Selling a Cheaper Mousetrap: Entry and Competition in the Retail Sector

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Abstract

In models of imperfect competition, entry of a lower-cost competitor tends to reduce output prices of all market participants; this effect is likely to be larger in small (less-competitive) markets and for product categories with high cross-price elasticities of demand. In this paper, I quantify the price effect of a low-cost entrant in the retail sector using a case-study approach. I consider the effect of Wal-Mart entry on average city-level prices of various consumer goods by exploiting variation in the timing of store entry. The analysis combines two unique data sets, one containing opening dates of all US Wal-Mart stores and the other containing average quarterly retail prices of several narrowly-defined commonly-purchased goods over the period 1982-2002. I focus on 13 specific items likely to be sold at Wal-Mart stores and analyze their price dynamics in 160 US cities before and after Wal-Mart entry. An instrumental-variables specification corrects for measurement error in Wal-Mart entry dates. The results vary by product type and by city size in interesting ways. I find an economically large and statistically significant decline in the prices of drugstore items such as toothpaste, shampoo, and facial tissue, but no effect on prices of convenience-store items (alcoholic beverages, Coke, and cigarettes) or clothing items. These results are consistent with the intuition that Wal-Mart provides a closer substitute to most drugstores than to convenience stores and clothing stores. The price impact on drugstore items is much stronger in small cities than in large ones, consistent with theory.

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"Wal-Mart, unlike most of its US peers, is a price-setter rather than a price-taker."
– *Financial Times*, February 19, 2003

"Even if you don't shop at Wal-Mart, the retail powerhouse increasingly is dictating your product choices – and what you pay – as its relentless price cutting helps keep inflation low."
– *USA Today*, January 29, 2003

"Wal-Mart's mania for selling goods at rock-bottom prices has trained consumers to expect deep discounts everywhere they shop, forcing competing retailers to follow suit or fall behind."
– *Washington Post*, November 6, 2003

1 Introduction

In models of imperfect competition, entry of a lower-cost competitor tends to reduce output prices. The effect is larger the smaller the initial number of firms and the larger is the cost advantage of the entrant; it is smaller when competing firms face high cross-price elasticities of demand. In this paper, I quantify the price effect of a low-cost entrant in the context of retail markets, using a case study of Wal-Mart entry, and show that Wal-Mart's price impact varies by city size and by product category in intuitive ways.

Popular media accounts claim that Wal-Mart's prices are lower than its competitors', and that the mere existence of Wal-Mart in a market pushes competitors' prices down. Taken to its logical extreme, this argument (made by *USA Today* reporter Jim Hopkins) implies that the low inflation in retail prices in the 1990s may be in part attributable to Wal-Mart's moderating effect. Wal-Mart's low labor costs and the retail chain's logistics and distribution innovations make it the prototypical low-cost entrant. Broadly, there are two mechanisms by which Wal-Mart's expansion could have affected retail prices and consumer inflation rates: an aggregate mechanism and a market-specific mechanism. The aggregate mechanism works through Wal-Mart's interactions with both suppliers (manufacturers and importers) and other large retail chains. This mechanism can lower prices in communities not served by Wal-Mart if it leads to lower costs for other retailers.[1] The market-specific mechanism works through competition (and possibly learning) at the local level.

The focus of this paper is on the second mechanism. Wal-Mart's entry into a given market (city or town) can lower prices by increasing the competitive pressure incumbents (and future entrants) face. If retailers provide homogeneous services (not only selling homogeneous products, but having homogeneous retailer characteristics), Wal-Mart's lower costs (and prices) could lead competitors to lower their prices. This would be the expected outcome in any standard competitive model, such as Cournot competition. It is also to be expected in a model with equilibrium price dispersion, that recognizes retailers may be heterogeneous (for example, with respect to location) even if they sell identical items. Models of price dispersion in the retail sector go back as far as Hotelling (1929) and Chamberlin (1933), where monopoly power

[1] The argument for this mechanism is as follows. By demanding lower prices from suppliers, Wal-Mart forces manufacturers to cut costs, possibly by relocating overseas. Competing retail chains (notably Target, but also many smaller chains) also increase efficiency by emulating Wal-Mart's innovations in logistics and distribution (McKinsey Global Institute 2001). The result is lower prices in chain stores across the country, some in locations that have no Wal-Mart stores.

over “nearby” consumers is attributed to transportation costs they would have to incur to shop elsewhere. In an alternative model offered by Varian (1980), some consumers do not know which store has the cheapest price because “sales” (price mark-downs) occur randomly and are equally likely in all stores. In this model, the cost of becoming informed about the price distribution keeps stores’ monopoly power over some customers. Reinganum (1979) generates a distribution of prices using a fixed cost of sampling additional stores. Because, in these models, a non-degenerate distribution of prices can persist in equilibrium, entry of a competitor with lower costs need not drive other stores to match its lower prices. If the new store is located in a sufficiently inconvenient part of town, it may charge lower prices without leading to any reduction in competitors’ (incumbents’) prices. But most of the theories cited above, and others like them, will predict that entry of a lower-cost competitor is likely to lead to price reductions by incumbents.

How large these effects are will depend on the size of the market. The smaller the market the larger is the deviation from a competitive equilibrium, so any additional entrant is likely to have a price effect; this effect will be amplified if the entrant also has a cost advantage. As the number of competing firms increases, markets move towards the competitive equilibrium so entry will have a smaller impact; also, the market power of any single firm (including a low-cost entrant) will be smaller. These priors are reinforced by the seminal Bresnahan and Reiss (1991) paper. Bresnahan and Reiss show that entry thresholds decline sharply with the number of competitors, but stabilize quickly, so that markets with more than 5 participants (e.g., druggists, dentists, or tire dealers) behave almost competitively. In one sector – tire dealerships – they find that prices in markets served by duopolists have on average 8% lower tire prices than markets served by monopolists, but subsequent additions of competitors are correlated with much smaller price declines. In the one urban market in their study, the southern San Francisco Bay Area with over 200 tire dealers, tire prices were only 10% lower than in a market served by a quadropoly or quintopoly. These results imply that entry of a low-cost competitor such as Wal-Mart will likely lead to large price reductions in smaller markets, but have a lesser price effect in larger markets.

I test these predictions on average prices of 13 specific goods such as toothpaste, cigarettes, and jeans, by exploiting exogenous variation in the timing of store entry in different markets. I combine two unique data sources on Wal-Mart store locations and retail prices in 160 US cities over a 20-year period, from 1982-2002. The Wal-Mart data include store locations and opening dates of all U.S. Wal-Mart stores. Price data from the American Chamber of Commerce Research Association (ACCRA) consist of average retail prices of 13 everyday products across multiple establishments in each city.

The methodology follows Basker (2003) closely, with two innovations. In Basker (2003), I consider the effect of Wal-Mart entry on *county-level* employment in the retail and wholesale sectors, using 1749 counties (slightly more than half of all US counties). Because price data are available at the city (or town) level, rather than the county level, I disaggregate the Wal-Mart data to the city level. Second, as in Basker (2003), I apply an instrumental-variables (IV) procedure to correct for measurement error in the timing of Wal-Mart entry, using store numbers to infer their planning dates. But with only 160 cities in my sample, there is a risk that the first stage will generate a spurious relationship between store planning and store opening dates, so I use a split-sample IV (SSIV) procedure that estimates this relationship using all cities in the Wal-Mart data set.

I find that the price effect of Wal-Mart entry differs by product category and by city size. For drugstore products – toothpaste, shampoo, aspirin, tissues and detergent – Wal-Mart entry reduces average retail prices by an economically large and statistically significant 3-4%. When the effect in small and large cities is estimated separately, I find a much larger effect – 5-6% – in small cities, consistent with theoretical predictions and the Bresnahan and Reiss (1991) findings. Prices of convenience-store items – alcoholic beverages, Coke, and cigarettes – are unaffected by Wal-Mart entry, as are prices of clothing items (jeans, man's shirt, boy's underwear). The likely explanation for this combination of findings is that drugstore items are substantially more homogeneous (with respect to retailer attributes as well as product attributes) than clothing, so Wal-Mart entry is unlikely to have a significant impact on clothing prices. Convenience-store items are heavily weighted towards alcoholic beverages, whose markets are generally less competitive than other retail markets due to state and local regulation; many Wal-Mart stores do not sell these items at all. In addition, alcohol, cigarettes and Coke may be more likely to be impulse purchases, and therefore likely to be associated with higher (subjective) search costs.

The remainder of this paper is organized as follows. Section 2 provides background information on Wal-Mart. Section 3 describes the data. The empirical methodology is outlined in Section 4, and results are shown in Section 5. Section 6 concludes with a discussion of the magnitude of the price effect and its implications.

2 Wal-Mart Background

The first Wal-Mart store opened in Rogers, Arkansas in 1962. By the time the company went public in 1969 it had 18 stores throughout Arkansas, Missouri, and Oklahoma. The company slowly expanded its geographical reach, building new stores and accompanying distribution centers further and further away from its original location, and continued, at the same time, to build new stores in areas already serviced. Figure 1 shows maps of the 48 contiguous states with approximate locations of Wal-Mart stores over time to illustrate this point. By 1998 Wal-Mart had approximately 2400 stores in all 50 states and about 800,000 employees in the United States. The company grows – as measured by the number of employees and the number of stores it operates – by the week. The largest retailer in both the U.S. and the world, Wal-Mart currently operates in 12 countries.

Wal-Mart is extremely efficient even compared with other "big-box" retailers. Lehman Brothers analysts have noted Wal-Mart's "leading logistics and information competencies" (Feiner 2001). The *Financial Times* has called Wal-Mart "an operation whose efficiency is the envy of the world's storekeepers" (Edgecliffe-Johnson 1999). Wal-Mart's competitive edge is driven by a combination of conventional cost-cutting and sensitivity to demand conditions and by superior logistics and distribution systems. The chain's most-cited advantages over small retailers are economies of scale and access to capital markets, whereas against other large retail chains the most commonly cited factor is superior logistics, distribution, and inventory control.[2]

3 Data

To assess Wal-Mart's effect on retail prices, I combine data on the locations and opening dates of Wal-Mart stores with retail price data.

[2] Details on Wal-Mart's operations can be found in Harvard Business School's three case studies about Wal-Mart (Ghemawat 1989, Foley and Mahmood 1996, and Ghemawat and Friedman 1999).

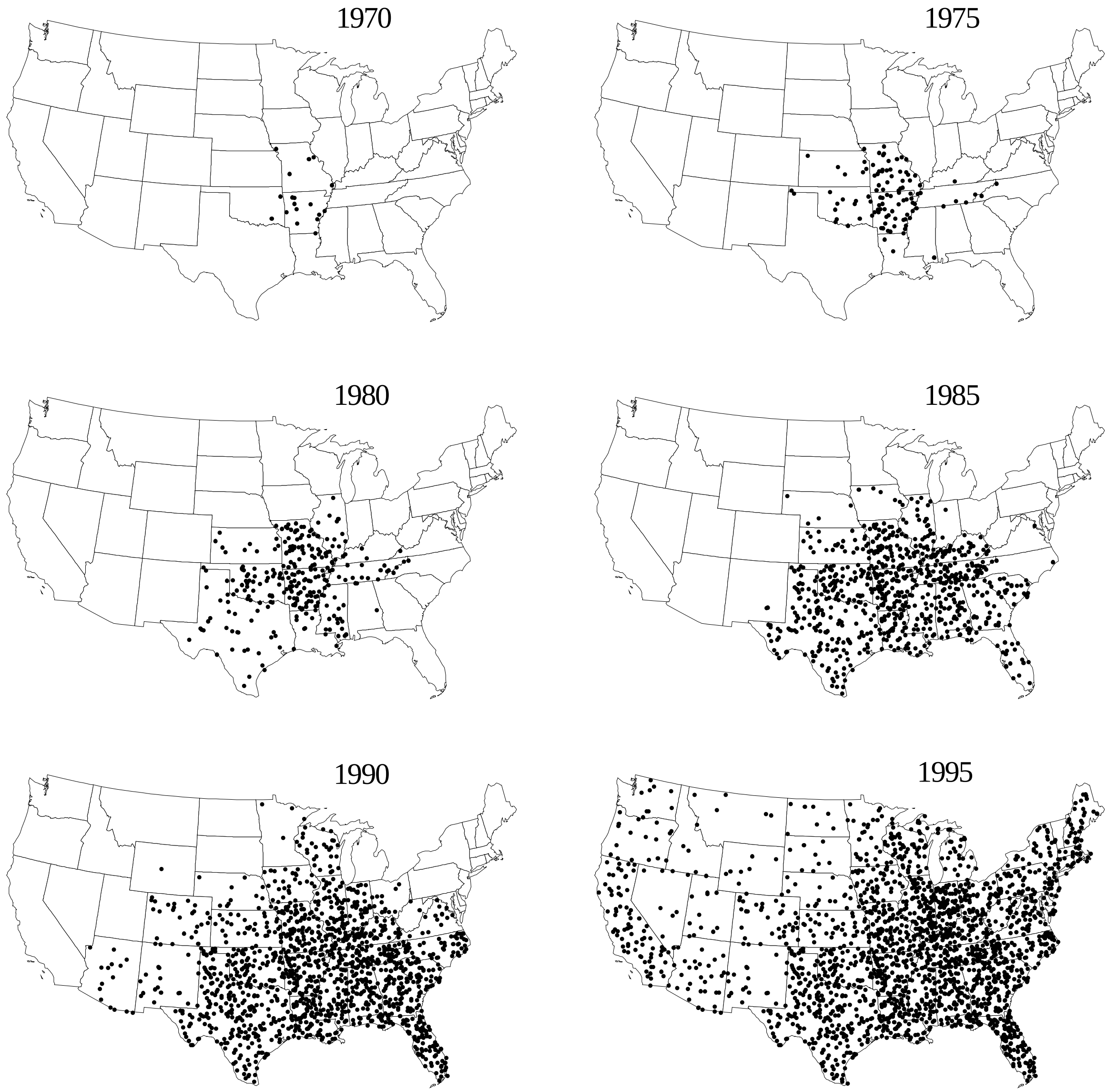

Figure 1: Approximate Locations of Wal-Mart Stores, Various Years

3.1 Wal-Mart Stores

The Wal-Mart store data are described in detail in Basker (2003). I briefly review the data sources.[3]

Data on the locations and opening years of 2,382 Wal-Mart stores in the United States were collected from Wal-Mart annual reports, Wal-Mart editions of Rand McNally Road Atlases and annual editions of the *Directory of Discount Department Stores*. The available data include store location (by city) and store number. Approximate opening dates of individual stores can be inferred by comparing lists of existing stores from consecutive years.[4] The variable $\mathbf{WMopen_{jt}}$ gives the number of new stores to open in city j in year t based on these directories and store lists. Table 1 summarizes these sources. For the years 1990-1993, in which no satisfactory store list exists (the *Directory of Discount Department Stores* was not properly updated during those years), I assign opening dates to stores using a probabilistic algorithm that uses information on the number of stores opening in each state each year.

I also construct an alternate (counterfactual) set of Wal-Mart entry identifiers using a combination of company-assigned store numbers (available from the Rand McNally atlases) and the net change in the number of stores each year (from company annual reports). Wal-Mart assigns store numbers roughly in sequential order, with store #1 opening first, followed by store #2, and so on; store numbers appear to be assigned early in the store planning process. Following this practice, I assign entry dates to stores sequentially, based on their store numbers. This assignment method provides a very good approximation to the likely order in which the stores were planned. Aggregating these store-level entry dates to the city-year level, I construct the variable $\mathbf{WMplan_{jt}}$, which takes on the value of the number of stores that would have opened in city j in year t had the stores opened in the order in which they were planned.

3.2 Retail Prices

Retail prices are obtained from the American Chamber of Commerce Research Association. I use prices of 13 products in 160 cities over 21 years, from 1982-2002.

The American Chamber of Commerce Research Association (ACCRA), through local Cambers of Commerce, surveys 5-10 retail establishments in the first week of each quarter in participating cities. Participating cities vary from quarter to quarter, with some cities moving in and out of the sample frequently, while others are included more regularly; 250-300 cities are surveyed each quarter during the sample period. Of these, I selected 160 cities that were surveyed at least once per year in most years. Most of these cities (approximately 85%) had one Wal-Mart store open during the sample period. Each year between 132-155 cities are in the sample. Price data for approximately 55% of the cities are available annually; another 29% are available for at least 19 of the 21 years. The cities are described in more detail in the next section.

The prices collected by ACCRA cover approximately 50 goods and services. From the list of items, I selected 13 goods that were homogeneous or nearly so, and likely to be sold at most Wal-Mart stores (I exclude grocery items because most Wal-Mart stores over the sample period do not include a grocery section). The selected products are listed in Table 2. (I begin my sample period in 1982 because most of these products were introduced into the ACCRA price list in that year.) In some of the analysis below I group products into categories as follows.

[3] Requests for store-opening data from Wal-Mart corporation were denied. I have also tried to obtain opening dates from local newspapers, but succeeded in only a handful of cases.

[4] Vance and Scott (1994) list store entries to 1969, the year the company become publicly traded.

Aspirin, detergent, Kleenex, shampoo and toothpaste are classified as "drugstore products"; beer, cigarettes, Coke, liquor and wine are classified as "convenience-store products"; and shirt, pants and underwear are classified as "clothing." The distinction is meant to capture differences in product type as well as market structure: convenience-store items are sold in many drugstores as well as in convenience stores, but these items are sold in a much broader class of retail outlets than are the "drugstore items," and (unlike toothpaste and aspirin) are often associated with "impulse" purchases.

Because product definitions change over the sample period, and because not every city is in the data set each quarter, I first mean-adjust the prices by removing the average price of each item in each quarter, to get

$$p_{kjq} = \ln\left(P_{kjq}\right) - \ln\left(\overline{P}_{kq}\right) \tag{1}$$

where P_{kjq} is the price of item k in city j at time q, and $\overline{P}_{kq}$ is the average price of item k at time q (across all cities in the sample that quarter). Here q indexes quarters, e.g., $q = 1982:1, 1982:2, \ldots$.

To combine the quarterly price data with the annual Wal-Mart data, these quarterly observations need to be aggregated to an annual level by averaging mean-adjusted prices across four consecutive quarters. Aggregating using calendar-years would lead to bias in the estimated effect of Wal-Mart on entry, because the price observation for the year of entry would be an average of the pre-entry price and the post-entry price. To attenuate this bias, I define a year as the period July-June (i.e., quarter 3 in year t through quarter 2 in year $t+1$); this definition provides the closest match for Wal-Mart data.[5,6] The annual price observation for year t is defined as

$$p_{kjt} = \sum_{q=t\ :\ 3}^{t+1\ :\ 2} p_{kjq}. \tag{2}$$

3.3 Sample Cities

The sample cities, determined by price-data availability, are shown in Figure 2, and some summary statistics are shown in Table 3. The average city in the sample had approximately 200,000 residents in 2000 (the median city had approximately half as many residents). The large apparent decrease in the number of establishments between 1987 and 1997 is due to a change in Census industrial coding from SIC to NAICS.[7,8,9]

[5] Wal-Mart's store openings are not uniformly distributed throughout the year (stores hardly ever open in the November-December holiday season, and there tends to be a flurry of openings in early January), but in 2001-03, approximately 52% of store openings (including renovations) occured in the first half of the year. Earlier monthly data are not available.

[6] Aggregating by calendar-years provides qualitatively similar results, with slightly smaller coefficient estimates. Appendix A provides a detailed explanation for this choice of temporal aggregation.

[7] The number of retail establishments at the city level is available only for the Economic Census years 1982, 1987 and 1997. No breakdown of retail establishments by sub-category (e.g., drugstore, general-merchandise store, etc.) is available at the city level.

[8] Wal-Mart entry does not lead to sharp decreases in the number of retail establishments; on average at the county level, 5 retail establishments close within 5 years of Wal-Mart entry (Basker 2003).

More information about the switch from SIC to NAICS is available at `http://www.census.gov/epcd/www/naics.html`.

[9] The right-skew implied by deviation between median and mean is comparable to the one obtained from a census of US cities.

Table 1: Directory Sources for Wal-Mart Opening Dates

Years	Source
1962-1969	Vance and Scott [1994]
1970-1978	Wal-Mart Annual Reports
1979-1982	*Directory of Discount Department Stores*
1983-1986	*Directory of Discount Stores*
1987-1989	*Directory of Discount Department Stores*
1990-1993	See text
1994-1997	*Rand McNally Road Atlas*

Table 2: Product Definitions over Time

Product Name	Description
Aspirin	100-tablet bottle, Bayer brand (to 1994:3)
	0.5oz Polysporin ointment (from 1994:4)
Detergent	49oz Tide/Bold/Cheer laundry detergent (to 1991:3)
	42oz Tide/Bold/Cheer laundry detergent (1991:4-1996:3)
	60oz Cascade dishwashing powder (from 1996:4)
Kleenex	200-count Kleenex tissues (to 1983:4)
	175-count Kleenex tissues (from 1984:1)
Shampoo	11oz bottle, Johnson's Baby Shampoo (to 1991:2)
	15oz Alberto VO5 (from 1991:3)
Toothpaste	6-7oz Crest or Colgate
Beer *	6-pack, 12oz containers, excluding deposit, of:
	Schlitz or Budweiser (to 1989:3)
	Miller Lite or Budweiser (1989:4-1999:4)
	Heineken (from 2000:1)
Cigarettes	Carton, Winston, king-size (85mm.)
Coke	2-liter Coca Cola, excluding deposit
Liquor *	Seagram's 7-Crown 750ml (to 1988:3)
	J&B scotch, 750ml (form 1988:4)
Wine *	1.5 liter Paul Masson/Livingston/Gallo Chablis or Chenin Blanc
Shirt	Man's dress shirt, Arrow
Pants	Levi's 501/505 jeans, rinsed/washed/bleached size 28/30-34-36 (to 1999:4)
	Men's Docker's "no wrinkle" khakis size 28/30-34/26 (from 2000:1)
Underwear	3 boys' cotton briefs, Fruit of the Loom (to 1983:4)
	3 boys' cotton briefs, size 10-14, cheapest brand (from 1984:1)

* Where the price of alcohol is regulated by state law, these prices were set to missing.

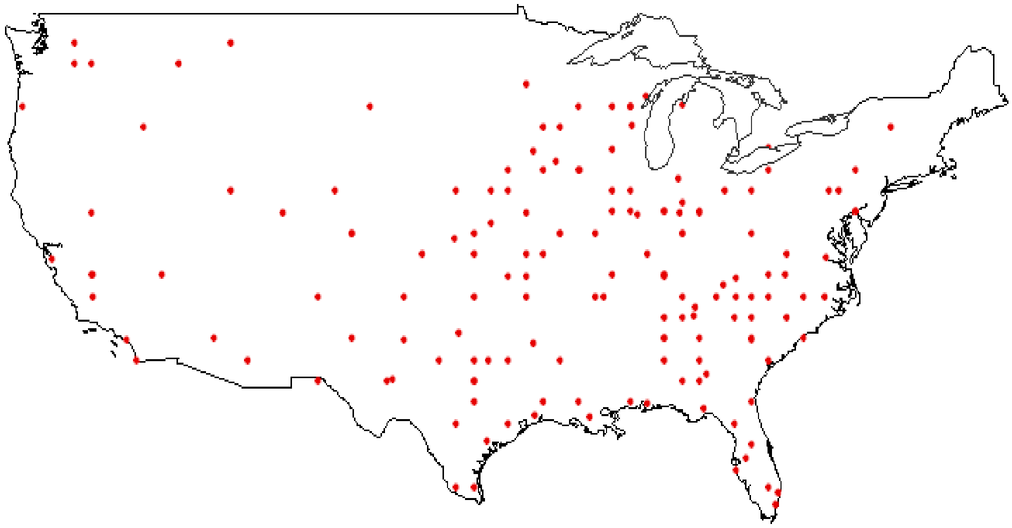

Figure 2: Locations of Sample Cities

Table 3: Sample Cities Summary Statistics

	Mean	Percentiles 25th	50th	75th
Population (1980)	172,648	43,055	75,959	184,430
Population (1990)	190,028	47,903	89,553	196,165
Population (2000)	211,153	53,264	94,954	226,700
Retail Establishments, SIC (1982)*	1,826	579	930	1,796
Retail Establishments, SIC (1987)†	2,192	684	1,151	2,227
Retail Establishments, NAICS (1997)†	1,063	372	557	1,158
Per-Capita Income (1979)‡	17,348	15,627	17,150	18,704
Per-Capita Income (1989)‡	18,748	16,807	18,165	20,697

Source: Author's calculations from *County and City Data Book*, Various Years

* Mean calculated using only 142 of 160 cities; percentiles include all cities

† Mean calculated using only 144 of 160 cities; percentiles include all cities

‡ Real 2002 dollars

4 Empirical Methodology

4.1 Ordinary Least Squares (OLS) Regressions

For each product k I estimate a once-and-for-all effect of Wal-Mart entry on prices:

$$\Delta p_{kjt} = \beta \Delta p_{kj,t-1} + \sum_t \delta_{kt}\, \text{year}_t + \theta_k \text{WalMart}_{jt} + \text{u}_{kjt} \tag{3}$$

where $\mathbf{\Delta p_{kjt}}$ is the change in the price of product k in city j between years $(t-1)$ and t; $\mathbf{year_t}$ is a year fixed effect; $\mathbf{WalMart_{jt}}$ is the an indicator which equals one the year Wal-Mart opens in city j; and $\mathbf{u_{jt}}$ is an error term. The term $\mathbf{\Delta p}_{kj,t-1}$ is included to allow for mean-reversion of prices.[10] Standard errors are clustered at the city level to allow for arbitrary autocorrelation in the error term.

Equation 3 is a transformation of the level equation

$$p_{kjt} = \alpha_k + \beta p_{kj,t-1} + \sum_t \delta_{kt}\, \text{year}_t + \theta_k \left(\max_{s \le t} \text{WalMart}_{js} \right) + \varepsilon_{kjt}$$

where the term

$$\max_{s \le t} \text{WalMart}_{js}$$

equals one if a Wal-Mart store has opened in city j in year t or earlier, and zero otherwise. As is evident from the levels transformation, the coefficient θ_k captures the average difference between the pre-entry and post-entry prices of product k and represents a *permanent* effect of Wal-Mart entry on prices. I also show some dynamic regressions, allowing price adjustment to take place over several periods:

$$\Delta p_{kjt} = \alpha_k + \beta \Delta p_{kj,t-1} + \sum_t \delta_{kt}\, \text{year}_t + \theta_k (L)\, \text{WalMart}_{jt} + \text{u}_{kjt} \tag{4}$$

where $\theta_k (L)$ is a lag polynomial with one lead and three lags:

$$\theta^k (L) = \theta^k_{-1} F^1 + \theta^k_0 + \theta^k_1 L + \theta^k_2 L^2 + \theta^k_3 L^3$$

with L the lag operator and F the lead operator. For example,

$$F^1 (\text{WalMart})_{jt} = \text{WalMart}_{j,t+1}$$

is an indicator function which equals 1 one year *before* Wal-Mart entry, while

$$L^1 (\text{WalMart})_{jt} = \text{WalMart}_{j,t-1}$$

equals 1 one year *after* Wal-Mart entry. As explained in Appendix A, the coefficient θ_{-1} can differ from zero even if there are no pre-entry price changes on the part of incumbents, due to the nature of the temporal aggregation of quarterly price observations to annual averages.

In some specifications, I stack multiple products into a single regression to estimate the

[10] Using ACCRA price data for 48 cities over the period 1975-1994 (where available) or 1982-1994 (for most products), Parsley and Wei (1996) find strong evidence for price convergence. Point estimates for the coefficient β, not presented in the paper, are in the range $[-0.25, -0.15]$ and are highly statistically signficant.

average effect of Wal-Mart entry on a class of products (such as drugstore items). Year fixed effects are allowed to differ by product; standard errors are still clustered at the city level (rather than at the city*product level), allowing arbitrary correlations in the error terms across products within the same city.

The OLS estimates are consistent if Wal-Mart entry is correctly measured and exogenous to changes in the price of item k. Unfortunately, $\mathbf{WMopen_{jt}}$ is measured with error and may be endogenous to prices movements. An instrumental-variables specification is used to correct these problems.

4.2 Instrumental Variables (IV)

Measurement error in the Wal-Mart entry variable $\mathbf{WMopen_{jt}}$ takes a particular form: while the entered cities are correctly identified, the *timing* of entry may be incorrectly measured due to errors in the directories. Some stores are listed only one or two years after they open, others are listed when entry is anticipated but delayed. In addition, the *Directory of Discount Department Stores* was not updated between 1990 and 1993, so stores that opened in the intervening period all register as having opened in 1993. The counter-factual variable $\mathbf{WMplan_{jt}}$ is also measured with error, by construction: it represents the number of stores that would have opened had stores always opened in the order in which they were planned. Recall that $\mathbf{WMplan_{jt}}$ is the number of stores that would have opened in year t in city j had stores opened in exactly the same order that they were planned (numbered), while $\mathbf{WMopen_{jt}}$ is the number of stores in city j in year t that appear for the first time in a store list or directory for that year.

An instrumental-variables approach, in which leads and lags of $\mathbf{WMplan_{jt}}$ is used to instrument for leads and lags of $\mathbf{WMopen_{jt}}$ can be used to correct for this measurement error if the measurement errors in the two variables is classical and uncorrelated. That the measurement error across the two variables is uncorrelated seems plausible. Because $\mathbf{WMopen_{jt}}$ and $\mathbf{WMplan_{jt}}$ are both discrete, measurement error is not classical, as noted by Kane, Rouse, and Staiger (1999): the actual number of Wal-Mart stores in city j in year t differs from the measured number by an integer whose expected mean is different from zero.[11] This induces a slight bias in the instrumental-variables results reported here.[12]

The first-stage regression is

$$\mathrm{WMopen}_{jt} = \widetilde{\alpha} + \widetilde{\beta}\Delta p_{kj,t-1} + \sum_t \widetilde{\delta}_t \,\mathrm{year}_t + \widetilde{\theta}\,(L)\,\mathrm{WMplan}_{jt} + \widetilde{\mathrm{u}}_{jt} \tag{5}$$

where $\widetilde{\theta}\,(L)$ is a lag polynomial with two leads and and four lags:

$$\widetilde{\theta}\,(L) = \widetilde{\theta}_{-2}F^2 + \widetilde{\theta}_{-1}F^1 + \widetilde{\theta}_0 + \widetilde{\theta}_1 L + \widetilde{\theta}_2 L^2 + \widetilde{\theta}_3 L^3 + \widetilde{\theta}_4 L^4 \tag{6}$$

with L the lag operator and F the lead operator. This regression is intended capture as much as possible the relationship between store planning dates and opening dates. The large set of

[11] The reason is that when the directories report zero new Wal-Marts in town, given that store closings are exceedingly rare, the expected number of openings is some (small) positive number. When the reported number of new Wal-Marts is one, the actual number is either zero or one, so the expected number is less than one.

[12] Kane, Rouse and Staiger (1999) suggest a GMM estimator to address this problem. Unfortunately, due to the size of the panel , their solution is not computationally feasible in this setting. While the bias could be large in theory, in the static returns-to-schooling example Kane, Rouse and Staiger use, the bias is approximately 5% of the IV coefficient estimate.

leads and lags is used to generate the best predictor of opening date.[13]

4.3 Endogeneity

Another potential difficulty in assessing the impact of Wal-Mart entry on the price level is the possible endogeneity of Wal-Mart's entry decision with respect to the competitive structure of the retail sector (which is correlated with average prices). There are two dimensions to this potential endogeneity: Wal-Mart may select the cities it enters non-randomly, and it may choose the timing of entry non-randomly.

The cross-sectional dimension (choice of cities) is very plausible; for example, Wal-Mart may prefer to enter cities with less-competitive retail markets (hence higher pre-entry prices) or with a larger fraction of search-savvy lower-middle income families (whose presence leads to *lower* average retail prices; see Frankel and Gould 2001). This concern is greatly mitigated by the fact that Wal-Mart entry is observed in all 160 sample cities (in 23 of the cities, entry was before 1982), and these cities are diverse with respect to all standard economic and demographic variables (as Table 3 showed).

The timing dimension is important if Wal-Mart can schedule its entry to coincide with high retail prices. The concern is that Wal-Mart's exact entry date could be manipulated to coincide with high prices (e.g., by waiting for another retail to exit preemptively, once Wal-Mart's entry intentions are known); Wal-Mart's measured effect on prices – the estimated coefficients $\widehat{\theta}_k$ – would then be spuriously large (in absolute terms). The instrumental-variables strategy I use to correct for measurement error in timing of entry can also correct for this potential endogeneity. The identification strategy assumes that Wal-Mart plans its store entries well in advance of entry and cannot accurately forecast exact market conditions at the time for which entry is planned. The company may fine-tune opening dates based on current market conditions, but planning occurs sufficiently in advance – and prices are sufficiently flexible – that planning dates can be treated as exogenous to retail prices at the time of Wal-Mart entry.

Ideally, we would like to estimate the coefficient θ from the equation

$$p_{kjt}^{WM} = p_{kjt}^{0} + \theta_k$$

where $\mathbf{p_{kjt}^{WM}}$ is the average of mean-adjusted residual log prices (from Equation (2)) of product k in city j in year t in the presence of a Wal-Mart store, and $\mathbf{p_{kjt}^{0}}$ is the same variable in the absence of the Wal-Mart store. Since we cannot observe both $\mathbf{p_{kjt}^{WM}}$ and $\mathbf{p_{kjt}^{0}}$ for a given product-city-year combination, OLS estimates implicitly assume that

$$\Delta p_{kjt}^{0} = \alpha + \sum_t \delta_{kt}\,\mathrm{year}_t + \mathrm{u}_{kjt} \tag{7}$$

$$\mathbb{E}\left(\mathrm{u}_{kjt} \mid \mathrm{WMopen}_{jt}\right) = 0. \tag{8}$$

That is, the presence of a Wal-Mart store in city j in year t is uncorrelated with the error term in the price-change equation: Wal-Mart entry is exogenous to future changes in price.

The instrumental-variables strategy described above corrects for this endogeneity concern under two identifying assumptions: the number of *planned* Wal-Mart stores for city j and year t are independent of the error term in Equation (7); and *planned* Wal-Mart stores affect retail prices only insofar as they are correlated with the *actual* construction of Wal-Mart stores. These

[13] First-stage regression results are in Appendix B.

assumptions imply that

$$\mathbb{E}\left(\mathrm{u}_{kjt} \mid \mathrm{WMplan}_{jt}\right) = 0 \tag{9}$$

replaces Equation (8). As this discussion suggests, the IV estimator $\widehat{\theta}_k$ will be biased if plans to build a Wal-Mart store spur price changes even if Wal-Mart does not actually open a store in that city the year it planned to. Since price changes for retail items such as those I analyze here can be made with little pre-planning, anticipatory price changes are unlikely.

4.4 Split-Sample IV (SSIV)

In Basker (2003), I analyzed the effect of Wal-Mart entry on county-level retail- and wholesale-sector employment in 1749 counties. Because my sample in this paper is an order of magnitude smaller – 160 cities – the power of the first-stage regression is lower (though still very high), and the estimated relationship between $\mathbf{WMopen_{jt}}$ and $\mathbf{WMplan_{jt}}$ in this sample could be spurious. (Figure 3 compares the relationship between $\mathbf{WMopen_{jt}}$, on the x-axis, and $\mathbf{WMplan_{jt}}$, on the y-axis, in the full set of cities in the Wal-Mart data with the relationship observed in the sample of 160 cities. The area of each circle is proportional to the number of stores it represents.)

To address this concern, I employ a split-sample instrumental variables specification (SSIV). The SSIV procedure has two stages, a "stage-zero" regression in which I construct the instrument, and a two-stage least squares (2SLS) regression (consisting of first- and second-stage regressions) in which I apply the instrument. This implementation of SSIV is somewhat different from the original one proposed by Angrist and Krueger (1995). Angrist and Krueger apply a two-stage procedure, but use different samples for the first- and second-stage regressions. I use a single consistent sample for the first- and second-stage regressions, but create the instrument using a larger sample in an antecedent "stage-zero" regression.[14]

In the "stage-zero" regression, I use the full population of 2,165 cities in which Wal-Mart stores opened between 1962 and 1997 to estimate

$$\mathrm{WMopen}_{jt} = \widetilde{\alpha} + \sum_t \widetilde{\delta}_t \, \mathrm{year}_t + \widetilde{\theta}\,(L)\, \mathrm{WMplan}_{jt} + \widetilde{\mathrm{u}}_{jt} \tag{10}$$

where $\widetilde{\theta}\,(L)$ is as in Equation (6). The difference between this SSIV procedure and the IV estimation described above is that the full sample of cities over 37 years is used to ensure that the relationship is not spuriously estimated.[15] Consistent with Figure 3, which shows the weight of observations below the 45° line, the most significant variable in the stage-0 regression is the the first lag of the LHS variable.

From Equation (10) I obtain the predicted value of $\mathbf{WMopen_{jt}}$ based on this long-run relationship between store planning dates and store opening dates. This predicted value, $\mathbf{WMhat_{jt}}$, is my instrument for in the 2SLS regression using the sample of 160 cities over the period 1982-2002. (Note that all 160 cities experienced Wal-Mart entry no later than 1997.) When dynamic equations are estimated of the form of Equation (4), I use the relevant leads and lags of $\mathbf{WMhat_{jt}}$ to instrument for leads and lags of $\mathbf{WMopen_{jt}}$.

Results from single-sample IV regressions are similar to those based on the SSIV model, but

[14] My SSIV estimates are not biased towards zero as in Angrist and Krueger, so do not require their correction.

[15] Zero-stage and first-stage regression results are shown in Appendix B. F statistics from a test of joint significance in the stage-zero regression is 3,824; first-stage F statistics are always above 100 with p-values well below 0.01.

may have lower power due to a slightly weaker first-stage regression. The results presented are also not sensitive to the specific form of the stage-0 regression.

5 Results

5.1 OLS Results

Before proceeding to the main part of the paper where I present Split-Sample IV results, I show some results from OLS regressions of Equation (3).

Table 4 shows results from 16 separate OLS regressions. The top five rows show estimated θ from product-specific regressions, and the bottom row shows estimates from regressions where multiple products are stacked together. The "combined drugstore" regression, for example, stacks all five drugstore items into a single regression to increase the power of the estimation; separate year fixed-effects are included for each product. In each case the point estimate $\widehat{\theta}_k$ is given with asymptotic standard errors in parentheses. No individual-product price change is statistically distinguishable from zero (with the exception of the price of underwear), although the composite drugstore price does decline by a small but significant 1%.

As in Basker (2003), measurement error may cause attenuation bias in these coefficient estimates; endogeneity could bias them as well (though the sign of this bias is unknown). I turn next to the instrumental-variables results that address these concerns.

5.2 IV Results

Instrumental-variables results (from a single-sample estimation) are shown in Table 5. As above, the top five rows show estimated θ from product-specific regressions, while the bottom rows show estimates from regressions where multiple products are stacked together. All five drugstore items (aspirin, detergent, Kleenex, shampoo and toothpaste) have negative coefficients, suggesting Wal-Mart entry is associated with a (permanent) decrease in prices; three of these are significant with 95% confidence. In contrast, all five "convenience-store" products have coefficient smaller than 0.01 in absolute value; none of these are significant. When we stack the products together, the price effect of Wal-Mart on drugstore items (with 13,930 observations) is strongly significant (at the 99% confidence level), while the combined effects on other products is insignificantly different from zero. On average, entry of Wal-Mart is associated with a one-time decline in prices of drugstore items of approximately 3.6%.

5.3 SSIV Results

Table 6 shows split-sample IV results. The results are broadly similar to the IV results presented above, with most of the drugstore coefficients larger in absolute terms and/or more significant. Of the non-drugstore items, the only significant effect is on the price of shirts, which is estimated to increase by 4%.[16]

[16] Since clothes are the least homogeneous of the products considered here, this effect could be the result of increased product differentiation by incumbents, which would simultaneously increase the average price and the variance of prices.

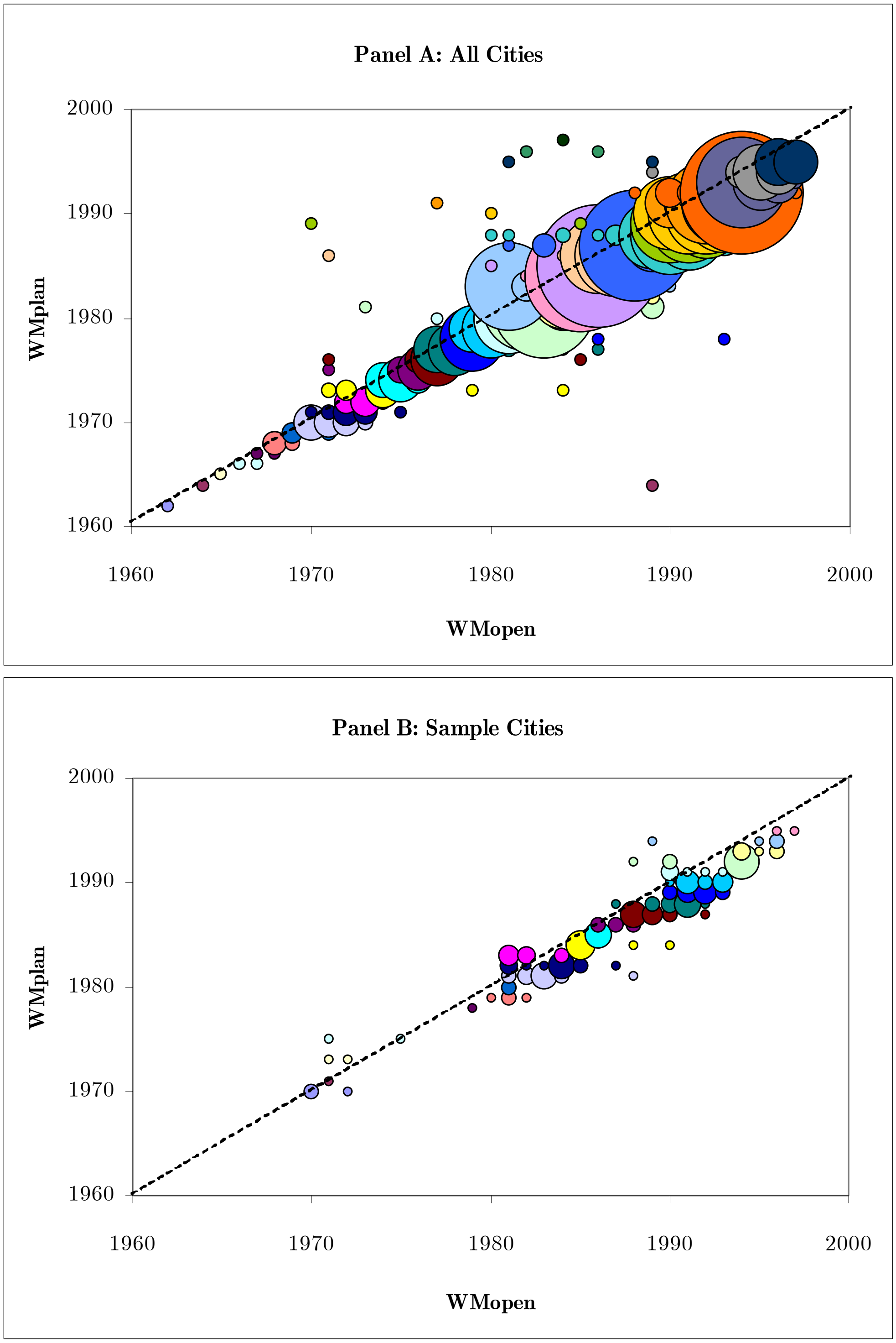

Figure 3: Store Opening Dates (Directories) vs. Planned Opening Dates (Store Numbers)

Table 4: Once-and-for-All OLS Estimates

Product	Theta	Product	Theta	Product	Theta
Aspirin	-0.0060	Beer	-0.0054	Shirt	0.0093
	(0.0081)		(0.0050)		(0.0088)
Detergent	-0.0115*	Cigarettes	-0.0005	Pants	-0.0010
	(0.0061)		(0.0027)		(0.0082)
Kleenex	-0.0051	Coke	0.0173**	Underwear	-0.0232**
	(0.0051)		(0.0079)		(0.0116)
Shampoo	-0.0116*	Liquor	0.0016		
	(0.0069)		(0.0045)		
Toothpaste	-0.0175**	Wine	-0.0137*		
	(0.0074)		(0.0080)		
Combined	-0.0104**	Combined	0.0000	Combined	-0.0052
Drugstore	(0.0041)	Convenience	(0.0031)	Clothing	(0.0062)

Note: Robust standard errors in parentheses (clustered at the city level)

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Once-and-for-All IV Estimates

Product	Theta	Product	Theta	Product	Theta
Aspirin	-0.0427**	Beer	0.0055	Shirt	0.0310
	(0.0176)		(0.0105)		(0.0198)
Detergent	-0.0399***	Cigarettes	0.0099	Pants	-0.0105
	(0.0143)		(0.0083)		(0.0193)
Kleenex	-0.0190*	Coke	0.0072	Underwear	-0.0361
	(0.0101)		(0.0182)		(0.0277)
Shampoo	-0.0213	Liquor	-0.0032		
	(0.0166)		(0.0116)		
Toothpaste	-0.0552***	Wine	-0.0026		
	(0.0182)		(0.0185)		
Combined	-0.0357***	Combined	0.0038	Combined	-0.0058
Drugstore	(0.0104)	Convenienc	(0.0075)	Clothing	(0.0150)

Note: Robust standard errors in parentheses (clustered at the city level)

* significant at 10%; ** significant at 5%; *** significant at 1%

5.4 Dynamics

To see whether the above results mask more elaborate price dynamics, I estimate the alternative specification given in Equation (4) using split-sample IV.[17]

Estimated price dynamics depend on both the "real" dynamics and on the aggregation from quarterly price observations to annual data, as explained in Appendix A. If there is a once-and-for-all effect on prices in the quarter of entry, most of this effect will be estimated in the year of entry, but even the best aggregation method will involve some mismatch between the annual and quarterly data; in that case we would estimate some (small) price change in both the year before and the year after entry. If actual price behavior is characterized by a dynamic response – for example, a price decrease in the quarter of entry, followed by a price increase six months later, and perhaps another decrease 9 months after that – the estimated dynamics will be more complicated. (I work out an example with up to 10 quarterly price changes in Appendix A.)

While specific coefficients may not match exactly with the timing of price changes, the long-run effect of Wal-Mart entry on prices can be estimated correctly as the sum of the lead and lag coefficients $\sum_{s=-1}^{3} \widehat{\theta}_s$.[18]

Results for drugstore items are shown in Table 7. The coefficient θ_{-1} shows the average change in price in the year *preceding* Wal-Mart entry; θ_0 shows the average change in price in the year of entry; and $\theta_1 - \theta_3$ show average price changes over the next three years. The last two rows in Table 7 show the sum of the coefficients $\theta_{-1} - \theta_3$ and $\theta_0 - \theta_3$ and the respective p-value tests for a zero long-run effect. The first five columns show estimates for each of the drugstore items in turn; the last three columns show estimates for the three item categories: drugstore, convenience and clothing. (Detailed product-by-product results for these items are presented in Appendix B.)

Interestingly, the estimates show a decline (on average, 1-2% per year) in all drugstore items both the year preceding Wal-Mart entry and the year of entry. The price of aspirin is estimated to decline by a striking 5% in the year preceding entry; all other price declines are substantially smaller than that. Larger declines in 3 of the 5 drugstore items are estimated in the second year following entry. Prices increase on average in the second year after Wal-Mart entry and fall again in the third year.[19] The net effect over the long run is a decline of 3-7% in prices; the composite drugstore price declines by a very significant 5.5%. This long-run effect is larger than the once-and-for-all effect estimated earlier, which is expected since the once-and-for-all estimation is biased towards zero (see Appendix A for details).

Prices of convenience-store items and clothing react very little to Wal-Mart entry. Both sets of items exhibit some price fluctuations, but the long-run effect is nil.

5.5 City Size Effect

In this section I test whether the Bresnahan and Reiss (1991) result that smaller cities have less competitive retail markets holds in my data. The testable hypothesis is that Wal-Mart's effect on prices should be larger for small cities. None of the cities in my sample are as small as the cities Bresnahan and Reiss consider in their paper – mean population in their sample is

[17] Results using single-sample instrumental-variables are in Appendix B.

[18] To minimize concerns that this sum of coefficients includes "pre-entry" price effects of Wal-Mart, I also compute the sum $\sum_{s=0}^{3} \widehat{\theta}_s$, beginning with the year of entry. As explained in Appendix A, however, this sum will tend to underestimated Wal-Mart's price impact if prices decline in the first quarter following entry.

[19] This effect is not due to negative autocorrelation in the price data. Results are robust to an AR(1) correction using a Cochrane-Orcutt specification.

Table 6: Once-and-for-All SSIV Estimates

Product	**Theta**	**Product**	**Theta**	**Product**	**Theta**
Aspirin	-0.0538***	Beer	0.0044	Shirt	0.0390**
	(0.0189)		(0.0104)		(0.0192)
Detergent	-0.0373**	Cigarettes	0.0084	Pants	-0.0042
	(0.0152)		(0.0084)		(0.0195)
Kleenex	-0.0224**	Coke	0.0147	Underwear	-0.0400
	(0.0113)		(0.0200)		(0.0292)
Shampoo	-0.0236	Liquor	-0.0053		
	(0.0167)		(0.0124)		
Toothpaste	-0.0541***	Wine	0.0060		
	(0.0185)		(0.0200)		
Combined Drugstore	-0.0383*** (0.0110)	Combined Convenience	0.0060 (0.0076)	Combined Clothing	-0.0023 (0.0147)

Note: Robust standard errors in parentheses (clustered at the city level)

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Dynamic SSIV Estimates

	Aspirin	Detergent	Kleenex	Shampoo	Toothpaste	Combined Drugstore	Combined Convenience	Combined Clothing
θ_{-1}	-0.0495*	-0.0165	-0.0178	-0.0008	-0.0127	-0.0194	0.0029	-0.0107
	(0.0296)	(0.0236)	(0.0165)	(0.0257)	(0.0205)	(0.0143)	(0.0120)	(0.0216)
θ_0	-0.0055	-0.0181	-0.0023	-0.0129	-0.0162	-0.0112	0.0008	0.0283
	(0.0343)	(0.0270)	(0.0207)	(0.0325)	(0.0259)	(0.0168)	(0.0152)	(0.0256)
θ_1	-0.0347	-0.0074	-0.0166	-0.0372	-0.0767**	-0.0344*	0.0137	-0.0455*
	(0.0355)	(0.0322)	(0.0229)	(0.0345)	(0.0355)	(0.0182)	(0.0149)	(0.0270)
θ_2	0.0527	-0.0290	0.0119	0.0582*	0.0677	0.0323*	-0.0289**	-0.0032
	(0.0371)	(0.0335)	(0.0250)	(0.0325)	(0.0411)	(0.0193)	(0.0138)	(0.0281)
θ_3	-0.0242	-0.0034	-0.0064	-0.0453**	-0.0301	-0.0219	0.0101	0.0160
	(0.0289)	(0.0220)	(0.0181)	(0.0225)	(0.0314)	(0.0146)	(0.0108)	(0.0219)
$\sum_{t=0}^{3}\theta_t$	-0.0117	-0.0579**	-0.0135	-0.0372	-0.0552**	-0.0352**	-0.0044	-0.0043
p-value	0.6833	0.0261	0.3856	0.1781	0.0350	0.0334	0.7072	0.8482
$\sum_{t=-1}^{3}\theta_t$	-0.0612**	-0.0743***	-0.0313**	-0.0380*	-0.0679***	-0.0546***	-0.0015	-0.0150
p-value	0.0111	0.0021	0.0365	0.0978	0.0066	0.0005	0.8864	0.4117

Note: Robust standard errors in parentheses (clustered at the city level)

* significant at 10%; ** significant at 5%; *** significant at 1%

below 4,000, and near 200,000 in my sample. While establishment breakdowns are not available at the city level, approximately 10% of retail establishments in the US in 1982 were clothing stores (SIC 5600) and 3.8% of retail establishments were "drug stores and proprietary stores" (SIC 5910).[20] (Both fractions declined over the 1980s and 1990s, each by approximately one percentage point.) On average, a city with 600 retail establishments (roughly the 25th percentile in my sample in 1982) is likely to have fewer than 25 drugstores – well within the intermediate range (between quintopolies and urban markets) considered by Bresnahan and Reiss.

Large cities are likely to have more competitive retail markets not only because of the larger numbers of stores but because of compositional differences in market structure. Evidence from the California alcoholic-beverage retail market (all stores selling alcoholic beverages for off-premise consumption) suggests that large cities have a smaller ratio of chain stores to independent (stand-alone) stores than small cities, suggesting retailers in large cities have less monopoly power (Dinlersoz, forthcoming).

To test for a differential effect of entry on small and large cities, I split my sample into two by the number of retail establishments in 1982. "Small" cities have fewer than 930 retail establishments in 1982, "large" cities have at least 930. The number of retail establishments is available only for cities with 1980 population above 25,000 – the largest 142 cities of 160 in the sample. The percentiles listed in Table 3 (including the median used to determine "small" vs. "large" city cutoffs) assume that cities with population below 25,000 in 1980 had fewer than 580 retail establishments.[21] The median "small city" has 1982 population of 43,000; the median "large city" has 1982 population approximately 184,000.[22]

I allow the coefficient θ to take on different values for small and large cities, estimating θ^S and θ^L separately within a single regression. I report results for the three broad categories – drugstore items, convenience-store items and clothes – in Table 8.

Panel A shows static results. Wal-Mart entry is estimated to reduce drugstore-items' prices by 5.5% in small cities, and by 2.5% in large cities. An F test for equality of these coefficients is reported below them; equality of the effects is rejected (p-value 0.01). For convenience-store items and clothing, estimated effects for both small and large cities are very small, and not significantly different from zero.

Panel B shows dynamic effects. Drugstore prices in small cities are estimated to decline by 2.5% in the year of entry, and by another 5% the following year. They then increase by 3.5% and fall by the same amount in the fourth year, so the net long-run effect of Wal-Mart entry on drugstore prices in small cities is estimated to be a decline of nearly 8.5% (a percentage point less if we compute the long-run effect by adding up coefficients starting from θ_0 instead of θ_{-1}). The estimated post-entry effect for large cities is smaller: a long-run price decline of 3% (or nil if we add up only the entry and post-entry coefficients). Prices of convenience items and clothes are largely unaffected by Wal-Mart entry in both small and large cities.

These findings suggest that Wal-Mart entry has a larger impact on small cities than on large ones, as theory predicts. One necessary caveat is that price surveys may be more likely to include Wal-Mart stores in small cities than in large ones, leading to a mechanical effect of Wal-Mart entry on average prices (though Wal-Mart's lower prices rather than through a competitive impact on other retailers).

[20] Convenience stores do not have a unique SIC code.

[21] Among the remaining cities, the correlation between 1980 population and 1982 number of retail establishments is 0.98.

[22] An alternative cutoff rule using the median 1980 population yields similar results, and is shown in Appendix B.

Table 8: Once-and-for-All and Dynamic SSIV Estimates by City Size

	Drugstore		Convenience		Clothes	
	Small	Large	Small	Large	Small	Large
Panel A: Once-and-for-All Estimates						
θ	-0.0556***	-0.0246*	-0.0038	0.0136	-0.0150	0.0078
	(0.0140)	(0.0135)	(0.0094)	(0.0099)	(0.0170)	(0.0196)
F stat	3.3341		2.1356		0.9940	
p-value	0.0697		0.1459		0.3203	
Panel B: Dynamic Estimates						
θ_{-1}	-0.0077	-0.0263	0.0184	-0.0059	-0.0211	-0.0040
	(0.0161)	(0.0182)	(0.0169)	(0.0159)	(0.0292)	(0.0285)
θ_0	-0.0255	0.0020	-0.0302	0.0285	0.0186	0.0358
	(0.0207)	(0.0235)	(0.0221)	(0.0227)	(0.0318)	(0.0350)
θ_1	-0.0493**	-0.0180	0.0335	-0.0082	-0.0313	-0.065
	(0.0235)	(0.0260)	(0.0267)	(0.0242)	(0.0367)	(0.0400)
θ_2	0.0340	0.0152	-0.0378	-0.0284	-0.0262	0.0250
	(0.0262)	(0.0286)	(0.0259)	(0.0232)	(0.0359)	(0.0466)
θ_3	-0.0363*	-0.0020	0.0190	0.0143	0.0222	0.0046
	(0.0187)	(0.0221)	(0.0176)	(0.0189)	(0.0254)	(0.0385)
$\sum_{t=0}^{3}\theta_t$	-0.0770***	-0.0028	-0.0155	0.0062	-0.0168	0.0003
p-value	0.0000	0.8991	0.2691	0.7288	0.5084	0.9916
$\sum_{t=-1}^{3}\theta_t$	-0.0848***	-0.0292*	0.0030	0.0003	-0.0379	-0.0037
p-value	0.0000	0.0964	0.8459	0.9809	0.1070	0.8749

Note: Robust standard errors in parentheses (clustered at the city level)

* significant at 10%; ** significant at 5%; *** significant at 1%

6 Discussion and Conclusion

This paper tests the hypothesis that Wal-Mart entry leads to lowers average retail prices in the markets it enters. Using a unique panel data set that combines average retail prices for 13 specific goods and a complete time-series of Wal-Mart store locations, I estimate the effect of Wal-Mart entry on prices. I find that for items typically sold in drugstores, such as aspirin and shampoo, average prices decline following Wal-Mart entry. This decline is economically large – approximately 3.5% – and statistically significant. While prices may increase in subsequent years, there is no evidence that average prices increase to a level higher than the pre-entry prices. This aggregate effect is driven by smaller cities, which experience drugstore-item price declines of 5-6%. For items typically sold in convenience stores – alcoholic beverages and cigarettes – I find no effect of Wal-Mart entry on prices. This could be due to the fact that, for reasons of state law and local regulation (e.g., required distance from elementary schools and churches), many Wal-Mart stores do not sell alcoholic beverages. There is also no effect of entry on prices of clothing items like jeans and men's shirts.

This average-price effect masks a large amount of intra-market variation in competitive response to Wal-Mart entry. Because the ACCRA data cannot be disaggregated to the store level, it is impossible to estimate the distribution of responses. But theory suggests that stores selling the closest substitutes to Wal-Mart – for example, those that are located near Wal-Mart, or that are similar on other dimensions – will have the most elastic price responses to Wal-Mart entry. Stores located far from Wal-Mart are likely to have very small price responses, because their clienteles' cross-price elasticity of demand will be low.

Are these effects large? As usual, the answer depends on our perspective. From a macroeconomic perspective, they are very small. The products for which I find a statistically-significant price effect are classified in the "personal-care" category, which has a combined weight of less than 1% in the Consumer Price Index (CPI) compiled by the BLS. If Wal-Mart expansion across the United States has produced an average decline of 4% in drugstore prices, one market at a time, over the last 40 years, we would not be able to detect this effect in the CPI.[23]

From an industrial-organization perspective, on the other hand, these effects are quite large. To achieve a 5.5% price decline without any efficiency gains, a store may have to forgo as much as 50% of its gross profit margin. (Using the lower estimate of a 3.5% price decline, a 30% reduction in gross profit margins would still be needed.) While figures on profit margins for Wal-Mart competitors in the entered markets are not available, a useful benchmark is provided by the University of Chicago Graduate School of Business study of Dominick's Finer Foods (DFF) in the Chicago metropolitan area. Over the period 1989-1994, the GSB collected scanner data, including gross profit margins, from Dominick's for thousands of individual items.[24] Several of the items included in this analysis are also included in the DFF database. Table 9 shows average gross profit margins for broad categories as well as for specific brands for which the two data sets overlap. For example, the average gross profit margin on toothpaste is 11.6%, meaning that on average 88.4% of the price of an analgesic reflects the wholesale cost of the drug. The average

[23] Wal-Mart aggressive entry into the grocery market – with Supercenter store formats as well as the smaller "Neighborhood Markets" – could lead to a larger macroeconomic impact: unlike "personal care" items, food items constitute 15-17% of the CPI, with the bulk of this weight coming from the "food at home" subcategory. The first Supercenter opened in 1988; by the end of 2002, 45% of all Wal-Mart stores included a grocery section.

[24] These data are available on-line at
`http://gsbwww.uchicago.edu/kilts/research/db/dominicks/index.shtml`
and are described in detail in Peltzman (2000) and Chevalier, Kashyap and Rossi (2003).

profit margin for Colgate brand toothpaste is lower, 8.4%.[25] If these gross profit margins are representative of grocery stores, drugstores and convenience stores throughout the country, then a 7% decline in the price of Colgate or Crest toothpaste is equivalent to a drop of 70% in gross profits on that product. The average profit margin on items classified as "drugstore products" in this study is 11.4%; an average decline of 5.5% in the prices of these items is equivalent to a drop of 48% in their gross profit margin.

[25] As noted in the data description at
`http://gsbwww.uchicago.edu/kilts/research/db/dominicks/movement.shtml`
these gross profit margins reflect wholesale prices at the time the product was purchased by DFF, not replacement cost.

Table 9: Average Gross Profit Margins, Dominick's Finer Foods

Category	Brand	Average Gross Profit Margin (%)
Analgesics	All	13.6
	Bayer	9.6
Beer	All	8.1
	Budweiser	9.2
	Heineken	10.5
	Miller Lite	13.6
	Schlitz	7.4
Cigarettes	All	14.7
	Winston	10.9
Dish Detergents	All	13.0
	Cascade	11.8
Laundry Detergents	All	9.5
	Bold	10.2
	Cheer	8.9
	Tide	7.7
Soft Drinks	All	11.9
	Coca Cola	8.8
Shampoo	All	9.3
	Alberto	11.2
Toothpastes	All	11.6
	Colgate	8.4
	Crest	10.1

Source: Author's Calculations from University of Chicago GSB Micro-Marketing Project, Dominick's Finer Foods

A Temporal Aggregation

This appendix explains the temporal aggregation of quarterly price observations to "fiscal year" annual averages, and the implications of this aggregation for the once-and-for-all and dynamic coefficient estimates.

To start, assume that Wal-Mart entry produces a once-and-for-all effect; that is, there is some price p_0 that holds in all periods before Wal-Mart entry, after which the price changes to some p_1 instantaneously and permanently. Let $\Delta \equiv p_1 - p_0$ be the difference between these two prices. Recall that quarterly price observations are made during the first week of each quarter. For simplicity we assume that they are made on the first day of each quarter, i.e., January 1, April 1, July 1, and October 1.[26] Panel A of Table 10 shows, for each quarter in which a store might open, the vector of quarterly prices in year $(t-1)$, their arithmetic average, the vector of quarterly prices in year t, their arithmetic average, and the difference between the two average prices that would be observed. The last row in panel A shows the estimated coefficient that would be expected in a once-and-for-all regression that used data aggregated into calendar years:

$$\begin{aligned} \widehat{\Delta}_t &= \frac{1}{4}\left(\frac{3}{4}\Delta + \frac{1}{2}\Delta + \frac{1}{4}\Delta + 0\right) \\ &= \frac{3}{8}\Delta. \end{aligned}$$

Panel B of the same table shows similar calculations under an alternative aggregation method, using "fiscal years" instead of calendar years. We define a fiscal year $\widehat{t}$ as starting July 1 of year t and ending June 30 of year $(t+1)$. Again assuming entry is equally likely in each quarter, the resulting estimate of the once-and-for-all impact of entry would be

$$\begin{aligned} \widehat{\Delta}_{\widehat{t}} &= \frac{1}{4}\left(\frac{3}{4}\Delta + \Delta + \frac{3}{4}\Delta + \frac{1}{2}\Delta\right) \\ &= \frac{3}{4}\Delta. \end{aligned}$$

While the estimated impact is still lower than the actual impact of entry (in absolute terms), this fiscal-year aggregation is associated with a substantially lower bias than the calendar-year aggregation.

Dynamic estimates of the once-and-for-all effect are described in Table 11. With calendar-year aggregation, more than half of the impact of Wal-Mart is estimated in the "wrong" year – one year after entry – although the long-run effect, given by the sum of changes over 5 years, is Δ. With fiscal-year aggregation, most (75%) of the impact is estimated in the "right" year, but some of the remaining impact is attributed to the year *preceding* entry. The long-run effect is again the full effect, Δ. Note that the actual impact of Wal-Mart in this exercise is a once-and-for-all effect on price, with estimated dynamics due to incorrect aggregation of quarterly observations. I refer to these dynamics as "accounting dynamics", as opposed to actual price dynamics.

If instead of a once-and-for-all impact on prices, Wal-Mart entry generates a dynamic price

[26] This simplification is not strictly correct but is a close approximation of the true distribution of entry dates. During 2001-2003, nearly 20% of entries (including renovated stores) occured in the fourth quarter, with the remainder distributed approximately equally among the first three quarters.

response, the results could be even more uneven.

Now suppose instead that we have some real (non-accounting) dynamics: in the first quarter after entry, the price changes by Δ_1; it changes by another Δ_2 the following quarter (where Δ_1 and Δ_2 may have either the same or opposite signs); by Δ_3 in the third quarter, and so on for 10 quarters (up to Δ_{10}). The long-run effect is a price change of $\left(\sum_{n=1}^{10} \Delta_n\right)$. Table 12 shows the estimated coefficients in this scenario.

Three main conclusions emerge from this analysis. First, estimated price dynamics may misrepresent actual price dynamics due to the aggregation problem. Second, as long as prices "settle down" to a new long-run equilibrium price within 10 quarters of Wal-Mart entry, the sum of coefficients on one lead and three lags of the Wal-Mart variable (as well as the coefficient for year of entry) will correctly capture the long-run effect on prices. Finally, using the sum of the instantaneous effect and three lags (without the lead coefficient) will slightly bias our estimate of the long-run effect.

B Additional Empirical Results

B.1 Stage-Zero and Stage-One Regressions

Table 13 show split-sample IV first-stage regressions. The first column shows the coefficient on $\mathbf{WMhat_{jt}}$ in the first-stage of the SSIV regression used to estimate once-and-for-all ("static") price effects of Wal-Mart entry. Only the contemporaneous value of $\mathbf{WMhat_{jt}}$ is included as an instrument in those regressions. In the regressions estimating dynamic effects, one lead and three lags of $\mathbf{WMhat_{jt}}$ are included as additional instruments (so that the equation is exactly identified). F statistics at the bottom of the table again show tests for joint significance of all included $\mathbf{WMhat_{jt}}$ leads and lags. F statistics are somewhat higher in the SSIV first-stage regressions than in the IV first-stages because the stage-zero prediction is more accurate due to the use of more cities over a longer time period.

Table 14 shows first-stage IV regressions and the stage-zero regression coefficients for the SSIV specification. The first five columns show the coefficients on the two leads, one contemporaneous, and four lags of $\mathbf{WMplan_{jt}}$ for each of five LHS variables, including one lead, one contemporaneous, and three lags of $\mathbf{WMopen_{jt}}$. Each of these regressions includes 2,786 observations – the number of observations in a single-product regression. The "window" of significant coefficients moves with the lead or lag on the LHS. For example, the largest coefficient in the first-stage regression for $\mathbf{WMopen_{j,t-1}}$ is θ_0, the coefficient on $\mathbf{WMplan_{jt}}$; the largest coefficient in the first-stage regression for $\mathbf{WMopen_{jt}}$ is θ_1, the coefficient on $\mathbf{WMplan_{j,t+1}}$. (First stage regressions include also year fixed effects and lagged price levels, not shown here.) The sixth column shows the stage-zero regression used to create $\mathbf{WMhat_{jt}}$. Because this regression includes all cities with Wal-Mart stores over 36 years (nearly 90,000 observations), instead of only 160 cities over 20 years, coefficient estimates are much more precise. F statistics at the bottom of the table show tests for joint significance of all leads and lags of $\mathbf{WMplan_{jt}}$ included in the regression.

B.2 SSIV Price Dynamics for Convenience-Store and Clothing Products

Tables 15 and 16 show estimated price dynamics for convenience-store items and clothes, respectively. At the product level, a total of 40 coefficients are estimated, three of them significantly different from zero at the 95% confidence interval; this rate of rejection is consistent with the

Table 10: Observed Prices by Quarter of Entry, Calendar vs. Fiscal Aggregation

Entry Quarter	P_{t-1}	$\overline{P}_{t-1}$	P_t	$\overline{P}_t$	$\overline{P}_t - \overline{P}_{t-1}$
			Panel A: Calendar-Year Aggregation		
1	(p_0, p_0, p_0, p_0)	p_0	(p_0, p_1, p_1, p_1)	$\frac{1}{4}p_0 + \frac{3}{4}p_1$	$\frac{3}{4}\Delta$
2	(p_0, p_0, p_0, p_0)	p_0	(p_0, p_0, p_1, p_1)	$\frac{1}{2}p_0 + \frac{1}{2}p_1$	$\frac{1}{2}\Delta$
3	(p_0, p_0, p_0, p_0)	p_0	(p_0, p_0, p_0, p_1)	$\frac{3}{4}p_0 + \frac{1}{4}p_1$	$\frac{1}{4}\Delta$
4	(p_0, p_0, p_0, p_0)	p_0	(p_0, p_0, p_0, p_0)	p_0	0
average					$\frac{3}{8}\Delta$
			Panel B: Fiscal-Year Aggregation		
1	(p_0, p_0, p_0, p_1)	$\frac{3}{4}p_0 + \frac{1}{4}p_1$	(p_1, p_1, p_1, p_1)	p_1	$\frac{3}{4}\Delta$
2	(p_0, p_0, p_0, p_0)	p_0	(p_1, p_1, p_1, p_1)	p_1	Δ
3	(p_0, p_0, p_0, p_0)	p_0	(p_0, p_1, p_1, p_1)	$\frac{1}{4}p_0 + \frac{3}{4}p_1$	$\frac{3}{4}\Delta$
4	(p_0, p_0, p_0, p_0)	p_0	(p_0, p_0, p_1, p_1)	$\frac{1}{2}p_0 + \frac{1}{2}p_1$	$\frac{1}{2}\Delta$
average					$\frac{3}{4}\Delta$

Table 11: Dynamic Estimates of Once-and-for-All Effects by Aggregation Type

Lead/Lag	Calendar	Fiscal
$\widehat{\Delta}_{t-1}$	0	$\frac{1}{16}\Delta$
$\widehat{\Delta}_{t}$	$\frac{3}{8}\Delta$	$\frac{3}{4}\Delta$
$\widehat{\Delta}_{t+1}$	$\frac{5}{8}\Delta$	$\frac{3}{16}\Delta$
$\widehat{\Delta}_{t+2}$	0	0
$\widehat{\Delta}_{t+3}$	0	0
$\sum_{s=0}^{3} \widehat{\Delta}_{t+s}$	Δ	$\frac{15}{16}\Delta$
$\sum_{s=-1}^{3} \widehat{\Delta}_{t+s}$	Δ	Δ

Table 12: Estimated Dynamics with up to 10 Quarterly Price Changes (Fiscal Aggregation)

Lead/Lag Parameter	Value under Fiscal Aggregation
$\widehat{\Delta}_{t-1}$	$\frac{1}{16}\Delta_1$
$\widehat{\Delta}_{t}$	$\frac{5}{8}\Delta_1 + \frac{5}{8}\Delta_2 + \frac{3}{8}\Delta_3 + \frac{3}{16}\Delta_4 + \frac{1}{16}\Delta_5$
$\widehat{\Delta}_{t+1}$	$\frac{5}{16}\Delta_1 + \frac{3}{8}\Delta_2 + \frac{5}{8}\Delta_3 + \frac{13}{16}\Delta_4 + \frac{5}{8}\Delta_5 + \frac{5}{8}\Delta_6 + \frac{3}{8}\Delta_7 + \frac{3}{16}\Delta_8 + \frac{1}{16}\Delta_9$
$\widehat{\Delta}_{t+2}$	$\frac{5}{16}\Delta_5 + \frac{3}{8}\Delta_6 + \frac{5}{8}\Delta_7 + \frac{13}{16}\Delta_8 + \frac{5}{8}\Delta_9 + \frac{5}{8}\Delta_{10}$
$\widehat{\Delta}_{t+3}$	$\frac{5}{16}\Delta_9 + \frac{3}{8}\Delta_{10}$
$\sum_{s=0}^{3}\widehat{\Delta}_{t+s}$	$\left(\sum_{n=1}^{10}\Delta_n\right) - \frac{1}{16}\Delta_1$
$\sum_{s=-1}^{3}\widehat{\Delta}_{t+s}$	$\sum_{n=1}^{10}\Delta_n$

Notes: Δ_k is the (actual) change in price in the k-th quarter following Wal-Mart entry; $\widehat{\Delta}_{t+s}$ is the estimated price change in the s-th year after Wal-Mart entry.

Table 13: First-Stage SSIV Regressions

	Static 1st Stage	Dynamic First Stage SSIV Regressions				
	WMopen_{jt}	$\mathrm{WMopen}_{j,t+1}$	WMopen_{jt}	$\mathrm{WMopen}_{j,t-1}$	$\mathrm{WMopen}_{j,t-2}$	$\mathrm{WMopen}_{j,t-3}$
θ_{-1}		0.7823***	-0.1584***	0.0863	0.0521	0.0086
		(0.0528)	(0.0542)	(0.0553)	(0.0579)	(0.0596)
θ_0	0.8879***	0.1091	0.8840***	-0.1991***	0.0561	-0.0347
	(0.0360)	(0.0697)	(0.0717)	(0.0730)	(0.0765)	(0.0788)
θ_1		0.1885***	0.0995	0.8110***	-0.1584**	0.1938**
		(0.0717)	(0.0737)	(0.0751)	(0.0787)	(0.0810)
θ_2		-0.1305**	0.1673**	0.2106***	0.7932***	-0.3556***
		(0.0659)	(0.0678)	(0.0690)	(0.0723)	(0.0745)
θ_3		0.0441	-0.1082**	0.0513	0.2841***	1.0521***
		(0.0473)	(0.0486)	(0.0495)	(0.0519)	(0.0535)
F test	608	127	134	127	129	115
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs	2,786	2,786	2,786	2,786	2,786	2,786

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 14: First-Stage IV and Stage-Zero SSIV Regressions

	IV First Stage Regressions					Stage 0
	$WMopen_{j,t+1}$	$WMopen_{jt}$	$WMopen_{j,t-1}$	$WMopen_{j,t-2}$	$WMopen_{j,t-3}$	$WMopen_{jt}$
θ_{-2}	0.0419**	0.0198	-0.0029	-0.0053	-0.0265	0.0319***
	(0.0201)	(0.0207)	(0.0211)	(0.0225)	(0.0240)	(0.0030)
θ_{-1}	0.0369**	0.0368*	0.0170	-0.0200	-0.0322	0.0256***
	(0.0185)	(0.0191)	(0.0194)	(0.0207)	(0.0221)	(0.0030)
θ_0	0.3440***	0.0352*	0.0392**	0.0280	-0.0439**	0.1099***
	(0.0176)	(0.0181)	(0.0184)	(0.0196)	(0.0210)	(0.0030)
θ_1	0.2690***	0.3379***	0.0300*	0.0323*	-0.0005	0.4113***
	(0.0169)	(0.0174)	(0.0178)	(0.0189)	(0.0202)	(0.0030)
θ_2	0.1619***	0.2844***	0.3110***	0.0276	0.0194	0.2747***
	(0.0161)	(0.0166)	(0.0169)	(0.0180)	(0.0192)	(0.0030)
θ_3	0.0258	0.1640***	0.2850***	0.3090***	-0.0002	0.0854***
	(0.0161)	(0.0166)	(0.0169)	(0.0180)	(0.0193)	(0.0030)
θ_4	-0.0041	0.0245	0.1606***	0.2868***	0.2806***	0.0240***
	(0.0157)	(0.0161)	(0.0164)	(0.0175)	(0.0187)	(0.0030)
F test	92.8	96.0	91.0	76.4	35.2	3824
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs	2,786	2,786	2,786	2,786	2,786	88,765

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

null hypothesis that average prices of convenience-store items and clothing are unaffected by Wal-Mart entry.

B.3 IV Price Dynamics

Table 17 shows dynamic IV estimates using a single-sample procedure. Most of the long-run price-decline estimates for drugstore items are larger than in the SSIV estimates shown in the text (Table 7), but the results are (weakly) less significant. The latter is to be expected with a poorer instrument.

B.4 Size Regressions by 1980 Population

Table 18 shows both once-and-for-all and dynamic regressions by city size, where small and large cities are defined relative to 1980 median population in the sample (approximately 76,000 people). The correlation between number of establishments and population is strong, but not perfect, so these results differ slightly from those presented in Table 8 in the main text (Section 5.5). The long-run effect of Wal-Mart entry – *exclusive* of the pre-entry period – on drugstore prices is estimated at a decline of 6.7% for small cities – one percentage point less than in Table 8 – and the effect in large cities is estimated at an (insignificant) decline of 1.3%, a percentage point more than in Table 8. The long-run effect *inclusive* of the pre-entry period are strikingly similar to those presented in Table 8.

Table 15: Dynamic SSIV Estimates, Convenience-Store Items

	Beer	Cigarettes	Coke	Liquor	Wine	Combined Convenience
θ_{-1}	-0.0227	-0.0003	0.0272	0.0030	0.0040	0.0029
	(0.0213)	(0.0097)	(0.0266)	(0.0188)	(0.0313)	(0.0120)
θ_0	0.0211	0.0021	0.0008	-0.0175	-0.0002	0.0008
	(0.0249)	(0.0132)	(0.0384)	(0.0240)	(0.0410)	(0.0152)
θ_1	0.0074	0.0155	-0.007	0.0291	0.0248	0.0137
	(0.0232)	(0.0158)	(0.0393)	(0.0245)	(0.0381)	(0.0149)
θ_2	-0.025	-0.0091	-0.0274	-0.0269	-0.0638*	-0.0289**
	(0.0197)	(0.0145)	(0.0361)	(0.0241)	(0.0347)	(0.0138)
θ_3	0.0013	-0.0062	0.0263	-0.0069	0.0397	0.0101
	(0.0145)	(0.0099)	(0.0263)	(0.0158)	(0.0299)	(0.0108)
$\sum_{t=0}^{3}\theta_t$	0.0048	0.0022	-0.0074	-0.0222	0.0005	-0.0044
p-value	0.8118	0.8441	0.7792	0.2533	0.9866	0.7072
$\sum_{t=-1}^{3}\theta_t$	-0.0178	0.0020	0.0198	-0.0192	0.0045	-0.0015
p-value	0.2430	0.8434	0.4657	0.2124	0.8698	0.8864

Note: Robust standard errors in parentheses (clustered at the city level)

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 16: Dynamic SSIV Estimates, Clothes

	Shirt	Pants	Underwear	Combined Clothing
θ_{-1}	-0.0115	0.0037	-0.0204	-0.0107
	(0.0305)	(0.0332)	(0.0353)	(0.0216)
θ_0	0.0760*	0.0217	-0.0165	0.0283
	(0.0398)	(0.0395)	(0.0529)	(0.0256)
θ_1	-0.0475	-0.0647*	-0.0179	-0.0455*
	(0.0457)	(0.0346)	(0.0549)	(0.0270)
θ_2	-0.0436	0.0171	0.0122	-0.0032
	(0.0438)	(0.0368)	(0.0487)	(0.0281)
θ_3	0.0300	-0.0067	0.0253	0.0160
	(0.0324)	(0.0271)	(0.0392)	(0.0219)
$\sum_{t=0}^{3} \theta_t$	0.0148	-0.0325	0.0031	-0.0043
p-value	0.6446	0.3047	0.9378	0.8482
$\sum_{t=-1}^{3} \theta_t$	0.0033	-0.0289	-0.0173	-0.0150
p-value	0.8900	0.2582	0.6384	0.4117

Note: Robust standard errors in parentheses (clustered at the city level)

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 17: Dynamic IV Estimates, Drugstore Items

	Aspirin	Detergent	Kleenex	Shampoo	Toothpaste	Combined Drugstore	Combined Convenience	Combined Clothing
θ_{-1}	-0.0605**	-0.0145	-0.0274	-0.0067	-0.0156	-0.0249*	0.0048	-0.0234
	(0.0303)	(0.0233)	(0.0174)	(0.0251)	(0.0208)	(0.0147)	(0.0117)	(0.0222)
θ_0	0.0057	-0.0206	0.0073	-0.0073	-0.0126	-0.0057	-0.0006	0.0433
	(0.0340)	(0.0250)	(0.0213)	(0.0309)	(0.0233)	(0.0168)	(0.0145)	(0.0263)
θ_1	-0.0425	-0.0062	-0.0239	-0.0407	-0.0783**	-0.0382*	0.015	-0.0561*
	(0.0366)	(0.0307)	(0.0239)	(0.0349)	(0.0340)	(0.0194)	(0.0148)	(0.0298)
θ_2	0.0598	-0.0277	0.0202	0.0619*	0.0652	0.0359*	-0.0321**	0.0020
	(0.0392)	(0.0320)	(0.0263)	(0.0340)	(0.0406)	(0.0207)	(0.0148)	(0.0320)
θ_3	-0.0434	-0.0079	-0.0269	-0.0578	-0.0208	-0.0314	0.0205	0.0090
	(0.0441)	(0.0281)	(0.0257)	(0.0421)	(0.0462)	(0.0253)	(0.0175)	(0.0344)
$\sum_{t=0}^{3}\theta_t$	-0.0205	-0.0624**	-0.0232	-0.0438	-0.0465	-0.0394*	0.0028	-0.0018
p-value	0.5730	0.0346	0.2291	0.2554	0.1970	0.0671	0.8410	0.9494
$\sum_{t=-1}^{3}\theta_t$	-0.0809**	-0.0769**	-0.0507**	-0.0505	-0.0621	-0.0643***	0.0076	-0.0252
p-value	0.0432	0.0132	0.0206	0.1982	0.1332	0.0091	0.5907	0.3601

Note: Robust standard errors in parentheses (clustered at the city level)

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 18: Once-and-for-All and Dynamic SSIV Estimates by 1980 Population Size

	Drugstore		Convenience		Clothes	
	Small	Large	Small	Large	Small	Large
	Panel A: Once-and-for-All Estimates					
θ	-0.0585***	-0.0186	0.0068	0.0051	0.0031	-0.0076
	(0.0142)	(0.0131)	(0.0095)	(0.0098)	(0.0170)	(0.0200)
F stat	5.6218		0.0199		0.2281	
p-value	0.0189		0.8880		0.6336	
	Panel B: Dynamic Estimates					
θ_{-1}	-0.0194	-0.0156	0.0067	0.0004	-0.0178	-0.0037
	(0.0181)	(0.0206)	(0.0180)	(0.0167)	(0.0308)	(0.0310)
θ_0	-0.0195	-0.0043	-0.0041	0.0049	0.0423	0.0144
	(0.0244)	(0.0217)	(0.0246)	(0.0202)	(0.0417)	(0.0315)
θ_1	-0.0426*	-0.0260	0.0205	0.0076	-0.0466	-0.0497
	(0.0253)	(0.0269)	(0.0245)	(0.0206)	(0.0448)	(0.0416)
θ_2	0.0148	0.0474	-0.0311	-0.0281	-0.0086	0.0172
	(0.0272)	(0.0331)	(0.0225)	(0.0240)	(0.0441)	(0.0470)
θ_3	-0.0193	-0.0303	0.0085	0.0148	0.0168	0.0038
	(0.0185)	(0.0245)	(0.0150)	(0.0198)	(0.0289)	(0.0349)
$\sum_{t=0}^{3}\theta_t$	-0.0665***	-0.0132	-0.0062	-0.0008	0.0038	-0.0143
	0.0009	0.5815	0.6945	0.9637	0.8904	0.6712
$\sum_{t=-1}^{3}\theta_t$	-0.0859***	-0.0288	0.0005	-0.0005	-0.0139	-0.0179
p-value	0.0000	0.1359	0.9678	0.9703	0.5194	0.4570

Note: Robust standard errors in parentheses (clustered at the city level)

* significant at 10%; ** significant at 5%; *** significant at 1%

References

[1] Angrist, Joshua D. and Alan B. Krueger (1995). "Split-Sample Instrumental Variables Estimates of the Returns to Schooling." *Journal of Business and Economic Statistics* 13:2, 225-235.

[2] Basker, Emek (2003). "Job Creation or Destruction? Labor-Market Effects of Wal-Mart Expansion." University of Missouri Department of Economics mimeograph.

[3] Bresnahan, Timothy F. and Peter C. Reiss (1991). "Entry and Competition in Concentrated Markets." *Journal of Political Economy* 99:5, 977-1009.

[4] Chain Store Guide (1979-1982, 1987-1993). *Directory of Discount Department Stores*. New York: Business Guides, Inc.

[5] Chain Store Guide (1983-1986). *Directory of Discount Stores*. New York: Business Guides, Inc.

[6] Chamberlin, Edward (1933). *The Theory of Monopolistic Competition*. Cambridge, MA: Harvard University Press.

[7] Chevalier, Judith A., Anil K. Kashyap and Peter E. Rossi (2003). "Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data." *American Economic Review* 93:1, 15-37.

[8] Dinlersoz, Emin M. (forthcoming). "Firm Organization and the Structure of Retail Markets." *Journal of Economics and Management Strategy*.

[9] Edgecliffe-Johnson, Andrew (1999). "A Friendly Store from Arkansas." *Financial Times*, June 19, 1999.

[10] Feiner, Jeffrey M., et al. (2001). *Wal-Mart Encyclopedia X: Building a Global Brand*. New York: Lehman Brothers.

[11] Foley, Sharon, and Takia Mahmood (1996). "Wal*Mart Stores, Inc." Harvard Business School Case Study 9-794-024.

[12] Frankel, David M., and Eric D. Gould (2001). "The Retail Price of Inequality." *Journal of Urban Economics* 49:2, 219-239.

[13] Ghemawat, Pankaj (1989). "Wal-Mart Stores' Discount Operations." Harvard Business School Case Study 9-387-018.

[14] Ghemawat, Pankaj and Gregg Friedman (1999). "Wal-Mart in 1999." Harvard Business School Case Study N9-799-118.

[15] Hopkins, Jim (2003). "Wal-Mart's Influence Grows." *USA Today*, January 29, 2003.

[16] Hotelling, Harold (1929). "Stability in Competition." *Economic Journal* 39:153, 41-57.

[17] Kane, Thomas J., Cecilia Elena Rouse, and Douglas Staiger (1999). "Estimating Returns to Schooling When Schooling is Misreported." Princeton Industrial Relations Section Working Paper 419.

[18] The Lex Column (2003). "The Wal-Mart Way." *Financial Times*, February 19, 2003.

[19] McKinsey Global Institute (2001). "US Productivity Growth 1995-2000: Understanding the contribution of Information Technology Relative to Other Factors." Washington DC: MGI.

[20] Parsley, David C. and Shang-Jin Wei (1996). "Convergence to the Law of One Price without Trade Barriers or Currency Fluctuations." *Quarterly Journal of Economics* 111:4, 1211-1236.

[21] Peltzman, Sam (2000). "Prices Rise Faster than They Fall." *Journal of Political Economy* 108:3, 466-502.

[22] Reinganum, Jennifer F. (1979). "A Simple Model of Equilibrium Price Dispersion." *Journal of Political Economy* 87:4, 851-858.

[23] Sheshinski, Eytan and Yoram Weiss (1977). "Inflation and Costs of Price Adjustment". *Review of Economic Studies* 44:2, 287-303.

[24] US Bureau of the Census (various years). *County and City Data Book*. Washington, DC: US Government Printing Office.

[25] Vance, Sandra S., and Roy V. Scott (1994). *Wal-Mart: A History of Sam Walton's Retail Phenomenon*. New York: Twayne Publishers.

[26] Varian, Hal (1980). "A Model of Sales." *American Economic Review* 70:4, 651-659.

[27] Wal-Mart Stores, Inc. (1971-2001). *Annual Report*.