

Pre-Pandemic Retail and Warehouse Productivity and Hours Growth, and Post-Pandemic Implications

Michael Mandel  
Progressive Policy Institute  
Draft, August 28, 2020

[mmandel@progressivepolicy.org](mailto:mmandel@progressivepolicy.org)

Many thanks to the [Productivity Measurement Initiative](#) at Brookings' Hutchins Center on Fiscal & Monetary Policy for support for this research.

## Abstract

Pre-pandemic data show a sharp slowdown in measured productivity growth in retail trade despite a pronounced shift to ecommerce. To explain this measured slowdown, we treat consumer distribution of goods as the joint product of unpaid household shopping hours and paid labor hours in retail trade, ecommerce fulfillment, and local delivery. Using data from the American Time Use Survey, we show that per capita unpaid hours devoted to nongasoline nongrocery shopping fell by 27% between 2007 and 2018. This decline reduced unpaid shopping time by 10.5 billion hours in 2018. At the average 2018 nonfarm business compensation of \$42.30 per hour, this decline in shopping hours was worth roughly \$444 billion to consumers.

We then used two different approaches for estimating productivity growth in retail trade, taking into account the decline in unpaid household shopping hours. These two approaches boost the retail productivity growth rate in the 2007-2018 period by 1-1.5 percentage points. Moreover, retail productivity growth in the 2000-2007 period may have been overestimated, suggesting that productivity growth in retail has accelerated due to ecommerce.

## I. Introduction

Even before the pandemic, Americans were spending much less time shopping than they once did. The American Time Use Survey (ATUS) shows a steady downward trend in per capita hours devoted to consumer purchases, including travel and online research. Between 2007 and 2018, per capita time spent shopping for goods other than gasoline and groceries fell by 27%, even as per capita real consumption of these goods rose by 25%. The net result was roughly a 70% increase in the “productivity” of household shopping hours, most likely the result of the shift to ecommerce.

Meanwhile, measured output per paid hour in the broad retail trade sector rose by only 25% over the same 11-year stretch. Indeed, almost every individual industry in the retail sector showed a measured labor productivity growth slowdown over this period, despite the clear digitization of retail and the general belief that online retail requires much less labor per dollar of sales. In 2018, McKinsey Global Institute estimated that online sales were two times more productive than store sales (McKinsey Global Institute, 2018).

If we think about productivity growth as a key measure driving improvements in living standards, it is not obvious why we should focus on market productivity to the exclusion of nonmarket productivity. This point has been made many times previously, most recently by Coyle (2018) and Coyle and Nakamura (2019), who rightfully emphasize the importance of the shifting boundary between household and market production in the Information Economy. In this situation, a good measure of productivity requires the ability to measure the value of non-priced activities (see for example, Brynjolfsson et al, 2019).

But an appreciation of nonmarket productivity growth also helps us understand how labor-saving technological change can create jobs. Pre-pandemic, the assumption had been that the shift to ecommerce has going to lead to a collapse in brick-and-mortar retail employment. This was known as the “retail apocalypse,” a term that came into wide use in 2017 (Thompson, 2017).

Yet the story of “jobless ecommerce” does not fit the observed facts. The leader in ecommerce, Amazon, has been a prodigious job creator, reaching 300,000 workers in less than 20 years, faster than any other company in U.S. history (Mandel 2017). Its hockey-stick employment growth in its first two decades closely matched and then exceeded that of the first two decades of General Motors (General Motors, 1928).

In fact, ecommerce seems to operate as a machine for shifting hours from the household sector to the market, as paid workers take over the “picking and packing” and delivery functions that households used to do themselves. Ecommerce fulfillment centers can employ thousands of workers and are often treated as major economic development projects. In 2017, for example, Walmart opened an ecommerce fulfillment center in Polk County, Florida, that employed 1500 workers and received major tax abatements. It is worth noting that in 2017, the whole state of Florida had only 5 retail trade establishments with more than 1000 workers.

Pre-pandemic, the aggregate gains in local delivery and warehouse labor hours associated with ecommerce more than made up for the decline in “brick-and-mortar” hours. We note here that shifts between household hours and market hours can greatly influence our understanding of the relationship between automation and market employment. Bessen (2020) shows how automation that drives down costs can boost demand enough to create more jobs, potentially by shifting hours out of the household sector. Similarly, Acemoglu and Restrepo (2018) propose a model in which the creation of new tasks induces demand for labor.

### ***This paper***

This paper proposes that the productivity impact of ecommerce is showing up as falling household shopping hours, which is not captured by traditional market-based productivity measures. First, we discuss the pre-pandemic evolution of consumer goods distribution as a joint production requiring both unpaid household time and paid time of retail employees. We

focus in particular on the shift of activities such as “picking and packing” from individual consumers to heavily digitized warehouses.

The next two sections discuss the paid and the unpaid inputs to the joint production function, respectively. We show that paid hours devoted to distribution of consumer goods have been rising, while unpaid household shopping hours have been falling. In particular, per capita household shopping hours except groceries, food, and gasoline fell by 27% between 2007 and 2018. Not coincidentally, measured productivity growth in retail slowed, while the “productivity” of goods consumed per unpaid household shopping hour accelerated.

We then propose two approaches for integrating household shopping hours into the retail productivity calculation. The “output-adjusted” approach boosts retail productivity growth by about 1 percentage point in the 2007-2018 period, which reduces the productivity slowdown but doesn’t eliminate it. The “input-adjusted” approach increases retail productivity growth by 1.5 percentage points in the 2007-2018 period, but also suggests that measured productivity growth in the 2000-2007 period was overstated. The implication is that ecommerce has led to an acceleration of productivity growth in retail.

## II. Pre-Pandemic Evolution of Consumer Goods Distribution

Our theoretical framework throughout this paper is to model the distribution of consumer goods as joint production requiring both unpaid household time and paid time of retail employees. The expression  $RT$  represents the joint production function for retail trade, where  $M_i$  is a vector of market labor inputs, and  $H_j$  is a vector of nonmarket household labor inputs.

$$(1) RT (M_i, H_j)$$

Different business models for retail are associated with different breakdowns of market and nonmarket labor inputs. For example, before the ecommerce era, big box brick-and-mortar

stores represented one particular joint production model between household and market hours. Big box stores generate their efficiencies by economies of scale in procurement, shipping and handling, and distribution. They buy in bulk from large factories in the U.S. and overseas; they ship in bulk via containers that require no additional handling; they distribute in bulk through large warehouse centers.

Consumer would “go shopping”, meaning that they would travel to the store, spend time picking out the items they wanted, stand in line to pay, and travel back home. In other words, the production function for brick-and-mortar retail shopping required the input of consumers’ time. With big box stores, consumers get lower prices, but they have to travel longer distances to the warehouse centers, with less service, since they have to do all the picking themselves.

How many hours did households devote to goods shopping in the pre-ecommerce era, and how did that compare to the number of paid hours in retail trade? Bridgman et al (2012) reported that average shopping hours increased from 1965 to 1985, based on relatively small periodic surveys. In 1985, for example, they reported that adult Americans spent roughly 3.3 hours per week on shopping, up from 2.9 hours in 1975. The nature of the questions, however, make it hard to know exactly what is being included.

A much clearer estimate comes from the American Time Use Survey, which the BLS started publishing in 2003. In that year, ecommerce averaged less than 2 percent of retail sales. On average, Americans spent 4.1 hours per week shopping for consumer goods, including travel, research, and waiting. With 229 million Americans 15 years and over, that came to a total of 49 billion hours of unpaid shopping time in 2003.

By comparison, the number of paid hours in the retail trade industry amounted to 25.5 billion hours in 2003. In other words, unpaid household shopping hours were roughly double that of paid retail sector worker hours in 2003. As we will see later in this paper, this gap has narrowed considerably in recent years.

It's worth noting here that some shopping activities have enjoyment value. Soloveichik (2018) suggests that the positive aspect of shopping should be considered as well, such as test drives offered by auto dealers and the fun of trying on new clothes. However, many of the unpaid shopping hours involved low-productivity tasks like standing in cashier lines. In this paper we treat unpaid household shopping hours as inputs to consumer good distribution rather than entertainment.

With the growth of ecommerce, it became clear that the joint production function for the consumer goods distribution changed. The vector  $M_i$  of market labor inputs broadened to include workers in ecommerce fulfillment centers and local delivery personnel. The consumer orders via a website, and then simply receives the goods at home rather than travelling to the store. Warehouse workers had to take on many of the "picking and packing" functions that that the consumer used to do.

This required a major investment in warehousing digitization. To be sure, warehouses had long utilized automation. The initial stage of warehouse automation came in the 1960s, when "automated guided vehicles" (AGV) were introduced to warehouses for moving heavy loads. Late in the 1960s and 1970s, these were tied into automated storage/retrieval systems (AS/RS). In the 1980s, warehouse automation developed into fully automated stacked storage areas, cranes, and pallet conveyors, which dramatically reduced the footprint and labor needed. After the late 1980s the AS/RS systems became obsolete and more emphasis was paid on reducing inventories, small batch production and Just in time delivery.

However, the dot.com boom of the 1990s showed that classic warehouse automation was not sufficient to deal with the needs of ecommerce fulfillment. The key event was the failure of Webvan in 2001. Webvan was a grocery delivery that burned through more than \$1 billion in capital in two years (Cohan, 2013). Former executives at Webvan realized that the company

failed, in part, because of an inability to efficiently move items through the warehouse. So, they created a robotic warehouse automation system called Kiva for the purpose of:

....receiving, depalletizing and storing items and bringing dynamically-stored shelves containing ordered items to the picker/packer to pick, pack and ship while the Kiva robot returned the shelves to the most appropriate area in a free-form dynamic warehouse and autonomously went off to bring the next shelf to another picker/packer. (Tobe, 2016)

The Kiva system executed what was known as “random stow”, which means that storing incoming goods where there is space rather than in pre-defined locations (Quartz, 2018). This process, analogous to random access memory in computer storage, reduces the time required to store incoming goods, reduces the amount of time needed to pick items for shipping (since they are spread throughout the warehouse), and reduces the amount of space needed. It does require more sophisticated data systems to keep track of the individual items.

Amazon acquired Kiva in 2012. At that point Amazon’s fulfillment centers still only partially automated, with one press story describing an Amazon employee using a tricycle to get to far-off items. By 2019 Amazon reportedly had 200,000 warehouse robots installed across its network of ecommerce fulfillment centers (Del Ray, 2019).

The efficiencies enabled by warehouse automation had multiple implications. First, warehouse automation reduced the cost of offering free two-day delivery to Amazon Prime customers. Warehouse automation also reduced the cost of offering fulfillment services directly to third party sellers, since the system is agnostic to who owns the items and can easily track and absorb a wide variety of goods for sale.

Third, and perhaps most interesting, warehouse automation made buying online and having items shipped directly to the consumer economically competitive with the then-dominant model, the Walmart-type big box store.



In groceries, ecommerce has taken a bit of a different turn. Personal shopping systems such as Instacart employ “shoppers” who pick and pack the required grocers, and then perhaps deliver it. Technology enables the shoppers to report to the ultimate buyer in real time about the availability of the required items, and the acceptability of substitutes. This direct connection reduces the uncertainty of grocery shopping by proxy, making it more applicable to fresh meat and produce. In effect, technology has enabled much more of grocery shopping to be moved into the market sector.

### **III. Measuring Market Hours and Productivity**

Tracking  $M_i$ , the market labor inputs into consumer goods distribution, is not easy in the era of ecommerce. In earlier work we used the fact that many ecommerce fulfillment centers are large enough and located in sparse enough counties to produce a noticeable ‘bump’ in QCEW data when they open (Mandel 2017). A careful comparison of press reports and third party lists of fulfillment centers with QCEW data shows that most fulfillment centers offering platforms to multiple sellers, such as Amazon’s, are categorized in NAICS 493 (warehousing and storage). That’s appropriate, because the definition of NAICS 493 includes providing logistics services to other companies. Note that some states such as Indiana and Ohio, had been assigning ecommerce fulfillment centers to NAICS 4541, but they have been gradually shifting to 493. Single-retailer fulfillment centers are either in parent industry or in 493.

Similarly, local delivery, with the exception of the US Post Office, appears to be mostly reported in NAICS 492, couriers and messengers. That’s based on an examination of the pattern of job gains in recent years in large cities with extensive ecommerce delivery.

For ease of discussion in this paper, we'll use the label "consumer distribution sector" to refer to these three industries (retail + 492 +493). Obviously, this collection of industries includes warehouses and delivery operations directed towards business-to-business transactions

Table 1 reports on the hours worked in retail trade, couriers and messengers, and warehousing and storage at the last four business cycle peaks. We can see that since 2000 the gains in local delivery (couriers and messengers) and ecommerce fulfillment (warehousing) have compensated for the moderate losses in retail hours.

We note that Table 1 shows the rapid growth of the warehousing industry and its increased economic importance. (Figure 1). Under the SIC classification, "public warehousing" was only 0.2% of private sector employment. As of July 2020, the warehousing and storage industry had almost 1.2 million jobs—that's roughly 1% of private sector employment, making it one of the larger industries in the U.S.

Table 2 reports on productivity growth for selected retail industries, couriers and messengers and warehousing. Measured productivity growth in retail trade, as reported by the Bureau of Labor Statistics (BLS), slumped from 3.8% in the 2000-2007 business cycle to 2.3% in the 2007-2019 business cycle. This slump was broad, afflicting general merchandise stores, a category which includes department stores and big box retailers such as Walmart. (Kurz, Lengermann, and Mandel (2019) suggest that this apparent slump may be due, in part, to an undercounting of ecommerce sales).

Surprisingly, the ecommerce industries also experienced a productivity slump. Warehousing, in particular went from a 0.8% productivity growth rate in the 2000-2007 business cycle to a -0.7% annual productivity decline in the 2007-2019 business cycle. In other words, the rapid growth of heavily automated and successful ecommerce fulfillment centers has been accompanied by an actual decline in measured productivity in NAICS 493 from 2007 to 2019. It's possible that the "output" of ecommerce fulfillment centers is being booked by the parent ecommerce

companies. But that would show up as an acceleration of productivity growth in retail trade, and in electronic shopping in particular, which is not what Table 2 shows.

We note that even though the BLS still reports productivity growth in electronic shopping (NAICS 4541), that is no longer a useful measurement. Brick and mortar retailers do a large part of retail sale online, integrated with their store operations. Indeed, employment in NAICS 4541 has stopped rising in recent years. As a result, future versions of NAICS may eliminate this industry.

#### **IV. Measuring Household Shopping Hours**

The American Time Use Survey provides with a way of tracking unpaid household shopping hours  $H$ . We start with the published number for time spent on “consumer goods purchases” We use 2007 as our starting point, because that is the business cycle peak. It also represents a time when Amazon, the leading online retailer, was still relatively small. Between 2007 and 2018 per capita time spent on the ATUS published category “consumer goods purchases” dropped by 15% for Americans 15 and over. This includes time spent researching purchases, including comparison shopping on the Internet. However, it does not include time travelling to purchase consumer goods.

We need to make several adjustments to the published household hours measure. First, we remove time spent buying groceries and gasoline. Pre-pandemic, less than 3 percent of groceries were bought online, and obviously gasoline can’t be purchased online. As Figure 2 shows, both groceries and gasoline show no decline in time spent shopping in the 2007-2018 time period.

Second, we remove time spent paying for food in restaurants, which is part of the published measure but not part of the NAICS retail trade sector. Third, we add in the relevant travel time measures. Note that the resulting measure of non-gas non-grocery shopping hours still includes time spent paying for movies, sporting events, and accommodations, which are not part of the retail trade or consumer distribution sector. However, the amount of time paying for these items is likely to be small compared to the time actually shopping for goods.

So, our target measure of household shopping hours is per capita hours spent on consumer goods purchases, including travel time and excluding groceries, gasoline, and restaurant food. Figure 3 and Table 3 show a 27% decline in average time spent on consumer goods purchases from 2007 to 2018, ex of groceries, food and gas.

We can calculate the change in the “productivity” of unpaid shopping hours. Table 4 shows that real personal consumption expenditures on goods excepting gasoline and food purchased for off-premises consumption per unpaid shopping hour rose at 4.8% per year from 2007 to 2018.

What about before 2007? Time shopping in 2005 is only minimally different than 2007, and the difference is not statistically significant. Let’s assume that there is no change in per capita shopping time before 2007. Then productivity of unpaid shopping hours rose at 3.8% per year from 2000 to 2007, implying that productivity growth of unpaid shopping hours was accelerating.

## V. **Combining Market Labor Productivity and Unpaid Shopping Productivity**

To briefly review: The fundamental premise of ecommerce is to shift shopping hours from unpaid household sector to the paid market sector. Because ecommerce companies can invest in technology, the result is that productivity of consumer distribution of goods increases. But the gains are felt in the unpaid household sector rather than the market sector.

Figure 4 shows why omitting the change of household hours from our productivity calculations is likely to have a big impact. The grey line shows aggregate household shopping hours for all consumer goods except groceries, food, and gasoline, assuming that per capita shopping hours are fixed at the 2007 level—in other words, no effect of ecommerce. The red line shows aggregate household shopping hours, assuming the per capita shopping hours decline as shown in Table 3. The blue line tracks market hours in the consumer distribution sector, removing gasoline and the grocery industry. We can see from this chart that the change in household shopping hours from ecommerce has a significant effect on aggregate labor inputs into consumer distribution of goods.

In this section we describe two approaches for incorporating the household sector into retail sector productivity calculation. In the “output-adjusted” approach, a decline in household shopping hours has a positive impact on the growth of the output of the retail trade sector. In the “input-adjusted” approach, we construct a weighted average of household and market hours growth rates and use that in the denominator of the productivity calculation.

We apply these two approaches to two different definitions of the retail trade sector. A narrow definition, which includes all consumer goods except groceries, food and gasoline, and a broad definition, which also includes NAICS 492 and 493.

The top panel of Table 5 reports on measured productivity growth in the narrow and broad retail sectors, without any adjustments from household hours. We see a sharp productivity slowdown in the 2007-2018 business cycle.

The simplest way to adjust retail trade output for household hours is to assume that shopping hours have an opportunity cost  $w$ . Then we can write the joint production function as:

$$(2) \quad RT(M)^{-w(H-H_0)}$$

where  $M$  is the market labor inputs,  $w$  is the opportunity cost or implicit wage,  $H$  is aggregate household shopping hours, and  $H_0$  is aggregate household shopping hours assuming that per-capita shopping hours are set at the base year level—in this case, 2007. In this case the productivity of the retail sector becomes

$$(1) \quad [RT(M)^{-w(H-H_0)}]/M$$

The second panel of Table 5 calculates retail productivity growth assuming that consumers value their time at the average 2018 nonfarm business compensation rate of \$42.30 per hour. The 27% decline in per-capita household shopping time between 2007 and 2018 reduces aggregate household shopping time in 2018 by 10.5 billion hours (the difference between the grey and the red lines). The result is that the decline in shopping hours was worth roughly \$444 billion to consumers in 2018.

The output-adjusted approach translates into a 1 percentage point increase in the productivity growth rate from 2007 to 2018 for both the narrow and broad definitions of retail trade. We note that the slowdown in productivity growth is less pronounced, but still there. Using a lower wage rate would reduce the size of the adjustment.

To implement the input-adjusted approach, we assume that output of the retail trade sector does not depend on household hours. Instead, we construct a Törnqvist index for the labor inputs that weights the growth rate of household and market hours using labor compensation. The implicit wage for household hours is drawn from the nonfarm business hourly compensation series. The corresponding compensation series is drawn from the BLS industry productivity database.

The results are presented in the third panel of Table 5. The productivity growth rate is adjusted upwards by 1.4-1.5 percentage points in the 2007-2018 period. However, note that the productivity growth rate was adjusted downwards in the 2000-2007 period. That's because aggregate household shopping hours rose faster than market hours in that period, just due to an increase in the number of adults in the population over that period. In other words, households were doing more of the work.

As a result, the productivity slowdown has disappeared in the third panel and been replaced by a moderate productivity acceleration. This obviously depends on the implicit wage rate.

## **VI. Post-Pandemic Implications**

The analysis in this paper, of course, was all based on pre-pandemic data. The pandemic dramatically accelerated the adoption of ecommerce, especially in areas such as groceries where online-enabled deliveries have become far more common. At the same time many brick-and-mortar stores were forced to close and/or go bankrupt.

Retail employment declined by 1.2 million from June 2019 to June 2020. Hours worked in retail trade fell by 6 percent. Including NAICS 492 and 493, hours in the consumer distribution sector fell by 5 percent. This decline may be somewhat overstated, since independent workers engaged with delivery companies such as Instacart may not be reported as retail workers.

At the same time, retail sales in June 2020 were actually 5 percent higher in nominal terms than they were in June 2019. In real terms, personal consumption of goods rose by 5.7 percent. So on a short term basis, measured productivity in retail is likely to rise in the pandemic.

In addition, to the extent that consumer have switched to ordering online rather than shopping in person, household shopping hours may have gone down as well. That suggests a strong increase in productivity over this stretch. This sudden and unexpected shift makes it even more imperative for economists to incorporate changes in household shopping hours into measurements of retail productivity growth.



## References

Acemoglu, Daron and Pascual Restrepo. 2018. The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment. *American Economic Review* 2018, 108(6): 1488–1542

Aguiar, Mark and Erik Hurst. 2007. Measuring Trends in Leisure: The Allocation of Time Over Five Decades. *The Quarterly Journal of Economics*, Volume 122, Issue 3, August 2007, Pages 969–1006,

Baily, Martin Neal, and Robert J. Gordon. 1988. The productivity slowdown, measurement issues and the explosion of computer power. *Brookings Papers on Economic Activity*, no. 2:347-420.

Bessen, James. 2020. Automation and Jobs: When Technology Boosts Employment. *Economic Policy*<https://doi.org/10.1093/epolic/eiaa001>

Bridgman, Benjamin, Andrew Dugan, Mikhail Lal, Matthew Osborne, and Shaunda Villones. 2012. Accounting for Household Production in the National Accounts, 1965–2010. *Survey of Current Business* 92 (May): 23–36.

Brynjolfsson, Erik, Avinash Collis, W. Erwin Diewert, Felix Eggers, and Kevin J. Fox. 2019. GDP-B: Accounting for the Value of New and Free Goods in the Digital Economy. NBER Working Paper No. 25695. March 2019

Cohan, Peter. 2013. Four Lessons Amazon Learned from Webvan's Flop. *Forbes*, June 17, 2013. <https://www.forbes.com/sites/petercohan/2013/06/17/four-lessons-amazon-learned-from-webvans-flop/#62d01f488147>

Coyle, Diane, 2018. Do-It-Yourself Digital: The Production Boundary and the Productivity Puzzle, *Economica*, online version of record August 2018: <https://onlinelibrary.wiley.com/doi/10.1111/ecca.12289>

Coyle, Diane and Leonard Nakamura. 2019. Towards a Framework for Time Use, Welfare and Household-centric Economic Measurement.

Del Ray, Jason. 2019. How robots are transforming Amazon warehouse jobs — for better and worse. *Vox*. December 11, 2019.

General Motors. 1928. Twentieth Annual Report of General Motors Corporation.

Kurz, Christopher, Paul Lengermann and Benjamin Mandel. 2019. New economy, same old consumption? E-commerce and implications for economic measurement. Presentation, Brookings Hutchins Center Productivity Measurement Initiative conference, September 2019.

Mandel, Michael. 2017. How Ecommerce Creates Jobs and Reduces Income Inequality. Progressive Policy Institute Policy Brief.

McKinsey Global Institute. 2018. Solving the productivity puzzle: The role of demand and the promise of digitization.

Quartz. 2018. Random Stow. Quartz, March 19, 2018. <https://qz.com/emails/quartz-obsession/1232247/>

Soloveichik, Rachel. 2018. Accounting for Improved Brick and Mortar Shopping Experiences: Explaining the Post-2002 Wholesale and Retail Slowdown.

Thompson, Derek. 2017. What in the World Is Causing the Retail Meltdown of 2017? The Atlantic. April 10, 2017.

Tobe, Frank. 2016. The technology gap left by Amazon's acquisition of Kiva Systems. The Robot Report, April 13, 2016.

**Table 1: Market Hours in Consumer Distribution Sector, Business Cycle Peak Years (millions)**

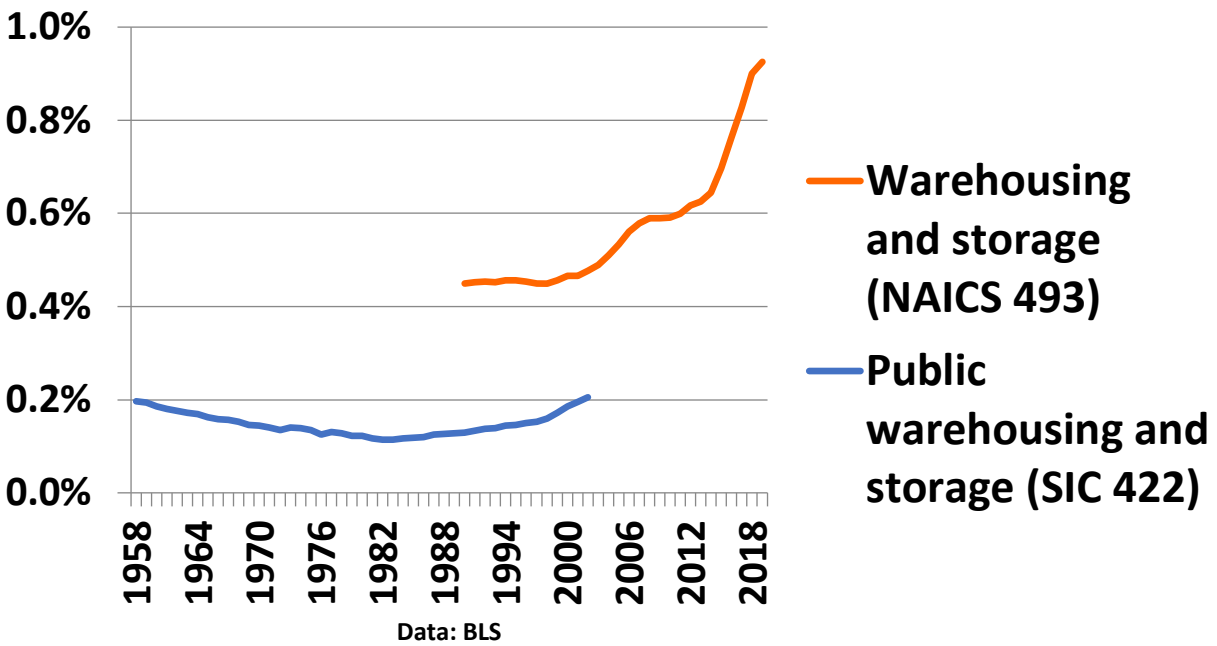
	<b>1990</b>	<b>2000</b>	<b>2007</b>	<b>2019</b>
<b>Retail trade</b>	23438	26097	25670	25225
<b>Couriers and messengers (NAICS 492)</b>	665	1150	1038	1456
<b>Warehousing and storage (NAICS 493)</b>	747	974	1256	2264
<b>Total</b>	<b>24850</b>	<b>28221</b>	<b>27963</b>	<b>28946</b>

**Data: Bureau of Labor Statistics (industry productivity database)**

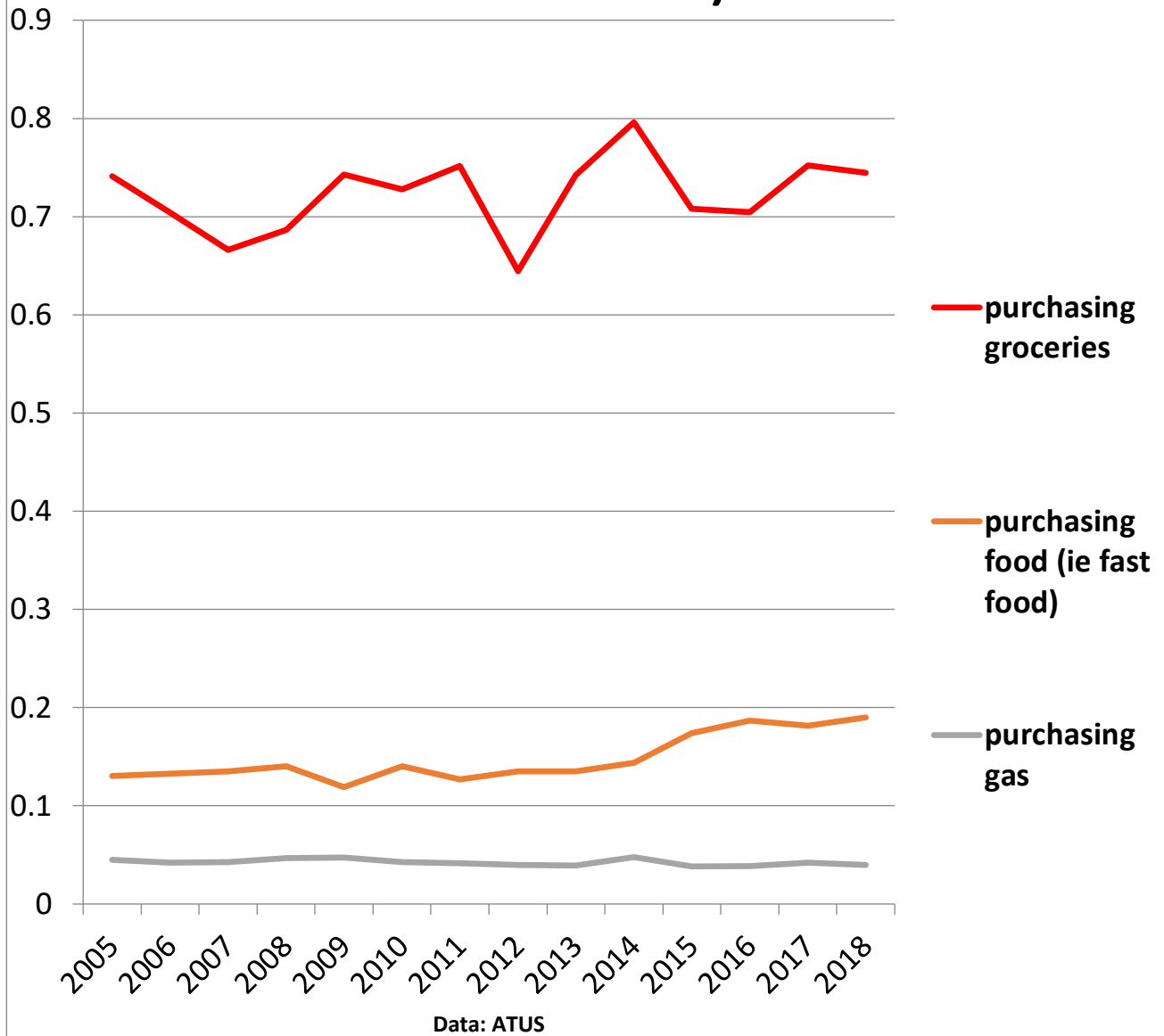
**Table 2. Labor Productivity Growth in Consumer Distribution Industries (annual rate)**

	<b>1990-2000</b>	<b>2000-2007</b>	<b>2007-2019</b>
<b>Retail trade</b>	3.7%	3.8%	2.3%
<b>General merchandise</b>	4.9%	3.4%	1.8%
<b>Electronic shopping and mail order</b>	14.0%	14.7%	6.0%
<b>Couriers and messengers</b>	-0.9%	0.9%	-5.3%
<b>Warehousing*</b>	4.3%	0.8%	-0.7%
*Data series starts in 1992			
Data: Bureau of Labor Statistics productivity database			

**Figure 1. Employment in Warehousing and Storage as Share of Private Sector Jobs**



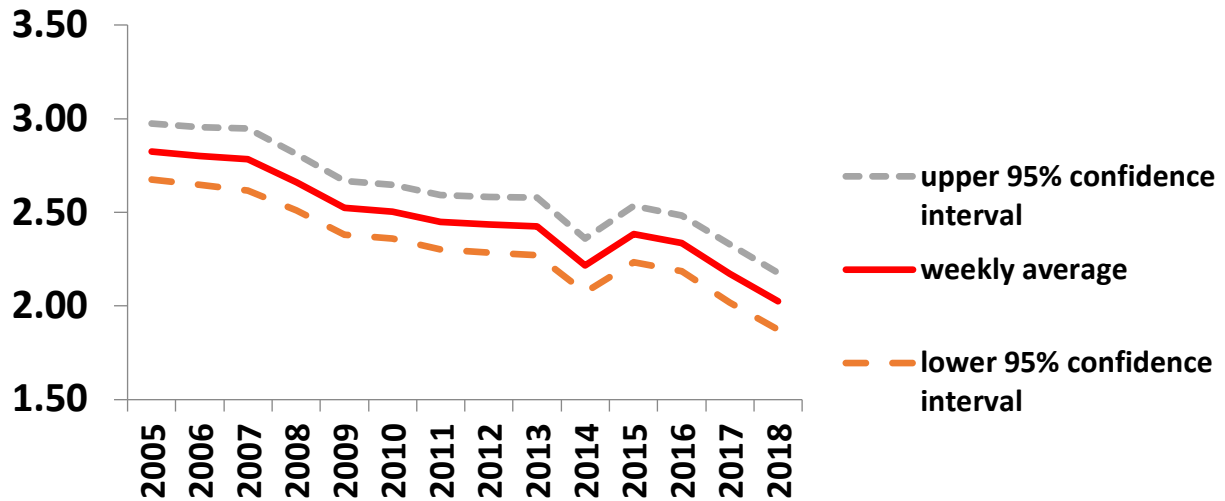
**Figure 2. Time spent Purchasing Groceries, Food, and Gas (Average Hours Per Week)**



**Table 3. Time Spent on Shopping for Consumer Goods and Related Travel, Except Groceries, Food, Gas**

	95% confidence interval		
	weekly average hours	lower	upper
<b>2005</b>	2.82	2.67	2.97
<b>2006</b>	2.80	2.65	2.95
<b>2007</b>	2.78	2.62	2.95
<b>2008</b>	2.66	2.51	2.81
<b>2009</b>	2.52	2.38	2.67
<b>2010</b>	2.50	2.36	2.65
<b>2011</b>	2.45	2.30	2.59
<b>2012</b>	2.43	2.29	2.58
<b>2013</b>	2.42	2.27	2.58
<b>2014</b>	2.22	2.07	2.36
<b>2015</b>	2.38	2.23	2.53
<b>2016</b>	2.34	2.19	2.48
<b>2017</b>	2.17	2.02	2.33
<b>2018</b>	2.03	1.87	2.18
<b>percentage change 2007-18</b>	-27%		

**Figure 3. Time Spent Shopping for Consumer Goods and Related Travel, Except Groceries, Food, Gas\* (average weekly hours per person)**



\*Includes research for consumer purchases Data: ATUS

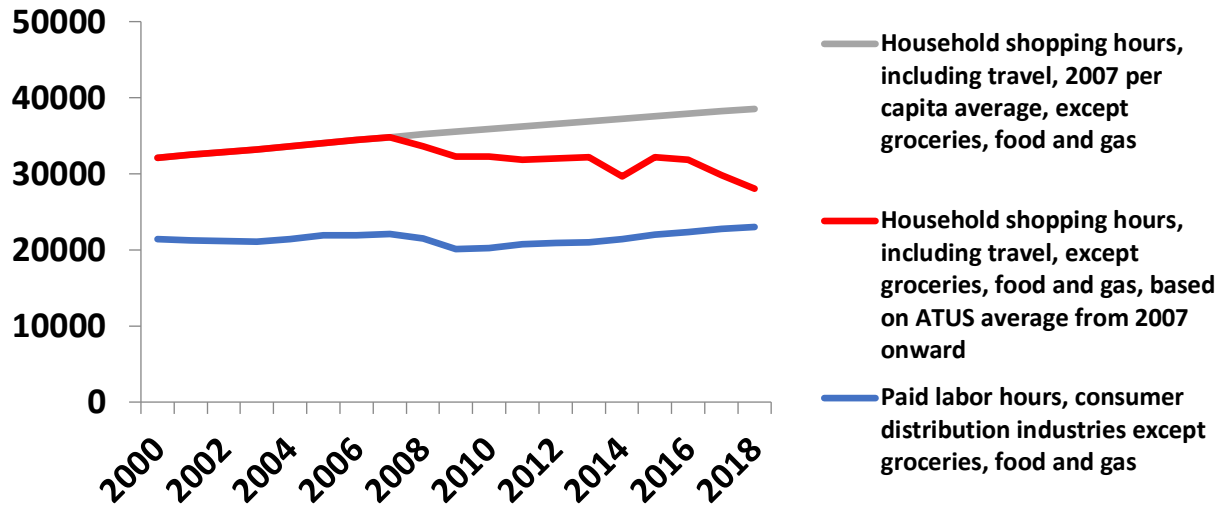


**Table 4. Productivity Growth of Unpaid Shopping Hours**

	2000-2007	2007-2018
<b>Per capita shopping time*</b>	0%	-27%
<b>Number of Americans 15 and over</b>	8%	11%
<b>Aggregate shopping hours*</b>	8%	-20%
<b>Real consumer spending on goods**</b>	40%	35%
<b>Productivity of unpaid household shopping hours*</b>	30%	68%
<b>Annual productivity growth of unpaid shopping hours*</b>	3.8%	4.8%
<b>*less groceries, food, and gasoline</b>		

**\*\*less gasoline and food purchases for off premises consumption**

# Figure 4. Household and Market Labor Inputs into Shopping (millions of hours annually)



Source: BLS industry productivity database; ATUS

**Table 5: How Ecommerce-Driven Reduction of Household Shopping Hours Affects Measured Retail Productivity Growth**

<b>(Average annual productivity gain)</b>		
	2000-2007	2007-2018
<b>Original</b>		
<b>Narrow definition</b>	4.2%	2.6%
<b>Broad definition</b>	3.9%	1.9%
<b>Output-adjusted</b>		
<b>Narrow definition</b>	4.2%	3.6%
<b>Broad definition</b>	3.9%	2.9%
<b>Input-adjusted</b>		
<b>Narrow definition</b>	3.5%	4.0%
<b>Broad definition</b>	3.4%	3.6%
<b>Narrow definition: Retail trade less gasoline and grocery industries</b>		
<b>Broad definition: Narrow retail definition plus NAICS 492 and 493</b>		