

A Hedonic Regression Model for Refrigerators

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1. INTRODUCTION

The Consumer Price Index is an indicator of changes in consumer prices for goods and services. In order to measure only price changes over time, statistical agencies use a fixed basket of goods and services which is updated regularly to keep it consistent with consumer behavior. Using a fixed basket ensures that the quality and the quantities of goods in the basket are fixed, so that the index reflects pure price changes.

According to *Statistics Canada (1992, 22-23)*, the CPI is often used to determine the amount by which it would be necessary to adjust incomes, wages and other payments to maintain previous purchasing power in the face of changing consumer prices. It is used in this manner to adjust government payments resulting from social programs such as the Canada Pension Plan, Old Age Security and the Guaranteed Income Supplement. Some labour-management contracts also contain cost-of-living adjustment (COLA) clauses, through which wages and salaries are tied to the CPI in a variety of ways. Many other financial arrangements make reference to the CPI in adjusting terms of payment. A partial list includes rental agreements, insurance coverage, private loans, spousal maintenance, and child support allowances.

In yet another application, the CPI is used to “deflate” various macro-economic series expressed in current dollars; that is, to transform them into constant-dollar series. The “Personal expenditure on consumer goods and services” component of the National Accounts and the values of retail sales and average wages are examples of series that are deflated with consumer price indexes. The Bank of Canada, which is interested in measuring inflation precisely because their primary goal is to have a low, stable and

predictable rate of inflation, also uses the CPI as a gauge of the impact of public policy changes.

Recently, Boskin et al. (1996) concluded that traditional methods used to measure pure price changes might overestimate actual changes.¹ For the USA, the CPI was overestimated 1.1 % per year prior to 1996 according to the Boskin Report. Some of the potential sources of bias in the CPI are product substitution, new goods, outlet substitution and quality change, among which quality change (0.6% per year) accounts for the biggest share in Boskin Report. For Canada, Crawford (1993) estimated the upper limit for CPI total annual bias to be 0.5%. The Boskin Commission proposes use of the hedonic regression method as an alternative to manufacturers' cost estimates in making quality change adjustments. They also respond to those who object to hedonics because of practicality issues. They recommend that an independent group be organized, arguing that "Such a group could pursue more fundamental research in cooperation with the BLS (Bureau of Labour Statistics) and provide a framework for experimentation with various alternative data collection and estimation approaches."²

The purpose of this paper is to investigate the use of hedonic methods as an alternative to traditional methods of quality adjustment for refrigerators by analyzing the relation between refrigerator prices and quality. Section 2 explains the hedonic regression model and how it has been applied in real world applications by statistical agencies, as well as presenting the theoretical background of hedonic functions. Section 3 provides an historical overview of the use of hedonic regression models, section 4 discusses the data

¹ From this point on I will refer to Boskin et al. (1996) as the "Boskin Report."

² The Boskin Report is available in html format. No page numbers are present.

and section 5 presents the empirical results of an application of hedonic estimation to a sample of refrigerator prices for home use. Finally section 6 presents the conclusions of this paper.

2. THE HEDONIC REGRESSION MODEL

2.1 METHODS OF QUALITY ADJUSTMENT IN THE CPI

For most consumer goods, Statistics Canada currently uses the following procedure to make quality adjustments to the CPI. The traditional "matched model" method of measuring price changes uses prices for the same sample every time by specifying each variety in the sample, thus ensuring the price difference between periods reflects only pure price changes. Problems associated with this method arise when the price changes observed are not representative of the movement for that good. Triplett (1969) mentions a study by Burnstein (1961) where a price index for refrigerators which complied with BLS specifications from mail-order catalogs was constructed. He also constructed an index for all refrigerators and comparison of the two indexes revealed that the index derived from the prices of refrigerators that conformed with BLS specifications was downward biased. In a similar manner, Rees (1961), using mail-order catalogs, constructed indexes for ten non-durables. Three out of the ten indices coincided with the BLS indexes; Rees compared the procedure he used to BLS methods for one of the other seven indexes and concluded that "inspection of the (BLS) worksheets revealed serious errors in following the BLS specifications."

When an item being priced is no longer available in the market, the Statistics Canada field representative must find a replacement that has comparable specifications. If

this is not possible, a very similar item is priced and the quality difference is determined by the field specialist. The field representative completes a form called a Quality Price Change Report (QPCR), and he/she specifies on it the observed price difference between the new and the old selection, the estimated quality difference between them and the pure price change. For clothing in the CPI in Canada, the price collectors are asked to use comparative judgment in cases of replacements. However, the decisions of the field representative depend on the personal abilities and knowledge of the individual collecting the price.

Another problem is that although the range of acceptable quality is defined by the official specifications, the matched models may not be identical. The stricter the selection process is, the less likely it is that this kind of error occurs. However, excluding more variants of a good raises the problem of representative index movement. Berndt (1991) suggests using regression analysis to reduce the severity of this tradeoff.

To minimize the effect of unrepresentative samples, substitution is done for items initially included as described above. In this case, the problem of discontinuous variants is solved using "overlapping" method, in which the initial item and the replacement are priced at a point in time when they are both available. The ratio of the prices is then used as an adjustment factor for the replacement. Lowe (1999) lists a number of limitations of this kind of replacement. First, an item is replaced when it is no longer available in the market. In such a case, the price is usually discounted to clear stocks. Second, new items may be introduced at a very high price to capture those customers placing a great value on having the latest version. Third, a new item, usually a substitute to those present in the market as a new bundle of characteristics not available at all before, may be introduced at

a low introductory price to attract customers until it is accepted in the market. Fourth, the manufacturer or the retailer may misjudge their expectations on price, which have to be corrected later. Fifth, the purchaser may not correctly estimate the relative qualities of the former item and the replacement when there are no common characteristics or when a new feature previously unavailable is introduced within the replacement.

Another possibility is to adjust price changes for alterations in the good itself. For example, if a water dispenser becomes part of the standard refrigerator over a pricing period, then the previous price of the refrigerator can be adjusted for acquiring the additional feature.

Lowe (1999) discusses the fact that new features first appear in the high end models of the quality range with a significant premium. By the time these features are widely inserted in models that are replacing older models in the sample, they lose their initial values but the hedonic function in use was estimated using higher values of these features. This can be avoided by updating the hedonic function regularly.

2.2 THEORETICAL FOUNDATION

The theoretical background for the hedonic method was developed after the applications. The hedonic theory was first described by Rosen in 1974. In his article, he analyzed buyer and seller choices and the meaning and nature of market equilibrium.

Rosen describes hedonic prices as

the implicit prices of attributes that are revealed to economic agents from observed prices of differentiated products and the specific amounts of characteristics associated with them. (page 34)

The *hedonic hypothesis* states that each good possesses a set of characteristics

$x = (x_1, x_2, \dots, x_n)$, where x_i is the amount of characteristic i in good x . When you buy a product, you actually buy this prebundled set of characteristics. Rosen (1974) describes a good as a space such that every point in this n dimensional space corresponds to a different bundle of characteristics, even though some of these defined points never exist in the market as they were not manufactured at all. In addition, there exists a function $f(x) = f(x_1, \dots, x_n)$ defined for spaces $x > 0$, that determines the price of good x ; in other words, $p = f(x)$. If N varieties of the good exist, then P is an $N \times 1$ vector of their prices of and x is a matrix of their characteristics $N \times n$.

In the theoretical appendix to Triplett (2004), Triplett demystifies the hedonic hypothesis with his grocery cart example:

Suppose grocery stores offered consumers choices among preloaded carts of groceries containing different quantities of groceries in each cart. The price for each cart is posted, but not the prices of the individual items loaded into the cart. One could estimate a hedonic function for grocery carts: The price attached to the cart of groceries is the dependent variable in equation, and the quantities of groceries in each cart make up the right-hand side variables —loaves of bread, boxes of breakfast cereal, heads of cabbage, and so forth. The estimated implicit prices for groceries from the hedonic function can then be interpreted as the prices of these groceries as they would have been if they had been posted on the grocer's shelves.³ (page 2)

With the hedonic price regression, one is estimating the price function. Rosen (1974) suggests that if one adopts the convention of measuring x_i such that they are all "goods," then consumers place positive values on all of them. Then $p(x)$ is an increasing function of x_i 's, $\partial p / \partial x > 0$. There is no restriction on $p(x)$ being linear. The estimated price function does not reveal either consumer preferences or the production function but it tells us the market equilibrium prices of characteristics. Both consumers and producers

³ The grocery cart example was first given in Triplett (1976).

make their decisions by maximization, and competitive equilibrium prices, where demand equals supply, prevail.

Rosen (1974) describes $p(x)$ as

the minimum price of any package of characteristics. If two brands offer the same bundle, but sell for different prices, consumers only consider the less expensive one and identity is irrelevant to their purchase decision. (page 37)

However, when we introduce manufacturer or brand as an exogenous variable in the hedonic model, then we can explain price differences for 'identical' bundles offered by different manufacturers, because the manufacturer is a proxy for other quality features that can not be measured but are perceived by consumers. Of course, it must be remembered that one can never include all the x_i 's, as quality is not readily explained quantitatively. The implicit market equilibrium involving hedonic prices is elucidated in Rosen (1974).

Hedonic price models are not just functions relating quantities to prices; rather, they are aggregations of the prices of characteristics in the bundle. Given our hedonic price function $p = f(x)$, we can define *implicit* or *hedonic prices* as partial derivatives of the hedonic function:

$$\frac{\partial p(x)}{\partial x_i} = \frac{\partial f(x)}{\partial x_i} \quad i=1, \dots, n. \quad (1)$$

The right hand side of this equation represents how much the price of the good x changes if you increase the amount of characteristic x_i incrementally, holding the levels of all other characteristics constant.

To specify the hedonic function, first we need to know the characteristics vector x .⁴ Brachinger (2002) defines a good as the set of all variants of the good, for which the

⁴ It is an implicit assumption of the hedonic approach that goods are not homogeneous. Goods as such empirically do not exist. What empirically exist are more concrete examples or variants of the idea of a certain good, all of which are more or less different.

price can be estimated with the same regression equation. The observed price of these variants of the good varies in itself. He describes the suggested statistical model for the prices as

$$P_j = f(x_j, \beta) + u, \quad (2)$$

where $x_j = (x_{1j}, x_{2j}, \dots, x_{nj})$ is the characteristic vector for variant j ; and $\beta = (\beta_1, \dots, \beta_n)$ is the vector of unknown coefficients, where β_k is the implicit price of characteristic k . The variable u is the random error term and the classical assumptions hold; i.e. $E(u | x_j) = 0$ and $\text{Var}(u | x_j) = \delta^2$.

The characteristics vector and the parameters may change over time, so we can write the price of variant j that we observe at time t as

$$P_j^t = f(x_j^t, \beta^t) + v_j^t, \quad j=1, \dots, N, \quad (3)$$

where N is the population size, $x_j^t = (x_{j1}^t, \dots, x_{jn}^t)$ is the characteristics vector for variant j at time t , $\beta^t = (\beta_0^t, \dots, \beta_n^t)$ is the parameter vector at time t , and $E(v_j^t | E(x_j^t)) = 0$.

Once we have estimated the parameter vector, the hedonic price can be used to construct price indices. For example, to construct a true hedonic Laspeyres price index, one compares the hedonic price of a particular good at two different times while holding the quality of the good x , at its level in the base period, x_0 . It is defined by

$$\text{HPI}_{0,t}^L = \frac{P_{\text{qcorr}}^{h,t}}{P^0} = \frac{P(x^0, \beta^t)}{P(x^0, \beta^0)} \quad (4)$$

where $P_{\text{qcorr}}^{h,t}$ is the quality adjusted hedonic price of the good at time t .

2.3 FUNCTIONAL FORMS

An important issue in the estimation of hedonic regression models is the choice of functional form. A hedonic function is an aggregation of the implicit prices of the characteristics contained in a good. Pakes (2004) discusses the implications of theoretical constraints on the choice of functional form and concludes that “the functional form to be used is not constrained, any functional form rich enough to include significant variables will work and there are no constraints on the coefficients either”(page 9).

Pakes points out that especially in “high tech” industries, the estimation model will differ over time when there is entry into those characteristics markets with high markups. He notes that Court and Griliches suggest estimating a surface which relates prices and characteristics and time and then using the estimated surface to obtain estimates of price changes for products with constant characteristics. Also, one must not ignore in this perspective that changing consumer preferences affect the resulting market equilibrium and thus the prices. Due to varying preferences, for similar reasons the hedonic function for a good may be unique to the particular market in question.

Pakes (2004) uses the following example to explain why there are no constraints on the coefficients:

Assume people that are sick with this disease care about their ability to grip objects and their overall health (we include the health index because the drugs that treat Rheumatoid Arthritis can have toxic side effects). The drugs actually marketed are defined by their content of various chemicals, and the transformation from chemicals to “grip ability” and “overall health” varies by individual. We simplify slightly and assume that there are two types of drugs that treat Rheumatoid Arthritis (type A and type B). The National Institute of Health performed a series of tests and the results showed that for the vast majority of patients drug type A is as effective as drug B and is far less toxic. In particular the “toxicity” rating of drug A (measured as the fraction of people whom the drug causes serious harm to) is essentially zero. On the other hand Drug B is effective on most of the, say, 5% of the population that drug A does not help, but has a toxicity rating of 0.7.

Once the results of these tests are made public drug companies rush to produce different versions of the type A drug. Indeed companies keep entering into that part of the market until the expected discounted value of profits from marketing

such a drug falls below its development costs. The large number of producers of type A drugs generates competition in that drug's market and this forces down mark-ups on drugs of type A. Of course the large number of patients consuming these drugs implies that the firms that produced it are still able to cover their development costs (even given the small mark-ups). The market for drugs of type B is too small to support more than one firm, so that producer sells its product at a "monopoly" price. The marginal cost of production is similar for both types of drugs, so the hedonic function will be largely determined by differences in mark-ups. Since mark-ups are higher for the more toxic drug, we should expect the hedonic regression of price against efficacy and toxicity to pick up a strong positive coefficient on toxicity. (page 10)⁵

According to Brachinger (2002), one of four functional forms can be used to estimate hedonic price models. None of them is considered to be superior to the others. Which one will perform best is unknown before the estimation is done.

The first functional form is the **ordinary linear** model given by

$$p = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_k * x_k \quad (5)$$

where

$$\frac{\partial p(x)}{\partial x_i} = \beta_i \quad (6)$$

is the implicit price of characteristic *i*. If characteristic *i* is a quantity, such as capacity (Cu./Ft.) or amount of kWh per year energy consumption, then x_i is a continuous variable. If characteristic *i* is a categorical variable (such as whether the refrigerator has water filtration or not) - i.e., it has the value 0 or 1 depending on whether the feature is present - then x_i is a dummy variable. The regression coefficients show the marginal change in price with respect to a unit change in the corresponding characteristic x_i of the good.

The second model is **log-linear**, described as

⁵This is an example taken from Cockburn and Anis (1998).

$$\ln p = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_k * x_k \quad (7)$$

with hedonic prices given by

$$\frac{\partial p(x)}{\partial x_i} = \beta_i * p \quad (8)$$

In this model the coefficient β_i indicates the rate at which price will increase with respect to characteristic i at a given level of characteristic i .

Another model is the **double- log** model where

$$\ln p = \ln \beta_0 + \beta_1 * \ln x_1 + \beta_2 * \ln x_2 + \dots + \beta_k * \ln x_k \quad (9)$$

and the implicit prices are given by

$$\frac{\partial p(x)}{\partial x_i} = \frac{\beta_i}{x_i} * p \quad (10)$$

The coefficient β_i indicate the percentage change in price for a 1 percent change in characteristic i at a given level.

The last model is the **linear- log** model :

$$p = \ln \beta_0 + \beta_1 * \ln x_1 + \beta_2 * \ln x_2 + \dots + \beta_k * \ln x_k \quad (11)$$

and the hedonic prices are

$$\frac{\partial p(x)}{\partial x_i} = \frac{\beta_i}{x_i} \quad (12)$$

where coefficient β_i shows how much price will increase for a 1 percent change in characteristic x_i .

For any of the models described above, the implicit price of a characteristic that is represented as a dummy variable in the model is the difference in the right-hand side of the equation between the two cases where the dummy variable equals 1 or 0. For example, for the log linear model, the difference in the logarithm of prices when one of

the dummy variables is 0 and when it is 1, keeping everything else the same is the implicit price of the variable in question. That is to say, the coefficient estimate is the implicit price in the case of dummy variables.

3. A BRIEF HISTORICAL OVERVIEW

3.1 EARLY APPLICATIONS OF THE HEDONIC REGRESSION MODEL

In chapter 4 of his book *The Practice of Econometrics*, Berndt (1991) discusses some of the early contributions to the literature on hedonics. The first published article that applied hedonic techniques is by Waugh (1928), who explains the relationship of vegetable prices and quality characteristics using what he called the method of multiple correlation analysis. In his paper, Waugh uses physical characteristics to explain price differences for asparagus, tomatoes and cucumbers sold at the wholesale market in Boston.

Next, Court (1939) estimated a hedonic price equation for cars for the purposes of what would today be an anticompetitive pricing case before the Competition Tribunal. The US Bureau of Labour Statistics (BLS) had stated that over the period 1925-1935, GM brand new car prices had increased 45 % on average. However, the BLS had been using only average list prices; quality improvements were not taken into account. Court applied what he called the hedonic pricing method to estimate parameters for such automobile characteristics as physical design and operating characteristics, which contribute to the utility from 'consumption' of cars. He regressed list prices on the model of car purchased, time and other car characteristics such as power, speed, internal space, etc. He constructed a model from which, by keeping all other variables the same, one

could measure the pure price change over time. His model implied that GM brand average new car prices had actually decreased about 55% over the period 1925-1935.

Griliches (1961) followed Court, by investigating suggested retail automobile prices in the US. He regressed prices on various characteristics of a car: quality variables such as horsepower, weight and length; and dummy variables for possession of other quality attributes in the US for the years 1937, 1950 and 1954 through 1960. The main problem in his regression was multicollinearity between characteristics. He found that the value of quality changes measured in implicit prices of different years varies. Quality changes at their 1950 implicit prices account for all of the price changes between 1950 and 1960. However, if we were to value these changes at their 1960 implicit prices, the same quality changes represent almost half of the price increase over the same period. This example shows that the hedonic function of a good varies over time.

Chow (1967) studied mainframe computer rental prices over the period 1955-1965. His intention in this study was to distinguish between the effect of technological improvement on demand and other effects on demand for computer rentals. Although he was unable to include all the relevant variables, his estimates were statistically significant and he computed a quality adjusted price index.

In most studies, the research was not initially intended to be used for price indexes. For clothing items, hedonic models were first constructed to help identify relevant quality characteristics. Eventually hedonic models became sufficiently developed to be used for quality adjustments.

3.2 THE EXPANDING ROLE OF HEDONIC METHODS

Statistical agencies first applied hedonic methods to housing price indexes due to the severe heterogeneity in characteristics of new construction. In 1968, the US Census Bureau was the first federal agency to adopt the hedonic method. The traditional 'matched model' method did a poor job of correcting for quality differences between houses with unique combinations of regional location, area of floor space, number of rooms and bathrooms, construction year, neighbourhood and many other quality attributes.

Many years later, the US Bureau of Economic Analysis began producing hedonic price indexes for computer equipment and peripherals in December 1985. The Bureau of Labour Statistics' slow incorporation of hedonic methods in price index construction ended in January 1988 when the BLS introduced an age adjustment for the rent index. Clothing indexes were considered next, beginning in 1991. In 1998, hedonic methods were introduced for the computer index, followed by the television index in 1999. Over the last few years, the use of hedonics has developed further and hedonic methods have been employed for additional goods, mainly goods durable in nature – major appliances, camcorders, DVD players, etc.

In the Netherlands, the first quality adjusted price index for cars was estimated in 1966. In Canada, hedonic methods were first used in 1974 in the New Housing Price Index for Vancouver. However, the use of hedonic methods was not widespread. The Boskin Report served as a trigger to encourage statistical agencies all over the world to adopt alternative methods of estimation and sampling. Recently, Statistics Canada started conducting studies of new methods; the first attempts to explore the use of the hedonic

approach involved clothing, computers and software and television sets.⁶ Statistics New Zealand put hedonics into practice for used cars in 2001 and some major household appliances in 2002. The Statistics Bureau of Japan added Desktop PCs and notebook PCs into the CPI in 2000, and uses hedonic methods for constructing price indexes for them. The same methods are used in calculating a price index for digital cameras also. The National Institute for Statistics and Economic Studies in France uses hedonics for dishwashers, TVs, books, PCs and men's long sleeved shirts.

The Ottawa Group was created in 1994 to provide "a forum for specialists to share their experiences and discuss research on crucial problems of measuring price change. Without avoiding theoretical issues, the focus of the Group is on applied research, particularly, though not exclusively, in the area of consumer price indices."⁷

The Group examines the advantages and disadvantages of various concepts, methods and procedures in the context of realistic operational environments, supported by concrete examples whenever possible.

Moulton (2001) notes that according to Landefeld and Grimm (2000), 18% of US GDP final expenditures are deflated using indexes that are calculated with hedonic methods. The Boskin Report states that if the change in the CPI overstated the change in the cost of living by an average of 1.1 percentage points per year over the next decade, this bias would contribute about \$148 billion to the deficit in 2006 and \$691 billion to the national debt by then. The bias alone would be the fourth largest federal program, after social security, health care and defence. By 2008, these totals will reach \$202 billion and

⁶ Makle, Terri (1998)

⁷ www.ottawagroup.org, Background

\$1.07 trillion, respectively.

Moulton (2001) states that hedonic research has often led to improvements in sampling for the matched model indexes. In fact, US statistical agencies have found that hedonic analysis is a useful tool, whether used in the background as a guide to application of the matched model method, or used directly in making quality adjustments for sample items that are being replaced. Looking for new methods of measuring quality changes for items in the CPI has become one of the main purposes of hedonic method studies.

4. BACKGROUND FOR REFRIGERATORS AND DATA

4.1 BACKGROUND

I selected refrigerators as the subject of this study after discussions with commodity officers at Statistics Canada. The attributes of refrigerators vary depending on the manufacturer and thus provide quite a number of choices for consumers.

Currently, Statistics Canada is looking for ways of utilizing hedonic estimation methods for quality adjustment purposes in the CPI. Already, it is using hedonic models for personal computers, and the Prices Division has started a research program to investigate the possibility and the practicality of using the hedonic approach for clothing items. Markle (1998) constitutes one of the first outputs of this program.

It has been less than 100 years since the first known home-use refrigerator was marketed. According to the website www.inventors.about.com, the first public demonstration of refrigeration was shown made by William Cullen at the University of Glasgow in 1748. However, he did not see any practical purpose in his discovery. It was

not until 1913 that the first refrigerator designed for home use was Domelre, manufactured in Chicago by Domelre.⁸

During the 1940s, use of refrigeration systems became very common in the typical household. Automatic defrost and automatic ice makers first appeared in the 1950s and 60s. Later on new features were added to the refrigerator and environmental concerns brought energy efficiency with them.

The Canadian Appliance Manufacturers Association in its *2004 Major Appliance Industry Trends and Forecast*, states that

The refrigeration market continues to expand with both side-by-side refrigerators and refrigerators with the freezer on the bottom gaining in popularity. Water filtration is a growing feature, which is expected to increase in demand as taste and safety continue to be of paramount importance to consumers. Similarly, through-the-door ice and water dispensing systems and in-the-door ice units will continue to grow in popularity as consumers look for convenience.

Given the size of the refrigerator in the kitchen, styling will play a more significant role in the future. Colors continue to focus on stainless steel and the stainless-look finish that does not show fingerprints.

They also report some statistics and their expectations regarding market conditions. In 2003, 45% of sales were estimated to be 16.5 – 19.4 cu. ft. sized refrigerators. Excluding compacts, forecasts of market share for 2004 are as follows: 2-Door Top Freezer Refrigerators, 70.5%; Side by Sides, 13.5% and 2-Door Bottom Mount Refrigerators, 16%. (page 29 and tables 4.6 and 4.8)

According to the *Consumer Reports* website, displays that show actual temperature, tilt-down bottom-freezer drawers and tilt-down wire racks and slide-out shelves in the freezer work well. Adjustable door bins, glass shelves, displays that show the temperature setting, a temperature-controlled drawer, and a water filter are reported to

⁸ <http://inventors.about.com/gi/dynamic/offsite.htm?site=http://www.rogersrefrig.com/history.html>

be important features.

The key features are the position of the freezer compartment and capacity. These determine the price range one will pay; side-by-sides are usually more expensive than the top freezer type, and the larger the refrigerator the more costly it will be. Refrigerators consist of a bundle of characteristics that do not change much over time. In samples collected for the CPI, items are replaced by others that differ in secondary characteristics. When using hedonic price models for estimating quality changes, it is preferable to have product attributes that do not change continuously so that we can derive a model from cross sectional data and use it to adjust for replacements.

Refrigerators are covered under 'Refrigeration and Air Conditioning Appliances' and included in the Household Appliances category of the CPI together with others such as cooking appliances, laundry and dishwashing appliances and other appliances. The first Refrigeration index was published in September 1978. The adjusted weights associated with the 2001 basket, effective July 2004 are 0.20 for 'Refrigeration and Air Conditioning Appliances' and 0.74 for 'Household Appliances'. Adjusted weight for 'Refrigeration and Air Conditioning Appliances' in the 2001 basket effective July 2004, for Canada is 0.20; it constitutes 28% of major appliances. The level of the Refrigeration and Air Conditioning Appliances index in September 2004 was 97.8 (1992=100) and thus it has declined by 2.2% since 1992.

Major appliances are good candidates for the application of hedonic methods because they have a wide variety of combinations of features that change quickly over time due to technological improvements and/or competitiveness. Under these

circumstances, statistical agencies have to take into account market conditions when goods disappear or new goods are introduced.

Only a few studies of hedonic regression models for refrigerators seem to have been published. Triplett and MacDonald (1977) computed new indexes of output for refrigerators, using hedonic methods to adjust for quality change. The hedonic technique is applied in a new way (it is used to make quality adjustments to prices before they are used in the index), and the results are compared with those from methods used in previous hedonic investigations. Shepler (2001) wrote a paper on developing a hedonic regression model for refrigerators in the US CPI as part of research to extend the use of hedonic regression models for quality adjustment purposes. She used the existing CPI sample, with a supplemental sample, to develop a log-linear hedonic function for refrigerators in the US. She used her model for quality adjustments between July 1999 and April 2000. She found that the impact of using hedonic price function for quality adjustments was negligible due to the small proportion of substitutions in the index.

4.2 DATA

For the purposes of the CPI, Statistics Canada collects prices for refrigerators for the ten provinces and the three territories. Samples in the price survey are obtained by a judgmental selection of geographical area, types and locations of outlets. The selection of outlets is based on the volume of retail sales revenues, time and budget constraints.

The description of a representative refrigerator (in the CPI specification) is as follows:

Frost-free refrigerator, 16.5 to 29.4 cubic feet, two door model with freezer compartment above the refrigerator section.

Freezer: Ice cube tray(s) and/or ice bucket, interior full or half shelf and freezer door shelf.

Refrigerator: Adjustable glass and/or wire cantilever full or half shelves. Meat, fruit and vegetable drawers, door shelves and/or bins (fixed or adjustable), egg storage and dairy compartments.⁹

As indicated in the specification, the types of refrigerators priced for CPI purposes are limited by size and freezer type; the selection is the top seller capacity-wise. Thus to estimate a hedonic regression model for refrigerators, if SC data were used, all the available types would not be included in the estimation model. In comparison to the Sears department store online catalogue, the SC data lack diversity in values for some important characteristics of refrigerators. For the construction of the consumer price index, SC collects five to six prices on average at a representative city in each province, a total of 76 observations at a time.

However this sample size was not chosen for the purposes of estimating a hedonic regression model. Lowe (1999) states

Many of the problems at the detailed level arise from having too small a sample, so that too much dependence is placed on the evaluation of replacements. It may not be practicable to obtain a large fraction of all clothing sales, but for many consumer durables the range of choices at any one time is limited. Electronic data recording allows us (potentially) to collect a much larger volume of data, and that could help alleviate the problems of substitution and of including new varieties. The returns from investing in such data, even in using matched samples without capturing characteristics data, are more likely to produce useful results than trying to estimate quality changes for these commodities on a supposedly representative small sample. (Page 26)

In other words, a sample of just 76 observations is likely to be too small for the estimation of a reliable hedonic model.

⁹ This specification is drawn from an internal Statistics Canada document.

Shepler (2001), who developed a hedonic regression model for refrigerators in the US CPI, also found that the existing CPI refrigerator sample was not sufficient for modeling and collected a supplemental sample. Her final sample for estimation purposes contained 327 observations.

Since collecting a supplemental sample for Canada was out of the question, I was required to use another source of data. The online catalogue of Sears, on October 2nd, 2004, had 173 top freezers, 129 bottom freezers and 156 side-by-side refrigerators available. It provides a relatively large sample of detailed and reliable information on product characteristics for my purpose.¹⁰ This sample is not a judgmental or limited. If I had used SC data, some of the characteristics attributed to refrigerators would have needed to be collected independently from other sources, which is cost-inefficient and time-consuming. Even though the SC database goes back to the 1990s, it is inadequate for the estimation of a reliable hedonic function. This is a serious limitation, because for hedonic methods, the model is only as good as the included relevant quality features.

The overall quality of the data was good. I deleted a total of 32 observations for which the KW/hrs of energy consumption were unavailable, and also another observation for which the colour was titanium. All of the refrigerators in my sample are frost-free. There are three types of refrigerators: freezer on top, side-by-side refrigerator/freezer and freezer on bottom.¹¹ The model was specified with types as independent variables and the natural log of price as the dependent variable. Dummy variables for brand, colour, icemaker, sound reduction, water filtration, temperature and humidity controls, shelf type

¹⁰ Appendix I contain a sample showing the extent and format of information available in the Sears online catalogue.

¹¹ Appendix II contains a glossary which defines all the available features of refrigerators.

and other miscellaneous features were also included as independent variables. A complete list of the explanatory variables is provided in Table I. A sale price dummy was included because around 77% of the prices had a sale price reported. The unweighted mean price for all refrigerators in the sample is \$1692.15.¹² Since the unweighted mean prices for each type are \$1074.61, \$ 1905.52 and \$2132.87 for top, bottom and side-by-side freezer refrigerators respectively, including type as dummy variables captures this effect. The unweighted mean price for “regular” priced refrigerators in the sample is \$1566.05 and the unweighted mean price for “sale” priced refrigerators is \$1730.44.

The finding that the unweighted mean sale price is higher than unweighted mean regular price is unexpected, but may be because the high-end models were more likely to be discounted for sales; buyers of cheaper refrigerators may not need a price incentive. Histograms of the sale and regular price presented in Chart I show the frequency distributions of prices. They show that refrigerators sold at the regular price have more observations from the high-end market, which explains the result obtained.

Since I decided to include a constant term in the model, it was necessary to exclude one of each group of dummy variables. Among brands, *Frigidaire GPS* was excluded, since I had only 2 observations for this brand.¹³ The rest of the data is separated into sub-brands as it was suggested by Shepler (2001). Brand is thought to serve as a proxy for unmeasured quality characteristics. Liegey (2003) mentions that Triplett and McDonald (1977) found brand to be a statistically significant determinant of refrigerator prices in their refrigerator hedonic regressions.

¹² Sales information was not available.

¹³ The choice on reference group does not change the coefficient vector or the diagnostic test results.

When it comes to color, *bisque* was not included as an explanatory variable since the other colors -white, black and stainless steel- are more in demand. 'Stainless steel' and 'stainless look' were combined into a single category because stainless look refrigerators were few in number. Fresh food and freezer capacities were included separately instead of including the total capacity, as the split between these two differs even among same-size refrigerators.

As a measure of energy efficiency, Shepler (2001) suggests that rather than including kilowatt hours of electricity used per year, one should use the energy star rating as a variable because

Kilowatt hours of electricity used per year was believed to be an important price factor; however it is strongly related to total capacity since in general larger refrigerators require more electricity. This variable would be preferable to the kilowatt hours used variable since it is unlikely that it would be highly correlated with any other variables.¹⁴

However, instead of using the energy star rating, in order to reduce collinearity in my model I used kilowatt hours per year used per Cu./Ft. By normalizing the energy use variable in this manner, the concerns discussed in Shepler (2001) are eliminated.

Dummy variables are also included for reversible door, water filtration, sound reduction, door kit, adjustable shelf, crisper humidity control, meat bin temperature control, snack bin, dairy compartment, freezer basket, freezer can rack, freezer light and miscellaneous freezer features. Different icemaker options are grouped together so that a single dummy variable indicates whether or not an icemaker is included.¹⁵ Grouping icemaker options could be an improvement on the model of Shepler (2001). Finally, with

¹⁴ No page number available in html format.

¹⁵ See Appendix II for complete descriptions of these options.

respect to shelf type, *glass* is excluded; the other options are *wire* and *spill-proof glass*.

Having spill-proof glass in particular is considered to be an important feature. Grouping them as wire or glass would lose the detail on spill-proof glass, while including it as a dummy variable would result in a correlation between *glass* and *spill-proof glass*.

5. REGRESSION MODEL AND RESULTS

The preliminary model is a linear model which includes all the variables created from the information available.¹⁶ Since a refrigerator that does not have any of the characteristics defined would not be a refrigerator and thus should have no value or price attached to it, suppressing the constant in the hedonic equation for refrigerators would seem logical. However, to be able to perform various diagnostic tests in *Stata*, I need to have a constant term in the equation, since otherwise the software does not accept the test commands.¹⁷ Note that if the regression equation does not include a constant, then R^2 is no longer bounded between 0 and 1. Thus all the results reported in subsequent tables are for equations with a constant term if not specified otherwise.

First I tested powers of the dependent variable, *price*, for a transform that converts the dependent variable into a normally distributed variable. A normal distribution for the dependent variable is desirable to help ensure that residuals are normally distributed, which is necessary for hypothesis testing. For each of the transformations - cubic, square, square root, log, reciprocal root, reciprocal, reciprocal square and cubic - a χ^2 test statistic for a test of skewness and kurtosis calculated. The results are as reported by skewness and kurtosis test. The transform with the smallest χ^2 value is chosen. As Table

¹⁶ After the data were ready for use with any statistical software, I chose *Stata* because it has a point and click interface and was very easy to learn for basic econometric analysis. It also provides detailed explanations of its commands. Regression results for a preliminary model with a constant term are in Appendix III.

¹⁷ Regression results for a preliminary model without a constant term are in Appendix IV.

II indicates, the log transformation has the smallest chi square value, so the logarithm of *price* is the transformation that is the most normally distributed among other transformations. Thus, I will continue with the log-linear model, equation (7) from now on.

Prior to doing further diagnostic testing, I estimated a log-linear regression using the same set of explanatory variables. The results of this model are presented in Table III.¹⁸ The adjusted R^2 for the log-linear model is 0.9189 which means that almost 92% of the variation in the dependent variable, *LogPrice*, can be explained by the included variables. The reported F value is greater than $F_{42, 383}$ at the 5 % significance level, which is the level of significance used through out this paper for all tests if not specified otherwise. Thus we can reject the null hypothesis H_0 : all slope coefficients are equal to 0.¹⁹ For tests of individual significance, I will proceed with results of this log-linear model with all variables included.

However, the *Stata* dropped two of the explanatory variables, *SidebySide* and *DairyComp* from this regression, due to a dependency among the independent variables in the proposed model. Which variable it drops is somewhat random, but it will always drop one of the variables in the dependency. If I run auxiliary regressions for the dropped variables, I can identify and show the dependency. An R-squared value of 1.00 and a residual sum of squares of zero were obtained for both of the auxiliary regression models.²⁰ Not surprisingly, *SidebySide* is dropped from the model because it is perfectly collinear with *Top* and *Bottom*. For *DairyComp*, perfect collinearity exists with *SnackBin*,

¹⁸ Appendix V shows the regression results without the constant term.

¹⁹ Statistical tables do not show $F_{42, 383}$; using $F_{40, 100}$ secures the reliability of the conclusions.

²⁰ Table IV and Table V show the regression results for *SidebySide* and *DairyComp*

which was not expected.

Starting from the first model shown in Table III, one can develop the final model after doing diagnostic tests, for unusual and influential data, normality of the errors, multicollinearity and other problems. First, I tested for outliers. A scatterplot matrix can be used as a diagnostic tool to search for non-linearities and outliers in the data. The continuous independent variables that are plotted are *Price*, freezer capacity (*FreezerCap*), fresh food capacity (*FFCap*) and kilowatt hours per year per Cu./ft. (*KWHYCAP*). The scatterplot matrix in Chart II shows that there are two observations that are far away from the rest of the points. These two influential observations are those observations for which *KWHYCAP* is greater than 40 units. They may be outliers, observations with large residuals; or if it is a leverage, an observation with an extreme value on a predictor variable, then in both cases, they can affect the coefficient estimates. If these two observations are influential, then removing them from the sample will change the coefficient estimates substantially.

To detect outliers the DFITS statistic that measures the overall influence of each observation on the parameter estimates can be examined. The rule of thumb for identifying influential observations is to check if the absolute value of DFITS for that observation is greater than $2 \cdot \sqrt{k/N}$, where k is the number of estimated coefficients and N is the sample size. For my sample $k=42$ and $N=425$ and $2 \cdot \sqrt{42/425} = 0.6287$.²¹

After deletion of the observations identified as outliers, I re-estimated the regression model. After comparing the t-values reported for this model (Table VII) to those of the coefficients for the previous model (Table III), it can be seen that some of the previously

²¹ Table VI lists the observations for which DFITS exceeded this critical value.

insignificant coefficients became significant; those of *Whirlpoolgold*, *GE*, *Frigidaire*, *other_brand*, *SpillPG* and *SnackBin* are now statistically significant, but on the other hand the coefficient of *FreezerCanRack* is not significant anymore. Thus, in this case, the outliers have a substantial effect and it is appropriate that they are removed from the sample.

Next, I looked at the normality of errors issue. Normality of residuals is necessary for valid hypothesis testing; it ensures that the t and F statistics have the t and F distributions respectively. First, I created the residuals for this equation and plotted the kernel density plot, a standardized normal probability plot (pnorm plot) and the quantiles of errors against the quantiles of a normal distribution (qnorm plot). These plots are shown in Chart III. The pnorm plot is sensitive to non-normality in the middle range of data while the qnorm plot is sensitive to non-normality near the tails. As can be seen in Chart III, the pnorm plot shows no signs of non-normality, but the qnorm plot shows a little deviation, especially around the upper tail. This deviation from normality can be observed in the kernel density plot as well.

In addition, I carried out the Shapiro-Wilk test for normality of the errors. The null hypothesis is that the errors are normally distributed. The results of the test are presented in Table VIII. Since the p value is only 0.01294, at the 5% level of significance we must reject the null hypothesis.

Next, I check for heteroskedasticity. If the errors are homoskedastic, then there should be no obvious pattern when the residuals are plotted against the fitted values. The plot in Chart IV shows that the range of the data points is a bit wider at the right end,

which is an indication of heteroskedasticity. The results of the Breusch-Pagan test for heteroskedasticity, presented in Table VIII, confirm that heteroskedasticity is present, as it is impossible to reject the hypothesis that the variance of residuals is consistent at the 5% level of significance. For the final version of the hedonic price equation for refrigerators, a regression with robust standard errors that take into account the heteroskedasticity were computed.

Another potential problem in a model with too many explanatory variables is multicollinearity. When there is a strong interrelationship among independent variables, the estimates for a regression model become unstable, with large variances resulting in insignificant parameter estimates that make it impossible to draw reliable conclusions about the coefficient estimates. In addition, the estimated coefficients may vary from sample to sample or with the inclusion/deletion of an independent variable.

Multicollinearity is problematic when one's purpose is explanation rather than mere prediction.

To check for multicollinearity, I examined the VIFs, or variance inflation factors. The VIFs for the independent variables are presented in Table IX. A variable whose VIF value is greater than 10 needs further investigation. As Table IX shows, five variables had a VIF greater than 10.

I ran auxiliary regressions for each of these variables with a high VIF. The first is variable *SidebySide*, which has a VIF value of 31.70. As indicated in Table X, the auxiliary R^2 value is 0.9685. The t-statistics of the coefficient estimates suggest that the variables *Top* and *FreezerShelf* are the most closely related to *SidebySide*, which is to be

expected because both *Top* and *SidebySide* are refrigerator types (*Bottom* was dropped previously) and freezer shelves are found in side-by-side refrigerators. *Kenmore*, which has the second highest VIF value (15.85) has an auxiliary R^2 of 0.9299.²² The t values for all of the other brand variables are high in this equation, probably because the brand excluded to avoid the dummy variable trap (*Frigidaire GPS*) accounts for only two observations. Thus if a refrigerator is not Kenmore brand, it has to be one of the others. In total, 91 of the 399 refrigerators, left after deleting twenty-six influential observations are Kenmore.

After comparing the regression results for the new sample after deleting possible outliers (Table VIII) to the model that excludes the variable *Kenmore* (Table XII), I decided to drop *Kenmore* because the coefficient estimates change drastically.²³ Some of the insignificant coefficients in the previous model, like those of *Whirlpool*, *GE*, *Frigidaire*, *KenmoreElite* and *filterwater*, became significant when *Kenmore* is excluded or vice versa or their coefficients changed sign. However when I excluded the variable *SidebySide*, the t values and coefficients estimates did not change in any way that affects hypothesis testing.²⁴

The auxiliary regression results for *FreezerShelf* show an adjusted R^2 of 0.9244 and an F value of 122.66.²⁵ The t values imply that *FreezerShelf* is correlated mainly with refrigerator types; side-by-side types have only shelves in the freezer and bottom type refrigerators do not have shelves but baskets in their freezers. When *FreezerShelf* was dropped due to multicollinearity, the t values and coefficients estimates did not

²² Table XI

²³ Kenmore with the Frigidaire GPS, which has only 2 observations becomes the reference group for brand.

²⁴ Table XIII

²⁵ Table XIV

change significantly.²⁶ In the end, I decided to drop *Kenmore*, *SidebySide* and *FreezerShelf* to get rid of multicollinearity as much as possible.

Thus far, I have assumed that the relationship between the *LogPrice* and the exogenous variables is linear. If this assumption is violated, then linear regression attempts to fit a straight line to data that does not follow a straight line. In the case of multiple regression, one can plot the standardized residuals against each of the independent variables to see if there is a nonlinear pattern. Using an augmented component-plus-residual plot to show the relationship between a given independent variable and the response variable, given that other independent variables are also in the model, one can identify nonlinearities in the data. The plots in Chart V were constructed using the sample of 399 observations. The smoothed lines are parallel around the center but then there is a single observation that causes some curvature to appear. After this observation was deleted, the smoothed lines seem very close to the regression line in Chart VI. Thus overall I do not think there is a serious non-linearity problem.

Specification errors can occur if one or more relevant variables are omitted from the model or some irrelevant variables are included in the model. If relevant variables are omitted, the coefficient estimates will be biased and the variances of the coefficient estimates are smaller than those of the true model. If irrelevant variables are added then the coefficient estimates are still unbiased but they are also less efficient. Omitted variables may or may not be correlated with the included variables. In the correlated case, coefficients of included correlated variables pick up part of the effect of omitted variables on price.

²⁶ Table XV

Two tests for model specification were performed, and the results of both are presented in Table VIII. The link test is based on the idea that if a regression is properly specified, then one should not be able to find any additional variables that are significant except by chance. For the link test, the log of price is regressed on the predicted values from the original regression model, and the squares of the predicted values. Then a t-test of the null hypothesis that the coefficient of the squared predicted value is zero is carried out. If the model is correctly specified then this new variable should not have much explanatory power. The results of the link test indicate that at the 5% level of significance we can not reject the null hypothesis, since the p-value is 0.184.

Ramsey's regression specification error test (RESET) for omitted variables was also carried out. This test amounts to estimating the equation $y = xb + zc + u$, where z is an $N \times 3$ matrix containing the second, third and fourth powers of predicted values from the original model, and then testing the hypothesis that $c = 0$. If we accept the null hypothesis that $c = 0$, then we accept that the model is correctly specified.

The results of this test, shown in Table VIII, indicate that at the 5% level of significance, we can not reject the null hypothesis that model has no omitted variables because the p value is greater than 0. Thus the model appears to be well-specified.

The final model after the diagnostic tests is presented in Table XVI. The final sample size is 398. An R^2 of 0.9483 is reported. That is, around 95 % of the variation in *LogPrice* is explained by the model. The F-statistic is 260.18, implying that we can reject the null hypothesis that the overall model has no explanatory power at the 5% level of significance.²⁷

²⁷ Statistical tables do not report exact value of F 39.358 at 5% significance level. Instead F40, ∞ can be found and thus used.

The results for the most part meet a priori expectations. The coefficients of all the brand variables except *other_brand* are positive although not all are statistically significant. The positive coefficients imply that holding all else constant, nearly all other brands have higher prices than the reference brand FrigidaireGPS and Kenmore. *Kitchenaid*, *whirlpool*, *whirlpoolgold* and *jenn_air* are the major brands that have significantly higher prices than the reference brands. Although Shepler (2001) had suggested separating sub-brands into individual variables to improve the model specification, regrouping might work better as the coefficients of *ge*, *frigidaire*, *frigidairegallery* and *other_brand* were all statistically insignificant at the 5% level of significance. As for other variables, the parameter estimates for *soundred*, *tempctr*, *icemaker*, *filterwater*, *doortkit*, *crisperhctrl*, *meattempctrl* and *snackbin* were all positive, which is consistent with expectations. Sound reduction reduces the noise the refrigerator makes with the help of extra insulation and specially designed fan blades. *Tempctr* means the refrigerator has temperature control that keeps the refrigerator at optimal cooling temperature, lowering the energy use. Crisper humidity control and meat temperature control keep the meat and fruit and vegetable compartments at optimal temperature and humidity, ensuring fresher perishables.

Specially designed bins such as a snack bin in the fresh food section or a can rack and baskets in the freezer facilitate custom storage. The results imply that consumers do indeed value these features and make their choice of products accordingly.

The coefficients of the different refrigerator type variables do not all have the same signs. *SidebySide* is the base type category. The coefficient of *Top* is negative and

significant, implying that top freezer refrigerators cost less than side by side refrigerators. But the coefficient of *Bottom* is positive and significant, implying that the reverse is true for bottom type refrigerators. Our prior expectation was that bottom freezers as well as side-by-side refrigerators are more trendy than top freezer models.

The results also indicate that refrigerator color is an important price factor. We know that white is the most common color in the market, but other colors are becoming fashionable, especially stainless steel. Although the coefficient estimates suggest that there are no significant price differentials between *white*, *black* and *bisque* (the reference colour) refrigerators, the coefficient of *stainless steel* is relatively large. This result is not surprising since stainless steel is used primarily in high-end products.

The coefficients of *FFCap* and *FreezerCap*, capacity of fresh food and freezer sections, are both positive and significant imply that size of refrigerators is a main price factor. Surprisingly, the coefficient of *KWHYCAP*, the energy consumption variable, kilowatt hours per year per cu./ft., is positive but insignificant, contrary to what I expected. One would expect consumption of less electricity to be a desired feature, but the results seem to imply that it has little impact on price. I think consumers are not fully aware of the global climate change problem and how our energy consumption at home contributes to it. I would expect the coefficient of energy consumption to be significant, once the Government of Canada takes more concrete actions to inform the public about the impact of climate change on people's lives and the economy and an agreement on the Kyoto Protocol is reached worldwide or if the price of electricity rises.

The *Sale price dummy* has a negative and significant coefficient estimate. Price decreases by around 1% if a refrigerator is not sold at the regular price. The

coefficient of *Spill-proof glass* is significant and positive. It eases cleaning the shelves. However, on the contrary the coefficient of *adjshelf* is insignificant, implying that adjustable shelving is not an important factor in refrigerators. Coefficients of both types of freezer container, *freezerbasket* and *freezercanrack*, are positive and significant because storage is improved with baskets and racks compared to a simple compartment.

Finally, I want to test the parameter stability of the model because if the results imply that the coefficient estimates for two random samples taken from the sample I used in this study are the same, then I can conclude that a large sample is not necessary as in Shepler (2001). For this I will use the Chow test.

To perform the test, I first divide the sample into two equal-sized random disjoint subsamples and run hedonic regressions for each subset.²⁸ The value of the test statistic is 0.8125. With 40 degrees of freedom in the numerator and 318 degrees of freedom in the denominator, it is impossible to reject the null hypothesis that the coefficient estimates of two sub samples are equal at the 5% level of significance.

Because Shepler (2001) presents the only other recent hedonic regression model for refrigerators, it is interesting to compare her results with mine. Some similar results were obtained. Although comparisons of the magnitude of the parameter estimates are not logical since her study is for the US market, drawing an analogy between these two papers is reasonable. As in this paper, Shepler (2001) finds that the coefficient of *saleprice* in her log-linear regression for refrigerators is significant. Her model implies that total capacity is an important price feature for refrigerators; I found that coefficient

²⁸ Regression results for sub samples are in Table XVII and XIII.

estimates for both *FreezerCap* and *FFCap* are significant, though fresh food capacity has a bigger effect on price. Similarly, the coefficient estimates of *Bottom* in both models are significant and positive. We can see here that markets in different geographical areas follow similar trends.

Both sound insulation and water filtration are found to be preferred features in both studies. However, the coefficient of *energy saver switch* in Shepler's model is negative and significant. It is because the *energy saver switch* variable represents moisture formation on the outside of top freezers. Thus, the variable name is misleading. In Shepler's model, options such as ice maker installed, ice maker ready and no ice maker have statistically significant negative coefficient estimates. This is because the reference option is installed ice maker and water dispenser. If her base category was no ice maker, then the coefficient estimates of other three options would be positive. This is why the coefficient estimate for *icemaker* in my model is significant and positive.

A important difference between Shepler's results and mine is the impact of colour on price. I have found that there are no significant price differentials between white and black refrigerators over bisque refrigerators; but in her model coefficient estimates for colors are all significant and positive. When it comes to explanatory power, her model has an adjusted R^2 of 0.9488. I can say that although there are some differences in included independent variables, because the dependent variable is log of price, the strength of both models in explaining variations in *LogPrice* is almost the same.

In arriving at this final model of the hedonic price function, I had to deal with the problems of functional form and choosing a characteristic vector that was sufficient to capture aspects of quality on the one hand, and avoid multicollinearity on the other. The

results suggest that the model is reasonably reliable and that most potential problems have been avoided or resolved.

6. CONCLUSION

This major paper demonstrates the feasibility of constructing hedonic price equations when reliable data are available. I was able to develop an hedonic price function for refrigerators that has a high degree of explanatory power. If you buy a fixed set of quality features bundled together by Kenmore for \$1000, the same pre-bundled characteristics will cost you \$1420 if it was manufactured by KitchenAid, whereas the 'same' refrigerator would be only sold for another \$30 more with a Frigidaire sticker on it.²⁹ Similarly, for a stainless steel refrigerator, you have to pay \$165 more over a bisque refrigerator which costs \$1000, keeping everything else the same. If you want to buy the door trim kit later, you should not pay any more than 27 % of the purchase price. Increasing the fresh food capacity by 1 Cu. /ft. increases the price by 6.4 %.

This paper could be further extended by employing the final hedonic price equation to analyze the dependability of the quality adjustment methods used by Statistics Canada. This could be done by taking samples of cross sectional data and checking if the adjustments made by field representatives were reliable. I can not deny the fact that my data come from a single retailer, although it is known to be one of the biggest department stores in Canada. One needs to make price checks from other retailers of refrigerators to see how far the pricing policy of Sears might have affected the estimation. This way, one

²⁹ Kenmore and KenmoreElite are housebrands. Since I used Sears catalogue, some brands which are available in the market can not be used with this model.

can explore if the Sears product range does cover the whole market geography-wise.

After this is tested, one should check if sample size is a significant factor in sampling. If it can be shown that 'same' hedonic price equations can be obtained from different samples from different retailers and/or geographic areas, then the budget and time used for price measurements can be used for other purposes.

As Berndt (1991) mentions, in one type of hedonic price analysis the matched model method is employed whenever the appropriate data are available, and then hedonic regression methods are used to impute missing prices for newly introduced or just discontinued models, thereby accounting more fully for the price changes associated with turnover of models available in the market. In another type of hedonic price analysis, the price index is estimated directly from a regression equation. In either case, hedonic price analysis forms the basis of the measurement of quality change. Statistics Canada could start using the first approach as a first step and gain some insight into the practicality of hedonic price indexes.

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Waugh, F.W.(1928) "Quality Factors Influencing Vegetable Prices." *Journal of Farm Economics* 10(2): 185-196.

Refrigerator history at <http://www.ideafinder.com/history/inventions/story057.htm/>

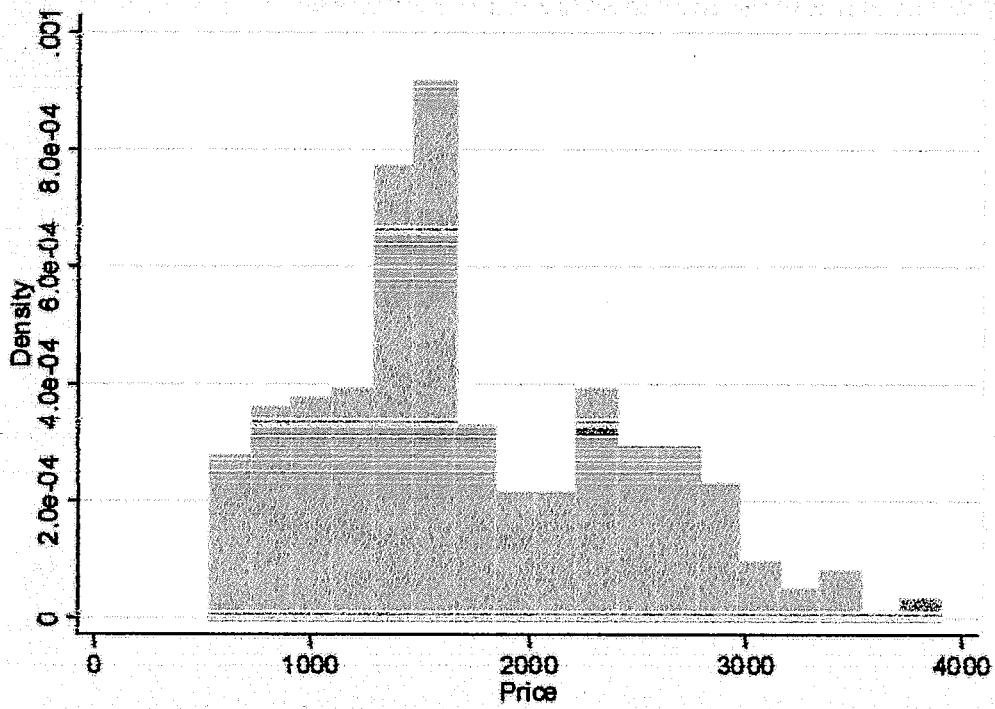
The History of Household Wonders at
<http://www.historychannel.com/exhibits/modern/fridge.html>

Consumer Report website, at
[http://www.consumerreports.org/main/detailv4.jsp?CONTENT%3C%3Ecnt_id=378171
&FOLDER%3C%3Efolder_id=162697&ASSORTMENT%3C%3EEast_id=333135
&bmUID=1099980234029](http://www.consumerreports.org/main/detailv4.jsp?CONTENT%3C%3Ecnt_id=378171&FOLDER%3C%3Efolder_id=162697&ASSORTMENT%3C%3EEast_id=333135&bmUID=1099980234029)

History of Refrigerators
<http://inventors.about.com/gi/dynamic/offsite.htm?site=http://www.rogersrefrig.com/history.html>

CHART I

Histogram for 'Sale' Price



Histogram for 'Regular' Price

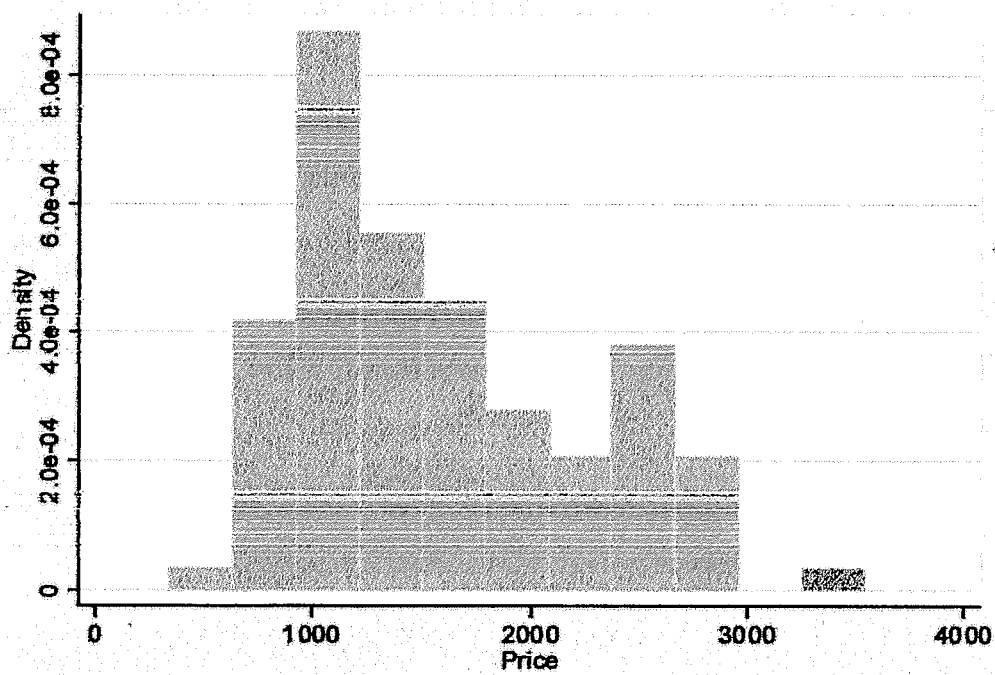


CHART II

Scatterplot matrix of LogPrice, FreezerCap, FFCap and KWHYCAP

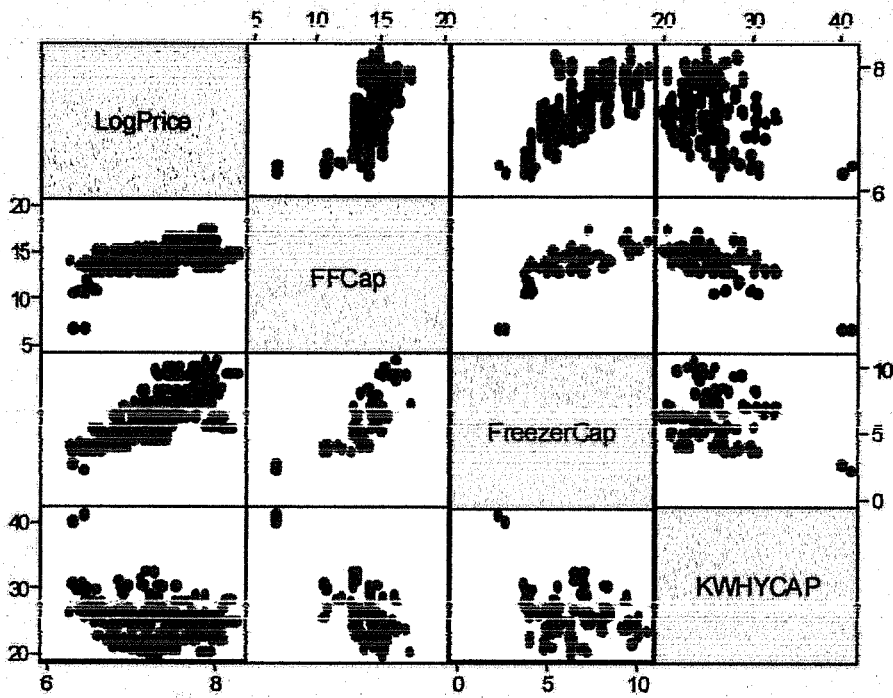
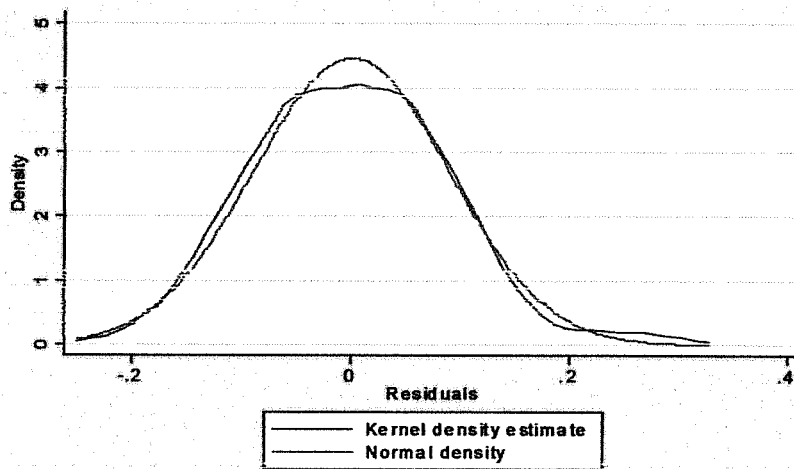
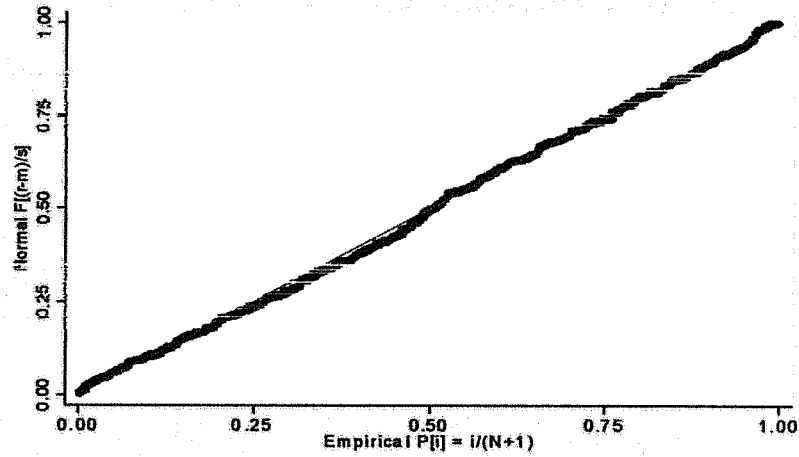


CHART III

Kdensity plot of residuals



Pnorm plot of residuals



Qnorm plot of residuals

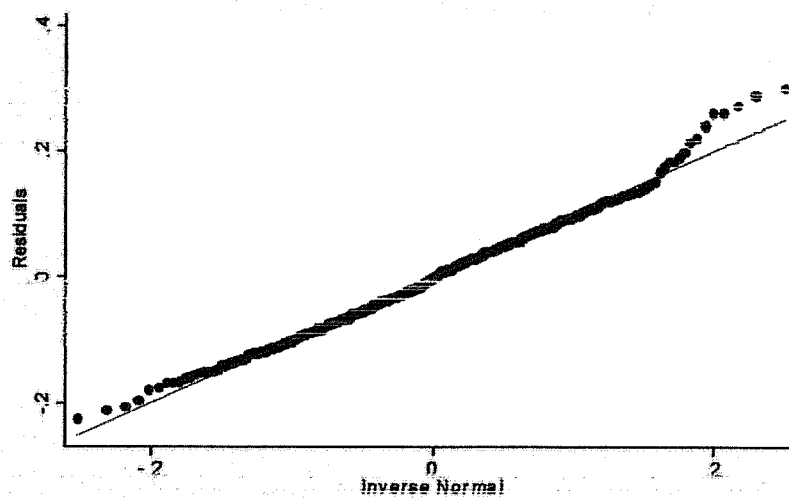


CHART IV

Residuals versus the fitted values of LogPrice

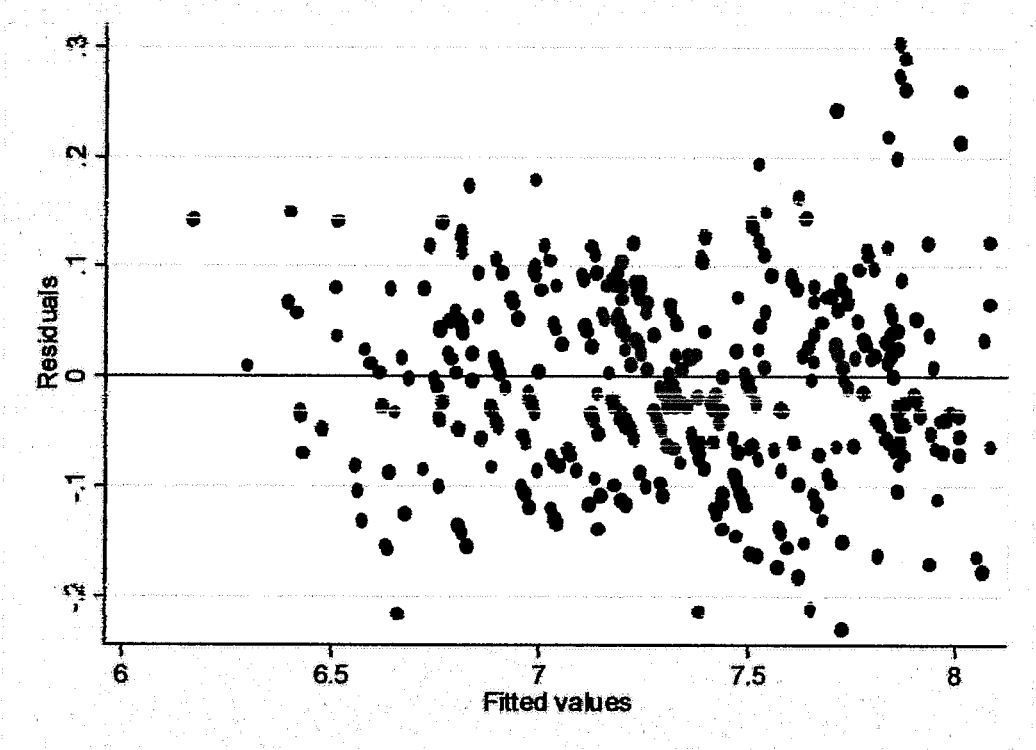
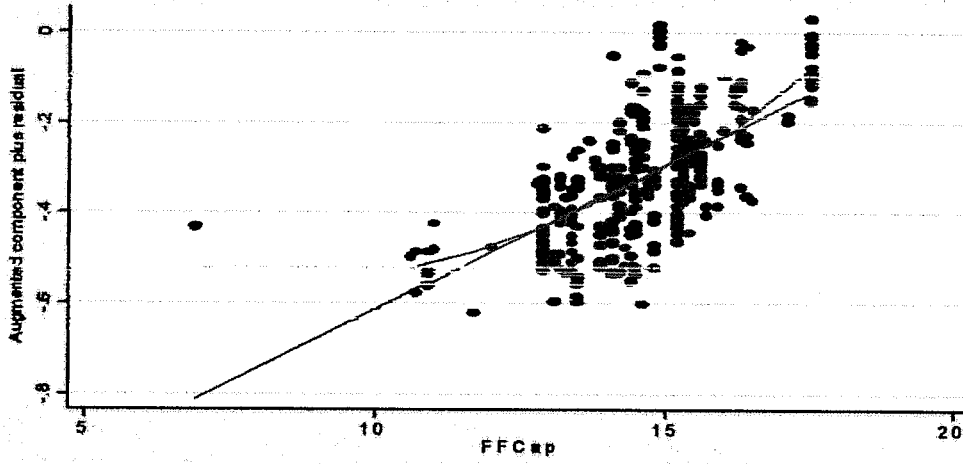
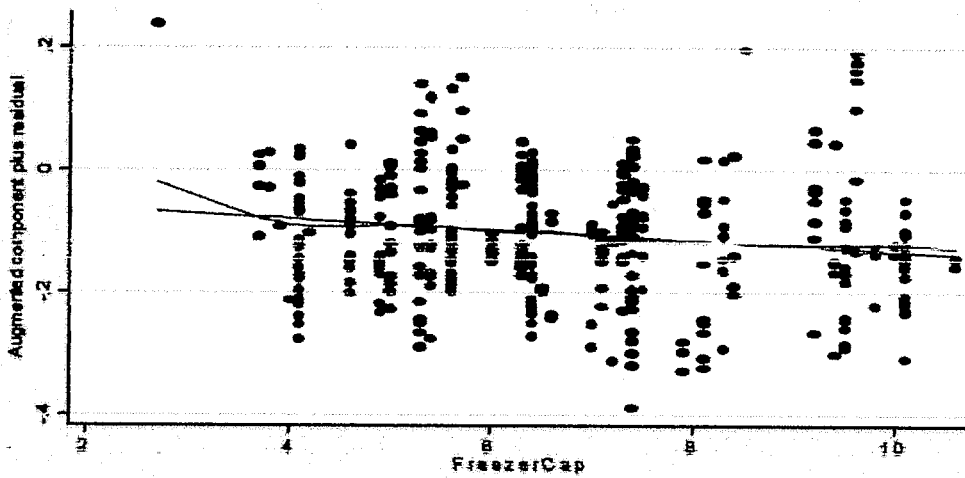


CHART V

Augmented component-plus-residual plot for FFCap, fresh food capacity



Augmented component-plus-residual plot for FreezerCap, freezer capacity



Augmented component-plus-residual plot for KWHYCAP, energy use

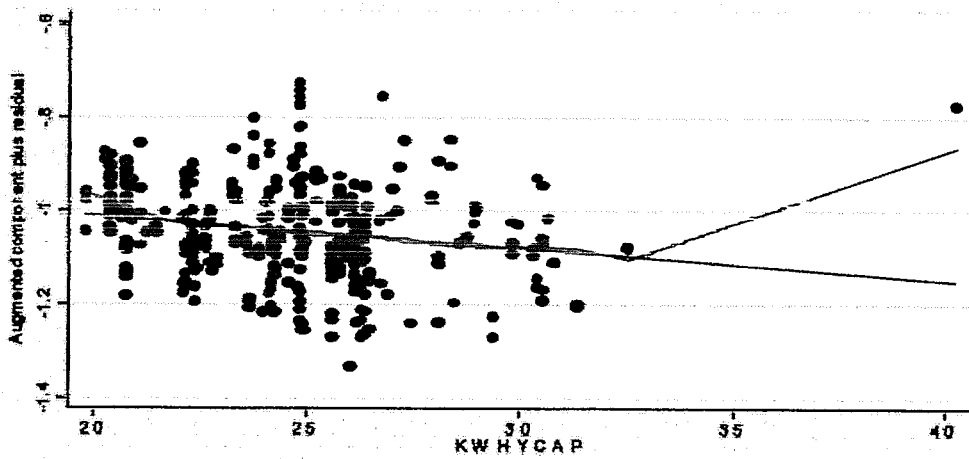
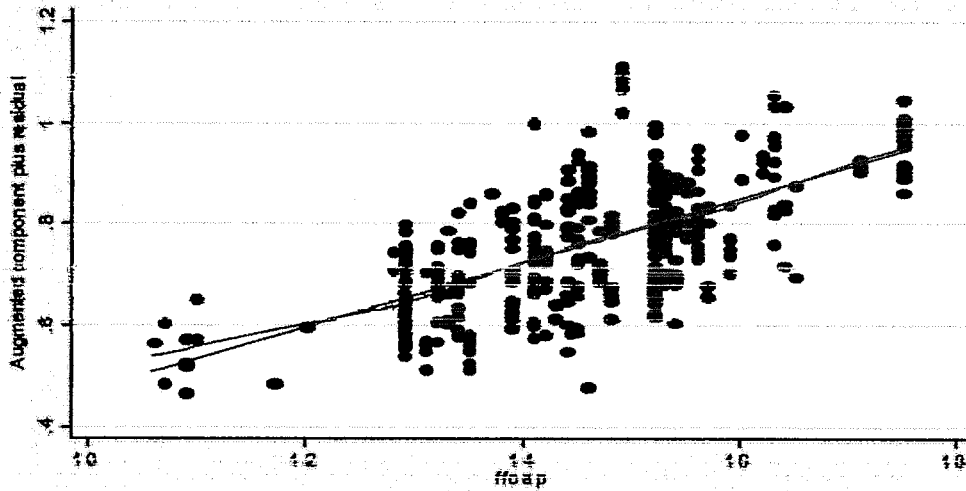
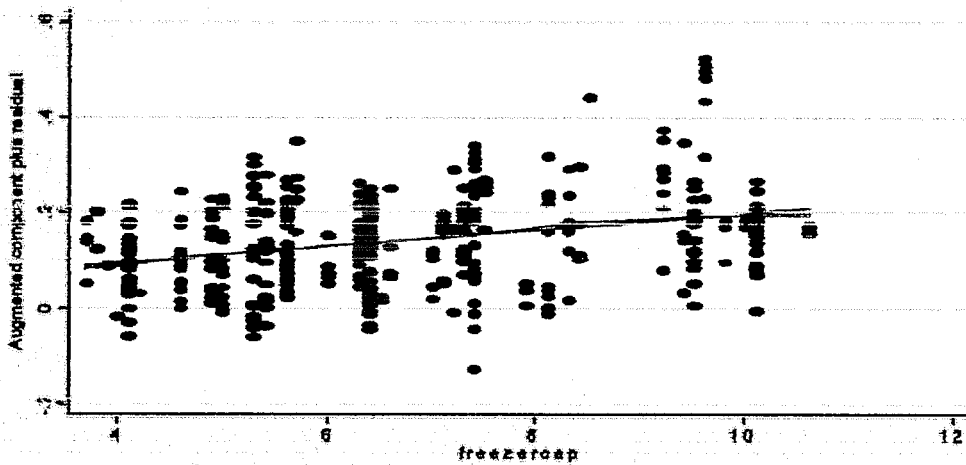


CHART VI

Augmented component-plus-residual plot for FFCap, after deleting the outlier



Augmented component-plus-residual plot for FreezerCap, after deleting the outlier



Augmented component-plus-residual plot for KWHYCAP, after deleting the outlier

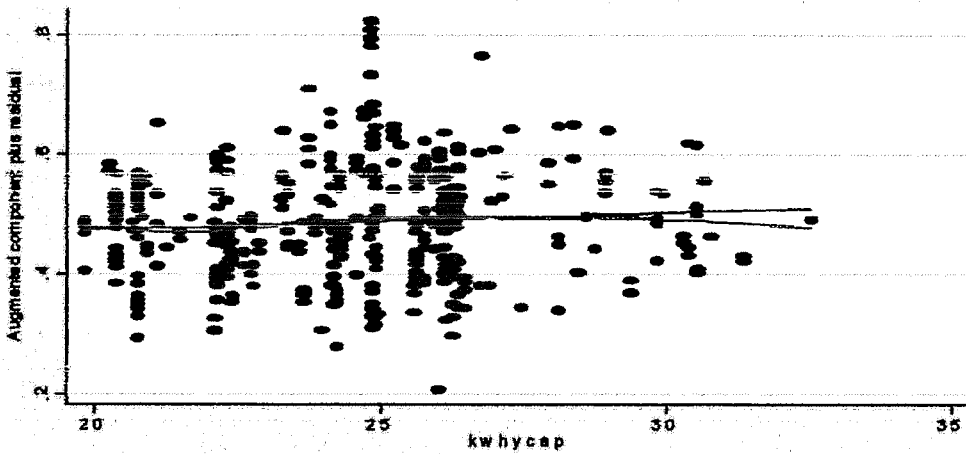


TABLE I
List of Explanatory Variables

Brand : Dummy variable equal to 1 if that brand, 0 otherwise. (*KitchenAid, Whirlpool, WhirlpoolGold, GE, GE Profile, Frigidaire, Frigidaire GPS, Frigidaire Gallery, Kenmore, Kenmore Elite, Maytag, Amana, JennAir, other_brand*)

Type : Dummy variable equal to 1 if that type, 0 otherwise. (*Top, Bottom, SidebySide*)

Colour : Dummy variable equal to 1 if that colour, 0 otherwise. (*white, black, stainless steel, bisque; bisque is excluded*)

Saleprice : Dummy variable equal to 1 if sale price is reported, 0 otherwise.

FFCap : fresh food capacity

FreezerCap : freezer capacity

KWHYCAP : energy consumption, kilowatt hours of electricity per year per Cu./ft.

TempCtr : number of temperature controls in a refrigerator

RevDoor : Dummy variable equal to 1 if doors are reversible, 0 otherwise.

Icemaker : Dummy variable equal to 1 if there is icemaker, 0 otherwise.

FilterWater : Dummy variable equal to 1 if there's water filtration, 0 otherwise

SoundRed : Dummy variable equal to 1 if there is sound reduction package, 0 otherwise

DoorTKit : Dummy variable equal to 1 if there is door trim kit, 0 otherwise

ShelfType : Dummy variable equal to 1 if that type of shelf, 0 otherwise. (*SpillPG, glass, wire; glass is excluded*)

AdjShelf : Dummy variable equal to 1 if shelves are adjustable, 0 otherwise. (one of adjustable, cantilever or crank adjusted)

CrisperHCtrl : Dummy variable equal to 1 if there is crisper humidity control, 0 otherwise.

MeatTempCtrl : Dummy variable equal to 1 if there is meat bin temperature control, 0 otherwise.

SnackBin : Dummy variable equal to 1 if there is a snack bin, 0 otherwise.

DairyComp : Dummy variable equal to 1 if there is a dairy bin/compartiment, 0 otherwise.

IntLight : the number of interior lights

AdjDoorBin : the number of adjustable bins in the door

Freezerbasket : Dummy variable equal to 1 if there is freezer basket available, 0 otherwise.

FreezerShelf : Number of freezer shelves in the freezer

FreezerCanRack : Dummy variable equal to 1 if there is a can rack in freeze, 0 otherwise.

FreezerLight : Dummy variable equal to 1 if there is a light in freeze, 0 otherwise.

FreezerMisc : Dummy variable equal to 1 if there is any other feature about freezer, 0 otherwise. (ice bucket, ice tray etc.)

TABLE II*Ladder results*

Transformation	formula	chi2(2)	P(chi2)
cubic	Price ³	.	0.000
square	Price ²	73.47	0.000
raw	Price	21.28	0.000
square-root	sqrt(Price)	19.75	0.000
log	log(Price)	14.47	0.001
reciprocal root	1/sqrt(Price)	22.72	0.000
reciprocal	1/Price	58.22	0.000
reciprocal square	1/(Price ²)	.	0.000
reciprocal cubic	1/(Price ³)	.	0.000

TABLE III

Regression results for log-linear model with all variables included

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]	
KitchenAid	.239778	.0549301	4.37	0.000	.1317758	.3477803
Whirlpool	.0361483	.0583748	0.62	0.536	-.078627	.1509235
WhirlpoolG-d	.1200445	.0608505	1.97	0.049	.0004016	.2396875
GE	-.0947923	.0490044	-1.93	0.054	-.1911437	.0015591
GEProfile	-.0934593	.0626968	-1.49	0.137	-.2167324	.0298137
Frigidaire	-.0747561	.0590631	-1.27	0.206	-.1908845	.0413724
Frigidaire~y	-.0766807	.0686291	-1.12	0.265	-.2116177	.0582563
Kenmore	-.1210295	.0543926	-2.23	0.027	-.227975	-.0140841
KenmoreElite	-.1130792	.0670717	-1.69	0.093	-.2449541	.0187957
Maytag	-.0350879	.0593037	-0.59	0.554	-.1516894	.0815136
Amana	-.0236007	.0610659	-0.39	0.699	-.1436671	.0964656
jenn_Air	.1973912	.0656988	3.00	0.003	.0682157	.3265668
Other brand	-.0566569	.0461258	-1.23	0.220	-.1473484	.0340347
Top	-.1652649	.0582981	-2.83	0.005	-.2798892	-.0506405
Bottom	.0752161	.0645924	1.16	0.245	-.0517841	.2022163
SidebySide	(dropped)					
white	-.0031484	.0199332	-0.16	0.875	-.0423406	.0360437
black	.0143879	.021173	0.68	0.497	-.027242	.0560178
stainless ~l	.1462943	.0214398	6.82	0.000	.1041398	.1884488
SalePrice	-.1026606	.0216765	-4.74	0.000	-.1452805	-.0600407
FFCap	.0531152	.009944	5.34	0.000	.0335636	.0726669
FreezerCap	.026113	.0102908	2.54	0.012	.0058795	.0463464
KWHYCAP	.0042665	.0049072	0.87	0.385	-.0053821	.013915
TempCtr	.0173248	.0254319	0.68	0.496	-.0326788	.0673284
RevDoor	-.0835	.0247705	-3.37	0.001	-.1322032	-.0347968
Icemaker	.0666778	.0318411	2.09	0.037	.0040725	.1292832
FilterWater	.1203763	.0282228	4.27	0.000	.0648853	.1758674
SoundRed	.0344549	.021906	1.57	0.117	-.0086162	.0775261
DoorFKit	.1934026	.0508603	3.80	0.000	.0934023	.293403
SpillPG	.0395065	.0284371	1.39	0.166	-.0164058	.0954187
Wire	-.0798263	.0460718	-1.73	0.084	-.1704116	.0107591
AdjShelf	.03503	.0380756	0.92	0.358	-.0398335	.1098935
CrisperHCo~l	-.0098052	.0270039	-0.36	0.717	-.0628997	.0432893
MeatTempCo~r	.1064611	.0239307	4.45	0.000	.0594091	.1535132
SnackBin	.0752192	.0479637	1.57	0.118	-.0190859	.1695243
DairyComp	(dropped)					
IntLight	.0707046	.0185179	3.82	0.000	.0342951	.1071142
AdjDoorBin	.0007483	.0092312	0.08	0.935	-.0174018	.0188985
Freezerbas~t	.0480992	.0105478	4.56	0.000	.0273602	.0688381
FreezerShelf	-.0477354	.012408	-3.85	0.000	-.0721317	-.0233391
FreezerCan~k	.1416276	.0510339	2.78	0.006	.041286	.2419693
FreezerLight	.040071	.028907	1.39	0.166	-.0167652	.0969072
FreezerMisc~e	.0573617	.0221501	2.59	0.010	.0138107	.1009127
_cons	5.961159	.2781098	21.43	0.000	5.414346	6.507972

Number of obs = 425 F(41, 383) = 118.24
 Prob > F = 0.0000 Adj R-squared = 0.9189

TABLE IV

Results for the model where SidebySide variable is regressed on rest of the variables

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]
KitchenAid	-1.33e-14
Whirlpool	-2.38e-14
WhirlpoolG-d	-1.46e-14
GE	-1.47e-14
GEProfile	-1.34e-14
Frigidaire	-1.36e-14
Frigidaire-y	-3.35e-15
Kenmore	-1.22e-14
KenmoreElite	-2.12e-14
Maytag	-6.59e-15
Amana	-1.94e-14
jenn_Air	-1.05e-14
Other_brand	-1.05e-14
Top	-1
Bottom	-1
white	-4.27e-15
black	-8.72e-16
stainless_l	1.20e-15
Saleprice	3.87e-15
FFCap	2.50e-16
FreezerCap	-3.11e-15
KWHYCAP	-1.35e-15
TempCtr	1.37e-14
RevDoor	9.30e-15
Icemaker	1.98e-14
FilterWater	-9.03e-15
SoundRed	-1.76e-15
DoorTKit	3.79e-15
SpillPG	8.64e-15
Wire	-5.06e-15
AdjShelf	1.46e-17
CrisperHCo-l	-6.46e-15
MeatTempCo-r	-9.58e-16
SnackBin	-3.65e-15
DairyComp	{dropped}
IntLight	-5.68e-16
AdjDoorBin	-3.14e-15
Freezerbas-t	-2.03e-15
FreezerShelf	-3.66e-15
FreezerCan-k	-4.74e-15
FreezerLight	-1.67e-14
FreezerMis-e	-2.88e-16
_cons	1

Number of obs = 425 F(41, 383) = .
 Prob > F = . Adj R-squared = 1.0000

TABLE V

Results for the model where DairyComp is regressed on the rest of the variables

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]
KitchenAid	-4.14e-17
Whirlpool	-5.12e-17
WhirlpoolG-d	-3.19e-17
GE	-3.54e-17
GEProfile	-3.44e-17
Frigidaire	-4.22e-17
Frigidaire-y	-4.60e-17
Kenmore	-2.75e-17
KenmoreElite	-8.36e-17
Maytag	-1.25e-17
Amana	-5.71e-17
jenn Air	-3.81e-17
Other_brand	-1.48e-17
Top	8.17e-18
Bottom	5.49e-17
SidebySide	(dropped)
white	6.87e-18
black	4.56e-18
stainless -l	6.62e-18
Saloprice	1.39e-17
FFCap	-9.70e-18
FreezerCap	-1.38e-17
KWHYCAP	-1.61e-17
TempCtr	1.49e-17
RevDoor	9.83e-18
Icemaker	4.26e-17
FilterWater	-1.88e-17
SoundRed	-2.69e-17
DoorTKit	-1.85e-17
SpillPG	-2.21e-17
Wire	-2.91e-17
AdjShelf	1.67e-17
CrisperHCo-l	-3.06e-17
MeatTempCo-r	2.49e-17
SnackBin	i
IntLight	-1.43e-17
AdjDoorBin	-5.56e-18
Freezerbas-t	2.19e-17
FreezerShelf	2.50e-17
FreezerCan-k	1.37e-17
FreezerLight	-4.61e-18
FreezerMisc	1.36e-17
_cons	6.66e-16

Number of obs = 425 F(41, 383) = .
 Adj R-squared = 1.0000 Prob > F = .

TABLE VI

List of observations that are above cut-off point of DFITS

1.	-1.172182
4.	-.981274
5.	-.8162144
8.	-.8571852
10.	-.7206846
16.	-.7173367
20.	-.6479048
22.	-.6608177
385.	.7863081
401.	.6937709
404.	.7580321
405.	.6304837
407.	.693916
408.	.6909858
409.	1.050382
412.	.6519078
413.	.6909401
416.	.7257116
417.	1.823237
419.	.7855322
420.	.7680341
421.	1.387822
422.	1.288762
423.	1.345549
424.	1.458658
425.	2.316694

TABLE VII

Regression results for the new sample after deleting possible outliers

Variable	Coefficient Estimate	Standard Error	t statistic	p-value	[95% Conf. Interval]	
kitchenaid	.2392436	.0450241	5.31	0.000	.1506978	.3277894
whirlpool	.0325766	.0469578	0.69	0.488	-.059772	.1249252
whirlpoolg~d	.0988702	.0489874	2.02	0.044	.0025301	.1952104
ge	-.095603	.0411356	-2.32	0.021	-.1765017	-.0147044
geprofile	-.0762174	.051451	-1.48	0.139	-.1774026	.0249678
frigidaire	-.1100993	.0480254	-2.29	0.022	-.2045476	-.0156511
frigidaire~y	-.0944801	.0561868	-1.68	0.094	-.2049789	.0160187
kenmore	-.1632801	.04514	-3.62	0.000	-.2520539	-.0745064
kenmoreelite	-.0998243	.0562	-1.78	0.077	-.210349	.0107004
maytag	-.0388392	.0485015	-0.80	0.424	-.1342237	.0565454
amana	-.0508478	.0500227	-1.02	0.310	-.149224	.0475284
jenn_air	.2549654	.054034	4.72	0.000	.1487004	.3612303
other brand	-.0770335	.0370003	-2.08	0.038	-.1497995	-.0042675
top	-.2067677	.0252355	-8.19	0.000	-.2563965	-.1571388
bottom	(dropped)					
sidebyside	.0519039	.0558521	0.93	0.353	-.0579367	.1617444
white	.0053245	.0156134	0.34	0.733	-.0253813	.0360303
black	.0185076	.0165404	1.12	0.264	-.0140212	.0510364
stainless~l	.1505256	.0167309	9.00	0.000	.1176221	.1834291
saleprice	-.092922	.0176455	-5.27	0.000	-.1276241	-.0582199
ffcap	.0007953	.0000736	0.51	0.609	.0028275	.0045032
freezercap	.0205205	.0080252	2.56	0.011	.0047379	.0363032
kwhycap	.0062043	.0039833	1.56	0.120	-.0016294	.0140381
tempctr	.0087466	.0199249	0.44	0.661	-.0304383	.0479314
revdoor	-.0699967	.0197386	-3.55	0.000	-.1088152	-.0311783
icemaker	.0872111	.0258393	3.38	0.001	.0363947	.1380275
filterwater	.0473427	.023034	2.06	0.041	.0020434	.0926421
soundred	.033033	.0172773	1.91	0.057	-.000945	.0670111
doortkit	.2236979	.0523406	4.27	0.000	.1207632	.3266325
spillpg	.0738842	.0228011	3.24	0.001	.0290429	.1187255
wire	.0175246	.0393997	0.44	0.657	-.0599601	.0950093
adjshelf	.0355699	.031388	1.13	0.258	-.0261586	.0972985
crisperhco~l	.0347814	.0223799	1.55	0.121	-.0092316	.0787944
meattempco~r	.0775265	.0195831	3.96	0.000	.0390138	.1160393
snackbin	.095111	.0393255	2.42	0.016	.0177722	.1724498
dairycomp	(dropped)					
intlght	.076245	.0151031	5.05	0.000	.0465427	.1059473
adjdoorbin	.0021105	.0076574	0.28	0.783	-.0129487	.0171698
freezerbas~t	.0440396	.0085365	5.16	0.000	.0272515	.0608277
freezersshelf	-.0640886	.0110919	-5.78	0.000	-.0859023	-.042275
freezercan~k	.0542035	.0457694	1.18	0.237	-.0358079	.144215
freezerlight	.0176531	.0228224	0.77	0.440	-.0272302	.0625365
freezermisc	.072363	.0197334	3.66	0.000	.0334946	.1111114
_cons	5.728207	.2070963	27.66	0.000	5.320925	6.135489

Number of obs = 399 F(41, 357) = 182.24
Adj R-squared = 0.9492 Prob > F = 0.0000

TABLE VIII

TEST	Statistic	degrees of freedom	p-value
Shapiro-Wilk W test for normality	2.228	-	0.01294
Breusch-Pagan test for heteroskedasticity	7.94	1	0.0048
Ramsey RESET test	2.36	3,355	0.0715

Linktest

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]
_hat	.4930881	.3810455	1.29	0.196	-.2560427 1.242219
_hatsq	.0348184	.0261606	1.33	0.184	-.016613 .0862499
_cons	1.839123	1.384491	1.33	0.185	-.8827703 4.561016

Number of obs = 398 F(2, 395) = 3642.31
 Adj R-squared = 0.9483 Prob > F = 0.0000

TABLE IX

Variance inflation factors for independent variables

Variable	VIF	1/VIF
sidebyside	31.70	0.031543
kenmore	15.85	0.063073
freezersshelf	14.70	0.068006
kitchenaid	11.60	0.086183
maytag	10.20	0.098031
freezercap	9.05	0.110473
amana	8.62	0.115998
icemaker	7.35	0.136005
top	6.53	0.153130
ge	6.29	0.158931
filterwater	5.86	0.170711
geprofile	5.83	0.171418
kenmoreelite	5.37	0.186108
whirlpool	5.29	0.188897
jenn air	5.26	0.189981
ffcap	5.14	0.194686
kwhycap	5.06	0.197479
frigidaire	4.62	0.216310
freezerbas-t	4.60	0.217260
intlght	4.57	0.218906
whirlpoolg-d	4.33	0.231140
revdoor	4.30	0.232717
adjdoorbin	4.01	0.249407
meattempco-r	3.51	0.284680
other_brand	3.15	0.317235
freezermis-e	3.05	0.327510
tempctr	2.79	0.358913
soundred	2.75	0.363929
freezerlight	2.65	0.377120
white	2.54	0.393568
saleprice	2.42	0.412761
frigidaire~y	2.40	0.415818
stainless~l	2.32	0.430374
spillpg	2.21	0.452614
black	2.10	0.477215
wire	2.00	0.499663
crisperhco-l	1.82	0.550340
adjshelf	1.47	0.678330
snackbin	1.34	0.744630
doortkit	1.20	0.832189
freezercan~k	1.15	0.872851
Mean VIF	5.54	

TABLE X

Auxiliary regression for SidebySide

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]	
kitchenaid	-.0364867	.0425616	-0.86	0.392	-.1201889	.0472156
whirlpool	.0286776	.0444092	0.65	0.519	-.0586582	.1160133
whirlpoolg~d	.0326303	.0463236	0.70	0.482	-.0584703	.1237308
ge	.0099768	.0389222	0.26	0.798	-.066568	.0865217
geprofile	.0242684	.0486701	0.50	0.618	-.0714467	.1199836
frigidaire	.0719331	.0452861	1.59	0.113	-.0171271	.1609933
frigidaire~y	.0903848	.0529533	1.71	0.089	-.0137539	.1945235
kenmore	.0166037	.042706	0.39	0.698	-.0673824	.1005898
kenmoreelite	.0553915	.0531002	1.04	0.298	-.0490361	.159819
maytag	.0116227	.0458918	0.25	0.800	-.0786286	.1018741
amana	-.0024513	.0473352	-0.05	0.959	-.0955413	.0906386
jenn air	-.0375801	.0510926	-0.74	0.462	-.1380595	.0628992
other_brand	.013371	.0350055	0.38	0.703	-.0554712	.0822132
top	-.2144313	.0210192	-10.20	0.000	-.2557679	-.1730947
white	.0077842	.0147689	0.53	0.598	-.0212605	.0368289
black	.0102838	.0156424	0.66	0.511	-.0204787	.0410462
stainless~l	.000566	.0158321	0.04	0.971	-.0305695	.0317016
saleprice	-.0517475	.016472	-3.14	0.002	-.0841416	-.0193535
ffcap	-.0167131	.0075886	-2.20	0.028	-.031637	-.0017892
freezercap	.0449718	.0072143	6.22	0.000	.0306842	.0592595
kwhycap	.0161719	.0036712	4.41	0.000	.0089521	.0233916
tempctr	.0515894	.0186563	2.77	0.006	.0148997	.088279
revdoor	-.0441058	.0185321	-2.38	0.018	-.0805513	-.0076603
icemaker	.0367643	.0243739	1.51	0.132	-.0111696	.0846983
filterwater	.0481381	.0216476	2.22	0.027	.0055657	.0907105
soundred	-.0707407	.0159159	-4.44	0.000	-.1020411	-.0394403
doortkit	.023311	.0495134	0.47	0.638	-.0740627	.1206847
spillpg	.0314747	.0215119	1.46	0.144	-.0108309	.0737803
wire	.0030348	.0372827	0.08	0.935	-.0702859	.0763555
adjshelf	.0037454	.0297011	0.13	0.900	-.0546652	.0621559
crisperhco~l	-.0414317	.0210641	-1.97	0.050	-.0828566	-6.78e-06
meattempco~r	.0514474	.0183305	2.81	0.005	.0153984	.0874964
snackbin	.0676662	.0370406	1.83	0.069	-.0051783	.1405108
intlght	.0629164	.0138995	4.53	0.000	.0355814	.0902514
adjdoorbin	-.0017079	.0072455	-0.24	0.814	-.0159569	.0125411
freezerbas~t	.0374378	.0078318	4.78	0.000	.0220357	.0528399
freezersshelf	.1571637	.0064164	24.49	0.000	.1445451	.1697824
freezercan~k	-.0093714	.0433077	-0.22	0.829	-.0945409	.075798
freezerlight	.0061118	.021594	0.28	0.777	-.0363552	.0485787
freezermis~e	-.00583	.0186708	-0.31	0.755	-.0425481	.0308882
_cons	-.6797255	.1926497	-3.53	0.000	-1.058593	-.3008582

Number of obs = 399 F(40, 358) = 274.79
 Adj R-squared = 0.9649 Prob > F = 0.0000

TABLE XI

Auxiliary regression results for Kenmore

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]
kitchenaid	-.8224743	.0298229	-27.58	0.000	-.8811243 -.7638242
whirlpool	-.8048355	.034834	-23.10	0.000	-.8733405 -.7363305
whirlpoolg~d	-.8448114	.0360021	-23.47	0.000	-.9156136 -.7740092
ge	-.7234409	.0292878	-24.70	0.000	-.7810386 -.6658431
geprofile	-.9424105	.033884	-27.81	0.000	-1.009047 -.8757738
frigidaire	-.8314594	.0350818	-23.70	0.000	-.9004518 -.7624671
frigidaire~y	-.8009807	.0503554	-15.91	0.000	-.9000102 -.7019513
kenmoreelite	-.9957494	.0394992	-25.21	0.000	-1.073429 -.9180697
maytag	-.8858655	.0321364	-27.57	0.000	-.9490653 -.8226657
amana	-.885225	.0352331	-25.12	0.000	-.9545149 -.8159351
jenn_air	-.9278267	.0399728	-23.21	0.000	-1.006438 -.8492157
other brand	-.5158953	.0336647	-15.32	0.000	-.5821008 -.4496899
top	-.0342089	.0294913	-1.16	0.247	-.0922069 .023789
sidebyside	.0254192	.06538	0.39	0.698	-.1031579 .1539963
white	-.0129671	.0182679	-0.71	0.478	-.048893 .0229588
black	-.0007012	.0193661	-0.04	0.971	-.0387868 .0373843
stainless~l	-.0180012	.0195661	-0.92	0.358	-.05648 .0204777
saleprice	-.056262	.0204449	-2.75	0.006	-.0964691 -.0160548
ffcap	.0234303	.0093714	2.50	0.013	.0050004 .0418603
freezercap	-.0012760	.0093396	-0.14	0.882	-.0197545 .0172019
kwhycap	.0090056	.0046395	1.94	0.053	-.0001184 .0181297
tempctr	.0139522	.0233171	0.60	0.550	-.0319035 .0598079
revdoor	.0163644	.0230945	0.71	0.479	-.0290535 .0617822
icemaker	-.0660759	.0300514	-2.20	0.029	-.1251754 -.0069764
filterwater	.027239	.0269306	1.01	0.312	-.0257231 .0802011
soundred	.0517804	.0200429	2.58	0.010	.0123637 .0911971
door~kit	-.0212464	.0612772	-0.35	0.729	-.1417447 .099252
spillpg	-.0140241	.0266861	-0.53	0.600	-.0665052 .038457
wire	-.0325392	.0460986	-0.71	0.481	-.1231973 .0581189
adjshelf	-.0235927	.0367291	-0.64	0.521	-.0958245 .0486392
crisperhco~l	.0403714	.0261162	1.55	0.123	-.0109891 .0917319
meattempco~r	.0845167	.0224893	3.76	0.000	.0402888 .1287445
snackbin	.0544307	.0459539	1.18	0.237	-.0359427 .1448041
intlght	-.0130168	.0176699	-0.74	0.462	-.0477667 .0217332
adjdoorbin	-.0011179	.0089654	-0.12	0.901	-.0187493 .0165136
freezerbas~t	-.0138367	.009968	-1.39	0.166	-.0334399 .0057666
freezersshelf	.0104829	.012975	0.81	0.420	-.0150338 .0359997
freezer~can~k	.0395319	.0535478	0.74	0.461	-.0657758 .1448396
freezerlight	.0133964	.026712	0.50	0.616	-.0391357 .0659286
freezermis~e	.070242	.0228045	3.08	0.002	.0253945 .1150896
_cons	.2570952	.2420952	1.06	0.289	-.2190121 .7332026

Number of obs = 399 F(40, 358) = 132.95
 Adj R-squared = 0.9299 Prob > F = 0.0000

TABLE XII

Regression results for model excluding Kenmore

Variable	Coefficient Estimate	Standard Error	t statistic	p-value	[95% Conf. Interval]	
kitchenaid	.3735373	.0258977	14.42	0.000	.3226065	.4244681
whirlpool	.1639902	.0302493	5.42	0.000	.1045016	.2234789
whirlpoolg~d	.2368112	.0312637	7.57	0.000	.1753277	.2982947
ge	.0225205	.025433	0.89	0.376	-.0274965	.0725374
geprofile	.0776595	.0294243	2.64	0.009	.0197932	.1355258
frigidaire	.0256615	.0304645	0.84	0.400	-.0342504	.0855733
frigidaire~y	.0363041	.0437278	0.83	0.407	-.0496915	.1222998
kenmoreelite	.0627618	.0343005	1.83	0.068	-.004694	.1302176
maytag	.1058051	.0279067	3.79	0.000	.0509234	.1606868
amana	.0936919	.0305959	3.06	0.002	.0335216	.1538621
jenn_air	.406461	.0347118	11.71	0.000	.3381965	.4747256
other_brand	.007202	.0292339	0.25	0.806	-.0502898	.0646938
top	-.201182	.0256098	-7.86	0.000	-.2515465	-.1508175
sidebyside	.0477534	.056775	0.84	0.401	-.0639009	.1594078
white	.0074418	.0158636	0.47	0.639	-.0237557	.0386393
black	.0186221	.0168172	1.11	0.269	-.0144508	.051695
stainless~l	.1534648	.0169909	9.03	0.000	.1200504	.1868793
saleprice	-.0837355	.017754	-4.72	0.000	-.1186508	-.0488203
ffcap	.0648796	.008138	7.97	0.000	.0488754	.0808839
freezerap	.0207289	.0081593	2.54	0.011	.0046827	.0367751
kwlrpuzp	.0047333	.0040269	1.17	0.241	-.0031833	.0126571
tempctr	.0064685	.0202482	0.32	0.750	-.0333519	.0462888
revdoor	-.0726687	.0200549	-3.62	0.000	-.1121089	-.0332286
icemaker	.098	.0260962	3.76	0.000	.0466789	.1493211
filterwater	.0428951	.0233861	1.83	0.067	-.0030963	.0888866
soundred	.0245783	.017405	1.41	0.159	-.0096505	.0588072
doortkit	.227167	.0532077	4.27	0.000	.1225281	.3318058
spillpg	.0761741	.0231737	3.29	0.001	.0306003	.1217478
wire	.0228376	.0400313	0.57	0.569	-.0558885	.1015637
adjshelf	.0394221	.0318949	1.24	0.217	-.0233028	.1021471
crisperhco~l	.0281896	.0226789	1.24	0.215	-.016411	.0727902
meattempco~r	.0637267	.0195294	3.26	0.001	.0253199	.1021334
snackbin	.0862236	.0399056	2.16	0.031	.0077447	.1647024
intlght	.0783704	.0153443	5.11	0.000	.0481941	.1085467
adjdoorbin	.002293	.0077854	0.29	0.769	-.0130178	.0176039
freezerbas~t	.0462988	.0086561	5.35	0.000	.0292757	.063322
freezersshelf	-.0658003	.0112673	-5.84	0.000	-.0879587	-.0436419
freezercan~k	.0477488	.0465	1.03	0.305	-.0436988	.1391963
freezerlight	.0154658	.0231963	0.67	0.505	-.0301523	.0610839
freezermis~e	.0608339	.019803	3.07	0.002	.021889	.0997788
_cons	5.686229	.2102316	27.05	0.000	5.272785	6.099673

Number of obs = 399 F(40, 356) = 180.38
 Adj R-squared = 0.9474 Prob > F = 0.0000

TABLE XIII

Regression results for model excluding SidebySide

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]	
kitchenaid	.2373498	.0449694	5.28	0.000	.1489125	.3257871
whirlpool	.034065	.0469215	0.73	0.468	-.0582114	.1263415
whirlpoolg~d	.1005639	.0489441	2.05	0.041	.0043097	.1968181
ge	-.0950852	.041124	-2.31	0.021	-.1759603	-.0142102
geprofile	-.0749578	.0514234	-1.46	0.146	-.1760876	.0261721
frigidaire	-.1063657	.0478479	-2.22	0.027	-.2004641	-.0122674
frigidaire~y	-.0897888	.0559489	-1.60	0.109	-.1998187	.0202411
kenmore	-.1624183	.0451219	-3.60	0.000	-.2511556	-.0736811
kenmoreelite	-.0969493	.0561041	-1.73	0.085	-.2072844	.0133858
maytag	-.0382359	.0484879	-0.79	0.431	-.1335928	.057121
amana	-.050975	.050013	-1.02	0.309	-.1493312	.0473811
jenn air	.2530148	.0539829	4.69	0.000	.1468513	.3591783
other_brand	-.0763395	.0369858	-2.06	0.040	-.1490761	-.0036028
top	-.2178975	.0222082	-9.81	0.000	-.2615725	-.1742225
white	.0057286	.0156044	0.37	0.714	-.0249592	.0364163
black	.0190413	.0165273	1.15	0.250	-.0134614	.051544
stainless~l	.150555	.0167277	9.00	0.000	.1176581	.1834519
saleprice	-.0956079	.0174038	-5.49	0.000	-.1298345	-.0613813
ffcap	.0678379	.0080179	8.46	0.000	.0520697	.083606
freezercap	.0228496	.0076224	3.00	0.003	.0078593	.0378390
kwhycap	.0070437	.0038788	1.82	0.070	-.0005844	.0146719
tempctr	.0114243	.0197117	0.58	0.563	-.0273409	.0501894
revdoor	-.072286	.0195805	-3.69	0.000	-.1107933	-.0337787
icemaker	.0891193	.0257527	3.46	0.001	.0384737	.1397649
filterwater	.0498413	.0228722	2.18	0.030	.0048606	.094822
soundred	.0293613	.0168163	1.75	0.082	-.0037098	.0624324
doortkit	.2249078	.0523144	4.30	0.000	.1220256	.32779
spillpg	.0755179	.0227289	3.32	0.001	.030819	.1202167
wire	.0176821	.0393919	0.45	0.654	-.0597864	.0951506
adjshelf	.0357643	.0313813	1.14	0.255	-.0259505	.0974792
crisperhco~l	.032631	.0222557	1.47	0.143	-.0111374	.0763993
meattempco~r	.0801969	.0193675	4.14	0.000	.0421086	.1182852
snackbin	.0986232	.039136	2.52	0.012	.0216577	.1755886
intlght	.0795106	.0146858	5.41	0.000	.0506293	.108392
adjdoorbin	.0020219	.0076553	0.26	0.792	-.0130332	.017077
freezerbas~t	.0459828	.0082748	5.56	0.000	.0297094	.0622562
freezersshelf	-.0559312	.0067794	-8.25	0.000	-.0692637	-.0425987
freezercan~k	.0537171	.0457577	1.17	0.241	-.0362704	.1437047
freezerlight	.0179704	.0228155	0.79	0.431	-.026899	.0628397
freezermis~e	.0720004	.019727	3.65	0.000	.0332051	.1107958
_cons	5.692927	.203548	27.97	0.000	5.292627	6.093227

Number of obs = 399 F(40, 358) = 186.84
 Adj R-squared = 0.9492 Prob > F = 0.0000

TABLE XIV

Regression results for FreezerShelf

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]	
kitchenaid	.4858177	.2129927	2.28	0.023	.0669435	.9046918
whirlpool	.1922672	.2235177	0.86	0.390	-.2473054	.6318399
whirlpoolg~d	.1976797	.2331855	0.85	0.397	-.2609059	.6562653
ge	.1257874	.195894	0.64	0.521	-.2594603	.511035
geprofile	.1035258	.2450974	0.42	0.673	-.3784858	.5855373
frigidaire	.1253033	.2287398	0.55	0.584	-.3245393	.5751459
frigidaire~y	.2265826	.2674561	0.85	0.397	-.2993999	.7525651
kenmore	.1736181	.2148913	0.81	0.420	-.2489899	.596226
kenmoreelite	-.0476227	.2677751	-0.18	0.859	-.5742324	.4789871
maytag	.3533418	.2303485	1.53	0.126	-.0996643	.806348
amana	.1693249	.2381845	0.71	0.478	-.2990917	.6377415
jenn air	.8069326	.2539093	3.18	0.002	.3075914	1.306274
other_brand	.3619895	.1752614	2.07	0.040	.0173183	.7066607
top	(dropped)					
bottom	-1.228534	.1012065	-12.14	0.000	-1.427568	-1.0295
sidebyside	2.756394	.1835394	15.02	0.000	2.395443	3.117345
white	-.0139439	.0743925	-0.19	0.851	-.1602451	.1323573
black	-.0555935	.0787583	-0.71	0.481	-.2104805	.0992935
stainless~l	.0010016	.0797209	0.01	0.990	-.1557785	.1577817
sales~l	.1201712	.0830053	1.53	0.127	-.0366414	.2929037
ffcap	.0861881	.0381992	2.26	0.025	.0110651	.1613111
freezercap	.0130527	.038233	0.34	0.733	-.0621367	.0882422
kwhycap	.0062112	.0189773	0.33	0.744	-.0311098	.0435321
tempctr	.0583651	.0948896	0.62	0.539	-.128246	.2449761
revdoor	-.0936395	.0939217	-1.00	0.319	-.2783472	.0910681
icemaker	-.3546856	.1216861	-2.91	0.004	-.593995	-.1153762
filterwater	-.0389229	.1097351	-0.35	0.723	-.2547293	.1768835
soundred	.1666942	.0818516	2.04	0.042	.0057238	.3276647
doortkit	-.2873587	.2489342	-1.15	0.249	-.7769157	.2021983
spillpg	-.1959966	.1081496	-1.81	0.071	-.4086848	.0166917
wire	-.1064297	.187651	-0.57	0.571	-.4754666	.2626071
adjshelf	-.0319811	.1495506	-0.21	0.831	-.3260892	.2621269
crisperhco~l	.0693413	.1065747	0.65	0.516	-.1402499	.2789324
meattempco~r	-.2928214	.092019	-3.18	0.002	-.4737872	-.1118556
snackbin	-.3396151	.1865191	-1.82	0.069	-.7066258	.0269956
intlght	.0293621	.071948	0.41	0.683	-.1121318	.170856
adjdoorbin	-.1200253	.0359309	-3.34	0.001	-.1906875	-.0493631
freezerbas~t	-.261718	.0382512	-6.84	0.000	-.3369433	-.1864928
freezercan~k	-.0800621	.2180449	-0.37	0.714	-.5088719	.3487477
freezerlight	.0675082	.1086879	0.62	0.535	-.1462387	.2812552
freezermis~e	.073746	.0939469	0.78	0.433	-.111011	.2585031
_cons	1.116621	.9685222	1.15	0.250	-.7880871	3.021329

Number of obs = 399 F(40, 358) = 122.66
 Adj R-squared = 0.9244 Prob > F = 0.0000

TABLE XV

Regression results for model excluding FreezerShelf

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]	
kitchenaid	.2081082	.0466785	4.46	0.000	.1163097	.2999068
whirlpool	.0202544	.0489851	0.41	0.680	-.0760803	.1165892
whirlpoolg-d	.0862012	.0511039	1.69	0.093	-.0143003	.1867027
ge	-.1036646	.0429312	-2.41	0.016	-.1880937	-.0192355
geprofile	-.0828522	.0537144	-1.54	0.124	-.1884877	.0227832
frigidaire	-.1181299	.0501296	-2.36	0.019	-.2167153	-.0195444
frigidaire-y	-.1090015	.0586145	-1.86	0.064	-.2242734	.0062704
kenmore	-.1744071	.0470946	-3.70	0.000	-.2670239	-.0817903
kenmoreelite	-.0967723	.0586844	-1.65	0.100	-.2121816	.0186371
maytag	-.0614844	.0504821	-1.22	0.224	-.1607631	.0377944
amana	-.0616996	.0521994	-1.18	0.238	-.1643556	.0409564
jenn air	.2032501	.0556456	3.65	0.000	.0938168	.3126835
other_brand	-.1062329	.0384095	-2.61	0.009	-.1757695	-.0246963
top	(dropped)					
bottom	.2855027	.02218	12.87	0.000	.2418833	.3291221
sidebyside	.082018	.0402236	2.04	0.042	.0029136	.1611223
white	.0062182	.0163035	0.38	0.703	-.0258445	.0382809
black	.0220705	.0172603	1.28	0.202	-.0118738	.0560148
stainless ~l	.1504614	.0174713	8.61	0.000	.1161022	.1848206
sales ~l	-.1011363	.0163664	-5.51	0.000	-.1372559	-.0650166
ffcap	.0631817	.0083716	7.55	0.000	.0467181	.0796453
freezercap	.019684	.008379	2.35	0.019	.0032058	.0361622
kwhycap	.0058063	.004159	1.40	0.164	-.0023728	.0139854
tempctr	.005006	.0207956	0.24	0.810	-.0358908	.0459029
revdoor	-.0639955	.0205835	-3.11	0.002	-.1044752	-.0235158
icemaker	.1099424	.0266682	4.12	0.000	.0574965	.1623884
filterwater	.0498373	.024049	2.07	0.039	.0025421	.0971324
soundred	.0223498	.0179382	1.25	0.214	-.0129277	.0576274
doortkit	.2421143	.0545553	4.44	0.000	.1348252	.3494034
spillpg	.0864454	.0237016	3.65	0.000	.0398336	.1330572
wire	.0243455	.0411247	0.59	0.554	-.0565309	.1052219
adjshelf	.0376196	.0327748	1.15	0.252	-.0268358	.1020749
crisperhco~l	.0303374	.0233564	1.30	0.195	-.0155956	.0762705
meattempco~r	.0962931	.0201665	4.77	0.000	.0566334	.1359527
snackbin	.1168893	.0408767	2.86	0.004	.0365007	.1972779
intlght	.0743633	.0157678	4.72	0.000	.0433541	.1053724
adjdoorbin	.0098028	.0078745	1.24	0.214	-.0056832	.0252888
freezerbas~t	.0608128	.008383	7.25	0.000	.0443267	.0772988
freezercan~k	.0593346	.0477857	1.24	0.215	-.0346414	.1533106
freezerlight	.0133266	.0238195	0.56	0.576	-.0335172	.0601704
freezermis~e	.0675767	.020589	3.28	0.001	.0270862	.1080673
_cons	5.449877	.2122569	25.66	0.000	5.03245	5.867394

Number of obs = 399 F(40, 358) = 170.53
 Adj R-squared = 0.9446 Prob > F = 0.0000

TABLE XVI

Regression results for the final model with robust standard errors

Variable	Coefficient	Robust Standard Error	t statistic	p-value	[95% Conf. Interval]	
kitchenaid	.3537245	.0292293	12.10	0.000	.2962419	.4112072
whirlpool	.1594806	.0347704	4.59	0.000	.0911008	.2278604
whirlpoolg-d	.2335381	.0327696	7.13	0.000	.169093	.2979832
ge	.0324978	.024145	1.35	0.179	-.014986	.0799815
geprofile	.0870039	.0259794	3.35	0.001	.0359124	.1380954
frigidaire	.0300199	.0396502	0.76	0.449	-.0479566	.1079964
frigidaire~y	.0297024	.0330548	0.90	0.369	-.0353037	.0947085
kenmoreelite	.0779045	.0281097	2.77	0.006	.0226236	.1331854
maytag	.1029955	.0311915	3.30	0.001	.0416539	.1643371
amana	.1063071	.0305051	3.48	0.001	.0463154	.1662987
jenn air	.3736844	.0369962	10.10	0.000	.3009273	.4464416
other brand	-.0224165	.0285285	-0.79	0.433	-.078521	.033688
top	-.0907647	.0365234	-2.49	0.013	-.1625921	-.0189373
bottom	.197237	.0355584	5.55	0.000	.1273075	.2671666
white	.0074747	.0148417	0.50	0.615	-.0217131	.0366625
black	.0209218	.0158866	1.32	0.189	-.0103209	.0521646
stainless ~l	.1533407	.0164395	9.33	0.000	.1210106	.1856707
saleprice	-.0949673	.020972	-4.53	0.000	-.1362111	-.0537234
ffcap	.0624979	.0078957	7.92	0.000	.0469702	.0780256
freezercap	.0164162	.0083485	1.97	0.056	-.006696	.0320344
kwhycap	.0018918	.0038998	0.49	0.628	-.0057776	.0095611
tempctr	.0061636	.0222603	0.28	0.782	-.0376138	.0499409
revdoor	-.0627384	.0191195	-3.28	0.001	-.1003391	-.0251378
icemaker	.121057	.024954	4.85	0.000	.0719821	.170132
filterwater	.0449636	.0209828	2.14	0.033	.0036986	.0862286
soundred	.0128529	.0229519	0.56	0.576	-.0322846	.0579905
doorokit	.2422328	.095248	2.54	0.011	.0549169	.4295487
spillpg	.0839677	.0240076	3.50	0.001	.036754	.1311813
wire	.0253528	.0373188	0.68	0.497	-.0480388	.0987444
adjshelf	.0346833	.0298615	1.16	0.246	-.0240426	.0934092
crisperhco~l	.018266	.0218959	0.83	0.405	-.0247947	.0613267
meattempco~r	.0766352	.0202549	3.78	0.000	.0368016	.1164687
snackbin	.1487597	.0337675	4.41	0.000	.0823521	.2151673
intlght	.0754457	.0150614	5.01	0.000	.0458258	.1050657
adjdoorbin	.0088834	.0080369	1.10	0.272	-.0069714	.0246394
freezerbas~t	.0625464	.0074599	8.38	0.000	.0478757	.0772171
freezercan~k	.0521565	.0175571	2.97	0.003	.0176285	.0866844
freezerlight	.0138059	.0232067	0.59	0.552	-.0318327	.0594444
freezermis~e	.0560797	.0206831	2.71	0.007	.015404	.0967553
_cons	5.491753	.2116531	25.95	0.000	5.075513	5.907992

Number of obs = 398 F(39, 358) = 260.18
R-squared = 0.9483 Prob > F = 0.0000

TABLE XVII

Regression Results for subsample group 1

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]	
kitchenaid	.3580666	.0371934	9.63	0.000	.2846099	.4315233
whirlpool	.1709773	.0406399	4.21	0.000	.0907136	.2512409
whirlpoolg-d	.2670906	.0487894	5.47	0.000	.1707318	.3634494
ge	.021318	.0344604	0.62	0.537	-.0467411	.0893771
geprofit	.1988127	.0408531	2.66	0.009	.028128	.1894974
frigidaire	.01447	.0492368	0.29	0.769	-.0827726	.1117125
frigidaire-y	.0712448	.0599169	1.19	0.236	-.047091	.1895805
kenmoreelite	.072192	.0466331	1.55	0.124	-.0199083	.1642923
maytag	.1029188	.040508	2.54	0.012	.0229157	.1829219
amana	.0924426	.0439217	2.10	0.037	.0056975	.1791877
jenn_air	.4330645	.0468061	9.25	0.000	.3406226	.5255065
other_brand	-.0157852	.0476592	-0.33	0.741	-.1099119	.0783414
top	-.1004212	.0541728	-1.85	0.066	-.2074123	.0065699
bottom	.1559915	.0491508	3.17	0.002	.0589189	.2530641
white	.0155173	.0240859	0.64	0.520	-.0320522	.0630868
black	.0273333	.0269904	1.01	0.313	-.0259726	.0806393
stainless ~l	.1495924	.0256979	5.82	0.000	.0988393	.2003456
saleprice	-.1308844	.0248707	-5.26	0.000	-.180004	-.0817649
ffcap	.0663203	.0128426	5.16	0.000	.0409562	.0916843
freezercap	.0116802	.0117106	1.00	0.320	-.0114481	.0348086
kwhycap	.0044787	.0059267	0.76	0.451	-.0072265	.0161839
tempctr	-.0006635	.0282378	-0.02	0.981	-.056433	.0551059
revdoor	-.0804342	.0297987	-2.70	0.008	-.1392866	-.0215818
icemaker	.1595102	.0382597	4.17	0.000	.0839475	.2350729
filterwater	.0009457	.0333831	0.03	0.977	-.0649858	.0668772
soundred	.0599469	.024286	2.47	0.015	.0119821	.1079116
dwkkit	.0243651	.0398222	0.61	0.543	-.1721835	.2221136
spillpg	.0819929	.0281724	2.91	0.004	.0263524	.1376333
wire	.0691395	.0565144	1.22	0.223	-.0424763	.1807552
adjshelf	.0731444	.0445949	1.64	0.103	-.0149303	.1612191
crisperhco~l	.0262308	.0296811	0.88	0.378	-.0323893	.0848509
meattempco~r	.0269209	.0277987	0.97	0.334	-.0279815	.0818233
snackbin	.1357852	.0624501	2.17	0.031	.0124464	.259124
intlght	.0632715	.0219437	2.88	0.004	.0199327	.1066103
adjdoorbin	.0181892	.0104196	1.75	0.083	-.0023895	.0387679
freezerbas~t	.0697659	.0112906	6.18	0.000	.0474669	.0920649
freezercan~k	.0392949	.0699719	0.56	0.575	-.0988993	.1774891
freezerlight	.0242322	.0325359	0.74	0.458	-.040026	.0884904
freezermis~e	.0628119	.030081	2.09	0.038	.0034021	.1222218
_cons	5.389263	.3199367	16.84	0.000	4.757389	6.021137

Number of obs = 199 F(39, 159) = 110.75
 Adj R-squared = 0.9558 Prob > F = 0.0000

TABLE XVIII

Regression Results for subsample group2

Variable	Coefficient Estimate	Standard Error	t statistic	p-value	[95% Conf. Interval]	
kitchenaid	.3444418	.0447076	7.70	0.000	.2561444	.4327393
whirlpool	.1739919	.0673715	2.58	0.011	.0409335	.3070504
whirlpoolg~d	.2150231	.0496523	4.33	0.000	.1169601	.3130861
ge	.0312094	.0462012	0.68	0.500	-.0600379	.1224567
geprofile	.0718646	.0510525	1.41	0.161	-.028964	.1726931
frigidaire	.0517543	.0488836	1.06	0.291	-.0447907	.1482993
frigidaire~y	-.0063551	.0752499	-0.08	0.933	-.1549733	.1422631
kenmoreelite	.0719351	.0576159	1.25	0.214	-.041856	.1857262
maytag	.0556652	.0488474	1.14	0.256	-.0408082	.1521387
amana	.0825118	.0538906	1.53	0.128	-.0239219	.1889455
jenn air	.3057775	.0603115	5.07	0.000	.1866625	.4248924
other_brand	-.0089494	.0446635	-0.20	0.841	-.0971596	.0792608
top	-.0447467	.0703602	-0.64	0.526	-.1837078	.0942145
bottom	.2476884	.0596673	4.15	0.000	.1298458	.365531
white	-.0138859	.0252256	-0.55	0.583	-.0637064	.0359346
black	.0148394	.0263066	0.56	0.573	-.0371162	.0667949
stainless ~l	.1396419	.027439	5.09	0.000	.08545	.1938339
saleprice	-.0689731	.0331184	-2.08	0.039	-.1343818	-.0035644
ffcap	.051296	.0134653	3.81	0.000	.0247021	.0778898
freezercap	.0222685	.0137749	1.62	0.108	-.0049368	.0494738
whirlpool	.0022073	.0060441	0.32	0.751	-.0115074	.0159219
tempctr	-.0206989	.0374642	-0.55	0.581	-.0946905	.0532927
revdoor	-.0641973	.033159	-1.94	0.055	-.1296861	.0012915
icemaker	.0991251	.0425065	2.33	0.021	.0151749	.1830753
filterwater	.0597586	.0406804	1.47	0.144	-.0205849	.1401022
soundred	-.0115889	.0302147	-0.38	0.702	-.0712628	.048085
doortkit	.2914847	.0761541	3.83	0.000	.1410805	.4418888
spilling	.0578435	.0505364	1.14	0.254	-.0419656	.1576526
wire	-.005278	.0737433	-0.07	0.943	-.1509207	.1403647
adjshelf	-.0160696	.0561085	-0.29	0.775	-.1268837	.0947445
crisperhco~l	.003839	.0482296	0.08	0.937	-.0914142	.0990923
meattempco~r	.117943	.0323753	3.64	0.000	.0540018	.1818841
snackbin	.1266653	.071486	1.77	0.078	-.0145193	.2678499
intlght	.0982792	.0266089	3.69	0.000	.0457267	.1508316
adjdoorbin	.0098064	.0147989	0.66	0.509	-.0194214	.0390341
freezerbas~t	.0651609	.0140805	4.63	0.000	.0373518	.0929699
freezercan~k	.0628165	.072098	0.87	0.385	-.0795767	.2052097
freezerlight	.0370903	.0399961	0.93	0.355	-.0419019	.1160826
freezermis~e	.0686529	.0323746	2.12	0.036	.0047132	.1325926
_cons	5.669282	.3752236	15.11	0.000	4.928217	6.410347

Number of obs = 199 F(39, 159) = 63.39
 Adj R-squared = 0.9247 Prob > F = 0.0000

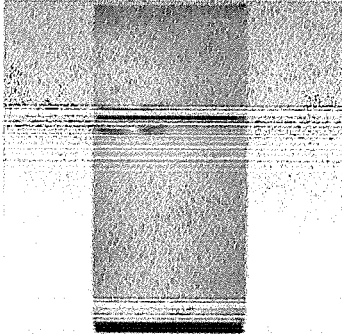
APPENDIX I

This is just a single example.

Product Feature Sheet

KitchenAid

21.6 Cu. Ft. Top Freezer Refrigerator



KitchenAid
For the way it's made

Brand Info

Sears number 463 688 226

Mfg. number KTRA22EMSS

Cabinet: Black Handles: Stainless Steel

Regular Price \$1,899.99

Now \$1,819.99 until Nov 28

[Add to Basket](#) →

For Details, Click on Features to view Product

Glossary

IMPORTANT: Sizes quoted are approximate. Always measure the actual merchandise before making final plans and cutouts.

General Features

<u>Total Capacity (Cu./Ft.)</u>	21.6
<u>Size</u>	Large (20.2 to 22.0 cu./ft. inclusive)
<u>Fresh Food Capacity (Cu./Ft.)</u>	15.2
<u>Freezer Capacity (Cu./Ft.)</u>	6.4
<u>Product Width (In.)</u>	32.5
<u>Product Height (In.)-Excluding hinge cover</u>	65.5
<u>Product Depth (In.)-Excluding handles</u>	31.5
<u>Defrost System</u>	Frost Free
<u>Temperature Controls</u>	Two
<u>EnerGuide Rating (KWH/Year)</u>	448
<u>Reversible Doors</u>	Yes
<u>Rollers/Wheels</u>	Two Adjustable and Two Non-Adjustable
<u>Icemaker/Dispensers</u>	Ice Maker in Freezer
<u>Filtered Water</u>	With Filter Monitor
<u>Sound Reduction Package</u>	Yes
<u>Cooling Coils Location</u>	Bottom
<u>Door Trim Kit</u>	No
<u>Door Panel Options</u>	None
<u>Miscellaneous Feature(s)</u>	ENERGY STAR ®

Fresh Food Section

<u>Shelf Type</u>	Spill-Proof Glass (Three Pullouts)
<u>Shelf Suspension</u>	Cantilever
<u>Number of Shelves</u>	One Full, Four Partial
<u>Crispers</u>	Two On Rollers With Humidity Control

<u>Meat Keeper</u>	On Rollers
<u>Snack Bin</u>	None
<u>Dairy Compartments</u>	One
<u>Food Storage Accessories</u>	Can Rack and Egg Bin
<u>Other Storage Accessories</u>	-
<u>Interior Lights</u>	Two
<u>Adjustable Door Bins</u>	Three
<u>Door Shelves</u>	One Full
<u>Miscellaneous Feature(s)</u>	-

Freezer Section

<u>Number of Shelves</u>	One Full
<u>Number of Pullout Baskets</u>	One
<u>Number of Door Bins/Shelves</u>	Two
<u>Can Rack</u>	Yes
<u>Freezer Light</u>	Yes
<u>Miscellaneous Feature(s)</u>	-

APPENDIX II

GLOSSARY FOR REFRIGERATORS

Side-by-Side The vertical design offers several advantages over the same-size top freezer models, including eye-level access to a large freezer section, the option of a water and ice dispenser and a shorter door swing radius for use in compact spaces.

Top Freezer The freezer is located above the fresh food compartment. The freezer is usually larger in this design and can accommodate oversized items such as frozen turkeys and pizzas. Top freezer models have the most energy efficient layout.

Bottom Freezer The most frequently used compartment (fresh food) is located at the top of the fridge at eye-level. The freezer is at the bottom and is usually larger than those of the top freezer. Bottom freezer models can come with a freezer door that swings open, or the freezer can be in a drawer style for easy viewing from above.

Compacts and Specialty This category includes all refrigerators without freezer sections, small bar and college dorm fridges, and manual defrost models.

Total Capacity (Cu./Ft.) The amount of space available for food storage in the fresh food and freezer compartments. All space is measured in cubic feet.

Size

Top Freezer	Bottom Freezer	Side by Side
<ul style="list-style-type: none">• Small - Up to 17.0 cu. ft inclusive• Medium - 17.0 to 19.9 cu. ft inclusive• Large - 20.2 to 22.0 cu. ft. inclusive• Extra Large - More than 22.0 cu. ft.	<ul style="list-style-type: none">• Medium - up to 19.9 cu. ft inclusive• Large - 20.2 to 22.0 cu. ft. inclusive	<ul style="list-style-type: none">• Medium - 20.0 to 22.1 cu. ft inclusive• Large - 22.2 to 24.1 cu. ft. inclusive• Extra Large - More than 24.1 cu. ft.

A more detailed glossary for refrigerators can be found at <http://www.sears.ca/e/ma/prodinfo/bibyglss/rfig.htm>

Fresh Food Capacity (Cu./Ft.) The amount of food storage space available in the refrigerator's fresh food section compartment. All space is measured in cubic feet.

Freezer Capacity (Cu./Ft.) The amount of food storage space available in the refrigerator's freezer compartment. All space is measured in cubic feet.

Defrost System Frostfree - Ice never builds up in this maintenance-free refrigerator.

Manual Defrost - Turn the refrigerator off to let warm air melt any build up of ice.

Auto Cycle Defrost - The defrost system automatically turns on and off during timed cycles. The freezer compartment must be manually defrosted about once or twice a year depending on usage.

Temperature Control(s) The temperature control automatically keeps your refrigerator at the optimal cooling temperature.

EnerGuide Rating (KWH/Year) The EnerGuide rating is your guide to energy efficiency. It tells you how energy efficient a particular model is. The label provides information on the amount of kWh per year the model will use under normal circumstances. The lower the number, the less electricity the appliance uses.

Reversible Doors Reversible doors can be adjusted to swing open to the right, or to the left. All top freezer and bottom freezer refrigerators are shipped right hand hinge only.

Rollers / Wheels Adjustable rollers on the bottom of the refrigerator make it easy to move it away from the wall for quick clean-ups. Adjustable rollers can also serve as levelers when a kitchen floor is uneven.

Icemaker/Dispensers There's no need to refill ice trays and risk a spill with an automatic icemaker. A continuous supply of ice is produced until the bin is full. Plumbing hook-up is required. Most icemakers are sold separately.

Water and Ice Dispenser - The refreshing taste of nature's best is always on hand with a built-in chilled water dispenser. Also dispenses cubed or crushed ice. To keep kids and pets from playing with the dispenser, some dispensers have a lock out feature. Dispensers vary from electronic to manual.

Filtered Water You will be drinking safe, clean water with the addition of a built-in water filter on a refrigerator dispenser. The filter should be replaced every 6 to 12 months, depending on use.

Sound Reduction Package Extra insulation is added to the refrigerator to reduce noise. Specially designed fan blades also reduce the sound.

Door Trim Kit Factory-installed trim kits let you create a custom look to compliment your kitchen cabinetry.

FRESH FOOD SECTION

Shelf Type Wire Shelves - Coated with rust resistant paint. Offer durability.

Glass Shelves - Tempered glass shelves

Spill Proof Shelves - A spill-proof ledge on the tempered glass shelves keeps liquids contained, preventing a small mess from becoming bigger.

Shelf Suspension Fixed Shelf - Glass or wire shelves that cannot be moved.

Adjustable Shelves -Customize the interior by adjusting the shelves. Some limitations apply. With this kind of flexibility you can make the most of your storage space.

Cantilever - Oversized containers can easily be accommodated when these bracket-supported shelves are adjusted for a custom fit.

Crank Adjusted - A turn of a crank quickly changes shelf height to accommodate large food and beverage containers. Shelf height can be adjusted without removing the food.

Number of Shelves Refers to the total number of shelves included in the food section. Full, partial width and a combination of the two may be provided so you can customize the look and function of the refrigerator.

Crispers Crispers keep perishable fruits and vegetables fresher for a longer time. Optional humidity controls are available. Clear crispers offer easy visibility, while white crispers must be opened to view the contents.

Meat Keeper Compartments keep meats fresher for a longer period of time. Some models offer temperature controls.

Snack Bin This multi-purpose plastic bin holds a variety of food items.

Dairy Compartments Storage for butter, cream cheese and other dairy products.

Food Storage Accessories Wine Rack - This rack attaches under a shelf to provide convenient storage for large wine bottles or pop bottles.

Can Rack -. This rack attaches to a shelf to provide storage for up to 8 cans. Many compact refrigerators have can dispensers built in the door.

Egg Bin - A plastic storage container designed to hold eggs.

Interior Lights Lights automatically turn on when you open the refrigerator or freezer door. Not all refrigerators have interior lights.

Adjustable Door Bins Door storage space can be customized. Bins are adjustable and can be taken to table or to the sink for cleaning.

FREEZER SECTION

Door Shelves Fixed shelves cannot be moved. Available in a variety of depths.

Number of Shelves Refers to the total number of shelves included in the food section. Full, partial width and a combination of the two may be provided so you can customize the look and function of the refrigerator.

Number of Pull Out Baskets Pull-out baskets store more food and provide easier access to items.

Number of Door Bins/Shelves Refers to the number of door bins and shelves.

Can Rack This rack attaches to a shelf to provide storage for up to 8 cans. Many compact refrigerators have can dispensers built in the door.

Freezer Light An interior light automatically goes on when you open the freezer door.

Miscellaneous Features Any other feature (s) the product offers.

Storage Accessories Any other storage accessories the product offers

APPENDIX III

Regression Results for preliminary model with all variables included

Variable	Coefficient Estimate	Standard Error	t statistic	p-value	[95% Conf. Interval]	
KitchenAid	386.0006	122.4837	3.15	0.002	145.1759	626.8253
Whirlpool	-63.90277	130.1649	-0.49	0.624	-319.83	192.0245
WhirlpoolG~d	118.5986	135.6853	0.87	0.383	-148.1827	385.3799
GE	-280.9522	109.2707	-2.57	0.011	-495.7977	-66.10666
GEProfile	-340.4212	139.8022	-2.44	0.015	-615.297	-65.54539
Frigidaire	-218.6898	131.6996	-1.66	0.098	-477.6345	40.2549
Frigidaire~y	-206.3806	153.0301	-1.35	0.178	-507.2648	94.50364
Kenmore	-270.723	121.2852	-2.23	0.026	-509.1912	-32.2548
KenmoreElite	-304.6004	149.5573	-2.04	0.042	-598.6566	-10.54419
Maytag	-185.1735	132.236	-1.40	0.162	-445.173	74.82597
Amana	-139.2475	136.1654	-1.02	0.307	-406.9729	128.4778
jenn_Air	346.8822	146.4961	2.37	0.018	58.84503	634.9194
Other brand	-131.0672	102.8519	-1.27	0.203	-333.2923	71.15788
Top	-61.9156	129.9937	-0.48	0.634	-317.5063	193.6751
Bottom	277.0494	144.029	1.92	0.055	-6.13718	560.236
SidebySide	(dropped)					
white	4.736079	44.44724	0.11	0.915	-82.65507	92.12723
black	16.20538	47.21184	0.34	0.732	-76.62146	109.0322
stainless~l	265.3473	47.80674	5.55	0.000	171.3508	359.3438
Saleprice	-95.49589	48.33455	-1.98	0.049	-190.5302	-46.16079
FFC~p	77.26189	22.17324	3.48	0.001	33.66539	120.8584
FreezerCap	74.08531	22.94646	3.23	0.001	28.96851	119.2021
KWHYCAP	21.73181	10.94223	1.99	0.048	.2174498	43.24617
TempCtr	-49.82778	56.70836	-0.88	0.380	-161.3265	61.6709
RevDoor	-181.1517	55.23353	-3.28	0.001	-289.7506	-72.55279
Icemaker	67.27719	70.99977	0.95	0.344	-72.32094	206.8753
FilterWater	232.5082	62.9316	3.69	0.000	108.7735	356.2429
SoundRed	14.27828	48.84635	0.29	0.770	-81.76228	110.3189
DoorTKit	366.2877	113.4089	3.23	0.001	143.3057	589.2697
SpillPG	30.48078	63.40929	0.48	0.631	-94.19311	155.1547
Wire	34.28649	102.7315	0.33	0.739	-167.7018	236.2747
AdjShelf	15.37488	84.90154	0.18	0.856	-151.5566	182.3063
CrisperHCo~l	-25.02482	60.21365	-0.42	0.678	-143.4155	93.36588
MeatTempCo~r	264.8474	53.36107	4.96	0.000	159.9301	369.7647
SnackBin	73.09448	106.95	0.68	0.495	-137.1882	283.3771
DairyComp	(dropped)					
IntLight	143.1441	41.29151	3.47	0.001	61.95766	224.3305
AdjDoorBin	-2.822708	20.58383	-0.14	0.891	-43.29416	37.64875
Freezerbas~t	97.18713	23.51972	4.13	0.000	50.9432	143.4311
FreezerShelf	-77.83513	27.6675	-2.81	0.005	-132.2343	-23.43592
FreezerCan~k	300.3325	113.796	2.64	0.009	76.58951	524.0755
FreezerLight	-94.85364	64.45708	-1.47	0.142	-221.5877	31.88041
FreezerMis~e	160.6915	49.39053	3.25	0.001	63.58101	257.8021
_cons	-753.6442	620.1327	-1.22	0.225	-1972.935	465.6465

Number of obs = 425 F(41, 383) = 59.00
 Adj R-squared = 0.8487 Prob > F = 0.0000

APPENDIX IV

Regression results for preliminary model with all variables included- no constant term

Variable	Coefficient Estimate	Standard Error	t statistic	p-value	[95% Conf. Interval]	
KitchenAid	386.0006	122.4837	3.15	0.002	145.1759	626.8253
Whirlpool	-63.90277	130.1649	-0.49	0.624	-319.83	192.0245
WhirlpoolG-d	118.5986	135.6853	0.87	0.383	-148.1827	385.3799
GE	-280.9522	109.2707	-2.57	0.011	-495.7977	-66.10666
GEProfile	-340.4212	139.8022	-2.44	0.015	-615.297	-65.54539
Frigidaire	-218.6898	131.6996	-1.66	0.098	-477.6345	40.2549
Frigidaire-y	-206.3806	153.0301	-1.35	0.178	-507.2648	94.50364
Kenmore	-270.723	121.2852	-2.23	0.026	-509.1912	-32.2548
KenmoreElite	-304.6004	149.5573	-2.04	0.042	-598.6566	-10.54419
Maytag	-185.1735	132.236	-1.40	0.162	-445.173	74.82597
Amana	-139.2475	136.1654	-1.02	0.307	-406.9729	128.4778
jenn_Air	346.8822	146.4961	2.37	0.018	58.84503	634.9194
Other brand	-131.0672	102.8519	-1.27	0.203	-333.2923	71.15788
Top	-815.5598	564.2829	-1.45	0.149	-1925.04	293.9203
Bottom	-476.5948	574.3874	-0.83	0.407	-1605.942	652.7525
SidebySide	-753.6442	620.1327	-1.22	0.225	-1972.935	465.6465
white	4.736079	44.44724	0.11	0.915	-82.65507	92.12723
black	16.20538	47.21184	0.34	0.732	-76.62146	109.0322
stainless ~l	265.3473	47.80674	5.55	0.000	171.3508	359.3438
Saleprice	-95.49589	48.33455	-1.98	0.049	-190.5302	-46.16079
FFCap	77.26189	22.17324	3.48	0.001	33.66538	120.8584
FreezerCap	74.08531	22.94646	3.23	0.001	28.96851	119.2021
KWHYCAP	21.73181	10.94223	1.99	0.048	.2174498	43.24617
TempCtr	-49.82778	56.70836	-0.88	0.380	-161.3265	61.6709
RevDoor	-181.1517	55.23353	-3.28	0.001	-289.7506	-72.55279
Icemaker	67.27719	70.99977	0.95	0.344	-72.32094	206.8753
FilterWater	232.5082	62.9316	3.69	0.000	108.7735	356.2429
SoundRed	14.27828	48.84635	0.29	0.770	-81.76228	110.3189
DoorTRit	366.2877	113.4089	3.23	0.001	143.3057	589.2697
SpillPG	30.48078	63.40929	0.48	0.631	-94.19311	155.1547
Wire	34.28649	102.7315	0.33	0.739	-167.7018	236.2747
AdjShelf	15.37488	84.90154	0.18	0.856	-151.5566	182.3063
CrisperHCo~l	-25.02482	60.21365	-0.42	0.678	-143.4155	93.36588
MeatTempCo~r	264.8474	53.36107	4.96	0.000	159.9301	369.7647
SnackBin	73.09448	106.95	0.68	0.495	-137.1882	283.3771
DairyComp	(dropped)					
IntLight	143.1441	41.29151	3.47	0.001	61.95766	224.3305
AdjDoorBin	-2.822708	20.58383	-0.14	0.891	-43.29416	37.64875
Freezerbas~t	97.18713	23.51972	4.13	0.000	50.9432	143.4311
FreezerShelf	-77.83513	27.6675	-2.81	0.005	-132.2343	-23.43592
FreezerCan~k	300.3325	113.796	2.64	0.009	76.58951	524.0755
FreezerLight	-94.85364	64.45708	-1.47	0.142	-221.5877	31.88041
FreezerMis~e	160.6915	49.39053	3.25	0.001	63.58101	257.8021

Number of obs = 425 F(42, 383) = 436.45
 Prob > F = 0.0000 Adj R-squared = 0.9773

APPENDIX V

Regression Results for log-linear model with all variables included- no constant term

Variable	Coefficient Estimate	Standard error	t statistic	p-value	[95% Conf. Interval]	
KitchenAid	.239778	.0549301	4.37	0.000	.1317758	.3477803
Whirlpool	.0361483	.0583748	0.62	0.536	-.078627	.1509235
WhirlpoolG-d	.1200445	.0608505	1.97	0.049	.0004016	.2396875
GE	-.0947923	.0490044	-1.93	0.054	-.1911437	.0015591
GEProfile	-.0934593	.0626968	-1.49	0.137	-.2167324	.0298137
Frigidaire	-.0747561	.0590631	-1.27	0.206	-.1908845	.0413724
Frigidaire-y	-.0766807	.0686291	-1.12	0.265	-.2116177	.0582563
Kenmore	-.1210295	.0543926	-2.23	0.027	-.227975	-.0140841
KenmoreElite	-.1130792	.0670717	-1.69	0.093	-.2449541	.0187957
Maytag	-.0350879	.0593037	-0.59	0.554	-.1516894	.0815136
Amana	-.0236007	.0610659	-0.39	0.699	-.1436671	.0964656
jenn_Air	.1973912	.0656988	3.00	0.003	.0682157	.3265668
Other brand	-.0566569	.0461258	-1.23	0.220	-.1473484	.0340347
Top	5.795894	.253063	22.90	0.000	5.298327	6.293461
Bottom	6.036375	.2575945	23.43	0.000	5.529899	6.542851
SidebySide	5.961159	.2781098	21.43	0.000	5.414346	6.507972
white	-.0031484	.0199332	-0.16	0.875	-.0423406	.0360437
black	.0143879	.021173	0.68	0.497	-.027242	.0560178
stainless ~l	.1462943	.0214398	6.82	0.000	.1041398	.1884488
Saleprice	-.1026606	.0216765	-4.74	0.000	-.1452805	-.0600407
FFCap	.0531152	.009944	5.34	0.000	.0335636	.0726669
FreezerCap	.026113	.0102908	2.54	0.012	.0058795	.0463464
KWHYCAP	.0042665	.0049072	0.87	0.385	-.0053821	.013915
TempCtr	.0173248	.0254319	0.68	0.496	-.0326788	.0673284
RevDoor	-.0835	.0247705	-3.37	0.001	-.1322032	-.0347968
Icemaker	.0666778	.0318411	2.09	0.037	.0040725	.1292832
FilterWater	.1203763	.0282228	4.27	0.000	.0648853	.1758674
SoundRed	.0344549	.021906	1.57	0.117	-.0086162	.0775261
DoorTKit	.1934026	.0508603	3.80	0.000	.0934023	.293403
SpillPG	.0395065	.0284371	1.39	0.166	-.0164058	.0954187
Wire	-.0798263	.0460718	-1.73	0.084	-.1704116	.0107591
AdjShelf	.03503	.0380756	0.92	0.358	-.0398335	.1098935
CrisperHCo~l	-.0098052	.0270039	-0.36	0.717	-.0628997	.0432893
MeatTempCo~r	.1064611	.0239307	4.45	0.000	.0594091	.1535132
SnackBin	.0752192	.0479637	1.57	0.118	-.0190859	.1695243
DairyComp	(dropped)					
IntLight	.0707046	.0185179	3.82	0.000	.0342951	.1071142
AdjDoorBin	.0007483	.0092312	0.08	0.935	-.0174018	.0188985
Freezerbas~t	.0480992	.0105478	4.56	0.000	.0273602	.0688381
FreezerShelf	-.0477354	.012408	-3.85	0.000	-.0721317	-.0233391
FreezerCan~k	.1416276	.0510339	2.78	0.006	.041286	.2419693
FreezerLight	.040071	.028907	1.39	0.166	-.0167652	.0969072
FreezerMis~e	.0573617	.0221561	2.59	0.010	.0138167	.1009127

Number of obs = 425 F(42, 383) = 35585.37
 Prob > F = 0.0000 Adj R-squared = 0.9997