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RAW MATERIAL VARIABILITY IN FOOD MANUFACTURING

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Raw Material Variability in Food Manufacturing

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Abstract

Food manufacturing firms discard or substantially discount millions of dollars in finished goods each year due to suboptimal quality outcomes. We characterize the operational decisions of a food manufacturing firm and link them to strategic decisions that affect finished goods quality under raw material variability, which is uncertainty about the characteristics of the raw material inputs to the production process. We then consider the firm's supply chain choices, boundaries, and technological investment options that allow for control of raw material variability, and we characterize the strategic decisions available to the firm. Our final goal is to provide managerial insights into how firms facing raw material variability consider and select among their strategic options. Recent food manufacturing literature discusses food waste, regulation, supply chain management, and innovation, but little work has been done to connect inter- and intra-firm decisions. We contribute to the literature by showing that firms facing operational challenges need to consider their strategic options as integral to the manufacturing process.

JEL Codes: D22, L66, M11, Q13

KEYWORDS: Food Manufacturing, Production Management, Supply Chain Management, Agribusiness

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1 Introduction

Food manufacturing is a major global industry, with approximately $3 trillion in revenues (Hartman, 2015). Food and beverage manufacturing represented 14.7 percent of the total value of shipments from all U.S. manufacturing facilities in 2011 (USDA, 2017), and large manufacturing plants (those with 100 or more employees) accounted for 77 percent of total shipments. Processed foods have become deeply integrated into the modern American diet. Processed food firms face significant challenges in safety, traceability, regulations, consumer preferences, and manufacturing. Our research addresses the challenges created by raw material variability in food manufacturing. We partner with a large manufacturer of –flour based snack foods to study their production processes and strategic options. Our research uses variability, or uncertainty, in wheat-flour characteristics to study the operational and strategic decisions of the firm. First, we characterize the operational decisions of the firm given raw material variability. We then consider the firm's supply chain choices, boundaries, and technological investment options that allow for control of raw material variability, and we characterize the strategic decisions available to the firm. Our work is important for several reasons: it is the first work of which we are aware to conduct an economic analysis of raw material variability in food manufacturing; we believe that there is economic opportunity for improvement in food manufacturing efficiency, including improvement in firm profits and the reduction of manufacturing food waste. Our overarching goal is to provide managerial insights into how firms facing raw material variability consider and select among their strategic options.

Working with a firm whose primary raw material is wheat-flour provides insights into a major component of the American diet. According to the United States Department of Agriculture, Americans consumed approximately 135 pounds of wheat per capita in 2014 (Bond and Liefert, 2016). The standard American diet consists of significant grain consumption (Grotto and Zied, 2010) as a portion of total caloric intake. The bread and baked snack industry is comprised of several major segments: large commercial bakeries, specialty bakeries, and local or retail bakeries, all of which compete for market share. They will generate nearly $70 billion in revenues in 2016. Our research focuses on commercial and specialty bakeries that are large enough to manage and plan their own supply chains and make strategic decisions that relate to their operational capabilities.

During informal interviews (Bourquard, 2016a, 2015), members of the baking and bread manufacturing industry have expressed that there are costs and challenges associated with flour variability and degradation prior to use. These are the costs manufacturers face above their costs of production and procurement compared to firms in non-biological industries. We believe these costs are a key differentiator between the processed food and non-food industries and that they are economically important.

We use a multi-stage process to analyze the operational and strategic decisions of a processed food manufacturing firm. First, we apply an econometric analysis to the manufacturing controls and flour characteristics to determine their relationships to finished goods quality outcomes. We then use the technical coefficients from the econometric analysis to parameterize an operations model to characterize the full set of operational decisions available to a firm. Finally, we use cost and price data to analyze the strategic options available to the firm. This paper presents the econometric analyses as well as proposes the operations model appropriate for the second stage.

2 Literature

We draw on several important threads of literature for our work. Primary research upon which we build includes the fields of supply chain management, perishability, and operations research. We also review briefly some research related to wheat-flour degradation.

Modern supply chain management can be traced to *Industrial Dynamics* by Jay W. Forrester (Forrester, 1961), who stated:

> Industrial dynamics is the study of the information-feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise. It treats the interactions between the flows of information, money, orders, materials, personnel, and capital equipment in a company, an industry, or a national economy (p.13).

Forrester, according to John Mentzer et al. (2001), identified the key issues and dynamics that comprise the modern field of supply chain management. The growth over the past several decades of the study of management science, particularly emphasizing the role of strategically managing inputs and outputs of the firm, has proliferated an enormous number of papers dealing with multitudinous aspects of the supply chain. This project draws from several key texts, including *The Logic of Logistics* by Simchi-Levi, Chen, and Bramel (2005) and *Fundamentals of Supply Chain Theory* by Snyder and Shen (2011).

Work in supply chain management emphasizes a system approach beyond minimizing transportation costs or reduced inventories. Instead, it illuminates the trade-offs present in the supply chain, the impacts decisions have on the system as a whole, and the decisions to optimally match supply and demand. The supply chain literature focuses on a variety of problem types, including network design, production and inventory planning, procurement, and transportation. Each set of problems makes various assumptions regarding customer demand, input availability, infrastructure, and product storage (Simchi-Levi et al., 2005).

The research question we propose is best viewed as an integrated production, inventory, and procurement problem, but with added perishability and quality challenges. We focus on single or multi-location manufacturers who's primary input is an agricultural derivative, wheat-flour, that presents variability challenges to the manufacturer.

Early work in supply chain problems included work on optimal order quantities (Arrow et al., 1951) wherein the policy maker only chose the order size, leaving price, demand, or bargaining as exogenous. The work allowed comparisons between certain and uncertain demand environments, as well as proving that optimal order quantities under static conditions will be constant. Thus, the policy maker is determining what inventory to hold based on their known depletion of stocks. This is a cost minimization program given some constraints and known parameters for demand, and order and holding costs.

Our work accounts for the variability in the raw material used in manufacturing. Related to this is the literature around perishability. Significant work has been undertaken around deterioration with known or predicted deterioration distributions, such as Covert and Philip (1973), who use a Weibull distribution to demonstrate changes between deteriorating and non-deteriorating inventory ordering plans. Similar work was undertaken by Tadikamalla (1978), who use a gamma distribution for deterioration. Both authors cite Ghare and Schrader's 1963 work "A model for exponentially decaying inventory," in which they demonstrate a relation for optimum cycle time using a standard procedure for economic order quantity determination. Significant work between the 1960s and 1980s was conducted studying the blood bank problem. The research contributed to improved blood distribution and storage, where demand is random, usage is unknown but less than demand, and product lifetimes are limited. As stated by Prastacos (1984), contributions from blood banking research include methodological improvements for perishable inventories, as well as the application of the results to useful management rules and decision support systems.

The development of these lines of research into theory and applied perishability problems led Nahmias in 1982 to note, "that although blood banking problems appear to have dominated the interest of researchers and underlie most of the theoretical perishable inventory models developed, one would think that food management problems would have a far greater economic impact" (p.703). Indeed, more recent literature has looked at food manufacturing problems with perishability issues.

Work in the 1960s, such as Brown, Lu, and Wolfson (1964) focused heavily on obsolescence, of particular concern as technology products entered mass production. Additional work from which perishability research developed studied fashion. Murray and Silver (1966) note that most work relied on either deterministic or stochastic sales with known probabilities. They introduce uncertainty with information updating (Bayesian updating) to the model of how much a retailer purchases (or how much a producer should manufacture).

We address some challenges of intermediate raw material deterioration or variability, by which we will assume final consumer demand is known or can be met through current production. While a manufacturer knows with a high degree of certainty how much they need to produce, they do not know the condition of the wheat-flour at the time it arrives. There are two periods during which the flour deteriorates: transit and storage. Additionally, creating exact specifications in flour is challenging, resulting in variability in initial blends. Authors have addressed storage deterioration, one of the most known works from Fries (1975), who addresses optimal ordering policy for perishable commodities. Fries includes a fixed lifetime for inventory units, and treats the units as if they are waiting to be sold to final customers, which has marginal application to our research.

Most of the work in food manufacturing focuses on perishability for products destined for final sale. Entrup's 2005 dissertation focused on integrating self-life into production planning through an analysis of advanced planning systems, or firm level software. This work developed differences between firms producing fresh inventory versus traditional firms without degradation problems. The research focused on yogurt, sausage, and poultry firms making production decisions knowing that their outputs were perishable.

Perishable inputs can impose significant costs on wholesalers and retailers, who attempt to balance the trade-off between preservation effort costs and benefits. Cai et al. (2010) explore exactly this problem using a model in which a distributor determines optimal order quantity, level of preservation-effort, and sales price, while accounting for wholesale price, preservation costs, spoilage, and demand. They explore decentralized and centralized systems, as well as incentive schemes to induce coordination in the supply chain. They find that under decentralization, the distributor always orders less than they would for non-perishable products, and that profits are generally higher under a coordinated supply chain. In the coordinated case, the distributor and wholesaler share chain profits by adjusting the wholesale price based on spoilage. Optimal wholesale prices set by producers can be characterized in a Stackelberg game wherein the producer considers the reactions of the distributor. Thus, in both coordinated and non-coordinated systems, the supply-buyer relationship involves strategic decisions by both parties.

Two recent literature reviews provide some context and updates regarding inventory systems with deterioration and supply chains with perishability. Bakker, Riezebos, and Teunter (2012) provide an overview of the literature for inventory systems facing deterioration challenges published between January 2001 and December 2011. Their sample includes 227 papers published across 38 journals. Using the classification system developed by Goyal and Giri (2001), they identify three types of deterioration in the literature: (1) fixed lifetime, or predetermined deterioration, (2) age dependent deterioration rate, using a probabilistically distributed lifetime (such as in Covert and Philips 1973), and (3) time or inventory dependent deterioration rates, such as models with a constant deterioration rate per stocked item. Bakker et al. (2012) also find that while stochastic demand is more realistic, only 20 percent of papers they review include it. This implies that the emphasis of much of the literature over the decade they studied focused not only supply and demand conditions, but on optimizing chain decisions to meet known demands. They have several findings of the state of the literature: (1) most models assume deterministic settings, making them useful for intuition but less realistic in a business setting; (2) price discounting based on perishability is very common in the literature, which corresponds well with the 'real world;' (3) most models account for stock-outs and backlogging, improving their realistic application; (4) multi-echelon models are gaining importance due to the need for chain integration; (5) few authors account for detailed inventory age data; (6) there is a need for more stochastic modeling in perishable inventory systems; (7) and lastly, their is a need for modeling substitutability in perishable inventory control.

Shukla and Jharkharia (2013) focus their literature review on fresh produce supply chain management covering a 20 year period from 1991 to 2011. They find that while there is an increasing interest in fresh produce supply chain management, there is no dedicated journal for the topic. Most of the literature they review is primarily interested in maximizing consumer satisfaction and producer revenue, while post-harvest losses are only secondarily considered. They state that just over 50 percent of papers published on fresh produce supply chains are from operations management (OM) journals, while almost 35 percent are from agricultural journals. Importantly, OM journal publications focus on applying existing tools and techniques to fresh produce problems, while agricultural journals typically place more focus on product characteristics. They attribute an increase in publications in the last five years of their study window to global issues of food and fuel price increases and disease challenges, such as bird and swine flu.

The challenge, as noted by Blackburn (2009), is that most perishability models consider inventory management problems. In his paper, Blackburn considers post-harvest losses of fresh produce due to heat and time in transportation, although he does not consider post harvest processing challenges. Whether or not Blackburn knew it, he was responding to a call for further research into agricultural supply chains by Lowe and Preckel (2004), as well as by Boehlje (2003), who indicate that management of the transport, distribution, and storage of agricultural commodities is "essential to profitability." While Lowe, Preckel, and Boehlje do not address product degradation, they discuss supply chain challenges related to product differentiation and proliferation in commodity markets. They describe changes to corn markets due to genetic engineering, bringing about the need for significant changes to transportation and distribution systems. This is not dissimilar to what we observe in flour markets: a variety of types with heterogeneous qualities and applications.

Wheat-flour transportation presents unique challenges in commodity transport. Moving and storing raw wheat is relatively easy, even under non-optimal conditions. Wheat is estimated to have a shelf life of 20 years when stored appropriately (Wang and Flores, 1999). Farmers are able to store the unmilled grain on-farm with very low storage losses. Once wheat is turned into flour, the miller is faced with a challenge of transport or storage (Bourquard, 2016b). Flour is warm as it comes out of the milling process, and under many environmental conditions, moisture condenses in the transport container. The moisture, which can also build up during transport due to fluctuations in ambient temperatures, potentially invite mold, bacteria, and fungus (Posner and Hibbs, 1997). Additionally, lipids and baking quality are highly correlated with flour moisture content and storage temperature (Clayton and Morrison, 1972). Lipid changes can have significant impacts on flour quality, including inviting mold growth or impacting gluten characteristics (Wang and Flores, 1999). Higher levels of lipids due to moisture content result in higher mold content and lower quality gluten.

Most studies conducted of wheat-flour changes under storage use various laboratory storage techniques, such as bags or plastic containers, and leave flour for extended periods of time at different temperatures. Changes can be detected in quality anywhere from 30 days to 6 months. Some studies, cited by Wang (1999), indicate that there is an optimal aging for wheat-flour to maximize baking performance. Newly milled flour presents some challenges to bakers, whereas flour aged longer than 4 years could result in total deterioration. Prolonged storage of flour seriously damages baking qualities under most storage conditions. Wang admits in his introduction that aging of flour "is an extremely complicated and poorly understood phenomenon."

Finally, the presence of high quality gluten is a key component of bread making. Gluten, the protein found in wheat, is comprised on gliadins and glutenin, is key to loaf quality (Huebner et al., 1997), and may degrade with time and temperature.

We believe that there are gaps in the literature that we are filling. Ahumada and Villalobos (2009) indicate in their review of the literature that state of the art models in agri-food supply chains are lagging their manufacturing counterparts. They also indicate there is room for development in agricultural supply chains of internal logistics, which have been more deeply explored in traditional manufacturing supply chain literature. There is also a need for further research in the tactical planning of perishable and non-perishable agricultural foods, including robustness to uncertainty (Ahumada and Villalobos (2009)). We intend to model raw materials for manufacturing firms facing uncertainty.

3 Problem Description and Models

Processed food manufacturing firms take agricultural raw materials, such as wheat-flour, and transform them into finished goods for consumption. The manufacturing process involves the application of additional inputs, such as non-biological raw materials, energy, labor, and capital. The labor-capital interface is through the controls of the manufacturing process, which are used in response to variability in the primary raw material ingredient. In many non-food manufacturing environments, where firms assemble intermediate goods into final goods, the formula for assembly does not change. Similarly, to manufacture intermediate goods from non-biological raw materials, such as steel manufacturing, firms typically need fewer adjustments to the controls to produce intermediate goods within the required specification range. Processed food manufacturing firms need to adjust their manufacturing controls frequently to accommodate changes in the characteristics of the raw materials. This can result in higher scrap and waste for food manufacturers than non-food manufacturers. For example, steel manufacturers who use scrap as their primary inputs, such as mini-mills in the US, are able to put out-of-specification finished product back through the manufacturing process, resulting in lost time and revenue but minimizing scrap and waste. Many food products, once produced, are not reusable if they are out-of-specification after manufacture. Instead, the firm must discard or dispose of the non-premium product through alternative marketing channels at lower price levels. This results in lost revenue, time, and product. For many manufacturers, this cost can be significant, resulting in millions of dollars of lost revenues each year.

Working with data from our industry partner, our research will develop and apply two methods. First, we develop an econometric model to determine the technical coefficients for the controls in the manufacturing process relative to finished goods quality outcomes. Second, we characterize the entire optimal set of control settings for all possible raw material characteristics. We use price and cost data in the second step to analyze the strategic options facing a processed food manufacturer.

We address two very broad questions in our methodology. The econometric step aims to answer the question: *What process controls and flour characteristics are important to the quality outcomes of manufactured goods, and what is their relative magnitude?* The mathematical optimization model is used to answer the question: *What are the strategic implications of raw material variability in food manufacturing?*

This paper presents preliminary results from the first model, in which we determine and discuss the technical coefficients. We then present our proposed model for the second stage and discuss its application. Our goal is to use the models to characterize the entire set of optimal choices for the firm, both operationally and strategically.

3.1 Our Industry Partner

We collect our primary data at a large snack-food manufacturing facility in the US. The facility manufactures hundreds of millions of dollars of finished goods each year and is owned by a national, publicly traded, food manufacturing firm. The primary ingredient at the facility with which we partner is wheat-flour (flour), which is also their largest cost-center. In addition to wheat-flour, they use a variety of non-agricultural inputs, such as water and salt, for which variability is not a concern.

The facility procures flour from three separately owned millers. The procurement process is complex, but can be summarized simply: the manufacturing firm purchases wheat-futures and takes delivery to the millers; the millers manufacture the flour according to a set of minimum or maximum specifications for the protein, moisture, and ash characteristics. The millers then deliver the flour to the manufacturing facility by truck, multiple times per day. The manufacturer pays for the wheat-futures, as well as pays the miller's costs of production. They also have the opportunity to negotiate a 'milling margin' with the miller, which is the miller's basic profit margin. In this way, the costs of the miller are relatively transparent to the manufacturer. In addition, the manufacturer has full information about the quality of the flour delivered by each miller.

At the time the manufacturer orders flour from each miller, they also know the demand they are facing for each product line. In practice there is some minor uncertainty regarding late orders, but the uncertainty is small and for this paper we take demand as known. In future research we will allow for stochastic demand, however, the snack-food industry's demand is generally known in the short-term and is not typically economically cyclical.

Short-term mismatches in demand can be managed through safety stock, which we will also consider in future research.

Once flour is delivered and the characteristics are revealed, the production manager matches flour batches to product lines. Flour is used typically within 24 hours of arriving at the manufacturing facility. Production is undertaken, the control decisions are made, and the results are revealed. Figure 1 in the Appendix provides an overview of the manufacturing process. The following section details the flour, control, and quality variables of interest in our analysis.

3.2 The Datasets

We use three primary datasets for our analysis:

- Flour reports: details of each flour batch, including moisture, protein, and ash measurements taken by both the flour millers and the manufacturing firm, as well as the mixing tolerance index, flour supplier, and delivery date.
- Production data: details the flour batch, control settings, and intermediate quality test results for production of a particular batch of finished goods
- Finished goods quality: details the final quality measurements, taken directly before packaging, that determine the disposal of the finished good as either premium product, second-tier product, or trash.

We combine these datasets with price and cost information provided by the manufacturing facility at which we collect data. The production data are captured on the manufacturing floor by the staff. We have approximately 725 observations across all products between January and March 2017. This work uses approximately 110 observations from a specific product line. Flour intake reports are captured electronically; our dataset includes observations from August 1, 2016 through March 31, 2017. Finished goods quality data are matched to the production sheets. These are captured electronically by the firm.

We continue to work with the firm to capture and record data, and intend to collect 12 months worth of production data to observe an entire calendar year, as well as a crop year change over. This paper relies on production data collected between January and March 2017 and flour data collected between August 1, 2016 and March 31, 2017.

3.2.1 Variables and Flour Characteristics

Table 3 in the appendix provides a list of variables and their descriptions used in the analysis. The variables can be divided into three categories: raw material characteristics, manufacturing controls, and quality outcomes. The raw material characteristics and quality outcomes are random variables. Manufacturing controls are those variables over which the firm exercises control. When we elaborate the model in future research, the manufacturing firm will also select the miller by treating the supply chain as a control in the manufacturing process.

We focus on four flour characteristics: protein content, moisture content, ash content, and mixing tolerance index. Figure 3 in the appendix (Section A)provides a graph of the variation in flour protein and moisture between August 1, 2016 (point 0) and December 31, 2016 (point 900).[1] The area between the red lines represents the crop-year changeover faced by the manufacturing firm.

Protein and moisture content data are provided as percentages of weight. Ash content, also provided as a percentage of weight, is the mineral material of flour, derived primarily from the wheat from which the flour was manufactured. The mixing tolerance index (MTI) is the difference in Brabender Units from when dough has reached its maximum viscosity prior to gluten's breakdown, and 5 minutes after peak time. MTI measures a flour's tolerance to mixing, with high numbers indicating intolerance to mixing, particularly over-mixing.[2] According to industrial bakers, all four characteristics are important to the manufacturing process.

3.3 The Manufacturing Process

Figure 1 in the appendix offers an overview of the vertical supply and manufacturing chain of interest, and Figure 2 provides an overview of the manufacturing process. Here, we detail the manufacturing process to help contextualize the models in the following sections. The process is roughly divided into two components: supply chain decisions and manufacturing decisions.

Supply chain decisions involve supplier and quantity selections - from whom to purchase

[1] We have removed the graph's vertical axis label to comply with a non-disclosure agreement.

[2] See North Dakota State University's Wheat Quality and Carbohydrate Research Lab for further information.

flour, and how much from each miller. The supplier selection process is a strategic question from Section 4.2 that we intend to address after characterizing the optimal set of controls for all flour inputs, Section 3.5. We will characterize the trade-offs in supplier selection and the strategic decisions to purchase from more than one supplier.

Manufacturing decisions are those controls available to the bakers to turn flour (and other ingredients) into finished goods. This stage is after the flour characteristics have been revealed and the baking team is determining how to set the controls to produce high quality finished goods.

The manufacturing process starts at the mixing stage, where the operator determines how much water (measured in pounds) to combine with the flour and additional ingredients to make the dough. The flour and additional ingredients quantities are fixed by the recipe for any given product on a given production line. The facility operates several production lines, some of which are configured for only one product, while others can produce multiple products. After adding the water, the operator determines how long in minutes to mix the dough; the mix time is categorical and based on the mixing tolerance index (see Section 3.2.1).

Once the dough is made it is extruded and cut. The extruder, measured in pounds per square inch of pressure, shapes the snack product and the cutter, measured in cuts per minute, separates one product from another. The product then proofs on a conveyor belt before traveling under a salter. At the proofing stage, the "piece weight" intermediate quality measurement is taken, measured in grams. Once salted (measured in pounds of salt), it travels through various oven zones. The oven zone temperatures, measured in degrees Fahrenheit, are adjustable by the operator. Depending on the product and production line, there are differing numbers of oven zones. The final oven zones are configured for drying, and the speed at which the products are sent through (the kiln speed) is also adjusted. After this, the finished product is sent to the packaging line. There is a moisture check taken prior to drying, and a final moisture check taken directly before packaging. Table 3 in the appendix provides a summary of the variables in the system and their units. For some products, the measurements are invariant - for example, the cooker speeds are never adjusted through the oven, instead, the temperature is adjusted. For others, adjustments are made frequently.

We focus on isolating the controls in the manufacturing process for one product on one production line at a time in order to hold constant the differences between products and production lines.

At each stage of the production process, the operator knows what came before: when adding water, they know the characteristics of the flour; when setting the extruder and cutter controls, they know the water and salt quantities; when setting the oven controls, they know the extruder and cutter settings.

The manufacturing process is an engineering process designed (tuned) to produce a particular product. We are not analyzing behaviors, we are analyzing a system in which each of the controls is relevant to the outcome. Our goal is to figure out the relationships between controls and flour attributes and to apply them in a model of the manufacturing system.

3.4 Determining the Relationships Between Inputs and Controls

Broadly, the econometric models help address the question: *What process controls and flour characteristics are important to the quality outcomes of manufactured goods, and what is their relative magnitude?* However, their primary purpose is to generate the technical coefficients to be used in the mathematical optimization model, described in Section 3.5, *Characterizing the Optimal Control Sets for All Potential Inputs.*

We fit an ordinary least squares model to test the manufacturing system and establish technical coefficients for an operations model. Equation 1 provides the econometric model:

$$g_{i,k}(a_k, x_k) = b + a_k\alpha_i^t + (a_k^2)\alpha_{i2}^t + x_k\beta_i^t + (x_k^2)\beta_{i2}^t + y_k\gamma_i^t + \epsilon_{i,k} \tag{1}$$

Where:

$g(\cdot)$ = dependent quality variable given the control settings and flour characteristics

b = intercept

i = product disposal category, i.e. premium versus non-premium

k = product lines

a = flour attributes vector

x = production process controls

y = interaction terms, a function of production controls (x) and flour attributes (a)

α = flour attribute coefficients, α_{i2} for squared attributes

β = production control coefficients, β_{i2} for squared controls

γ = interaction terms coefficients, and

ϵ = error term

t = transpose operator

We discuss the specific application and results the model in Section 4.1, *Technical Coefficients for Inputs and Controls*. Our technical coefficients for the mathematical model are taken from α, β and γ, the coefficients from the regression in equation 1. The result of this equation, $g_{i,k}(a_k, x_k)$ represents the observed outcome per batch of the production process given the observed raw material characteristics, a_k, and the observed production control settings, x_k, for the product line k and finished goods quality i. We include squared terms for both the flour characteristics and process controls vectors. We also include an interaction term, y_k, for interactions within controls and characteristics.[3]

We believe ordinary least squares is an appropriate choice for our purposes. We meet the assumptions of linear regression (Greene, 2012): 1. the model is linear in parameters, 2. the is no exact linear correlation between the independent variables, 3. the independent variables are exogenous, 4. a test for heteroskedasticity indicates its possibility, for which we correct using White standard errors, 5. our data generation process is well known and independent, and 6. our disturbances are normally distributed as indicated by their quantile plots.

We are aware of other methods, such as Huang and Liu (1994) and Aigner et al. (1977), who broadly apply maximum-likelihood methods to the problem of estimating production functions. However, we differ from them in our goals; while many authors seek to establish efficiency frontiers for industries or firms (see Battese and Coelli (1988)), we seek to characterize the production function of a single firm without concern for technical efficiency at this stage. Future research may address technical efficiency. We also do not account for labor or capital inputs in our current model, as they are held fixed for any given level of output quality. We believe additional efficiency is unlikely to be gained through alternative methods at this time.

[3]We do not at this time interact the terms between controls and flour attributes.

3.5 Characterizing the Optimal Control Sets for All Potential Inputs

The mathematical optimization model is used to answer the broad question: *What are the strategic implications of raw material variability in food manufacturing?* Here, we define a profit function for each product line based on whether or not the finished goods quality is within the "premium" or "non-premium" outcome ranges, and can therefore be sold at full or reduce prices. We then determine the probability that a production run, based on the revealed raw material characteristics, can be made premium or non-premium given the available control settings. We use this to establish the expected profit function.

$$\pi_k = \sum_i^n r_i g_{i,k}(\widetilde{a_k}, x_k|\alpha_i, \beta_i, \alpha_{i2}, \beta_{i2}, \gamma_i) - c^t x_k \tag{2}$$

$$\max_x E[\pi] = \left\{ \sum_i^n r_i Pr_i \left[\underline{g_{i,k}} \leq g_{i,k}(\widetilde{a_k}, x_k|\alpha_i, \beta_i, \alpha_{i2}, \beta_{i2}, \gamma_i) \leq \overline{g_{i,k}} \right] - c^t x_k \right\} \tag{3}$$

Where:

i = product disposal category

k = product lines

$\widetilde{a}$ = random flour attributes variable

x = production process controls

α = flour attribute coefficient

β = production control coefficient

γ = Interaction term coefficient

$\underline{g}$ = lower boundary of acceptable finished goods quality outcome

$\overline{g}$ = upper boundary of acceptable finished goods quality outcome

r = value of product in disposition i per production batch

c = cost of control x

t = the time period of interest

Equation 2 uses $g_{i,k}(a_k, x_k|\alpha_i, \beta_i, \alpha_{i2}, \beta_{i2}, \gamma_i)$ from equation 2. Here, we are characterizing $g(\cdot)$ contingent on our already established technical coefficients, α_i, β_i, and γ_i. We multiply $g(\cdot)$ by the appropriate revenue, or product value, r for the product's disposition. We use equation 2 in equation 3 by establishing the probability Pr_i of a production batch being in "premium" or "non-premium" ranges given the random flour characteristics $\widetilde{a_k}$. Equation 3 is the expected profit function we intend to maximize with respect to the controls x_k. Equation 3 characterizes the entire set of control options available to the firm for all potential raw material characteristics.

4 Results

Table 1 provides correlations between each of the flour characteristics of interest in this paper. Table 2 provides the results of the regression analysis. There are a set of relationships in the correlation table that are important in our determination of the variables used in the regression analyses. Protein and moisture have a positive and statistically significant relationship with each other. MTI has a negative and statistically significant relationship with both moisture and protein. For the current regressions, we use only MTI and ash content as explanatory variables, leaving out moisture and protein.

Pearson Correlation Coefficients				
	Moisture	**Protein**	**Ash**	**MTI**
Moisture	1.00 (——)	0.40*** (0.0001)	-0.08 (0.3375)	-0.29*** (0.0009)
Protein	0.40*** (0.0001)	1.00 (——)	0.06 (0.4592)	-0.45*** (0.0001)
Ash	-0.08 (0.3375)	0.06 (0.4592)	1.00 (——)	0.05 (0.5407)
MTI	-0.29*** (0.0009)	-0.45*** (0.0001)	0.05 (0.5407)	1.00 (——)

Table 1: Correlations between Flour Characteristics, p-values in parentheses
*** Indicates significance at 1% level

At this time, our regression has 108 observations for a specific product line. As we are able to add further data to the regression, we believe that the correlations will be less important in determining the outcomes of the analyses, but potential multi-collinearity means we include only MTI and ash. MTI, an index from 1 to 600 (potentially but unrealistically)[4] has a relationship to protein and moisture quantity, although it is more closely related to protein quality. Baking operators use MTI to determine the mix time for the dough. It provides a good proxy for flour quality. Section 4.1 provides the technical coefficients and regression results. Section 4.2 provides a qualitative description of the strategic options of the firm, with some context of our ultimate research goals.

4.1 Technical Coefficients for Inputs and Controls

Table 2 provides the results of our linear regression, using *Bake Moisture* as the dependent variable. Bake moisture is a quality measure taken after the product comes out of the oven, and is measured as a percentage of product weight. There are ten explanatory variables: *MTI, ash content, extruder pressure, added water, added salt, oven temperatures for zones 1-4* and *kiln speed* (not time). The "kiln speed" is the belt speed through oven zone 4, which is often changed to accommodate moisture needs.

Most of the results are not surprising. An increase in MTI (which can naturally denote higher absorbency and higher quality protein) increases the bake moisture at a decreasing rate. The negative coefficients on oven zones 1 and 3 are expected - an increase in the temperature reduces the bake moisture. Speeding up the kiln results in higher bake moisture, intuitive as the product goes through the final oven zone faster. We find the interaction between the kiln speed and final oven zone as significant, which is also expected given their close relationship to bake moisture. Lastly, the relationship between the extruder and added water is slightly significant, which is reasonable as the two decisions follow one another in the manufacturing process.

The biggest surprise is the sign on oven zones 2 and 4, which are positive. Oven zone 2 is not necessarily purposed to drying the product (different oven zones are for different purposes), but oven zone 4 is the final stage and is to extract final moisture. The sign and the magnitude are surprising. Further investigation may reveal whether oven zone 4 is "set" ex-ante or ex-post some knowledge by the baking operator. It may be used in

[4]In our data, MTI ranges from approximately 50 to 115.

response to information about the flour and dough characteristics.[5] We add the caveat when interpreting these coefficients in isolation that this is a complex manufacturing system with many components.

Overall, we believe that this regression reasonably specifies the technical coefficients required by the optimization problem. We continue to refine the production function while working with our industry partner to understand the food science interactions revealed by our results. We address the connections between the results from this section and the firm's strategy in the following section, *The Strategic Options of the Firm*.

4.2 The Strategic Options of the Firm

Our goal is to provide a link between the firm's operational and strategic activities. We look at raw material variability as an important operational component of food manufacturing firms, and interviews with food manufacturers have demonstrated that the industry is interested in our work as well. Raw material variability is particularly important in food versus non-food industries. Not only is there daily biological variability in food manufacturing, there is annual variation related to crop year changes (see Figure 3), and vagaries related to weather and terroir.

We are in the process of numerically analyzing this section of our research. Equations 2 and 3 provide some insights into our work. We maximize revenue with respect to the controls available to the baker, such as added water or salt, machine speeds, and oven temperatures, given the random flour attributes vector. Once we develop a firm level operational model with several product lines, we can then answer strategic questions related to the costs of managing raw material variability.

Our strategic questions include vertical integration - would it be better for firms facing variability to control the variability inside the firm through their controls or outside the firm by ownership - or technology - at what point do technological investments in automation (for example) become economically feasible. Comparative statics across the decisions and raw material characteristics can provide insights into the managerial decisions faced by firms.

[5] A regression of oven zone 4's temperature on the preceding variables about which an operator has knowledge reveals that MTI, ash, added water, and added salt are all statistically significant in determining zone 4's temperature. We continue to define the nature of these relationships to ensure our production function is correctly specified.

5 Discussion and Conclusions

Our work is in its preliminary stages. We are still collecting and organizing data and working toward refining our econometric approach to the technical coefficients. We plan to generate numerical results to the mathematical model over summer 2017, with preliminary results in late summer and early fall. A challenge we face at this time is the availability of quality data. As we add observations across product lines we will have greater insights into the manufacturing process.

We believe our work is unique, insightful, and economically meaningful. Firms with which we have spoken express multi-million dollar opportunities to more fully understand their operational and strategic options, particularly related to managing raw material variability. We also believe there is significant academic interest in looking inside the firm at the daily operations and resulting revenue outcomes. In the future, our "mapping" of the system, including the supply chain, may provide some information about food waste in manufacturing, food safety, transparency, supplier selection processes, and supply chain management. We also believe that providing a link between operations and strategy is of itself an interesting and interdisciplinary activity.

Dep. Variable:	Bake Moisture	**R-squared:**	0.3581
Method:	Least Squares	**Adj. R-squared:**	0.2122
No. Observations:	108	**F-statistic:**	2.45
Df Model:	20	**Prob (F-statistic):**	0.0022
Df Residuals:	88		

	coef	**std err**	**P>|t|**
Intercept	-939.4009	751.5922	0.2147
MTI	0.2577^{**}	0.1234	0.0397
MTI^2	-0.0004^{**}	0.00015	0.0283
Ash	51.7878	178.0365	0.7718
Ash^2	-12.5936	191.5007	0.9477
Extruder	-2.0420^{*}	1.1809	0.0873
Extruder^2	-0.0001	0.0011	0.9153
Water	8.1249	8.9168	0.3647
Water^2	-0.0250	0.0270	0.3574
Salt	4.9663	2.9898	0.1003
Salt^2	-0.0145^{***}	0.0054	0.0082
Oven 1	-0.1867^{***}	0.0652	0.0053
Oven 2	0.0823^{***}	0.0301	0.0075
Oven 3	-0.0413	0.0257	0.1119
Oven 4	0.6650^{***}	0.1785	0.0003
Kiln Speed	0.3882^{***}	0.0961	0.0001
Kiln Speed^2	0.000007^{**}	0.000003	0.0248
MTI & Ash	-0.4227	0.2673	0.1173
Water & Salt	0.0221	0.0190	0.2476
Kiln & Oven 4	-0.0009^{***}	0.0002	< 0.0001
Extruder & Water	0.0127^{*}	0.0076	0.0966

Table 2: Quality Outcome Regression: Bake Moisture. White standard errors are provided. Results are rounded to four decimal places where possible. *** 1% level, **5% level, *10% level

A Tables and Figures

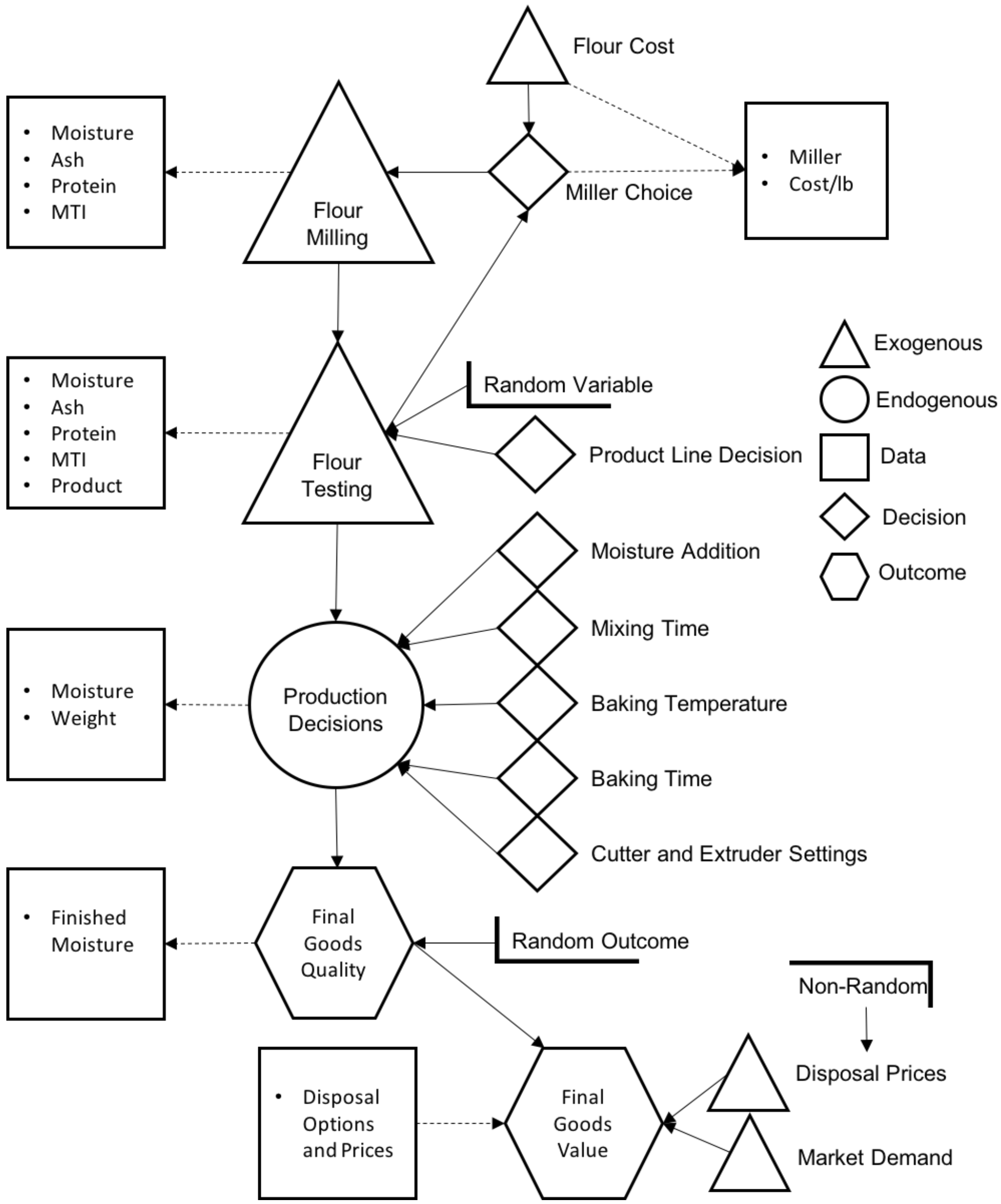

Figure 1: Diagram of the modeling process.

Production Data		
Variable	*Units*	*Description*
date	Discrete	Year, month, and day of manufacture
product	Discrete	Product being manufactured
oven	Discrete	Production line on which product was manufactured
coamoist	Percent	Certificate of analysis flour moisture level
coaprotein	Percent	Certificate of analysis flour protein level
lbswater	Pounds	Pounds of water added to the dough
lbssalt	Pounds	Pounds of salt added to the dough
supplier	Discrete	Flour miller
zone1-7	Degrees F	Oven zones 1 through 7 in baking line
proof		Proof belt speed
cooker		Cooker speed
bake		Baking speed through the oven
kiln		Speed through the drying kiln
pieceweight	Grams	Weight of pre-baked products
bakemoist	Percent	Product moisture after baking prior to kiln
doughmoist	Percent	Dough moisture prior to baking
doughtemp	Degrees F	Dough temperature prior to baking
watertemp	Degrees F	Temperature of water added to dough
extruder	PSI	Pressure of extruder used to shape dough
cutter	Cuts/minute	Cutter speed use to separate product
lbsflour	Pounds	Flour added to the dough
mixtime	Minutes	Minutes of mixtime for dough
Flour Data		
Variable	*Units*	*Description*
date	Discrete	Date of flour delivery
supplier	Discrete	Flour miller
coaash	Percent	Certificate of analysis ash level in flour
sohmoist	Percent	Firm measurement of moisture level in flour
sohprotein	Percent	Firm measurement of protein level in flour
sohash	Percent	Firm measurement of ash level in flour
mti	Percent over time	Mixing tolerance index of dough softening
Finished Goods Quality Data		
Variable	*Units*	*Description*
product	Discrete	Product line
date	Discrete	Date of manufacture
moisture	Percent	Moisture of finished good

Table 3: Summary of data collection.

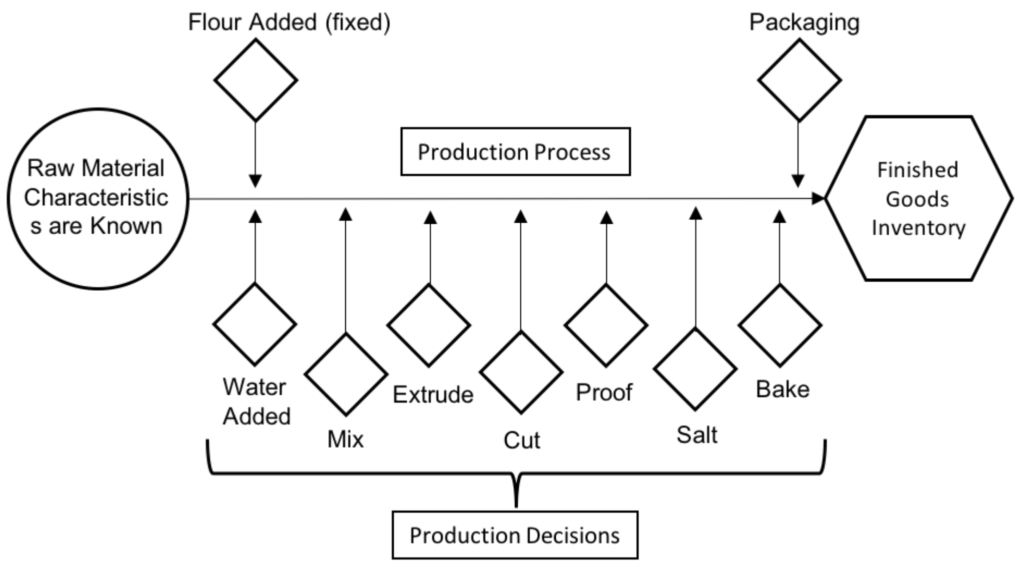

Figure 2: Diagram of the manufacturing process.

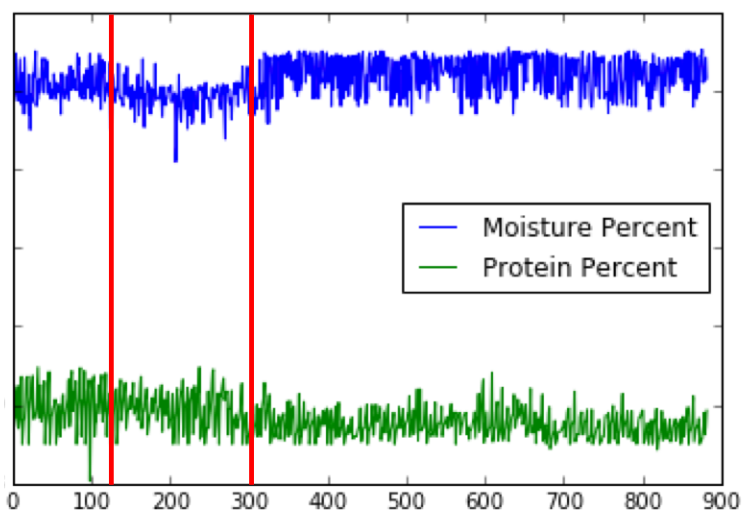

Figure 3: Moisture and protein measurements over time for delivered flour. The space between the red lines is the crop year changeover. We block the scale from view at this stage of the research for compliance with a non-disclosure agreement.

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