

Life-Cycle Prices and Production

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We use scanner data and time diaries to document how households substitute time for money through shopping and home production. We document substantial heterogeneity in prices paid for identical goods for the same area and time, with older households shopping the most and paying the lowest prices. Doubling shopping frequency lowers a good's price by 7 to 10 percent. We estimate the shopper's price of time and use this series to estimate an elasticity of substitution between time and goods in home production of roughly 1.8. The observed life-cycle time allocation implies a consumption series that differs markedly from expenditures. (JEL D12, D91)

This paper studies how households substitute time and money. Using a novel dataset, we document that households that shop more intensively pay lower prices for identical goods. We merge these data with household time diaries to estimate parameters of the shopping and home production technologies employed by households to minimize the total cost of consumption. Our results indicate that much of the well-documented decline in household expenditures starting at middle age can be attributed to the shopping and home production behavior of older households.

The economic theory that motivates this paper originated in two seminal works of the 1960s. Gary Becker (1965) formalized the notion that consumption is the output of a production function that combines market goods and time. Such a “home production” function allows households to optimally substitute time for expenditures in

response to fluctuations in the relative cost of time. A similar implication lies behind George Stigler's (1961) model of search. In the presence of informational frictions, the same good may sell for different prices at a given point in time. By shopping more intensively, a household can lower the market price for a given basket of goods.

These theoretical insights are now familiar. However, the quantitative importance of these margins is difficult to pin down.¹ The first contribution of this paper is to explore how prices for goods vary across households in practice, and to what extent this variation accords with standard theory. To do this, we use data from ACNielsen's Homescan Panel. This survey collects grocery scanner data at the level of the household. Each purchase in the database records the actual price paid by the household at the level of the Universal Product Code (UPC). The dataset is novel in the sense that it has detailed demographics about the shopper making the purchases, and it tracks the household purchases across multiple retail outlets. Because the data also include information about the shopping trip, we can infer the household's shopping intensity.

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¹Recent empirical papers documenting price dispersion and returns to search in retail prices include Alan Sorensen (2000), Jeff Brown and Austan Goolsbee (2002), Peter Pashigan, Sam Peltzman, and Jeanne-Mey Sun (2003), and David McKenzie and Ernesto Schargrodsky (2004). A classic reference is Robert Blattberg et al. (1978). Peter Rupert, Richard Rogerson, and Randall Wright (1995, 2000), Ellen McGrattan, Rogerson, and Wright (1997), Jeffrey Campbell and Sydney Ludvigson (2001), and Aguiar and Hurst (2005, 2006) provide recent empirical evidence on the importance of home production.

We find that the price paid for a particular bar-coded item is essentially flat up through middle age and then declines sharply thereafter. Specifically, households in their late forties pay, on average, 4 percent more for identical goods than households in their late sixties. This is consistent with the fact that market labor hours, earnings, and time demands from children all decline after middle age. Additionally, we document that higher-income households pay higher prices than lower-income households, and dual-worker couples pay higher prices than single-worker couples.

Given the price data, as well as information on shopping frequency in the Homescan data and minutes spent shopping in the American Time Use Survey (ATUS), we are able to estimate the parameters of the shopping technology that maps time and quantity purchased into price. We find that, holding constant the amount of goods purchased, households that shop more frequently pay lower prices. Specifically, all else equal, our preferred specifications suggest that a doubling of shopping frequency reduces prices by 7 to 10 percent.

Consistent with the fact that older households pay lower prices, we find that older households shop much more intensively than middle-aged households. We explore a number of potential shopping strategies that may generate lower prices from increased shopping time. We find that older households shop more frequently at the same stores rather than visit more stores, compared to their younger counterparts. Repeat shopping is also associated with more extensive use of store and manufacturers' discounts. The tendency to shop frequently and to exploit discounts together explain three-quarters of the difference in prices between older and middle-age shoppers.

Optimality implies that a shopper equates the marginal return to additional shopping to the opportunity cost of time. With this in mind, we use the observed shopping behavior as well as the estimated returns to shopping to calculate the shopper's opportunity cost of time for each household. We show that the cost of time is hump-shaped over the life cycle. The hump in the price of time is reminiscent of the typical wage profile, but the implied price of time from shopping peaks in the mid-thirties much earlier than wages. There are a number of reasons why

this alternative measure of time is preferable to wages, including that many agents do not work, the observed wage may not be the marginal return to labor (due to nonlinear wage schedules, human capital accumulation on the job, etc.), and the fact that individuals may not be able to adjust labor hours freely at the margin.

A second contribution of the paper is that we use the price data and detailed data on time spent in home production from the ATUS to estimate the parameters of a home production function. The identification assumption is that the opportunity cost of time of the shopper is the same as that of the person undertaking home production. In particular, agents equate the marginal rate of transformation (MRT) between time and goods in home production to the MRT in shopping. Note that we do not need to assume that the cost of time in home production is the market wage. This allows us to calculate a price of time for retirees and married-couple households with only one worker.² We estimate an elasticity of substitution between time and goods in home production of approximately 1.8. This parameter plays a crucial role in many explanations of labor supply, in terms of both long-run trends and business-cycle fluctuations.³

With the home production function in hand, we calculate implied household consumption using observed inputs of time and market goods. We document that this series varies over the life cycle in a manner distinct from household expenditures. Specifically, the ratio of implied consumption to expenditures rises rapidly from middle age through retirement. The life-cycle profile of this ratio reflects the changing cost of time as households age, and highlights the danger of inferring the life-cycle profile of consumption directly from expenditures. Indeed, we estimate that the

²Several previous researchers have estimated this parameter assuming that the market wage is the price of time in home production. These include Rupert, Rogerson, and Wright (1995), who use micro data, and McGrattan, Rogerson, and Wright (1997) and Yongsun Chang and Frank Schorfheide (2003), who use macro data. In Section VII, we compare our results to these previous estimates.

³For business cycles, see Jess Benhabib, Rogerson, and Wright (1991), Jeremy Greenwood and Zvi Hercowitz (1991), and Greenwood, Rogerson, and Wright (1995). For long-run trends in market labor, see Aguiar and Hurst (2006) and Greenwood and Guillaume Vandenbroucke (2006).

large increase in shopping and home production time post-middle age offsets the decline in expenditure implying a nondecreasing consumption profile in the latter half of the life cycle.

There is a growing interest in the role of non-market activities and the allocation of work between the market and the household. The insights from modeling household production have already proved fruitful in explaining, for example, the baby boom (Greenwood, Ananth Seshadri, and Vandenbroucke 2005) and the excess sensitivity of consumption to predictable income changes (Baxter and Jermann 1999). In a previous paper (Aguiar and Hurst 2005), we used detailed food diaries from the US Department of Agriculture to show that even though food expenditure falls sharply, food intake remains constant as households transition into retirement. We argued that consumption is able to remain constant despite falling expenditure because households are spending more time shopping for groceries and more time preparing meals.

I. Theoretical Preliminaries: Household Cost Minimization

In this section, we map out our empirical strategy using a simple model of cost minimization. To set notation, let $p_{i,t}^j$ represent the price of good $i \in I$ at time t purchased by household $j \in J$. Let $q_{i,t}^j$ denote the corresponding quantity. Household expenditures during month m can be expressed as $X_m^j = \sum_{i \in I} p_{i,t}^j q_{i,t}^j$. In Section IA, we introduce a price index, p_m^j , and a corresponding composite good, Q_m^j , that allows us to write expenditures as $X_m^j = p_m^j Q_m^j$. Note that prices of individual goods (and hence the aggregate index) vary across households. The dataset described in the next section allows us to explore how and why prices differ across households. We are careful to construct the index in a way that allows cross-household comparisons despite the fact that households' shopping baskets differ. In Section III, we document how this price index varies over the life cycle.

To reflect the ability to use time to reduce price, we treat the price paid by household j as a function of time input, s_m^j .⁴ All else equal,

we assume the price paid declines in shopping time, with the returns to shopping diminishing as shopping intensity increases. That is, $\partial p / \partial s < 0$, $\partial^2 p / \partial s^2 > 0$. For a given amount of shopping time, the price paid also depends on what may be loosely termed "shopping needs." For example, a shopper who spreads shopping time over numerous goods may pay a higher price per good than a shopper who devotes the same total time to finding the best bargain for a single good. That is, the relationship between shopping time and price depends on whether shopping time is diluted across many items. Let \mathbf{N} represent a vector of characteristics of the shopping basket that may influence price paid. As will be clear in subsequent sections, our dataset allows us to consider a number of candidate elements of \mathbf{N} .

These considerations imply that a household faces a shopping "technology" given by a price function $p(s, \mathbf{N})$. The goal of Section V is to estimate the parameters of this function. In particular, we estimate the elasticity of price with respect to shopping time.

Before stating how an optimizing household will exploit the shopping technology, we note that shopping is just one way in which a household may substitute time for goods outside of market labor. Following Becker (1965), we assume that, in addition to the shopping technology, households are able to convert time into consumption goods using home production. Specifically, consider a household that wishes to consume C units of a consumption good at a point in time. Consumption goods are commodities produced by combining time and market goods via a home production function, $f(h, Q)$, where h is the time input into home production and Q is the quantity of the composite market good.

Cost minimization can now be stated as (dropping household and time subscripts):

$$(1) \quad \min_{s, h, Q} p(s, \mathbf{N})Q + \mu(s + h)$$

rage of sales and discounts. Shoppers may visit multiple stores to find the lowest price for a particular set of goods. Shoppers may avoid high-priced convenience stores at the cost of time spent driving to a supermarket and waiting in line. Shoppers may study Sunday paper inserts to find coupons or discounts linked to a particular store. Below, we explore the use and effectiveness of these and other alternative strategies using our micro dataset.

⁴ There are a number of ways this may be accomplished. For example, shoppers may shop frequently to take advan-

subject to

$$f(h, Q) = C,$$

where μ is the opportunity cost of time. The price of time is assumed to be the same for the shopper and the home producer, but does not necessarily equal a market wage. We do assume that households are not at a corner in their time allocation regarding shopping and home production. That is, at the optimum, households perform some shopping and home production but allocate time to some alternative activity as well. Inada conditions on the respective utility (with respect to leisure), shopping, and home production functions would be sufficient. Note that the other choices a household makes (for example, labor supply and the intertemporal allocation of consumption) are captured by μ and C . Our empirical strategy exploits the fact that conditional on these other choices, a household faces a static cost-minimization problem about whether to allocate time to shopping and home production or purchase market goods instead.⁵

The first-order condition for shopping time is given by

$$(2) \quad -\frac{\partial p}{\partial s}Q = \mu.$$

This condition implies that for a given shopping bundle, as the price of time (μ) falls, shopping intensity (s) increases and the price paid declines. The empirical validity of this assertion is explored in Section IV. Note that this first-order condition, together with a parameterized shopping function, provides a mapping between shopping time and the price of time, conditional on a basket of goods. We exploit this insight in Section VI to calculate the implied price of time over the life cycle.

The first-order condition for home production time is

$$(3) \quad \frac{\partial f}{\partial h}\lambda = \mu,$$

⁵While there is no need to assume that consumption is separable across goods, we assume that the price and home production functions are (weakly) separable. That is, the goods not captured by our dataset do not shift the marginal rate of transformation between time and goods in shopping or home production.

where λ is the multiplier on the constraint. The first-order condition for Q is

$$(4) \quad \frac{\partial p}{\partial Q}Q + p = \lambda \frac{\partial f}{\partial Q},$$

where we allow Q to be an element of \mathbf{N} in $p(s, \mathbf{N})$ with $\partial p / \partial Q > 0$. Combining terms, we have that the MRT between time and goods in shopping equals the MRT in home production:

$$(5) \quad \frac{\frac{\partial f}{\partial h}}{\frac{\partial f}{\partial Q}} = -\frac{\frac{\partial p}{\partial s}Q}{\frac{\partial p}{\partial Q}Q + p}.$$

We use this condition together with the parameterized price function to estimate the parameters of the home production function in Section VII.

Given the parameters of the home production and the inputs h and Q , in Section VIII we estimate the life-cycle profile of consumption, $C = f(h, Q)$. Specifically, we contrast consumption with household expenditure, X . There is a distinction between the two, given that time is an input into shopping and home production. Also in Section VIII, we calculate the relative contribution of these alternative uses of time in driving a wedge between measured expenditure and ultimate consumption.

II. Data

Our price data are from ACNielsen's Homescan Panel.⁶ The Homescan dataset is designed to capture all consumer grocery packaged goods purchased by the household at a wide variety of retail outlets. We use the Homescan dataset for Denver, covering the period January 1993 through March 1995. The survey is designed to be representative of the Denver metropolitan statistical area, and summary demographics line up well with the estimates from the 1994 Panel Study of Income Dynamics (PSID) (see Table A1 in the Data Appendix).

⁶The Data Appendix contains additional detail about this dataset, as well as our time-use dataset.

Respondents in the Homescan survey remain in the survey up to 27 months. The survey is implemented at the household level and contains detailed demographics, which are updated annually. Specifically, we know the characteristics of the household: the head’s age, sex, race, education, and employment status; and family composition and household income. Employment status and household income are measured as categorical variables.

Households selected for the Homescan sample are equipped with an electronic home scanning unit. After every shopping trip, the shopper scans the UPC of all the purchased packaged goods. The shopper provides three additional pieces of information regarding each transaction: the date, the store, and the total amount of discounts received due to promotions, sales, or coupons. The scanners are programmed to include the stores in the household’s shopping area (including grocery stores, convenience stores, specialty stores, super centers, and price clubs). ACNielsen maintains a dataset of current prices for stores within the metropolitan area. Given the store and date information, ACNielsen can link each product scanned by the household to the actual price for which it was selling at the retail establishment. In terms of associated demographics and coverage of multiple outlets, the Homescan dataset is superior to retail-based scanner data for life-cycle analysis.

Within the Homescan dataset, we have 2,100 separate households and over 950,000 transactions. For our analysis, we focus on households in which the average age of the “primary shopper” is greater than or equal to 25 and less than 75. This restriction leaves us with 2,056 households. For each household and month, we calculate various measures, such as number of stores visited and average price paid, that are described in detail in the following sections. To match with the annual demographic data and to reduce measurement error, we average over the monthly observations within a household-year. As detailed in the Appendix, our sample consists of 4,854 household-year observations. All reported standard errors are adjusted for heteroskedasticity and clustered to account for the fact that household observations across years are not independent.

One should keep in mind that the dataset is essentially a cross section at a given point

in time (the panel dimension covers only 27 months). Therefore, when we discuss life-cycle patterns, we will be comparing different cohorts. This may, for example, overstate the decline in expenditure between households with middle-aged heads (richer cohorts) and households with older heads (poorer cohorts). Likewise, it could cause us to understate the increase in expenditure between households with young heads and those with middle-aged heads. However, this should not be as important an issue for the normalized variables we focus on, such as the ratio of consumption to expenditure.

In the Data Appendix, we discuss and quantify a number of potential data quality issues with the Homescan data. These issues include: representativeness of the households in the Homescan sample, coverage of the goods scanned by households in the sample, and sample attrition.

III. Life-Cycle Prices

A. Price Index

Given that households buy a variety of different goods during each shopping trip, we need to define an average price measure for each household. Recall that we denote the price of good $i \in I$ purchased by household $j \in J$ on shopping trip (date) t by $p_{i,t}^j$, and the corresponding quantity, $q_{i,t}^j$. Total expenditure during month m is simply

$$(6) \quad X_m^j = \sum_{i \in I, t \in m} p_{i,t}^j q_{i,t}^j.$$

At the same point in time, there may be another household purchasing the same good at a different price. We average over households within the month to obtain the average price paid for a given good during that month, where the average is weighted by quantity purchased:

$$(7) \quad \bar{p}_{i,m} \equiv \sum_{j \in J, t \in m} p_{i,t}^j \left(\frac{q_{i,t}^j}{\bar{q}_{i,m}} \right),$$

where

$$(8) \quad \bar{q}_{i,m} \equiv \sum_{j \in J, t \in m} q_{i,t}^j.$$

We then aggregate the individual prices into an index. We do so in a way that answers the question of how much more or less than the average is the household paying for its chosen basket of goods. That is, if the household paid the average price for the same basket of goods, the cost of the bundle would be:

$$(9) \quad Q_m^j = \sum_{i \in I, t \in m} \bar{p}_{i,m} q_{i,t}^j$$

We then define the price index for the household as the ratio of expenditures at actual prices divided by the cost of the bundle at the average price, \bar{p}_m^j :

$$(10) \quad \tilde{p}_m^j \equiv \frac{X_m^j}{Q_m^j}$$

We normalize the index by dividing through the average price index across households within the month, ensuring that for each month the index is centered around one:

$$(11) \quad p_m^j \equiv \frac{\tilde{p}_m^j}{\frac{1}{J} \sum_j \tilde{p}_m^{j'}}$$

The price index (10) shares the typical feature (as with Laspeyres and Paasche indices) that the basket of goods is held constant as we vary the prices between numerator and denominator. To the extent that relative price movements induce substitution between goods, there is no reason to expect that the household would keep its basket constant.

One subtle difference does exist between the substitution bias inherent in our index and that presented by the typical price index. In a standard price index, the relative price of two goods may differ across time periods. In our framework, the range of prices for any good is the same across households, but the relative price of time varies. This results in variation in the relative *purchase* price of goods. However, it is in theory feasible for household j to purchase goods at the prices paid by household j' —and vice versa. This is not true in intertemporal price comparisons, such as the CPI. By revealed preference, households in our sample would never be better off if they paid prices (inclusive of time shopping) recorded by other households that period, including the average price.

It is important to note that differences in our price index between households do not reflect differences in the quality of goods purchased. The price differentials are for the *identical* goods as measured by UPC codes. The UPC codes are very specific. For example, a liter bottle of Pepsi, a six pack of Pepsi cans, and a twelve-pack of Pepsi cans all have distinct UPC bar codes.

B. Life-Cycle Prices

In this subsection, we use our price index to explore how prices paid for the same goods vary across households at different stages of the life cycle. Standard economics suggests that, all else being equal, households with a lower opportunity cost of time will spend more time searching/shopping to reduce the price paid for a given market good. This follows directly from the first-order condition (2) of Section I. Given the fact that wages, market work hours, and the time demands of raising children are high during middle age relative to later in the life cycle, this suggests that, all else equal, the price paid for the same good will be higher in middle age relative to later in the life cycle.⁷

The results in Figure 1 and Table 1 support this conjecture. Figure 1 plots the log price index relative to households whose primary shopper is between 25 and 29 years old. Column I of Table 1 is the regression counterpart of Figure 1, reporting the results of a regression of log price on age-range dummies for our 4,854 household-year observations. The results indicate that prices paid are roughly constant for households early in their life cycle. After the age of 49, however, prices start to fall sharply. Specifically, relative to households in their late forties, households in their early fifties pay prices that are 1.2 percent lower, while households in their late fifties, early sixties, and late sixties/early seventies pay prices that are 3.1 percent, 3.0 percent, and 3.9 percent lower, respectively (p-values of all differences < 0.01).

The evolution of family size over the life cycle affects more than just the opportunity cost

⁷Classic references on the life-cycle profile of market hours and wages are Jacob Mincer (1974) and Gilbert Ghez and Becker (1975).

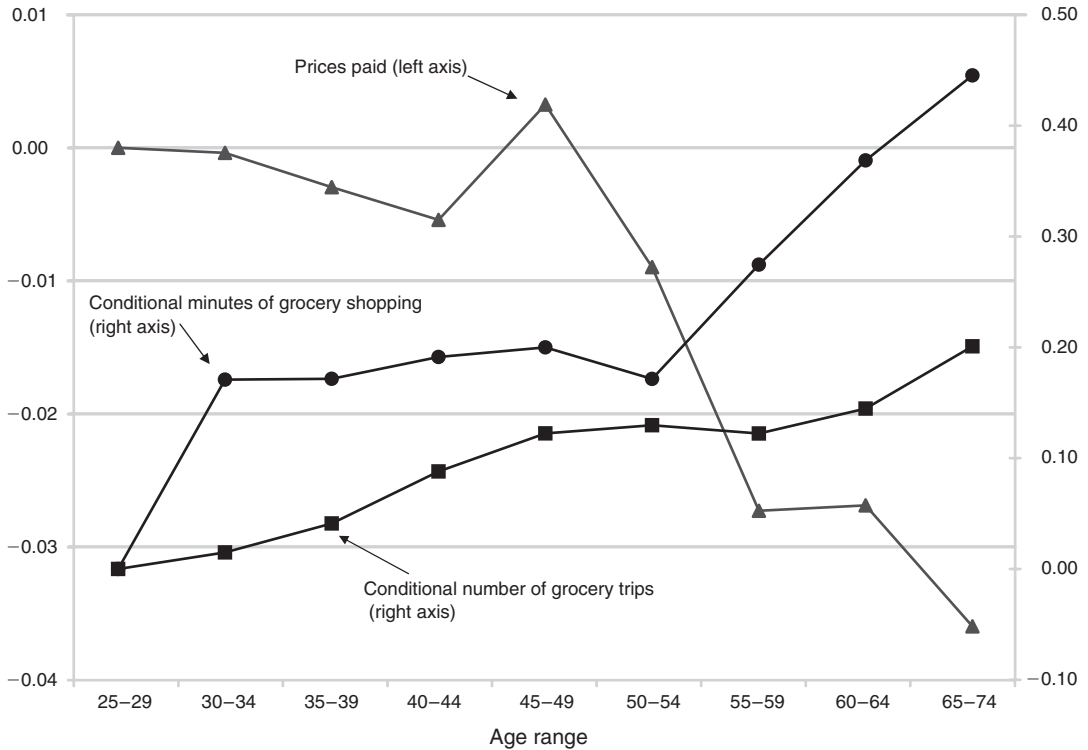


FIGURE 1. PRICE PAID AND SHOPPING FREQUENCY OVER THE LIFE CYCLE: LOG DEVIATION FROM 25- 29-YEAR-OLDS

Notes: The figure plots price paid (left axis) and shopping intensity (right axis) over the life cycle. All values are expressed as log differences relative to 25- 29-year-olds. Shopping intensity is measured as the number of grocery trips per month (squares) and the number of minutes spent grocery shopping per week (circles). The shopping intensity numbers (but not prices paid) are conditional on household shopping needs. The data for this figure are the coefficients from the age dummies found in Table 1, column I (for prices), column IV (for conditional grocery trips), and column VI (for conditional minutes of grocery shopping). See the note to Table 1 for details about the relevant samples.

of time. A larger family consumes more goods, and this raises the return to shopping for a given price of time, as well as alters the nature of the consumption basket. Nevertheless, the life-cycle pattern of prices is robust to the inclusion of several measures of shopping needs. In Column II of Table 1, we regress log price on age dummies as well as controls for the amount of goods purchased. These “shopping needs” controls include the household’s average log number of UPC codes purchased per month, the average log number of product categories, and the log of our quantity variable Q defined by equation (9). The product category is defined by Homescan with such classifications as “dairy milk—refrigerated” or “soft drinks—low calorie.” The coefficients on the age dummies suggest that the

inclusion of these controls does not significantly alter the life-cycle pattern of prices.

IV. Life-Cycle Shopping

A. Shopping Time

The preceding discussion and the model of Section I argued that prices vary over the life cycle because the price of time—and therefore shopping time—varies over the life cycle. In this section we explore whether shopping time varies over the life cycle and relate it to price paid. To do so, we use two datasets. First, we use data from Homescan to measure the frequency of grocery shopping trips and which type of stores were visited. However, Homescan does

TABLE 1—PRICE PAID AND SHOPPING TIME OVER THE LIFE CYCLE:
LOG DEVIATION FROM AGE 25 TO 29

Regressors	Dependent variable					
	ln(Price)		ln(Shopping trips per month)		Shopping time (Minutes per week)	
	I	II	III	IV	V	VI
Age 30–34	–0.000 (0.006)	0.001 (0.006)	0.11 (0.04)	0.01 (0.03)	14.16 (7.70)	10.86 (7.82)
Age 35–39	–0.003 (0.006)	–0.001 (0.006)	0.15 (0.04)	0.04 (0.03)	15.28 (7.67)	10.91 (7.82)
Age 40–44	–0.005 (0.007)	–0.005 (0.006)	0.16 (0.05)	0.09 (0.03)	15.47 (7.38)	12.29 (7.48)
Age 45–49	0.003 (0.007)	0.000 (0.007)	0.14 (0.05)	0.12 (0.03)	13.18 (7.49)	12.91 (7.52)
Age 50–54	–0.009 (0.008)	–0.012 (0.008)	0.13 (0.05)	0.13 (0.03)	9.03 (7.45)	10.90 (7.63)
Age 55–59	–0.027 (0.009)	–0.031 (0.009)	0.09 (0.05)	0.12 (0.03)	15.67 (8.27)	18.42 (8.85)
Age 60–64	–0.027 (0.008)	–0.029 (0.008)	0.11 (0.05)	0.14 (0.03)	22.82 (8.73)	25.98 (9.07)
Age 65–74	–0.036 (0.008)	–0.039 (0.007)	0.12 (0.05)	0.20 (0.03)	29.14 (8.06)	32.70 (8.30)
Include controls for shopping needs	No	Yes	No	Yes	No	Yes
N	4,854	4,854	4,854	4,854	16,678	16,678

Notes: Columns I and II report results of regressing the average log price index for each household-year on age dummies, without and with controls for shopping needs, respectively. Specifications III and IV show the results of regressing average log shopping trips per month for each household-year on age dummies, without and with controls for shopping needs, respectively. The data in columns I–IV are from ACNielsen Homescan and include all households in the sample whose primary shopper's age is greater than or equal to 25 and less than 75. Columns V and VI report the results of regressing time spent grocery shopping (in minutes per week) on age dummies, without and with controls for shopping needs, respectively. The data are from the ATUS and include all individuals in the sample between the ages of 25 and 74, inclusive. The omitted age group in each regression is 25–29. The mean shopping time and log shopping trips per month for 25–29-year-olds are 58.29 minutes per week and 1.67, respectively. The shopping needs controls in specifications II and IV include the log number of different UPCs purchased during the month, the log number of different product categories purchased per month, and the log of the composite index, Q . The shopping needs controls in specification VI include controls for household size. Specifications V and VI also include day of week controls to account for the fact that the weights provided by ATUS do not necessarily generate intervals that are uniformly distributed across days of the week. Robust standard errors clustered at the household level are included in parentheses.

not record the length of each shopping trip, just the number of transactions. We therefore supplement the Homescan data using the 2003 ATUS.

Households in the ATUS fill out time diaries over a given 24-hour period. The ATUS staff then categorizes the responses into one of over 400 time-use categories. One of those categories is time spent shopping for food or groceries. This measure is distinct from time spent shopping for other goods, time spent ordering take-out food, or time spent at restaurants. We also embed travel time associated with food shopping into the household's total time spent grocery

shopping.⁸ We multiply average times by seven to convert the reported ATUS minutes per day into minutes per week. Restricting the ATUS sample to households between the ages of 25 and 74 provides a sample of 16,678 individuals. (See

⁸The ATUS also includes the category “researching purchases” to capture time spent on comparison shopping. We do not include this category in our measure of shopping time because it applies to all shopping, not just groceries. However, we have redone the analysis, including comparison shopping in our grocery shopping measure, and found essentially no change in the results.

the Data Appendix for a full discussion of how we constructed our sample from the ATUS.)

Table 1, columns III–VI, document the life-cycle pattern of shopping intensity. Columns III–IV use the Homescan data, and columns V–VI use the ATUS data. The dependent variable for the Homescan columns is the log number of shopping trips per month. A shopping trip is defined by the date and store of the transaction. That is, transactions at two stores on the same day are counted as two trips. Similarly, two transactions at the same store on two different days are counted as two trips. The dependent variable in the ATUS columns is the mean level of time spent shopping for groceries expressed in units of “minutes per week.” We do not use the log time spent, as many respondents record zero shopping time for their 24-hour diary period.

Columns III and V report the results of shopping time regressed on five-year age dummies with no controls for shopping needs.⁹ We see that relative to those age 25 to 29 (the omitted group), middle-age and retirement-age households shop intensively. However, these unconditional regressions mix the life-cycle variation in the price of time and the variation in shopping needs. As discussed in Section I, our model predicts that shopping time varies monotonically with the price of time *conditional* on a particular shopping basket.

To address this, columns IV and VI add controls for shopping needs. For the Homescan data used in column IV, we use the same controls used in our price regressions of column II, namely, the average number of UPC codes purchased, the average number of product categories purchased, and our composite quantity measure Q , all expressed in logarithms. Because detailed measures of shopping quantities are unavailable in the ATUS, for column VI we control for shopping needs using measures of family size. In particular, we add dummy variables indicating whether the household head was married and whether the household had 0, 1, 2, 3, 4, or 5+ children.

In contrast to the price regressions of column II, the presence of these additional controls has a sizeable effect on the life-cycle shopping

pattern. In particular, the conditional shopping time increases nearly monotonically throughout the life cycle. Relative to those age 25 to 29 and conditional on the shopping basket, Homescan shoppers age 45 to 49 and 65 to 74 shop 12 and 20 percent more frequently (column IV). For reference, Homescan shoppers age 25 to 29 undertake an average of 6.5 shopping trips per month. Relative to those age 25 to 29 and conditional on family size, ATUS respondents age 45 to 49 shop on average 13 more minutes per week, and those age 65 to 74 shop an additional 33 minutes per week (column VI). Given that the average time spent grocery shopping for those age 25 to 29 is 58 minutes per week, these differences represent increases of 22 and 57 percent, respectively.

To relate these movements in shopping intensity to the life-cycle profile of prices, in Figure 1 we plot the percentage change in ATUS shopping time and Homescan shopping frequency, conditional on controls for shopping needs. For the ATUS series, we convert the level differences reported in column VI of Table 1 to percentage differences using the mean shopping time of 58 minutes per week for respondents age 25 to 29. The figure highlights the fact that while both measures of shopping intensity increase over the life cycle, the time diaries reveal a sharp uptick in the rate of increase after age 55. This sharp increase roughly coincides with the downturn in prices paid. For either measure, the general increase in shopping time over the life cycle tracks the overall decline in prices paid—the correlation of the life-cycle price series with the Homescan series is -0.76 , and the correlation of the price series with the ATUS series is -0.86 .

In the next subsection, we will use our Homescan micro dataset to shed light on exactly how additional shopping time lowers the price paid. Before doing so, we note that the model of Section I has implications beyond the life cycle. In particular, the first-order condition (2) relates shopping intensity to the opportunity cost of time. One reason we have focused on the life cycle is that it provides a good proxy for the price of time. Alternative proxies are wages or labor force status. While the Homescan dataset does not have wage data, it does have categorical data on household labor income. As household income increases, the average price paid by households increases monotonically. For

⁹The ATUS regressions always include dummies for the time diary’s day of the week.

example, we find that conditional on shopping needs, households earning more than \$70,000 a year pay 2.1 percent higher prices than households earning less than \$30,000 a year (p -value < 0.01). At the same time, such high-income households make 16 percent fewer shopping trips per month. Likewise, among married-couple households, those households in which both spouses work pay 2.3 percent higher prices and make 10 percent fewer shopping trips, all else equal. Moreover, the semi-elasticity of shopping time with respect to log wages in the ATUS sample is -7.5 (p -value = 0.04).¹⁰ In sum, there is a consistent relationship between several measures of the opportunity cost of time and both the price paid and shopping intensity.

B. Shopping Strategies

To explore the mechanisms through which shoppers translate time into lower prices, we begin by decomposing the Homescan frequency of shopping trips discussed above into two components. The first component is the number of different retail establishments visited per month (“stores per month”). The second is the monthly frequency with which the shopper visited each retail establishment (“trips per store”). The product of the two components is our original measure of total number of shopping trips per month.

In Figure 2, we plot the life-cycle profile of the two component measures. Each series is constructed in the same manner as the overall frequency measure depicted in Figure 1. In particular, both series are expressed as log deviations from age 25 to 29 and are conditional on our measures of shopping needs. For reference, shoppers age 25 to 29 average 3.0 different stores per month and 2.3 trips per store. The figure indicates that older shoppers visit the same number of stores as their younger counterparts. Accordingly, all of the increase in total shopping trips by older households reflects more frequent visits to each store. Specifically, shoppers over the age of 65 undertake 10 percent more

“trips per store” than shoppers age 45 to 49 and 17 percent more than those age 25 to 29.

This raises the additional question of how a shopper obtains lower prices by visiting the same stores multiple times. One possibility is that frequent visits allow shoppers to exploit in-store discounts. Homescan records the amount saved on each purchase due to discounts. This measure includes, without distinction, both store discounts, such as via membership cards, and manufacturers’ discounts, such as coupons. Figure 3 plots the propensity to use discounts and the share of expenditures saved by discounts over the life cycle. As before, both series are conditional on shopping needs and reflect differences with respect to shoppers age 25 to 29.

The propensity to use a discount during a month is roughly constant between the ages of 25 and 49, at 52 percent of households. However, after the age of 49, monthly discount use increases sharply with age. Shoppers over the age of 65 are 16 percentage points more likely to use discounts than those age 45 to 49. Similarly, the share of total expenditure saved through discounts increases sharply after the age of 49. Conditional on shopping needs, the share of total expenditure saved through discounts is constant through the age of 49, at approximately 4 percent. Shoppers age 65 to 74, however, save an additional 3 percent of expenditures more than those age 45 to 49 (p -value < 0.01), all else equal.¹¹

In the Homescan micro data, there is a strong correlation between shopping frequency and either the propensity of discount use or the fraction saved using discounts. Specifically, a doubling of shopping frequency is associated with a 25 percentage point increase in the probability of discount use and a 1 percentage point increase in the fraction of expenditures saved. The sample averages of discount use and fraction saved are 55 percent and 4 percent, respectively. Given that in-store discounts and store sales change often, this suggests that frequent shopping may lead to lower prices through more extensive use of store discounts.

¹⁰The mean shopping time among the 9,985 respondents who report a wage (calculated as weekly earnings/weekly hours) in our ATUS sample is 65.2 minutes per week, suggesting an elasticity of roughly -0.12 .

¹¹These results are consistent with Ron Cronovich, Rennae Daneshvary, and R. Keith Schwer (1997), who find that retired households are more likely to use coupons than nonretired households.

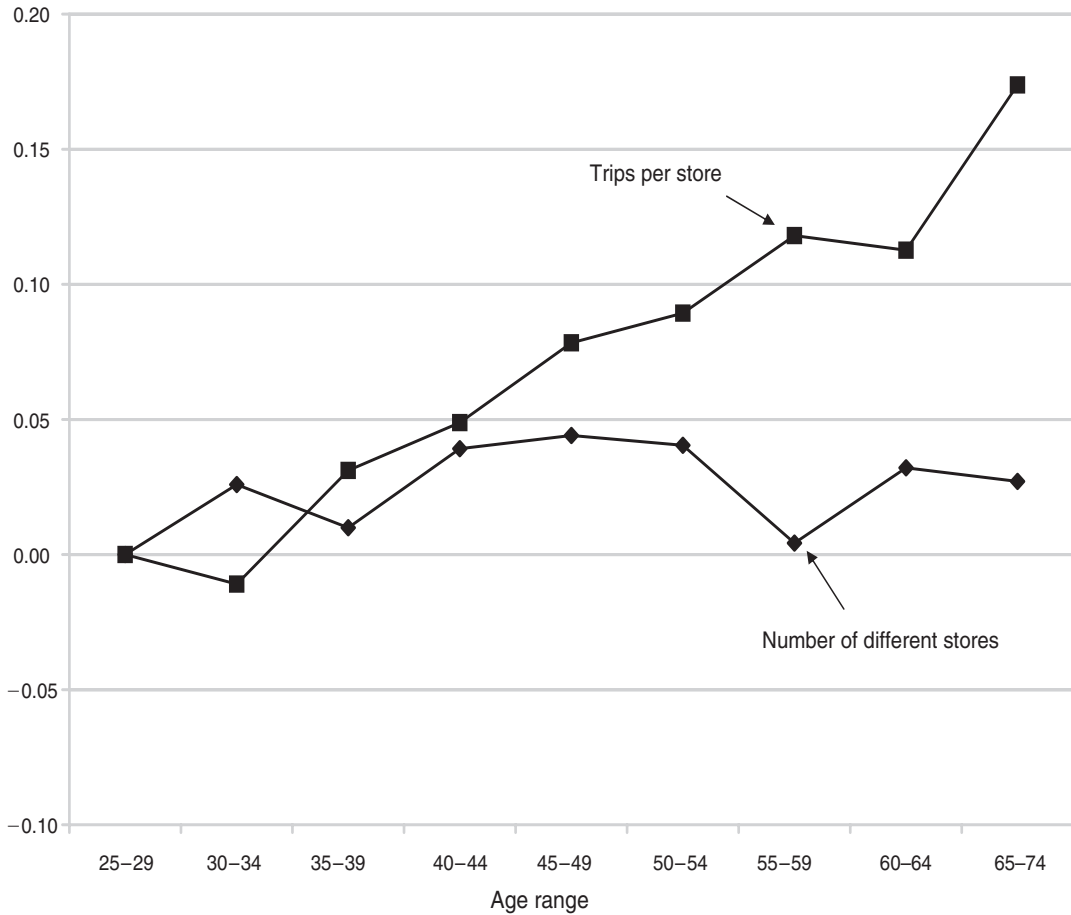


FIGURE 2. DECOMPOSITION OF SHOPPING FREQUENCY: LOG DEVIATION FROM 25- 29-YEAR-OLDS

Notes: Data from ACNielsen Homescan. Sample used is the same as described for columns I–IV of Table 1. This figure reports the coefficients on age dummies from a regression of log shopping intensity on age dummies and controls for household shopping needs. All values expressed as log deviations from 25- 29-year-olds. The shopping needs controls are the same as used in columns II and IV of Table 1. The figure shows two measures of shopping intensity: the log of the number of different stores that the household frequents per month (diamonds), and the log of the average number of trips per month made by a household to each store (squares). See text for details.

Given that older shoppers shop more frequently and take advantage of more discounts, a natural question is whether these behaviors explain the life-cycle pattern of prices depicted in Figure 1. To answer this, we reestimated the regression of Table 1, column II, including the average number of stores frequented per month, the number of trips per store, the frequency of discount use, and the share of expenditures saved through discounts (not reported). These additional controls explain most of the life-cycle

pattern of prices. In particular, the 4 percent differential in price paid between those age 45 to 49 and those age 65 to 74 drops to 1 percent. In other words, 75 percent of the decline in price post–middle age can be explained by shopping intensity and discount use.

We now consider—and reject—several alternative shopping strategies that may also explain the price patterns documented in Table 1. First, older households may shop at different types of stores than either younger or middle-age

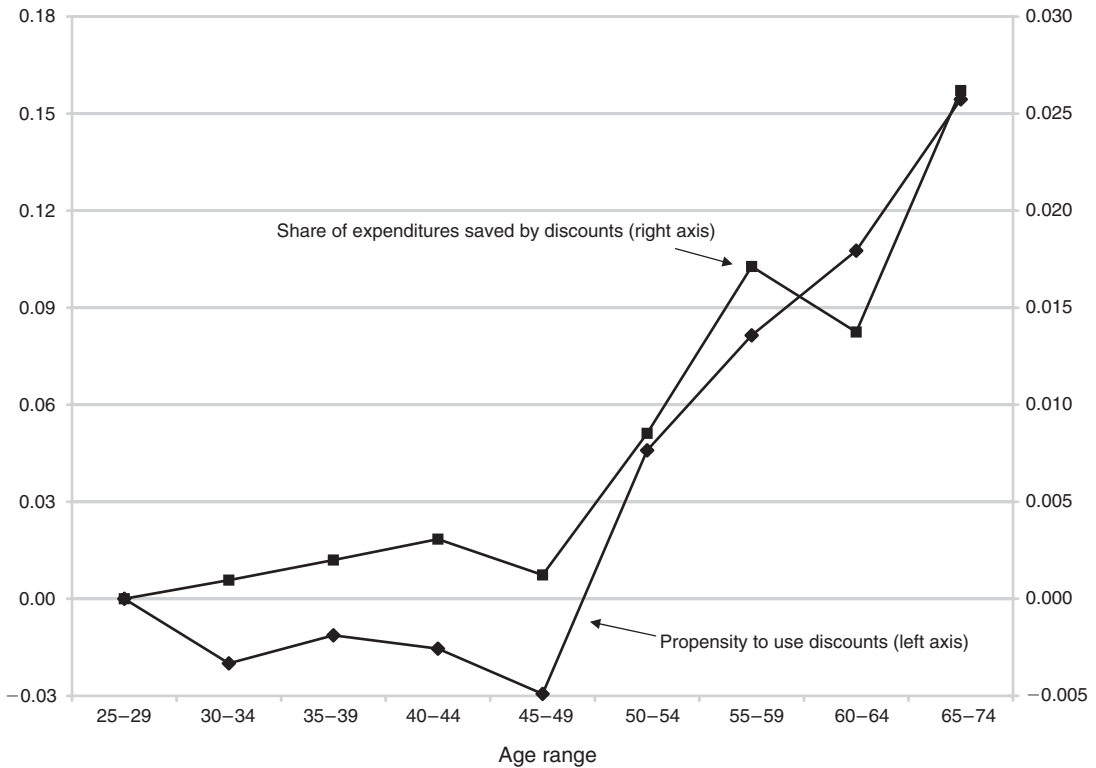


FIGURE 3. DISCOUNT USE OVER THE LIFE CYCLE: PERCENTAGE-POINT DEVIATION RELATIVE TO 25- 29-YEAR-OLDS

Notes: Data from ACNielsen Homescan. Sample used is the same as that for columns I–IV of Table 1. Figure reports the coefficients on age dummies in a regression of discount use (diamonds, left axis) or share of expenditures saved using discounts (squares, right axis) on age dummies, and controls for household shopping needs. All values represent percent differences relative to 25- 29-year-olds. The shopping needs controls are the same as described in the note to Table 1. Discount use refers to the fraction of households using either store or manufacturer discounts as part of their shopping trip at any time during a month. Share of expenditures saved using discounts refers to the ratio of money saved by store and manufacturer discounts during a month relative to total gross monthly expenditures. The mean discount use and share of expenditures saved by discounts for 25- 29-year-olds are 51.9 percent and 3.7 percent, respectively.

households. For example, it may be the case that middle-age shoppers pay a higher price for standard grocery items because they shop at stores with greater ambience, with better service, or that carry premium items. The higher price is then payment for these corollary goods and services. Similarly, busy middle-age shoppers may pay a premium at convenience stores in exchange for quicker trips.

There is, however, no evidence that this is the case. Specifically, we divide the Homescan retail establishments into five groups: grocery stores, discount stores, convenience stores, drug stores, and other. Discount stores include both

club stores and “big box” chain stores. Table 2 reports the share of total expenditures purchased at the different types of stores over the life cycle. Compared to households age 35 to 49, older households spend slightly more at grocery and drug stores and spend slightly less at convenience and discount stores. The fact that older households do not frequent convenience stores is not surprising, given their lower opportunity cost of time. The fact that older households shop at discount stores less frequently is a function of the size of their shopping bundles. Once we control for differences in shopping needs over the life cycle, there is no differences in spending

TABLE 2—COMPARISON OF EXPENDITURE SHARES AT DIFFERENT SHOPPING OUTLETS, BY AGE GROUP

Variable	Age range				p-value difference III vs. II	p-value difference IV vs. II
	I 25–34	II 35–49	III 50–59	IV 60–74		
Percent of expenditures at all grocery stores	0.77	0.75	0.75	0.77	0.98	0.05
Percent of expenditures at discount stores	0.13	0.14	0.12	0.12	0.06	0.05
Percent of expenditures at convenience stores	0.02	0.02	0.01	0.01	0.29	<0.01
Percent of expenditures at drug stores	0.01	0.02	0.02	0.02	0.40	0.11
Percent of expenditures at “other”	0.07	0.08	0.10	0.08	0.10	0.95
Percent of chain expenditures at grocery chain 1	0.13	0.12	0.11	0.10	0.35	0.23
Percent of chain expenditures at grocery chain 2	0.19	0.22	0.23	0.27	0.62	0.02
Percent of chain expenditures at grocery chain 3	0.48	0.48	0.49	0.45	0.71	0.09
Percent of chain expenditures at grocery chain 4	0.12	0.09	0.09	0.09	0.72	0.70
Percent of chain expenditures at grocery chain 5	0.07	0.08	0.08	0.09	0.97	0.25

Notes: Data are from ACNielsen Homescan. This table shows the share of monthly household expenditures at given shopping outlets by age. The sample size for the age ranges in columns I–IV are 1,058, 2,135, 755, and 906, respectively. Expenditure shares are computed for each household-year pair and averaged over households within each age range. The “other” category in the top half of the table refers to all stores that do not fall into the four main shopping outlet categories (such as liquor stores, pet stores, and vending machines). The expenditure shares for the five store categories sum to one within each age range. In the lower half of the table, we separately analyze the share of expenditures purchased at the five largest grocery store chains in the data. The share of expenditures is computed as the expenditures at each grocery chain relative to the sum of all expenditures at the five largest grocery chains. As a result, the expenditure shares for the five largest grocery store chains also sum to one within each age group.

patterns between old and young households at grocery and discount stores.

Given that grocery stores represent the largest fraction of purchases, we examine them in more depth in the bottom rows of Table 2. Roughly 68 percent of all grocery purchases within the Homescan dataset occurred at the top five grocery chains, measured by share of expenditures within the Homescan dataset. Table 2 shows the share of grocery expenditures at the top five chains accounted for by each chain over the life cycle. The results indicate that there is little variation over the life cycle as to which chains are patronized. Relative to younger households, older households have a slightly lower share of expenditures at chains 1 and 3, and a

slightly higher share of expenditures at chain 2. However, including store chain effects into a price regression explains none of the life-cycle variation in prices paid. Moreover, we have rerun our analysis restricting the sample to purchases made at the top five grocery chains and found that the life-cycle profiles of prices documented in Figure 1 and Table 1 persist. Specifically, we found that shoppers age 50 to 54, 55 to 59, 60 to 64, and 65 to 74 pay 0.6 percent, 2.4 percent, 1.9 percent, and 3.4 percent lower prices than 45- 49-year-olds. We conclude that differences in where households shop explain little of the life-cycle variation in prices paid.

Another issue we can rule out is that older households are more willing to switch brands

to take advantage of sales or discounts. This is a strategy distinct from searching for discounts on one's favorite brand. Switching from one's preferred brand to take advantage of a competing brand's sale entails a direct loss of utility in consumption (offset by a gain in resources). However, a large marketing literature documents the fact that brand loyalty is invariant to age (for example, see Stephen Hoch et al. 1995 and P. B. Seetharaman, Andrew Ainslie, and Pradeep Chintagunta 1999). The Homescan data reaffirm this conclusion. We measure brand loyalty as the average number of brands within each product category purchased by the household per year. That is, how many brands of orange juice does the household typically purchase, how many brands of peanut butter, etc. Averaging over product categories yields a summary measure of brand loyalty for each household. There is no evidence that older shoppers are more prone to switch brands. If anything, the point estimates suggests older shoppers are more brand loyal than are younger shoppers.

Finally, we consider the possibility that older shoppers "stock up" during a sale by purchasing a large quantity when the price is low and then waiting until the next sale to restock. This strategy will yield a lower average price at the cost of storing a larger inventory of goods at home. Such a strategy implies that, for each good, the quantity purchased by older shoppers is more sensitive to price variations.

To test this, we regress log quantity on log price for each household-UPC pair.¹² Note that the null hypothesis for this exercise is that every household observes sales equally, but the older shoppers respond more aggressively. Under this null (which is an alternative to our search/shopping time premise), price movements are exogenous to the household. With these estimates in hand, we test whether the estimated elasticities vary by age. Specifically, we regress the estimated elasticities on age dummies and a UPC fixed effect. We find no evidence that elasticities vary by age. The p-value for the test of joint significance of the age dummies is 0.28.

¹²We also performed the analysis including, as an additional regressor, the log price of competing goods, measured as the average price within the product category that quarter, and found similar results.

In summary, we find that the predominant reason older households pay lower prices is because they shop more frequently and are more likely to avail themselves of store and manufacture discounts. The relative shopping intensity of older shoppers reflects frequenting a given store more often rather than frequenting a greater number of stores.

V. The Price Function

In this section, we estimate the sensitivity of price to the variation in shopping time, and parameterize the price function $p(s, \mathbf{N})$ introduced in Section I. As described in Section I, with this elasticity in hand, we will be able to infer a shopper's opportunity cost of time.

Our benchmark specification assumes a log-linear functional form

$$(12) \quad \ln p_m^j = \alpha_0 + \alpha_s \ln s_m^j + \sum_{k=1}^K \alpha_{N_k} N_k + \varepsilon_m^j,$$

where k indexes the K elements of \mathbf{N} . We have also explored a polynomial specification and found similar elasticities (evaluated at the sample means). The polynomial specification confirms that $\partial^2 p / \partial s^2 > 0$.

Our primary measure of shopping time is the frequency of shopping trips recorded in the Homescan dataset. Frequency may be a noisy measure of shopping time in that time per trip may not be constant. Therefore, we also report estimates using the amount of time allocated to shopping reported in the ATUS. We describe below the manner in which we link the ATUS data with the Homescan data. Recall from Figure 1 that these two measures of shopping intensity track each other closely over the life cycle.

For our shopping-basket characteristics, we use the log of our quantity index, Q , the log number of UPC codes purchased per month, and the log number of product categories purchased per month. These controls are the same as those used in Tables 1 and 2.

Our estimates of the elasticity of price with respect to shopping intensity are reported in Table 3. The first column estimates (12) using OLS, and finds α_s to be -0.01 . In other words, a doubling of shopping frequency lowers prices paid by 1 percent, conditional on the quantity purchased. The estimated elasticity with respect

TABLE 3—THE ELASTICITY OF PRICE WITH RESPECT TO SHOPPING INTENSITY

	I	II	III	IV
Estimated elasticity: α_s	-0.010 (0.006)	-0.189 (0.035)	-0.074 (0.032)	-0.037 (0.013)
Measure of shopping intensity	Shopping trips per month	Shopping trips per month	Shopping trips per month	Minutes spent shopping per month
Regression type	OLS	IV	IV	OLS
Instrument set	None	Age dummies	Income dummies	None

Notes: This table reports the results from a regression of log price on log shopping intensity and controls for household shopping needs. In columns I–III, the measure of shopping intensity is the log number of grocery shopping trips per month, averaged within a household over each year. These regressions are estimated using a sample of 4,854 household-year pairs from the Homescan data. This sample is the same as the sample used in columns I–IV of Table 1. In column IV, the measure of shopping intensity is the minutes per week spent shopping for groceries. The regression in column IV is estimated using data from both Homescan and ATUS. To merge the two datasets, we compute the means of the relevant variables in both datasets for each age-sex-marital status cell. This regression included 27 averaged observations (9 age ranges and 3 sex-marital status groups). See text for full details. The controls for shopping needs were the same as the shopping needs controls used in columns I–IV of Table 1. Columns II and III are estimated via instrumental variables. The instrument set for column II consists of nine age-range dummies. The instrument set for column III consists of four income-category dummies. The F-statistic on the first stage for the instrument sets in columns II and III are 17.7 and 32.1, respectively. Robust standard errors clustered at the household level are included in parentheses.

to Q (not reported) is 0.02. That is, a doubling of the amount of goods purchased by the household, holding constant shopping time, increases prices paid by approximately 2 percent.

There are two potential concerns about the OLS estimates presented in column I of Table 3. First, shopping time may be measured with error. Second, it is possible that shopping productivity differs across people such that those who are skilled at shopping both shop less and pay lower prices. Both of these issues may bias our OLS estimate of α_s downward. To address these concerns, we instrument for shopping intensity using several alternative instruments.

First, we use our nine age ranges as an instrument for shopping frequency. This corresponds to our premise that the value of time varies over the life cycle, which in turn will influence shopping intensity conditional on a shopping basket. The first stage is reported in Table 1, column VI, and has an F-statistic on the age dummies of 17.7. The IV estimate of α_s when age categories are used as instruments is -0.19 , which we report in column II of Table 3. In other words, doubling shopping frequency results in a reduction of prices paid of 19 percent, all else equal.

An alternative measure of the opportunity cost of time is the wage. Given the nature of the dataset, we use income categories as our proxy for wage rates. As noted in Section IVA, shopping frequency declines with income in the

Homescan dataset. The F-statistic on the instruments in the first stage is 32.1. The IV estimate of α_s when income categories are used as instruments is -0.07 (shown in column III of Table 3), which is midway between the OLS estimate and our first IV specification.

It is possible that household income may be correlated with the prices households pay for reasons that are not associated with the opportunity cost of time. For example, higher-income people are more likely to own cars, which facilitate grocery shopping. In this case, higher-income people may shop more frequently despite their higher opportunity cost of time. If aspects of shopping technology differ by our broad income categories in such a way that higher income-households have better shopping technology, our estimated elasticity in column III of Table 3 may still be biased downward.

To test this, we explored a third instrument set that includes a series of family-size dummies, corresponding to households with 1, 2, 3, 4, 5, or 6+ individuals. The premise here is that a shopper with more children faces a higher opportunity cost of time. In our first stage, we find that having a larger household significantly reduces shopping frequency, conditional on shopping needs. Specifically, we find that households with three individuals shop approximately 14 percent less than singles and 10 percent less than households with two individuals, all else

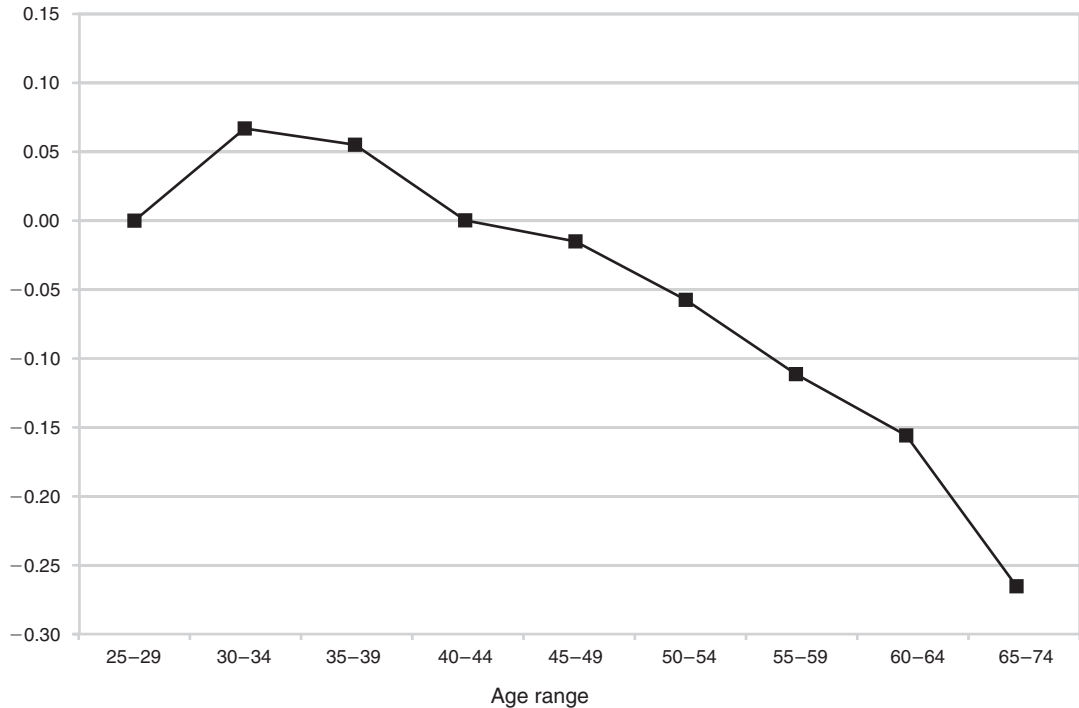


FIGURE 4. IMPLIED OPPORTUNITY COST OF TIME: LOG DEVIATION FROM 25- 29-YEAR-OLDS

Note: Opportunity cost of time implied by households shopping behavior from the Homescan data. See text for details.

equal. Households with four individuals shop 19 percent less than singles. The F-statistic on the household size dummies in the first stage is 34.7. Using household size as our instrument set yields a point estimate of -0.073 , nearly identical to that obtained using income (not shown in the table). We have also estimated the elasticity using all three instrument sets simultaneously. The estimated elasticity is -0.10 (not shown in the table). Assuming the validity of age and household size as an instrument for the price of time, a Hausman test does not reject the validity of income categories as instruments (p-value = 0.85).

Similar results are found using a two-sample procedure that uses data from the ATUS on actual time spent grocery shopping. We merge data from Homescan and the ATUS by creating demographic cells in both datasets defined by age, sex, and marital status. Specifically, we use nine age ranges (those displayed in Figures 1 and 2), two marital status categories, and two

sex categories. As married-couple households all have the same gender composition, this leaves us with only three sex-marital status combinations, yielding a total of 27 cells. For each cell in the ATUS dataset, we calculate the sample average of time spent shopping for groceries and merge this into the Homescan dataset. Note that the measure of time use varies only according to our demographic cells. We therefore collapse each cell in the Homescan sample and run a “between effects” regression. Using the combined data, we estimate α_s to be -0.04 (p-value < 0.01). These estimates are slightly smaller in magnitude than the coefficients shown in column III of Table 3, which uses shopping frequency as the measure of shopping intensity.

In summary, we find that our core IV estimates suggest an elasticity between price and the frequency of shopping trips that is between 7 and 10 percent, although the range of estimates widens when we use OLS or IV with age as the lone instrument. The elasticity of price with

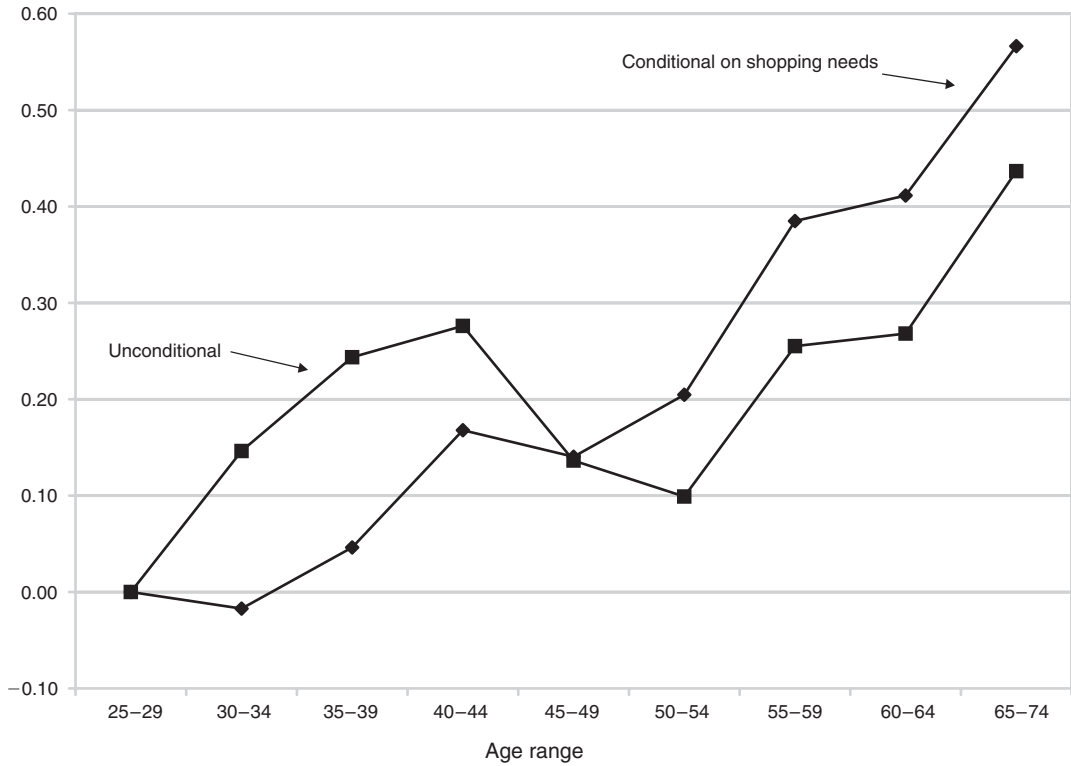


FIGURE 5. TIME SPENT IN FOOD PREPARATION AND CLEAN-UP: LOG DEVIATION FROM 25- 29-YEAR-OLDS

Notes: Data from ATUS. Sample used is the same as that for columns V–VI of Table 1. Figure plots the coefficients on age dummies from a regression of amount of time spent on food preparation and clean-up during a month on age dummies with (diamonds) and without (squares) controls for household shopping needs. All values represent percent differences relative to 25- 29-year-olds. Levels are converted to log deviations using the unconditional average amount of time spent in food preparation and clean-up for 25- 29-year-olds of 204 minutes per week. The controls for shopping need are the same that are used in column VI of Table 1.

respect to shopping intensity as measured by minutes spent shopping per week is 4 percent.

VI. The Life-Cycle Price of Time

In this section, we use the estimates of Section V to calculate the implied cost of time for the shopper. Recall from Section I that cost minimization requires equality between the price of time and the marginal return on shopping (equation (2)). The marginal return to shopping can be written $-(\partial p/\partial s)Q = -(\partial \ln p/\partial \ln s) pQ/s = -\alpha_s(X/s)$, where α_s is the elasticity of price with respect to shopping time. If this elasticity is a constant, the opportunity cost of time is proportional to the ratio of expenditures to

shopping time. We present results assuming that the price function is log-linear in shopping time. However, we have estimated a polynomial price function that allows for interactions and higher-order terms. The implied price of time from that exercise does not differ markedly from the one depicted below.

We plot the implied price of time using our Homescan data in Figure 4. The implied price of time increases by roughly 7 percent between the mid-twenties and the early thirties. The price of time then declines gradually through middle age before accelerating its descent after age 49. The cost of time for persons 65 to 74 is approximately 33 percent less than for those age 30 to 34. This pattern differs from that of life-cycle

wages in that wages tend to increase well into middle age. The life-cycle asymmetry in the cost of time depicted in Figure 4 is more akin to that of market labor hours. (For a recent discussion of life-cycle hours and wages, see Susumu Imai and Michael Keane 2004.)

The wedge between the cost of time and wages should not be surprising. Not all shoppers are able to adjust labor supply at the margin, whether employed or not. Indeed, the sharp increase in the shopper's cost of time in the early thirties may be driven by the arrival of children rather than by labor market forces. Moreover, reported wages are conditional on working and are therefore not directly informative regarding the unemployed or shoppers out of the labor force. This highlights the benefit of the price dataset in calculating the value of time for different types of households.

VII. Home Production

As discussed in Section I, at any point in time, an optimizing household will choose the least-cost method of acquiring consumption goods. In particular, at the margin, households should be indifferent between allocating another unit of time to shopping rather than to home production. In this section, we use this fundamental premise to leverage our price data into an estimator of a home production function.

We use the time diaries of the ATUS to measure time spent in home production. We define home production in two ways. First, we consider time spent preparing meals and cleaning up after meals. This category of time use is perhaps most closely tied to food expenditures. Second, we define home production broadly as all household work (cleaning, cooking, home repair, etc.).

Figure 5 shows how time spent on food preparation varies systematically over the life cycle, both unconditionally and conditional on marital status, the presence of children, and family size. We plot the percentage change in time spent in home production (measured as food preparation and clean-up) relative to respondents age 25 to 29.¹³ The unconditional series has a “double-

hump” shape, with a peak at age 40 and a peak in retirement. The first hump reflects the fact that middle-age households have a greater need for home production due to larger families. Conditioning on family size eliminates the first hump and generates a conditional home production series that increases steadily through middle age and then accelerates late in the life cycle. The conditional series for time spent on home production over the life cycle resembles that of shopping depicted in Figure 1.

As discussed in Section I, how agents allocate time between shopping and home producing reveals information about the nature of the two technologies. Specifically, cost minimization implies that the MRT between time and goods in home production equals the MRT in shopping (equation (5)). Notice that once we specify a home production function, this first-order condition, together with our estimates of $\partial p/\partial s$, $\partial p/\partial Q$, p , Q , and h , will allow us to estimate the parameters of the home production function.

To see why the availability of the price data is crucial to estimating the home production function, consider the case where we do not observe prices (or assume every household faces the same price). Estimation would rely on the fact that the marginal return to home production equals the price of time. The price of time would have to be inferred either from wages or leisure. As noted above, the former is problematic because many households have a single earner and the wage of the sole earner is not necessarily the opportunity cost of time of the home producer. Even with two-earner families, it is not clear that workers have the ability to smoothly vary labor supply at the margin. Lastly, for households where both spouses are retired, no wage data will be available. Imputing the cost of time from leisure requires the measurement of leisure (usually taken as a residual) and knowledge of preferences over leisure, both of which are questionable undertakings. Our approach exploits the assumption that the opportunity cost of time for the shopper equals the opportunity cost of time for the home producer, a much more plausible assumption. Moreover, it strikes us as

¹³Specifically, we regress minutes per week on age-range dummies, day-of-week dummies, and (when indicated) demographic controls. We convert the level differences

obtained from the coefficients on age dummies into percentage changes using the mean home production time of respondents age 25 to 29.

reasonable that households can smoothly adjust between the shopping and home production margins.

We restrict our home production function to have a constant elasticity of substitution between time and market goods:

$$(13) \quad f(h, Q) = (\psi_h h^\rho + \psi_Q Q^\rho)^\frac{\sigma}{\rho},$$

where the elasticity of substitution is given by $\sigma = 1/(1 - \rho)$. We allow the function to be homogeneous of arbitrary degree γ , although we will not be able to identify this parameter. Given (13), the MRT between time and goods from the home production function is

$$(14) \quad \frac{\psi_h \left(\frac{h}{Q}\right)^{\rho-1}}{\psi_Q \left(\frac{h}{Q}\right)}.$$

Substituting (14) into (5) and taking logs on both sides (and rearranging), we have

$$(15) \quad \ln\left(\frac{h}{Q}\right) = \sigma \ln\left(\frac{\psi_h}{\psi_Q}\right) - \sigma \ln\left(\frac{-\frac{\partial p}{\partial s} Q}{\frac{\partial p}{\partial Q} Q + p}\right).$$

We construct the empirical counterpart of the last term in (15) by fitting the MRT in shopping from our price data using the coefficients reported in Table 3 together with observations on p and Q . Unfortunately, our price data do not contain data on time spent in home production (our dependent variable). We therefore merge data from Homescan and the ATUS using our 27 demographic cells. The merge procedure is the same we used for shopping time, and described in Section V.

As before, we collapse each cell and run a between-effects regression. Averaging over a number of households in each demographic group should reduce the errors-in-variables inherent in our data. The averaging will also correct for idiosyncratic “productivity” shocks that are uncorrelated with demographics. Note that we assume all demographic cells possess the same technology. This may be problematic to the extent that the quantity of “home capital” may vary across cells. However, the Homescan dataset contains dummy variables for presence of home durables (microwave, dishwasher, garbage disposal, etc.). Inclusion of these dummy variables does not alter the results. Therefore, we

report the specifications without these controls, given the desire to preserve degrees of freedom.

The results are reported in Table 4. Collapsing our data by the 27 age-sex-marriage cells yields an estimate of $\sigma = 1.78$, with a standard error of 0.32 (column I). Column II repeats the column I specification with all housework rather than the narrower measure of food preparation and clean-up. The elasticity for all housework is 2.13. The third column restricts the sample to married-couple households and reports an elasticity of 1.45 using food preparation and clean-up.

Note that by exploiting the restriction that the price function is log-linear, we can rewrite the last term on the right-hand side of (15) as $\ln\{-\frac{\partial p}{\partial s} Q / (\frac{\partial p}{\partial Q} Q + p)\} = \ln[-\alpha_s / (1 + \alpha_Q)] + \ln(Q/s)$. Rearranging, we have

$$(16) \quad \ln(h) = \beta_0 + \sigma \ln(s) + (1 - \sigma) \ln Q,$$

where $\beta_0 = \sigma \ln[-\alpha_s \psi_h / (1 + \alpha_Q) \psi_Q]$. Equation (16) says that as we vary the opportunity cost of time, holding Q constant, a large variation in home production time relative to shopping time indicates that there is a relatively large elasticity of substitution between time and goods in home production. We estimate this specification and report the results in column IV of Table 4. The implied elasticity from the coefficient on $\ln s$ is 2.18, while that implied by the coefficient on $\ln Q$ is 1.85. The estimates are similar in magnitude, and the p-value of the test of equality between the two alternative estimates of σ is 0.36.

For comparison, Rupert, Rogerson, and Wright (1995) report an elasticity of substitution between home and market goods, which is roughly comparable to our elasticity, for employed single women of 1.8.¹⁴ This number is in line with our estimates. Moreover, restricting our sample to include only single women produces a similar estimated elasticity of 1.95. Their parameter estimates for other demographic groups are generally imprecisely estimated. This highlights the difficulty of relying on wages to value time for complex family structures, and underscores

¹⁴Specifically, the interpretation of the elasticity of Rupert, Rogerson, and Wright (1995) is the same as ours if their home good is a linear product of time input, and market work and home work are perfect substitutes in the utility over leisure. This parameterization is consistent with their estimates.

TABLE 4—ELASTICITY OF SUBSTITUTION IN HOME PRODUCTION

	I	II	III	IV
σ (elasticity of substitution between time and goods in home production)	1.78 (0.32)	2.13 (0.29)	1.45 (0.27)	
$\ln(s)$				2.18 (0.54)
$\ln(Q)$				-0.85 (0.33)
Source of variation (number of groups)	Age-sex-marital status (27)	Age-sex-marital status (27)	Age (9)	Age-sex-marital status (27)
Additional controls	Sex and marriage dummies, constant	Sex and marriage dummies, constant	Constant	Sex and marriage dummies, constant
Measure of h	Food prep and cleanup	All housework	Food prep and cleanup	Food prep and cleanup
Sample restrictions	None	None	Married households	None
Underlying sample size	4,854	4,854	2,694	4,854

Notes: This table reports estimates of the elasticity of substitution between time and goods in home production. Columns I–III refer to specification (15) in the text and use the log ratio of home production time to market goods as the dependent variable. Column IV refers to specification (16) and uses log home production time as the dependent variable. Column II uses all housework as our measure of home production time. All other columns use time spent on food preparation and clean-up as the measure of home production time. Time-use data are from the ATUS. Column III restricts the sample to married-couple households. The independent variable of interest in columns I–III is the log MRT between time and goods in shopping, using data from Homescan and the methodology discussed in Section VIII. The independent variables of interest in column IV are log shopping time and log Q . Shopping time refers to log shopping trips per month from Homescan. The implied elasticity is the coefficient on $\ln(s)$ and one minus the coefficient on $\ln(Q)$. These elasticity estimates are not significantly different at standard confidence levels. ATUS and Homescan data are merged using 27 demographic cells based on age, sex, and marital status. Regressions performed on cell averages. See text for additional details.

the value of the price data. It is interesting that our estimates and theirs coincide for employed single women, a demographic for which wage is most plausibly the relevant price at the margin. Several studies have used equilibrium models and aggregate data to back out an elasticity of substitution for home production that is close to our estimates using micro data. For example, McGrattan, Rogerson, and Wright (1997) estimate an elasticity between home time and home capital of 1.2 and an elasticity between home produced goods and market goods of 1.8, while Chang and Schorfheide (2003) estimate an elasticity of 2.3.

VIII. Life-Cycle Consumption versus Life-Cycle Expenditure

With a parameterized home production function, we can compare how life-cycle expenditure (an input into the home production

function) compares with life-cycle consumption (the output of the home production function). To do this, we fit (13) over the life cycle (using the parameters from column I of Table 4). Going from the ratios (the MRT) to levels requires us to assume a value for returns to scale, which we take to be one. It is also the case that we can estimate only the ratio $\psi \equiv \psi_h/\psi_Q$, so we normalize $\psi_Q = 1$. This assumption involves only a scaling of consumption and does not play a role in the analysis once we take log differences across age ranges. We allow ψ to vary by marital status and sex.¹⁵ We treat husbands and

¹⁵We calculate ψ using the fact that in a regression of $\ln(h/Q)$ on $\ln(s/Q)$, the constant (including dummies for marriage and sex) equals $\sigma \ln [(-\alpha_s \psi)/(1 + \alpha_Q)]$. We use the estimated α_s and α_Q from a regression of log price on $\ln s$ and $\ln Q$ using the 27 demographic cells. We also adjust ψ for the fact that our shopping time is expressed as trips per month, while home production is minutes per week.

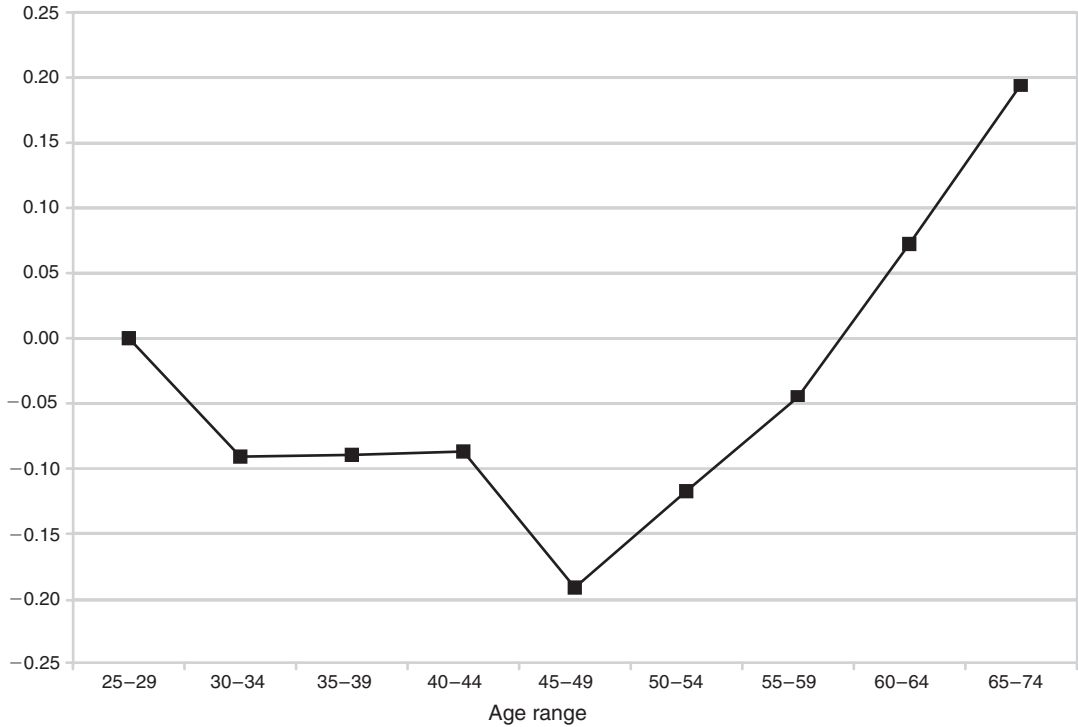


FIGURE 6. RATIO OF CONSUMPTION TO EXPENDITURE: LOG DEVIATION FROM 25- 29-YEAR-OLDS

Notes: Figure plots log deviation in the ratio of consumption to expenditure relative to 25- 29-year-olds. The ratio of consumption to expenditure is computed using the estimated parameters of the home production technology and data from both Homescan and ATUS. See text for details.

wives as perfect substitutes in home production and create a household measure of time input by summing the two. To control for changing family size over the life cycle, we normalize by household expenditure. Specifically, for each age range, we calculate

$$(17) \quad \frac{C}{X} = \frac{(\psi h^\rho + Q^\rho)^{\frac{1}{\rho}}}{X},$$

using the observed household averages for h , Q , and X together with our estimates of ψ and ρ .

Figure 6 plots this ratio as a function of age (relative to the average of those age 25 to 29). Note that any proportional scaling factor due

to changing household size is accounted for by the presence of household expenditures in the denominator. This figure highlights that households use different ratios of time and market goods in consumption over the life cycle. We see that the ratio is roughly constant (and low) until late middle age. After age 49, the ratio starts to increase dramatically, with a roughly 39 percentage point increase between 45 and 49 and 65 and 74. This pattern is the mirror image of that for the price of time (Figure 4).

This pattern also occurs simultaneously with the well-documented decline in expenditure post-middle age. Many authors have interpreted the decline in expenditure as a one-for-one decline in consumption, attributing this behavior to impatience (Pierre-Olivier Gourinchas and Jonathan Parker 2002), nonseparability between consumption and leisure in preferences (James Heckman 1974), or preferences that shift with

The constant adjustment factor is calculated as the average log difference of shopping time per week from our 27 ATUS demographic cells and the corresponding log trips per month from Homescan.

family size (Orazio Attanasio et al. 1999). Others have focused on the drop in consumption expenditures at retirement, suggesting that agents do not plan appropriately (B. Douglas Bernheim, Jonathan Skinner, and Steven Weinberg 2001). Our results, driven by the large life-cycle movements in time allocation to shopping and home production, suggest that consumption differs from expenditure over the life cycle. Figure 6 complements the results of Aguiar and Hurst (2005), in which we used food diaries to document the distinction between consumption and expenditure at the time of retirement.

To gain more insight, we can consider each component of the ratio of consumption to expenditure separately. The life-cycle pattern of household expenditures recorded in Homescan is roughly consistent with that reported for food expenditure at home in the PSID. Unconditionally, Homescan household expenditure declines by 27 percent between the ages of 45 and 49, and 65 and 74. The corresponding decline in the PSID is 33 percent. Some of the decline is certainly attributable to the drop in average family size post-middle age. Nevertheless, the decline in food expenditures in Homescan is still 19 percent, even after controlling for household size. The corresponding decline in the PSID conditional on family size controls is 16 percent.

On the other hand, our household consumption measure increases by 12 percent between 45 and 49, and 65 and 74. This latter increase in food consumption may reflect that the true real interest rate in regard to food consumption is relatively high in late middle age due to the declining price of time.¹⁶

¹⁶The fact that consumption increases slightly and expenditure declines post-middle age is consistent with the optimal response to an anticipated decline in the price of time. More specifically, a decline in the price of time encourages substitution away from goods and toward time in the production of consumption. This leads to lower market expenditures conditional on a consumption level. However, the lower total cost of consumption encourages delaying consumption until late in the life cycle, and hence more expenditures late in the life cycle. Which effect dominates depends on the relative magnitudes of the elasticities of substitution. The fact that the intra-temporal elasticity between market goods and time (which we estimate as close to two) exceeds the inter-temporal elasticity of substitution in consumption (typically estimated as less than one) implies that, all else equal, expenditure should decline

That the increase in consumption occurs despite the decline in expenditure is made possible by the large increase in time allocated to home production and shopping after middle age. One natural question is how much of the divergence between consumption and expenditure documented in Figure 6 is due to changing shopping behavior and how much is due to changing home production. In Aguiar and Hurst (2005), we were unable to distinguish between the relative importance of shopping and home production in explaining why consumption remained constant at retirement despite declining expenditure. The empirical analysis above coupled with the data from the ATUS and Homescan allows us to address this question directly.

Equation (17) implies that

$$(18) \quad \ln \left(\frac{C}{X} \right) = \frac{1}{\rho} \ln (\psi h^{\rho} + Q^{\rho}) - \ln X.$$

Taking derivatives and using “ \wedge ” to denote percentage change, we have

$$(19) \quad \widehat{\left(\frac{C}{X} \right)} = \theta \hat{h} + (1 - \theta) \hat{Q} - \hat{X},$$

where

$$(20) \quad \theta \equiv \frac{\psi h^{\rho}}{\psi h^{\rho} + Q^{\rho}}$$

is the elasticity of C/X with respect to home production. Constant returns to scale implies that the elasticity with respect to market goods is $1 - \theta$. Using the fact that $Q = X/p$, we can substitute and rearrange to obtain

$$(21) \quad \widehat{\left(\frac{C}{X} \right)} = \theta (\hat{h} - \hat{X}) - (1 - \theta) \hat{p}.$$

The first term on the right-hand side of equation (21) captures the substitution of time and goods in home production. If changes in consumption were accomplished with fixed proportions of time and market goods, this term would be zero. The second term on the right-hand side captures the ability to shop for bargains.

as the price of time declines. See Ghez and Becker (1975) for a derivation.

To decompose the 39 percent movement in C/X between 45 and 49, and 65 and 74, we compute the corresponding terms on the right-hand side of (21) using age-range averages. The value of $\hat{h} - \hat{X}$ evaluated between 45 and 49, and 65 and older, is approximately 77 percent, made up of a 50 percent increase in home production time and a 27 percent decrease in market expenditures.¹⁷ The change in price is 3.9 percent, as documented in Section IIIB. The elasticity θ is 0.33 for those age 45 to 49 and 0.42 for those age 65 to 74. Using the average of the two, the substitution toward time in home production accounts for a 28.9 percent decline in C/X , while additional shopping intensity accounts for a 2.5 percent decline.¹⁸ These calculations make it clear that the majority (92 percent) of the movement in C/X is due to increased home production. Roughly 8 percent of the movement is due to the increase in shopping intensity.

The important role that home production plays in driving a wedge between consumption and expenditure over the life cycle follows from the pattern depicted in Figure 5. Given the fairly high elasticity of substitution between time and market goods in home production, the decline in expenditures late in the life cycle is consistent with the large increase in time spent in home production by the elderly and the decline in the opportunity cost of time. In terms of textbook economics, agents late in their life cycle move along a production isoquant, substituting time for goods, as the relative price of time falls. Indeed, our index of consumption increases after the late fifties, implying that the decline in expenditure after the age of sixty is more than offset by the increase in home production time.

¹⁷The increase in home production of 50 percent is larger than the 30 percent depicted in Figure 5 due to the fact we are now using collapsed cells merged into the Homescan database, while Figure 5 directly used the microdata from the ATUS. Moreover, to calculate consumption for married-couple households, we sum the average time input for husbands and wives. Each of these factors accounts for roughly 10 percentage points of the difference.

¹⁸The sum of the two, 31 percent, differs from the 39 percent above due to the approximations involved with log-linearization.

IX. Conclusion

This paper has estimated the elasticity between time and money due to shopping and home production. We find that households can, and do, alter the relationship between expenditures and consumption by varying time inputs. Moreover, they do so in a way that is consistent with standard economic principles.

Using a novel dataset from ACNielsen that tracks grocery purchases at the household level, we find that prices paid for a given grocery item decline sharply after middle age. These price differences are sustained by the fact that older shoppers are more likely to undertake a shopping trip, spend more minutes shopping per week, and exploit store and manufacturer discounts than their younger and middle-age counterparts. Given the nature of our dataset, we can directly estimate parameters of the shopping and home production technologies. Specifically, using our preferred estimates, we find that doubling shopping frequency reduces prices paid by 7–10 percent, holding constant a household's shopping needs. Shopping intensity suggests that the opportunity cost of time for the shopper peaks in the thirties at roughly 33 percent more than that for those age 65 to 74. Additionally, we estimate an elasticity of substitution between market goods and time in home production of 1.8. The latter parameter is important for a growing number of macro models that specifically account for nonmarket production.

Collectively, our results highlight the dangers of equating consumption with expenditure. This distinction is of particular importance when discussing the life-cycle profile of expenditures. Some authors have interpreted the declining expenditure post-middle age to declining consumption, perhaps due to impatience, nonseparabilities in preferences between consumption and leisure, or preferences being a function of life-cycle demographics. However, we show that such a decline in expenditure is consistent with stable consumption. As the opportunity cost of time starts to decline after middle age, households invest more time in both shopping and home production, reducing the market cost of their consumption basket. This implies that, after middle age, household expenditures will decline even if consumption is constant.

This paper has contributed new data and insights regarding the ability to use shopping and home production to reduce the total cost of consumption. We realize, however, that the data have some limitations. First, the ACNielsen dataset contains only a subset of grocery items. We cannot state whether similar patterns hold for other goods. This concern is mitigated by time-use data. These data indicate that the life-cycle patterns for food shopping and home production extend to nongrocery shopping and home production outside the kitchen. Nevertheless, the results in this paper should be considered only suggestive of how households exploit time in the consumption of goods other than food. Second, the data are cross-sectional in nature, and, therefore, we must be cognizant that some of our life-cycle results may be confounded with cohort effects. However, cohort effects are less likely to be an issue for normalized variables, such as the ratio of consumption to expenditure, than for nonnormalized variables.

There is a growing interest in the role of nonmarket activities and the allocation of work between the market and the household. The insights of household production have already proved fruitful in explaining phenomena as disparate as baby booms and business cycles. While our focus has primarily been on the life cycle, we feel that the data and analysis presented in this paper support the broader emphasis on how time is spent outside of market labor.

DATA APPENDIX

This appendix describes the construction of our Homescan sample, issues related to attrition in the Homescan dataset, and the construction of our ATUS sample. All data and programs are available at http://www.e-aer.org/data/dec07/20050774_data.zip.

A. Sample Construction

The Homescan dataset for Denver has 957,570 observations and 51 variables. Each observation represents a transaction or “scanned item.” A transaction may involve multiple purchases of the same good (for example, if a household purchases two of the same item at a time it may enter this as one transaction with a “2” entered as the quantity variable, or it may enter it as two

transactions with a “1” entered as the quantity for each transaction). The date of the first transaction is January 1, 1993, and the last date recorded is April 1, 1995. We drop the 1,506 observations from April 1995, as that month has only one day in the sample, leaving 956,064 observations from 2,100 households.

For each household and month, we compute the price index, expenditure (total, by store, etc.), number of shopping trips (total, by store, etc.), and the number of goods (at the UPC level and the category level). The Homescan dataset reports the age and sex of the “primary shopper.” In principle, the primary shopper may change within a household across transactions. In practice, however, there is little variation within a household as to who is the primary shopper. Among households with more than one person, over 80 percent of transactions, on average, are handled by a single individual (identified by age and sex).¹⁹ If the average age of the primary shopper is less than 25 or greater than or equal to 75 in a particular household during a particular month, we do not compute the price index, expenditure, and quantity data for that household-month. This leaves us with 2,056 households and 41,175 monthly observations. There were two monthly observations where the value of monthly expenditures for the household equaled the value of monthly discounts received by the household (implying that net expenditure was zero for that month). We drop these two observations, leaving 2,056 households and 41,173 monthly observations. These monthly observations are backed by 920,295 individual transactions.

We average the observations within a household over the months of a given year in which the household participated in the survey. The

¹⁹Homescan also reports a categorical variable for the ages of the male and female heads. The categories are five-year ranges until age 54, then one ten-year range for 55–64, and finally one range for 65 and older. The average age of the primary shopper typically falls within the same category as the female head (76 percent of the time) and the male head (60 percent of the time). In over 90 percent of the cases, the shopper’s average age is within one category of either head. We use the shopper’s age, as it is a continuous variable and therefore allows us to create finer age ranges late in the life cycle than those provided for household heads. Moreover, the shopper’s age is likely to be more informative about the opportunity cost of time for the shopper than is the age of the household head.

TABLE A1—SUMMARY DEMOGRAPHICS

Variable	Homescan (1993–1995)	ATUS (2003)	PSID (1994)
Percent married	0.56	0.67	0.55
Percent with children	0.37	0.41	0.38
Percent employed			
Male	0.80	0.82	0.78
Female	0.69	0.74	0.63
Percent high school or less	0.31	0.44	0.52
Percent age 25–39	0.36	0.33	0.36
Percent age 40–54	0.36	0.37	0.33
Percent age 55 and older	0.27	0.28	0.28
Percent white	0.92	0.77	0.84
Sample size	2,056	16,678	6,508

Notes: This table includes summary demographics for Homescan and ATUS samples, as well as a reference wave (1994) of the PSID. For this table, Homescan demographics refer to 1994. If the household was not part of Homescan in 1994, we use data from 1993. The Homescan sample is restricted to include households in which the average age of the primary shopper is greater than or equal to 25 and less than 75. The ATUS sample is restricted to include households in which the respondent's age was greater than or equal to 25 and less than 75. The PSID sample is restricted to include households in which the head's age was greater than or equal to 25 and less than 75. For married households, head refers to the male (to accord with PSID methodology). Education, age, and race are those of the household head.

dataset is now organized such that an observation is a household-year pair. These observations are matched with the household demographic variables, which are reported by Homescan at an annual frequency. This household-year sample has 4,854 observations and 2,056 households, comprising 1,518 households in 1993, 1,609 in 1994, and 1,727 in 1995. This sample is used for all the analyses of the paper.²⁰ Summary statistics regarding the demographic composition of the sample and comparable statistics from the 1994 PSID are reported in Table A1.

B. Attrition

The nature of the survey raises the concern that shoppers may fail to scan in purchases, and that this failure may bias our results. Within our Homescan data, the average monthly expenditure

for packaged goods scanned is \$65 per month, expressed in current dollars. The comparable figure for “food at home” reported in the 1993 and 1994 waves of the PSID is \$323 per month. This implies that the Homescan dataset covers roughly 20 percent of total grocery expenditures reported in the PSID. The difference between the Homescan dataset and the PSID dataset likely comes from two sources. First, the Homescan dataset does not include meat, fresh foods, or vegetables. Moreover, as discussed below, it may be the case that households fail to scan all grocery items into the Homescan database.

There is the related issue of attrition from the Homescan sample over time. A direct assessment of the magnitude of attrition on the extensive margin is complicated by the fact that ACNielsen drops data from households that quickly withdraw from the survey. The median household is in the sample for 27 months (the maximum length). The mean is 21 months. The tenth percentile is 10 months. Fifty-eight percent of the households (1,191 households) are represented in every calendar year, 20 percent (416) are represented in two of the three years, and 22 percent (449) are represented in only one year.

However, we can observe attrition directly on the intensive margin. The median household reported 1 percent lower expenditure in the first quarter of 1994 than it did during the first quarter of 1993, and 1 percent lower expenditure in the first quarter of 1995 compared with the same quarter in 1994. The failure to record all transactions is not crucial to many of the facts regarding price dispersion documented in this paper, as long as the transactions a household does record are representative of that household's purchases (that is, as long as the omissions are random within a household). However, the failure to record all transactions may influence such items as total expenditures and frequency of shopping.

More importantly, the decline in household expenditure over the sample does not appear to vary with such demographics as age and education, suggesting that attrition is not highly correlated with our key controls. In a regression of the month-to-month decline in expenditure on age and time dummies, the p-value of the test that all (eight) age dummies are zero is 0.24. In a regression of the month-to-month decline in expenditure on education and time dummies,

²⁰Each household is in our analysis sample for up to three years. We therefore adjust the standard errors to account for potential correlation within a household across years (that is, “clustered” on household). In addition, we correct the standard errors for heteroskedasticity.

the p-value of the test that all (three) education dummies are zero is 0.72.

Taken together, these results indicate that the rate of attrition is fairly constant across demographic groups. However, the initial level of underreporting appears to be correlated with demographics. To assess this, we compared expenditures in Homescan with those in the PSID. Specifically, we created cells in the 1993 PSID by age of head (using eight categories) and education (less than high school, high school, some college, and college or more). For each cell, we calculated the average expenditure on food at home reported in the PSID, and we merged these values into the Homescan dataset. We then constructed the log ratio between Homescan households in 1993 and their corresponding PSID cells. This gap shows no correlation with the age of the household head (the p-value of the F test is 0.34).²¹ However, the gap is correlated with education. For example, reported expenditure in Homescan for households with a college-educated head is, on average, 16 percent of that reported in the PSID. The comparable share for high-school graduates is 21 percent (p-value of difference < 0.01). This suggests that households with more-highly educated heads are less likely than others to scan all purchases (or that they buy more goods outside the scope of Homescan, such as meat and produce). Again, for the main analysis, as long as the scanned items are representative of the household's purchases, this will not generate a bias. However, because of these results, we do not sum the Homescan transactions to infer how total expenditures vary with education or income.

C. American Time-Use Survey

The 2003 ATUS was conducted by the US Bureau of Labor Statistics (BLS). Participants in the ATUS are drawn from the existing sample of the Current Population Survey (CPS). Only one individual per household is sampled (including children). The individual was sampled approximately 3 months after he or she

completed the final CPS survey. At the time of the ATUS survey, the BLS updated the individual's employment and demographic information. Roughly 1,700 individuals completed the survey each month, yielding a total sample of 20,720 individuals. We use the 16,678 individuals who report an age greater than or equal to 25 and less than 75.

Each respondent in the ATUS was interviewed one time about how he or she spent time the previous day. The time diary is a detailed account of the respondent's activities, starting at 4 a.m. the previous day and ending at 4 a.m. on the interview day. "The interviewer recorded the activities verbatim and coders assigned a six-digit classification code to each activity. We construct our measure of shopping as the sum of "Grocery Shopping" (code 07-01-01) and "Traveling to/from the Grocery Store" (code 12-07-01). We construct our measure of food preparation as the four-digit activity "Food and Drink Preparation, Presentation, and Clean-up" (code 02-02). Total home production is defined as the two-digit level activity "Household Activities" (code 02), minus time spent on personal mail and e-mail (codes 02-09-03, 02-09-04), plus "Travel Related to Household Activities" (code 17-02).

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²¹ Using data from all years, there is a weak correlation with age. The p-value on a test of the age dummies using three years of Homescan data is 0.02. However, the correlation is driven by the young: the p-value on a test that the ratio is constant after the age of 40 is 0.23.

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