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Improved Forward Buying of Commodity Materials

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Abstract

This research presents the Enhanced Commodity Forward Buy (ECFB) heuristic, a new method for commodity purchasing, which allows strategic forward buying of commodities for products that include commodity components or materials. The Enhanced Commodity Forward Buy addresses limitations of existing methods by considering stochastic demand and stochastic commodity prices for products that contain both commodity and non-commodity materials. We conduct a simulation test of the new heuristic on 10 commodity indices using actual historical market prices, over a range of holding costs, markup margins, commodity percentages of the product's cost of goods sold, and demand distributions. The results of the simulation show that compared with five other buying methods, the Enhanced Commodity Forward Buy heuristic's ability to adapt to variations in both demand and commodity prices allows it to generate higher profits when demand is uncertain and commodity prices are volatile.

Keywords: heuristics; purchasing; forward buying; commodities

1. Introduction

Raw materials, which are often largely or even solely composed of commodities, may represent up to 60% of the value of a finished product (Leybovich, 2012). In a competitive market, the profitability of these types of finished goods is sensitive to commodity market price fluctuations. In particular, if the market price of a commodity material increases, firms' profits often suffer when the business conditions preclude firms from passing on the increased costs to consumers (Zsidisin *et al.*, 2013). This precise scenario has impacted numerous firms as the volatility of commodity markets has increased in recent years (Cohen and Kunreuther, 2007). For example, recent oil price increases reduced the profitability of petrochemicals and products containing oil based plastics, which decreased the profits of a number of major corporations including Unilever, Kimberly-Clark, BASF, and Proctor and Gamble (Blas, 2012). Similarly, in the second quarter of 2012, the Coca-Cola Corporation's profit decreased by 0.4% (compared to Q2 2011) despite a 3% increase in revenue. Coca-Cola specifically attributes the decrease in profit to higher costs for commodity ingredients including sugar and corn syrup (Choi, 2012). This issue is extremely important to many manufactures; a recent survey (Prime Advantage, 2013) of small and mid-sized manufacturers in the US reports that 90% of respondents view raw materials cost pressure as their top concern.

The profitability of commodity inclusive products is regularly impacted by price shifts in the commodity markets, particularly when the commodity costs represent a significant portion of the production costs (Martínez-de-Albéniz and Simchi-Levi, 2005). These market price shifts can be quite substantial; for example, using historical commodity data from Index Mundi (IndexMundi.com as shown in Figure 1, over the four year period of this study, the average price for the 10 commodity indices realized a 36% price gain, trailed by a price drop of similar magnitude, which was followed by a period of instability in which the prices fluctuated by up to 20%. Such volatility is often viewed negatively; however, many proactive firms have developed strategies to minimize the risk and impact of such market turbulence on their businesses (Christopher and Holweg, 2011). To address these scenarios, new procurement strategies, such as forward buying (where the commodity components of products are purchased when market prices are favorable and held in inventory in anticipation of future demand at times) have been developed to specifically address the instability of open markets (Pollitt, D., 1998). Although a number of forward buying heuristics have been developed previously, none of these existing strategies consider uncertain demand, nor do they consider products that contain both commodity and non-commodity materials. In this paper, we develop the Enhanced Commodity Forward Buy (ECFB) heuristic to address these limitations.

< Insert Figure 1 Here >

In the next section, we discuss existing forward buying heuristics, found in the literature, which serve to motivate the ECFB method that we propose. In the third section, we describe ECFB and present a numerical example for clarity. In the fourth section, we present a simulation study that uses historical commodity index prices to compare the performance of ECFB with the performance of five alternative buying strategies. We discuss our results, conclusions, and possible extensions in the final two sections of the paper.

2. Literature Review

Kingsman (1986) noted that a major area of a company's operations is purchasing materials with fluctuating prices. In particular, he documented the lack of attention that had been paid to this problem. A number of strategies have been developed to address this issue since his article, but the opportunity still exists to improve purchasing strategies under demand fluctuations. Some firms may adopt a simple procurement strategy where they order the materials required to build their inventory level up to the forecasted mean demand level. Although simple to implement, the effectiveness of this method is limited when the demand and material prices are both stochastic. Golabi's (1985) method of forward buying began to address the first limitation by considering stochastic prices: Using a forecast of future material process, the method forward buys materials when current purchase price is lower than expected future purchase price considering holding costs; however, the method assumes that demand remains at mean level despite the price changes. Gavirneni (2004) begins to address both limitations, by determining production levels using a modified newsvendor equation to handle possible next period price changes and non-perishable commodities; although the method doesn't forward buy beyond the next period. The GOGA (Manikas et al., 2009) method combines the non-perishable newsvendor from Gavirneni (2004) and forward buying of Golabi (1985) to buy the mean demand into the future to improve expected profit. Although successful, GOGA suffers from two major limitations. First, the GOGA heuristic only considers buying and reselling pure commodities (as opposed to products that include both commodity and non-commodity materials). Second, the future demand used in the GOGA forward buying decision is modeled deterministically. We will now outline these methods below, plus our proposed enhancement:

2.1 Stochastic Purchase Price with Deterministic Future Demand

Golabi (1985) proposed a method whereby material for future periods is bought as long as the marginal cost is less than the marginal savings. The differential between lower purchase costs and higher holding costs is translated into a series of non-increasing price thresholds. Golabi's equation (1) uses the purchase price (x), the known cumulative price distribution for each period ($F(x)$) and the cost to hold one unit of stock for one period (h) to specify the next price point such that forward buying n periods is optimal. Each threshold price is computed according to:

$$A_{n+1} = \int_{0}^{A_n} x\,dF(x) + \int_{A_n}^{\infty} A_n\,dF(x) - h \qquad \textbf{(1)}$$

A limitation of Golabi's method is that it assumes that the demand for the current and all future periods is known. Williams and Tokar (2008) note in a literature review that the assumption of deterministic demand is convenient, but may be detrimental to the model's validity to real-world scenarios. Magirou (1982) uses a similar method to Golabi (1985), with the addition of allowing a fixed storage capacity and selling beyond the forecast demand in the commodities market for oil.

2.2 Buying with Uncertain Future Demand

The method from Gavirneni (2004) addresses more realistic demand information scenarios by accounting for demand uncertainty through the use of a newsvendor model. The newsvendor model for single selling period situations has been widely applied to numerous operations management problems to determine optimal production and inventory levels when demand is uncertain (Cachon and Terwiesch, 2006).

< Insert Table I Here >

The newsvendor equation is one of the most influential and widely examined inventory tools found in the literature (Petruzzi and Dada, 1999). The model, which assumes that unused inventory is discarded each period, employs the critical fractile. In a scenario where an item is not perishable and can be held as inventory to be sold at the full price in the future, there is no salvage value and the overage cost c is not incurred (because the item will be sold in a future period). To address this scenario, the newsvendor model (for which the notation is described in Table I) is modified and the overage cost $(c - s)$ is replaced by a one period holding cost (h). This modified newsvendor (that considers non-perishable rather than perishable demand), has the order up to level shown in (2).

$$y = \Phi^{-1}\left(\frac{p-c}{p+h-c}\right) \quad \textbf{(2)}$$

Gavirneni (2004) modified the standard newsvendor similarly to consider the holding cost of a product with non-perishable demand in a situation where future purchase costs fluctuate. His modification replaces the purchase cost in the denominator with the next period's expected purchase cost. Thus the cost of keeping inventory is the holding cost for that inventory plus the difference between current purchase cost and future expected purchase cost. His formulation, shown in (3), explicitly accounted for the possibility of purchase price fluctuations like those found in commodities procurement. However, the equations in (2) and (3) are single period models only.

$$y = \Phi^{-1}\left(\frac{p-c}{p+h-\bar{c}}\right) \quad \textbf{(3)}$$

Although Gavirneni (2004) does consider a future purchase cost change, his model only determines the inventory level for the current period and it does not forward buy materials for future use. Gavirneni and Morton (1999) move closer to forward buying heuristic with their model which considers stochastic demand with a one-time price increase for speculative buying. Gavirneni and Morton's method has been shown to be effective, however its applicability to our scenario (in which period-to-period commodity prices may decrease or increase when looking to forward buy [as shown in Figure 1]) is limited. In this paper, we develop the ECFB heuristic to address the following limitations of the aforementioned prior methods:

- Buying the mean demand each period does not accommodate stochastic demand, nor the impact of predicted future price changes.
- A normal newsvendor equation accommodates stochastic demand, but does not address predicted future price changes. Both the newsvendor for perishable items and the modified newsvendor for non-perishable items are single-period models that do not address predicted purchase price changes.
- Golabi's (1985) method was designed for forward buys under stochastic purchase prices, but cannot handle stochastic demands.
- Gavirneni's (2004) method is a single period model that the modified newsvendor for non-perishable items is based upon. This model buys for the current period only considering stochastic demand, and the next period's forecasted purchase price.
- GOGA (Manikas et al., 2009) combined Golabi's (1985) method with Gavirneni's (2004) method. The GOGA method uses Gavirneni's method to buy for the current period, and may forward buy mean demand based upon Golabi (1985). This model does not consider stochastic demand for forward buys.

3. Problem Statement and Proposed Heuristic

Our proposed method considers stochastic demand and prices not only in the current period, but in all periods for forward buying. Repeated application of optimal stochastic calculations will give the highest expected profit over the previously listed methods. In this section, we discuss the details of the problem and the heuristic developed to overcome the limitations of existing forward buying strategies.

3.1 The Problem

A firm that procures commodities for use in the production of a finished good is aware of the current prices to purchase materials. At each ordering opportunity, the company needs to decide how much of the commodity to order to cover current and potential future demand. The remainder of the Cost of Goods Sold (COGS) is assumed to be non-commodity materials and labor that are assumed to not vary over the time horizon. The decision the company makes is whether or not to buy more than required in the current period to take advantage of anticipated commodity price increases. The expected price savings resulting from purchasing commodity materials before they are needed must outweigh the holding costs associated with storing those materials as inventory until needed (cost of capital, etc.). We assume that although the firm may buy a quantity of commodities to potentially cover several periods of demands, no long term fixed-contract arrangements are in place. As Chandrashekar and Dougless (1996) note that although it is tempting to suggest a long-term fixed price contract for commodities, in a volatile market it is very difficult to negotiate a viable contract.

3.2 Assumptions

This section outlines assumptions concerning the business situations where our proposed method can be applied with maximal effect.

Condition 1: Demand is stochastic with a known distribution.

Condition 2: The purchase price of the commodity exhibits randomness.

Condition 3: Fabrication of finished good products must be done prior to realizing that period's demand, and the period length is insufficiently long to produce additional sellable goods, even if the commodities are on hand.

Condition 4: There are no viable substitute products to fill demand. If backorders are allowed with no loss of revenue nor goodwill penalty, then the problem can be mathematically reduced to a Silver-Meal algorithm as done in Şenyiğit and Erol (2010).

Condition 5: Demand is independent between periods, and unmet demand is lost (no backorders). Demand in one period does not affect other periods because any unmet demand is filled by another player in the market.

It is possible that some firms that procure commodities may or may not relax one or more conditions above, but demand and price uncertainty always are valid conditions in industries that buy and use commodities.

3.3 The Proposed Heuristic

Our forward buying heuristic, which we designate as the Enhanced Commodity Forward Buy (ECFB) method, builds on aspects of several previous buying methodologies. In equation (3), Gavirneni's (2004) model assumes the product is resold as a pure commodity; therefore, the cost, c, represents the total COGS. In contrast, our scenario examines finished products that use a commodity as one of its components. To account for the additional non-commodity materials and the labor required to convert the materials into a finished good, we modify equation (3) to include the term, v, which denotes the additional value (labor, materials, etc.) included in the COGS. Our revised equation is shown in (4). Note that we also modified the Newsvendor equation (2) to include the v term for use in our simulation exercise.

$$y = \Phi^{-1}\left(\frac{p - c - v}{p + h - \bar{c} - v} \right) \quad \textbf{(4)}$$

In the ECFB method, the price thresholds from (1) are used to determine how many periods to forward buy. For each rolling current period, the modified ratio in (4) is used to account for uncertainty in the demand. Further, for forward buys, the quantity of commodities to buy in future periods is found from repeated application of (4). The current period commodity purchase order up to level is the sum of the current and future period quantities. For period 0, commodities have additional value (v) added to create the total COGS of the finished good for sale. The notation for ECFB is listed in Table II:

< Insert Table II Here >

The critical ratio from (4) is used to determine the order up to inventory level of finished goods in the current period, as well as the commodity forward buy order up to levels to cover future periods. For the normally distributed demand with mean of μ and standard deviation σ, $y = \mu + z*\sigma$, where z is the inverse standard distribution of CDF computed in (4).

The events of the proposed heuristic and the market in each period throughout the rolling planning horizon are:

1. Forecast estimated future commodity price
2. Using equation (1), calculate n, the number of additional periods for which the commodity should be bought (i.e. n values greater than 0 represent a decision to forward buy the commodity and hold it in inventory).
3. For the current period (Period 0), calculate the order up to quantity and produce those finished goods with commodities based on equation (4). If $n > 0$, for periods 1 through n, calculate y_i, the quantity of commodities based on repeated application of (4), that are needed for conversion to finished goods in future periods. Determine net finished good requirements, and net commodity requirements based on current inventories.
4. Procure commodities, as needed, based on calculations in step 3. Items are assumed to be procured instantaneously as done in Chowdhury and Sarker (2001).
5. Produce any finished goods from on hand commodities to achieve y_0, finished good level for sale in period 0. Commodity stocks are decremented accordingly.
6. Let D be the demand realized for the period. Sell minimum of D and y_0. Unmet demand is lost.
7. Finished goods inventory position is decremented by $min(D, y_0)$.
8. Each remaining unsold unit of finished goods and commodity incurs a holding cost h based on either the COGS or current commodity price, respectively.

3.4 Numerical Example

To clarify the ECFB heuristic, we present a simple numerical example comparing a base case (in which only the forecasted mean demand for the current period is purchased) with ECFB. In this example, we assume the actual commodity price was \$100 in the last period prior to the start of the simulated time horizon. Further, we assume that the commodity composes 10% of the total finished good cost of goods sold (COGS). Therefore, the total COGS is \$100/10% = \$1000, of which \$900 is non-commodity material and labor. We also assume a period holding cost is 1.5% of the COGS (equating to an annual holding rate of 18%). We then determine the selling price by adding a markup to the COGS; in this example, we assume a 20% markup, so that the item which costs us \$1000 to produce will be sold for \$1200 per unit. We assume that business conditions prevent us from raising this price during our time horizon; therefore the price is held constant, regardless of the current COGS (which will change as the commodity materials' prices fluctuate). Finally, we assume that customer demand has a mean of 10,000 and standard deviation of 500. The forecasted commodity prices and actual commodity prices for three periods and the detailed calculations for our ECFB method are shown in Table III.

< Insert Tables IIIa, b, and c Here >

3.4.1 Base Case Example. The Base case buys the forecasted mean each period. In period 0, the commodity price has dropped to $80 and the mean demand is 10,000. We buy 10,000 commodity units for $800,000 ($80 each). We add $900 more of value/materials to each of these 10,000 units, resulting in total COGS of $9,800,000. Realized demand is 9,200, generating revenue of $11,040,000. This leaves 800 finished goods in stock, for holding costs of $11,760 (1.5% * [$900 + $80] * 800). In period 1, we buy 9,200 more commodities, and use our 800 on hand to fabricate 10,000 finished goods. We procure and build finished goods for sale similarly for period 2. The total profit for these three periods is $6,082,240.00.

3.4.2 ECFB Example. The ECFB method differs from the base method in that it buys forward the number of periods according to (1). Equation (1) compares the commodity price differential ($82 forecasted price in period 1 versus $80 actual price in period 0) with the costs of holding a commodity unit for one period. The holding cost is $1.20 (1.5% * $80), less than the $2.00 expected price increase in period 1; therefore, we should not only buy what we expect to sell in period 0, but also procure commodities that we expect to need for period 1. The forecasted commodity price in period 2 is $81, from which we calculate that the $1 savings ($81 - $80) by buying now would not offset two periods of holding costs.

Rather than have 10,000 finished goods available for sale in period 0, as done in the base case, we need 10,801, as calculated using (4). Previously, (1) informed us to buy commodities now for use in period 1. For the period 1 forward buy, we use (4) with our forecast of the future costs to buy commodities in period 1. We forward buy 10,784 commodity units for future use, but do not yet convert them to finished goods. Therefore, in period 0, we have an order up to level of 21,585 (10,801 to sell now and 10,784 in commodities to hold for future periods). Equations (1) and (4) are reapplied similarly for periods 1 and 2. The ECFB method generates a total profit of $8,054,080.50 for these three periods.

4. Simulation Evaluation

We use simulation to test the ECFB heuristic against five other commodity-purchasing methods. The six methods evaluated are:

1. ECFB
2. Buying the mean demand each period
3. Using the Newsvendor from equation (2) modified to include v, to account for additional value included in the COGS beyond commodities
4. Forward buys using Golabi's method from equation (1)
5. Gavirneni's equation, modified as (4) to include v
6. GOGA

The simulation procedure compares the total profit that each of these six methods would generate when applied to datasets that are based on the actual market prices for 10 commodity group price indices (Table IV).

< Insert Table IV Here >

We created and evaluated 10,000 unique datasets (i.e. 1,000 datasets for each of the 10 commodity groups), each consisting of 48 months of data. Each dataset was constructed using a mix of parameters: Annual Holding Cost (%), Commodity Portion of the COGS (%), Markup (%), Monthly Demand and commodity specific monthly prices. To create an individual dataset within a commodity group, we first randomly select the Annual Holding Cost (%), the Commodity Portion of the COGS (%), the Markup (%), the mean demand, and the standard deviation of demand (see Table V for a description of the distributions of the parameters used to create the datasets). These factors are held constant for all 48 months of the dataset. Next, the Monthly Demand levels for each of the 48 months in the dataset are randomly generated using the mean demand and its standard deviation, under the assumption that demand is normally distributed. Similar to Eilon and Anketell (2001), we assume a normal demand distribution with a known mean and standard deviation.

< Insert Table V Here >

Each month, the COGS is calculated as the sum of the costs of the commodity and non-commodity materials in the product. The commodity cost portion of the COGS is equal to the market price of the commodity when it was purchased (i.e. it may be based on a historical price if the commodity had been forward bought and held in inventory). As Leybovich (2012) notes from his survey of manufacturers, the raw materials for a typical manufacturer constitute 15% to 20% (discrete) or 50% to 60% (process) percent of overall product costs. As commodities may be all or a portion of the raw materials used, we use 60% as an upper bound for our simulation for the Commodity Portion of the COGS (%) parameter. The commodity index prices correspond to the actual market prices for the 48 month period beginning in January, 2010 and ending in December, 2013 (Index Mundi, 2014), the last full year of data available at the commencement of this study. For our analysis, we used the data for all ten major commodity index groups for which historical data was tracked by Index Mundi (Index Mundi, 2014).

The unit selling price, which is constant for all 48 months in a dataset (since we assume that the market precludes manufacturers from passing on cost increases to consumers), is determined as follows: First, we use the appropriate commodity index price from the period before the simulation began (December, 2009) as the baseline commodity price. We then divide this baseline commodity price by the Commodity Portion of COGS (%) to calculate the unit COGS. Finally, the desired Markup (%) is added to the COGS to arrive at the unit selling price. The total profit in a period is calculated as the total units sold multiplied by per unit selling price minus the sum of all costs incurred during the period (which include commodity and non-commodity material purchases, costs to convert materials into finished goods, and the raw material and finished goods holding costs). Similar to Lin and Chen (2003), the goal is to maximize the total net profit.

All six of the buying methods require a future commodity price forecast. Using a variation of the method developed by Chatfield (2000), the forecast for the next period is calculated as $F_{t+1} = \alpha_t + \beta_t * t$, where α_t is the local intercept based on the current market price, and β_t is the local slope, which we calculate by using the three most recent data points. For forecasts two or more periods out, we use a naïve forecast based on the F_{t+1} term to determine the local intercept and slope because the actual price data is not yet known. We do not make any claims to this being the best commodity price forecasting method possible, but rather that it is simple to implement. The price forecasts are used consistently by all methods, thus no method is advantaged from the goodness of the commodity price forecast.

The simulation was conducted using the 10,000 datasets (1,000 per commodity grouping) and the forecasting method discussed above. Each dataset was evaluated by all six of the buying methods, resulting in 6,000 runs per commodity index for an overall total of 60,000 runs. Applying all six buying methods to each dataset, rather than creating a unique dataset for every run, mitigates the potential that an outlying dataset might disproportionately skew the results for a single buying method. For each run, the total profit generated over the 48 month period was calculated and used to evaluate the relative performance of the six buying methods.

5. Results

Table VI, which presents the average profit increase generated by each buying method relative the base method (Buy Forecasted Mean), shows that the ECFB method performs comparatively well. Across the pooled sample of all 10 commodity index groups, the average profit generated by ECFB are 4.1% higher (11.0% versus 6.9%) compared to those generated by the next best method (GOGA). When applied to the individual commodity indices, the ECFB method produced the highest average profit in all 10 of the commodity index groups, with average profits ranging from 1.1% to 5.8% higher than the next best method (GOGA was the second best method in 8 of the 10 commodity indices, Newsvendor was the second best for 2 indices).

< Insert Table VI Here >

We utilize Ordinary Least Squares regression to evaluate the simulation results in further detail. The first set of regression models allow us to identify which factors significantly impact profitability while also comparing the profitability of the six buying methods. We ran separate regressions for each of the 10 commodity index groups as well as an additional regression for the pooled results of the 10 groups.

The regression models include five control variables (Annual Holding Cost (%) [HC], Commodity Portion of COGS (%) [COM], Markup (%) [MU], and the Coefficient of Variation of Demand [CV]) and five binary variables indicating which of buying methods 2 through 6 [M2 to M6 (M2=buying mean demand, M3=modified newsvendor from (2), M4=Golabi (1985) (1), M5=Gavirneni (2004) (4), and M6=GOGA from Manikas et al. (2009)] is being used in an individual simulation run (note: the ECFB method is represented when the five binary indicator variables representing the other buying methods are all set equal to zero). The coefficient of each binary indicator variable indicates the change in profitability that occurs when that method is used compared to the ECFB method. For a firm *i*, the profit model is expressed as:

$$Profit_i = b_0 + b_1 HC + b_2 COM + b_3 MU + b_4 CV + b_5 M2 + b_6 M3 + b_7 M4 + b_8 M5 + b_9 M6 + e_i \qquad \textbf{(5)}$$

The regression results, shown in Table VII, indicate that when compared to ECFB, the other five buying methods generate significantly lower profits for the pooled sample of the 10 commodity index groups (i.e. all of the binary indicator variables' coefficients' [representing the profit difference between ECFB and the other methods] are negative and significantly different from zero). The GOGA method generates the second highest average profit, however its average profit is $466,483 lower than the average profit generated using ECFB. Although ECFB generates statistically significant higher profits than GOGA across the pooled sample of the 10 commodity groups, the difference between the two methods is not significantly different from zero (at the $p < 0.05$ level) within the 10 individual groups. ECFB generates significantly higher profits than Method 2 (buying the forecasted mean) within all 10 individual commodity indices. ECFB also significantly outperforms Method 3 (Newsvendor), Method 4 (Golabi), and Method 5 (Gavirneni) respectively in two, seven, and six of the ten commodity groups. These results provide strong evidence that ECFB will normally significantly outperform the other five methods and, in the worst case, achieve parity with the best of the other methods.

< Insert Table VII Here >

The second set of regression models specifically examines the ECFB method's results. These models evaluate the sensitivity of the method to changes in the five control variables included in the previous models. The regression model is expressed as:

$$Profit_i = b_0 + b_1 HC + b_2 COM + b_3 MU + b_4 CV + e_i \qquad \textbf{(6)}$$

Table VIII shows that profits decrease significantly for all 10 indices as the commodity's contribution to the total COGS (i.e. the Commodity %) increases. We find a similar result in Table VII. These findings are likely the result of a combination of factors: The selling price, which is determined by the starting month's Markup % and COGS, is fixed in all 48 periods in a dataset; therefore, we would expect that increased commodity prices, like those experienced for most of the 48 month simulation period (see Figure 1), should result in increased COGS and hence, reduced per unit return. We do know expect this relationship to hold true over a time period in which the average commodity price equals the initial starting commodity price. More straightforwardly, Tables VII and VIII also show that profits increase significantly as the Markup (%) increases, which is expected because an increase in the Markup (%) results in a higher per unit return.

< Insert Table VIII Here >

In the analysis of all six buying methods (Table VII), the coefficient of variation of demand is significantly related to lower profits across the pooled sample and individually in six of the ten commodity groups. However, when ECFB is examined alone (Table VIII), the coefficient of variation of demand is not significant for the pooled sample and it is only significant in four of the commodity groups. This finding is not surprising because ECFB is the only method to account for stochastic demand in current as well as future buying periods, consequently it makes intuitive sense that ECFB's profitability should be impacted less by demand variation compared to the other five buying methods.

Our finding, in Table VII, that the holding cost percentage is significantly related to profits only in a few commodity groups in both analyses is less intuitive. As holding costs are increased, forward buying may become too costly. If the expected commodity purchase price differential forecasted for Period 1 never outweighs the holding term, the forward buying methods basically decompose into single period models. The implication is that the ECFB method, at worst, will perform similarly to the other methods in the presence of very high holding costs (relative to commodity price fluctuations). However, if future commodity prices become more volatile, only ECFB is poised to automatically adapt and improve expected profits.

To further explore the impact of the percentage of finished product that is composed of commodities, we conducted an additional analysis. As shown in Table IX, we split the Commodity % into three groups by creating two new binary indicator variables: Low Commodity % (which is equal to 1 for commodity percentages 15% to 30% and equal to zero otherwise) and High Commodity % (which is equal to 1 for commodity percentages 45% to 60% and equal to zero otherwise) – Medium commodity percentages (30% to 45%) are represented by cases where both indicator variables equal zero. Profitability for the ECFB method was then regressed on these two indicator variables; the results of the regression find an average profit of $7.94 million across the ten commodity groups when there is a medium Commodity % level (i.e. the intercept value represents the case where both indicators = 0, corresponding to a Commodity % between 30% and 45%). When the Commodity % is low (between 15% and 30%) the average profit across the ten indices increases dramatically by $16.17 million up to $24.11 million. When the Commodity % is high (between 45% and 60%) the average profit across the ten indices decreases to $5.65 million. These results are consistent within each of the ten commodity index groups. These findings clearly demonstrate that as the commodity percentage within the final product increases, firms can expect that the profitability of the product will decrease.

< Insert Table IX Here >

6. Conclusions

We have developed a new purchasing heuristic that extends and improves on prior forward buying methods. Our method overcomes the limitations of prior methods that consider demand deterministically and those that buy for a single period only. The ECFB method also considers finished goods that contain both commodity and non-commodity materials, while allowing for fluctuating commodity purchase prices, stochastic demands, and multi-period procurement scenarios. We believe our tests of ECFB on simulated demand data, using the most recent market data from the 10 available commodity price indices, under a range of business parameters, demonstrates the robustness of this proposed new method of procuring commodities for use in products with a limited market pricing flexibility.

In our simulation, ECFB outperformed five other buying methods across our pooled sample of commodity groups and within each of the ten individual commodity indices. These results support our contention that the ECFB method will likely produce superior profitability for firms selling commodity inclusive products in any industry operating within competitive markets with limited pricing flexibility. This finding is important for firms as improved commodity purchasing strategies, such as ECFB, represent an element of a business strategy that can improve a supply chain's ability to withstand market uncertainty and volatility (Kouvelis *et al.*, 2006).

7. Impact of the Research

Any firm that needs to buy and use commodities has a significant expense in the purchasing cost and storage of those commodities. With modest predictability in future commodity prices coupled with variability in price and demands, being able to forward buy intelligently can allow a firm to improve its lifetime expected profits. Our proposed method here, as demonstrated on simulated demand data scenarios using real historical commodity prices can serve as a recommended way for firms to buy, hold, and use commodities to their financial advantage. For business practitioners, using the calculations presented in this research to examine order up to levels for procurement (including forward buys) can be used to compute "what if" we had used these order amounts in the prior year (or period of interest). The benefit of our method over the actual procurement, inventory, and production decisions at the company can help prove that adoption of this algorithm is a worthwhile endeavor for the corporation.

8. Future Research

There are several future research avenues that may potentially build upon the method we have presented here. Our method does assume that from whom the commodities are purchased does not affect firm retail performance, but rather obtaining the lowest cost is paramount. Joo *et al.* (2010) studied multinational firms and found that buying fair-trade coffee at a higher price was associated with better retail performance. An interesting future avenue of research would be to look at profitability not just as the difference of a set price and purchase cost of commodities, but with the demand curve being affected by the social responsibility of the firm. Additionally, we used a simplistic forecasting method for our simulation. However, future research might also take into account the ramifications of biased forecasts as done by Lee and Shih (1989). Having errors that were not normally distributed may alter the purchaser's view of the stochastic distribution of future commodity prices.

For researchers, we have developed a new method to determine purchasing decisions, safety stock levels, and production timing given stochastic purchase prices and stochastic demands over time. The potential benefit of varying forecasting methods could be examined. Implications of non-stationary demand distributions on profitability is also an area that research can build upon and potentially enhance the method we have presented. Finally, most valuable for the field would be practitioners and researchers potentially joining forces to implement this method (or a modification of it) at real firms and report on the longer term actual profit differentials as a case study.

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Figure 1 Commodity Prices over the Study Period

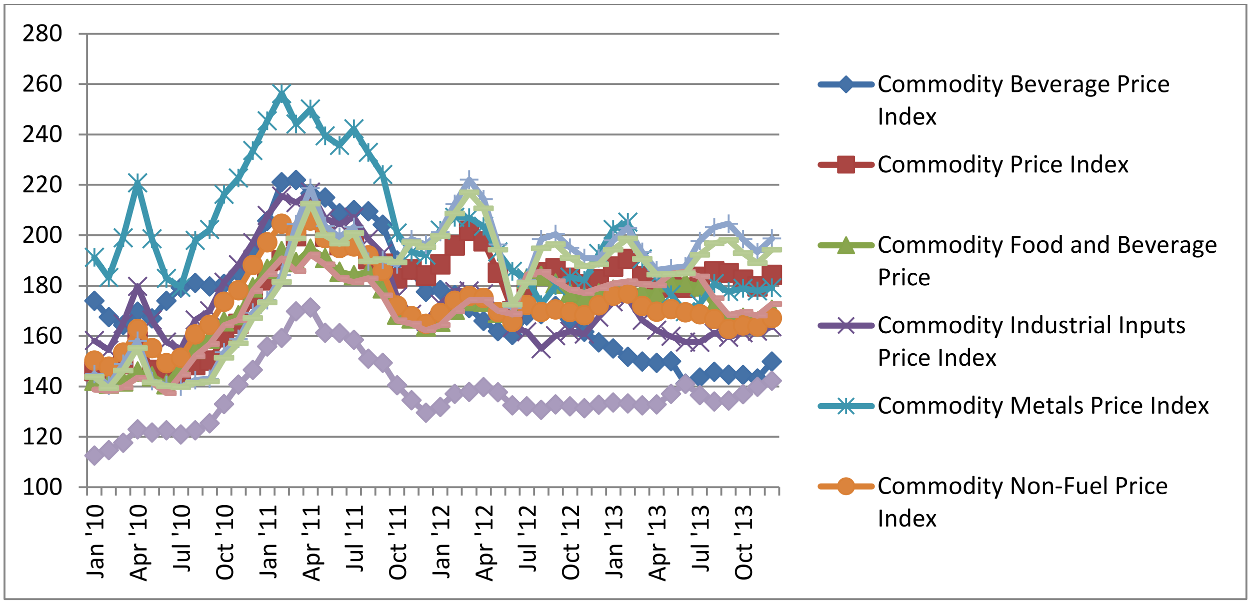

Table I Modified Newsvendor and Gavirneni Methods Notation

Symbol	Description
p	The selling price of the item per unit to the end consumer
c	The cost to purchase the item in period 0, the current period
$\bar{c}$	The expected cost to purchase the item in period 1
h	The holding cost for one period
y	The order-up-to level for period 0
Φ	The cumulative distribution function (CDF) of demand in period 0
Φ^{-1}	The inverse cumulative distribution function (CDF) of demand

Table II ECFB Notation

Symbol	Description
p	The selling price of the finished good per unit to the end consumer
c	The cost to purchase the commodity in period 0, the current period
$\bar{c}$	The expected cost to purchase the commodity in period 1
v	Additional value (material and/or labor) that, in addition to *c*, composes the total COGS of the finished good
h	The holding cost for one period. In period 0, *h* is based on the total COGS; for periods > 0, *h* is based on commodity purchase price.
n	Number of periods beyond the current period to forward buy
y_i	The order-up-to level for period i *(i=0,….n)*, where in period 0 the order-up-to level is for finished goods read for sale. For future periods, this term indicates commodities to forward buy and hold for future conversion to finished goods.
Φ^{-1}	The inverse cumulative distribution function of demand
D	Realized demand for period 0

Table IIIa Three Period Numerical Example Data

Period	0	1	2	
Realized demand	9,200	12,200	11,000	
Commodity price actual	80	105	90	
Commodity price forecast	---	82	81	83

Table IIIb Base Case Numerical Example

Base Method		
Period 0		
	10,000	needed FG to sell in period 0
	10,000	order up to level
	10,000	purchase q commodities
	$ (800,000.00)	purchase cost at $80 per unit
	$ (9,000,000.00)	value add to make 10,000 FG (at $900.00 value add per)
	$ 11,040,000.00	revenue from selling 9,200 units
	$ (11,760.00)	holding cost of 800 FG (10,000 - 9,200)
Period 1		
	10,000	needed FG to sell in period 1
	9,200	Net FG needed (800 on hand from prior period)
	$ (966,000.00)	buy 9,200 commodities
	$ (8,280,000.00)	value add to make 9,200 more FG units
	$ 12,000,000.00	revenue from selling 10,000 units (we cannot fill al 12,200 demand)
Period 2		
	10,000	needed FG to sell in period 2
	10,000	commodities to buy
	$ (900,000.00)	purchase cost at $90 per unit
	$ (9,000,000.00)	value add to make 10,000 FG units
	$ 12,000,000.00	revenue from selling 10,000 units (we cannot fill all 11,000 demand)
	$ 6,082,240.00	**Total profit for three periods**

Table IIIc ECFB Numerical Example

ECB Method

Period 0		
	10,801	needed FG to sell in period 0
	10,784	of commodities to buy now and hold for future use
	21,585	order up to level
	21,585	purchase q commodities
	$ (1,726,800.00)	purchase cost at $80 per unit
	$ (9,720,900.00)	value add to make 10,801 FG (at $900.00 value add per)
	$ 11,040,000.00	revenue from selling 9,200 units
	$ (23,534.70)	holding cost of 1,601 FG (10,801 - 9,200)
	$ (12,940.80)	holding costs of 10,784 commodity
Period 1		
	10,490	order up to level (no forward buys recommended)
	8,889	net FG needed (1,601 on hand from prior period)
	-	net commodities to buy (8,889 - 10,784)
	$ (8,000,100.00)	value add to make 8,889 more FG units
	$ 12,588,000.00	revenue from selling 10,490 units (we cannot fill all 12,200 demand)
	$ (2,274.00)	holding costs of 1,895 commodity
Period 2		
	10,658	order up to level (no forward buys recommended)
	10,658	net FG needed (0 on hand)
	8,763	net commodities to buy (10,658 - 1,895)
	$ (788,670.00)	purchase cost at $90 per unit
	$ (7,886,700.00)	value add to make 8,763 FG units
	$ 12,588,000.00	revenue from selling 10,658 units (we cannot fill all 11,000 demand)
	$ 8,054,080.50	**Total profit for three periods**

Table IV Commodity Price Indices

1. Commodity Agricultural Raw Materials
2. Commodity Beverage Price Index
3. Commodity Price Index
4. Commodity Fuel (Energy) Index
5. Commodity Food and Beverage Price Index
6. Commodity Food Price Index
7. Commodity Industrial Inputs Price Index
8. Commodity Metals Price Index
9. Commodity Non-Fuel Price Index
10. Crude Oil (Petroleum), Price Index

Table V Parameter Distributions for Replications

Annual Holding Cost (%)	~U(18%, 24%)
Commodity Portion of COGS (%)	~U(15%, 60%)
Markup (%)	~U(30%, 100%)
Mean Demand	~U(1000, 2000)
Standard Deviation of Demand	~U(1, Mean Demand / 3)

Table VI Simulation Results - Average Profit by Forward Buying Method and Commodity Index (1,000 Data Sets per Index)

Method Indicator Variables	***All Commodity Indices Combined***	***Commodity Agricultural Raw Materials***	***Commodity Beverage Price Index***	***Commodity Price Index***	***Commodity Fuel (Energy) Index***	***Commodity Food and Beverage Price Index***	***Commodity Food Price Index***	***Commodity Industrial Inputs Price Index***	***Commodity Metals Price Index***	***Commodity Non-Fuel Price Index***	***Crude Oil (Petroleum), Price index***
ECFB	$17,739,212	$12,758,982	$18,157,166	$18,978,851	$20,813,857	$15,781,025	$16,395,628	$17,005,625	$19,817,516	$16,139,897	$21,543,570
Buy Forecasted Mean	$16,244,504	$11,468,307	$16,976,264	$17,443,388	$19,131,504	$14,657,054	$15,309,907	$15,150,914	$17,645,431	$14,949,094	$19,713,180
Newsvendor	$17,171,238	$12,167,075	$17,893,403	$18,426,421	$20,270,848	$15,508,427	$16,141,282	$16,023,434	$18,656,594	$15,758,766	$20,866,125
Golabi	$16,463,342	$11,706,171	$17,012,267	$17,629,642	$19,305,827	$14,709,867	$15,358,773	$15,620,757	$18,229,886	$15,077,881	$19,982,345
Gavirneni	$17,160,027	$12,162,494	$17,887,051	$18,416,294	$20,250,596	$15,500,492	$16,131,172	$16,016,173	$18,640,143	$15,754,558	$20,841,302
GOGA	$17,394,926	$12,410,040	$17,935,093	$18,618,187	$20,443,679	$15,560,357	$16,186,770	$16,508,308	$19,250,301	$15,895,461	$21,141,067
Average Profit Improvement (%) ECFB versus next best result	1.98%	2.81%	1.24%	1.94%	1.81%	1.42%	1.29%	3.01%	2.95%	1.54%	1.90%
n	60,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000

Table VII Comparison of Buying Methods across Seven Commodity Indices

Method Indicator Variables	***All Commodity Indices Combined***	***Commodity Agricultural Raw Materials***	***Commodity Beverage Price Index***	***Commodity Price Index***	***Commodity Fuel (Energy) Index***	***Commodity Food and Beverage Price Index***	***Commodity Food Price Index***	***Commodity Industrial Inputs Price Index***	***Commodity Metals Price Index***	***Commodity Non-Fuel Price Index***	***Crude Oil (Petroleum), Price index***
Intercept	17,371,607 *** (340,839)	14,638,930 *** (675,930)	17,496,323 *** (1,031,620)	20,256,950 *** (1,061,096)	9,753,224 *** (1,148,843)	14,584,702 *** (849,066)	12,711,640 *** (954,138)	20,971,419 *** (954,266)	22,719,253 *** (1,103,627)	16,598,617 *** (947,585)	21,953,057 *** (1,088,889)
Holding Cost %	-32,262 * (14,488)	-118,847 *** (29,007)	-18,999 (43,639)	-108,372 * (44,629)	452,475 *** (48,788)	-23,737 (36,462)	149,730 *** (40,433)	-216,639 *** (40,195)	-171,213 *** (47,304)	-102,280 * (40,419)	-68,719 (46,196)
Commodity %	-610,607 *** (2,185)	-437,479 *** (4,221)	-661,107 *** (6,713)	-635,502 *** (6,696)	-670,799 *** (7,408)	-560,517 *** (5,607)	-598,201 *** (6,093)	-581,425 *** (5,967)	-695,373 *** (7,018)	-559,831 *** (6,048)	-694,674 *** (7,194)
Markup %	377,449 *** (1,408)	264,078 *** (2,870)	399,475 *** (4,314)	398,680 *** (4,223)	431,641 *** (4,635)	346,733 *** (3,505)	365,513 *** (4,008)	353,451 *** (3,889)	422,175 *** (4,552)	359,781 *** (3,925)	428,667 *** (4,570)
Coefficient of Variation of Demand	-3,465,027 *** (299,127)	460,791 (587,087)	-2,899,303 ** (908,022)	-4,510,506 *** (909,888)	-5,735,471 *** (1,011,160)	677,511 (769,155)	-7,591,086 *** (845,280)	-3,456,396 *** (833,465)	-3,899,850 *** (963,354)	-3,117,668 *** (819,466)	-5,826,484 *** (967,148)
Method 2: Buy Forecasted Mean	-1,494,707 *** (100,025)	-1,290,675 *** (197,137)	-1,180,902 *** (305,661)	-1,535,463 *** (299,485)	-1,682,353 *** (338,069)	-1,123,972 *** (253,847)	-1,085,720 *** (280,254)	-1,854,711 *** (276,115)	-2,172,085 *** (324,049)	-1,190,803 *** (276,493)	-1,830,389 *** (324,254)
Method 3: Newsvendor	-567,974 *** (100,025)	-591,907 ** (197,137)	-263,763 (305,661)	-552,430 (299,485)	-543,009 (338,069)	-272,598 (253,847)	-254,346 (280,254)	-982,190 *** (276,115)	-1,160,923 *** (324,049)	-381,132 (276,493)	-677,444 * (324,254)
Method 4: Golabi	-1,275,870 *** (100,025)	-1,052,811 *** (197,137)	-1,144,899 *** (305,661)	-1,349,209 *** (299,485)	-1,508,030 *** (338,069)	-1,071,158 *** (253,847)	-1,036,855 *** (280,254)	-1,384,868 *** (276,115)	-1,587,630 *** (324,049)	-1,062,016 *** (276,493)	-1,561,224 *** (324,254)
Method 5: Gavirneni	-579,184 *** (100,025)	-596,488 ** (197,137)	-270,115 (305,661)	-562,558 (299,485)	-563,261 (338,069)	-280,534 (253,847)	-264,455 (280,254)	-989,452 *** (276,115)	-1,177,374 *** (324,049)	-385,339 (276,493)	-702,268 * (324,254)
Method 6: GOGA	-344,285 *** (100,025)	-348,941 (197,137)	-222,073 (305,661)	-360,664 (299,485)	-370,178 (338,069)	-220,668 (253,847)	-208,857 (280,254)	-497,316 (276,115)	-567,215 (324,049)	-244,437 (276,493)	-402,503 (324,254)
n	60,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000
F	16,642.1 ***	2,106.6 ***	1,997.5 ***	2,032.2 ***	1,870.2 ***	2,099.9 ***	1,996.0 ***	1,957.6 ***	2,026.3 ***	2,001.4 ***	2,109.6 ***
Adjusted R^2	71.40%	75.96%	74.97%	75.29%	73.71%	75.90%	74.96%	74.59%	75.24%	75.01%	75.98%

Parameter significance, * ⇒p< 0.05; ** ⇒p < 0.01; *** ⇒p< 0.001.

Notes: Regression Analysis - Profitability on Holding Cost %, Commodity %, Markup%, Coefficient of Variation of Demand, Forward Buying Method. Standard Errors shown in parentheses.

Table VIII Performance of ECFB Method across Commodity Indices

Method Indicator Variables	***All Commodity Indices Combined***	***Commodity Agricultural Raw Materials***	***Commodity Beverage Price Index***	***Commodity Price Index***	***Commodity Fuel (Energy) Index***	***Commodity Food and Beverage Price Index***	***Commodity Food Price Index***	***Commodity Industrial Inputs Price Index***	***Commodity Metals Price Index***	***Commodity Non-Fuel Price Index***	***Crude Oil (Petroleum), Price index***
Intercept	17,106,671 *** (843,765)	14,674,190 *** (1,693,302)	17,085,225 *** (2,538,937)	21,059,965 *** (2,622,776)	9,443,652 *** (2,843,260)	14,258,736 *** (2,110,080)	12,124,218 *** (2,349,671)	20,512,672 *** (2,374,177)	22,216,332 *** (2,741,199)	16,339,364 *** (2,339,210)	21,513,746 *** (2,695,641)
Holding Cost %	-55,756 (36,527)	-152,675 * (73,990)	-29,248 (109,421)	-184,401 (112,190)	424,099 *** (122,985)	-33,906 (92,350)	150,725 (101,411)	-237,614 * (101,796)	-191,633 (119,664)	-118,635 (101,596)	-93,814 (116,535)
Commodity %	-626,361 *** (5,508)	-449,582 *** (10,767)	-677,672 *** (16,832)	-651,799 *** (16,833)	-688,386 *** (18,673)	-577,475 *** (14,202)	-612,555 *** (15,283)	-595,680 *** (15,110)	-714,021 *** (17,752)	-574,009 *** (15,203)	-712,093 *** (18,147)
Markup %	389,121 *** (3,550)	273,380 *** (7,320)	410,795 *** (10,817)	410,604 *** (10,615)	445,110 *** (11,685)	357,821 *** (8,877)	375,850 *** (10,053)	365,132 *** (9,848)	435,935 *** (11,516)	370,233 *** (9,866)	442,048 *** (11,527)
Coefficient of Variation of Demand	63,436 (754,161)	3,645,399 * (1,497,515)	155,952 (2,276,775)	-712,044 (2,287,307)	-1,603,487 (2,548,917)	3,365,540 (1,948,109)	-5,030,741 * (2,120,050)	499,508 (2,110,773)	458,327 (2,436,960)	-350,846 (2,059,801)	-1,387,713 (2,439,759)
n	10,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
F	6,208.3 ***	777.4 ***	750.9 ***	761.0 ***	698.8 ***	782.6 ***	748.0 ***	722.6 ***	752.6 ***	748.5 ***	784.7 ***
Adjusted R^2	71.29%	75.66%	75.02%	75.27%	73.64%	75.78%	74.94%	74.29%	75.06%	74.95%	75.83%

Parameter significance, * $\Rightarrow p < 0.05$; ** $\Rightarrow p < 0.01$; *** $\Rightarrow p < 0.001$.

Notes: Regression Analysis: Profitability on Holding Cost %, Commodity %, Markup %, and Coefficient of Variation of Demand. Standard Errors shown in parentheses.

Table IX ECFB Profitability and Commodity %

Independent Variables	***All Commodity Indices Combined***	***Commodity Agricultural Raw Materials***	***Commodity Beverage Price Index***	***Commodity Price Index***	***Commodity Fuel (Energy) Index***	***Commodity Food and Beverage Price Index***	***Commodity Food Price Index***	***Commodity Industrial Inputs Price Index***	***Commodity Metals Price Index***	***Commodity Non-Fuel Price Index***	***Crude Oil (Petroleum), Price index***
Intercept	7,941,056 *** (191,359)	5,738,759 *** (599,965)	9,438,572 *** (643,650)	7,884,836 *** (556,570)	8,500,439 *** (596,425)	9,284,683 *** (668,438)	8,457,898 *** (599,309)	11,949,482 *** (644,807)	6,512,794 *** (527,045)	5,752,988 *** (570,110)	5,519,972 *** (444,614)
Low Commodity % (15% to 30%)	16,172,672 *** (270,663)	14,698,902 *** (806,323)	18,569,495 *** (923,507)	16,690,215 *** (800,955)	15,658,992 *** (840,290)	18,894,342 *** (952,671)	15,995,269 *** (823,392)	18,449,065 *** (933,128)	14,823,879 *** (759,639)	17,669,060 *** (820,171)	11,589,049 *** (624,592)
High Commodity % (45% to 60%)	-2,296,405 *** (271,173)	-2,038,760 * (856,195)	-2,252,624 * (917,067)	-2,012,380 * (797,802)	-2,442,827 ** (834,770)	-2,464,086 ** (931,712)	-2,469,817 ** (824,514)	-3,125,214 ** (947,132)	-1,957,606 ** (756,038)	-1,829,776 * (801,584)	-2,015,966 ** (628,304)
N	10,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
F	2760.6***	263.2***	301.5***	321.3***	276.7***	303.5***	311***	297.4***	284.8***	342.7***	277.8***
Adjusted R^2	35.57%	34.42%	37.56%	39.07%	35.57%	37.72%	38.30%	37.24%	36.23%	40.62%	35.65%

Parameter significance, * ⇒$p< 0.05$; ** ⇒$p < 0.01$; *** ⇒$p< 0.001$.

Notes: Regression Analysis: Profitability on Low Commodity (= 1 for Commodity Percentages 15% to 30%, = 0 otherwise) and High Commodity (= 1 for Commodity Percentages 45% to 60%, = 0 otherwise) Indicator Variables. Standard Errors shown in parentheses.