### Title
Firm Entry and Wages: Impact of Wal-Mart Growth on Earnings Throughout the Retail Sector




### Authors
Dube, Arindrajit
Lester, T. William
Eidlin, Barry



### Publication Date
2007-08-06

# FIRM ENTRY AND WAGES: IMPACT OF WAL-MART GROWTH ON EARNINGS THROUGHOUT THE RETAIL SECTOR

Arindrajit Dube
T. William Lester
Barry Eidlin

*Abstract:* This paper estimates the effect of Wal-Mart expansion on wages, benefits, and skill-composition of retail workers during the 1990s. We exploit the spatial pattern of Wal-Mart diffusion, radiating outward from the original store in Benton county, Arkansas, to control for potential endogeneity in store openings using both instrumental variable and control function approaches. Estimates from state and county level data suggest that store openings reduced both the average earnings and health benefits of retail workers. At the county level, a new Wal-Mart is found to reduce retail earnings, on average, by .5 to .9 percent. Moreover, we find that changes in skill-composition explain only a small part of compensation reduction, indicating that the decline in retail wages reflect a reduction in labor market rents.

Arindrajit Dube
Research Economist
Institute for Research on Labor and Employment
University of California, Berkeley

T. William Lester
Doctoral Candidate, City and Regional Planning,
University of California, Berkeley

Barry Eidlin
Doctoral Candidate, Department of Sociology
University of California, Berkeley

JEL Classifications: J31, J38, L81

## 1. Introduction

There is a growing literature on the importance of heterogeneity among firms competing in the same product market. In the retail industry, existing research shows that the vast majority of the productivity gains in the nineties occurred through the entry of new establishments, which typically were parts of larger chains. Similarly, there is a large literature showing substantial differences in pay between firms in the same industry, and substantial pay differences between industries for similar workers. However, little empirical evidence exists on how entry and exit of heterogeneous firms have changed labor market outcomes. In the retail context, did new higher productivity establishments have different wages compared to incumbent establishments? Moreover, how did entry affect the pay practices of competitors? And to what extent do such changes in wages reflect a difference in skill mix of the workforce, as opposed to changes in labor market rents?

In this paper, we use the growth of a single large employer, Wal-Mart to examine the causal effects of its diffusion on wages and benefits in the retail industry. The growth of Wal-Mart is interesting for several reasons. Since opening its first store in 1962 in Rogers, Arkansas, Wal-Mart has grown to become the world's largest company with a net income of \$11.2 billion on net worldwide sales of over \$312.4 billion for the 2006 fiscal year.[1] The chain grew rapidly over the 1990's to become the largest employer in the United States with 1.3 million workers. The sheer scale of its presence and growth allows us to study how it may have affected the retail labor market. In popular press, Wal-Mart has often been characterized as a low-wage and low-benefits employer, and resistant to the unionization of its workforce (Ehrenreich 2001, Featherstone 2004, Miller 2004). In spite of this popular perception,

[1] 2006 Wal-Mart Stores Annual Report.

however, to date there is little academic work on how the company's expansion may have transformed the retail wage structure.

Furthermore, there is substantial academic and anecdotal evidence that Wal-Mart and other big-box stores offer lower prices to consumers, in large part due to their scale, purchasing power, and supply chain efficiencies (see for example Ghemawat et. al (2003)) . Hence, Wal-Mart's phenomenal growth also allows us to study how the diffusion of a low-cost "lean" retailer affects wages and rents in the labor market.

Finally, economic pressure from Wal-Mart has been used as a rationale by competing retailers to seek wage and benefit cuts, as evidenced by the 2003 contract negotiations between Southern California grocery chains and their unions (Goldman and Cleeland 2003; Pearlstein 2003). Whether there is systematic effect of Wal-Mart's growth on competitors, however, is yet largely unexplored.

Using a database of Wal-Mart store openings, we identify Wal-Mart's effect on earnings of retail workers at the county and state level using the Quarterly Census of Employment and Wages (QCEW). Exploiting the pattern of Wal-Mart's expansion—radiating out of its Southern origin in Benton County, Arkansas—we devise a novel instrumental variable (IV) strategy: we use distance from Benton County interacted with time as a predictor of Wal-Mart store openings. This allows us to control for endogeneity of Wal-Mart entry that might contaminate estimates of Wal-Mart's effect on earnings. We also test for selection of Wal-Mart into counties where the effect on earnings is greater (or less) using a control function approach. In addition, we use an instrumented event-study methodology to confirm the time-path of earnings around the time of a store opening. Finally, using the March Current Population Survey (CPS), we test whether the wage effects can be explained by changing skill mix of the workforce, and further estimate the impact of Wal-Mart on the rate of employer-sponsored health insurance coverage.

We find that at the county level, the endogeneity of Wal-Mart store openings is a serious problem: omitted variables bias tends to attenuate the OLS estimate towards zero. IV estimates that exploit the spatial diffusion of Wal-Mart stores find that a single Wal-Mart store opening reduces the average retail earnings in a county by 0.5 - 0.9 percent. Moreover, the instrumented event-study results show a sharp drop in earnings around the time of Wal-Mart store opening, which provides further internal validity to our instrumenting strategy. Wal-Mart entry leads to a robust and statistically significant earnings reduction for workers in the general merchandise (around 1 percent) and grocery sectors (around 1.5 percent), but not for other non-competing retail sub sectors. In addition to a fall in average earnings per worker, we find that the retail sector total wage bill in a county falls by a similar or greater magnitude upon Wal-Mart entry.

The magnitude of the omitted variable bias in the OLS estimates is much smaller when we use state level variation, which suggests that endogeneity in location decisions are particularly pronounced at the county level. Evidence from the Current Population Survey suggest somewhat larger wage reductions than evidence from the QCEW. Ten new Wal-Mart stores in a state are found to reduce the average hourly wage of retail workers by around 2 percent. Finally, we show that ten new Wal-Mart store openings in a state lead to roughly a 1 percentage point reduction in the job-based health insurance rate for retail workers.

The wage reductions are only present in metropolitan counties, which employ the vast majority (83%) of retail workers. This can be explained by lower wage rates in rural counties (where more workers are close to the minimum wage). We also present some other theoretical rationales for such a finding. **Furthermore,** controlling for demographic composition of the retail workforce produced nearly identical estimates of Wal-Mart's effect on wage and health benefits. Hence, the wage reduction is likely to represent a fall in labor market rents and not just a change in the skill mix of retail workers.

The remainder of the paper is structured as follows. Section two discusses the literature. Section three presents theoretical rationales about how a low-cost retailer like Wal-Mart might choose to pay lower wages, and how it might affect wages of competitors. We present a simple model where retailers face a tradeoff between price and service quality, which in turn depends on wages. Section four describes our data sources and presents our identification strategy. Section five reports both descriptive statistics, and our key empirical results, as well as results from a variety of specification and robustness tests. Finally, section six concludes by reviewing the implications of our findings.

## 2. Literature Review

There was a considerable amount of restructuring in the retail industry over the 1990s. This restructuring is characterized by several trends including: (1) increased consolidation of retailers into large national chains; (2) introduction of new technology for inventory control and marketing; (3) restructuring of labor processes including deskilling and reskilling of jobs; and (4) weakening of unions (Davis et al. 2005; Belman and Voos 2004). The nineties also saw substantial productivity increases in the retail industry, and a majority of this increase came from the substitution of lower productivity establishments by higher productivity ones, especially from the expansion of high-productivity chains ( Foster, Haltiwanger and Krizan 2007). Given Wal-Mart's size and growth over this period, it was likely responsible for a large portion of this change.

While there is a good amount of evidence of how this churning process of establishment entry and exit has affected productivity in the retail sector, this is not the case for the impact on the labor market. At present, the few studies that directly measure the effect of Wal-Mart or big-box stores generally on employment, wages, and working conditions in the retail sector produce ambiguous results and have many limitations.

Davis et al. (2005) use a detailed matched employer-employee dataset to examine the impact of big-box retailers (including Wal-Mart) on human resource (HR) practices in the food retailing industry. They find that traditional grocery stores, which tend to be characterized by greater use of internal labor markets (ILMs), do not qualitatively alter their labor market practices in the face of spatially localized competition from big-box retailers that sell food (e.g. a Wal-Mart supercenter). They do find that firms with stronger ILMs are more likely than non-ILM establishments to go out of business when faced with increased competition from mass merchandisers. However, this study does not measure the net employment or wage change after big-box entry; moreover, the authors are not able to control for possible endogeneity in big-box location decisions.

Basker (2004) examined the impact of Wal-Mart entry on job creation, finding that "Wal-Mart entry has a small positive effect on retail employment at the county level while reducing the number of small retail establishments in the county" (p. 19). However, she did not look at the effect on wages. Moreover, Basker's identification strategy (using store numbers which reflect the planned sequence of opening as an instrument for the actual sequence of opening) may not control for endogeneity bias in her estimates. It is possible that most of the endogeneity in openings operates through the planning stage, as opposed to deviations from the planned openings. Goetz and Swaminathan (2004) look at the relationship between Wal-Mart penetration and overall county-level poverty rates using data from 1987 and 1997. They find that the growth in Wal-Mart stores between the two years is correlated with a more muted reduction in poverty rates. They attempt to control for endogeneity using initial values of poverty and other "pull factors" to instrument the number of Wal-Marts in 1997, but it is not clear to us that these "pull factors" satisfy the assumption of excludability. Moreover, they only consider two years, and do not use the timing of store openings more precisely.

The few studies that attempt to empirically estimate the impact of Wal-Mart entry on county or regional-level wage rates focus on a small set of counties in primarily rural states (Ketchum and Hughes 1997; Hicks and Willburn 1999). For example, Hicks and Willburn (1999) found a positive wage impact on a set of fourteen counties in West Virginia. However, their methodology was unable to attribute this wage growth uniquely to Wal-Mart's entry, as it was not able to control for endogeneity problems, or even county-specific factors. Moreover, it is unclear whether the wage impact of Wal-Mart entry in these rural counties are useful in understanding the way Wal-Mart's growth may be transforming the retail labor market nationwide. Because of the methodological shortcomings of previous studies, it remains to be seen whether there is a general "Wal-Mart effect" on retail sector wage levels as a whole, based on nationwide data. Since writing this paper, we became aware of a similar effort by Neumark, Zhang and Ciccarella (2006), who use a similar identification strategy to estimate the effect of Wal-Mart on the level of employment and the wage bill of retail workers. This work was done concurrently to our own (between 2004 and 2006). Unlike our paper, however, Neumark et al. do not provide evidence on the impact on average earnings or wages, or non-wage benefits; nor do they not look at changes in skill composition of workforce or try to discern any effects on labor market rents. Moreover, unlike this paper, they do not address concerns that time varying regional trends may confound the distance-time based identification strategy.

## 3. Theoretical Framework

There are both technological and institutional explanations for why Wal-Mart may have lower wages, and why it might put downward pressure on wages of competitors. Wal-Mart's lower procurement costs and supply chain efficiencies are well documented (Basker 2007 , Ghemawat et. al 2003, Gill et. al 1997). A retailer combines the purchased goods and sales labor to produce the final output, i.e., the combined bundle of goods and services for the shopper. If quality-adjusted labor and raw goods are substitutes in this production function, a fall in the supply cost of goods would lead the company to demand lower skilled workers, or lower worker effort level, leading to a lower wage level for workers. In this section, we present a simple model of employer behavior where this is indeed the case and for reasons that are easily interpretable.

The key aspect of the model is that retailers choose to compete on both price and quality of service. Service quality depends on wages, either because higher wages can attract better workers or because higher wages motivate workers more through an efficiency wage mechanism. Although the difference between these two channels is important in as much it means that lower wages imply lower rents as opposed to a different skill mix, the model presented here is general enough to accommodate both possibilities. We will show that retailers like Wal-Mart with lower cost of procuring goods due to supply-chain efficiencies will also tend to pay lower wages and compete more on price than service quality. Moreover, to the extent Wal-Mart's entry increases the product demand elasticity facing competitors, it reduces their incentive to provide higher wages and service quality.

We assume that a retailer maximizes profit $\Pi(p,e) = Q(p,e)\left(p - w(e)l - c\right) - F$. Here $Q$ is the total quantity of goods sold, $c$ is the unit supply cost, i.e., what the retailer pays suppliers to procure the good, and $p$ is the sales price charged by retailers. The demand elasticity $\frac{\partial Q}{\partial p}\frac{p}{Q} = \eta$ is negative. Additionally, retailers hire employees with skill or effort level *e,* which also denotes service quality. Higher service quality sells more goods, i.e., $\frac{\partial Q}{\partial e}\frac{e}{Q} = \xi > 0$, but requires higher wages, i.e., $\frac{\partial w}{\partial e}\frac{e}{w} = \mu > 0$. The positive relationship between labor quality (*e*) and wages exists either because employers face a positive wage-skill gradient in a competitive labor market, or because higher efficiency wages are required to improve worker effort. Service quality can be thought of broadly. It may entail more attention to customers, better disposition and presentation, answering customers' questions more accurately or promptly, or anything else that affects overall shopping experience and hence increases sales. Finally, *l* is the "raw" unit labor requirement to sell goods, and *F* is the fixed cost of production. Note that a higher wage increases worker and service quality, *e,* which increases sales, but doesn't change the unit "raw" labor requirement, *l*. This is the way in which we incorporate the notion that a higher wage specifically improves worker and service quality, as opposed to overall labor productivity.

The first order conditions with respect to *p* and *e* are as follows:

(1) $$\frac{\partial Q}{\partial p}\left(p - w(e)l - c\right) + Q(p,e) = 0 \quad \Rightarrow \quad p = \frac{1}{1 - \frac{1}{|\eta|}}\left(w(e)l + c\right)$$

(2) $$\frac{\partial Q}{\partial e}\left(p - w(e)l - c\right) - Q(p,e)\cdot l \cdot \frac{\partial w}{\partial e} = 0 \quad \Rightarrow \quad w(e) = \frac{\xi(p - c)}{\left(\mu + \xi\right)l}$$

The first condition is standard, stating that price is a markup over variable cost, where the markup is a function of the product demand elasticity. The second condition states that the optimal wage balances between the marginal profit from selling more goods and the increased inframarginal labor cost from a higher wage. Equation (1) can be substituted into equation (2), and with some rearranging of terms, it can shown that the optimal wage satisfies:

(3) $w(e^*) = \frac{c}{l\left(\frac{\mu|\eta|-1}{\xi}-1\right)}$

Several key insights of this model follow immediately:

1) All else equal, a retailer with a lower goods cost *c* will pay a lower wage, i.e., $\frac{\partial w}{\partial c} = \frac{w^*}{c} > 0$ as long as there is an interior solution. The intuition is that when the cost of procuring goods fall due to supply chain efficiencies, a retailer can "buy out" the higher effort level or skill needed to sell the goods, i.e., goods cost and wages are substitutes.

2) All else equal, a greater degree of product market competition (reflected by a higher $|\eta|$) implies a lower optimal wage, i.e., $\frac{\partial w}{\partial |\eta|} < 0$. A more elastic demand for the product means the markup has to be lower, and increased wage costs are harder to pass through to consumers. Consequently, service quality becomes more "expensive" from the retailer's perspective, and it reduces wages.

3) All else equal, a greater elasticity of demand with respect to product quality implies a greater optimal wage, i.e., $\frac{\partial w}{\partial \xi} > 0$. Intuitively, when there is more competition on quality at the market level, firms find it worthwhile to increase wage and service quality to attract customers.

The first point can help us understand why entry of a low-cost big box store would reduce wages. Imagine a single incumbent retailer, *R*, servicing the market with a high goods cost *c*. If the entry of lower-cost Wal-Mart triggers the shutdown condition for *R*, we have a situation where a lower cost retailer has substituted for a higher cost one in the market. If all the other characteristics of Wal-Mart and *R* are the same, equilibrium wages for retail workers will be lower, since $\frac{\partial w}{\partial c} > 0$.

Now consider a situation when an incumbent retailer does not have to exit due to Wal-Mart's entry as it still earns positive profits, and consider its optimal wage from equation (3). We do not explicitly solve for a monopolistic competition model with a low cost entrant, but a general finding of such a model is that entry increases the elasticity of product demand $|\eta|$ facing incumbent retailers. As discussed above, *ceteris paribus*, such an increase in the product demand elasticity leads to a wage reduction at competing firms, due to an increase in the elasticity and hence a decrease in the markup. Of course, $\xi$ may also change in light of Wal-Mart entry. Wal-Mart's lower service quality may increase the elasticity of demand with respect to quality facing the incumbent, as the incumbent retailer finds it more profitable to attract customers using a higher service quality (or niche) strategy. Overall, then, the incumbent's new wage may be either lower because of competitive pressure—as lower markups make it harder to pass the costs of service quality to customers. Or it may be higher as the incumbent retailer finds it worthwhile to increase wages and service quality to compete on the quality niche.

A further result from this model involves the elasticity of the wage as a function of required quality, i.e., $\mu$. As we note above, the impact of a low cost entrant on wages is greater when the initial equilibrium $w^*$ is greater in relation to the supply cost of goods, *c*. In places with higher overall wages where the *w(e)* schedule is shifted upwards, the elasticity of wage with respect to quality (i.e., $\mu$ ) will be greater at any given level of *e*. To see this, consider a particular wage schedule $w(e)=\omega_0+\omega(e)$. The elasticity $\frac{\partial w}{\partial e}\frac{e}{w}=\mu(e)$ is equal to $\frac{\frac{\partial \varpi}{\partial e}e}{\varpi_0+\varpi(e)}$, which in turn is a rising function of $\omega_0$. What this means is that in urban areas, which have generally higher wages than in rural areas, *ceteris paribus*, the impact from entry of a low wage retailer on wages may be greater.[2]

Finally, since wages are generally lower in rural areas than in urban ones, the entrant of a low-cost competitor is less likely to drive wages down further as the minimum wage becomes binding. This provides another rationale why the wage impact might be lower in rural areas.

Whether the reduction in wages and increase in worker quality reflects a shift in the composition of workers or increased rents to more incentivized employees is an empirical question, and we address this issue in our results.

Besides technological reasons, Wal-Mart may pay lower wages due to lack of unionization of its workforce. Wal-Mart's anti-union orientation has been well documented (see Human Rights Watch (2007), or Basker(2007) for a review), so as Wal-Mart enters a market, higher compensated unionized jobs may be substituted with lower compensated ones. Moreover, increased competition from a low-cost competitor like Wal-Mart might reduce

---

[2] Showing that $\mu(e)$ is lower in urban areas does not prove that $\mu(e^*_{urban})<\mu(e^*_{rural})$, but $\mu'(e)$ >0 is a sufficient condition for $\mu(e^*_{urban})<\mu(e^*_{rural})$. Note that in the case where the variable part of the function $w(e)=\omega_0+\omega(e)$ has a constant elasticity, such that $\frac{\partial\omega}{\partial e}\frac{e}{\omega}=\nu$, this condition is satisfied. Intuitively, a higher starting wage in the wage/quality schedule means a lower elasticity of wage with respect to quality, implying a lower equilibrium wage.

overall product market rents for competitors, and hence wages. This might be particularly true in places with higher union density, like in urban areas. Moreover, increased elasticity of product demand through competition implies an increased elasticity of labor demand, which is the well known Marshall's Law. If employers and the union bargain over the wage, but the employer sets the employment level *ex-post* unilaterally, under a large set of union preferences this leads to a lower negotiated wage level due to the increased threat of employment reduction by a firm facing a more competitive market. All of these mechanisms point to why retail wages may fall due to entry by a low-cost competitor when the incumbent retailers are paying higher wages and rents.

## 4. Data and Empirical Methodology

### 4.1. Data Sources

To track Wal-Mart entry over time by county, we use a database of Wal-Mart store openings made available by the retailer on its website in late 2005.[3] [4] We use two different data sources to evaluate the impact of Wal-Mart store openings on earnings. The first is the county-level Quarterly Census of Employment and Wages (QCEW) dataset compiled by the U.S. Bureau of Labor Statistics. The QCEW dataset is based on information filed by all private employers with State unemployment insurance agencies. Data on total employment (headcount) and the total earnings (wage bill) is reported at the 3-digit SIC level (Standard Industrial Classifications). We construct the average earnings for workers in a given industry by dividing the wage bill by the headcount measure for that industry.

---

[3] Wal-Mart posted its store opening dates on http://www.walmartfacts.com in 2005.

[4] An earlier version of the paper used store opening data compiled by Emek Basker. For more information about this dataset, see Basker, 2004. Generally, we had obtained similar results for our findings using the actual timing of the store openings. However, the Basker data seems to have a noticeable amount of measurement error, as Basker herself notes.

We are not able to distinguish between a reduction in average annual earnings that is due to lower hours of work from one that is due to lower hourly wages in the QCEW. (We deal with this issue by using the CPS, which does have data on hours.) The QCEW contains county-year level observations, with data on employment, total earnings and average earnings for the following industries: (1) retail overall (SIC 52), (2) general merchandise (SIC 53), (3) grocery (SIC 54), (4) rest of retail, (5) restaurants (SIC 58), and (6) the full labor force. We exclude counties with incomplete data (due to non-disclosure in the case of very small counties) for each industry.[5] Thus, for each retail segment we only use counties which have a full panel of disclosed data for that industry. The excluded counties are overwhelmingly small and rural and contain little employment in the general merchandise or grocery sectors. The final dataset was supplemented by the spherical distance between the geographic center of a county to Benton county, Arkansas, the location of the first Wal-Mart store. For state level analysis, we use the spherical distance between the center of the state to Benton county.

The second data source is the March Supplement to the Current Population Survey. Unlike the QCEW, the March CPS allows us to investigate both hourly wages (as opposed to annual earnings) as well as health benefits of retail workers, and additionally has demographic information about retail workers. However, most counties are not identifiable in the CPS, preventing a replication of the results from the QCEW at the county level. Moreover, rotations of counties in the sampling frame mean that not all counties are surveyed every period. For this reason, we conduct the CPS-based analysis at the state level, while providing analogous state level results using the QCEW for comparability. We create a state-year panel of average wages, own-employment sponsored health insurance (ESI) coverage rate, and

[5] To avoid identifying individual respondents the QCEW withholds data for industries in counties with very few employers or where a single firm represents more than 80% of the total industry employment. These ‘non-disclosed’ cases are flagged in the data.

demographics for (1) retail workers, (2) non-retail workers, and (3) lower educated non-retail workers. The average wage is defined as the annual earnings divided by weeks worked and usual hours worked per week. Demographic information includes proportion female, average age, proportion non-white, and proportion with high school education or less—for each of the three groups of workers. This information is then merged with the state level database of Wal-Mart store openings.

We restrict our analysis to the 1992-2000 period for several reasons. First, this is the period when Wal-Mart expanded outside the South and into major metropolitan areas. If the Wal-Mart effect is heterogeneous, and particularly depresses earnings in higher rent urban areas, then this period is a natural candidate. Second, focusing on a single episode of economic expansion reduces possible confounding effects due to cyclicality. Moreover, changes in industry codes and the nature of data collection makes the QCEW prior to 1988 less reliable. Similarly, health insurance questions were asked substantially differently in the March CPS before 1988, focusing more on household as opposed to individual worker coverage.[6]

### 4.2. Estimating Impact on Average Earnings

*4.2.1 The Spatial Nature of Wal-Mart Growth*

Between 1992 and 2000, Wal-Mart increased its number of U.S. stores by almost 40%, from 1,800 to 2,500 (Figure 1). Figure 2 reports the distribution and growth of stores by region, showing a heavy concentration of Wal-Mart stores in the South and the Midwest in 1992, and rapid growth in the West and Northeast over the nineties. This store distribution reflects the company's Southern origin, and a pattern of outward expansion. Figure 3 shows

[6] Extending the analysis to 1988 produces quantitatively similar findings.

that Wal-Mart went from having at least one store in 1,323 of 3,064 counties (42%) in 1992, to 1,673 of 3,064 counties (53%) in 2000. Wal-Mart's growth over the more recent period has come disproportionately from expansions in metropolitan areas (Figures 3 and 4). Figure 4 shows that while metropolitan counties accounted for 51% of stores in 1992, they accounted for 74% of store openings between 1992 and 2000.

Identifying the impact of Wal-Mart's expansion on wage levels may be confounded by possible endogeneity in store openings, as Wal-Mart may choose to enter counties likely to experience greater economic growth, which may in turn be associated with greater wage hikes. The primary way we address the endogeneity issue in this paper is by exploiting the spatial pattern of Wal-Mart growth. "Ground zero" for Wal-Mart is Benton County, in Arkansas.[7] Over time, Wal-Mart spread out over the rest of the country. But it did not do so in a haphazard manner. For instance, it didn't jump to New York, then to California, to then back to Tennessee. Rather, the spatial diffusion was much more like a ripple: the retailer used the strategy of growing in areas near existing operations before jumping to farther areas until the country was covered, and then grew evenly thereafter.

Until the early nineties, most of Wal-Mart's store openings were concentrated in the South and somewhat in the Midwest. This can be verified visually by Map 1 (showing the spatial distribution of stores in 1992). Moreover, the closer was an area to Benton county in 1992, the higher was the number of Wal-Mart *stores*. (Figure 5). In contrast, by the early nineties, the "Wal-Mart wave" of *store openings* had reached outer rings in distance from Arkansas. As shown in Figure 6, during the early nineties, the greater the distance from Arkansas, the greater was the number of store openings. This follows the logic of Wal-Mart's

[7] Wal-Mart opened its first store in the town of Rogers, which is part of this county; and its present day headquarters is located in Bentonville, also in Benton County.

expansion, which took advantage of distribution networks in an area before skipping to other regions. This "wave" phenomenon came to an end in the late nineties, when the wave smoothened out with a more even pace of growth throughout the distance gradient. This observation can also be verified by looking at the correlation coefficient between *store openings* and distance from Benton county by years (Table 1, second column): starting from a weak negative correlation in 1992, the correlation becomes strongly positive through 1998, at which point it reverses and falls back to close to zero by 2000. Correspondingly, the correlation between the *number of stores* and distance starts off as strongly negative in 1992, and falls close to zero by 2000, reflecting the growth away from Arkansas over this period (Table 1, first column).

The primary reason behind this growth pattern is that Wal-Mart wanted to make the most out of its local infrastructure such as distribution networks (Holmes 2005). Holmes argues that these economies of density can help explain the growth process exhibited by Wal-Mart. An earlier paper by Thomas Graff also documented Wal-Mart's strategy of locating Supercenters in places where they already had an existing grocery distribution network (Graff 1998). Graff contrasts this with Kmart, which seemed to set up its supercenters without taking advantages of such economies of density. A corollary to this pattern of growth is that, on average, the farther a county is from Benton, the later it experienced Wal-Mart growth until Wal-Mart "filled up" the landscape (around 1998), at which point it grew more evenly throughout the country.

The timing of growth allows for an interesting identification strategy. We can use the distance from Benton county (denoted as *dist* in equations below) as an instrument for the change in the number of Wal-Mart stores in a given county for a given year. Consequently, in the second stage we would only use the variation in Wal-Mart growth that is related to how far the county is from Benton county and the time period in question. Over our period of study (1992-2000), we see a rising and positive correlation between growth and distance until 1998, at which point growth becomes more even by distance (Figure 6). If there is an actual negative effect of Wal-Mart diffusion on wages, one would expect to see the relationship between wage changes and distance to be neutral starting in 1992, become negative over the mid nineties, and then become neutral again by 2000. This is the basis of the spatial identification strategy we employ in this paper.

*4.2.2 Regression Specifications using QCEW*

Our simplest specification is a fixed-effect model, which regresses the natural log of average annual earnings of various types of retail workers (ln(*earn*)) on the number of Wal-Marts that year (*WM*), and county and year dummies. To control for local labor market conditions, we include the log of average earnings for the total workforce in the county as an added regressor ($earn^T$). Moreover, we also include the log of restaurant worker earnings as an added control for low-skilled workforce conditions as one of the specifications.

$$(1)\ \ln(earn_{it}) = \beta_0 + \beta_1 \ln(earn_{it}^T) + \beta_2 \ln(earn_{it}^R) + \varphi WM_{it} + \overrightarrow{\Lambda} \cdot year_t + \overrightarrow{\Omega} \cdot County_i + e_{it}$$

A fixed-effect model does not rule out the possibility that Wal-Mart is entering counties that would otherwise have experienced faster wage growth. Formally, it may be that $Cov(WM_{it}, e_{it}) \neq 0$, that the number of Wal-Mart stores is correlated with the residual wage in that county. As described above, we use distance-time interaction to instrument for Wal-Mart growth. To implement this strategy empirically, we utilize a flexible specification in the first stage by forming *J* discrete distance quantiles (or rings) defined by the distance between the geographic center of a county from Benton, and interact these with year dummies. In the baseline specification, *J*=10, but we later try alternative values for *J*, as well as linear and quadratic specifications. The predicted number of Wal-Marts is a function of the distance quantile of the county and the year, as well as other second stage covariates, and is used in the second stage to estimate the impact on earnings. The next two equations formalize this approach:

(2) $\widehat{WM}_{it} = \eta_0 + \sum_{jt} \eta_{jt} \cdot Year_t \cdot Dist_j + \mathbf{X}\Gamma + \vec{\Theta} \cdot County_i$

(3) $\ln(earn_{it}) = \beta_0 + \mathbf{X}\mathrm{B} + \varphi \widehat{WM}_{it} + \vec{\Lambda} \cdot year_t + \vec{\Omega} \cdot County_i + e_{it}$

The vector $\mathbf{X}$ includes the log of average non-retail earnings, as looking at the relative earnings of retail workers controls for overall spatial trends in wages over this period that may be correlated with the radial pattern of Wal-Mart expansion. Restaurant wages are included as controls in some specifications for a similar reason. If Wal-Mart reduces wages through market channels, then restaurant wages may also be affected. To the extent they reduce wages through changing rents associated with retail jobs, however, wages of restaurant workers should be unaffected.

As a further check on diverging regional trends, we devise a much more localized form of IV estimation. This “neighbor difference” IV (IVND) considers the deviation in earnings between a county and the average of its neighboring distance ring. First we do a spatial first-difference: we take the *difference* in the number of Wal-Marts in a county *i* in ring *D* and the average number of stores in counties in the next inner ring *D-1*. The same first differencing is done for earnings. We then estimate the effect of Wal-Mart stores on earnings in the spatially-first-differenced form, having instrumented the first-differenced number of Wal-Mart stores by distance-time interaction.

(4) $\ln(earn_{it}^{ND} \mid i \in D) = \ln(earn_{it} \mid i \in D) - E\left(\ln(earn_{jt}) \mid j \in (D-1)\right)$

(5) $(WM_{it}^{ND} \mid i \in D) = (WM_{it} \mid i \in D) - E\left(WM_{jt}) \mid j \in (D-1)\right)$

(6) $\widehat{WM}_{it}^{ND} = \eta_0 + \sum_{jt} \eta_{jt} \cdot Year_t \cdot Dist_j + \mathbf{X}\Gamma + \vec{\Theta} \cdot County_i$

(7) $$\begin{aligned} \ln(earn_{it}^{ND}) &= \beta_0 + \mathbf{X}\mathrm{B} + \varphi \widehat{WM}_{it}^{ND} + \vec{\Lambda} \cdot year_t \\ &+ \vec{\Omega} \cdot County_i + e_{it} \end{aligned}$$

The standard first-differencing (over time) would control for differential trends by county. The "neighbor distance" specification does something similar, but allows for spatially correlated trends. By using only local variation between neighboring areas in the timing of Wal-Mart growth, it controls for arbitrary and time varying trends in retail wages that are shared by counties in two contiguous rings. This localized IV method allays the potential concern that differential trends in retail wages in different parts of the country may be correlated with the spatial diffusion of Wal-Mart store openings.

We also utilize an event study approach with an 8 year window that includes a larger set of leads and lags of the number of Wal-Mart stores (instrumented by distance-year interactions) to tease out the time path of earnings.[8] The estimated time path allows one to visually assess the impact of store openings on earnings over time, and gives additional evidence on the plausibility of the identifying assumptions. A fall in earnings close to the time of entry indicates that our results are unlikely to be driven by arbitrary regional trends that may be contaminating our results.

(8) $\ln(earn_{it}) = \beta_0 + \sum_{k=-4}^{3} \varphi_k L^j(\Delta\widehat{WM}_{it}) + \vec{\Lambda} \cdot year_t + \vec{\Omega} \cdot County_i + e_{it}$

The basic instrumental variable produces consistent estimates of the average treatment effect if the following assumptions hold:

[8] Because we have information on the number of Wal-Mart stores in a county through 2005 and prior to 1992, inclusion of leads and lags does not reduce the years included in the estimation sample.

(A1) $e_{it} \perp dist_{ij}$ ,

(A2) $\varphi_i \perp \Delta WM_{it}$ .

The first is an exclusion restriction, which requires that the residual retail earnings in year *t* is stochastically independent of the distance quantile. The "neighbor difference" IV replaces (A1) with the weaker assumption that the residual retail earnings are independent of the distance quartile *within neighboring rings.*

(A1b) $(e_{it} \perp dist \,|\, dist_{ij} \in \{dist_j, dist_{j+1}\})$

The second assumption (A2) states that the true effect of Wal-Mart on retail earnings is uncorrelated with Wal-Mart growth—that the treatment effect is independent of the treatment status. This is always satisfied in a constant coefficient model. However, in a random coefficient model, if the treatment effect ($\varphi_i$) is both heterogeneous and is correlated with the intensity of treatment (i.e., Wal-Mart penetration), the IV approach no longer estimates the average treatment effect, for either the entire population or those who are treated. Rather, it estimates the average treatment effect for an arbitrary subset of the population whose treatment status is affected solely by the variation in the instrument. This could be a concern if, for example, Wal-Mart targets highly unionized areas where the wage reduction from its entry would be particularly large. From a theoretical perspective, this certainly is feasible, and this type of selection effect would exert a negative bias on the IV estimates, leading them to overestimate the extent to which Wal-Mart openings affect retail earnings. Under certain assumptions, a control function approach can correct for both confoundedness due to omitted variables (correlated with Wal-Mart entry) as well as selectivity of Wal-Mart entry by treatment effect (see Card 2001; Chay and Greenstone 2005; Garen 1986; Heckman and Vytlacil 1999). The control function (CF) can be implemented through a two-stage process, where the first stage (as before) regresses the number of Wal-Mart stores on a function of time and distance. In the second stage, we include the treatment variable, as well as both the residuals from the first stage and the residuals interacted with the treatment variable as added regressors.

(9) $$WM_{it} = \eta_0 + \sum_{jt} \eta_{jt} \cdot Year_t \cdot Dist_j + \mathbf{X}\Gamma + \overrightarrow{\Theta} \cdot County_i + \varepsilon_t$$

(10) $$\widehat{res}_{it} = \hat{\varepsilon}_{it}$$

(11) $$\begin{aligned} \ln(earn_{it}) &= \beta_0 + \mathbf{X}\mathrm{B} + \varphi WM_{it} + \delta_1 \widehat{res}_{it} + \delta_2 \left( \widehat{res}_{it} \cdot WM_{it} \right) \\ &\quad + \overrightarrow{\Lambda} \cdot year_t + \overrightarrow{\Theta} \cdot County_i + e_{it} \end{aligned}$$

Inclusion of just $\widehat{res}_{it}$ in the second stage is identical to the two-stage least squares estimation. The additional $\widehat{res}_{it} \cdot WM_{it}$ term allows for the possibility that Wal-Mart store openings are occurring at times and places where the effect of treatment is particularly high or low. Hence, in the presence of potential correlation of Wal-Mart entry and the latent effect of treatment, the fitted $\varphi$ is a consistent estimator of the average treatment effect. The coefficient $\delta_1$ measures the importance of omitted variable bias. The coefficient $\delta_2$ measures the selection effect—the extent to which Wal-Mart entry may be correlated with the (heterogeneous) treatment effect.

We estimate all the models for the retail sector overall, for the general merchandise sector (which includes discount stores and department stores such as Wal-Mart, Kmart, Target, Costco, and Sears), as well as for grocery. We then estimate the models for other retail sectors together (except for restaurants), and for restaurants separately.

We also estimate the effect of Wal-Mart on log of *total* retail wage bill (as opposed to log of average earnings). The purpose of this exercise is to provide more evidence on whether the reduction in the average earnings is mainly due to (1) an addition of new lower paying jobs, while not changing the quantity or wages of existing jobs; or (2) a deterioration of overall job quality – either through substituting better paying jobs for lower paying ones, or through driving down the wages of existing jobs. In the wage bill regressions, we add the non-retail wage bill and the restaurant wage bill as controls analogous to earnings in those subsectors in the regressions above.

Finally, all of the above regressions are estimated using weights corresponding to the county population levels from the 2000 census to ensure that the treatment effect will be representative of the population as a whole. We also present unweighted estimates for comparison. Standard errors are clustered by county to control for autocorrelation, and are robust to heteroskedasticity. Since we have multiple instruments (distance-year dummies), we use GMM to estimate the equations for all IV specifications.

The effect of an added Wal-Mart on the average earnings of retail sub sectors may be different in metropolitan counties than rural ones, both because MSA counties are denser and because urban areas tend to have greater incidence of high rent firms – especially in grocery, which is unionized mainly in urban and suburban areas. Therefore, we also report estimates for the retail earnings and wage bill regressions separately for counties that are part of Metropolitan Statistical Areas (MSAs) and those that are not, using the 1999 MSA definitions.[9]

Finally, as an alternative instrumenting strategy, we estimate equations 3 and 8 (the basic and event study IV estimates) for retail earnings and the wage bill using state-year interactions as the instrument instead of distance-year interactions. This effectively uses

[9] The MSA definition is kept constant to avoid an artificial "growth" in Wal-Mart stores in a MSA as counties may be added over time.

between state variation (similar to the state-level regressions below), controlling for endogeneity in the timing of Wal-Mart entry into a county, but not into a state. If most of the endogeneity is local in nature, the results using distance-year instruments should be similar to those using state-year instruments. For robustness, we also present results from other first stage specifications including different distance quantiles and more parsimonious relationships between store openings and distance/time.

*4.2.3 Regression Specifications using the March CPS*

We use the March CPS to estimate Wal-Mart's impact on hourly wages, to control for demographic shifts induced by Wal-Mart entry, and to estimate the impact on health coverage. On average, the March CPS over the 1992-2000 period had 8,294 retail workers each year. As we noted earlier, most individuals do not have county identifiers, so we conduct the analysis at the state level. On average, each state had a mean of 168 retail workers each year, with a minimum of 48 and a maximum of 758.

To assess comparability with QCEW, we first re-estimate the OLS and IV panel regressions at the state level using the QCEW. We then re-estimate these using CPS data without any controls, as well as a full range of local labor market and retail-worker demographic controls:

$$\begin{aligned}(12)\quad \ln(wage_{it}) &= \beta_0 + \beta_1 \ln(wage_{it}^{N}) + \beta_2 \ln(wage_{it}^{low\text{-}ed}) + \overline{\Omega}\cdot\overline{X}_i + \varphi WM_{it} + \overline{\Lambda}\cdot year_t \\ &\quad + \overline{\Omega}\cdot County_i + e_{it}\end{aligned}$$

$X$ is a vector of characteristics of retail workers in a state—proportion male, proportion non-white, average age, as well as proportion with high school or lower level of educational attainment. As in our previous specification, $wage_{it}^{N}$ is the average wage earned by non-retail workers in state *i* in year *t*. In contrast to the QCEW specification, however, we replace the earnings of restaurant workers with a more direct measure of labor market conditions facing low-skilled workers: wage of non-retail workers with high school or lower level of educational attainment.

Analogous to wages, we also use the March CPS to estimate the impact of Wal-Mart entry on the job-based health coverage ( $y_{it}$ ):

$$\text{(13)} \quad \begin{aligned} \ln(y_{it}) = \beta_0 + \beta_1 \ln(y_{it}^{N}) + \beta_2 \ln(y_{it}^{low\text{-}ed}) + \vec{\Omega} \cdot \overline{X}_i + \varphi \widehat{WM}_{it} + \vec{\Lambda} \cdot year_t \\ + \vec{\Omega} \cdot County_i + e_{it} \end{aligned}$$

## 5. Findings

### 5.1 Impact of Wal-Mart Growth County-Level Retail Earnings

*5.1.1 Effect on average earnings*

Table 2 presents our main analysis of the impact of Wal-Mart on average earnings per worker across the entire retail sector. The baseline county-level OLS results (columns 1 and 2) show little evidence of a Wal-Mart effect. However, after adjusting for the endogeneity of store-openings and county-level wage trends, all estimates are negative and statistically significant. The IV estimate is the biggest in magnitude, while the OLS is the smallest, with the CF estimate is somewhere in between.

A comparison of the OLS and IV estimates suggest that omitted variables exert an upward bias in the OLS specification, attenuating the coefficient toward zero. This suggests that Wal-Mart entry is correlated with local trends in wages. This is consistent with an economic model where Wal-Mart chooses locations with greater growth in future demand, which would have counterfactually meant higher retail wages. The IV estimates correct for this upward bias by using variation in Wal-Mart growth unlikely to be correlated with local labor market conditions.

Besides this “omitted variables” bias, there can also be a “selection bias”—whereby Wal-Mart targets areas where wages are particularly high, say because competitors are paying higher rents to workers. As discussed above, in this case there may be heterogeneous effects of Wal-Mart entry, leading to a possible bias in the IV coefficients. Comparing the IV estimates with the CF estimates indicates that the CF coefficients are slightly smaller in absolute value. However, the “selection term” (WM*residual) is not statistically significant, meaning we cannot reject the null that there is no selection bias in the IV estimates. Overall, the net effect of the positive omitted variable bias is much larger than the negative selection effect (if it exists at all)--an outcome we find consistently in the remainder of the analysis.

Table 1 also presents the results of our alternative IV specifications. The “neighbor difference” IV specifications (columns 7 and 8) produce very similar results compared to the standard IV approach. This suggests that differential spatial trends in retail wages are unlikely to drive the results here.

Instrumenting county level store openings with state-year interactions (columns 9 and 10) produces results that are similar to the distance IV estimates, indicating that most of the endogeneity problem occurs at a more localized (i.e., county) level.

*5.1.2 Time path of Wal-Mart’s effect on wages*

We present the results of the event-study approach for average retail sector earnings graphically in Figure 7 along with the 95% confidence interval bands around the point estimates. The instrumented lags and leads show stable or slightly rising earnings until the year prior to entry (t-1), when earnings fall sharply. This stability in the pre-period and a fall around the time of entry provide further validation of our IV method, in that the distance-time interaction is not correlated with regional/time trends which may contaminate the findings.

Overall, the extent of wage loss in t+3 (which is a mixture of lags of 3 and greater and represents a "longer run" effect) is around -0.008, and is in the range of estimates in Table 2. The reduction in the year prior to Wal-Mart entry could reflect an anticipation effect, as the announcement of store opening precedes the actual opening by at least a year. However, since this is the effect of a predicted (instrumented) store opening, we should not read too much into the whether the earnings start falling at t-1 or t.

*5.1.3 Effect on average earnings in retail sub-sectors*

In Table 3 we repeat our OLS, IV and CF analysis for the more detailed retail sub-sectors which are most affected by competition from Wal-Mart—i.e, general merchandise (which includes Wal-Mart) and grocery. Additionally, we also examine the impact of Wal-Mart on non-competing sectors (rest of retail and restaurants). Looking at general merchandise (row 1), we find that the presence of an additional Wal-Mart corresponds to lower earnings in all of the specifications. In this sector the directly measured (OLS) Wal-Mart effect (-0.0089) is negative and significant at the 1% level, despite the fact that Wal-Mart tended to enter local labor markets with rising wages. When controlling for endogeneity the coefficients are somewhat higher in magnitude. The IV estimates suggest that an additional Wal-Mart reduces the average earnings of general merchandise workers by -0.011 and these coefficients are all statistically significant at the 1% level.

Earnings in the grocery sector are also reduced by Wal-Mart's presence (row 2). In this case the OLS coefficients are smaller and less precise, but the CF and IV estimates indicate a negative and statistically significant effect that is slightly higher in magnitude than the general merchandise sector. This finding confirms our expectation that Wal-Mart would reduce wages further in sectors which tend to have higher unionization rates (i.e. sectors with higher rents).

Looking at other retail sectors ("Rest of Retail" in Table 3), we do not see any clear pattern once we control for endogeneity bias. Overall, then, the Wal-Mart effect appears to be concentrated in the retail sub sector where the store competes—i.e., general merchandise and grocery. As for other retail sub sectors, the coefficient on Wal-Mart is not statistically significant in most of the specifications.

Finally, we find that for restaurant workers (another set of low wage workers), Wal-Mart has no clear effect on earnings. The OLS and CF specifications show no significant effect, while the IV result indicates a small negative impact (-0.0054). The IVND specification suggests a somewhat greater impact.

Overall, we find a strong effect of Wal-Mart entry on the two sub sectors that are affected directly (general merchandise and grocery), and weak or no effect in other retail sub sectors. The disaggregated results provide further internal validation of our findings on overall retail earnings.

*5.1.4 Robustness checks: first and second stage estimates*

Our first stage specification was based on distance deciles, allowing for a flexible pattern of growth of Wal-Mart as one moves further away from Benton county. Moreover, we used population weights to make the estimated treatment effect representative. Finally, we included non-retail earnings as a control in all the specifications. In Table 9, we perform sensitivity analysis (Table 9) on all these dimensions for our IV estimates.[10] Altogether, we present 9x4=36 specifications. 1) We have nine different first-stage specifications denoted by

[10] Since the CF estimates were substantially similar to our IV estimates, we do not report results from the specification checks here.

row numbers. We consider alternative numbers of distance deciles (between 8 and 18); two parsimonious specifications where we interact distance deciles with quadratic terms in time, and a fully continuous quadratic specification in distance and time; and finally another parsimonious specification where we instrument the number of Wal-Marts by the average number of Wal-Marts in distance-decile-year cells. 2) We also consider four different second stage specifications denoted by column numbers, and report the estimates with and without controls for non-retail earnings, and with and without population weights.

Overall, all these 36 estimates produce negative coefficients, and all but one are significant at the 5% level (the other one is significant at the 10% level). The number of distance bins *per se* does not seem to matter very much. Considering column 1 (which includes our preferred specification at row 2), rows 1 to 6 produce coefficients between -0.0075 and -0.0037.

Estimates including controls for non-retail earnings are often similar to those without, and usually only somewhat smaller—especially when weights are used. For example, in our preferred specification with N=10 and weights, not including non-retail earnings as a control produces an estimate of -0.008 (row 2, column 3), as opposed to -0.0069 (row 2 column 1).

The estimates with and without population weights are not substantially different. Considering our preferred specification with N=10, comparing the first and second columns produce estimates of -0.0069 and -0.0066, both being significant at the 5% level. As we will see below, the wage impact is concentrated in MSA counties only, which constitute a minority of the balanced panel sample. The fact that the weighted and unweighted estimates are similar in magnitude may appear to be a puzzle in light of that fact. However, the reason why this is not surprising is that the vast majority (74%) of store openings in this period happened in MSA counties (see Fig. 4), meaning that the variation in stores used in the regressions is coming mainly from larger counties—whether or not we use population weights. The first stage F statistics are typically larger when we do not use weights.

Considering more parsimonious formulations (rows 7 and 8) which use quadratic terms in time interacted with either distance deciles or quadratic terms in distance, we encounter two important findings. First, the second stage estimates are nearly the same in these specifications as compared to our preferred specification of N=10 (row 2). Secondly, the parsimonious specifications without weights have much larger first stage F statistics (over 10). This is not unexpected; these specifications have much fewer instruments than the flexible year-cross-distance-quantile specifications. Along the same line, if the number of Wal-Marts in a county is instrumented by the *average* number of Wal-Marts in year-distance cells, (row 9) we get similar second stage results, but much greater first stage F statistics (close to 100). The fact that these higher first stage F statistics were associated with quantitatively similar second stage estimates allays concerns that the finding of negative earnings effects in the paper is driven by a weak-instrument bias.

Overall, the specification checks in this and the previous section indicate that there is a substantial and statistically significant effect of Wal-Mart growth on average earnings of retail workers. This finding is generally robust to the nature of the first stage specification, weighting and inclusion of other controls.

*5.1.5 Effects on retail sector wage bill*

In addition to measuring the impact on average wages we also estimate Wal-Mart's influence on the wage bill (i.e., total earnings by all workers) in retail sectors. This measures the combined effect of reduced wages and the net job growth (or loss) associated with new

Wal-Mart stores. In Table 4 we report the findings using OLS, IV and CF approaches, as well as the alternative IV specifications (IVND and state-year interactions).

All five approaches show a reduction in the wage bill across the entire retail sector. The OLS estimate is small and insignificant, but the CF and IV specifications show a substantial and statistically significant impact (around -0.015). This suggests that a Wal-Mart store opening reduces the combined earnings of retail workers in a typical county by around 1.5%. Again, the IV and CF specifications suggest that the OLS estimate is biased downward (in magnitude) due to omitted variables bias, and not affected much by selection bias. Analogous to the average wage impacts (Table 1) we see that using the state-year interaction (columns 9 and 10) as the instrument produces point estimates very close to the distance-based IV result (columns 5 and 6). We note, however, that the "neighboring difference" formulations (columns 7 and 8) produce much smaller and either marginally significant or insignificant estimates.

Overall, we interpret the evidence to indicate that a Wal-Mart store opening reduces total earnings of retail workers in the county when both wages and employment are taken into account. Indeed, the wage bill coefficients are typically larger than the average earnings coefficient, suggesting that in our sample there was no compensating positive employment growth associated with a Wal-Mart store opening. However, the contrary results from the "neighboring difference" specifications suggest some caution in interpreting the evidence on this question. However, as we show later, the results from MSA counties are quite robust in this regard.

### 5.2 Retail Wages, Skills, and Health Insurance Coverage

In this section, we analyze whether the reduction in average earnings from Wal-Mart entry can be explained by changes in hours of work, skill composition, or fringe benefits. We use the March CPS, which allows us to examine average hourly wages (as opposed to earnings per worker), employer-sponsored health insurance (ESI), and the demographics of the retail workforce—namely, gender, age, education, and race. All regressions include state and year fixed effects. For comparison, we also report the equivalent state-wide regressions using the QCEW. The first two columns report the OLS coefficients on log average earnings using the QCEW dataset. Here we detect a smaller direct impact that is only significant when controlling for the earnings levels in other sectors. It is reasonable to expect that the impact of one additional Wal-Mart store is diluted when we aggregate to the state level which is a much larger economy. Three separate specifications are reported from the March CPS analysis. Column 3 uses only fixed-effects while columns 4 and 5 control for the wage levels of workers with lower levels of educational attainment and general demographic conditions in each state.

The IV estimates for the QCEW (columns 6-7) and CPS (columns 8-10) are similar in magnitude to their corresponding OLS specifications. We already previewed this finding when we saw that instrumenting store openings by state-year interactions produced results similar to instrumenting with distance-year interactions suggesting that much of the endogeneity in Wal-Mart entry is local in nature. Comparing the specifications with and without controls for retail workforce demographics (columns 9-10), we find that relatively little of the wage reduction can be explained by observed skill mix; the coefficient changes from -0.0021 to -0.0017 when added controls are included. The CPS based results suggest that 10 new stores in a state reduces average wages by around 2 percent. In principle, we could also have controlled for time-invariant unobserved skills by matching March CPS data across years. But the number of workers switching in and out of retail in the dataset is too small to conduct a meaningful analysis. However, controlling for usual human capital linked variables (which are all significant predictors of wages in the retail market) did not substantially alter the estimate, which suggests that at least some of the wage changes are not due to skill-related factors and instead reflect a reduction in labor market rents.

We should note that the estimated reduction in wages from the CPS is about four times the estimated reduction in earnings per worker from the QCEW. Ten new Wal-Mart stores are found to reduce retail earnings by 0.5% according to QCEW, and by 2% according to the CPS. We think that key differences between the two datasets may partly explain why we may observe a larger wage impact in the CPS. First, the QCEW earnings figures include additional forms of compensation besides hourly or annual wages.[11] These methods of compensation are not typically relevant to the section of the retail workforce likely to be impacted by the Wal-Mart effect (i.e. retail clerks). In contrast, the March CPS wage figure does not include stock options and other forms of bonus payment. Secondly, to the extent that average hours of work per person rises from Wal-Mart entry, that can explain the more muted response in earnings-per-worker as compared to wages per hour. Finally, the population in question is different in the two datasets: the QCEW aggregates earnings for retail workers over a year where each worker effectively gets a weight equal to the number of months they spent in the retail sector. In contrast, the March CPS measure averages the wages of all workers who worked at all in the retail sector, each weighted equally. However, the size of the difference in the estimates from the two datasets remains somewhat of a puzzle in our opinion.

Finally, we estimate the impact of Wal-Mart entry on the rate of employer sponsored health insurance among retail workers at the state level (reported in Table 6). We include

[11] Specifically the QCEW includes bonuses, stock options, the cash value of meals and lodging, tips and other gratuities, and, in some states, employer contributions to certain deferred compensation plans such as 401(k) plans.

OLS and IV specifications with covariates similar to those in Table 4. The IV specification suggests that an additional Wal-Mart store opening is associated with a reduction in the ESI coverage rate of 0.1% for retail sector workers. While this effect may appear small, it is important to note that this represents the impact of a single Wal-Mart store. The total impact of 10 new stores in a state is to reduce ESI coverage by 1 percentage point among retail employees.

### 5.3 Impact of Wal-Mart Growth on Retail Earnings in MSA and non-MSA Counties

#### *5.3.1 Effect on average earnings*

Lastly, we repeat our analysis on earnings of retail workers based on the QCEW separately for metropolitan and non-metropolitan counties. As described in section 3, to the extent Wal-Mart's effect on wages operates through a reduction in rents, the effect may be more pronounced in metropolitan areas, due to the greater presence of unions and higher rent firms.

Our baseline results of Wal-Mart growth on average earnings of workers are reported in Table 7. The first stage regression (predicting the number of Wal-Mart stores based on the distance of the county from Benton county) is done separately for non-MSA counties, to account for a possibly different time pattern of Wal-Mart expansion by metro status over this period.

As Table 7 shows, Wal-Mart entry reduces average earnings in metro counties, but not in rural ones. Interestingly, for metro counties, the OLS estimates are close to zero, while estimates controlling for endogeneity are all negative and similar to the analysis with the full set of counties. In contrast, for non-metro counties, we do not find a clear result. The OLS estimates are negative, the IV and CF estimates are sometimes positive and never significantly different from zero, while the "neighboring difference" ones are negative and significant.

Overall, the evidence does not point to a clear reduction of average earnings from Wal-Mart entry in non-metro counties.   This finding is consistent with the argument that lower initial wages in rural areas diminish the impact of Wal-Mart on retail wages.   This is both because mechanically, minimum wages are more likely to be binding for  non-MSA counties' retail workers, which means there is less  scope for a wage reduction. For example, average earnings were 22% higher in MSA counties in our sample.   Furthermore, as we showed in section two, when service quality depends on worker quality and hence wages,  the impact of a low cost entrant on wages is greater for higher initial values of the equilibrium wage—which is more likely to be the case in urban areas.

*5.3.2  Effect on retail wage bill*

We also report the effect of Wal-Mart entry on total wages in metro and non-metro counties in Table 8.  Similar to our results for the pooled sample, we find a strong negative effect of a store opening on the wage bill for metro counties which is usually larger than the effect on average earnings.   In the national sample, the "neighboring distance" specification was the only one without a clear negative effect on the wage bill  (Table 4).  In metro counties, however, we find a clear effect of a Wal-Mart store opening on the wage bill for *all* specifications, including the "neighboring difference" IV variety.  This strengthens the evidence that at least in metro areas, a store opening reduces both the average and total earnings of retail workers.

Similar to our evidence on average earnings, we find that for non-metro counties, there is very little evidence of any systematic effect.  The signs of the coefficients vary by specification, and none (save the OLS estimates) are statistically significant.

## 6. Conclusion

Wal-Mart played an important role in reshaping retail in the United States over the 1990s. The evidence presented here shows that it also had an important effect on the retail labor market. Using a variety of identification strategies, we find strong evidence that Wal-Mart entry reduced average and total retail earnings, retail wages, and health benefits for retail workers over this period—primarily in urban areas. At the county level, a single Wal-Mart store reduced retail earnings by ½ percent. At the state level, on average, ten new Wal-Mart stores reduced average earnings (or wages) by between ½ to 2 percent, and reduced job-based health coverage by 1 percentage point. The earnings losses were concentrated in retail sub sectors affected by competition from Wal-Mart—general merchandise and grocery. Moreover, instrumented event-study evidence shows a sharp decline in earnings around the time of Wal-Mart store openings. Finally, the fact that earnings fell for grocery workers demonstrates that store openings changed average earnings not only through a composition effect (i.e., substituting lower paid jobs for better paid ones), but also through driving down wages of competitors. The bulk of the reduction in compensation was not due to changes in workforce characteristics, suggesting that Wal-Mart reduced labor market rents for retail workers.

In light of the fact that Wal-Mart also seems reduce consumer prices, a question may arise regarding the effect on *real* as opposed to *nominal* wages. First, we should note that the decline in *relative* earnings of low-end retail workers is relevant for understanding the evolution of inequality. The gains from price reductions are shared more broadly among low and high (nominal) wage workers than the reductions in wages which accrue disproportionately to low-wage workers. Also, while price savings may indeed offset some of the wage reductions, they are quite unlikely to reverse it. Although a full analysis is beyond the scope of this paper, some back of the envelope calculations are instructive. Let us postulate that Wal-Mart's prices are around 25% lower than competitors, which is about the middle of the range suggested by Basker (2007). Moreover, Wal-Mart's market share in retailing is around 35%. Finally retail expenditure as a fraction of overall consumer budget is only around 15% (food at home, household goods, apparel, etc.) (see Bernstien, Bivens, and Dube 2006). This suggests that Wal-Mart's contribution to the national Consumer Price Index is somewhere around 0.25 x 0.15 x 0.35 = 0.013 or 1.3%. In contrast, our estimates from the CPS suggest that 10 new Wal-Mart stores in a state reduce average retail wages by 2%. With an average of 76 stores per state, this suggests a net *nominal* wage reduction of 15.2% for retail workers and a real wage reduction of 15.2% -1.3% = 13.9%. To be sure, this is a crude estimate; but it does show the order of magnitudes involved when evaluating the net effect on retail workers.

The totality of evidence suggests that the expansion of low-cost retailing has put a downward pressure on the wages of the retail workforce. Moreover, it also seems to have lowered labor market rents for workers during this period. Given the importance of the retail industry as an employer of low-wage workers, the transformation of retailing is an important factor to consider when explaining the evolution of wages in the low-end labor market.

## 7. References


Andersson, Fredrik, Harry Holzer, and Julia Lane. 2002. "The Interaction of Workers and Firms in the Low-Wage Labor Market." *LEHD working paper.*

Basker, Emek. 2004. "Job Creation or Destruction: Labor Market Effects of Wal-Mart Expansion." *Review of Economics and Statistics* 87(1), 174–183.

Basker, Emek. 2007. "The Causes and Consequence of Wal-Mart Growth." *Unpublished Manuscript.*

Bernstein, Jared, Josh Bivens and Arindrajit Dube. 2006. "Wrestling with Wal-Mart: Tradeoffs between Profits, Prices, and Wages." *EPI Working Paper*.

Card, David. 2001. "Estimating the Return to Schooling: Progress on Some Persistent Problems." *Econometrica* 69 (5): 1127-1160

Chay, Kenneth and Michael Greenstone. 2005. "Does Air Quality Matter? Evidence from the Housing Market." *Journal of Political Economy*, April: 376-424.

Davis, Elizabeth, Freedman, Matthew, et. al. 2005. "Product Market Competition and Human Resource Practices: An Analysis of the Food Retail Sector" *Unpublished Manuscript.*

Dube, Arindrajit, and Ken Jacobs. 2004. "Hidden Cost of Wal-Mart Jobs: Use of Safety Net Programs by Wal-Mart Workers in California." Berkeley, Calif.: University of California, Berkeley Center for Labor Research and Education.

Ehrenreich, Barbara. 2001. *Nickel and Dimed: On (Not) Getting by in America*. New York: Metropolitan Books.

Featherstone, Liza. 2004. "Will Labor Take the Wal-Mart Challenge?" in *The Nation*.

Foster, Lucia, John Haltiwanger, and C.J. Krizan. 2007. "Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s." *Review of Economics and Statistics* 88(4): 748-758.

Garen, John. 1984. "The Returns to Schooling: A Selectivity Bias Approach with a Continuous Choice Variable." *Econometrica* 52: 1199-1218.

Ghemawat, Pankaj, Ken A. Mark, and Stephen P. Bradley. 2004. "Wal-Mart Stores in 2003." Cambridge, Mass.: Harvard Business School Case Study.

Gill, Penny, and Jules Abend. 1997. "Wal-Mart: The Supply Chain Heavyweight Champ." *Supply Chain Management Review* 1:8-16.

Goetz, Stephan J., and Hema Swaminathan. 2004. "Wal-Mart and County-Wide Poverty." in *AERS Staff Paper No. 371*. College Park, Penn.: Department of Agricultural Economics and Rural Sociology, Pennsylvania State University.

Goldman, Abigail, and Nancy Cleeland. 2003. "An Empire Built on Bargains Remakes the Working World." in *Los Angeles Times*. Los Angeles.

Graff, Thomas O. 1998. "The Locations of Wal-Mart and Kmart Supercenters: Contrasting Corporate Strategies." *The Professional Geographer* 50 (1), 46-57.

Heckman, James and Edward Vytlacil. 1999. "Local Instrumental Variables and Latent Variable Models for Identifying and Bounding Treatment Effects." *Proceedings of the National Academy of Science*, 96: 4730-34.

Hicks, M.J. & Wilburn, K. 2001. "The Regional Impact of Wal-Mart Entrance: A Panel Study of the Retail Trade Sector in West Virginia." *Review of Regional Studies,* 31 (3).

Human Rights Watch. 2007. "Discounting Rights: Wal-Mart's Violation of US Workers' Rights to Freedom of Association." *Human Rights Watch Report*, 19 (1).

Ketchum, B.A., & Hughes, B.W. 1997. "Wal-Mart and Maine: The Effect on Employment and Wages." Maine Business Indicators, XLII (3)

Miller, Rep. George. 2004. "Everyday Low Wages: The Hidden Price We All Pay for Wal-Mart." Washington, D.C.: Democratic Staff of the Committee on Education and the Workforce, U.S. House of Representatives.

Neumark, David, Junfu Zhang, and Steven Ciccarella. 2005. "The Effects of Wal-Mart Openings on Local Labor Markets." *Unpublished manuscript.*

Pearlstein, Steven. 2003. "Wal-Mart's Hidden Costs." Pp. 1 in *Washington Post*. Washington, DC.

Wal-Mart Stores. 2006. "Annual Report to Shareholders."

## 7. Figures and Tables

**Figure 1 Number of Wal-Mart stores in the United States, 1992-2000.**

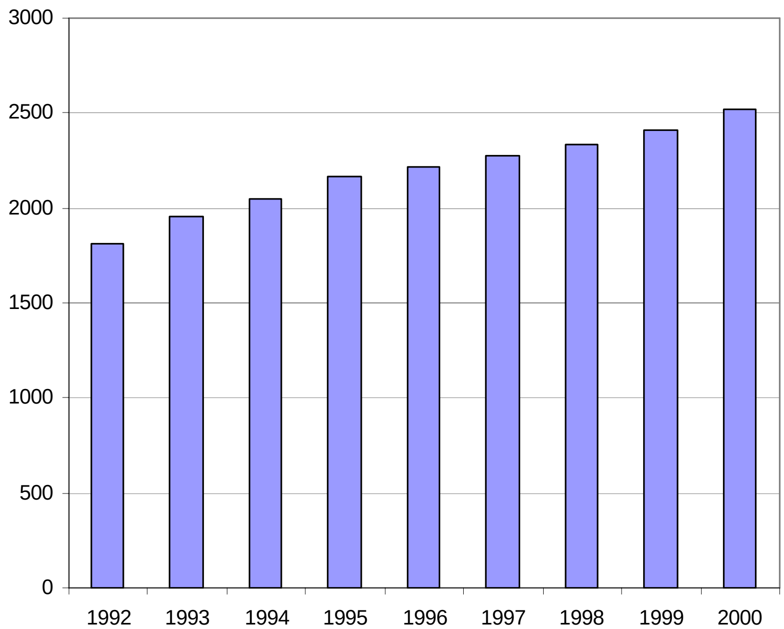



**Figure 2 Distribution and Growth of Wal-Mart stores by region, 1992-2000.**

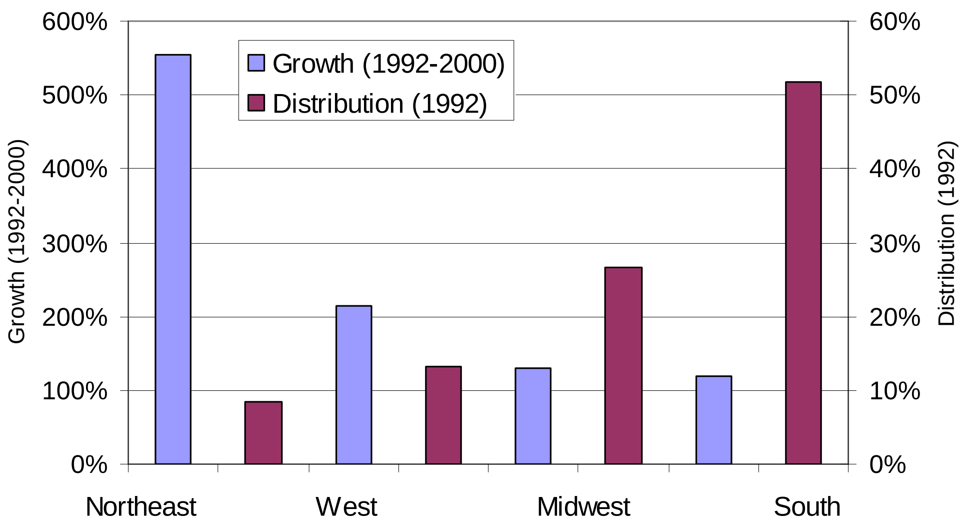


**Figure 3. Number of counties with at least one Wal-Mart store – by Metropolitan status, 1992 and 2000**

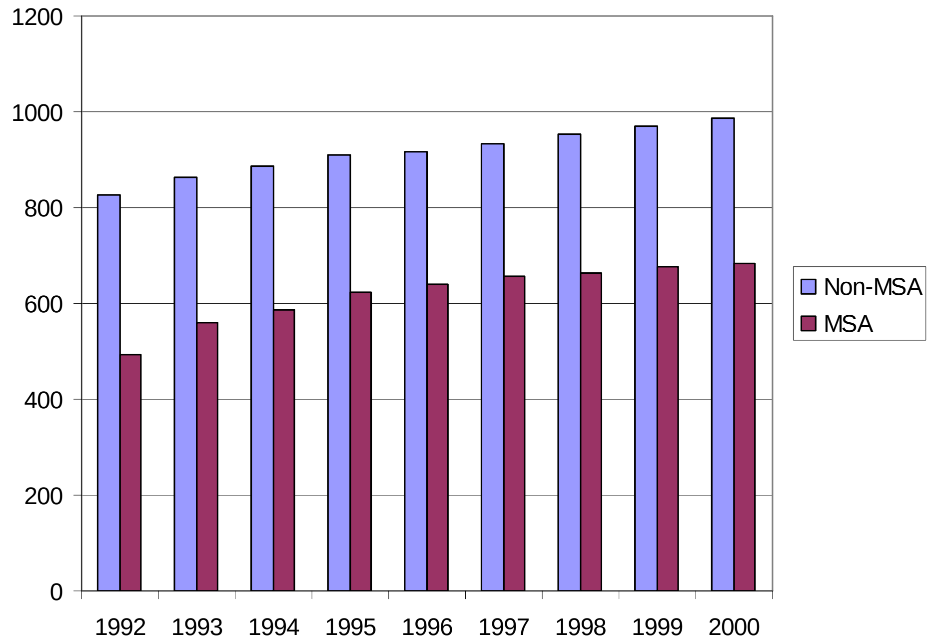



**Figure 4. Metropolitan composition of existing stores and store openings**

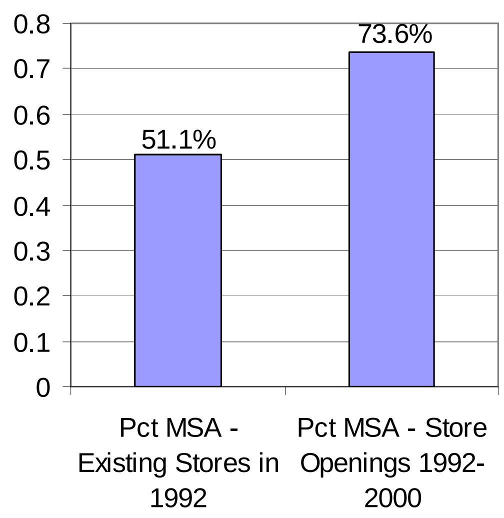


**Figure 5  Number of Wal-Mart Stores - by Distance Deciles**

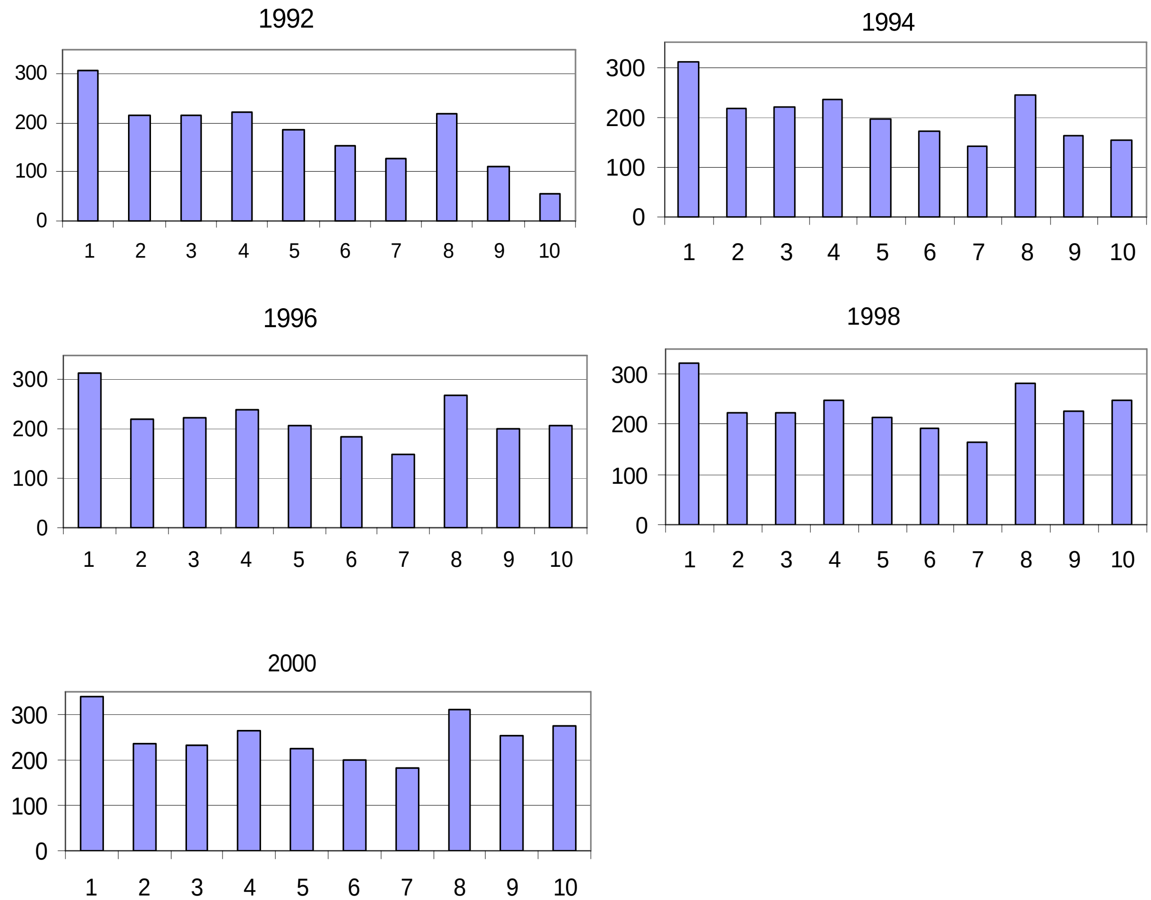


**Figure 6 Number of Wal-Mart Store Openings - by Distance Deciles**

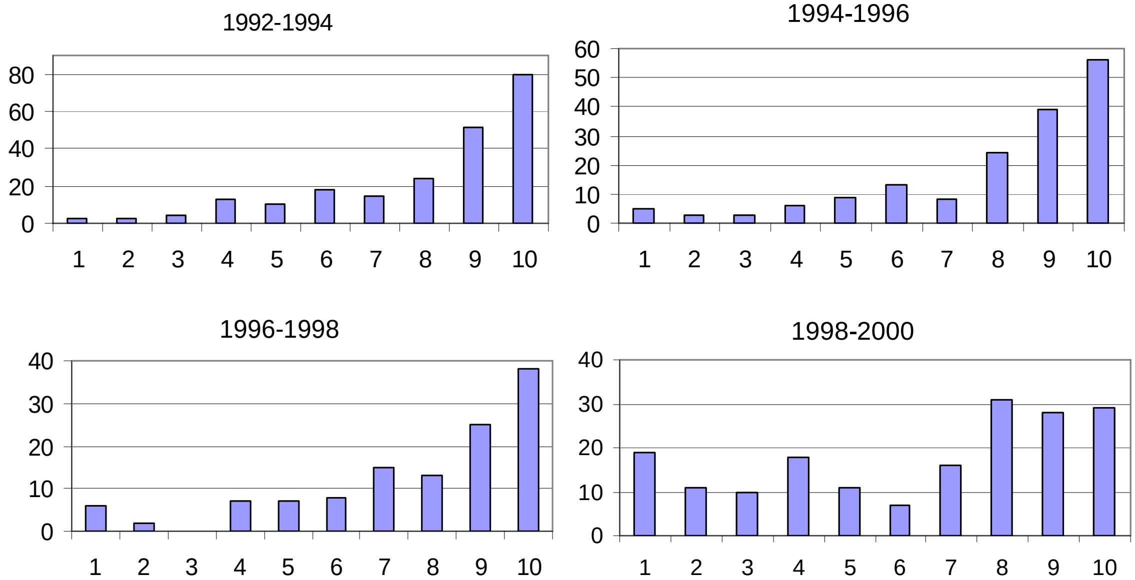


**Figure 7  IV Time path of Wal-Mart effect on average retail wages– all Counties (QCEW)**

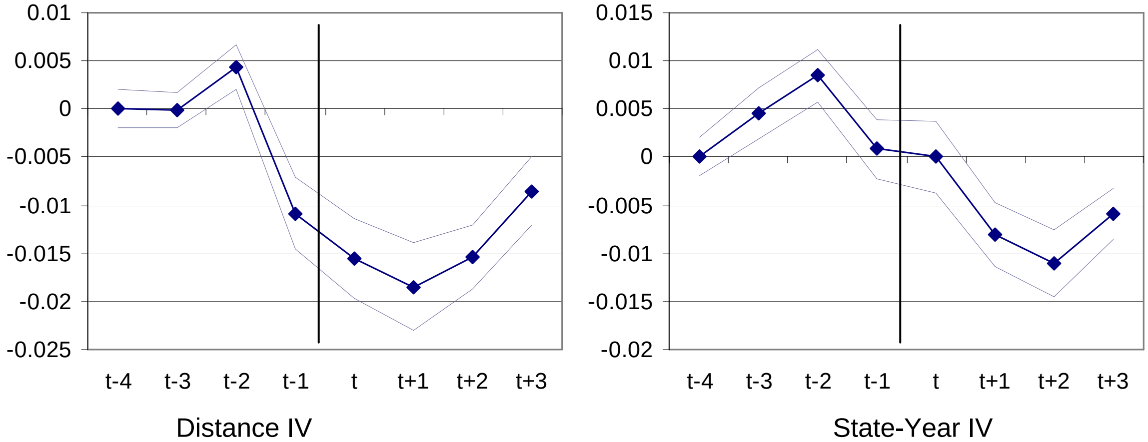
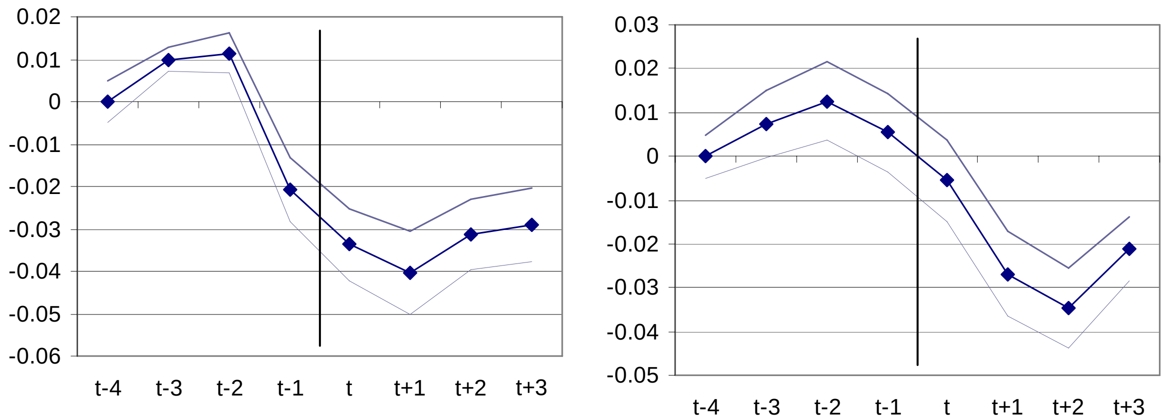



**Figure 8  IV Time path of Wal-Mart effect on total retail wage bill– all Counties (QCEW)**




Distance IV State-Year IV

**Figure 9  IV Time path of Wal-Mart effect – MSA Counties (QCEW)**

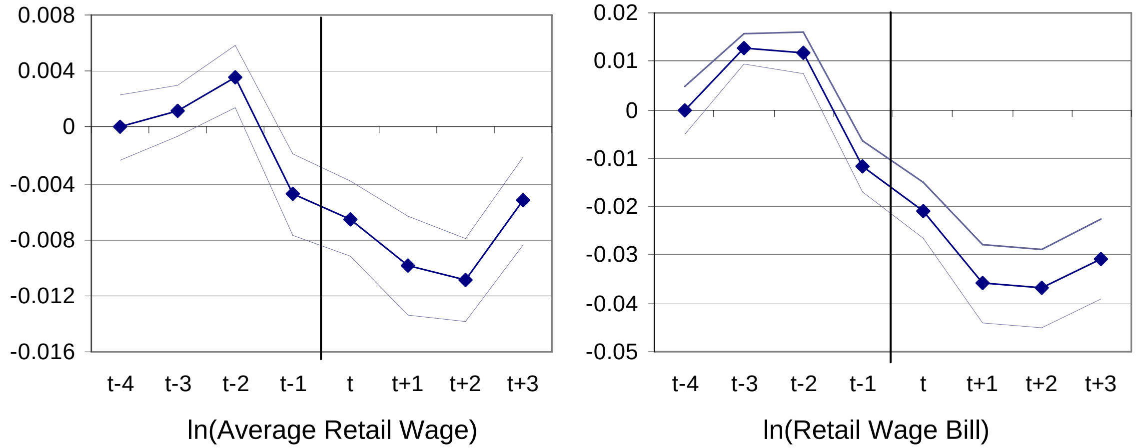



**Figure 10  IV Time path of Wal-Mart effect - non MSA counties (QCEW)**

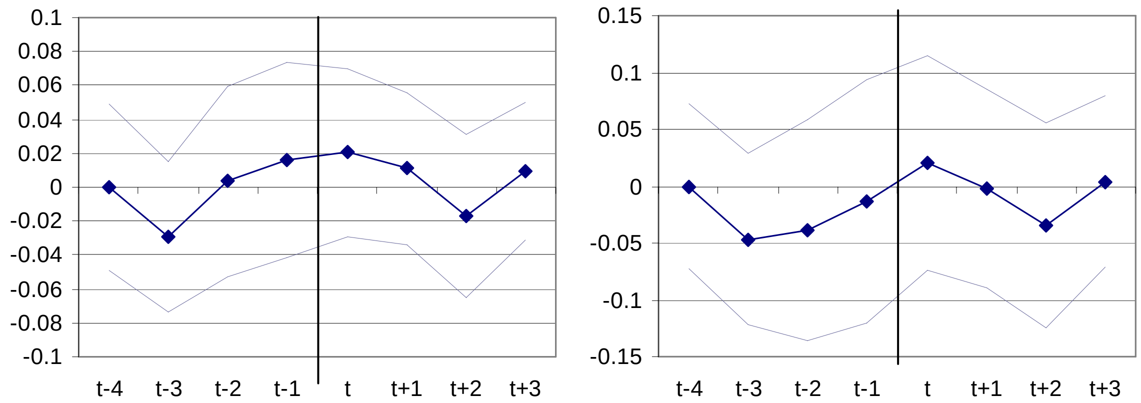


**Table 1 Correlation with Distance from Benton County: Number of Stores and Store Openings**

| | Correl(Dist from AK, WM) | Correl( Dist from AK, ΔWM) |
|---|---|---|
| 1992 | -0.346 | -0.018 |
| 1993 | -0.279 | 0.098 |
| 1994 | -0.1996 | 0.2033 |
| 1995 | -0.1132 | 0.2532 |
| 1996 | -0.0804 | 0.2358 |
| 1997 | -0.0489 | 0.2544 |
| 1998 | -0.0113 | 0.1838 |
| 1999 | -0.0067 | 0.024 |
| 2000 | -0.0085 | -0.0262 |

**Table 2 Impact of a Wal-Mart Store on Log of Average Retail Earnings in (QCEW)**

| | OLS (1) | OLS (2) | CF (3) | CF (4) | IV (5) | IV (6) | IVND (7) | IVND (8) | State-Year IV (9) | State-Year IV (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| WM | 0.0004 | -0.0002 | -0.0047 | -0.0041 | -0.0069 | -0.0047 | -0.0086 | -0.0084 | -0.0039 | -0.0037 |
| | (0.0009) | (0.0008) | (0.0019)* | (0.0017)* | (0.0010)** | (0.0010)** | (0.0016)** | (0.0014)** | (0.0018)* | (0.0017)* |
| Residual | | | 0.0067 | 0.0056 | | | | | | |
| | | | (0.0020)** | (0.0018)** | | | | | | |
| WM*Residual | | | -0.0000 | -0.0001 | | | | | | |
| | | | (0.0003) | (0.0002) | | | | | | |
| N | 15702 | 15701 | 15702 | 15701 | 15701 | 15701 | 14220 | 14220 | 15701 | 15701 |
| 1st Stage F-Stat | | | | | 4.40 | 3.97 | 6.36 | 4.32 | 9.89 | 9.92 |
| *Controls:* | | | | | | | | | | |
| Year | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| County fixed effects | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| ln(Non-retail earnings) | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| ln(Restaurant earnings) | N | Y | N | Y | N | Y | N | Y | N | Y |

Clustered standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

**Table 3 Impact of a Wal-Mart Store on Log of Average Earnings in Retail Subsectors (QCEW)**

| | OLS | OLS | CF | CF | IV | IV | IVND | IVND |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| General Merchandise | | | | | | | | |
| WM | -0.0089 | -0.0089 | -0.0104 | -0.0104 | -0.0111 | -0.0112 | -0.0091 | -0.0088 |
| | (0.0034)** | (0.0034)** | (0.0060)+ | (0.0060)+ | (0.0019)** | (0.0019)** | (0.0028)** | (0.0028)** |
| Residual | | | 0.0039 | 0.0039 | | | | |
| | | | (0.0049) | (0.0049) | | | | |
| WM*Residual | | | -0.0004 | -0.0004 | | | | |
| | | | (0.0007) | (0.0007) | | | | |
| N | 10579 | 10578 | 10562 | 10561 | 10579 | 10578 | 9323 | 9323 |
| 1st Stage F-Stat | | | | | 4.97 | 4.25 | 6.62 | 4.16 |
| Grocery | | | | | | | | |
| WM | -0.0028 | -0.0029 | -0.0157 | -0.0154 | -0.0205 | -0.0209 | -0.0109 | -0.0138 |
| | (0.0017) | (0.0017)+ | (0.0039)** | (0.0038)** | (0.0029)** | (0.0029)** | (0.0026)** | (0.0027)** |
| Residual | | | 0.0167 | 0.0164 | | | | |
| | | | (0.0039)** | (0.0039)** | | | | |
| WM*Residual | | | -0.0001 | -0.0001 | | | | |
| | | | (0.0004) | (0.0004) | | | | |
| N | 15134 | 15132 | 15099 | 15098 | 15134 | 15132 | 13652 | 13652 |
| 1st Stage F-Stat | | | | | 4.42 | 4.01 | 6.31 | 4.32 |
| *Controls:* | | | | | | | | |
| Year | Y | Y | Y | Y | Y | Y | Y | Y |
| County fixed effects | Y | Y | Y | Y | Y | Y | Y | Y |
| ln(Non-retail earnings) | Y | Y | Y | Y | Y | Y | Y | Y |
| ln(Restaurant earnings) | N | Y | N | Y | N | Y | N | Y |

Clustered standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

**Table 3 Impact of a Wal-Mart Store on Log of Average Earnings in Retail Subsectors (QCEW) (Continued)**

| | OLS | OLS | CF | CF | IV | IV | IVND | IVND |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Rest of Retail | | | | | | | | |
| WM | 0.0025 | 0.0021 | 0.0006 | 0.0022 | -0.0002 | 0.0006 | 0.0073 | -0.0007 |
| | (0.0009)** | (0.0008)** | (0.0024) | (0.0021) | (0.0010) | (0.0009) | (0.0018)** | (0.0012) |
| Residual | | | 0.0034 | 0.0015 | | | | |
| | | | (0.0024) | (0.0020) | | | | |
| WM*Residual | | | -0.0002 | -0.0004 | | | | |
| | | | (0.0006) | (0.0004) | | | | |
| N | 8703 | 8703 | 8703 | 8703 | 8703 | 8703 | 7668 | 7668 |
| 1st Stage F-Stat | | | | | 5.57 | 4.86 | 8.18 | 4.98 |
| Restaurants | | | | | | | | |
| WM | 0.0019 | | -0.0023 | | -0.0054 | | -0.0075 | |
| | (0.0009)* | | (0.0023) | | (0.0012)** | | (0.0027)** | |
| Residual | | | 0.0041 | | | | | |
| | | | (0.0026) | | | | | |
| WM*Residual | | | 0.0002 | | | | | |
| | | | (0.0004) | | | | | |
| N | 15382 | | 15341 | | 15382 | | 13902 | |
| 1st Stage F-Stat | | | 4.41 | | 4.41 | | 6.32 | |
| *Controls:* | | | | | | | | |
| Year | Y | Y | Y | Y | Y | Y | Y | Y |
| County fixed effects | Y | Y | Y | Y | Y | Y | Y | Y |
| ln(Non-retail earnings) | Y | Y | Y | Y | Y | Y | Y | Y |
| ln(Restaurant earnings) | N | Y | N | Y | N | Y | N | Y |

Clustered standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

**Table 4 Impact of a Wal-Mart Store on Log of Retail Wage Bill (QCEW)**

| | OLS<br>(1) | OLS<br>(2) | CF<br>(3) | CF<br>(4) | IV<br>(5) | IV<br>(6) | IVND<br>(7) | IVND<br>(8) | State-Year IV<br>(9) | State-Year IV<br>(10) |
|---|---|---|---|---|---|---|---|---|---|---|
| WM | -0.0030 | -0.0024 | -0.0214 | -0.0122 | -0.0158 | -0.0121 | -0.0044 | -0.0008 | -0.0233 | -0.0139 |
| | (0.0037) | (0.0026) | (0.0055)** | (0.0038)** | (0.0029)** | (0.0021)** | (0.0026)+ | (0.0026) | (0.0077)** | (0.0047)** |
| Residual | | | 0.0167 | 0.0102 | | | | | | |
| | | | (0.0050)** | (0.0035)** | | | | | | |
| WM*Residual | | | (0.1205)* | 0.0004 | | | | | | |
| | | | 0.0012 | (0.0007) | | | | | | |
| N | 15702 | 15702 | 15702 | 15701 | 15701 | 15701 | 14220 | 14220 | 15701 | 15701 |
| $1^{st}$ Stage F-Stat | | | 4.30 | 4.10 | 4.30 | 4.10 | 4.32 | 3.69 | 10.14 | 10.38 |
| Controls: | | | | | | | | | | |
| Year | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| County fixed Effects | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| ln(Total Wage Bill) | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| ln(Restaurant Wage Bill) | N | Y | N | Y | N | Y | N | Y | | Y |

Clustered standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

**Table 5 State Level Estimates on log of Average Retail Earnings (QCEW) and Hourly Wage(CPS)**

| | OLS (1) (QCEW) | OLS (2) (QCEW) | OLS (3) (CPS) | OLS (4) (CPS) | OLS (5) (CPS) | IV (6) (QCEW) | IV (7) (QCEW) | IV (8) (CPS) | IV (9) (CPS) | IV (10) (CPS) |
|---|---|---|---|---|---|---|---|---|---|---|
| WM | -0.0002 | -0.0004 | -0.0016 | -0.0017 | -0.0010 | -0.0004 | -0.0005 | -0.0023 | -0.0021 | -0.0017 |
| | (0.0002) | (0.0001)** | (0.0005)** | (0.0005)** | (0.0006)+ | (0.0001)** | (0.0001)** | (0.0005)** | (0.0005)** | (0.0004)** |
| Non-Retail Wage | | 0.5051 | | 0.5152 | 0.4852 | | 0.5280 | | 0.4416 | 0.4386 |
| | | (0.0412)** | | (0.1803)** | (0.1958)* | | (0.0301)** | | (0.1067)** | (0.0912)** |
| Restaurant Wage | | 0.0006 | | | | | 0.0003 | | | |
| | | (0.0004) | | | | | (0.0003) | | | |
| Non-Retail Low-Ed Wage | | | | -0.1230 | -0.1673 | | | | -0.1680 | -0.1664 |
| | | | | (0.1180) | (0.1228) | | | | (0.0782)* | (0.0638)** |
| Prop. Male - Retail | | | | | 0.4909 | | | | | 0.4602 |
| | | | | | (0.1425)** | | | | | (0.0756)** |
| Pct. Low-Ed | | | | | -0.3397 | | | | | -0.2347 |
| | | | | | (0.1297)** | | | | | (0.0666)** |
| Pct. White - | | | | | 0.0984 | | | | | 0.1532 |
| | | | | | (0.1901) | | | | | (0.0933) |
| Average Age | | | | | 0.0166 | | | | | 0.0193 |
| | | | | | (0.0046)** | | | | | (0.0028)** |
| Controls: | | | | | | | | | | |
| State Effects | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year Effects | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| N | 459 | 459 | 450 | 450 | 400 | 459 | 459 | 449 | 400 | 449 |
| 1st Stage F-Stat | | | | | | 7.70 | 4.78 | 9.92 | 6.16 | 7.22 |

Clustered standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

**Table 6 State Level Estimates on ESI Coverage (CPS)**

| | OLS<br>(1) | OLS<br>(2) | OLS<br>(3) | IV<br>(4) | IV<br>(5) | IV<br>(6) |
|---|---|---|---|---|---|---|
| WM | -0.0008 | -0.0008 | -0.0006 | -0.0011 | -0.0011 | -0.0011 |
| | (0.0002)** | (0.0002)** | (0.0003)* | (0.0002)** | (0.0002)** | (0.0002)** |
| Non-Retail ESI Cov. | | 0.2873 | 0.4866 | | 0.2756 | 0.4295 |
| | | (0.1091)** | (0.1612)** | | (0.0712)** | (0.1027)** |
| Non-Retail Low-Ed ESI Cov. | | | -0.1150 | | | -0.1540 |
| | | | (0.1060) | | | (0.0628)* |
| Pct. Male | | | 0.0909 | | | 0.0738 |
| | | | (0.0688) | | | (0.0319)* |
| Pct. Low-Ed | | | -0.0893 | | | -0.0730 |
| | | | (0.0597) | | | (0.0324)* |
| Pct. White | | | -0.0067 | | | -0.0358 |
| | | | (0.0725) | | | (0.0362) |
| Average Age | | | 0.0030 | | | 0.0038 |
| | | | (0.0019) | | | (0.0012)** |
| Controls: | | | | | | |
| State Effects | Y | Y | Y | Y | Y | Y |
| Year Effects | Y | Y | Y | Y | Y | Y |
| N | 450 | 450 | 400 | 449 | 449 | 449 |
| 1st Stage F-Stat | | | | 6.93 | 6.93 | 5.75 |

Clustered standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

**Table 7 Impact of a Wal-Mart Store on Log of Average Retail Earnings – MSA versus Non-MSA Counties (QCEW)**

| **ln(Average Earnings)** | OLS | OLS | CF | CF | IV | IV | IVND | IVND |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *MSA Counties* | | | | | | | | |
| WM | 0.0003 | 0.0000 | -0.0041 | -0.0031 | -0.0059 | -0.0033 | -0.0046 | -0.0069 |
| | (0.0010) | (0.0008) | (0.0019)* | (0.0016)+ | (0.0010)** | (0.0009)** | (0.0016)** | (0.0014)** |
| Residual | | | 0.0058 | 0.0046 | | | | |
| | | | (0.0022)** | (0.0019)* | | | | |
| WM*Residual | | | 0.0000 | -0.0001 | | | | |
| | | | (0.0003) | (0.0002) | | | | |
| N | 6480 | 6480 | 6480 | 6480 | 6480 | 6480 | 5832 | 5832 |
| 1st Stage F-Stat | | | | | 5.54 | 5.78 | 5.17 | 4.21 |
| *Non MSA Counties* | | | | | | | | |
| WM | -0.0071 | -0.0080 | 0.0007 | -0.0065 | 0.0066 | 0.0009 | -0.0229 | -0.0194 |
| | (0.0035)* | (0.0033)* | (0.0112) | (0.0104) | (0.0077) | (0.0070) | (0.0107)* | (0.0095)* |
| Residual | | | -0.0098 | -0.0033 | | | | |
| | | | (0.0121) | (0.0113) | | | | |
| WM*Residual | | | 0.0007 | 0.0021 | | | | |
| | | | (0.0040) | (0.0039) | | | | |
| N | 9222 | 9221 | 9222 | 9221 | 9222 | 9221 | 8478 | 8478 |
| 1st Stage F-Stat | | | | | 2.81 | 2.90 | 2.70 | 2.12 |
| *Controls:* | | | | | | | | |
| Year | Y | Y | Y | Y | Y | Y | Y | Y |
| County fixed effects | Y | Y | Y | Y | Y | Y | Y | Y |
| Ln(Total Wage Bill) | Y | Y | Y | Y | Y | Y | Y | Y |
| Ln(Restaurant Wage Bill) | N | Y | N | Y | N | Y | N | Y |

Clustered standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

**Table 8 Impact of a Wal-Mart Store on Log of Retail Wage Bill – MSA versus Non-MSA Counties (QCEW)**

| | OLS | OLS | CF | CF | IV | IV | IVND | IVND |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *MSA Counties* | | | | | | | | |
| WM | -0.0031 | -0.0019 | -0.0191 | -0.0098 | -0.0153 | -0.0095 | -0.0179 | -0.0357 |
| | (0.0040) | (0.0026) | (0.0060)** | (0.0038)** | (0.0023)** | (0.0018)** | (0.0030)** | (0.0041)** |
| Residual | | | 0.0119 | 0.0084 | | | | |
| | | | (0.0053)* | (0.0037)* | | | | |
| WM*Residual | | | 0.0016 | 0.0004 | | | | |
| | | | (0.0008)+ | (0.0008) | | | | |
| N | 6480 | 6480 | 6480 | 6480 | 6480 | 6480 | 5832 | 5832 |
| 1st Stage F-Stat | | | | | 5.26 | 4.97 | 5.04 | 3.85 |
| *Non MSA Counties* | | | | | | | | |
| WM | 0.0189 | 0.0236 | -0.0265 | -0.0090 | 0.0083 | 0.0175 | 0.0099 | 0.0166 |
| | (0.0080)* | (0.0072)** | (0.0248) | (0.0224) | (0.0162) | (0.0141) | (0.0185) | (0.0162) |
| Residual | | | 0.0475 | 0.0353 | | | | |
| | | | (0.0269)+ | (0.0241) | | | | |
| WM*Residual | | | (0.0351)** | 0.0045 | | | | |
| | | | 0.0084 | (0.0095) | | | | |
| N | 9222 | 9222 | 9222 | 9221 | 9222 | 9222 | 8478 | 8478 |
| 1st Stage F-Stat | | | | | 2.85 | 2.91 | 2.56 | 2.82 |
| *Controls:* | | | | | | | | |
| Year | Y | Y | Y | Y | Y | Y | Y | Y |
| County fixed effects | Y | Y | Y | Y | Y | Y | Y | Y |
| Ln(Total Wage Bill) | Y | Y | Y | Y | Y | Y | Y | Y |
| Ln(Restaurant Wage Bill) | N | Y | N | Y | N | Y | N | Y |

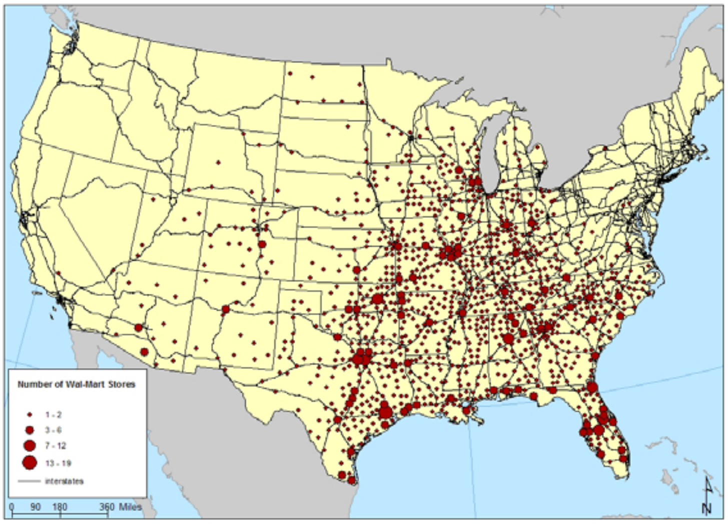
Clustered standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

**Table 9 Effect on Log of Average Retail Earnings – Robustness of First Stage Specifications, Weights, and Controls**

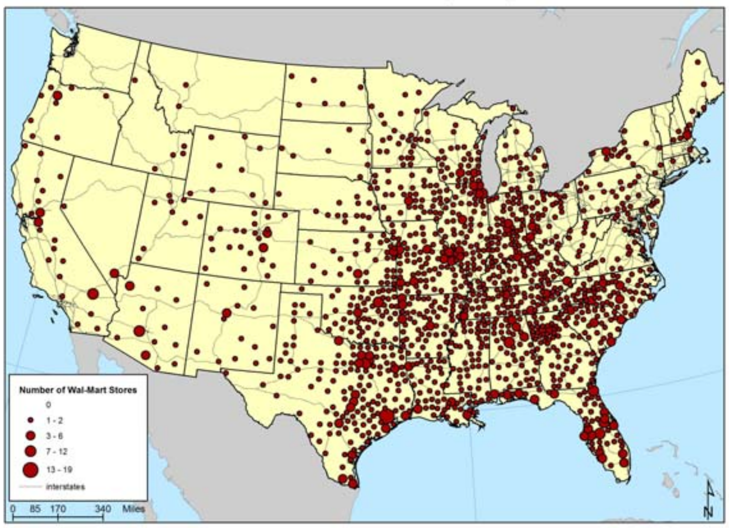
| ***First Stage Instruments*** | *(1)* | *1st Stage F-Stat* | *(2)* | *1st Stage F-Stat* | *(3)* | *1st Stage F-Stat* | *(4)* | *1st Stage F-Stat* |
|---|---|---|---|---|---|---|---|---|
| (1) *I(t)*x*I(d)*, N=8 | -0.0075 | 4.49 | -0.0083 | 7.14 | -0.01 | 4.48 | -0.0158 | 7.21 |
| | (0.0014)** | | (0.0039)* | | (0.0014)** | | (0.0043)** | |
| (2) *I(t)*x*I(d)*, N=10 | -0.0069 | 4.4 | -0.0066 | 6.36 | -0.008 | 4.48 | -0.0117 | 6.68 |
| | (0.0010)** | | (0.0028)* | | (0.0011)** | | (0.0041)** | |
| (3) *I(t)*x*I(d)*, N=12 | -0.0038 | 4.33 | -0.0073 | 5.29 | -0.0046 | 4.34 | -0.0139 | 5.85 |
| | (0.0009)** | | (0.0038)+ | | (0.0009)** | | (0.0042)** | |
| (4) *I(t)*x*I(d)*, N=14 | -0.0037 | 4.81 | -0.0052 | 5.2 | -0.0034 | 4.9 | -0.0112 | 5.52 |
| | (0.0009)** | | (0.0027)* | | (0.0009)** | | (0.0040)** | |
| (5) *I(t)*x*I(d)*, N=16 | -0.0054 | 4.66 | -0.0067 | 4.81 | -0.007 | 4.75 | -0.0118 | 4.92 |
| | (0.0009)** | | (0.0035)+ | | (0.0009)** | | (0.0038)** | |
| (6) *I(t)*x*I(d)*, N=18 | -0.0056 | 4.98 | -0.0073 | 4.34 | -0.0068 | 5.1 | -0.0115 | 4.35 |
| | (0.0009)** | | (0.0033)* | | (0.0008)** | | (0.0036)** | |
| (7) *I(t)*x*t*, *I(d)*x$t^2$, N=10 | -0.0083 | 4.35 | -0.0091 | 14.29 | -0.0103 | 3.98 | -0.0194 | 14.27 |
| | (0.0015)** | | (0.0042)* | | (0.0019)** | | (0.0046)** | |
| (8) $t$, $t^2$, $d$, $d^2$, $td$, $td^2$, $t^2d$, $t^2d^2$ | -0.0085 | 4.96 | -0.0069 | 48.72 | -0.0119 | 3.07 | -0.0117 | 48.85 |
| | (0.0020)** | | (0.0031)* | | (0.0025)** | | (0.0055)* | |
| (9) $\overline{WM}\left(I(d),I(t)\right)$, N=10 | -0.0043 | 8.43 | -0.0137 | 97.48 | -0.0049 | 8.68 | -0.0176 | 97.3 |
| | (0.0020)* | | (0.0054)* | | (0.0025)* | | (0.0064)** | |
| *Second Stage Control:* | | | | | | | | |
| ln(Non-retail Earnings) | Y | | Y | | N | | N | |
| *Population Weights:* | Y | | N | | Y | | N | |

Clustered standard errors in parentheses
\+ significant at 10%; * significant at 5%; ** significant at 1%

**Map 1: Store Locations 1992**




**Map 2: Store Locations 1996**




**Map 3: Store Locations 2000**