Shopping Frictions and Household Heterogeneity: Theory and Empirics*

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Abstract

This paper shows that price dispersion matters for shaping individual household consumption. Using detailed scanner data, I document that the high-earning employees pay from 2 to 7% higher prices than the low-earning ones for exactly the same or very similar goods. The causal link between the income level and paid prices is established by exploiting a quasi-experimental setup of the Economic Stimulus Act of 2008. Between 8 and 22% of the households' increase in spendings after a positive transitory income shock is explained by positive changes in the paid prices. Next, I present a novel and tractable theory to study search for consumption as part of the optimal savings problem. Due to frictions in the retail market, households have to exert some search effort to purchase the consumption goods. The proposed framework reconciles the documented patterns in a quantitatively meaningful way. A counterfactual analysis of the calibrated model shows that over two thirds of all households pay higher prices due to a negative externality generated by shoppers with low search intensity.

Keywords: search frictions, price dispersion, household heterogeneity, Nielsen, fiscal stimulus

JEL codes: E00, E21

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I. Introduction

How do households make consumption decisions in the presence of price dispersion? Most consumption-saving models typically assume that the Law of One Price always holds, meaning that each good is priced equally by all retailers. In this article I confront this view, both empirically and theoretically. To this end, I address the following questions: (*i*) how do paid prices of the same goods differ across the income distribution?; (*ii*) what theoretical frameworks are consistent with the observed differences?; (*iii*) what are macroeconomic implications of the new theories in comparison to the standard consumption models?

To address those questions, my paper makes two main contributions. First, I use detailed price scanner data and time-use survey to document substantial heterogeneity in prices and shopping behavior across the income distribution. I argue that the presented stylized facts cannot be rationalized by existing search models. Motivated by this, I propose a novel and tractable framework to study search for consumption as part of the optimal savings problem, which is a theoretical contribution of the article. As I show an equilibrium price distribution in this model features a search externality across different households. The calibrated version of the economy is used to illustrate the scale of the market externalities.

To study price heterogeneity across the income distribution, I use the Kilts-Nielsen Consumer Panel, detailed scanner data set tracking approximately 40,000-60,000 American households. In my analysis I use observations from 2004 through 2014. In that period, the KNCP collected information on 630 million transactions for nearly 2 million unique products defined at the barcode level, which were purchased in 87 million shopping trips. Using this data, I follow a methodology proposed by Aguiar and Hurst (2007). This approach relies on building an individual price index for each household in each period, which is the ratio of actual expenditures divided by the cost of the bundle at average prices paid by other consumers.[1]

With household price indices at hand, I document a number of new stylized facts on how the paid prices vary across different households. First, employees with earnings above the median level pay from 1.5% to 7.1% higher prices than employees with below-median

[1]In computing average prices, each product is defined locally or nationwidely and either at the bar-code level or by sharing the same features. Features are provided by Nielsen and consist of 19 very specific characteristics, such as flavor, package type, size, organic claims, or amount of salt. Consequently, even the broadest categories are conservative and group products that are very likely to be close substitutes for the consumers.

earnings. In addition to this, in my analysis employment and retirement are not associated with much lower household price indices. In both cases the price differentials are small and do not exceed 1.4% for any of the considered specifications. This suggests that the differences previously documented in the literature (*cf.,* Kaplan and Menzio, 2015; Aguiar and Hurst, 2007) might be driven by the high-income workers who were pooled with the low-income workers as one homogeneous reference group. Moreover, I explore how the paid prices changes with financial liquidity. To this end, I use households' responses on financial liquidity from a complementary survey in 2008 conducted on behalf of Broda and Parker (2014). I show that the financially constrained employees with low earnings pay between 0 and 2.8% lower prices than the unconstrained low-earning employees. Overall, those findings strongly suggest that the income and wealth are important dimensions for understanding heterogeneity in household price indices.

While the systematic price heterogeneity across individuals has been previously documented in many studies, to the best of my knowledge there is no evidence for the causal relationship between the economic status and prices indices. For this reason, I exploit random timing of the tax rebates from the Economic Stimulus Act of 2008. As I show in months after receiving a stimulus payment, households' price indices increase by between 0.4% and 1.3% in comparison to the pre-treatment months. The documented increase in the paid prices account for between 8 and 22% of the households' increase in overall consumption expenditures.

The last stylized fact on the prices relates to the variance of relative prices in a single transaction. As I show a single transaction of high earning households is subject to higher risk. This finding provides an additional desired property in the search for a theory consistent with data.

On the empirical side, I also explore how time spent shopping differs across households. To this end, I use data from the 2003–2018 waves of the American Time-Use Survey and a complementary Well-Being Module. I find that high-income households spend more time shopping by around 7%. This observation and the fact that richer households pay higher prices is not consistent with typical explanation linking more shopping time with lower prices. One alternative potential justification for this would be that richer individuals perceive shopping as a leisure activity while for the poorer households shopping is more like non-market work in which time spent on bargain hunting compensates cash scarcity. However, this theory is not true as using Well-Being Module I find that all measures of well-being while shopping for the rich households is not different from the well-being of other groups.

The presented empirical patterns can be used as a guide in selecting a theoretical framework consistent with data. First, the finding that high earners spend more time shopping but at the same time pay higher prices stays at odds with predictions made by existing random price-search theories in the spirit of Burdett and Judd (1983) and recently used by Kaplan and Menzio (2016). According to this class of theories, agents exerting higher search effort should result in paying lower prices. This would suggest that theories relying on the directed search in the spirit of Moen (1997) and recently exemplified by Bai *et al.* (2019) and Qiu and Ríos-Rull (2021) might be a better representation of price search. This class of models state that consumers with higher earnings and higher consumption decide to choose retailers that have shorter queues (for each unit of consumption) but higher prices. Per unit of consumption those consumers spend less time shopping but overall due to higher consumption they may spend more time shopping overall. Nonetheless, this class of theories is also imperfect representation of shopping. The directed search assumes perfect knowledge about prices and each household directs their shopping activity to stores with different price levels. If this were true then there should not be a systematic difference in the price variance of a single purchase across households with different level of income, which I documented as well. Consequently, those observations suggest that currently we lack a micro-founded representation of shopping that would be consistent with data.

In light of this conclusion, I propose a novel theory of search for prices with heterogeneous households. My framework integrates search for consumption in the tradition of Burdett and Judd (1983) and Butters (1977) into a life-cycle version of the standard incomplete-markets model due to İmrohoroğlu *et al.* (1995); Huggett (1996); Ríos-Rull (1996). The household's income is driven by idiosyncratic productivity shocks. Every household makes the decision about level of savings, that are used to insure against the future income fluctuations and to smooth the future consumption. The remaining disposable resources of the household are spent on consumption. I extend the benchmark incomplete-markets economy by adding frictions in the purchasing technology. Households have to exert effort to purchase goods. This effort can be decomposed into two components: 1. *price search intensity* – effort to search for price bargains, 2. *purchase effort* – effort required to purchase consumption of a given size. Both retailers and households' shopping come together at random through a frictional meeting process. Households that search for low price more intensively are able to find lower prices more often. Households exhibiting higher purchase effort are able to obtain more consumption. Retailers set their prices in response to the distribution of household search intensity. Sellers charging relatively high (low) prices sell less (more) often but with higher (lower) markups. In an equilibrium every seller yields the same profits, but for different prices the profit comes from a different combination of appropriation of consumer surplus and stealing customers of other competing retailers. To the best of my knowledge, the proposed model is the first to combine the optimal savings problem and search for consumption with endogeneous price distribution in a quantitatively meaningful way.

In the calibrated version of the model I show that the price channel accounts for around 8% of the overall consumption responses to transitory shocks, which matches the empirically documented lower bound. Finally, the model economy is used to evaluate the magnitude of price externalities across different households. The externality arises due to the fact that the retailers are not able to distinguish captive customers and bargain hunters. Consequently, search strategies of one individual affects the price distribution of other customers. In a counterfactual analysis, I show that over two thirds of all households pay higher prices due to a negative externality generated by shoppers with low search intensity.

II. Empirical Patterns

In this section I analyze shopping behavior of the American households. I contribute to the existing empirical literature by focusing on differential characteristics across working individuals. The empirical patterns are studied from three different angles, *i.e.* paid prices, time spent buying goods, and subjective well-being during shopping. For each dimension, different data sets are used. I show that the price differential between high earners and low earners is even larger than the ones previously studied in the literature: the non-employed vs. the employed and the retired vs. the employed, where the employed are treated as one homogeneous group (Aguiar and Hurst, 2007; Kaplan and Menzio, 2016). At the same time the high earners spend more time shopping than the low earners and their subjective perception of shopping does not differ from other individuals. The theoretical implications of those findings are discussed jointly in the conclusions of the section.

A. Consumer Prices

To document price differentials across households I use the Kilts-Nielsen Consumer Panel (KNCP) data set. A comparison of prices paid by different households is possible thanks to a methodology proposed by Aguiar and Hurst (2007). This approach relies on building an individual price index for each household in each period that depends on quantities and prices of purchased goods. The prices are expressed in relative terms compared to exactly the same (or very similar) products bought by other consumers in a given period of a given market. Next the constructed price indices are used to explore how paid prices vary across households.

Data. The KNCP is a panel data set tracking approximately 40,000-60,000 American households.[2] Each panelist uses in-home scanners or mobile apps to provide information to Nielsen about their grocery purchases from any outlet in all US markets. A purchase of every single product is linked to a certain shopping trip to a store made by the household. In addition to this, on an annual basis respondents report their socio-demographics characteristics. The sample of households is drawn from 54 geographic markets, known as Scantrack markets. In the analysis I use the data from all markets from 2004 through 2014. In that period, the KNCP collected information on 630 million transactions for nearly 2 million unique products defined at the barcode level, which were purchased in 87 million shopping trips.

Household price indices (Aguiar and Hurst, 2007). The used methodology follows closely the one proposed by Aguiar and Hurst (2007) with small adjustments. In the original paper the authors focus on households from Denver from January 1993 through March 1995, while in my analysis I study households from all 54 Scantrack markets which are projected on the representative sample of the US population with the use of weights. Consequently, the methodology has been adapted to new features of more recent releases of the KNCP. Products $i \in I$ are bought by households $j \in J$ on shopping trip (date) t in month m. Then the consumption expenditures of households j in month m is given by:

$$X_m^j = \sum_{i \in I, t \in m} p_{i,t}^j q_{i,t}^j. \tag{1}$$

where $p_{i,t}^j$ and $q_{i,t}^j$ are paid prices and quantities of product i, respectively. The average price

[2] Around 40,000 for years 2004-2006 and 60,000 for 2007 onwards.

of product i in month m in market r weighted by the number of purchases is as follows:

$$\bar{p}^r_{i,m} = \sum_{j \in J(r), t \in m} w_{j,m} p^j_{i,t} \left(\frac{q^j_{i,t}}{\bar{q}_{i,m}} \right), \tag{2}$$

where $\bar{q}_{i,m}$ is the overall number of purchases, $\bar{q}_{i,m} := \sum_{j \in J, t \in m} w_{j,m} q^j_{i,t}$ made by households (denoted by $J(r)$) from market r. The computed statistics are meant to be representative thanks to weights, $w_{j,m}$, provided by Nielsen, which sum up to the total number of households in the US. The hypothetical cost of consumption of the household j from market $r(j)$ if she paid the average prices for purchased products would be given by:

$$Q^j_m = \sum_{i \in I, t \in m} \bar{p}^{r(j)}_{i,t} q^j_{i,t}. \tag{3}$$

Then the household price index $\bar{P}_{j,t}$ can be obtained from:

$$\bar{P}_{j,t} := \frac{\frac{X^j_m}{Q^j_m}}{\sum_{j' \in J(r)} w_{j',m} \frac{X^{j'}_m}{Q^{j'}_m}}. \tag{4}$$

What is a Good? The employed empirical strategy requires making a stand about the definition of a good. Are a 20-oz. bottle of Coke and a 12-oz. can of Coke the same product or different ones? Alternatively, are a 12-oz. can of Coke and a 12-oz. can of Pepsi the same product or different ones? Some products exhibiting similar features may be very close substitutes to each other and it might be recommended to study them jointly. In order to be as agnostic as possible about what a good is I consider two conservative definitions. First, I define products at the bar-code level. In the second scenario, products featuring very similar characteristics are pooled together as one product.[3] All products are categorized by Nielsen into over 1,000 modules and some of goods are described by 19 characteristics, such as flavor, package type, size, organic claims, or amount of salt. Goods sharing *exactly all*

[3] In this scenario a 12-oz. can of Coke and a 12-oz. can of Pepsi are the same products as they have the same package, the same volume, and the same flavor, while 20-oz. bottle of Coke and a 12-oz. can of Coke are different products.

characteristics the same are considered as one product.[4]

Another choice that must be made in defining a good is the market region. Should the price of 12-oz. can of Coke purchased in New York be compared with the price of 12-oz. can of Coke purchased in Philadelphia? I consider two extreme cases, the market is defined either at the Scantrack level (*e.g.*, New York Coke is not comparable with Coke purchases in Philly) or nationwide (*e.g.*, New York Coke is compared with Coke bought in Oakland). After pooling goods with similar characteristics, the number of unique products drops from initial 1,990,173 to 473,879.

The employed methodology computes relative prices for each purchase of every good. Quite mechanically goods that were purchased only once in a given period in a considered market will exhibit the relative price equal to one.[5] Table 1 presents a share in the aggregate consumption of purchased goods with different numbers of observed transactions. As can be seen, for the narrowest definition of a good (bar code, Scantrack market) transactions of products bought only once account for almost 30% of the aggregate consumption. A positive share of such transactions leads to a bias of household price indices towards one. Therefore, while more inclusive definitions of goods might raise questions on the level of substitutability of different goods, the narrow definitions might underestimate the level of heterogeneity.[6] All in all, the results are reported for four combinations of definitions of goods and markets, with a remark that estimates for more restrictive definitions are lower bounds of the true price heterogeneity across households. Figure 1 depicts the distribution of price indices according to those definitions.

Table 1: Number of transactions for different goods and shares in the aggregate consumption

		No. of transactions			
Product aggregation	Area aggregation	≥ 1	≥ 2	≥ 10	≥ 20
Similar features	Nationwide	1	0.990	0.942	0.903
Similar features	Scantrack market	1	0.860	0.517	0.404
Bar code	Nationwide	1	0.963	0.814	0.723
Bar code	Scantrack market	1	0.713	0.287	0.209

[4]Products not described by Nielsen are still studied at the bar code level.
[5]That is an immediate result from formula (2) computed for a product with only one observed transaction.
[6]Nonetheless, even the most inclusive definition of goods applied in this study is quite conservative.

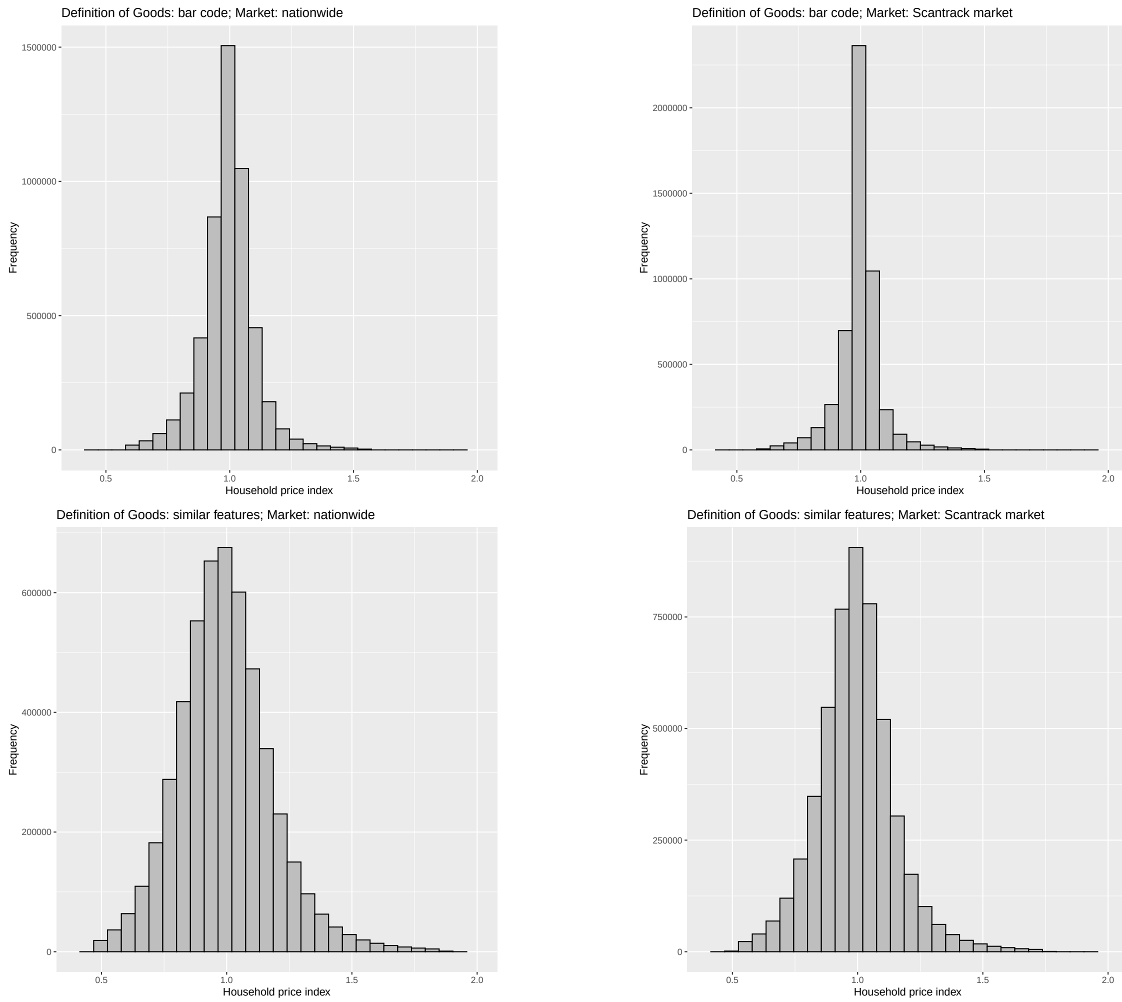


Figure 1: Distribution of household price indices.

A.1. High Earners Pay Higher Prices

I explore how the paid prices vary across different households by regressing logarithms of the household price indices, $\ln \bar{P}_{j,t}$ on the following dummies identifying different groups of households: households with the total annual household income above the median, non-employment status for either heads in working age (two dummies), retirement status for either heads in working age (two dummies), household composition (8 dummies), age dummies (for each head), year and month dummies, Scantrack region dummies. My main explanatory variable is the variable accounting for households with the total annual household income above the median. In the considered specification the reference group are households with with the total annual household income below or equal the median. Non-employment and retirement dummies are presented for comparison. In the KNCP the income variable is reported for 2 years prior to the panel year. For this reason, I use households' future reports 2 years ahead to get a measure of the current income. Households that are not present in the panel for future years are dropped.

Table 2 presents estimates of the regression for all four specifications of the household price indices. There are two immediate striking results. First, the high earning households pay between 1.5% and 7.1% higher prices than low earning households. Those price differentials are higher (or in the similar range) than the one documented for non-employed vs. employed (between 0.8% and 4.6% as documented by Kaplan and Menzio (2015)) or retired vs. working-age households (3.6% at the bar-code level as reported by Aguiar and Hurst (2007)). All estimates are very strongly statistically significant. Second, when the reference group of the analysis are not employed households but rather employed households earning below the median, it turns out that the price differential for retired and non-employed dwindle quite a lot. The effect of non-employment or retirement on prices is not higher than 1.5% compared to prices paid by the low earners. Those two results suggest that price heterogeneity across households with different levels of income is also a very important margin.

A.2. Hand-to-Mouth households pay lower prices

Another interesting dimension for studying the heterogeneity of paid prices is how it varies with different level of financial liquidity. To this end, I use a tax rebates survey conducted by Nielsen on behalf of Broda and Parker (2014) in 2008. In this survey panelists were asked: *"In case of an unexpected decline in income or increase in expenses, do you have at least two months of income available in cash, bank accounts, or easily accessible funds?"* The answer to this question can be a proxy identifying hand-to-mouth households, whose liquidity is not sufficient.

Table 3 presents estimates of the regression for a sample of households that answered to the question on the liquidity. Two new variables have been included, the liquidity state and the interaction of high earnings and the liquidity state. As can be seen the constrained households who do not earn above the median level pay between 0 and 2.8% lower prices. The effect for high-earning hand-to-mouth households is smaller (or even completely offset). Overall, those findings suggest that the price indices of consumption bundles purchased by households are associated not only with the current labor income but also with the household

Table 2: Household price indices across different income and employment states

	$\ln \bar{P}_{j,t}$			
	(1)	(2)	(3)	(4)
HH Earnings > median(HH Earnings)	0.020^{***}	0.015^{***}	0.071^{***}	0.052^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Non-employed in working age (Male)	-0.007^{***}	-0.006^{***}	-0.014^{***}	-0.010^{***}
	(0.001)	(0.001)	(0.002)	(0.002)
Non-employed in working age (Female)	-0.007^{***}	-0.004^{***}	-0.010^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.002)	(0.001)
Retired (Male)	-0.002	0.0001	-0.00002	-0.001
	(0.002)	(0.002)	(0.004)	(0.003)
Retired (Female)	0.002	0.001	0.002	0.001
	(0.002)	(0.002)	(0.004)	(0.003)
HH composition dummies	*Yes*	*Yes*	*Yes*	*Yes*
Age dummies (both heads)	*Yes*	*Yes*	*Yes*	*Yes*
Month dummies	*Yes*	*Yes*	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*
Scantrack market dummies	*Yes*	*Yes*	*Yes*	*Yes*
Product aggregation	Bar code	Bar code	Features	Features
Area aggregation	Nationwide	Scantrack	Nationwide	Scantrack
Number of observations	5,084,254	5,084,254	5,084,254	5,084,254
Number of panelists	150,153	150,153	150,153	150,153
R^2	0.034	0.016	0.071	0.042

Notes: Robust standard errors clustered at the household and year level are included in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

balance sheet.

Table 3: Household price indices and financial liquidity

	$\ln \bar{P}_{j,t}$			
	(1)	(2)	(3)	(4)
HH:HtM	-0.003	-0.007^{***}	-0.028^{***}	-0.024^{***}
	(0.002)	(0.002)	(0.004)	(0.003)
HH:HtM & HH Earnings > median(HH Earnings)	0.004	0.004	0.015^{**}	0.013^{**}
	(0.004)	(0.003)	(0.007)	(0.005)
HH Earnings > median(HH Earnings)	0.021^{***}	0.015^{***}	0.071^{***}	0.054^{***}
	(0.002)	(0.002)	(0.004)	(0.003)
Non-employed in working age (Female)	-0.009^{***}	-0.008^{***}	-0.014^{**}	-0.010^{**}
	(0.003)	(0.003)	(0.006)	(0.004)
Non-employed in working age (Female)	-0.008^{***}	-0.004^{**}	-0.007^{*}	-0.004
	(0.002)	(0.002)	(0.004)	(0.003)
Retired (Male)	-0.009	-0.004	-0.007	-0.003
	(0.006)	(0.005)	(0.011)	(0.008)
Retired (Female)	0.009^{*}	0.007	0.018^{*}	0.013^{*}
	(0.006)	(0.004)	(0.010)	(0.008)
HH composition dummies	Yes	Yes	Yes	Yes
Age dummies (both heads)	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Scantrack market dummies	Yes	Yes	Yes	Yes
Product aggregation	Bar code	Bar code	Features	Features
Area aggregation	Nationwide	Scantrack	Nationwide	Scantrack
Number of observations	284,112	284,112	284,112	284,112
Number of panelists	24,141	24,141	24,141	24,141
R^2	0.040	0.020	0.088	0.056

Notes: Robust standard errors clustered at the household level are included in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

A.3. Prices are causally related to income

While there is quite rich and robust evidence on systematic heterogeneity in price indices across different households, in fact, we do not know much about the causal nature of those differences. To the best of my knowledge, this issue has not been addressed in the previous studies at all. In particular, one could not rule out a possibility that some other confounding factors can drive both paid price and economic status of the households such as employment and income. The purpose of this section is: (i) to establish the causal relationship between price indices of individual consumption bundles and the income level of those households; (ii) to determine the importance of households' price adjustments in shaping households' expenditure responses to the economic stimulus payments (henceforth, ESP).

To this end, I exploit a quasi-experimental setup of the Economic Stimulus Act of 2008, a program consisting in sending tax rebates to about 130 million eligible taxpayers. Eligible households received their payments as tax rebates. For single individuals ESPs were between \$300 and \$600, while for married couples filing jointly, between \$600 and \$1,200.[7] Due to the magnitude of the whole program, the ESPs could not be paid at once. For this reason, some randomization in the timing of disbursement had to be introduced. The week in which the payment was wired was determined by the last two digits of the Social Security number, which made the timing a practically random assignment. Consequently, the ESPs can be interpreted as income shocks, which can shed some light on the causal impact of income on the individual price indices.

In this empirical exercise, I use again the tax rebates survey conducted by Nielsen on behalf of Broda and Parker (2014) in 2008. Information on the month of the ESPs is merged with data from the KNCP used in previous subsections. To recover the pass-through of income shocks on the prices paid by households I estimate the following regression:

$$\ln \bar{P}_{j,m} = \alpha_j + \beta_{-1} \cdot \sum_{s=-1}^{-3} R_{j,m-s} + \beta_0 \cdot \sum_{s=0}^{2} R_{j,m-s} + \beta_1 \cdot \sum_{s=3}^{5} R_{j,m-s} + \beta_2 \cdot \sum_{s=6}^{8} R_{j,m-s} + \eta_m + \varepsilon_{j,m}, \quad (5)$$

where the dependent variable is the household price index of household j in month m, $\bar{P}_{j,m}$, α_j is the household's fixed effect, η_m is the fixed effect of each month. The key indepedent variable is $R_{j,m}$ which is a dummy variable indicating whether the payment was received in month m. Coefficient β_0 corresponds to the average price reponse to the ESP in the month of the receipt and two subsequent months. Coefficient β_{-1} accounts for to the average price reponse to the anticipation of the ESP up to three months before the payment. Coefficients β_1 and β_2 represent the average price reponse to the ESP 3-5 or 6-8 months after the receipt, respectively. In the presented specification, periods at least four months prior the receipt of the ESP are the reference group.

[7] A detailed discussion on the exact structure of the program can be found in Sahm *et al.* (2010) and Parker *et al.* (2013).

Table 4 shows the results from estimating Equation (5) for the four definitions of goods presented before. The reported estimates strongly suggest that the income level has a causal impact on the level of paid prices. In addition to this, its impact is persistent in the horizon of even 8 months after receiving the tax rebate. As can be seen, the ESP, which in the used dataset amounted to on average $900, gives rise to higher price for exactly the same or very similar goods by between 0.4 and 1.3%.

Table 4: Price response to the ESP

Response to the ESP	$\ln \bar{P}_{j,t}$			
	(1)	(2)	(3)	(4)
Quarter before, β_{-1}	0.002	0.001	0.002	0.003
	(0.001)	(0.001)	(0.002)	(0.002)
Quarter of receipt, β_0	0.006***	0.004*	0.009**	0.008***
	(0.002)	(0.002)	(0.003)	(0.003)
One quarter after, β_1	0.008***	0.005**	0.009**	0.011***
	(0.003)	(0.002)	(0.005)	(0.004)
Two quarters after, β_2	0.008**	0.006**	0.011**	0.013***
	(0.003)	(0.003)	(0.006)	(0.005)
Month dummies	Yes	Yes	Yes	Yes
Product aggregation	Bar code	Bar code	Features	Features
Area aggregation	Nationwide	Scantrack	Nationwide	Scantrack
Number of observations	345,768	345,768	345,768	345,768
Number of panelists	29,289	29,289	29,289	29,289
R^2	0.589	0.549	0.605	0.565

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

To understand the magnitude of the identified impact, it is recommended to study the contribution of the price response in the response of the overall households' consumption expenditures. Suppose that a household receives the ESP in month τ. Then the expected expenditure response in month $\tau + s$ to the tax rebate can be decomposed into two elements:

$$\mathbb{E} \ln \left(\frac{\bar{P}_{j,\tau+s} Q_{j,\tau+s}}{\bar{P}_{j,\tau-1} Q_{j,\tau-1}} \right) = \underbrace{\mathbb{E} \left(\ln \bar{P}_{j,\tau+s} - \ln \bar{P}_{j,\tau-1} \right)}_{\text{Price channel}} + \underbrace{\mathbb{E} \left(\ln Q_{j,\tau+s} - \ln Q_{j,\tau-1} \right)}_{\text{Consumption channel}}, \tag{6}$$

where $Q_{j,m}$ is the amount of the composite good as in Aguiar and Hurst (2007), already defined before. The first element of the decomposition emboding the price channel of the response, $\mathbb{E}\left(\ln \bar{P}_{j,\tau+s} - \ln \bar{P}_{j,\tau-1}\right)$, is equal to $\beta_i - \beta_{-1}$ from Equation (5), where $i \in \{0, 1, 2\}$ is the quarter associated with month s after receiving the ESP. To identify the contribution of the price channel in the overall response, the remaining values, *i.e.* $\mathbb{E} \ln\left(\frac{\bar{P}_{j,\tau+s}Q_{j,\tau+s}}{\bar{P}_{j,\tau-1}Q_{j,\tau-1}}\right)$ and $\mathbb{E}\left(\ln Q_{j,\tau+s} - \ln Q_{j,\tau-1}\right)$, must be known as well. For this reason, I estimate the specification from Equation (5) but with different depedent variables. Namely, $\ln \bar{P}_{j,m}$ is replaced with $\ln\left(\bar{P}_{j,m}Q_{j,m}\right)$ and $\ln Q_{j,m}$.

Table 14 and 15, which are relegated to the appendix, present the estimation results. Table 15, reactions to $Q_{j,m}$, shows the results for four considered definitions of goods. Table 14, which reports the pass-through to overall expenditures, shows only one specification. The reason for this is that by construction $\bar{P}_{j,m}Q_{j,m}$ does not differ across definitions. The estimated overall responses of total expenditures to receipt of the ESP is equal to around 5.5-7.5% of the pre-treatment consumption, with some evidence on the anticipation response just prior receipt. Those findings are consistent with a very similar exercise conducted by Michelacci *et al.* (2021).[8] The reactions in $Q_{j,m}$ are relatively smaller than in $\bar{P}_{j,m}Q_{j,m}$ due to positive price adjustments from Table 4.

Table 5: Decomposition of the expenditure responses to the ESP

Product aggregation	Area aggregation	Price channel: $\frac{\mathbb{E}\left(\ln \bar{P}_{j,\tau+s} - \ln \bar{P}_{j,\tau-1}\right)}{\mathbb{E}\ln\left(\frac{\bar{P}_{j,\tau+s}Q_{j,\tau+s}}{\bar{P}_{j,\tau-1}Q_{j,\tau-1}}\right)}$			Consumption channel: $\frac{\mathbb{E}\left(\ln Q_{j,\tau+s} - \ln Q_{j,\tau-1}\right)}{\mathbb{E}\ln\left(\frac{\bar{P}_{j,\tau+s}Q_{j,\tau+s}}{\bar{P}_{j,\tau-1}Q_{j,\tau-1}}\right)}$		
		QTR_0	QTR_1	QTR_2	QTR_0	QTR_1	QTR_2
Bar code	Nationwide	12.5%	11.6%	12.0%	87.5%	88.4%	88.0%
Bar code	Scantrack	8.1%	8.5%	10.0%	91.9%	91.5%	90.0%
Features	Nationwide	22.2%	15.3%	18.1%	77.8%	84.7%	81.9%
Features	Scantrack	16.8%	16.3%	19.0%	83.2%	83.7%	81.0%

Table 5 shows the decomposition of the expenditure responses into two components, price changes and consumption changes. As it turns out, households' adjustments in the relative paid prices account for between 8 and 22% of the total changes in the overall consumption

[8]In fact, the authors use the same data sources as I do to study the response of total expenditures to the ESP. Apart from minor technicalities, the main difference is that they focus on changes in products entering households' consumption baskets. In my analysis, I concentrate on prices paid by households for the same or very similar products, which is not a subject of the analysis by Michelacci *et al.* (2021).

expenditures after receiving the tax payment.[9]

A.4. Price Variance in a Single Transaction is Higher for High Earners

In addition to studying variation of price indices across households, I look into the variance of relative prices $\frac{p_{i,m}}{\bar{p}_{i,m}}$ in a *single* transaction for both high earners and low earners. As shown in Table 6, a single transaction of high earning households is subject to higher risk for all definitions of a good. While this result may look rather technical, as I discuss later, it provides a desired property of a micro-founded search protocol for theoretical models. This result is discussed jointly with other findings at the end of the whole section.

Table 6: Price variance of a single transaction for high earners and low earners.

Product aggregation	Area aggregation	$\text{Var}\left(\frac{p^r_{i,m}}{\bar{p}^r_{i,m}} \| j \text{ is High Earner}\right)$	$\text{Var}\left(\frac{p^r_{i,m}}{\bar{p}^r_{i,m}} \| j \text{ is Low Earner}\right)$
Similar features	Nationwide	0.508	0.407
Similar features	Scantrack market	0.396	0.320
Bar code	Nationwide	0.178	0.152
Bar code	Scantrack market	0.156	0.128
	Number of transactions	207 millions	258 millions
	Number of customers	45,901	60,646

B. *Shopping effort*

To document shopping time differentials across households I use the American Time Use Survey (ATUS) data set. I follow the literature (e.g., Aguiar and Hurst, 2007; Aguiar *et al.*, 2013; Kaplan and Menzio, 2016) and I use time spent shopping as a proxy for the shopping effort. For this purpose I study time diaries, which document the allocation of time of the American households. In particular, I am interested in the relationship between shopping and labor market status, i.e. unemployment, retirement, and the level of labor earnings. I show that conditioned on being employed, the level of shopping effort exerted by households is positively correlated with the level of their earnings.

Data. In the analysis I use data from the 2003–2018 waves of the American Time-Use Survey. The ATUS is conducted by the U.S. Census Bureau and individuals are randomly

[9] To exclude the anticipation effect, I conducted a similar decomposition but with $\tau - 4$ as the reference period for measuring responses. The result is not very different. As can be seen in Table 16 of the appendix the price channel accounts for between 7 and 17% of the total changes in the expenditures.

selected from a subset of households from the Current Population Survey. Each wave is based on 24-hour time diaries where respondents report the activities from the previous day in specific time intervals. Next the ATUS staff categorizes those activities into one of over 400 types.

B.1. High Earners Spend More Time Shopping

I explore how the shopping time varies across different households by regressing logarithms of shopping time on the following dummies identifying different groups of individuals: individuals with the total annual income above the median, non-employment status, retirement status, year and age group dummies, and 'shopping needs.' I follow Aguiar and Hurst (2007) to control 'shopping needs,' which stem from differences in the family composition. For this reason, I add dummies indicating: 1. if the respondent has a partner (both spouse and unmarried), 2. whether the partner is unemployed, and 3. the number of children. The shopping time measures cumulative daily time (in minutes) spent obtaining goods or services (excluding education, restaurant meals, and medical care) and travels related to these activities. Some examples of activities captured by this variable are: grocery shopping, shopping at warehouse stores (e.g., WalMart or Costco) and malls, doing banking, getting haircut, reading product reviews, researching prices/availability, and online shopping. I restrict the dataset to individuals in age between 25 and 75 who are not self-employed.

Table 7 shows the result of the estimation. In comparison to the reference group (employed individuals earning below the median), all groups spend more time shopping. In particular, every day on average spend 2-2.5 minutes more shopping than the low earners. The estimate is highly significant and this number accounts for around 7% of the average shopping time, which amounts to 38 minutes a day. The estimates for other groups, retired and non-employed in working age, are equal to around 7 minutes a day and they are of the similar level to the existing in the literature.

C. Well-being of Shopping

In this section I document whether there is a significant difference in perception of shopping across different individuals. To this end, I use the ATUS Well-Being Module, where respondents answer what they feel during reported activities. In particular, I am interested in the answers related to shopping and whether different employment groups experience this

Table 7: Shopping time across different individuals

	Shopping time		
	(1)	(2)	(3)
Earnings>median(Earnings)	2.590***	2.049***	2.116***
	(0.450)	(0.451)	(0.446)
Nonemployed (in working age)	6.700***	6.712***	6.710***
	(0.508)	(0.508)	(0.503)
Retired	7.916***	7.644***	7.955***
	(0.755)	(0.791)	(0.783)
Age categories	Yes	Yes	Yes
Shopping needs	No	Yes	Yes
Year and day dummies	No	No	Yes
N	149,797	149,797	149,797
R^2	0.010	0.011	0.033

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

activity in a different way.

Data. The ATUS Well-Being (WB) Module is a complementary survey conducted by the U.S. Bureau of Labor Statistics in three waves 2010, 2012, and 2013. In this survey respondents are asked to evaluate their subjective well-being during reported activities. Those questions relate to experienced happiness, sadness, tiredness, stress, pain of activities. In all three waves there are over 75,000 respondents.

C.1. High Earners Do Not Enjoy Shopping More

In the WB module households report happiness, sadness, tiredness, stress, pain of activities on a scale from 0 (not at all) to 6 (completely). I regressed the reported answers on dummies indicating: respondents with the total annual income above the median, non-employment status, retirement status, the reported activity is shopping (defined as in the previous subsection), and the interaction of the shopping activity and employment status of the individual. In addition to this I controlled for age categories, 'shopping needs', and time dummies: year, day, and daytime.

Table 8 presents the results of the estimation. As can be seen, there is no significant difference (at the significance level 5%) in well-being experienced while shopping across different groups. Those results allow to rule out the possibility that for some groups shopping is non-market work, while for others is more like a leisure activity.

D. New Findings and Existing Price-Search Theories

The presented empirical findings are interesting in several dimensions. First, it is shown that price heterogeneity is substantial not only at the extensive labor margin as documented previously. In fact, the results suggest that the heterogeneity amongst workers across different income groups is even higher. Moreover, the finding that high earners spend more time shopping but at the same time pay higher prices stays at odds with with predictions made by existing random price-search theories in the spirit of Burdett and Judd (1983) and recently used by Kaplan and Menzio (2016). According to this class of theories, agents exerting higher search effort should result in paying lower prices. This would suggest that theories relying on the directed search in the spirit of Moen (1997) and recently exemplified by Bai *et al.* (2019) and Qiu and Ríos-Rull (2021) might be a better representation of price search. This class of models state that consumers with higher earnings and higher consumption decide to

Table 8: Well-being, shopping, and employment status

	WUTIRED	WUHAPPY	WUPAIN	WUSTRESS	WUSAD
	(1)	(2)	(3)	(4)	(5)
Activity:Shopping & Earnings>median(Earnings)	−0.084	0.044	−0.176*	−0.154	−0.082
	(0.106)	(0.093)	(0.092)	(0.100)	(0.077)
Activity:Shopping & Nonemployed (in working age)	0.031	−0.108	−0.242***	0.189**	−0.110
	(0.092)	(0.080)	(0.080)	(0.087)	(0.067)
Activity:Shopping & Retired	0.055	−0.014	−0.230**	0.076	−0.046
	(0.112)	(0.098)	(0.097)	(0.106)	(0.082)
Activity:Shopping	−0.256***	0.052	0.010	−0.033	−0.028
	(0.069)	(0.060)	(0.060)	(0.065)	(0.050)
Earnings>median(Earnings)	0.017	−0.108***	−0.354***	0.238***	−0.171***
	(0.022)	(0.019)	(0.019)	(0.021)	(0.016)
Nonemployed (in working age)	0.014	−0.104***	0.558***	0.090***	0.192***
	(0.020)	(0.018)	(0.018)	(0.019)	(0.015)
Retired	−0.571***	0.188***	0.513***	−0.684***	0.047**
	(0.031)	(0.027)	(0.027)	(0.029)	(0.022)
Age categories	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Shopping needs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year and day dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Daytime dummy and duration control	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	76,506	76,506	76,506	76,506	76,506
R^2	0.052	0.020	0.068	0.054	0.025

Notes:

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

choose retailers that have shorter queues (for each unit of consumption) but higher prices. Per unit of consumption those consumers spend less time shopping but overall due to higher consumption they may spend more time shopping overall. Nonetheless, this class of theories is also imperfect representation of shopping. The directed search assumes perfect knowledge about prices. Each household directs their shopping activity to stores with different price levels. If this were true then there should not be a systematic difference in the price variance of a single purchase across households with different level of income, which I documented. Consequently, the presented findings suggest that currently there is no one micro-founded representation of shopping that would reconcile all presented findings on price differential across different earnings groups.

III. A Life-Cycle Model of Shopping Effort

My framework integrates random search for consumption into a life-cycle incomplete markets model with heterogenous agents (*e.g.,* İmrohoroğlu *et al.*, 1995; Huggett, 1996; Ríos-Rull, 1996). Household income is driven by idiosyncratic productivity shocks. Every household makes the decision about level of savings, that are used to insure against future income fluctuations and to smooth the future consumption. The remaining disposable resources of household are spent on consumption. On top of the economy I introduced the frictional transactions technology. Households have to exert effort to purchase goods. This effort has two components: 1. effort to search for price bargains, 2. purchase effort required to purchase consumption of a given size. The former accounts for increasing probability that household during a single purchase samples a lower price, while the latter relates to the assumption that more consumption is possible by increasing a number of purchases[10]. The price search is present and documented in the literature (*e.g.,* Kaplan and Menzio, 2016) and the purchase effort is new and explained in more details later.

I first describe the setup of the economy. Next I characterize the model equilibrium and present some examples to shed some light on the shopping mechanism at work.

[10]In this regard, there is an important difference with the story of long queues with low prices and short queues with high prices offered by the directed search (*e.g.,* Moen, 1997; Bai *et al.*, 2019). The recent empirical literature due to Kaplan *et al.* (2016); Kaplan and Menzio (2015) shows that only 15% of the variance of prices is due to variation in the expensiveness of the stores at which a good is sold. This finding suggests to use the random search instead.

A. Building Blocks of the Economy

Demographics. The model period is one year. The stationary economy is populated by a continuum of households living T periods. Consumers work for T_{work} periods and next go into retirement for $T - T_{work}$ periods.

Preferences. Households exhibit preferences defined over stochastic sequences of consumption and overall shopping effort $\{c_t, f_t\}_{t=1}^{T}$ represented by the instantaneous utility function:

$$u(c_t) - v(f_t), \tag{7}$$

and the discount factor β. Households are expected utility maximizers. The utility from consumption, $u(c_t)$ is additively separable from the disutility from shopping effort, $v(f_t)$. Both functions are assumed to be increasing and $u(c_t)$ is concave while $v(f_t)$ is convex. Overall shopping effort f_t is a function of two shopping margins, a number of purchases m_t and search intensity s_t. It increases in both margins, *i.e.* $\frac{\partial f_t}{\partial m_t} > 0$, $\frac{\partial f_t}{\partial s_t} > 0$. Besides, both shopping margins affect each other's impact on f_t as follows $\frac{\partial^2 f_t}{\partial s_t \partial m_t} > 0$. It means that higher shopping effort m_t increases the marginal cost of searching for price bargains, s_t, and vice versa, the higher search intensity leads to a higher marginal cost of shopping effort.

Purchases (m_t). In order to consume goods c_t, households must spend some time for visiting stores. They make many repeated purchases (shopping visits) m_t in a given period. The level of the required effort is strictly increasing with consumption. Consumers make purchases, which are matched with goods offered by the retailers. Let D be the aggregate level of shopping effort (yet to be defined) of all households, R be the total amount of consumption purveyed by the retailers and $\theta = \frac{R}{D}$ be the market tightness of the consumption market. Both sides come together through a constant return to scale Cobb-Douglass function, $M(D, R) = D^{\alpha} R^{1-\alpha}$. A single shopping visit allows a household to purchase $\frac{M(D,R)}{D} = \theta^{1-\alpha}$ units of consumption. Thus, given an equilibrium market "tightness" θ, there is a linear relationship between consumption and the level of required shopping effort, *viz.*

$$c_t = m_t \theta^{1-\alpha}. \tag{8}$$

Note, that the efficiency of purchase $\theta^{1-\alpha}$ does not necessarily have to be less than one. This statistics tells us about the level of feasible consumption for a single purchase[11]. Suppose that a household wants to consume a certain amount of goods. In an economy with high θ she has to make fewer shopping trips to be able to purchase it.

Price Search (s_t). Apart from the number of purchases (which directly translates to the level of consumption), each household makes a decision on the intensity of search for price bargains, s_t. Suppose prices quoted by retailers are distributed according to a cdf $G(p) = Pr(x \leq p)$ with a lower bound $\underline{p}$, such that $G(\underline{p}) = 0$ and an *exogenously*[12] set upper bound ζ, such that $G(\zeta) = 1$. For a single purchase the price is sampled independently. Depending on the search intensity s_t, the purchase receives with probability of s_t two independent offers drawn from $G(p)$ and the lower one is paid, or with complementary probability of $1 - s_t$ one price is sampled and the customer is captive for this specific transaction. Thus the distribution of the effective price of a single purchase is a result of the compound lottery:

$$F(p; s_t) = (1 - s_t)G(p) + s_t \left(1 - [1 - G(p)]^2\right). \tag{9}$$

The first term, $(1 - s_t)G(p)$ tells us the probability that the purchase is captive *and* the effective price will be lower than p, while the second term is the probability that two prices are drawn and the minimum of those offers are lower than p[13]. A household can decrease the expected value of the price drawn from the lottery by increasing its search intensity s_t, but on the other hand, there is a trade-off since it increases the disutility from shopping visits[14].

The cost of the consumption bundle. The price of every purchase constituting the overall shopping effort (m_t) is sampled independently. It means that the overall cost of the consumption bundle $c_t = m_t\theta^{1-\alpha}$ is the realization of continuum of lotteries, *i.e.*

$$\int_0^{m_t\theta^{1-\alpha}} p(i)di, \tag{10}$$

where prices $p(i)$ are drawn from the cdf $F(p; s_t)$. Lemma 1 states that, while the cost of a single purchase is random and ex-ante unknown, the cost of many purchases is certain with

[11] In this regard, the interpretation of the efficiency of shopping effort differs from the probability that an unemployed worker matches with a vacancy used in the labor search literature. It is due to the fact that consumption is intuitively divisible while jobs are not.

[12] The relevance of this assumption is discussed more thoroughly later.

[13] Clearly, $Pr(x \geq \min\{p', p''\}) = (1 - G(p))^2$, so the cdf of the minimum of two prices is given by $Pr(x \leq \min\{p', p''\}) = 1 - [1 - G(p)]^2$.

[14] It is a consequence of assuming the positive cross partial derivative, $\frac{\partial f_t}{\partial m_t \partial s_t} > 0$.

probability one.

Lemma 1 (Cost of consumption bundle)**.** *Let the effective price of a purchase be distributed according to the cdf $F(p; s_t)$. Then the cost of consumption c_t given search intensity converges almost surely:*

$$\int_0^{m_t\theta^{1-\alpha}} p(i)di \overset{\text{a.s.}}{\to} \underbrace{m_t\theta^{1-\alpha}}_{c_t}\mathbb{E}(p|s_t), \tag{11}$$

where the effective price of consumption is equal to $\mathbb{E}(p|s_t) = \int pdF(p; s_t)$.

Proof. The lemma is an immediate result of applying the weak law of large numbers for random continuum in a version proposed by Uhlig (1996, Theorem 2). $\square$

It is convenient to make a decomposition of $\mathbb{E}(p|s_t)$ to disentangle the marginal effect of increasing search intensity on the effective price.

Lemma 2 (Linearity of the effective price function)**.** *For given distribution of the quoted prices $G(p)$ the effective price paid by households is a linear function with respect to search intensity s :*

$$\mathbb{E}(p|s_t) = p^0 - s_t MPB, \tag{12}$$

where:

i. $p^0 = \int_{\underline{p}}^{\zeta} xdG(x)$ *is the price for the fully captive consumer;*

ii. $MPB = \mathbb{E}\max\{p', p''\} - p^0 (\geq 0)$ *is the marginal (price) benefit of increasing the search intensity s_t, where $\mathbb{E}\max\{p', p''\}$ is the expected maximum of two independent draws of prices.*

Proof. To derive (12) I use the fact that the expected value of any non-negative random variable x distributed according to a cdf $H(x)$ can be computed integrating over its survival function (Billingsley, 1995, p. 79), namely:

$$\mathbb{E}(x) = \int_0^{\infty}(1 - H(x))dx. \tag{13}$$

The price of the consumption bundle is then a result of applying this property to equation (9):

$$\mathbb{E}(p|s_t) = \int_0^{\infty} 1 - G(x) - s_t \left(G(x) - [G(x)]^2\right) dx,$$

where $\int_0^\infty 1 - G(x)dx$ is the expected value for the captive offer and, using an analogous reasoning from Lemma 1, is also the price of consumption for the fully captive household that decides not to make any search for prices.

The residual part is equal to:

$$\int_0^\infty \left(G(x) - [G(x)]^2\right) dx =: MPB, \tag{14}$$

and which is clearly always positive as $\forall_x G(x) \geq [G(x)]^2$. For better interpretation it is convenient to reformulate equation (14):

$$\int_0^\infty \left(G(x) - [G(x)]^2\right) dx = \underbrace{\int_0^\infty 1 - [G(x)]^2 dx}_{\mathbb{E}\max\{p',p''\}} - \underbrace{\int_0^\infty 1 - G(x)dx}_{p^0}.$$

The expected maximum of two independent draws, $\max\{p', p''\}$ is distributed according to $[G(x)]^2$. It can be easily shown by the fact that $Pr(\max\{p', p''\} \leq x) = Pr(p' \leq x, p'' \leq x)$. Assuming independence of p' and p'' we get $Pr(p' \leq x) \cdot Pr(p'' \leq x) = [G(x)]^2$. Therefore, $\mathbb{E}\max\{p', p''\} = \int_0^\infty 1 - [G(x)]^2 dx$.

□

Lemma 1 shows that thanks to the fact that the cost of consumption is a sum of many repeated purchases the overall cost of the consumption basket can be pinned down deterministically. Each purchase is a result of different lottery price. Lemma 2 goes even further. It says that only two statistics of the price distribution, p^0 and MPB are needed to be known by households for making the optimal decision.

Productivity process. While being active in the labor market ($t \in \overline{1, T_{work}}$) every household faces the idiosyncratic wage risk. Log productivities follow an exogenous stochastic process:

$$\ln y_t = \kappa_t + \eta_t + \varepsilon_t,$$
$$\eta_t = \eta_{t-1} + \nu_t,$$

where $\varepsilon_t \sim_{\text{iid}} \mathcal{N}(0, \sigma_\varepsilon^2)$ and $\nu_t \sim_{\text{iid}} \mathcal{N}(0, \sigma_\nu^2)$. The deterministic part κ_t is a lifecycle component common to all households. The martingale part η_t and the serially uncorrelated part

ε_t account for the permanent and transitory components of the productivity, respectively. While being employed all households receive the labor income wy_t.

Retirement. Households older than T_{work} receive a deterministic retirement that is a function of their income in the last working-age period with replacement rate $repl$:

$$\log y_t = log(repl) \cdot \{\kappa_{T_{work}} + \eta_{T_{work}} + \varepsilon_{T_{work}}\}.$$

Budget constraint. Households can hold a single risk-free asset which pays a net return, r. Let a_{t+1} be the amount of asset carried over from t to $t+1$. Every household faces the sequence of intertemporal budget constraints:

$$\mathbb{E}(p|s_t)c_t + a_{t+1} \leq wy_t + (1+r)a_t, \quad \forall_{t \in \overline{1,T}}. \tag{15}$$

The effective price of consumption is a function of search intensity and is given by equation (12). It is worth noting that the intensity of search for prices s does not affect, at least directly, the level of consumption, but only the price of consumption. The shopping effort m_t affects the cost of consumption bundle only by the level of consumption expressed by the upper limit of the integral in formula (10). In addition to this every household faces the exogenous borrowing constraint $a_{t+1} \geq \underline{B}$.

Households' Decision Problem. The dynamic problem of a household of age t whose state is $x = (a, \varepsilon, \nu, \eta)$ is:

$$\mathcal{V}_t(a, \varepsilon, \eta) = \max_{c,f,m,s,p,a'} u(c) - v(f) + \beta \mathbb{E}_{\eta'|\eta} \mathcal{V}_{t+1}(a', \varepsilon', \eta') \tag{16}$$

s.t.

$$
\begin{aligned}
pc + a' &\leq (1+r)a + wy, \\
c &= m\theta^{1-\alpha}, \\
f &= f(m, s), \\
p &= p^0 - sMPB, \\
a' &\geq \underline{B}, \\
s &\in [0,1], \\
\log y &= \begin{cases} \kappa_t + \eta + \varepsilon, & \text{for } t \leq T_{work}, \\ log(repl) \cdot \{\kappa_{T_{work}} + \eta_{T_{work}} + \varepsilon_{T_{work}}\}, & \text{for } t > T_{work}, \end{cases} \\
\eta' &= \eta + \nu',
\end{aligned}
$$

The problem is not convex due to bilinearity in controls s and c in the budget constraint. This may cause that the first order conditions do not suffice and might lead to local solutions. However, this issue is solved by using envelope convexification of the bilinear constraint, which was proposed by McCormick (1976).

Retailers' problem. Sellers buy consumption goods at the cost standardized to one and quotes her price in every period conditioned on being matched with households' purchases. She maximizes the sales revenue:

$$
S(p) = \theta^{-\alpha} \sum_{t=1}^{T} \int \frac{\theta^{1-\alpha} m_t(x)(1+s_t(x))}{D} \underbrace{\left(1 - \frac{2s_t(x)}{1+s_t(x)} G(p)\right)}_{\substack{\text{Business}\\ \text{Stealing}}} \underbrace{(p-1)}_{\substack{\text{Surplus}\\ \text{Appropriation}}} d\mu_t(x), \qquad (17)
$$

where $\mu_t(x)$ is the distribution of households of age t over the individual states $x = (a, \varepsilon, \nu, \eta)$. In the problem of sellers there are two opposite motives. First, the net revenue $(p-1)$ from a single purchase is increasing with the set price. The second motive is generated by lack of information whether the matched buyer has the alternative offer for this purchase. The probability that the household has an alternative that with a better price than p amounts to $\frac{2s_t(x)}{1+s_t(x)}G(p)$. Thus, the probability of acceptance a given price price is the complementary event with probability $\left(1 - \frac{2s_t(x)}{1+s_t(x)}G(p)\right)$. Higher prices decrease the probability that the offer will be accepted by the buyer. Thus, these two motive can generate a price dispersion, in which there are retailers that have higher markups but their prices are rejected more often and retailers that cut their prices to increase the probability of the successful transaction. In an equilibrium the sellers are indifferent[15].

Relevance of exogenous reservation price ζ. A question that arises from the exogenous price ζ is about the commitment of households to pay sampled prices for all purchases. The repeated purchases can be interpreted as consumption in different subperiods of the year. If the subperiods are long enough it is reasonable to say that households agree to pay the lowest offered (but still high) price in order to avoid starving to death due to the lack of consumption. On the other hand, if subperiods are short enough households might prefer setting their own endogenous reservation price $\overline{p}$ and deferring from paying above this price. In this case, the model should be augmented by an additional control, $\overline{p}$. However, this extensions leads to some issues. First, lemma 2 does not hold and the constraint for the effective price is not linear with all controls. This is due to the fact that $\overline{p}$ replaces exogenous ζ. Second, there is no clear distinction between two motives, shopping effort m_t and search intensity s_t anymore. An additional increase in shopping effort accompanied by a decrease in $\overline{p}$ plays the same role as an increase in s[16].

Equilibrium. Having outlined the building blocks of the economy, I am in the position to define an equilibrium of the economy.

Definition 3 (Rational Stationary Equilibrium)**.** *A stationary equilibrium is a sequence of consumption and shopping plans $\{c_t(x), m_t(x), s_t(x)\}_{t=1}^{T}$, and the distribution of quoted prices $G(p)$ and paid prices $F(p; s_t(x))$, distribution of households $\mu_t(x)$ and interest rate r such that:*

1. *$c_t(x), m_t(x), s_t(x)$ are optimal given r, w, $G(p)$, $\underline{B}$, and θ;*

2. *individual and aggregate behavior are consistent:*

$$D = \sum_{t=1}^{T} \int (1 + s_t(x)) m_t(x) d\mu_t(x); \tag{18}$$

3. *retailers post prices p to maximize the sales revenues taking as given households' behavior;*

[15]In this sense, the mechanism is similar to the theory of homogenous hotel rooms with different prices given by Prescott (1975).

[16]However, search intensity s_t is still necessary for generating price dispersion.

4. the private savings sum up to an exogenous aggregate level $\overline{K}$:

$$\sum_{t=1}^{T} \int a_t(x) d\mu_t(x) = \overline{K}; \tag{19}$$

5. $G(p)$ *and* $F(p; s_t(x))$ *are consistent given the household distribution* $\mu_t(x)$*;*

6. $\mu_t(x)$ *is consistent with the consumption and shopping policies.*

B. Characterization of the Equilibrium

The dispersed distribution of posted prices is consistent with the solution to the maximization of the retailers' net sales revenue, (17). Lemma 4 presents properties of an equilibrium of this kind. The proof of the lemma is similar to ones used in Burdett and Judd (1983) and Kaplan and Menzio (2016).

Lemma 4 (Characterization of the Equilibrium Price Dispersion)**.** *The c.d.f.* $G(p)$ *exhibits following properties:*

i. $G(p)$ *is continuous.*

ii. supp $G(p)$ *is a connected set.*

iii. the highest price charged by retailers is equal to ζ*,*

iv. all retailers yield the same profit, $\forall_{p \in \text{supp } G(p)} S(p) = S^*$,

where supp $G(p)$ *is the smallest closed set whose complement has probability zero.*

Proof. The two first properties are an immediate result of Lemma 1 from (Burdett and Judd, 1983). Suppose that $G(p)$ has a discontinuity at some $p' \in \text{supp } G(p)$. The retailer posting an infinitesimally smaller price $p' - \epsilon$ would increase its profit as the probability of making a sale would change by a discrete amount. Furthermore, supp $G(p)$ is a connected set. Suppose there is a gap of zero probability between p' and p''. The seller's gain would be strictly higher at p'' as $p'' > p'$, and $G(p') = G(p'')$. This cannot occur in an equilibrium.

Next, suppose that (iii) is not true. Then $\max \text{supp } G(p) =: \overline{p} \leq \zeta$.[17] Moreover, we know that $G(\overline{p}) = G(\zeta) = 1$. If we substitute values of the c.d.f. for both prices into (17) all firms

[17]Recall that there is the exogenous upper-bound for prices ζ, so $\overline{p} \geq \zeta$ is not considered.

will have incentives to set higher price for higher demand, which leads us to contradiction. As a result, $\max \operatorname{supp} G(p) = \zeta$. Fact (iv) is an equilibrium condition. If there would be such a price p that would yield higher profit, each individual retailer would have incentives to set this price. □

It is convenient to decompose the aggregate shopping effort D defined in (18) into two components:

$$\Psi_{(-)} := \sum_{t=1}^{T} \int m_t(x)(1 - s_t(x))d\mu_t(x), \tag{20}$$

$$\Psi_{(+)} := \sum_{t=1}^{T} \int m_t(x)2s_t(x)d\mu_t(x), \tag{21}$$

$$D = \sum_{t=1}^{T} \int m_t(x)(1 + s_t(x))d\mu_t(x) = \Psi_{(-)} + \Psi_{(+)}. \tag{22}$$

Notice that $\Psi_{(-)}$ in (20) is an aggregate measure of visits where customers are captive and $\Psi_{(+)}$ in (21) where households draw two prices and choose the lower one. D from (22) is the measure of the aggregate shopping defined in (18) and is a sum of $\Psi_{(-)}$ and $\Psi_{(+)}$. Consequently, $\frac{\Psi_{(-)}}{D}$ and $\frac{\Psi_{(+)}}{D}$ are probabilities that a single draw is captive or matched with an alternative offer, respectively. By construction all offers of $\Psi_{(-)}$ are effective for the reason that buyers are captive during these purchases. On the other hand, only half of $\frac{\Psi_{(+)}}{D}$ is accepted by buyers and the remaining part is rejected. It is so because for this measure of offers consumers get two price offers and choose the lower one.

Properties from Lemma 4 can be used to derive the formula for an equilibrium price dispersion.

Theorem 5 (Equilibrium Price Dispersion)**.** *Given aggregate statistics of households' shopping decisions* $\{\Psi_{(-)}, \Psi_{(+)}, D\}$, *(where* $\Psi_{(-)}, \Psi_{(+)} > 0$*), the equilibrium price dispersion can be expressed in a closed form:*

$$G(p) = \begin{cases} 0, & \text{for } p < \underline{p}, \\ \frac{D}{\Psi_{(+)}} - \frac{\Psi_{(-)}}{\Psi_{(+)}} \cdot \frac{\zeta - 1}{p - 1}, & \text{for } p \in [\underline{p}, \zeta], \\ 1, & \text{for } p > \zeta, \end{cases} \tag{23}$$

where the lower bound of suppG(p) is:

$$\underline{p} = \frac{\Psi_{(+)}}{D} + \frac{\Psi_{(-)}}{D}\zeta. \tag{24}$$

Discussion of Theorem 5. Given p, the equilibrium price dispersion $G(p)$ is a linear function decreasing in: 1. the inverse odds ratio[18] of being matched with a non-captive customer, $\left(\frac{\Psi_{(+)}}{\Psi_{(-)}}\right)^{-1}$ and 2. the probability that a visiting buyer draws an alternative offer, $\frac{\Psi_{(+)}}{D}$. Suppose that there are two economies with the same aggregate shopping effort D and different level of search intensity, $\Psi'_{(+)} > \Psi''_{(+)}$. Due to the fact that $\frac{\partial G(p)}{\partial \frac{\Psi_{(+)}}{D}} > 0$ for every p from the the interior of supp $G(p)$, the price lottery of the economy with higher search intensity $\Psi'_{(+)}$ first-order stochastically dominates the price lottery of the economy with lower search intensity $\Psi''_{(+)}$. This observation leads to an immediate remark that economies with higher search intensity exhibit the lower expected value of the price lottery. The result is consistent with economic intuition. The higher fraction of buyers with alternative offers is, the stronger competition between retailers is observed. For a better understanding how the price equilibrium changes in $\Psi_{(+)}$ consider three cases:

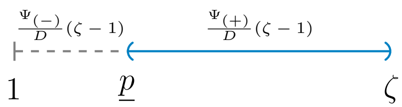
1. $\Psi_{(+)} = 0$ – the business stealing motive from (17) embodied by $\left(1 - \frac{2s_t(x)}{1+s_t(x)}G(p)\right)$ disappears and only the surplus appropriation motive occurs. Every customer is captive and this leads to a degenerate Diamond (1971)-type equilibrium, where all retailers charge the monopolistic price, ζ;

2. $\Psi_{(+)} = D$ *(hypothetical)* – every consumer draws two prices and chooses the lower one. Consequently, all retailers start playing a Bertrand game and the only price equilibrium is a degenerate competitive one, $p = 1$. Nonetheless, it is a purely hypothetical case since an equilibrium from Definition (3) with $\Psi_{(+)} = D$ never exists. If all prices are set competitively, then none of households have incentives to make any search. To them it pays off to be captive all the time but then $\Psi_{(-)} = D$ and $\Psi_{(+)} \neq D$, which contradicts the constituting assumption of the case that $\Psi_{(+)} = D$;

3. $\Psi_{(+)} \in (0, D)$ – there occurs a tug of war between two motives, 1. the appropriation of consumers' surplus and 2. business stealing. In every point of the support of the equilibrium price dispersion supp $G(p) = [\underline{p}, \zeta]$ retailers yield the same profit S^*.

[18] Notice that $\frac{\Psi_{(+)}}{\Psi_{(-)}} = \frac{\frac{\Psi_{(+)}}{D}}{1-\frac{\Psi_{(+)}}{D}}$.

Figure 2: The equilibrium support of $G(p)$.



> However, for each price there is a different composition of sources of this profit. The business stealing motive is the only motive for retailers charging $\underline{p}$, while the surplus appropriation only rationalizes the behavior of sellers that set ζ. Prices from the interior of supp $G(p)$ are supported by a combination of both. As the aggregate search $\frac{\Psi_{(+)}}{D}$ increases, retailers set lower prices and the lowest quoted price, $\underline{p}$ gets closer to the competitive pricing.

The lower bound $\underline{p}$ of supp $G(p)$ also depends on the aggregate search intensity in the economy. Interestingly, it is a convex combination of the competitive price (normalized to 1) and the monopolistic price ζ, where $\frac{\Psi_{(+)}}{D}$ and $\frac{\Psi_{(-)}}{D}$ are weights. The higher $\frac{\Psi_{(+)}}{D}$ is, the further $\underline{p}$ is from the monopolistic price and closer to the competitive price (see Figure 2).

Equilibrium price moments. Finally, p^0 and $\mathbb{E}\max\{p', p''\}$ from Lemma 2 can be pinned down using the closed form solution from Theorem 5.

Proposition 6. *Given households' aggregate shopping efforts $\Psi_{(-)}$ and $\Psi_{(+)}$, the price for captive customers (p^0) and the expected maximum of two independent draws ($\mathbb{E}\max\{p', p''\}$) can be expressed in a closed form:*

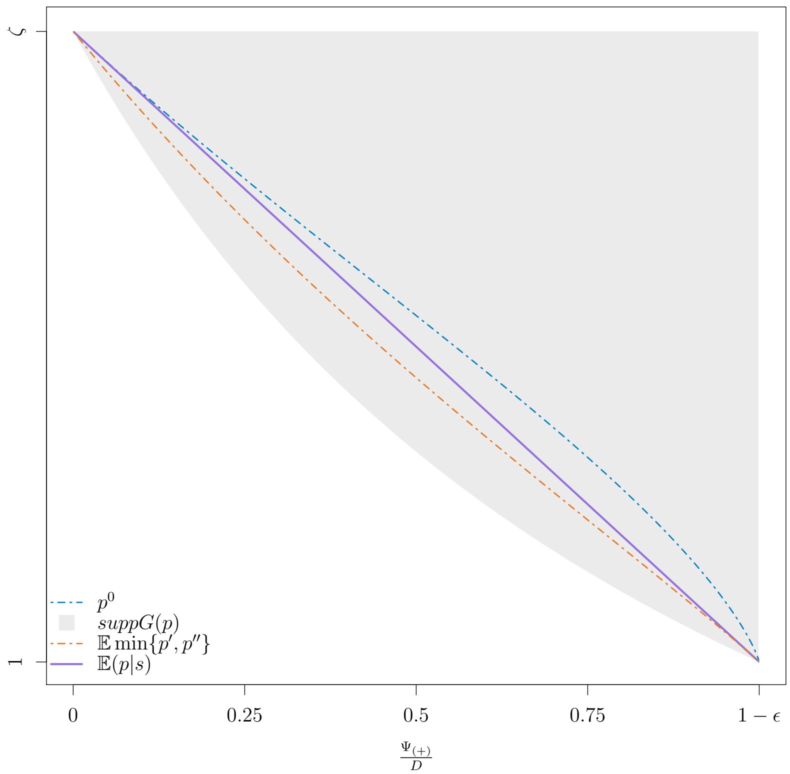
i. price of the captive customer:

$$p^0 = \underline{p} + \frac{\Psi_{(-)}}{\Psi_{(+)}}(\zeta - 1)\log\left(\frac{\zeta - 1}{\underline{p} - 1}\right) + \left(1 - \frac{D}{\Psi_{(+)}}\right)(\zeta - \underline{p})\,; \tag{25}$$

ii. the expected maximum of two independent draws:

$$\begin{aligned}\mathbb{E}\max\{p', p''\} =& \zeta - \left(\frac{D}{\Psi_{(+)}}\right)^2(\zeta - \underline{p}) + 2\frac{D\Psi_{(-)}}{\Psi^2_{(+)}}(\zeta - 1)\log\left(\frac{\zeta - 1}{\underline{p} - 1}\right) - \\ &- \left(\frac{\Psi_{(-)}}{\Psi_{(+)}}\right)^2(\zeta - \underline{p})\frac{\zeta - 1}{\underline{p} - 1}.\end{aligned}$$

Figure 3: Moments of equilibrium price distribution and the aggregate search intensity.



The moments from Proposition 6 are "sufficient" price statistics[19] that are required in the household's problem (16). For gaining a better insight into the mechanics of the equilibrium it is helpful to conduct the comparative statics with respect to the search intensity. Without loss of generality, in this exercise I focus on the representative consumer framework. For this case there is a one-to-one mapping between the individual search intensity of the consumer and the aggregate search intensity, *i.e.* $\frac{\Psi_{(+)}}{D} = \frac{2s}{1+s}$[20]. Figure 3 shows how the key price characteristics change in the probability of being matched with a non-captive customer, $\frac{\Psi_{(+)}}{D}$. First, the average effective price $\mathbb{E}(p|s)$ varies between the price of the fully captive customer p^0 and the expected minimum of two draws $\mathbb{E}\min\{p', p''\}$. Even though prices are sampled

[19]Recall that $MPB = \mathbb{E}\max\{p', p''\} - p^0$.

[20]Besides, notice that in this case the equilibrium cdf is distributed according to $G(p) = \frac{1+s}{2s} - \frac{1-s}{2s}\frac{\zeta-1}{p-1}$. Only the search intensity s matters, while the number of purchases m cancels out. In the heterogenous-agent framework it is analogous. The latter margin plays only a weighting role for purchases made by various households.

from a whole interval supp $G(p) = [\underline{p}, \zeta]$, the (unit) cost of the consumption bundle is the average price $\mathbb{E}(p|s)$ drawn from $F(p)$ and given by (12). As mentioned before, for $\Psi_{(+)} = 0$ there exists only the degenerate Diamond (1971)-type equilibrium, where $\mathbb{E}(p|s) = p^0 = \zeta$. An increase in $\frac{\Psi_{(+)}}{D}$ makes $\mathbb{E}(p|s)$ further from the captive price p^0 and closer to the expected minimum $\mathbb{E}\min\{p', p''\}$. In the limit case you can observe[21]:

$$\lim_{s \to 1^-} \mathbb{E}(p|s) = 2p^0 - \mathbb{E}\max\{p', p''\} = \mathbb{E}\min\{p', p''\}. \tag{26}$$

Higher search intensity in the economy fosters higher competition between retailers. As a result, all price statistics (p^0, $\mathbb{E}\min\{p', p''\}, \mathbb{E}\max\{p', p''\}, \mathbb{E}(p|s)$) tend towards the competitive solution, which in the model is normalized to unity.

A natural concern that arises here is the assumption on the exogeneity of the upper bound ζ of supp$G(p)$. The minimum price quoted by retailers responds to the level of search intensity, while the maximum price is constant all the time. However, it is not a problem. As Figure 4.a shows top percentiles decrease in search intensity. Effective price ($\mathbb{E}(p|s)$ in Figure 4.b) decreases even faster. For instance, 97^{th} percentile in a low search economy is close to the upper bound, ζ. In fact, the whole support is concentrated in this neighborhood. On the contrary, the same percentile is much closer to the competitive price in a high search economy. This observation is true especially for the paid prices (Figure 4.b). In fact, in spite of the exogeneity of ζ, prices paid by consumers can be successfully reduced by increasing search intensity, s.

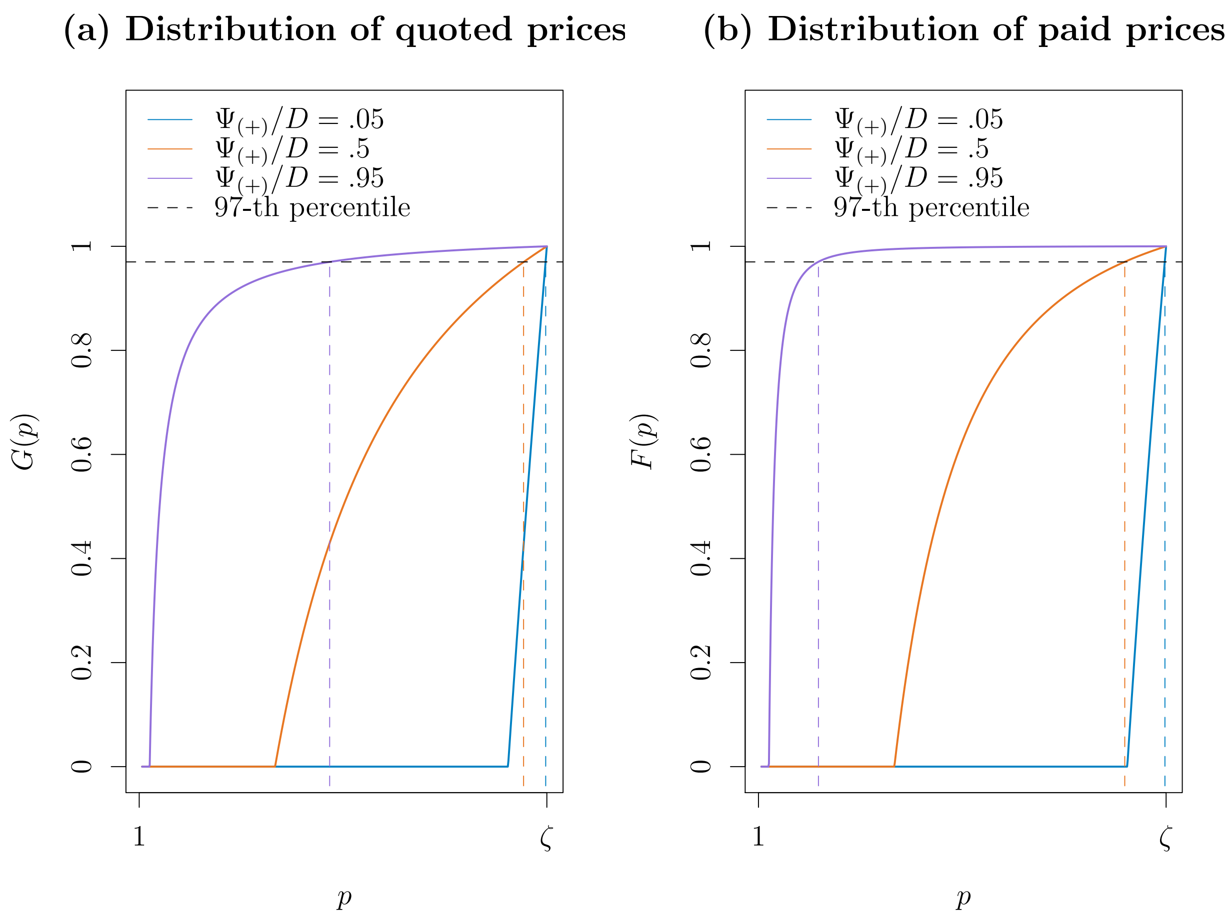
Solution to the household's problem. Finally, I am in the position to write the first order conditions that constitute the solution to the households' problem (16). The intertemporal decision is determined by:

$$\frac{u'(c)\theta^{(1-\alpha)} - v'(f)\frac{\partial f}{\partial m}}{p^0 - sMPB} \geq \beta(1+r)\mathbb{E}_{x'|x}\frac{u'(c')\theta^{(1-\alpha)} - v'(f')\frac{\partial f'}{\partial m'}}{p^0 - s'MPB}, \tag{27}$$

and $a' \geq \underline{B}$, with complementary slackness. The main departure from the textbook Euler equation is the additional convex cost, $v(f_t)$ and varying price, $p = p^0 - sMPB$, which is a function of the control, s in the considered case. For the CRRA specification the household

[21]Note $\max\{p', p''\} = \frac{p'+p''}{2} + |p' - p''|$ and $\min\{p', p''\} = \frac{p'+p''}{2} - |p' - p''|$. Then $\mathbb{E}\min\{p', p''\} + \mathbb{E}\max\{p', p''\} = \mathbb{E}p' + \mathbb{E}p'' = 2p^0$, which gives the latter equality in (26).

Figure 4: The equilibrium price dispersion for the different aggregate search intensities, $\frac{\Psi_{(+)}}{D}$.



makes also an intratemporal decision on its shopping behavior:

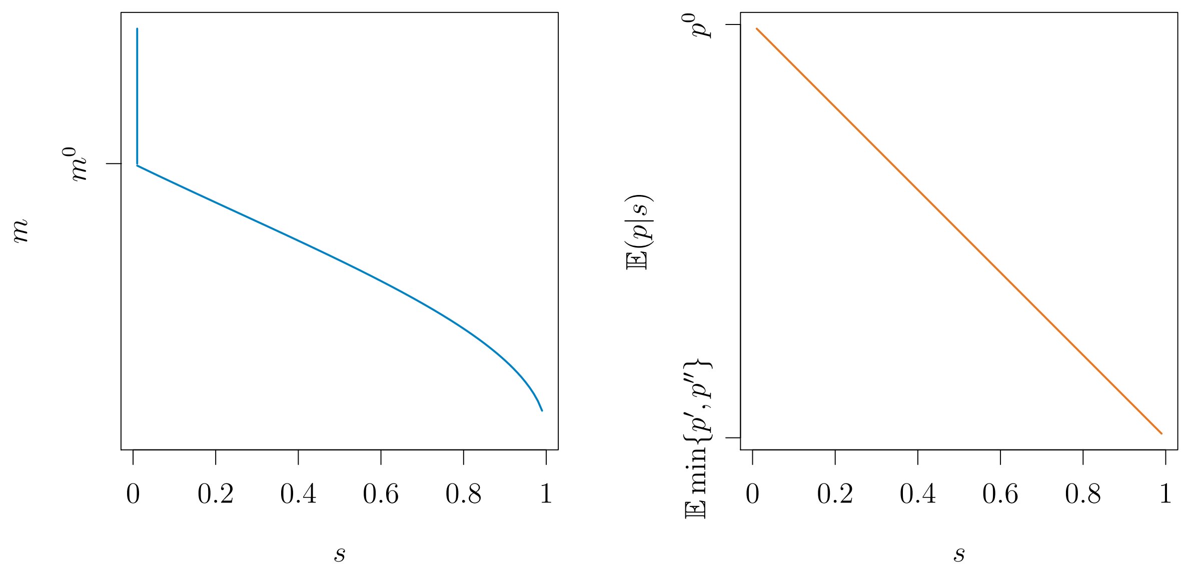
$$m \geq \left\{ \frac{\theta^{(1-\sigma)(1-\alpha)}}{(\frac{1+s}{1-s})^{\phi} \left(1 + \frac{2p^0}{(1-s)MPB}\right)} \right\}^{\frac{1}{\sigma+\phi}} \tag{28}$$

and $s \geq 0$, with complementary slackness[22]. First, as in the standard model, consumption goes along with the level of wealth. By construction, it affects m_t in the same way due to the linear relationship, $c_t = m_t\theta^{1-\alpha}$. Second, both shopping margins are Frisch complements

[22]Condition (28) is not defined in $s = 1$. However, the assumed functional specification meets an Inada-like condition, $\lim_{s\to 1^-} v(m_t, s_t) = \infty$, which guarantees that such a search intensity is never chosen.

to each other in the disutility function. Consequently, households with higher consumption exert lower search for prices, s_t. There is also a certain number of purchases m^0 (which translates directly into $c^0 = m^0\theta^{1-\alpha}$), above which households decide to be captive in every purchase, $\mathbb{E}(p|s = 0) = p^0$ (see Figure 5). However, as mentioned before it does not make them to pay ζ all the time because there is a positive externality generated by households with high search. This is embodied by $p^0 < \zeta$.

Figure 5: Optimal relationship between the number of purchases (m_t), price search (s_t) and the effective consumption price $\mathbb{E}(p|s)$.



IV. Taking the Model to Data

In this section I present my strategy for parametrization of the model and computation of the equilibrium. Model parameters are divided into two groups. Values of the first group (Table 9) are preset exogenously to standard values drawn from the literature. Values of crucial parameters which account for the shopping technology (Table 10) are determined internally using the method of simulated moments.

Demographics. The model is annual. Households enter the labor market when they are 25, they retire at age of 60 and die at age 90. This implies $T_{work} = 35$ and $T = 65$.

Preferences. The preferences over consumption are represented by a CRRA specification, $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$. The elasticity of relative risk aversion parameter $\frac{1}{\sigma}$ was set to .5. The disutility from overall shopping effort is modeled by an isoelastic function:

$$v(f) = \begin{cases} \frac{f^{1+\phi}}{1+\phi}, & \text{for } t \in 1, \ldots, T_{work}, \\ \chi^{ret} \frac{f^{1+\phi}}{1+\phi}, & \text{for } t \in T_{work}+1, \ldots, T. \end{cases} \tag{29}$$

Factor $\chi^{ret}(< 1)$ is supposed to capture a lower opportunity cost of shopping time for the retired consumers. The function of overall shopping effort f is chosen to meet assumptions on increasing in both margins and mutual complementarity. It is represented by a functional specification $f = \frac{1+s}{1-s}m$. Besides this form is convenient in the computational procedure, which is described and explained more carefully in the end of the section. Finally the discount factor β was chosen to replicate an aggregate wealth-income ratio of 2.5.

Interest rate and assets. I calibrate the discount factor β to generate an aggregate wealth-income ratio of 2.5. Following the RBC literature (Cooley and Prescott, 1995), the interest rate r was set to .025. Household debt contributes very little to wealth distribution. In aggregate it poses less than 1% of the total wealth and a median quarterly credit limit reported by households from the SCF amounts to merely 74% of quarterly labor income, which is not much in comparison to the mean net worth equal to over 900% of the labor income. For this reason, I assume households can save but cannot borrow, $\underline{B} = 0$ as modeled in Carroll (1997) or more recently in Krueger *et al.* (2016).

Income process. The income process is a combination of two components, transitory $\{\varepsilon_t\}$ and permanent $\{\eta_t\}$. Following the literature, the log variances of those shocks were set to $\sigma_\varepsilon^2 = .05$, $\sigma_\eta^2 = .01$. The age-dependent deterministic component, κ_t is approximated by a quadratic regression using the PSID data as in Kaplan and Violante (2010). In retirement, households receive a social security income payment that is a function of their income in the last working-age period with replacement rate *repl* (Guvenen and Smith, 2014; Berger *et al.*, 2015).

V. Quantitative results

A. Cross-sectional Distribution

The cross-sectional distributions of consumption expenditures and net wealth are another dimension describing the aggregate demand. For this exercise I generate simulated moments from both artificial economies and compare with data. Following the macroeconomic literature of inequalities (*e.g.,* Castañeda *et al.*, 2003; Krueger *et al.*, 2016), distributions are compared with the use of Gini indices and share of the total value held by chosen groups of households. The data counterparts were calculated using the 2006 wave of the Panel Study of Income Dynamics. I focus on households aged between 25 and 90 to make computed statistics compatible with the calibration of the models. Following Blundell *et al.* (2016) I dropped observations with extremely high net wealth (¿$ 20 millions). In the theoretical framework I do not model the household decision to purchase durables, so I focus on non-durables and services.

Table **??** presents the distributions of consumption expenditures in both economies and observed in the data. The shopping economy mirrors inequalities remarkably better than the SIM economy without product-market frictions. The Gini indices for consumption in the baseline SIM and in the shopping economy amount to .234 and .401 , respectively. The empirical counterpart computed from the PSID is equal to .353. This effect is generated mainly by groups exerting high search for price bargains, households with low consumption

Table 9: External choices

Parameter	Interpretation	Value	Source
T_{work}	Age of retirement	35	–
T	Length of life	65	–
σ	Risk aversion	2.0	convention
$repl$	Retirement replacement rate	.45	Guvenen and Smith (2014)
σ_ε^2	Variance of the transitory shock	.05	Kaplan and Violante (2010)
σ_η^2	Variance of the permanent shock	.01	Kaplan and Violante (2010)
r	Interest rate	.025	Cooley and Prescott (1995)
κ_t	Deterministic life-cycle income profile	–	Kaplan and Violante (2010)
$\underline{B}$	Borrowing constraint	0	convention

Table 10: Calibration targets and model values

Target	Data Value	Source	Model Value
Shopping effort:			
Shopping time of retired relative to the referential group	1.245	This paper	1.251
Shopping time of the top earn. tercile relative to the referential group	1.11	This paper	1.112
Age trend for shopping time	0	This paper	.010
Price dispersion:			
${}^{95^{th}\text{decile}}/_{5^{th}\text{decile}}$ of paid prices	1.7	Kaplan and Menzio (2016)	1.369
Price differential between high earners and low earners	.021	Aguiar and Hurst (2007)	.011
Price differential between retirees and working-age households	-.039	Aguiar and Hurst (2007)	-.051
Aggregate state:			
Aggregate wealth-income ratio	2.5	Kaplan and Violante (2010)	2.498

and retirees. First, households with low consumption search more intensively, which leads to lower effective prices paid by them. Consequently, the fraction of aggregate consumption expenditures is smaller than in the benchmark SIM model. Second, a drop in consumption expenditures after retirement is higher in the shopping economy as can be seen in Table **??**. This result is generated by the lower opportunity cost of time for retirees and is consistent with findings made by Aguiar and Hurst (2005, 2007).

The distributions of net wealth are presented in Table 12. As can be seen the shopping friction amplifies the wealth inequalities as well. The Gini indices in the baseline SIM and

Table 11: Calibrated parameters

Parameter	Value	Description
ϕ	.619	curvature of disutility from shopping
$\theta^{1-\alpha}$	.0948	matching efficiency
w	.0002	"wage"
ζ	162	maximum price
β	.969	discount factor

in the shopping economy amount to .569 and .667 , respectively. The empirical counterpart computed from the PSID is equal to .771. If we look at the fine print, the higher Gini index comes from the higher share of the total wealth held by the top quintile. In the shopping economy households from the top quintile own nearly 70% of total wealth, while in the data 82.6% is observed. In the SIM model only 55% is owned by households from the top quintile. The improvement in this moments is generated in the analogous way to consumption responses from the previous subsection. For this group of households increasing the current consumption is too costly. Instead it is beneficial to them to save more and increase consumption during retirement when the opportunity cost of time is lower. There is still discrepancy between inequalities generated by the shopping economy and observed in data. Admittedly, there are models outperform the shopping economy in this regard. Nonetheless, recall that those statistics were not used in the calibration process, while for instance in Castañeda *et al.* (2003) moments describing wealth inequalities were targets. Moreover, the shopping economy presented in this paper abstracts from important motives for wealth accumulation, such as bequests.

Table 12: Wealth distribution

		Quintile					Top Percentiles		
Economy	Gini	First	Second	Third	Fourth	Fifth	90-95	95-99	99-100
USA (PSID 2007)	.77	-.09	.008	.044	.13	.827	.137	.228	.309
Shopping	.658	.007	.028	.072	.221	.672	.156	.194	.111
SIM	.577	.007	.041	.120	.253	.579	.143	.160	.066

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Table 13: Household price indices across different income and employment states across time

	$\ln \bar{P}_{j,t}$			
	(1)	(2)	(3)	(4)
HH Earnings > median(HH Earnings)	0.010***	0.003***	0.076***	0.050***
	(0.001)	(0.001)	(0.001)	(0.001)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2005}$	−0.004***	−0.001***	−0.008***	−0.005***
	(0.001)	(0.0002)	(0.001)	(0.001)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2006}$	−0.004***	−0.002***	−0.005***	−0.005***
	(0.0005)	(0.0002)	(0.001)	(0.001)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2007}$	0.013***	0.015***	0.006***	0.013***
	(0.0004)	(0.0004)	(0.001)	(0.0004)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2008}$	0.015***	0.016***	0.007***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2009}$	0.012***	0.015***	−0.007***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2010}$	0.012***	0.015***	−0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2011}$	0.015***	0.018***	−0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2012}$	0.015***	0.018***	−0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2013}$	0.015***	0.018***	−0.007***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
(HH Earnings > median(HH Earnings))$\cdot\mathbb{I}_{2014}$	0.018***	0.021***	−0.018***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Product aggregation	Bar code	Bar code	Features	Features
Area aggregation	Nationwide	Scantrack	Nationwide	Scantrack
HH composition dummies	*Yes*	*Yes*	*Yes*	*Yes*
Retirement dummies	*Yes*	*Yes*	*Yes*	*Yes*
Non-employment dummies	*Yes*	*Yes*	*Yes*	*Yes*
Age dummies (both heads)	*Yes*	*Yes*	*Yes*	*Yes*
Month dummies	*Yes*	*Yes*	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*
Scantrack market dummies	*Yes*	*Yes*	*Yes*	*Yes*
Number of observations	5,084,254	5,084,254	5,084,254	5,084,254
Number of panelists	150,153	150,153	150,153	150,153
R^2	0.035	0.018	0.071	0.043

Notes: Robust standard errors clustered at the household and year level are included in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 14: Expenditure response to the ESP

Response to the ESP	$\ln\left(\bar{P}_{j,m} Q_{j,m}\right)$
Quarter before, β_{-1}	0.024^{***}
	(0.008)
Quarter of receipt, β_0	0.054^{***}
	(0.012)
One quarter after, β_1	0.073^{***}
	(0.016)
Two quarters after, β_2	0.076^{***}
	(0.020)
Month dummies	Yes
Number of observations	345,768
Number of panelists	29,289
R^2	0.659

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 15: Consumption response to the ESP

Response to the ESP	$\ln Q_{j,m}$			
	(1)	(2)	(3)	(4)
Quarter before, β_{-1}	0.022***	0.023***	0.022***	0.021***
	(0.008)	(0.008)	(0.008)	(0.008)
Quarter of receipt, β_0	0.048***	0.050***	0.045***	0.046***
	(0.012)	(0.012)	(0.012)	(0.012)
One quarter after, β_1	0.066***	0.068***	0.064***	0.063***
	(0.016)	(0.016)	(0.016)	(0.016)
Two quarters after, β_2	0.068***	0.070***	0.065***	0.063***
	(0.020)	(0.020)	(0.019)	(0.019)
Month dummies	Yes	Yes	Yes	Yes
Product aggregation	Bar code	Bar code	Features	Features
Area aggregation	Nationwide	Scantrack	Nationwide	Scantrack
Number of observations	345,768	345,768	345,768	345,768
Number of panelists	29,289	29,289	29,289	29,289
R^2	0.661	0.660	0.656	0.656

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 16: Decomposition of the expenditure responses to the ESP

Product aggregation	Area aggregation	Price channel: $\frac{\mathbb{E}\left(\ln \bar{P}_{j,\tau+s} - \ln \bar{P}_{j,\tau-4}\right)}{\mathbb{E}\ln\left(\frac{\bar{P}_{j,\tau+s}Q_{j,\tau+s}}{\bar{P}_{j,\tau-4}Q_{j,\tau-4}}\right)}$			Consumption channel: $\frac{\mathbb{E}(\ln Q_{j,\tau+s} - \ln Q_{j,\tau-4})}{\mathbb{E}\ln\left(\frac{\bar{P}_{j,\tau+s}Q_{j,\tau+s}}{\bar{P}_{j,\tau-4}Q_{j,\tau-4}}\right)}$		
		QTR_0	QTR_1	QTR_2	QTR_0	QTR_1	QTR_2
Bar code	Nationwide	10.4%	10.3%	10.7%	89.6%	89.7%	89.3%
Bar code	Scantrack	6.6%	7.3%	8.4%	93.4%	92.7%	91.6%
Features	Nationwide	15.8%	12.9%	14.9%	84.2%	87.1%	85.1%
Features	Scantrack	14.3%	14.6%	16.5%	85.7%	85.4%	83.5%