Food For Thought:
The Impact of Wal-Mart Supercenters on Grocery Prices

Abstract

Since becoming America's largest grocery chain in 2003, Wal-Mart Supercenters have introduced the retailer's trademark discount store tactics to the nation's grocery market. I analyze the retail giant's impact on grocery prices by looking at the effect of Wal-Mart Supercenter entry on the average quarterly prices of 10 grocery products in 212 markets around the country during the period from 1995-2005. Employing a fixed effects model I find significant long-run price decreases of between 1.7 and 4.4 percent for 8 of the 10 products. My results also suggest that Wal-Mart has a larger effect on prices in relatively smaller metropolitan areas. Building on earlier research regarding Wal-Mart's impact on the Consumer Price Index, I also examine the relationship between Wal-Mart market penetration and growth in the CPI for 25 different Consolidated Metropolitan Statistical Areas from 1990-2004, failing to find a statistically significant relationship between the two.

Introduction

Few other retailers inspire as much hate and admiration as Wal-Mart. While the retailing giant suffers the wrath of groups fighting to preserve small town main streets and those trying to unionize workers, it continues to be a popular destination for shoppers seeking lower prices In their study of Wal-Mart's entry into the United Kingdom, Alan Halsworth and Ian Clarke (2001) report that Wal-Mart opponents lament its perceived negative effect on incumbent retail establishments in small market towns while those who welcome the newcomer emphasize its "anti-inflationary effects." More recently Joseph Nocera writes in *The New York Times*, "a reasonable argument can be made that over the last 10 or 15 years, Wal-Mart has done more to keep inflation in check than Alan Greenspan has. After all, Mr. Greenspan, the Fed chairman, can't force Procter & Gamble to roll back a planned increase in the wholesale prices of toothpaste. Wal-Mart can - and does."[1]

Hence the question arises of whether one can measure empirically the "anti-inflationary effects" of Wal-Mart. The question becomes even more interesting when one considers that since 2003 the retailer has been the nation's largest grocer (Tom Weir, 2003) and, thus, may have an impact on grocery prices in addition to the non-durable and durable goods of which the retailer has long been a leading seller. Therefore, I study Wal-Mart's effect on prices through examining the impact of Wal-Mart Supercenters on grocery prices and through looking at the retailer's effect on the Consumer Price Index.

Without knowing much about Wal-Mart, one may wonder why this specific discount retailer would lead to significantly lower prices for consumer goods. Wal-Mart Corporation opened its first discount store in Rogers, Arkansas in 1962, selling a wide array of general

[1] **Nocera, Joseph.** "Our Love-Hate Relationship With Wal-Mart." *New York Times*, November 5, 2005, p.B1.

merchandise. Since the beginning, the company has pursued a strategy of minimizing costs in order to consistently offer shoppers the lowest prices possible. For example, as it expanded throughout the country, the retailer reduced shipping costs by building stores within a one day's drive of the nearest distribution center (Pankaj Ghemawat et al., 2004). Unlike traditional supermarkets which follow a so-called Hi-Lo model of pricing in which some items rotate into the "low" category each week as they go on sale, Wal-Mart follows an Every Day Low Prices strategy (EDLP) in which items remain at the same low price for long periods of time, with only occasional specials (Rajiv Lal and Ram Rao, 1997). Thanks to the cost savings highlighted above, the EDLP price at Wal-Mart generally beats all but the lowest sale prices found elsewhere. In addition, as the world's largest retailer, Wal-Mart's sheer size allows it to negotiate and receive discounts from suppliers because of the large quantities purchased (Global Insight, 2005).

Throughout its history, Wal-Mart has also been known for using the latest in technological innovation. In the 1980s the company began to develop a software system called Retail Link which provides its suppliers with near real-time information regarding sales. This technology allows the company to avoid stock-outs and to lower inventory costs by not holding excess merchandise. According to Ghemawat et al. (2004), by requiring all of its suppliers to be connected to the Retail Link system, Wal-Mart has forced suppliers to cater to the retailer's needs. Today Wal-Mart continues its history of technological innovation by requiring suppliers to use Radio Frequency Identification (RFID) tags on shipping pallets, ensuring that less merchandise will be lost in the warehouse (Ghemawat et al., 2004).

Wal-Mart's exploitation of technology has led to the retailer's superior productivity figures and an increase in the productivity of the retail sector in general. The McKinsey Global Institute's 1999 report on productivity growth in the United States highlights both Wal-Mart's use of IT and new managerial techniques as being primarily responsible for the jump in the growth of retail labor productivity from 5.3 percent annually between 1987 and 1995 to 10.1 percent annually between 1995 and 1999. This same report finds that despite attempts by competing discounters to mimic Wal-Mart's practices, in 1999 the company maintained a 41 percent lead in productivity over its competitors measured in terms of real sales per employee. Wal-Mart's supply chain management and productivity figures make it truly one-of-a-kind in retailing.

With the opening of the first Wal-Mart Supercenter in 1988, combining a traditional Wal-Mart discount store with a full-line grocery store, Wal-Mart began to apply the same cost minimizing strategies it had been using in the discount goods business to the grocery business. As of October 2005, the number of Wal-Mart Supercenters had grown to over 2000, whereas the number of Wal-Mart stores without a full-line of grocery offerings had fallen to around 1,100, as the retailer converts more stores to the Supercenter format every year.[2] While the grocery business was once characterized by many local chains, Wal-Mart has become a major player across the nation. Given its commitment to the EDLP model, it seems reasonable to hypothesize that Wal-Mart entry into a market exerts significant downward pressure on average grocery prices within that market. Jerry Hausman and Ephraim Leibtag (2004) note that prices at Wal-Mart Supercenters tend to be from 8 to 27 percent lower than those at traditional supermarkets. Thus the "Wal-Mart Effect" could come about through two channels. First, it could occur as consumers begin to shift their expenditures away from traditional supermarkets and toward Wal-Mart Supercenters to take advantage of lower prices. Second, Wal-Mart entry could also result in lower average prices as competing grocery stores lower their own prices as a result of competition from Wal-Mart.

[2] Wal-Mart website, "Wal-Mart Alignment." <http://www.walmartfacts.com/community/article.aspx?id=1481> cited December 20, 2005.

By analyzing average prices of 10 different grocery products in 212 markets around the country using data from the American Chamber of Commerce Research Association (ACCRA) over 42 quarters, ranging from the first quarter of 1995 through the second quarter of 2005, I attempt to quantify the impact of Wal-Mart Supercenters on grocery prices. Results of my empirical study described below indicate that Wal-Mart entry does indeed lead to average lower prices of a wide array of staple grocery items in markets throughout the country. The price effects range from a long-run decrease of 1.7 percent in the average price of potatoes to a long-run average price decrease of 4.4 percent for frying chickens. I find significant price effects for both products carrying a national brand and those with private labels. Price decreases appear greatest in cities with relatively smaller populations.

In addition to looking at the effect of Wal-Mart Supercenters on the prices of specific grocery items, I also build on earlier research conducted by Global Insight (2005) which examines the effect of Wal-Mart on the growth of the Consumer Price Index in metropolitan statistical areas (MSAs). Using a different measure of Wal-Mart penetration than that used in the earlier research to examine the period from 1990-2004, I fail to find a significant relationship between concentration of Wal-Mart stores and growth in the CPI for the 25 MSAs for which the Bureau of Labor Statistics (BLS) computes separate indexes.

Literature Review

Several theoretical and empirical articles on retail competition appear in the current economic literature. A theoretical model of retail competition applicable to Wal-Mart comes from Kyle Bagwell, Garey Ramey, and Daniel Spulber (1997) who propose a two-stage model of retail competition in which retailers enter a market during the first stage knowing nothing about the prices of competitors. In this stage, firms gather information on competitors' prices and subsequently invest in technology during the second stage in order to lower marginal cost and offer lower prices. Given Wal-Mart's penchant for investment in technological innovation in order to lower costs, this article appears to have been written with the retail giant in mind.

On the demand side of this model, consumers gather information on prices during the first stage which they share with one another in the second stage. Thus in the second stage of the two-stage model, consumers with low switching costs move to the lower priced retailers. A "shakeout" of retailers occurs as all consumers able to switch to the lower-priced retailers do so, leaving higher-priced firms to divide up the remaining consumers and forcing some retailers to exit the market. This "shakeout" resembles exactly what many people fear will happen when Wal-Mart enters a community, while at the same time demonstrating how Wal-Mart becomes a major player in a retail market.

In another theoretical article, Lal and Rao (1997) propose a model by which grocery stores following Wal-Mart's Every Day Low Prices strategy steal market share from traditional Hi-Lo chains by advertising lower relative market basket prices, thus attracting time-conscious consumers who do not wish to research sale prices on individual items at the Hi-Lo chain. These authors predict that traditional chains will respond by either lowering their own prices or increasing service offerings in order to win back the time-strapped consumers. However, Wal-Mart Supercenters often contain everything from fast-food restaurants to car service stations, amenities demanded by those short on time. This may limit the extent to which traditional grocers can win back customers without price cuts of their own.

In the empirical literature, several articles analyze the impact of Wal-Mart entry on retail markets. Naveen Khanna and Sheri Tice (2000) examine the reaction of discount retail chains' parent firms to the entry of Wal-Mart in specific markets. Their data set includes 860 markets in the U.S. during the period 1976-1994. Using the first three digits of zip codes to define a market, they look at the change in the level of investment by the parent firms, which is defined as an increase or decrease in the number of stores in a given market following a “Wal-Mart attack.”

These authors find that Wal-Mart entry has a significant impact on the investment decision made by rival firms, noting that sales per square foot, chain size, market population growth, percentage of a firm’s profits stemming from discount retailing, and dependence of a firm on a certain market are all positively related to increased investment by the parent firm in a given market following Wal-Mart entry. At the same time they note that market share, debt, and inside ownership are inversely related to investment levels following Wal-Mart entry. To examine whether or not Wal-Mart has a unique effect, they compare the behavior of chains in markets in which they compete with Wal-Mart to the behavior of those same chains in markets without Wal-Mart, finding a significant difference between the two.

More recently, David Neumark, Junfu Zhang, and Stephen Ciccarella (2005) analyze the effect of Wal-Mart on local labor markets, investigating the claim that Wal-Mart entry leads to lower wages and lower employment levels. Unlike previous researchers who had to rely on data gathered from various sources to determine the timing of Wal-Mart entry into a given market, these authors have access to data from Wal-Mart Corporation regarding store opening dates and square footage. Fearing an endogeneity problem arising from the fact that Wal-Mart may choose to open stores in areas with faster growing retail wages and employment, they instrument for Wal-Mart openings by looking at the distance of a given store from Wal-Mart headquarters in Bentonville, AR. Because the company expanded by spreading outward from its headquarters, distance from Bentonville, AR and the time period can be used to predict the location of Wal-

Mart store openings excluding the possible influence of local economic growth levels on opening decisions.

Using county and yearly fixed effects to control for innate differences between counties and for macroeconomic shocks, Neumark et al. (2005) look at retail employment per worker and retail payroll per worker at the county level as a function of years since the opening of the first Wal-Mart store in a given county. Without the use of their instrumental variable, they find a positive relationship between Wal-Mart presence and retail employment which is likely due to the fact that Wal-Mart enters faster growing counties. Once they employ the instrumental Wal-Mart variable, they find a negative relationship between these two variables, in which Wal-Mart presence reduces *retail* employment levels by 1.9-4.6 percent. Using the instrumental variable, they find that Wal-Mart presence also lowers retail payroll per worker by 3.5 percent. When looking at *total* employment in a given county, the authors find that Wal-Mart presence may actually lead to an increase in employment at the county level. However, when analyzing total payroll per worker, they conclude that Wal-Mart decreases this figure by 1.9 percent. However, one cannot say that wages decline by 1.9 percent, because the authors use payroll data from County Business Patterns which does not take into account hours worked, therefore allowing for the possibility that any decrease in payroll per worker comes about through a decrease in hours worked. Nevertheless, while this study highlights some of the negative aspects of Wal-Mart entry, in their conclusion the authors note the importance of analyzing Wal-Mart's price effect when determining the overall effect of Wal-Mart entry on a given locality.

In the literature concerning Wal-Mart's impact on grocery markets, Andrew Franklin (2001) analyzes the market share of the top four grocery chains in 100 metropolitan areas around the country following Wal-Mart Supercenter entry, finding that Supercenter entry does not have a significant effect on the four-firm concentration ratio in those markets. However, his data set only runs through 1999, near the beginning of Wal-Mart's drive toward Supercenter expansion and, thus, in the majority of the markets analyzed, Wal-Mart Supercenters had yet to capture even a 5 percent share of the market.

Perhaps the most valuable part of Franklin's study is that he examines which market characteristics Wal-Mart looks at when deciding to enter a market. Using a logit model to regress Wal-Mart presence on median household income in the nation's 100 largest markets, he finds Wal-Mart entry to be inversely related to median income. With a similar model, he finds no statistically significant relationship between Wal-Mart entry and market population. In addition to examining the relationship between certain market characteristics and Wal-Mart entry, Franklin also examines the relationship between market characteristics and Wal-Mart's market share. He finds a statistically significant inverse relationship between the median income in a given market and Wal-Mart market share. He also finds an inverse relationship between market population and Wal-Mart market share but a positive relationship between years since Wal-Mart opening and Wal-Mart market share, indicating that the retailer gains market share over time. This information suggests that when looking for new markets in which to open stores, Wal-Mart chooses those with lower-than-average incomes and that over time it becomes a bigger player in those with both lower-than-average populations and incomes. It also hints at the finding discussed below by Emek Basker (2004) that Wal-Mart tends to have larger price effects in smaller cities.

The study of outlet substitution bias in the CPI represents another branch of research applicable to Wal-Mart. Marshall Reinsdorf (1993) indicates that the advent of discount retailers such as Wal-Mart may lead to upward bias in the CPI. This problem arises because when rotating new outlets into the CPI sample, the BLS uses a procedure which chains forward the index based on prices at the old outlets. Thus, if the new sample of stores contains a Wal-Mart Supercenter which offers lower prices than the outlet it replaced, the BLS continues to link the quantities purchased at this new store to the index constructed using higher prices found at stores in the old sample, thus failing to ever directly compare prices between the two outlets. The BLS justifies this procedure by assuming that price differences between the old and new outlets are completely accounted for by the quality differences between them. As a result, the entry of Wal-Mart into the BLS sample has no effect on the CPI during the period in which it enters the sample. The retailing giant only impacts the CPI to the extent that Wal-Mart lowers future prices after being rotated into the sample or causes prices at all retailers to grow slower than they otherwise would have.

Reinsdorf (1993) demonstrates that during the 1980s, grocery outlets rotated into the CPI sample tended to have prices which were 1.23 percent lower than those found at outlets rotated out of the sample. He then compares the growth in the BLS Average Price Series Data (AP), which does not take into account quality differentials, to the growth of the CPI for various grocery items from 1980 to 1989. His results demonstrate that the CPI grew at 4.2 percent per year whereas the AP grew at a rate of 2.1 percent per year, thus indicating upward bias in the CPI. Being that the data in this study predate the advent of Wal-Mart Supercenters, outlet substitution bias may be an even more serious problem today.

Building on Reinsdorf's (1993) study of outlet substitution bias in the CPI, Hausman and Leibtag (2004) attempt to demonstrate such bias by examining both the direct effect of lower grocery prices offered at Supercenters, mass merchandisers, and club stores (SMC) and the response of incumbent grocery chains to these new retailers. Through a theoretical model of consumer choice, they demonstrate that if following the opening of an SMC, consumers actually substitute away from traditional supermarkets and towards these new outlets, revealed preference indicates that quality differentials cannot completely account for the price difference between the stores. In this case, consumers clearly value the lower prices at the SMC more than any supposed higher quality service at the supermarket. Additionally, the fact that competing grocery stores lower prices in response to SMC entry also indicates that quality differences cannot completely explain the difference in prices.

In the empirical section of their paper, using data from ACNielsen Homescan on grocery purchases in the nation's 34 largest markets, Hausman and Leibtag demonstrate just how quickly SMC have captured market share in these markets, increasing from 10.9 percent in January 1998, to 16.9 percent in December 2001. Using monthly data on consumer grocery purchases from this same organization for the period 1998-2001 in the same 34 markets, the authors construct a model to measure price changes in 20 specific grocery products as consumers shift expenditures to SMC. This model uses the average price paid for a product as the dependent variable, and the percentage of that specific product purchased in SMC as the explanatory variable, employing market fixed effects and monthly fixed effects to control for price differences between cities and seasonal effects or macroeconomic shocks. The authors employ two-stage least squares regression, using the proportion of total food expenditure in a given market at SMC as an instrumental variable and then estimate their model using an autoregressive process AR(1) to account for the possibility of autocorrelation. However, they note that using least squares with robust standard errors leads to similar results.

Hausman and Leibtag's findings indicate that as consumers shift expenditures towards SMC, the average price paid for groceries in a specific market declines by 0.75 percent per year leading to a total decrease of 3 percent over the four year sample period. The magnitude of the price decrease varies greatly by product, with no clear pattern emerging as to which types of products display the greatest price decreases. The authors also estimate the effect on the average price paid for grocery items in traditional supermarkets as consumers divert their dollars to SMC, finding a similar but smaller in magnitude effect. This study demonstrates empirically that consumers shift to SMC when given the opportunity and that traditional grocery stores respond to the competitive pressures of SMC with lower prices, indicating flaws with the BLS linking procedure. However, in spite of the catchy title, "Does the BLS Know That Wal-Mart Exists?," this study does not allow for conclusions about Wal-Mart in particular, since the SMC category includes everything from Wal-Mart Supercenters, to members-only merchandisers such as Costco, to mass merchandisers like Big Lots.

Specifically looking at Wal-Mart's effect on prices, Basker (2004) analyzes the effect of Wal-Mart discount store entry on the prices of nine non-grocery items and Coca-Cola, using quarterly price data from the American Chamber of Commerce Research Association (ACCRA) for 165 cities around the country during the period 1982-2002. As for data on Wal-Mart store openings, Wal-Mart Corporation refused to provide her with store opening dates and thus she constructs her own using company annual reports, the *Chain Store Guide Directory of Discount Department Stores,* and the Wal-Mart edition of the *Rand McNally Road Atlas.*

Basker's model uses the log of the price of a product in a given city during a specific quarter as the dependent variable. The independent variables include the product price lagged one quarter, a dummy variable indicating the presence of a Wal-Mart store in a given city in a given quarter, city and quarter fixed effects, and a city-specific time trend variable. Basker says that the coefficient on the Wal-Mart variable represents the instantaneous price effect of Wal-

Mart entry, namely by how much prices fall during the quarter of Wal-Mart entry. However, the word instantaneous can be misleading because the value of her Wal-Mart dummy variable takes a value of one to indicate the existence of a Wal-Mart store and it remains one after Wal-Mart entry. If average prices react to Wal-Mart entry a few quarters after entry once competitors respond with lower prices of their own, the Wal-Mart variable should pick-up this price drop as well. Therefore, this variable can be interpreted as the average quarterly price decrease due to Wal-Mart during the period of her study. Fearing that including the lagged price variable creates a problem because it may be correlated with the error term, Basker uses twice lagged price to instrument for lagged price.

Using ordinary least squares regression, she finds a significant decrease in prices for three items in her study: toothpaste, shampoo, and laundry detergent. She measures short-run decreases in the prices of these products to be between 0.7 and 0.8 percent. In order to estimate the long-run effect of Wal-Mart entry, which comes about due to lower lagged prices, she takes the coefficient on her Wal-Mart variable and divides it by one minus the coefficient on the lagged price. For the above mentioned products she finds that in the long-run prices decline by 3.5-4 percent. She explains the pattern of significance in her results by noting that the traditional discount store provides a fairly good substitute for a drug store whereas it provides a relatively poorer substitute for a clothing store, and therefore one may expect larger price decreases for common drug store items than for apparel items. One problem with the sample price data she employs is that some of the specific branded items surveyed by ACCRA, such as Levi's Jeans, were not sold at Wal-Mart during her sample period. Thus, it is not surprising that she fails to find a significant price decrease for specific clothing items: unless jeans sold at Wal-Mart are perfect substitutes for Levi's, Wal-Mart entry would not be likely to result in a large decrease in the price of jeans.

Fearing that her data may contain measurement errors concerning Wal-Mart entry dates, Basker (2004) modifies the above model by using data on Wal-Mart's planned entry into a market, as indicated by the sequential numbering of stores, to instrument for the opening date she calculates herself. She also notes a possible endogeneity problem in which Wal-Mart chooses to open stores in markets with less competitive retail markets or with higher prices, both of which would allow the retailer to have a larger effect on prices. The fact that Wal-Mart had entered 162 of the 165 economically diverse cities in her sample before the end of the period studied reduces the fear that Wal-Mart enters cities with less competitive retail markets. As for entering markets with higher prices, she believes that since stores must be planned years in advance, looking at planned entry rather than actual opening dates will get rid of some of this problem because it will be difficult for the retailer to predict periods of high prices in a given market.

Using this instrumental variable for Wal-Mart openings, she reruns her regressions, finding significant price decreases for five products: aspirin, detergent, Kleenex, shampoo, and toothpaste, with short-run price declines of 1.5-3 percent and long-run declines of 8-13 percent. However, her justification for using this instrumental variable relies on the fact that after planning a new store, Wal-Mart may manipulate actual opening dates to coincide with times of higher prices. It seems somewhat implausible that after undergoing all the expenditures of planning a store, Wal-Mart would look at price levels in a given market to make last minute adjustments to the store opening date. Therefore, one may question whether this instrumental variable is used to correct for a true problem or whether it is used because it leads to more significant results. Though Basker does not mention it, perhaps the planned variable is important because other retailers preemptively lower prices when expecting Wal-Mart entry.

In order to analyze the claim of Wal-Mart critics that the retailing giant engages in predatory pricing in order to drive competitors out of the market only to later raise prices, Basker (2004) also tests whether prices increase significantly five years following Wal-Mart entry. She introduces a second Wal-Mart variable into the equation which represents whether or not a Wal-Mart store has been open in a city for more than five years. This coefficient represents an additional price shock coming from Wal-Mart once the retailer is already established in a market. Basker finds this variable to be insignificant, indicating that prices do not increase five years after a Wal-Mart entry.

Adding a dummy variable for whether the number of retail establishments per capita in a city is above or below the median figure in her sample, Basker also finds a more robust "Wal-Mart Effect" in smaller cities, which tend to have a higher density of smaller, less competitive retail establishments, providing more room for Wal-Mart to lower prices. In these smaller cities, she finds a significant decrease in prices for six of the ten products, whereas she finds no statistically significant effect in the larger cities. The coefficients for the two different groups of cities are statistically different from one another for three products.

The most recent contribution to the growing literature on Wal-Mart's price effects came in November 2005 when Global Insight released a report on Wal-Mart's effect on the American economy. The GI study focuses on retail wages and employment figures, finding contrary to Neumark et al. (2005) that Wal-Mart leads to increased retail employment at the county level.[3]

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[3] One must note that Wal-Mart Corporation commissioned Global Insight to conduct this study, though Global Insight claims to have undertaken a "fair and balanced" assessment of Wal-Mart's impact on the economy. GI also hosted a November 4, 2005 conference in Washington, D.C. for academics to assess Wal-Mart's effect on the economy. Basker (2004), Hausman and Leibtag (2004), and Neumark et al. (2005) all presented the papers

They also find that while Wal-Mart's presence has led to a 2.2 percent decrease in the nominal wage at the national level, it has led to a 0.9 percent increase in the real wage due to a 3.1 percent decrease in consumer prices. Therefore, examination of Wal-Mart's price effects forms an integral part of GI's final report.

Specifically, GI (2005) analyzes the overall change in the CPI for all items for all-urban consumers between 1985 and 2004 in 24 consolidated metropolitan statistical areas (CMSA). Wal-Mart supplied GI with data on square footage by metropolitan area which allows the researchers to use change in Wal-Mart square footage per capita as one of their independent variables. This variable displays a large amount of variation between cities, as Wal-Mart presence grew by over 1.6 square feet per person in Kansas City while in New York, this same measure increased by just over 0.2 square feet per person. As control variables, GI analyzes prices and demographic characteristics likely to differ greatly between CMSAs including electricity prices by state, unemployment rates by CMSA, and population growth by CMSA, finding all of these variables to be significant except for population growth. Services comprise 60 percent of the CPI for all urban consumers, and thus GI includes the growth the CPI for services as an additional independent variable, allowing them to limit their analysis to the non-durable and durable goods sectors in which Wal-Mart actually competes.

Running an OLS regression, GI determines that every unit increase in Wal-Mart square footage per capita lowers the CPI for durable and non-durable goods for all urban consumers by 2.56 percent. Looking at specific CMSAs, they find that the impact of Wal-Mart since 1985 ranges from a decrease in the CPI of 1 percent in New York and Los Angeles, to a decrease of as much as 4 percent in Houston and Anchorage. In addition, they do a separate analysis of the CPI

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reviewed above at this event. While this conference was sponsored by Wal-Mart, as indicated by the findings of the above papers, the conference presented research showing both positive and negative effects of the retailer.

for food-at-home, finding that Wal-Mart has a significant effect which exceeds that found in the non-durables and durables segment. Interestingly, they find that over the relevant time period, the increase in square footage per capita of traditional Wal-Mart stores, which do not sell a full line of groceries[4], reduces the CPI for food-at-home by 11 percent, whereas an increase in square footage per capita of Wal-Mart Supercenters results in only a 6 percent decrease. This implies that grocery stores may lower prices in response to Wal-Mart discount store entry, perhaps because they fear future entry by Wal-Mart Supercenters. However, one would imagine that separating the effect of Wal-Mart discount stores from that of Wal-Mart Supercenters over such a long period may be difficult because so many Supercenters began life as discount stores.

While not focusing on Wal-Mart or even retail competition, one additional study provides useful insight into explaining price variations between cities. In their 1999 analysis of sales tax incidence, Timothy Besley and Harvey Rosen use ACCRA price data for 155 cities around the nation to compare sales tax regimes. Like Basker (2004) they incorporate city and quarter fixed effects into their analysis in order to control for price differences across cities, but they also highlight wage, rental, and energy prices as being key determinants of these price differences. These authors note the difficulty of finding local data on these prices and, thus, use ACCRA data on the price of a home service call for washing machine repair, apartment rents, and the price of a gallon of gasoline to proxy for each of these input prices.

Presentation of Model

Looking at the effect of Wal-Mart on prices in different cities involves controlling for inherent price differences across cities, macroeconomic shocks which affect prices across the nation, and different trends in the growth of prices. Economic theory, as well as the articles

[4] Wal-Mart discount stores commonly sell a limited variety of grocery items such as milk, snacks, and certain dry cereals, though with a much smaller selection than that available in a Supercenter.

reviewed above, suggests that retail prices are also influenced by the key input prices in a given area, namely the price of labor, the price of land, and the price of energy. Thus, these variables should also be included in the model. The following model, based on Basker (2004), is used to analyze the effect of Wal-Mart Supercenter entry on grocery prices.

$$P_{abt} = \alpha_{ab} + \beta_a P_{ab,t-1} + \theta_a WSuper_{bt} + \sum_t \delta_t quarter_t + \sum_b \tau_b trend_t + \vartheta_a unemployment_{bt} + \varpi_a rent_{bt} + \psi_a energy_{bt} + \varepsilon_{abt}$$

P_{abt} on the left-hand side of the equation represents the log of price for product *a*, in city *b*, during quarter *t*. A log transformation is applied to both sides of the equation so that the coefficient on the *WSuper* coefficient can be interpreted as a partial elasticity and that on the control variables as elasticities. This allows for a more meaningful comparison of the magnitude of the price declines across products.

The constant term α_{ab}, indicates a fixed effects model in which each cross-sectional unit, in this case each city, has a different intercept term. The fixed effects model controls for innate differences in price levels between cities. For example, if prices in Fairbanks, Alaska are consistently higher than prices in St. Cloud, Minnesota due to the higher transportation costs of shipping goods to Alaska, the fixed effects should capture such a difference. In my model the fixed effects represent what A. Colin Cameron and Pravin K. Trivedi (2005) refer to as "nuisance parameters" because the true interest lies in estimation of the *WSuper* coefficient (the presence of a Wal-Mart Supercenter) rather than the estimation of the individual intercepts for each city. Therefore, I do not report either the coefficients or the standard errors for the fixed effect parameters.

$P_{ab,\, t-1}$ stands for the log of the lagged price, one quarter earlier, because in the simplest model one would assume the price in the previous quarter to be the best predictor of the price in the subsequent quarter. Basker (2004) notes that the coefficient on the lagged price should be less than one, because a value of greater than one indicates an exploding time series. In her own research she computes values of between 0.7 and 0.8 for the coefficient on lagged price. Including lagged price allows for the calculation of a long-term effect of Wal-Mart entry, since the lower lagged price resulting from Wal-Mart entry continues to have influence over future prices, though at a diminishing rate since the coefficient must be less than one. Consequently, one can determine the long-run effect of Wal-Mart entry by computing the following formula: $\theta_a/(1-\beta_a)$.

WSuper represents the variable of interest for my study and indicates whether a Wal-Mart Supercenter exists in city b during quarter t. Assuming that Wal-Mart Supercenters actually lower prices, one would expect a negative sign on the coefficient. This coefficient (θ_a) represents the average quarterly drop in the price of product *a* in markets which experience Supercenter entry. Put differently, it represents how much prices differ in a given quarter from what they would have been if no Supercenter were present.

The *quarter* variable represents a dummy variable for each quarter and provides a way of controlling for the time period, and as such, controls for events that affect all of the cities in the sample during a specific quarter. These include macroeconomic shocks to the economy or a shock to the price of a specific product.

The *trend* variable includes a separate time trend variable for each city in the sample. This variable takes on a different value for each quarter, for example taking on a value of 1 for quarter 1 and 2 for quarter 2. This should capture the fact that prices grow over time due to inflation while accounting for differing trends over time in the growth of prices between cities. For example, if prices grow faster in a city with a large rate of population growth such as Las

Vegas, Nevada than in a slower growing city like Bismarck, North Dakota, this variable will capture the differing trends.[5]

Additional variables not used by Basker (2004) but used in my model include rent, the unemployment rate, and energy prices, which provide a measure of the price of key inputs for retailers. Including these variables directly in the model may provide an explanation of the variation between cities in a way that relying solely on fixed effects does not.

The $rent_{bt}$ variable stands for the rent in city b, during quarter t, and is used to proxy for land prices, providing an indication of the cost to a retailer of opening and maintaining an outlet in a specific geographic location. Unfortunately, data on commercial rents are not readily available, and, thus, following from Besley and Rosen (1999) and Jeffrey Campbell and Hugo Hopenhayn (2005), I use data on residential rents instead. Since higher rents indicate higher costs for retailers, one would expect a positive coefficient on this variable.

The $unemployment_{bt}$ variable stands for the unemployment rate in city b in quarter t and represents differing labor costs between sample cities. While one may be tempted to include local retail wages as a measure of differing labor costs between cities, these data are extremely hard to find on a yearly, much less a quarterly, basis. Global Insight (2005) suggests that using wage data directly in the model might create a simultaneity problem because higher wages may be due to higher prices. Therefore, they note that instead of including retail wages in the model, one can use the unemployment rate as a measure of local labor market pressures. In addition, Neumark et al. (2005) indicate that Wal-Mart may lower the local wage, leading to an endogeneity problem of including local wages in the model. These authors find a less clear impact of Wal-Mart on county-level employment, and thus the unemployment rate may be a

[5] Basker (2004) states: "The inclusion of both city fixed effects and city specific trends allows the average price in each city to take a separate (linear) path. This is a reduced form way of controlling for variables that change at low frequencies (like income and population) without including them directly," p.11.

more useful measure of labor costs. A low unemployment rate will put upward pressure on the wage rate, leading to upward pressure on prices and to the expectation of a negative sign on this coefficient.

The $energy_{bt}$ variable consists of the average electricity price in city b in quarter t. Because energy costs vary greatly across the nation, they may be responsible for some of the variation in retail prices between areas. Global Insight (2005) finds that electricity prices are good measures of energy costs because of the large amounts of electricity used by retailers for lighting and air conditioning stores. These prices are also useful because they reflect the price of the fossil fuels used in electricity generation. As energy costs rise, retail prices should also rise, resulting in a positive coefficient on this variable.

Data

Data on grocery prices comes from the American Chamber of Commerce Research Association's quarterly *Cost of Living Index.* In constructing the index, ACCRA relies on unweighted average prices from cities around the country gathered by local chambers of commerce which sample a minimum of five retail establishments in their jurisdiction during the first two weeks of every quarter. ACCRA designs the *Cost of Living Index* to be a measure of the cost of living for a mid-management household and, as such, advises its price collectors to "Select only establishments where individuals from professional and managerial classes would normally shop. Even if discount stores are a majority of your overall market, they shouldn't be in your sample *at all* unless upper-income professionals and executives really shop there."[6] Therefore, any price decrease resulting from Wal-Mart Supercenter entry in my sample likely represents the secondary effect of competitors lowering prices in response to Wal-Mart entry

[6]American Chamber of Commerce Research Association. *Cost of Living Index Manual*. December 2005. p.1.2. <http://www.coli.org/surveyforms/colimanual.pdf>

rather than the direct effect of price collectors recording lower prices at Wal-Mart. As a result, these data are likely biased against finding a "Wal-Mart Effect" because price collectors are less likely to visit Wal-Mart Supercenters than traditional grocery chains[7] and, as Hausman and Leibtag (2004) demonstrate, the price drops observed in traditional supermarkets in response to the entry of Supercenters, mass mechandisers, and club stores, tend to result in prices which are still higher than the prices found in Supercenters themselves. ACCRA reviews all data coming from local chambers of commerce to ensure accuracy and omits any cities whose data appear questionable.

Because the local chambers of commerce report prices on a voluntary basis, the number of cities included in the ACCRA sample fluctuates from quarter to quarter. In at least one quarter during the period of this study, 478 cities reported prices, while only 51 cities reported in all 42 quarters. Besley and Rosen (1999) note that there is no reason to believe that a city's decision not to report in certain quarters brings about any bias in the sample. In determining which cities to include in my study, I use only those which reported prices for 80 percent or more of the possible quarters, leaving 212 cities in the sample. These cities exhibit a great deal of diversity ranging from small towns to large metropolitan areas, though the South is overrepresented in the sample with 97 (46 percent) of the cities coming from that region, as defined by standard Census Bureau classifications. Interestingly, this breakdown of cities by census region mirrors the expansion path of Wal-Mart Supercenters across the country, beginning in the South and then spreading to the Midwest, West, and most recently the

[7] Customer profiles available from Ghemawat et al. (2003) indicate that the consumers shopping at Wal-Mart Supercenters tend to be from higher income brackets ($25,000-$70,000 per year) than those that shop at regular Wal-Mart discount stores (<$25,000-$60,000 per year), indicating that the Supercenters may be more likely to be included in the ACCRA sample than the traditional discount stores.

Northeast. This implies that if a "Wal-Mart Effect" indeed exists, my sample cities are well positioned to show it.[8]

Table 1: Summary Statistics-Sample Cities*

Mean Population	175,440
Median Population	70,922
Maximum Population	3,694,820
Minimum Population	5,409
Percentage of Cities in Midwest	26.4%
Percentage of Cities in Northeast	4.7%
Percentage of Cities in South	45.8%
Percentage of Cities in West	23.1%
Percentage of Cities with Wal-Mart Supercenter as of Quarter 1 1995	13.7%
Percentage of Cities with Wal-Mart Supercenter as of Quarter 2 2005	77.4%

*Source for population and region data: 2000 Census American Factfinder available at: http://factfinder.census.gov/home/saff/main.html?_lang=en.
Sources for Wal-Mart entry explained below.

In studying the effect of Wal-Mart Supercenters on grocery prices, I would ideally examine the prices of a market basket of grocery goods. However, my selection is limited to those items consistently available in the ACCRA survey during the period of my study. In choosing items, I avoid those that involve large seasonal price fluctuations in order to reduce the noise in the data, hence the absence of fresh fruits and vegetables. I also choose a mixture of branded and unbranded products because many of the savings at Wal-Mart Supercenters may stem from the company's private labels, which currently account for 20 percent of the retailer's total sales (Ghemawat et al, 2003). For example, ACCRA instructs its price collectors to record the price of white bread by simply choosing the brand with the lowest price per ounce, allowing for the influence of private labels, whereas in the case of parmesan cheese the price collector must purchase an eight-ounce-canister of the Kraft brand. The present study includes ten

[8] A full list of cities is located in Appendix 6.

products: white bread, cereal, corn flakes, frying chicken, margarine, milk, parmesan cheese, canned peaches, potatoes, and canned tuna fish. The use of data from 212 different cities means that despite missing values resulting from cities failing to report in certain quarters, the dataset contains over 7,000 observations for each product. A complete list of products and their definitions can be found in Table 2 below with summary statistics for each product price displayed in Table 3.

Table 2: Products and Their Definitions*

Product	**ACCRA Definition**
Bread	White bread loaf with lowest price per ounce in each store
Cereal	Corn flakes, 18 ounce, Kellogg's or Post Toasties
Coffee	Vacuum packed, 11.5 ounce can or brick, Maxwell House, Hills Brothers, or Folgers
Frying Chicken	Whole uncut: price per pound, lowest price
Margarine	1 pound Blue Bonnet or Parkay, stick form
Milk	1/2 gallon, whole milk, lowest price
Parmesan	8-ounce-canister, grated, Kraft brand
Peaches	29-ounce-can, Hunts, Del Monte, or Libby's
Potatoes	10-pound-sack, white or red, lowest price
Tuna	Chunk light, 6-ounce-can, Starkist, or Chicken of the Sea

*Source: American Chamber of Commerce Research Association. *Cost of Living Price Report.* December 2005. Retrieved January 30, 2006 from: http://www.coli.org/surveyforms/pricesurvey.pdf.

Table 3: Summary Statistics Product Prices for All Cities, All Quarters (Nominal Dollars)*

Product	Average over 42 quarters	Maximum Price	Minimum Price	Standard Deviation	Coefficient of Variation
Bread	$0.90	$2.59	$0.34	0.19	21.1%
Cereal	$2.52	$4.29	$0.91	0.46	18.3%
Coffee	$2.83	$5.44	$1.47	0.53	18.7%
Frying Chicken	$0.93	$1.79	$0.49	0.17	18.3%
Margarine	$0.74	$1.99	$0.34	0.18	24.3%
Milk	$1.66	$2.93	$0.82	0.27	16.3%
Parmesan	$3.57	$5.29	$1.98	0.43	12.0%
Peaches	$1.58	$3.07	$0.54	0.19	12.02%
Potatoes	$2.75	$13.40	$2.65	0.84	30.5%
Tuna	$0.68	$2.07	$0.33	0.12	17.6%

*Source: American Chamber of Commerce Research Association. *Cost of Living Index.* Louisville, KY: ACCRA, 1995 Quarter 1-2005 Quarter 2.

Some interesting observations can be made by looking at the minimum and maximum prices for various items in the survey. The extremely low minimum prices tend to be anomalies in the cities from which they come, suggesting the occurrence of a temporary special price. Since ACCRA thoroughly checks prices for outliers, it requires price collectors to provide proof of prices which seem unreasonable, such as the $0.33 can of tuna or $0.34 loaf of bread found in the table above. These low prices could be a result of the fact that ACCRA permits price collectors to use coupons distributed in a store for same-visit purchases. Thus, if a local chain distributes coupons for a given item, and price collectors visit several stores in that chain, an abnormally low average price would be recorded. Extremely high maximum prices tend to occur in cities which have high prices overall. For example, the maximum price of potatoes of $13.40 for a ten pound sack comes from Kodiak, AK, the city with the highest average price for nine of the ten items, most likely as a result of its location on an island in Alaska. Another high maximum price, the $5.44 coffee, occurs in Boston, MA, another one of the highest priced cities in the sample.

One of the most difficult parts of conducting research on Wal-Mart involves determining when Wal-Mart entered the grocery business in a given market. Wal-Mart entry can come through two channels: a new store can open as a Supercenter or, alternatively, an existing discount store can be converted to the Supercenter format.[9] In the case of the former, my task was made much easier than that of previous researchers thanks to a new section of the Wal-Mart

[9] While Wal-Mart also sells groceries at its Sam's Clubs warehouse stores, I exclude these from my study because they are "members only" stores and therefore not ready substitutes for traditional grocery stores. I also exclude Wal-Mart's more recent foray into the grocery business with an all-grocery format known as Neighborhood Markets, since according to Ghemawat et al. (2003) these outlets target a higher income clientele than the Supercenters, and therefore may be less focused on providing low prices. David Rogers (2003) supports this hypothesis in his analysis of the Oklahoma City grocery market, saying that surveys suggest that consumers find the Neighborhood Markets to have higher prices than the Supercenters.

website entitled "Data for Economic Analysis"[10] which appeared in late 2005 and includes a spreadsheet containing the store number, addresses, and opening dates of all Wal-Mart stores in the United States. While these data indicate whether a store currently operates as a Wal-Mart Supercenter, this information does not contain the date at which locations that were originally opened as discount stores converted to Supercenters. However, Wal-Mart also provides press releases for the years 2001-2005 which announce the opening dates of Supercenters converted from discount stores during that period. Because ACCRA price collectors record prices during the first two weeks of the quarter, I assign a store to the quarter in which it physically opened only if it opened within the first two weeks of that quarter. While competitors may lower prices in anticipation of a Supercenter opening, waiting until after a Supercenter actually opens its doors for business allows for the possibility of lower prices resulting from price collectors adding a Wal-Mart store to their sample.

Unfortunately, this still leaves the period from the first quarter of 1995 through the fourth quarter of 2000 during which the exact date of Supercenter conversions from discount stores cannot be determined. My attempts to contact Wal-Mart Corporation directly resulted in the reply that all available information can be found on the website, whereas contacting specific stores often led to debates among store employees concerning the date of conversion and suspicious managers unwilling to give out detailed information. Thus, for conversions occurring prior to 2001, Wal-Mart opening dates were imputed from the *Chain Store Guide Directory of Discount and General Merchandise Stores.* This allows for computation of store conversion dates by year, though an exact quarter cannot be assigned. Therefore, following the method of Basker (2004) I use the exact dates of Supercenter conversion, available on the Wal-Mart

[10] Wal-Mart Website. "Wal-Mart Alignment", http://www.walmartfacts.com/community/article.aspx?id=1481 cited 20 December, 2005.

website for the period 2001-2005, to determine the distribution of store openings between quarters, finding that 22.6 percent of conversions occurred in the first quarter, 30.3 percent in the second quarter, 26.1 percent in the third quarter, and 20.9 percent in the fourth quarter. I then use this distribution to assign values to the *WSuper* variable. For example, if the *Chain Store Guide Directory of Discount and General Merchandise Stores* indicates that a Supercenter conversion occurred in 1999, I assign the *WSuper* variable a value of 0 for the first quarter of 1999, and a probability of .226 for the second quarter of that year. The store receives its full weight in the first quarter of the year following its opening. For the 164 cities in my sample which experienced the entry of a Wal-Mart Supercenter by the end of my sample period, 29 cities already had a Wal-Mart Supercenter at the beginning of the sample period. An exact opening date is available for an additional 70 cities, which leaves 65 cities for which Wal-Mart openings rely on the probabilistic variable.

In addition to determining the opening date of stores, a determination has to be made about whether a Wal-Mart Supercenter competes in a given market for which ACCRA collects prices. For many of the cities included in the ACCRA sample this is a rather simple determination because the Wal-Mart Supercenter is located within the city limits. In larger metropolitan areas the determination can be more difficult. Previous studies such as Khanna and Tice (2000) used the first 3 digits of zip codes to define markets. However, use of this criterion would allow for the inclusion of stores located over twenty miles from the center city in a given market. This problem is compounded by the fact that Wal-Mart tends to open its Supercenters in rural areas located near major metropolitan areas before actually entering suburban and urban locations. With only one store located a considerable distance from the center city, it seems unlikely that the Wal-Mart Supercenter entry would have a substantial impact on average grocery prices in the market. Furthermore, ACCRA instructs its price collectors to focus on the urban and suburban portions of a metropolitan area, hence rural areas which may happen to fall into counties included in a given MSA, and which may be the first areas to get a Wal-Mart Supercenter, should not be included in this study. In an attempt to correct for this problem, I record an area as having a Wal-Mart Supercenter if a store was located within ten miles of the center city. These distances were determined using the Wal-Mart website, which contains a detailed store locator listing all of the stores near a given zip code and calculates the distance between that zip code and specific stores. For example, the *WSuper* variable for Minneapolis-St. Paul never takes a value other than zero in my dataset, because prior to the third quarter 2005 openings in Shakopee and Maple Grove, the nearest Supercenter to Minneapolis was located 26 miles away in Elk River.

Data for control variables used in my study include rental prices, electricity prices, and the unemployment rate. As mentioned above, the lack of data on commercial rents forces the use of residential rents, in this case the average rent for a two bedroom, unfurnished apartment, published in the ACCRA survey. One additional problem with these rents stems from the fact that smaller metro areas and the non-metropolitan areas included in the ACCRA survey often lack the type of apartments designed for “managerial and professional households” which ACCRA requests. Consequently, cities which report all other prices may fail to report data on rents, leading to more missing values in this category than in any of the other prices gathered by ACCRA.

Data on electricity prices comes from the Energy Information Administration (EIA), and again is far from ideal because the EIA only reports electricity prices at the state level and on an annual basis.[11] However, because regulation of electricity occurs at the state level, electricity prices vary more between than within states; therefore, the EIA prices may be an adequate proxy for local electricity prices.

Once again, the unemployment figures pose problems because they are not available on a quarterly basis for the entire period of my study and, thus, my data only includes unemployment on an annual basis. Not all cities in my sample are MSAs for which the Bureau of Labor Statistics computes unemployment statistics separately, thereby forcing the use of unemployment data at the county level. In the case of multi-county MSAs, I use the county containing the city from which the MSA derives its name.

Results

Using the statistical package *Eviews*, I pool the data together for each product and run ten separate regressions on an unbalanced panel. The city fixed effects in the model are estimated using the "within" estimator, meaning that the program transforms the data by subtracting the mean value from each observation within a cross-section and then running OLS on the transformed data. Cameron and Trivedi (2005) note that such a procedure leads to consistent coefficient estimates, whereas simply including a dummy variable for each cross-section and then running pooled OLS can lead to inconsistent estimation. To correct for the possibility of heteroscedasticity within each cross-section, White's standard errors are used in all regressions.

One problem with using the fixed effects estimator with a lag of the dependent variable as an independent variable is that it can lead to contemporaneous correlation of the lagged variable and the error term, leading to biased coefficient estimates (Peter Kennedy, 2003). According to Kennedy (2003) possible corrections for this problem include first differencing and subsequently finding an instrument to use IV estimation or alternatively using a GMM estimator.

[11] GI (2005) also relies on statewide electricity prices in its model of Wal-Mart's price effect.

In my model, due to the possibility for error in the measurement of Wal-Mart entry, first differencing does not provide a suitable correction because I use a dummy variable to enter Wal-Mart opening dates into the model. In the case of first differencing, the variable will have only one quarter in which the dummy takes a value of one. Consequently, if my calculation of the opening of Wal-Mart differs from the true opening by one quarter, no “Wal-Mart Effect” will be found. In addition, if it takes a few quarters for Wal-Mart’s competitors to reduce their prices, the first difference dummy will not pick-up the effect because it has a value of one for only the opening quarter. However, if one does not use first differencing and the opening variable differs from the true value by one quarter, the estimate of the *WSuper* coefficient will be biased downward but some effect will still appear. Another possible correction for contemporaneous correlation, Seemingly Unrelated Regression, also does not apply to my model, because as Nathaniel Beck and Jonathan Katz (1995) note, this correction should only be used when the number of time periods exceeds the number of cross-sections.

Despite these potential econometric problems, Kennedy (2003) notes that the fixed effects estimator has greater precision than either IV or GMM estimation, and thus in cases such as mine, in which the number of time periods exceeds 30, the greater precision outweighs the potential for biased estimates, and thus the fixed effects estimator should be used. Nevertheless, due to the potential bias imposed by using a lagged value of the dependent variable as an independent variable, I also report results without the lagged variable, which can be found in Appendix 1. These results do not differ qualitatively from those with the lagged variable, as all coefficients which were significant in the original specification remain significant.

Proceeding with OLS regression using fixed effects, I find the *WSuper* coefficient to be negative for nine of the ten products and statistically significant for seven products, with magnitudes ranging from -0.019 for margarine, to -0.037 for frying chicken. The coefficient on the lagged price ranges from a low of 0.11 for potatoes to a high of 0.33 for milk and is always statistically significant at conventional levels, indicating that lagged prices have predictive power and as such can be used to determine the long-run price effects of Wal-Mart entry. Coefficients on the electricity variable are only significant for cereal and parmesan cheese, and this variable has the wrong sign in the cereal regression. The rent variable was significant for parmesan, tuna, and bread, having the correct sign in each case, whereas the unemployment variable showed significance only for cereal, where it had the wrong sign.

Because the coefficients on rent, electricity price, and unemployment were significant in so few regressions, I perform joint Wald tests on all three of these variables for each separate product to determine whether their coefficients are significantly different from zero. With the exception of the cereal and parmesan regressions, which show joint significance at the 1 percent level, the results of this test indicate that rent, electricity price, and the unemployment rate should not be included in the model. The results of all regressions with the inclusion of the rent, electricity, and unemployment variables can be found in Appendixes 2 and 3. The results of regressions without the use of these control variables can be found in Table 4 below. Re-estimating the model without the cost variables does not lead to substantial changes in the *WSuper* variable. Due to the finding that the cost variables should not be included in my model, I report all subsequent regression results without the use of these control variables.

Table 4: Results without cost variables (electricity price, rental price, unemployment rate)

Product	WSuper Coefficient (θ)	Lag Coefficient (β)	Long-Run Effect (θ)/(1-β)
Bread Adjusted R^2=0.707	-0.027*** (0.007)	0.224*** (0.106)	-0.034***
Cereal Adjusted R^2=0.641	-0.024*** (0.007)	0.311*** (0.016)	-0.035***
Coffee Adjusted R^2=0.812	-0.018*** (0.004)	0.273*** (0.058)	-0.025***
Frying Chicken Adjusted R^2=0.661	-0.037*** (0.006)	0.158*** (0.014)	-0.044***
Margarine Adjusted R^2=0.685	-0.018*** (0.007)	0.287*** (0.015)	-0.026***
Milk Adjusted R^2=0.812	-0.023*** (0.004)	0.333*** (0.018)	-0.035***
Parmesan Adjusted R^2=0.698	-0.001 (0.005)	0.297*** (0.015)	-0.002
Peaches Adjusted R^2=0.712	-0.003 (0.004)	0.258*** (0.023)	-0.004
Potatoes Adjusted R^2=0.711	-0.014 (0.008) p-value=.103	0.125*** (0.016)	-0.017 p-value=.103
Tuna Adjusted R^2=0.568	-0.028*** (0.007)	0.182*** (0.022)	-0.034***

***Significant at 1% level

Technically speaking, the coefficients on the *WSuper* variable cannot be interpreted as partial elasticities because it is a dummy variable. Rather, the partial elasticity can be found by taking the antilog of the coefficient and then subtracting one from the result (Damodar Gujarati, 2003). However, because the coefficients in this case are so small, performing this procedure does not change the results when displaying three significant figures. Therefore, the coefficient on bread of -0.027 indicates that the presence of a Wal-Mart Supercenter in a given market leads to a 2.7 percent decrease in the price of bread for a given quarter. The long-run effect indicates that due to the influence of lagged prices on future prices, in the long-run bread prices decline by 3.4 percent. I perform Wald Tests on the hypothesis that $\theta_a/(1-\beta_a)=0$ in order to determine the significance level of the long-run effect.

Of the items which are statistically significant at conventional levels, frying chicken displays the largest coefficient, indicating a decrease of 3.7 percent in the average price for a given quarter and a long-run decrease of 4.4 percent. Margarine displays the smallest effect, with an average quarterly decrease of 1.8 percent and a long-run price drop of 2.6 percent. Potatoes, with a p-value of 0.103 in the above specification, come close to statistical significance at the 10 percent level, though given that the other coefficients which are statistically significant are significant at the 1 percent level, potatoes appear to be less significant than many of the other products in my sample.

To test the hypothesis that the magnitude of Wal-Mart's impact on prices increases as city size decreases, I rerun the above regressions using sub-samples of different sized cities. The first sub-sample excludes all consolidated metropolitan statistical areas (CMSA) in my sample (ie., the largest Census Bureau classifications, such as Los Angeles); the second excludes central cities with populations over 200,000, and the third excludes central cities with populations in excess of 100,000. Of the two products for which the *WSuper* coefficient was insignificant in the original specification, one, parmesan cheese, displays a coefficient significant at the 10 percent level in cities with less than 200,000 people, and a coefficient significant at the 5 percent level in cities with fewer than 100,000 inhabitants. For seven of the ten products, the magnitude of the *WSuper* coefficient increases as the city size decreases, qualitatively suggesting that the effect of Wal-Mart increases as city size decreases. The largest increase occurs for coffee where the size of the coefficient increases from -0.018 in all cities to -0.033 in cities with populations under 100,000. On the other end of the spectrum, the coefficients on frying chicken and tuna hover near the same value for all specifications, apparently displaying the same effect in cities regardless of population. Interestingly, the coefficient on potatoes increases with the removal of

CMSAs, but then decreases as city size further decreases, becoming statistically insignificant in the group of cities with less than 100,000 people. Results for regressions run on groups of different-sized cities can be found in Appendix 4.

To determine whether or not the results for different sized cities are significantly different from one another, I perform a Chow Test, finding no significant structural difference between the case in which all cities are pooled together and the case in which cities are divided into groups based on population size. However, because the Chow test only looks at a structural difference for the entire model, whereas in the present study interest lies in whether or not the *WSuper* coefficient differs significantly between samples of different-sized cities, I also employ an interaction dummy variable for city size in order to analyze the impact of Wal-Mart in cities with different populations. The model becomes as follows, in which D_1 represents metropolitan areas in which the center city has a population less than 200,000 and D_2 represents those with populations over 200,000.

$$\mathrm{P}_{abt} = \alpha_{ab} + \beta_a \mathrm{P}_{ab,t-1} + \theta_{1a} WSuper_{bt} * D_1 + \theta_{2a} WSuper_{bt} * D_2$$
$$\sum_t \delta_t quarter_t + \sum_b \tau_b trend_t + \varepsilon_{abt}$$

In all cases, with the exception of peaches, the coefficient on the *WSuper* variable has both a greater magnitude and a higher t-statistic for cities with populations under 200,000. In fact, with the exception of frying chicken, none of the coefficients on the *WSuper* variable for cities with populations greater than 200,000 are statistically significant. For three products: bread, margarine, and milk, a Wald test on the hypothesis that $\theta_{1a} WSuper_{bt} * D_1 = \theta_{2a} WSuper_{bt} * D_2$ indicates that the coefficients differ significantly between the two groups of different-sized cities. The largest statistically significant increase occurs in bread, for which the *WSuper* coefficient increases from -0.005 in cities with a population greater than 200,000 to -0.032 in cities with a population less than 200,000. Results for the key variables can be found in Table 5 below.

Table 5: Results based on population differences

Product	*WSuper*D$_1$ (θ_1)*	*WSuper*D$_2$ (θ_2)*
Bread^ Adjusted R^2=0.707	-0.032*** (.008)	-0.005 (.014)
Cereal Adjusted R^2=0.641	-0.027*** (.007)	-0.012 (.012)
Coffee Adjusted R^2=0.811	-0.021*** (.005)	-0.006 (.009)
Frying Chicken Adjusted R^2=0.661	-0.038*** (.007)	-0.035*** (.011)
Margarine^ Adjusted R^2=0.685	-0.025*** (.008)	0.007 (.016)
Milk^ Adjusted R^2=0.812	-0.027*** (.005)	-0.010 (.008)
Parmesan Adjusted R^2=0.698	-0.007 (.004) p-value=0.108	0.019 (.018)
Peaches Adjusted R^2=0.712	-0.002 (.005)	-0.008 (.007)
Potatoes Adjusted R^2=0.710	-0.016 (.010) p-value=.112	-0.008 (.017)
Tuna Adjusted R^2=0.578	-0.032*** (.008)	-.013 (.015)

^Difference between *WSuper*D1* and *WSuper*D2* significant at the 10% level
***Significant at the 1% level

In order to test the robustness of my model, I rerun my regressions using only data from the 135 cities in which a Wal-Mart Supercenter opened during my sample period. Neumark et al. (2005) suggest that these data may be more indicative of Wal-Mart's true impact because it limits the analysis to the change before and after the arrival of Wal-Mart rather than comparing areas which had Wal-Mart openings to those that did not. The results from this specification remain similar to those found in the original specification and are displayed in Appendix 5.

One potential econometric problem not controlled for above could arise due to the presence of serial correlation of errors within cross-sections, leading to underestimated standard errors, overestimated t-statistics, and thus incorrect statistical inference. Due to the presence of a lagged dependent variable as an independent variable, the Durbin-Watson *d* statistic is not applicable for my regressions. While the Breusch-Godfrey test would still be applicable, *Eviews* will not perform the test for panel data models. In addition, *Eviews* cannot compute Newey-West standard errors which are robust to serial correlation, meaning that the standard errors reported above do not control for the possibility of serial correlation. However, Cameron and Trivedi (2005) note that the use of the fixed effects model can greatly reduce serial correlation in the error terms, though it may not completely eliminate it, thus implying that serial correlation may not be a large problem in my model. Due to the concern over serial correlation I follow the example of Hausman and Leibtag (2004) and re-estimate my equations using an AR(1) model, finding that all products for which the *WSuper* variable was significant in the original specification remain significant.

Discussion

While the results which indicate that Wal-Mart Supercenter entry is associated with long-run average price declines of between 1.7 percent and 4.4 percent may seem rather small when compared to the 8-27 percent price differences between Wal-Mart Supercenters and their competitors reported by Hausman and Leibtag (2004), one must bear in mind that the sample of retailers from which the prices come likely does not contain many Wal-Mart Supercenters. Thus the fact that one observes any significant price decrease suggests that as Lal and Rao (1997) hypothesize in their theoretical model of grocery competition, traditional Hi-Lo supermarkets respond to the entry of an Every Day Low Prices competitor by lowering their own prices. The magnitude of the ““Wal-Mart Effect”” also seems in-line with earlier research by Hausman and Leibtag (2004) who find 3 percent declines in the average grocery prices paid by consumers economy-wide as they shift expenditure from traditional supermarkets to Supercenters, mass merchandisers, and club stores.

A lingering concern is that the *WSuper* coefficient on two of the products, parmesan cheese and canned peaches, is not significant in the original specification using all cities, and the coefficient on canned peaches never approaches statistical significance in any specification. However, when considering these two items in more detail, one can formulate a reasonable hypothesis as to why they fail to display results similar to those found for other products. Unlike the rest of the items in my sample, these two are not "staples" purchased during nearly every shopping trip, and, thus, consumers tend to have a less clear idea of what the price should be. Because these items do not constitute a large portion of a consumer's total budget, the consumer does not invest time researching prices, resulting in less price sensitivity for these items and more inelastic demand curves. Traditional Hi-Lo chains tend to advertise the items to which consumers are most price sensitive in weekly circulars, as these items rotate into the "low" category. With its Every Day Low Prices strategy, Wal-Mart attempts to beat these retailers by avoiding the weekly circular and offering a price which consistently matches the "low" price of other retailers. An interview with a current Wal-Mart Supercenter assistant manager reveals that unlike the other items in my sample, parmesan cheese and canned peaches are not items on which Wal-Mart consistently attempts to undercut the price of its competitors.[12] By looking at a larger sample of items, future research could identify whether Wal-Mart entry only leads to significantly lower prices for the "staple items" which consumers purchase most frequently and for which they are likely to exhibit the highest degree of price sensitivity, or whether lower prices can be found for all grocery items.

[12] Interview with Vas Mach, assistant manager of Wal-Mart Supercenter, Cambridge, MN. January 22, 2006.

In the case of potatoes, the one item which consistently appears near the border of statistical significance at conventional levels, the fact that they represent the sole fresh produce item in my sample may account for this difference because their price fluctuates more than that of other products and may be subject to seasonal variability. The coefficient of variation for potato prices of 30.5 percent exceeds that of the other items in my sample, indicating greater variation in this data. While the quarter dummies should capture seasonal fluctuations that affect all cities in the sample simultaneously, they will not capture any seasonal effects which vary from one location to another. For example, if potato prices drop in Idaho during the potato harvest but no corresponding drop in prices occurs in cities farther from Idaho, the use of quarter dummies will not account for the fluctuation. The high degree of variability in potato prices could indicate why the *WSuper* coefficient on potatoes becomes insignificant when restricted to the group of 132 cities with population under 100,000.

As for the failure of my control variables to show statistical significance, this likely results from the fact that none of these measures adequately capture price effects at the level of my cities. Considering that two out of the three are measures of annual prices rather than quarterly prices, and that one of them, electricity, contains data from a higher geographical unit of analysis than my price data, it should not be too surprising that I fail to find significance for these variables. Besley and Rosen (1999) also report difficulty with finding local cost variables that display statistical significance and note that omitting these variables from their equation and relying on city and time fixed effects leaves their analysis unchanged. Basker (2004) and Hausman and Leibtag (2004) both note that fixed effects should capture most of the inter-city variation in prices and estimate models without the use of any additional measures of price differences between cities. Thus the fact that these variables do not show significance should not be cause for grave concern.

The qualitative results of the regressions using different sub-samples of cities and the results of the dummy variable test suggest that city size does have an impact on Wal-Mart's price effects. Assuming that, as Campbell and Hopenhayn (2005) find, smaller cities have less competitive retail environments made up of less efficient retailers, this result makes intuitive sense. Wal-Mart entry may have a much stronger impact in smaller cities because the retailing giant's superior productivity figures allow its prices to vary much more from those of its competitors than in larger, urban areas where competing retailers share many of the same efficiencies. This finding of a larger magnitude "Wal-Mart Effect" in smaller cities could also result from the difficulty of assigning Wal-Mart entry in larger cities. My model only takes into account the effect of the first Wal-Mart Supercenter which opens in a given city. In large cities such as Houston or Dallas, which are now home to many Supercenters, the first store may not have much of an impact on the average prices collected by ACCRA. However, in smaller markets such as Marshfield, WI or Laramie, WY where only one Wal-Mart Supercenter exists, the effect of the first store will be much stronger. By obtaining information from Wal-Mart Corporation concerning square footage per capita, much like Global Insight (2005) and Neumark (2005), future researchers could analyze the role of increasing Wal-Mart penetration in these markets.

While my dataset does not contain enough products to determine conclusively whether a larger "Wal-Mart Effect" occurs for branded or unbranded products, both items for which ACCRA specifies specific brand names (cereal, coffee, tuna, and margarine) and those for which it does not (bread, frying chicken, and milk) exhibit significant decreases in price following Wal-

Mart entry. It appears that not all savings from Wal-Mart entry come about as a result of its private label because even when specific brand names are analyzed, prices still decrease as a result of Wal-Mart entry.

One of the major weaknesses of my model results from the fact that based on the data from ACCRA, one cannot be sure whether or not the sample includes prices from Wal-Mart Supercenters. As a result, I cannot say conclusively whether the results demonstrate only a secondary effect of Wal-Mart entry, leading to a downward bias on the *WSuper* coefficient, or whether the direct effect of lower prices recorded at Wal-Mart impacts the results, thereby attenuating some of this bias. Related to this problem is the fact that ACCRA constructs an unweighted average of prices, meaning that it fails to take into account the quantities purchased at different outlets. If consumers increasingly shift expenditures to lower priced outlets, so long as the mix of stores in the ACCRA sample remains unchanged, the average price fails to reflect this change in consumer behavior.

Another possible downward bias in my estimate of Wal-Mart's price effect would come about if competitors reduce prices in advance of Wal-Mart's opening in order to prepare for the Wal-Mart "attack." Because my *WSuper* variable only looks at what occurs after Wal-Mart entry, this type of preemptive action will not be accounted for in my model.

As for the opening dates themselves, the fact that my results rely on probabilistic determination of Wal-Mart Supercenter conversion dates for 65 cities increases the probability of error in my assignment of Wal-Mart opening dates. Unless this measurement error is correlated with some other drop in prices, this should lead to a downward bias in the estimate of the "“Wal-Mart Effect." Finally, my model does not account for the possibility that another discount retailer enters the market around the same time as Wal-Mart, meaning that the decrease in price attributed to Wal-Mart may actually be due to the entry of a competing retailer, for example, if Super Targets often open at the same time as Wal-Mart Supercenters. Due to the fact that Wal-Mart has far more Supercenters than either Kmart or Target, this is unlikely to be a large problem. Nevertheless, one additional area for future research would be to measure the price effects of competition between the leading Supercenter chains. Through assembling data on the locations and opening dates of Super Targets and Super Kmarts, one could analyze whether prices fall farther in those areas in which Wal-Mart must compete with one of the other leading Supercenter chains.

Introduction of CPI Analysis

After demonstrating that Wal-Mart Supercenters have a significant effect on the prices of select grocery items, the question still remains of whether one can measure the effect of Wal-Mart on aggregate price levels for different categories of goods. While Global Insight (2005) performs such an analysis, one must be somewhat skeptical of their results because Wal-Mart commissioned GI's assessment of the retailer's effect on the economy. Therefore, I try to replicate their findings in order to provide further evidence concerning the price effect of Wal-Mart. As noted in the literature review, Reinsdorf (1993) and Hausman and Leibtag (2004) both demonstrate that any observed impact of discount retailers such as Wal-Mart on the CPI likely understates their true effect, making any finding of a "Wal-Mart Effect" ever more telling of the retailing giant's impact on the American economy.

Presentation of CPI Model

GI (2005) examines the relationship between growth of the CPI and growth in Wal-Mart penetration in the 24 consolidated metropolitan areas (CMSA) for which the BLS constructs separate price indexes. GI's model includes variables which likely impact the price differences observed between cities, including electricity prices, the unemployment rate, and the rate of population growth. While I provide the rationale for the first of these two control variables in the explanation of my grocery price model, the justification for the inclusion of population relies on the belief that in rapidly growing MSAs, the demand for a product could increase faster than the supply, leading to upward pressure on prices and the expectation of a positive sign on this coefficient. To allow for a meaningful comparison between cities, the change in each of these independent variables at the MSA level is compared to the change at the national level. The growth of the CPI for services is also included as a control variable so that the regression only captures the effect of Wal-Mart on the durable and non-durable goods portions of the CPI.[13] Following from GI (2005) the model becomes as follows:

$$CPIGrowth_j - CPIGrowth_{US} = C + \beta_1 * (WMPENChange_j - WMPENChange_{US}) + \beta_2 * (URChange_j - URChange_{US}) + \beta_3 * (EPGrowth_j - EPGrowth_{US}) + \beta_4 (POPGrowth_j - POPGrowth_{US}) + \beta_5 (CPISGrowth_j - CPISGrowth_{US}) + \varepsilon$$

CPIGrowth represents the compound annual rate of growth in the CPI for all items from 1990-2004, in both metro area *j* and in the United States as a whole. *WMPENChange* is the change in Wal-Mart penetration in a market from 1990 to 2004 measured in terms of number of Wal-Mart stores per 100,000 residents. *URChange* includes the change in the unemployment rate measured as the 2004 rate minus the 1990 rate for both area *j* and for the entire nation. *EPGrowth* stands for the compound annual rate of growth in electricity prices from 1990 to 2004 in both MSA *j* and the country as a whole. Due to the lack of historical data on electricity prices

[13] The only components of the service sector as defined by the BLS on which Wal-Mart has any impact include photographic film processing and vehicle maintenance, the latter of which is only available at select locations.

at the metropolitan-area-level, like GI (2005), I use the price of electricity for the state in which a metropolitan area is located. *POPGrowth* signifies the compound annual rate of population growth for metro area *j* and for the entire U.S. Finally, *CPISGrowth* is the compound annual rate of growth in the CPI for services in metro area *j* and the entire country. I estimate the above equation using ordinary least squares regression.

Two key differences exist between the study carried out by GI (2005) and my own: the measurement of Wal-Mart penetration and the time period of the study. GI (2005) received historical data on Wal-Mart square footage per capita which they use to measure Wal-Mart's presence in a given market and the nation as a whole. Because I only have access to data available on the Wal-Mart website, I use the number of Wal-Mart stores per capita in a given year as a measure of Wal-Mart penetration, including both discount stores and Supercenters. Due to the unavailability of electricity price data and the unemployment rate data for the years prior to 1990, I restrict my analysis to the period from 1990-2004, whereas GI examines the period between 1985 and 2004.[14] The 1990-2004 period should still be adequate for finding an effect of Wal-Mart on the CPI because of the 25 MSAs included in my sample, 13 did not experience Wal-Mart entry until after 1990.[15] Restricting my analysis to this time period also allows me to include one additional metropolitan area in my sample, Tampa-St.Petersburg, Florida, for which the BLS did not begin constructing a consumer price index until 1987.

Like GI (2005) I estimate separate equations using multiple measures of the CPI as dependent variables in order to look at the effect of Wal-Mart in different sectors of the

[14] Global Insight (2005) also lacks data on the unemployment rate prior to 1990, because data on unemployment by metro area is only available from the BLS by MSA for the years after 1990. However, in their analysis they never explain how they deal with this problem, since they study the period from 1985-2004. While GI (2005) obtains information on electricity prices at the state level for the period prior to 1990, employees of the Energy Information Administration informed me that data from prior to 1990 are not compatible with the more recent data, hence GI must have performed some form of transformation on this data, which they do not discuss in their paper.
[15] A list of CMSA examined can be found in Appendix 7.

economy. The first measure is that described in the equation above, namely, the CPI for all items. Following GI (2005) I also estimate regressions for the CPI for food-at-home, looking at the possible effect of Wal-Mart on grocery price levels. The final two measures of the CPI analyzed by both GI (2005) and myself, include the CPI for all-items-less-food-and-energy and the CPI for commodities. The first of these final two measures allows one to focus on the traditional areas of strength of Wal-Mart discount stores while the second provides another method of removing services from the analysis.

Summary statistics for the cities from can be found in Table 6. The largest increase in Wal-Mart penetration occurred in Anchorage, which had no Wal-Marts in 1990 and 1.16 stores per 100,000 residents in 2004. Of cities which experienced Wal-Mart entry prior to 1990, the largest increase occurred in Milwaukee, where only 0.19 stores per 100,000 people existed in 1990, a figure which by 2004 had risen to 0.88 stores per 100,000 people. Not surprisingly, the smallest increase in Wal-Mart penetration occurred in St. Louis, a city in which Wal-Mart was already well established by 1990, with 1.28 stores per 100,000 people, increasing to 1.37 stores per 100,000 residents by 2004.

Table 6: Summary Statistics for CMSAs in CPI Analysis, 1990-2004

	Change in number of stores per 100,000 people	Electricity Price Growth (Compound annual rate)	Population Growth (Compound annual rate)	Unemployment Rate Change (2004 rate minus 1990 rate)	Growth in CPI for all items (Compound annual rate)	Growth in CPI for services (Compound annual rate)
Average across cities	0.405	1.0%	1.0%	0.444	2.7%	3.4%
Standard deviation across cities	0.253	1.1	0.7	1.053	0.2	0.003
US Average	0.461	0.8%	1.2%	-0.100	2.7%	3.4%

Results

While GI (2005) finds that increased Wal-Mart penetration leads to significant decreases in the CPI for all measures of the CPI which they examine, none of my results indicate a statistically significant impact of increased Wal-Mart penetration on the magnitude of CPI growth. In the first specification, using the CPI for all items as the dependent variable, both the coefficients on the growth of the CPI for services and the coefficient on population growth are statistically significant, while the coefficient on electricity price growth is nearly significant at conventional levels with a p-value of 0.1172. Table 7 summarizes these results. The coefficient interpretation for the population variable indicates that a 1 percentage point increase in the compound annual population growth rate leads to a 0.07 percentage point decrease in the compound annual growth rate of the CPI, whereas a 1 percentage point increase in the compound annual growth rate of the CPI for services leads to a 0.70 percentage point increase in the compound annual growth rate of the CPI for all goods. The coefficient on the Wal-Mart variable, though not significant, indicates that a 1 unit increase in the number of Wal-Marts per 100,000 head of population leads to a $5/100^{th}$ of a percentage point decrease in the compound annual growth rate of the CPI for all items.

Table 7: Results for CPI Growth, All Items, 1990-2004 as dependent variable

Variable	Coefficient
WMPen	-0.00050 (-0.00009)
EPGrowth	0.03700 (0.02200) p-value=0.117
URChange	-0.00030 (0.00200)
PopGrowth	-0.06800* (0.03400)
CPISGrowth	0.69900** (0.07500)
Constant	-0.00060 (0.00030)
Adjusted R^2	0.8438

**-Significant at 5% level
*-Significant at 1% level

Additional specifications of the model, including using the compound annual rate of growth in the CPI for commodities and the CPI for all items less-food-and-energy as dependent variables, lead to a similar pattern of results with regards to significance and the sign of the coefficients. The coefficient on the population variable is consistently significant and displays the opposite sign than predicted in all specifications. The unemployment rate displays a significant coefficient with the proper sign in the specification using the CPI for all items less-food-and-energy as the dependent variable. In the analysis using the CPI for food-at-home as the dependent variable, none of the coefficients are statistically significant, with results displayed in the Table 8.

Table 8: Results for CPI Growth, Food at Home, 1990-2004 as dependent variable

Variable	Coefficient
WMPen	-0.0001 (0.0004)
EPGrowth	-0.0031 (0.0899)
URChange	-0.0001 (0.0009)
PopGrowth	-0.1450 (0.1387)
Constant	-0.0006 (0.0010)
R^2	0.0550

Discussion of CPI Results

While I attempt to recreate GI's study as closely as possible, my results differ greatly from theirs. First of all, they find that population is not significant in any specifications of the model, whereas in mine it is significant in all but one, and with the opposite sign than expected! Perhaps the highest rates of population growth have been occurring in lower-cost cities where prices continue to grow at a slower rate than in slower growing, yet high-cost cities such as Boston and San Francisco. Additionally, GI's justification for inclusion of population growth might be incorrect; maybe demand for goods fails to outpace supply, thus not forcing the predicted price increases in cities with growing populations.

The most important finding above is that when using Wal-Mart penetration as measured by the number of stores per capita rather than the square footage per capita, I fail to find a significant "Wal-Mart Effect" when following methodology similar to GI (2005). This may be due to the fact that square footage per capita provides a more accurate picture of the true growth of Wal-Mart in an area. GI (2005) provides a graph of the change in Wal-Mart square footage per capita from 1985 to 2004 from which one can make a rough estimate of the values for each city. To determine how closely this measure of Wal-Mart penetration relates to my own, I calculate the correlation between change in Wal-Mart square footage per capita and the change in Wal-Mart stores per capita, resulting in a correlation coefficient of 0.25. Part of the reason for this relatively low correlation may be due to the fact that during the period of analysis, Wal-Mart began to increasingly focus its efforts on opening Supercenters and expanding existing stores into Supercenters, which tend to be nearly 100,000 square feet larger than the traditional discount store. For example, in the year 2003 Wal-Mart planned to open 40-55 new discount stores and to open 200-210 new Supercenters, including 140 which were to be converted from the discount format (Ghemawat et al., 2004). Thus the penetration of Wal-Mart in terms of square feet per capita in a given metropolitan area could increase without any corresponding change in the number of stores per capita.

Another problem with my analysis (and GI's) involves the timing of store openings. By only looking at the change in Wal-Mart stores per capita at two snapshots in time, 1990 and 2004, I fail to consider the order of openings. Thus if the majority of openings occurred near the end of the sample period, for example if they opened in 2003, the stores may not yet have had time to impact the CPI either by being rotated into the sample or through causing other retailers to lower their own prices. For example in the Minneapolis-St. Paul metropolitan area, of the 19 Wal-Mart stores open as of December 31, 2004, 7 had opened during either 2003 or 2004, which may have minimized their impact on the CPI during my sample period. Future research could avoid the timing problem by looking at the increase in number of stores on a year-to-year basis. An additional problem of conducting research on Wal-Mart using the CPI stems from the sheer lack of data. The fact that the CPI is computed for only 25 metropolitan areas results in a small sample size which makes it difficult to find truly meaningful results.

The failure of all included variables to show significance for the analysis of food-at-home is also troubling. GI (2005) finds the largest impact of Wal-Mart for this category of the CPI, though they note that with the exception of the unemployment rate, none of their other explanatory variables are significant for this specification and they find by far the smallest r-squared value when looking at food-at-home. Perhaps the most interesting part about their results is that through using separate measures of Wal-Mart square footage per capita excluding Supercenters and Wal-Mart Supercenter square footage per capita, they find that increased square footage of Wal-Mart discount stores, which sell only a limited selection of groceries, has a larger effect on the CPI for food-at-home than an increase in the square footage of the Supercenters per capita. Thus, even though my dataset fails to take into account the expansion of stores into Supercenters, one may have still expected my measure of Wal-Mart concentration to result in a significant coefficient. The fact that none of the control variables display significance for this specification, even though all three of these control variables showed significance in at least one of the other specifications, suggest that food prices are unique and do not respond well to other measures of prices in the economy.

Because the time period of my analysis and my measurement of Wal-Mart penetration differs from that employed by GI (2005) I cannot draw a direct comparison between my results and theirs. One must also take into account the fact that the methods used to construct the CPI bias it against finding a "Wal-Mart Effect." Nevertheless, the fact that one cannot demonstrate such an effect simply by looking at number of stores per capita in a given area suggests that more research is required, especially research not commissioned by Wal-Mart Corporation.

Conclusion

No matter what one thinks of the much discussed "Wal-Martization" of America, a decrease in consumer prices, all else held equal, leads to an increase in real income. Assuming that the average savings found in the products in my grocery sample can be applied to a market basket of grocery items, households could see a nearly 3.2 percent reduction in their overall grocery bill as a result of Wal-Mart entry. When one considers that according to the BLS 2003 Consumer Expenditure Survey the average consumer unit (roughly the equivalent of a household) spends $3,129 on food-at-home,[16] this amounts to roughly $100 in yearly savings for a household regardless of which grocery store it frequents. If a consumer unit chooses to divert their shopping to Wal-Mart stores, the savings will be even larger since they will directly reap the benefit of the lower prices found at Wal-Mart. On a national scale, using data from the Bureau of Economic Analysis's National Income and Product Accounts, which indicate that Americans spend $560 billion annually on food-for-off-premise-consumption-less-alcohol,[17] these savings could translate into a nearly $18 billion reduction in grocery expenditures.

While the finding of a significant impact of Wal-Mart on the CPI would have added further evidence of Wal-Mart's price effect, the failure of my analysis of the CPI to show significance does not disprove Global Insights (2005) findings. However, it does suggest that further research is needed in this area because one can come to different conclusions depending on which measure of Wal-Mart penetration is used.

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[16] **Bureau of Labor Statistics**, U.S. Department of Labor. *Consumer Expenditures in 2003.* Washington, DC: U.S. Government Printing Office, June 2005, <http://www.bls.gov/cex/csxann03.pdf.>

[17] **Bureau of Economic Analysis**. U.S. Department of Commerce. *National Income and Products Account Table 2.4.5*. <http://www.bea.gov/bea/dn/nipaweb/TableView.asp?SelectedTable=67&FirstYear=2003&LastYear=2004&Freq=Year.>

Wal-Mart may indeed be guilty of many evils, including the attempt to understate the hours of its employees, discrimination against women, and the destruction of small town mainstreets. Nevertheless, when examining Wal-Mart's effect on the American economy one must keep in mind the lower prices which it brings to millions of consumers every year. As this paper demonstrates, even those who do not patronize Wal-Mart may stand to benefit from the retailer's increasing dominance in the American grocery market.

Appendix 1: Results without lagged dependent variable

Product	*WSuper* Coefficient (θ)
Bread Adjusted R^2=0.556	-0.037*** (0.006)
Cereal Adjusted R^2=0.664	-0.032*** (0.007)
Coffee Adjusted R^2=0.680	-0.027*** (0.004)
Frying Chicken Adjusted R^2=0.661	-0.044*** (0.006)
Margarine Adjusted R^2=0.664	-0.021*** (0.007)
Milk Adjusted R^2=0.796	-0.032*** (0.004)
Parmesan Adjusted R^2=0.680	-0.001 (0.005)
Peaches Adjusted R^2=0.694	-0.002 (0.004)
Potatoes Adjusted R^2=0.710	-0.016* (0.008)
Tuna Adjusted R^2=0.556	-0.030*** (0.007)

***Significant at 1% level
**Significant at 5% level
*Significant at 10% level

Appendix 2: OLS Results with inclusion of rent, electricity price, and unemployment rate

Product	*WSuper* Coefficient (θ)	Lagged Price Coefficient (β)	Long-run effect θ/(1-β)
Bread Adjusted R^2=.717	-.027*** (.007)	.215*** (.017)	-.034***
Cereal Adjusted R^2=.649	-.025*** (.007)	.314*** (.017)	-.036***
Coffee Adjusted R^2=.806	-.019*** (.004)	.267*** (.060)	-.025***
Frying Chicken Adjusted R^2=.667	-.037*** (.006)	.159*** (.016)	-.044***
Margarine Adjusted R^2=.693	-.019*** (.007)	.289*** (.016)	-.027***
Milk Adjusted R^2=.814	-.026*** (.004)	.327*** (.019)	-.038***
Parmesan Adjusted R^2=.703	.001 (.006)	.288*** (.015)	.001
Peaches Adjusted R^2=.713	-.003 (.004)	.256*** (.025)	-.003
Potatoes Adjusted R^2=.701	-.014 (.009) p-value:0.151	.111*** (.016)	-.016 p-value: 0.151
Tuna Adjusted R^2=.573	-.027*** (.007)	.198*** (.017)	-.034***

***Significant at 1% level

Appendix 3: Control Variable Results

Product	Electricity Price (ϑ)	Rent (ϖ)	Unemployment Rate (ψ)
Bread	.0228 (.017)	.047* (.026)	.0004 (.002)
Cereal	-.100*** (.036)	-.021 (.023)	.004** (.002)
Coffee	.023 (.030)	-.018 (.018)	.001 (.002)
Frying Chicken	-.035 (.038)	.0003 (.0229)	.0005 (.0026)
Margarine	.041 (.044)	-.0003 (.029)	.0009 (.003)
Milk	-.017 (.024)	-.010 (.014)	.002 (.001)
Parmesan	.060** (.020)	.042** (.018)	-.0007 (.001)
Peaches	.025 (.021)	-.014 (.015)	-.002 (.001)

Potatoes	.038 (.057)	.031 (.037)	-.0002 (.003)
Tuna	.017 (.043)	.054** (.026)	-.002 (.002)

*Significant at 10% level
**Significant at 5% level
***Significant at 1% level

Appendix 4: Results for different sized cities

Product	Pop. <100,000 *WSuper* (θ)	Pop. <200,000 *WSuper* (θ)	Without CMSA *WSuper* (θ)	All Cities Included *WSuper* (θ)
Bread	-0.032*** (0.009)	-0.032*** (0.008)	-0.028*** (0.007)	-0.027*** (0.007)
Cereal	-0.029*** (0.009)	-0.027*** (0.008)	-0.026*** (0.007)	-0.024*** (0.007)
Coffee	-0.033*** (0.006)	-0.021*** (0.006)	-0.020*** (0.005)	-0.018*** (0.004)
Frying Chicken	-0.037*** (0.009)	-0.038*** (0.007)	-0.037*** (0.006)	-0.037*** (0.006)
Margarine	-0.023*** (0.006)	-0.026*** (0.008)	-0.019*** (0.008)	-0.018*** (0.007)
Milk	-0.028*** (0.006)	-0.027*** (0.005)	-0.022*** (0.004)	-0.023*** (0.004)
Parmesan	-0.011** (0.005)	-0.007* (0.004)	-0.002 (0.004)	-0.001 (0.005)
Peaches	-0.004 (0.006)	-0.002 (0.004)	-0.005 (0.004)	-0.003 (0.004)
Potatoes	-0.007 (0.013) p-value=0.583	-0.017 (0.011)p-value=0.109	-0.018** (0.010)	-0.014 (0.008) p-value=0.103
Tuna***	-0.028*** (0.010)	-0.030*** (0.008)	-0.028*** (0.007)	-0.028*** (0.007)

***Significant at 1% level, **Significant at 5% level, *Significant at 10% level

Appendix 5: Results using only cities which experienced Wal-Mart Supercenter entry between quarter 1 1995 and quarter 2 2005

Product	*WSuper* Coefficient (θ)	Lag Coefficient (β)	Long-Run Effect θ/(1-β)
Bread Adjusted R^2=0.720	-0.025*** (0.007)	0.202*** (0.0203)	-0.032***
Cereal Adjusted R^2=0.640	-0.023*** (0.006)	0.318*** (0.018)	-0.033***
Coffee Adjusted R^2=0.846	-0.017*** (0.004)	0.331*** (0.018)	-0.025***
Frying Chicken Adjusted R^2=0.650	-0.038*** (0.006)	0.155*** (0.018)	-0.045***
Margarine Adjusted R^2=0.643	-0.020*** (0.007)	0.263*** (0.019)	-0.027***
Milk Adjusted R^2=0.801	-0.023*** (0.004)	0.313*** (0.022)	-0.034***
Parmesan Adjusted R^2=0.668	-0.001 (0.005)	0.293*** (0.019)	-0.001
Peaches Adjusted R^2=0.693	-0.002 (0.004)	0.246*** (0.031)	-0.003
Potatoes Adjusted R^2=0.722	-0.017** (0.009)	0.140*** (0.015)	-0.020**
Tuna*** Adjusted R^2=0.533	-0.029*** (0.007)	0.168*** (0.028)	-0.035***

**Significant at 5% level
***Significant at 1% level

Appendix 6: List of Cities Included in Grocery Price Study and Population Data from 2000 Census

Birmingham AL	242,820
Cullman County AL	77,483
Decatur Alabama	53,929
Florence AL	36,264
Huntsville AL	158,216
Marshall County AL	82,231
Mobile AL	198,915
Montgomery AL	201,568
Fairbanks AK	30,224
Kodiak AK	6,334
Flasgstaff AZ	52,894
Lake Havasu AZ	41,938
Phoenix AZ	1,321,045
Prescott AZ	33,938
Tucson Arizona	486,699
Yuma AZ	77,515
Fayetteville AR	58,047
Forth Smith AR	80,268
Jonesboro AR	55,515
Fresno California	427,652
Los Angeles	3,694,820
Palm Springs CA	42,807
Riverside	255,166
San Diego CA	1,223,400
Colorado Springs CO	360,890
Denver Colorado	554,636
Fort Collins CO	118,652
Glenwood Springs CO	7,736
Grand Junction CO	41,986
Gunnison CO	5,409
Loveland CO	50,608
Pueblo CO	102,121
New Haven CT	123,626
Dover DE	32,135
Wilmington DE	72,664
Bradenton FL	49,504
Ft Walton Beach	19,973
Jacksonville	735,617
Orlando	185,951
Panama City	36,417
Pensacola FL	56,255
Sarasota FL	52,715
Tampa FL	303,447
West Palm Beach FL	82,103
Albany GA	76,939
Americus GA	17,013
Atlanta GA	416,474
Augusta GA	199,775
Bainridge GA	11,722
Douglas GA	10,639
Tifton GA	15,060
Valdosta GA	43,724
Boise ID	185,787
Twin Falls ID	34,469
Champaign-Urbana IL	103,913
Danville IL	33,904
Decatur IL	81,860
Peoria IL	112,936
Quincy IL	40,366
Springfield IL	111,454
Evansville IN	121,582
Fort Wayne-Allen County	205,727
Lafayette IN	56,397
South Bend IN	107,789
Ames IA	50,731
Cedar Rapids IA	120,758
Quad-Cities	213,086
Des Moines IA	198,682
Mason City IA	29,172
Waterloo IA	104,892
Dodge City KS	25,176
Garden City KS	28,451
Hays KS	20,013
Hutchinson KS	40,787
Lawrence KS	80,098
Manhattan KS	44,831
Salina KS	45,679
Bowling Green KY	49,296
Hopkinsville KY	30,089
Lexington KY	260,512
Louisville KY	256,231
Murray KY	14,950
Paducah KY	26,307
Somerset KY	11,352
Baton Rouge LA	227,818
Lafayette LA	110,257
Lake Charles LA	71,757
Monroe LA	53,107
Shreveport LA	200,145
Boston MA	589,141
Fitchburg-Leominster MA	39,102
Baltimore MD	651,154
Holland MI	35,048
Minneapolis MN	382,618
Rochester MN	85,806

St. Cloud MN	59,107
Hattiesburg MS	44,779
Jackson MS	184,256
Columbia MO	84,531
Joplin MO	45,504
Nevada MO	8,607
St. Joseph MO	73,990
St. Louis MO	348,189
Springfield MO	151,580
Billings MT	89,847
Bozeman MT	27,509
Great Falls MT	56,690
Helena MT	25,780
Missoula MT	95,802
Hastings NE	24,064
Lincoln NE	225,581
Omaha NE	390,007
Las Vegas NV	478,434
Reno-Sparks NV	180,480
Albuquerque NM	448,607
Farmington NM	37,844
Las Cruces NM	74,267
Los Alamos NM	11,909
Santa Fe NM	62,203
Buffalo NY	292,648
Glens Falls NY	14,354
Syracuse NY	147,306
Watertwon NY	26,705
Asheville NC	68,889
Charlotte NC	540,828
Dare County NC	29,967
Greenville NC	60,476
Marion NC	42,151
Raleigh NC	276,093
Wilmington NC	75,838
Winston-Salem NC	185,776
Bismarck ND	55,532
Fargo ND	90,599
Minot ND	36,567
Akron OH	217,074
Cincinnati OH	331,285
Cleveland OH	478,403
Dayton OH	166,179
Findlay OH	38,967
Lima OH	40,081
Mansfield OH	49,346
Toledo OH	313,619
Youngstown OH	82,026
Ardmore OK	23,711
Bartlesville OK	34,748
Muskogee OK	38,310
Oklahoma City OK	506,132
Pryor OK	8,659
Stillwater OK	39,065
Klamath Falls OR	19,462
Portland OR	529,121
Philadelphia PA	1,517,550
York County PA	40862
Camden SC	6,682
Charleston SC	96,650
Columbia SC	116,278
Hilton Head SC	33,862
Myrtle Beach SC	22,759
Sumter SC	39,643
Sioux Falls SD	123,975
Vermillion SD	9,765
Chatanooga TN	155,554
Clarksville TN	103,455
Cleveland TN	37,192
Dyersburg TN	17,452
Jackson TN	59,643
Johnson City TN	55,469
Kingsport TN	44,905
Knoxville TN	173,890
Memphis TN	650,100
Morristown TN	24,965
Nashville TN	569,891
Abilene TX	115,930
Amarillo TX	173,627
Beaumont TX	113,866
Conroe TX	36,811
Dallas TX	1,188,580
Houston TX	1,953,631
Lubbock TX	199,564
McAllen TX	106,414
Midland TX	94,996
Odessa TX	90,943
Paris TX	25,898
San Angelo TX	88,439
San Antonio TX	1,144,646
San Marcos TX	34,733
Texarkana TX	34,782
Tyler TX	83,650
Victoria TX	60,603
Waco TX	113,726
Weatherford TX	19,000
Cedar City UT	20,527
Logan UT	42,670
St. George UT	49,663
Burlington VT	38,889

Richmond VA	197,790	Eau Claire WI	61,704
Roanoke VA	94,911	Green Bay WI	102,313
Bellingham WA	67,171	Marshfield WI	18,800
Richaldn WA	38,708	Sheboygan WI	50,792
Spokane WA	195,629	Wausau WI	38,426
Tacoma WA	193,556	Cheyenne WY	53,011
Yakima WA	71,845	Gilette WY	19,646
Charleston WV	53,421	Laramie WY	27,204
Appleton WI	70,087		

Appendix 7: List of Consolidated Metropolitan Statistical Areas Included in CPI Study

Anchorage, AK
Atlanta-Sandy Springs-Marietta, GA
Boston-Cambridge-Quincy, MA-NH
Chicago-Joliet-Naperville, IL-IN-WI
Cincinnati-Middletown, OH-KY-IN
Cleveland-Elyria-Mentor, OH
Dallas-Fort Worth-Arlington, TX
Denver-Aurora, CO
Detroit-Livonia-Dearborn, MI
Honolulu, HI
Houston-Sugar Land-Baytown, TX
Kansas City, MO-KS
Los Angeles-Long Beach-Santa Ana, CA
Miami-Fort Lauderdale-Miami Beach, FL
Milwaukee-Waukesha-West Allis, WI
Minneapolis-St. Paul-Bloomington, MN-WI
New York-Northern New Jersey-Long Island, NY-NJ-PA
Philadelphia-Camden-Wilmington, PA-DE-NJ-MD
Pittsburgh, PA
Portland-Vancouver-Beaverton, OR-WA
St. Louis, MO-IL
San Diego-Carlsbad-San Marcos, CA
San Francisco-Oakland-Fremont, CA
Seattle-Bellevue-Everett, WA
Tampa-St. Petersburg-Clearwater, FL

Data Appendix

Variable	Source
P_{abt} , $rent_{bt}$	American Chamber of Commerce Research Association *Cost of Living Index.* Louisville, KY: ACCRA, 1995 Quarter 1-2005 Quarter 2. 1995 Quarter 1-2004 Quarter 1 and 2005 Quarter 1-2005 Quarter 2 available at James J. Hill Reference Library, St. Paul, MN. 2004 Quarter 2-2004 Quarter 4 available at St. Paul Central Library, St. Paul, MN. I use the price report pages of each index to find average prices which are labeled as follows: bread, cereal, coffee, fry chick, margarine, hgal milk, parmesan, peaches, potatoes, tuna, and rent. I take the natural log of each price before putting it into the equation.
$WSuper_{bt}$	Opening dates for new Supercenters come from: Wal-Mart Corporation. "Wal-Mart Alignment." Available at: http://www.walmartfacts.com/community/article.aspx?id=1481. Opening dates for converted Supercenters 2001-2005 come from: Wal-Mart Corporation News Room. "Store Openings." Available at: http://walmartstores.com/GlobalWMStoresWeb/navigate.do?catg=130&yearID=131 Dates for all other Supercenter openings imputed from: *Chain Store Guide Directory of Discount and General Merchandise Stores*. Tampa, FL: Business Guides, Inc., 1995-2001. Available at James J. Hill Reference Library, St. Paul, MN.
$unemployment_{bt,}$	Bureau of Labor Statistics. "Local Area Unemployment Statistics for Counties 1990-2004." Available at: http://www.bls.gov/lau/home.htm#data For 2005, preliminary data available from: Bureau of Labor Statistics Local Area Unemployment Statistics, "Create Customized Tables", available at: http://www.bls.gov/lau/home.htm#data I use the unemployment rate listed as a percentage in these tables.
$energy_{bt,}$, $EPChange_{j}$, $EPChange_{US}$	Energy Information Administration. Data for years 1990-2004 by state come from: Electric Power Annual 2004 Data Tables, EIA Table 861. Available at: http://www.eia.doe.gov/cneaf/electricity/epa/epa_sprdshts.html Data for the year 2005 come from: EIA Table 5.6.A., Average Retail Price of Electricity to Ultimate Consumers by End-Use-Sector, available at: http://www.eia.doe.gov/cneaf/electricity/epa/epat7p4.html

	For both of these tables, I use the commercial price (cents per kilowatthour). For the *energy*$_{bt}$ variable, I take the natural log of the price before putting it into my equation. For the *EPChange*$_j$ and *EPChange*$_{US}$ variables, I use the overall change from 1990-2004 for each metropolitan area and the United States as a whole to calculate the compound annual growth rate for each area and for the entire country.
URChange$_j$, *URChange*$_{US}$	MSA Unemployment Rates: Bureau of Labor Statistics Local Area Unemployment Statistics, "Create Customized Tables," available at: http://www.bls.gov/lau/home.htm#data. I use the annual average unemployment rate available in the non-seasonally adjusted tables. National Unemployment Rates: Bureau of Labor Statistics National Unemployment Rate, available at: http://www.bls.gov/cps/home.htm I subtract the 1990 value from the 2004 value for each CMSA and the nation as a whole to construct this variable.
WMPenChange$_j$, *WMPenChange*$_{US}$	Wal-Mart Store Opening Dates Come from: Wal-Mart Corporation. "Wal-Mart Alignment." Available at: http://www.walmartfacts.com/community/article.aspx?id=1481. Population Data for Metropolitan Statistical Areas 1990-1999 come from: U.S. Census Bureau. Population Estimates for Metropolitan Areas and Components. Annual Time Series (MA-99-3b). Available at: http://www.census.gov/popest/archives/1990s/MA-99-03b.txt Population Data for Consolidated Metropolitan Statistical Areas 2000-2004 come from: Census Bureau. Annual Estimates of the Population of Metropolitan and Micropolitan Statistical Areas: April 1, 2000 to July 1, 2004 (CBSA-EST2004-01). Available at: http://www.census.gov/population/www/estimates/Estimates%20pages_final.html Using the definitions of CMSAs available from the Census Bureau, I determine the number of zip codes in each metropolitan area by county and search the "Wal-Mart Alignment" database by zip code to determine the number of Wal-Mart's in each CMSA for a given year. Data on zip codes by county come from Melissa Data. Available at: http://www.melissadata.com/lookups/countyzip.asp

	I calculate the number of Wal-Mart stores per capita by dividing the number of Wal-Mart stores in a metropolitan area in a given year by the population of the area in that year. I then convert this to the number of stores per 100,000 inhabitants. I subtract the 1990 figure from the 2004 figure to find the change in Wal-Mart penetration.
$POPChange_j$ $POPChange_{US}$	See population sources listed above for $WMPenChange_j$ and $WMPenChange_{US}$. I calculate the overall population growth from 1990-2004 for each CMSA and for the entire nation and then convert the figure into a compound annual rate of growth.
$CPIGrowth_{US}$ $CPIGrowth_j$	All data on the Consumer Price Index, including that for all items, commodities, all items-less-food-and-energy, food-at-home, and services, comes from: Bureau of Labor Statistics, Consumer Price Index, Create Customized Tables, All Urban Consumers, available at : http://www.bls.gov/cpi/home.htm I use these tables to calculate the overall rate of growth in the CPI for each metropolitan area from 1990-2004 and for the country as a whole. I then convert this figure to a compound annual rate of growth.

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