made-to-Stock

Shipments Split (Units)	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Digital	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
iD	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inline	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
NFS	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
WHSL 3rd Party	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 15: Data Input Fields for Percentage Make-to-Stock

Third, the splits for Delivery Mode and Transit Lane, which are done together, apply at the Geography->Fiscal Year level. These two dimensions are grouped because of the strong tie between them. The template for this is shown in Figure 16Figure **15**. Baseline values are taken from the historical model for 2013 and 2014 and then assumed constant through 2018.

Throughput (% Units)		**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
DC	AF	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DC	TR	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DC	VL	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DRS	AF	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DRS	TR	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DRS	VL	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DSF	AF	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DSF	TR	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DSF	VL	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 16: Data Input Fields for Percentage Delivery Mode and Transit Lane

Lastly, the baseline values for inventory turns apply at the Geography->Product Engine->Status->Fiscal Year level. The inputs for this measure are done at a more granular level than other baseline inputs because of (1) the importance to the accuracy of the model and (2) the wide variability across the four dimensions specified. The template for this is shown in Figure 17Figure 16Figure **15**. Baseline values are taken from the historical model for 2013 and 2014 and then assumed constant through 2018.

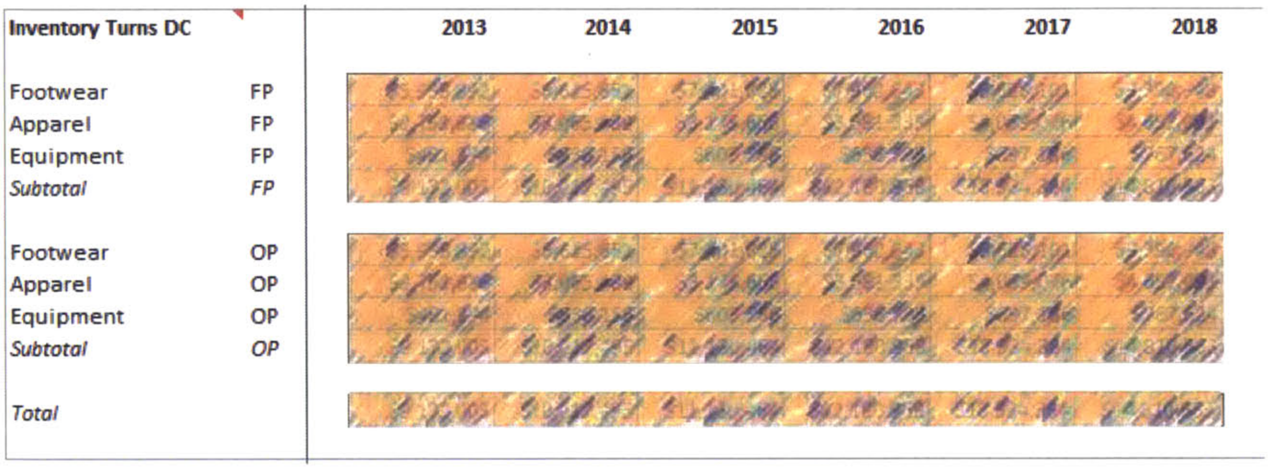

Figure 17: Data Input Fields for Inventory Turns

5.3 Step 3: User Inputs

During Step 3 the user has the chance to overwrite any of the values defined in both Step 1 and Step 2. This flexibility allows the user to create any scenario that they desire relative to the model inputs. While highly-flexible, only one variable should be altered at a time so that the effects of each discrete change can be studied and understood. Additionally, these overwritten values should make practical sense within the scope of Nike's business and the market. For example, it would not be realistic to overwrite the model inputs with values showing inventory turns improving by 100% year-over-year as this would require such drastic changes to the supply chain infrastructure that the model itself would need to be re-evaluated for accuracy.

5.4 Step 4: Inventory Prediction

Once the model inputs for a given scenario are all entered, the user must run a module in Alteryx called Process_Inputs.yxmd to import all of the inputs, run a series of calculations, and output the results. For each scenario, output is generated in two forms: a Tableau dashboard with the same standard visualizations and a comma separated value (CSV) file. The Tableau dashboard facilitates standard comparisons and analysis of the output measures while the CSV file preserves the data in a minimized but easily exported format. Each specific scenario will likely require the creation of additional analysis tables and charts to study the specific results of any user input changes. Tableau makes this ad hoc analysis simple for users familiar with the software or for those unfamiliar, the CSV can be analyzed through tools such as Excel.

The inventory predictions are a result of Equation 4: Converting Sales to Inventory. This Equation relies on Sales [USD], Inventory Turns, and Price Per Unit [USD/Unit] to generate an Inventory [units] value. This process and the additional equations involved in making forecasts and disaggregating and re-aggregating segments are described in Section 4.2.1.

5.5 Step 5: Run New Scenarios

After creating a baseline scenario via Steps 1-4, the user can create new scenarios via Step 5 through an iterative process back to Step 3. In practice, Step 5 simply redirects the user back to Step 3 where the user can overwrite baseline input values to create a new model scenario. For each desired scenario, the user saves a new set of inputs during Step 3, then re-runs the model during Step 4, and finally re-analyzes the results also during Step 4. This iterative process of running scenarios can continue ad infinitum or until all relevant analyses have been completed.

For each new scenario a new set of input and output files are generated and saved to a folder with the specified scenario name.

6 Model Results for Fiscal Year 16-18

The Predictive Inventory Model provides Nike with a large dataset of possible results; however, the relevancy of these results is dependent on the question being asked. For the purposes of this paper, the results from the baseline scenario will be presented for the time period FY15-18 with an emphasis on the key drivers impacting baseline inventory changes. The results of two brief sensitivity analyses are then presented as demonstrations of this feature in the predictive model.

6.1 Baseline Results

The baseline scenario utilizes the raw sales plan values that were aggregated from across the Nike organization. This scenario attempts to simulate what would happen to inventory at Nike if the sales plan was 100% accurate and the supply chain conducted business as usual while delivering on that sales plan. As stated previously, the sales plan does not maintain all levers at a constant breakdown, it simply collects the existing sales forecasts made throughout the organization. Specifically, the Geography mix, Product Engine mix, and Channel mix all vary within the sales plan. As such, the results from this baseline case convolve the effects of simultaneous shifts in these three levers.

Based on shifts in these three levers, the predictive model estimates a growth of 2% DSI from FY15 (May 31, 2015) to FY18 (May 31, 2018). The chart, stripped of absolute data for confidentiality purposes, in Figure 18 shows this small uptick in DSI at the global level. This information is critical to Nike because the historical trend for many years was to reduce the inventory year-over-year based on efficiency gains in the supply chain. As Nike has begun to stray further from a business dominated by Footwear sales in North America via Futures orders, the trend toward less inventory can no longer be relied upon. The inventory projections presented here take into consideration the subtle differences across each supply chain segment at Nike and produce a more complete picture of how inventory will change going forward.

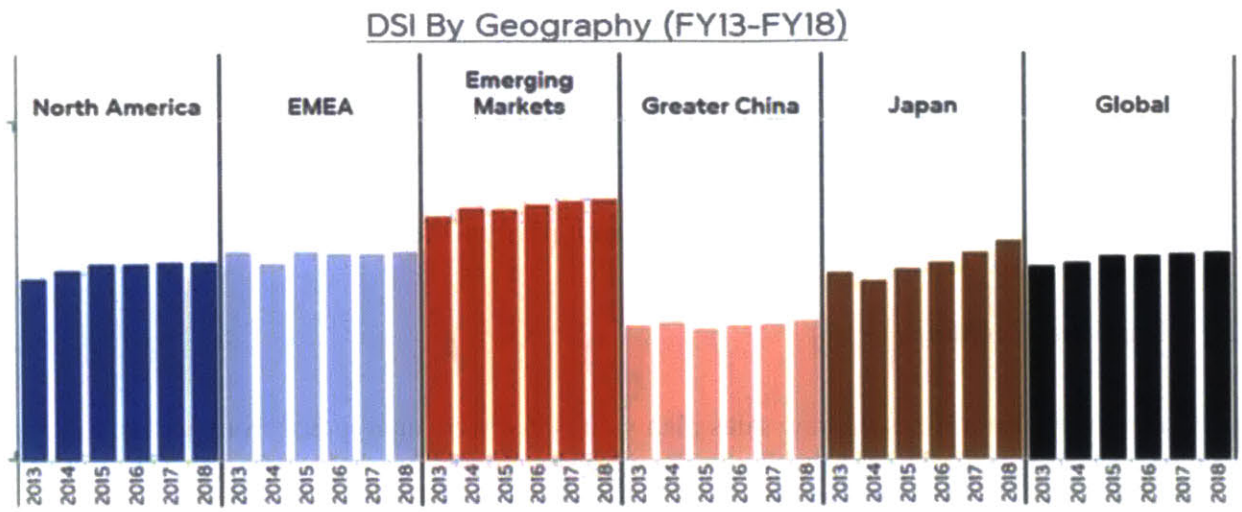

Figure 18: Baseline Model Results - DSI Projections (FY13-FY18)

While there are three levers at play in the baseline scenario, using comparable A/B scenarios in the model, it was determined that the two levers responsible for the 2% DSI growth over the next three years are relative increases in Apparel products and Direct-to-Consumer channels. Changes to Geography mix resulted in a near negligible decrease in DSI.

6.1.1 Apparel Growth

Sales of Apparel products are projected to grow 4% faster than sales of footwear products over the next three years as shown by Figure 19. Based on current inventory levels, Apparel sales require 26% more inventory throughout the supply chain than footwear. This relative difference in sales growth and inventory holding from across Product Engines is responsible for 47% of the global DSI growth over the next three years. These metrics were determined by re-running the baseline model with the Product Engine mix held constant from FY15-FY18 and comparing the results to the original baseline case. To hold the Product Mix constant, the breakdown of Footwear, Apparel, and Equipment as a percent of total units was assumed to remain at the same percentage for FY15-FY18 as achieved during all of FY14.

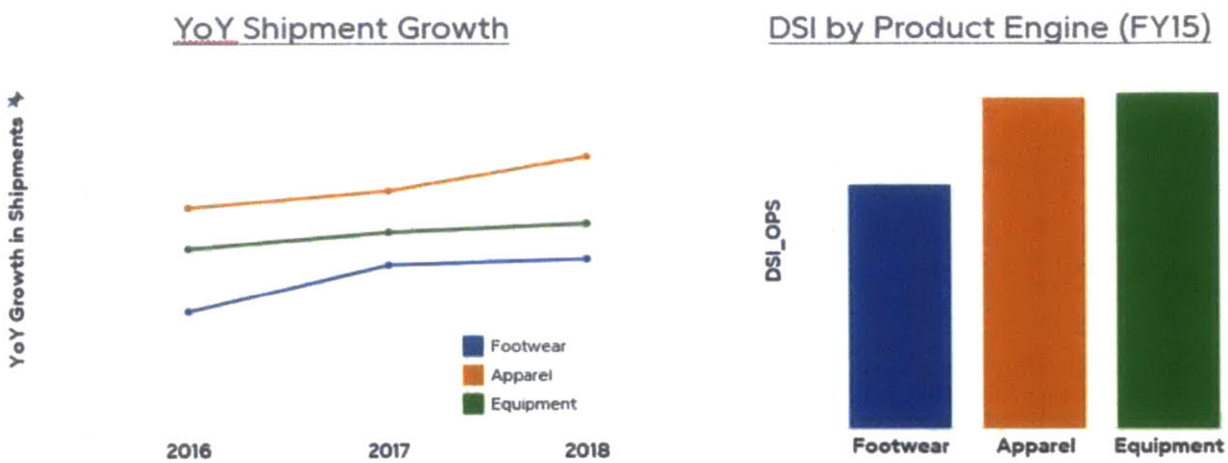

Figure 19: Baseline Model Results - Relative Growth in Apparel

6.1.2 Direct-to-Consumer Growth

Sales of Nike products through Direct-to-Consumer channels are projected to grow 7% faster than sales through wholesale channels over the next three years as shown by Figure 20. This is particularly problematic for Nike's inventory because Store Inventory is included in Nike's assets for Direct-to-Consumer channels (e.g. Inline, Factory, Digital, & iD) but not for the wholesale channel. Due to this difference in inventory allocation, DTC sales require 93% more total inventory and 3% more DC inventory than wholesale sales. This relative difference in sales growth and inventory holding from across Channels is responsible for 53% of the global DSI growth over the next three years. These metrics were determined by re-running the baseline model with the Channel mix held constant from FY15-FY18 and comparing the results to the original baseline case.

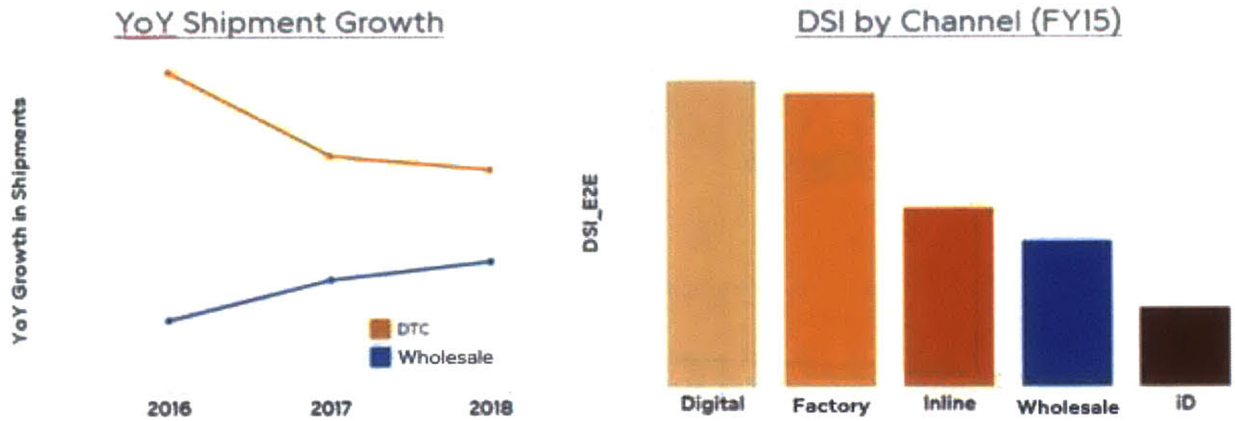

Figure 20: Baseline Model Results - Relative Growth in Direct-to-Consumer

6.2 Sensitivity Analysis Results

With an understanding of the drivers influencing the base case, namely product mix and channel mix, , it is now interesting to analyze additional scenarios with the model. Specifically, two levers were used as experimental examples of how the model can produce sensitivity analyses when model levers are varied.

6.2.1 Transit Lane - Air Freight Percentage

Total Logistics Cost is a key metric within Nike's Supply Chain organization.

$$Logistics\ Cost = Distribution\ Cost + Warehousing\ Cost + Transportation\ Cost$$

Equation 8: Formulation for Logistics Cost at Nike

A large portion of this cost comes from the increased transportation cost when shipments are sent via air freight rather than ocean freight. Due to this high cost of air freight, Nike repeatedly targets a reduction in the percentage of products shipped via air freight year-over-year. However, a myopic view of air freight cost does not take into account the reduced inventory holding costs due to the shorter lead times yielded from this transit lane. To approximate the impact on existing inventory due to the use of air freight, a new scenario was created in the predictive model that eliminated all air freight globally at Nike. The inventory previously transported via air freight was redistributed proportionally to ocean and truck transit lanes.

After running this new scenario through the model, the result was a 2% increase in global inventory at Nike. Using the FY14 closing inventory of \$3.9Bn this translates to \$78 million in additional inventory on Nike's balance sheet without layering on the additional cost of capital. All future decisions related to targeting Total Logistics Cost can now benefit from an understanding of this tradeoff. Actual implementation of a strategy to eliminate air freight will need to be phased in over time to not affect service levels.

Figure 21: Sensitivity Analysis Results - Transit Lane

6.2.2 Delivery Mode – Direct Ship Percentage

The decision to ship product directly to a wholesale partner's warehouse instead of processing it through Nike's geography specific distribution centers has a significant impact on overall inventory. By skipping the geography specific distribution center, Nike can save unnecessary inventory holding and processing costs while reducing lead times. This concept of "Direct Ship" is relatively new within Nike's supply chain but is already widely utilized by Nike in the United States, especially for footwear products.

An order that is sent via Direct Ship must be properly staged upstream at the consolidator so it can easily be split from other Nike shipments and sent to the proper wholesale partner's warehouse. Thus, the drawbacks of Direct Ship are reduced flexibility for the product while in-transit and the need to have sufficient order quantities to eliminate any break-pack or split-shipments that require activities be performed in the distribution center.

With a growing percentage of Direct Ship orders worldwide, a scenario was created to characterize the total potential savings from this program. With 10% more of the wholesale shipments using the Direct Ship delivery mode, Nike would save 7% of the total inventory units assuming an equal distribution across all segments. Again using the FY14 closing inventory of $3.9Bn this translates to a $273 million savings from reduced inventory on Nike's balance sheet without layering on the additional cost of capital.

Figure 22: Sensitivity Analysis Results - Delivery Mode

7 Conclusions and Recommendations

Due to the importance placed on accurately predicting inventory movements by Wall Street analysts and the corresponding significance to delivering shareholder value, Nike must continue refining their ability to understand and predict changes to inventory. In the past decade this task has been complicated by a changing, more fragmented retail environment and widespread segmentation of Nike's supply chain. The model developed and presented throughout this paper provides Nike with a tool to both understand historical movements in inventory and predict future changes.

7.1 Conclusions

The preliminary results of this model have provided significant insight to the inventory forecasts over the time period FY15 – FY18 with secondary analyses providing sensitivity results around the key inventory levers for the purposes of weighing tradeoffs during future decision making. The following key points summarize the learnings derived from this project:

- Higher segmentation increases supply chain complexity and makes it more and more difficult to accurately set Wall Street analyst expectations
- Variations in the underlying sales plan can have a significant impact on the inventory levels because different segments have wildly different inventory carrying consequences
- Relative growth in Apparel and Direct-to-Consumer will grow baseline inventory by 2% from FY15 – FY18 if the sales plans are accurate
- Future changes to supply chain strategy and tactics are required to drive inventory levels downward in the face of this upward pressure

7.2 Immediate Recommendations

With the model successfully handed off to the Performance Management team within the Global Supply Chain Innovation group at Nike, there are trained individuals capable of continuing to operate and improve the existing model. In the immediate future, the model should be used to support the target setting process for FY16 throughout the spring. As new historical data is made available and sales plan forecasts are revised, the model should be updated to reflect the new measure values and new predictions should be generated.

Outside of the target setting process, the model should be used to help analyze the impact on inventory related to strategic business decisions stretching out to FY18. This can be accomplished by creating scenarios to emulate the possible future-state supply chains for each side of the decision being analyzed.

Lastly, a parallel project should be launched to integrate the model into the standard Nike processes related to business planning. This would allow for standardized inputs to be collected from each of the existing business planning groups and better ensure the quality of the model inputs.

7.3 Long-term Recommendations

As Nike looks further toward the future of their business and grows toward their stated goal of being a $50 Billion company, there are a number of improvements that could help them get there either faster or with less pain along the way. During the course of this project a significant amount of time was dedicated to identifying and gathering the necessary dataset. As discussed during Section 1.2.2, the matrix organizational structure has far-reaching implications. One such implication is the difficulty of finding a complete and accurate dataset.

While this project made significant strides in bringing data to the surface from many layers deep in the Teradata data warehouse, additional administrative work preparing data could facilitate future projects like this one in a fraction of the time. Specific recommendations for the SRI dataset include:

- Create a standard set of data dimensions and include these on all product related data
- When adding new dimensions, force the inclusion of the dimension on all related data so that tables grow tall instead of wide (e.g. Do not separate inventory into three measures called `Footwear_Units`, `Apparel_Units`, and `Equipment_Units`; instead have a dimension called `Product_Engine` and a measure called `Units`.
- Keep forecasts and actuals in the same data warehousing so they are easily compared

As these recommendations are put into place, the value and accuracy of the model will slowly increase. The true challenge will be whether the advancement of the model can keep pace with the increasing product market complexity and supply chain segmentation.

8 References

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A.1 Appendix A – Sample Module from Alteryx

This image depicts a module used to process inbound data, determine the number of units and average transit time, and write the output to a local file. Alteryx completes these actions by linking together a series of graphical interface icons for each discrete data manipulation function.