Cyclical Dynamics of Shopping: Aggregate Implications on Labor and Product Markets

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Abstract

This paper answers why buyers in the data search for lower prices less intensively in recession, and what macro implications of this behavior are. To this end, I build a model of endogenous price hunting in decentralized labor and product markets. First, I propose two channels that explain the data: i) the standard income effect discussed in the literature, and ii) the cyclical change of price dispersion and return to shopping using the model. Second, I quantitatively show that while search frictions in the product market amplify business cycle fluctuations, endogenous shopping effort consistent with the data dampens them. In equilibrium, since sellers in recession post relatively higher prices to enjoy higher markups as buyers search less, firms in the labor market post relatively more vacancies. Third, I provide empirical evidence using the consumer panel and time use survey data to support the arguments.

JEL Classification: E31, E32, J64
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1 Introduction

Whereby do employed and unemployed buyers adjust their time to search for lower prices over the business cycle, and what are macro implications of the cyclical changes in price search? Economists have focused on the income effect on shopping effort as they have viewed the effort for finding lower prices, called shopping effort, as an insurance mechanism against lower-income.[1] If the income effect on shopping effort is the only crucial channel, we should observe a counter-cyclical shopping effort, and it would be more volatile for the employed buyers. And it predicts that the endogenous shopping effort is an amplifying business cycle fluctuations as buyers make sellers post low prices, and thus firms post vacancies less in recession. However, in the data, not only aggregate shopping time is procyclical, but also that of the unemployed is more elastic than that of employed buyers over the business cycle.[2]

In this paper, I build a model of endogenous price hunting in decentralized labor and product markets to explain the observed cyclical shopping behavior of the unemployed and the employed and explore its aggregate implications. I argue that the puzzling empirical findings result from interactions between optimal pricing strategies of sellers and optimal price hunting of buyers in response to aggregate labor productivity shocks. Results of quantitative analysis imply that prices and unemployment adjust sluggishly over the business cycle due to procyclical price search. I also provide empirical evidence of identified channels in the model using the Kilts-Nielsen Consumer Panel Data (KNCPD).

I propose two channels to explain empirical features using a simple model. I find that buyers devote more effort if they 1) have less income or 2) face higher return to shopping associated with higher price dispersion. They can find lower prices more likely if they devote more effort, and thus they can enjoy higher consumption levels even though expenditures are the same. But since exerting effort has a dis-utility cost, employed buyers who have higher income exert less effort by the *income effect*. And the return to price search is higher when prices are more dispersed. In equilibrium, prices are more dispersed as employed buyers have higher labor income. I call it as the *return effect*. While both employed and unemployed buyers face the return effect as an aggregate effect, only employed buyers have the income

[1] Kaplan and Menzio (2015) show that unemployed households make more shopping trips than employed households do by 15–30%, and they pay 1–4% lower prices for identical goods. See Aguiar and Hurst (2005, 2007) on how households adjust their time for shopping and on the return to shopping over the life-cycle. They show how households adjust their time for shopping and home-production when they retire or have lower labor income.

[2] See Kaplan and Menzio (2015, 2016) for empirical and theoretical studies of shopping. For cyclical behavior of shopping time in the data, see Petrosky-Nadeau et al. (2016). Petrosky-Nadeau et al. (2016) show those empirical features of shopping time using the American Time Use Survey. I investigate empirical features of shopping effort in Section 4 with longer time span.

effect, as the value of unemployment is fixed. Thus, unemployed buyers response to business cycles more elastically than employed buyers.

To explore what the aggregate implications of those identified channels have in aggregate variables, I build a dynamic stochastic model of endogenous price hunting in decentralized labor and product markets. The full model consists of the Diamond - Mortensen - Pissarides (DMP) random labor search and the Burdett and Judd (BJ) price search with endogenous price hunting, which is the extension of Kaplan and Menzio (2016) and Pytka (2018).

Using the model, I quantitatively show that the procyclical shopping effort in equilibrium dampens business cycle fluctuations measured by variabilities of unemployment or labor market tightness. That is, while search frictions in the product market amplify business cycle fluctuations as the job market tightness is not a jump variable any more as in Kaplan and Menzio (2016), price search intensities consistent with the data do not. Intuition is as follows. If buyers search for lower prices less intensively in recession, sellers can charge relatively higher prices to enjoy higher markups. It makes firms in the labor market post relatively more vacancies in recession to hire more workers. The opposite holds in boom. In words, the model predicts that endogenously rigid prices induce less variable business cycle fluctuations.[3]

The standard deviations of unemployment, labor market tightness, and posted prices in the simulation of benchmark model are 10.10%, 10.08%, and 14.44% lower than them in the model of fixed shopping as in Kaplan and Menzio (2016) respectively. Further, those of unemployment and labor market tightness in the benchmark model are 4.72 and 1.32 times larger than them in the DMP model. And the standard deviation of wages in the benchmark model is 36.02% less variable than it in the DMP model. Moreover, to analyze the effects of search friction in the product market and procyclical shopping effort clearly, I also implement a counter-factual study by imposing counter-cyclical shopping efforts. I find that unemployment, labor market tightness, and posted prices in the benchmark model are 20.20%, 20.55%, and 28.88% less variable than them in the counter-factual model.

I also study how wages and prices are linked as wages are not absorbing variables but they affect shopping effort and price posting decisions in the product market. First, I find that the standard deviation of posted prices in the benchmark model is only 51.26% of it in the rigid wage model. I here consider the (real) downward rigid wage model. Second, I investigate a fraction of sellers who adjust prices as in Head et al. (2012). The calibrated model implies that $91 - 93\%$ of sellers do not adjust prices in response to the labor productivity shock.

Lastly, I provide empirical evidence of the channels for shopping behavior using the ATUS

[3] Since there is no fiat money in the model, results here are *real rigidities*.

and the KNCPD. First, I re-examine the works of Petrosky-Nadeau et al. (2016) using the ATUS with a longer period. I find that 1) the elasticity of shopping time for unemployed buyers is higher than that of employed buyers in the state-level panel analysis, and 2) employed buyers spend less time shopping than unemployed buyers and employed buyers also devote less time, as they have higher earnings in the cross-sectional dimension. Secondly, I explore the empirical relationships between price dispersion, shopping intensity, and return to shopping using the KNCPD. Using the panel two-stage least squares to overcome concerns of endogeneity for price dispersion, I find that higher price dispersion leads to higher price search intensities. More interestingly, I show that while greater dispersion increases the number of visits to different stores, it either decreases the number of visits to the same store or does not have significant effects. Related to the return to shopping, the first margin is larger than that of the second, as in Kaplan and Menzio (2015).

This paper has three main contributions. First, I identify how endogenous price hunting and search frictions dampen and amplify business cycle fluctuations. The model of endogenous shopping effort consistent with the data induces rigid prices, and the endogenously rigid prices dampen business cycle fluctuations. This complements the literature of business cycles to study labor and product markets. Second, I propose a new channel − the return effect to explain the data theoretically with empirical evidence. While previous studies have focused on the side of buyers, this paper raises the importance of interactions between sellers and buyers. Lastly, I show that interactions between labor and product markets are crucial for the mechanism of endogenous price rigidity.

Related Literature This paper is related to the literature on shopping as well as on decentralized labor and product markets. Regarding the theory of shopping, Kaplan and Menzio (2016) propose a theory of decentralized labor and product markets, and Pytka (2018) provides a methodology for modeling endogenous price hunting under endogenous price distribution in the life-cycle. Also, Arslan et al. (2016) study endogenous price search intensities in a life-cycle model under exogenous price distribution to examine consumption and expenditure inequalities.

From a theoretical perspective, this study is closely related to Kaplan and Menzio (2016), who present a model of decentralized labor and product markets; however, the current study considers endogenous price hunting. This study shows that the case of endogenous shopping effort allows us to examine the interaction between buyers and sellers. In comparison with Arslan et al. (2016) and Pytka (2018), I study how buyers and sellers interact through shopping for aggregate fluctuations in the business cycle frequency.

This paper takes an approach similar to those of empirical studies. Petrosky-Nadeau et al. (2016) and Nevo and Wong (2018) study shopping time and shopping intensity at the business cycle frequency using the ATUS and the KNCPD, respectively. Petrosky-Nadeau et al. (2016) state that shopping time shows procyclicality, which does not seem to be consistent with the income effect of shopping proposed by Aguiar and Hurst (2005, 2007), and Nevo and Wong (2018) show that shopping intensity measured by fraction of price deals, coupons, etc., is countercyclical, and the return to shopping declines during a recession.

Based on these empirical findings, I provide a theory and evidence to explain the results of both Petrosky-Nadeau et al. (2016) and Nevo and Wong (2018). Unlike Nevo and Wong (2018), I measure shopping intensity based on the KNCPD as the total number of visits to stores and show that the number of visits to different stores is procyclical. Moreover, I show theoretically that the income and return effects can explain the highly elastic shopping effort of unemployed buyers and the weakly procyclical shopping effort of employed buyers. In particular, I provide empirical evidence for income and return effects using the KNCPD.

Aguiar and Hurst (2007) and Kaplan and Menzio (2015) conduct empirical studies on shopping, return to shopping, and price dispersion. Aguiar and Hurst (2007) propose a method for measuring price index at the household level and study how the household price index behaves with shopping intensity over the life-cycle. Kaplan and Menzio (2015) report various stylized facts regarding price dispersion using the KNCPD. In line with the current study, they show that the return to shopping is higher for higher number of visits to different stores. Moreover, Aguiar and Hurst (2005) focus on the importance of price search by distinguishing between expenditure and consumption. Based on the literature, I examine how the household price index behaves with shopping intensity over the business cycle using the proposed theory. I also study how each margin of the shopping intensity behaves differently over the business cycle.

Lastly, this paper is also related to the literature studying endogenous price rigidity and the linkage between wages and prices. As in Head et al. (2012), the model in this paper generates price rigidity endogenously without any adjustment cost like menu costs. The key contribution of this paper is to show that procyclical shopping effort makes sellers adjust prices sluggishly over the business cycle. Furthermore, by comparing results between the flexible and rigid wage models, this paper shows that prices are more rigid when wages are rigid. Related to this study, Christiano et al. (2016) investigate the labor-matching model to examine wage inertia endogenously by considering sticky prices from Calvo (1983). This study examines the exact opposite channel. The direction of this study is supported empirically by the work of Druant et al. (2009). They use firm-level survey data for European countries to show that while the sticky wages make prices sticky, the opposite does not hold. The current study proposes a theory to explain their empirical findings. In addition, in the labor search literature, Hall (2005), Gertler and Trigari (2009), Bils et al. (2016), and Gertler et al. (2016) have examined Calvo (1983) type of sticky wages in the DMP model. This paper explores the downward wage rigidity to analyze real wage rigidity. To do this, I use the methodology by Eggertsson et al. (2017).

The rest of the paper is organized as follows. Section 2 analyzes the simple static model to study the income and the return effects in equilibrium. Section 3 studies the full dynamic model and quantitative results. Section 4 provides empirical evidence to support the theory in Section 2 using the ATUS and the KNCPD. Section 5 concludes the paper.

2 Static Model

In this section, I investigate how an aggregate income change affects the equilibrium price distribution, return to shopping, and optimal price search intensities. To this end, I analyze a simple static model of endogenous price hunting. Even though the model here is simple, but the intuition in the static model is consistent with the fully characterized dynamic model in the Section 3. Furthermore, I empirically explore the cyclical dynamics of shopping effort, price dispersion and return to shopping in the Section 4 based on the channels identified here.

2.1 Environment

There are employed and unemployed buyers, and sellers who live only for one period. To be simple, I here assume that wage w, the value of unemployment z such that $w > z$, and the unemployment rate u are exogenous. Endogenous decisions in the labor market are discussed in Section 3.

The structure of product market, called as the Burdett and Judd (BJ) market, is as follows. Since the market is decentralized, both sellers and buyers search for each other to trade goods. In the model, sellers post prices first and employed and unemployed buyers search for lower prices given the quoted price distribution $G(p)$. Each buyer can find lower prices more likely by devoting more effort, but this is costly. In particular, each buyer $i \in \{e, u\}$ draws two prices and compare them with ψ_i share, and draw only one price and just buy it with $1 - \psi_i$ share.

Given buyers' optimal price search intensities, as the first mover, sellers post prices to maximize the ex-ante revenue. If a seller posts a high price, she could enjoy higher markup but fewer customers would buy it. And if she posts a low price, she could attract more customers but she would have lower markups. In equilibrium, the ex-ante revenue

$R(p) = R \in \mathbb{R}_+$ for all p in equilibrium where p is the posted price quoted by sellers with a support $p \in [\underline{p}, \bar{p}]$.[4]

Lastly, the total number of meetings in the BJ market is determined by the reduced form matching technology $N(b, s)$ where $b = (1-u)(1-\psi_e+2\psi_e) + u(1-\psi_u+2\psi_u) = 1+\psi_e+u(\psi_u-\psi_e)$ is an effective measure of buyers and $s = 1-u$ is the measure of sellers or worker-firm pairs, which is exogenous in the static model but an equilibrium outcome of the model in Section 3.

2.2 Individual Buyer's Problem

Given the quoted price distribution $G(p)$ and income $m_i \in \{w, z\}$, each employed and unemployed buyer chooses her shopping effort ψ_e and ψ_u optimally by solving the following problem:

$$\max_{c_i,\psi_i} u(c_i, \psi_i) \tag{1}$$

subject to

$$\mathbb{E}[p|\psi_i]c_i \leq m_i \tag{2}$$

$$\mathbb{E}[p|\psi_i] = \int p dF(p; \psi_i) \tag{3}$$

with an additively separable utility function

$$u(c_i, \psi_i) = \frac{c_i^{1-\alpha}}{1-\alpha} - \varphi_i \frac{\psi_i^{1+\xi}}{1+\xi} \tag{4}$$

where $\mathbb{E}[p|\psi_i]$ is an expected paid price by buyer i conditional on shopping effort ψ_i, c_i is the level of consumption, and $F(p; \psi_i)$ is the cumulative price distribution function conditional on price search intensities. The utility function $u(c, \psi)$ is a strictly increasing function of c but a strictly decreasing function of ψ. Thus, if buyers devote more effort, they could enjoy higher consumption but it is costly.[5]

One outstanding result in Pytka (2018) is that the expected paid price is *linear* in the

[4]Following Burdett and Judd (1983), there exists the non-degenerated price distribution $G(p)$ (that is, $\bar{p} > \underline{p}$) only if $0 < \psi_i < 1$ for each i. If $\psi_i = 0$ for all i, there exists only monopoly equilibrium. If $\psi_i = 1$ for all i, the market becomes a competitive market. The calibration in this paper supports the equilibrium of non-degenerated price distribution.

[5]I consider the concavity in consumption even though the model does not consider savings problem in both static and full dynamic model. Technically, because the budget set is not a convex set in this model, the model easily admits the corner solution if the utility function is not strictly concave for consumption. Also, I allow that $\varphi_e \neq \varphi_u$ in Section 3 to explain the empirical difference between ψ_e and ψ_u quantitatively. Intuitively, $\varphi_e > \varphi_u$ potentially capture the disutility from working effort as a reduced form fashion.

shopping effort ψ. First, given the quoted price distribution $G(p)$, the cumulative price distribution function $F(p;\psi)$ conditional on the price search ψ is

$$F(p;\psi) = (1-\psi)G(p) + \psi\left(1-(1-G(p))^2\right) \tag{5}$$

With $1-\psi$ probability, the probability of drawing the one price that is lower than p is $G(p)$. If buyers draw two prices with probability ψ, the probability of drawing prices such that both of them are higher than p is $(1-G(p))^2$. Thus, the probability of drawing the prices which are lower than p conditional on price search intensities is given by (5).

Given the conditional distribution function $F(p;\psi)$, we can easily derive the following expected paid price conditional on shopping effort, which is the result of Lemma 2 in Pytka (2018).[6]

$$\mathbb{E}[p|\psi] = p^0 - MPB \times \psi \tag{6}$$

where

$$p^0 = \int p dG(p) \qquad : \text{Average posted price} \tag{7}$$

$$MPB = \int G(p)\left(1-G(p)\right) = \mathbb{E}\max\{p', p''\} - p^0 \qquad : \text{Marginal Price Benefit (Return to Shopping)} \tag{8}$$

$$\text{where } p' \& p'' : \text{Prices (Samples drawn from distribution)} \tag{9}$$

Buyer's effective paid price (6) implies that the return to shopping is measured by the MPB term, the marginal price benefit, as $\frac{d\mathbb{E}[p|\psi]}{d\psi} = -MPB$. Technically, $\mathbb{E}\max\{p', p''\}$ implies on average the higher prices among the two prices p' and p'', and it is positively proportional to price dispersion. Thus, the MPB is positively proportional to price dispersion with the fixed average posted price p^0.

To better understand, I consider the simple case by assuming $\alpha = 2$ and (10) is the closed-form solution.[7] It clearly shows that the buyer i search more if she has less income m_i or face higher return to shopping MPB. Since the return to shopping MPB affects both employed and unemployed buyers in aggregate, the MPB is crucial in the analysis of aggregate economy, in particular over the business cycle.

[6] See Appendix A.1 for derivation or Pytka (2018) for more details.

[7] Because of the non-convexity of the budget set, it is hard to have an analytical solution or to use the first order condition. Technically, since the budget constraint is not straight line but is convex curve, if the utility function does not have enough curvature, the model easily admits the corner solution. Simple analytics in general value of α are discussed in Appendix A.2.

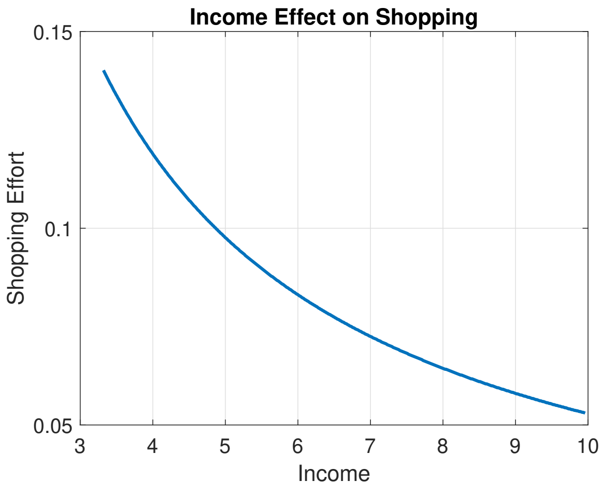


Figure 1: Income Effect under fixed $G(p)$

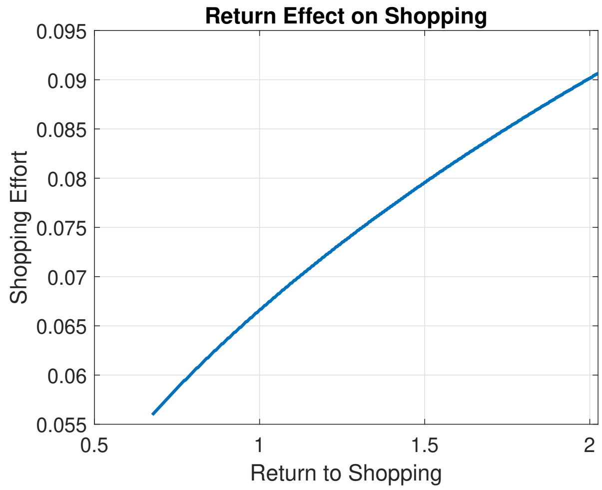


Figure 2: Return Effect given p^0 and w

$$\psi_i = \left(\frac{MPB}{\varphi_i m_i}\right)^{\frac{1}{\xi}} \tag{10}$$

Figure 1 and Figure 2 represent optimal price search intensity when buyers have different income and face different MPBs which are arbitrary given. Figure 1 shows that buyers devote less effort if they have higher income, *given* $G(p)$ and Figure 2 shows that they exert more effort if they face higher MPB, with return to shopping *given*, average price p^0, and income w. The first effect is called the income effect and the second is called the return effect. The main intuition is as follows. First, buyers who have a higher income, m, do not exert much effort in finding cheaper prices since it is costly. This is partially similar to the wealth effect in job search intensities. Secondly, buyers devote more effort if the return to shopping MPB is higher. And from (8), the return to shopping MPB is higher under higher price dispersion.

2.3 Static Model: Equilibrium Price Distribution and Shopping

I now investigate equilibrium dynamics of shopping effort, and argue that procyclical price dispersion and labor income explain cyclical dynamics of shopping time in the data. The price dispersion in the model increases in the boom as the upper support of price distribution $\bar{p}$ increases more than the lower support of it $\underline{p}$.

The reasons why the upper support $\bar{p}$ is more elastic than $\underline{p}$ with respect to business cycle fluctuations are 1) sellers internalize the heterogeneous purchasing power of buyers and 2) fixed value of unemployment z. Given $w > z$, while the upper support $\bar{p}$ is largely affected by employed buyers as they higher willingness to pay, the lower support $\underline{p}$ is largely affected by unemployed buyers. The more elastic upper support leads to the procyclical price dispersion, and thus procyclical return to shopping MPB.

The two channels proposed here explain why buyers devote more effort in the boom and why unemployed buyers are more elastic than employed buyers with respect to business cycle shocks. In the boom, unemployed buyers face higher return to shopping due to higher price dispersion with fixed purchasing power z. Thus, they unambiguously exert more effort to search for lower prices in the boom because it is more beneficial. Employed buyers also have an incentive to devote more effect as the return to shopping is higher. However, the higher income which is specific income effect to employed buyers makes employed buyers search less. Those explain why unemployed buyers are more elastic than employed buyers. Moreover, the calibration in Section 3 supports that the cyclical changes of return to shopping affect more than those of income.[8]

To see the above dynamics, I consider the seller's problem in the BJ market. Following Kaplan and Menzio (2016), the seller's ex-ante revenue when a seller post price p is formulated by (11).

$$
\begin{aligned}
R(p; w, u) = \mu(\sigma)\frac{u(1+\psi_u)}{b}\left[1 - \frac{2\psi_u \nu(\sigma) G(p)}{1+\psi_u}\right]\frac{z(p-c)}{p} \\
+ \mu(\sigma)\frac{(1-u)(1+\psi_e)}{b}\left[1 - \frac{2\psi_e \nu(\sigma) G(p)}{1+\psi_e}\right]\frac{w(p-c)}{p}
\end{aligned}
\tag{11}
$$

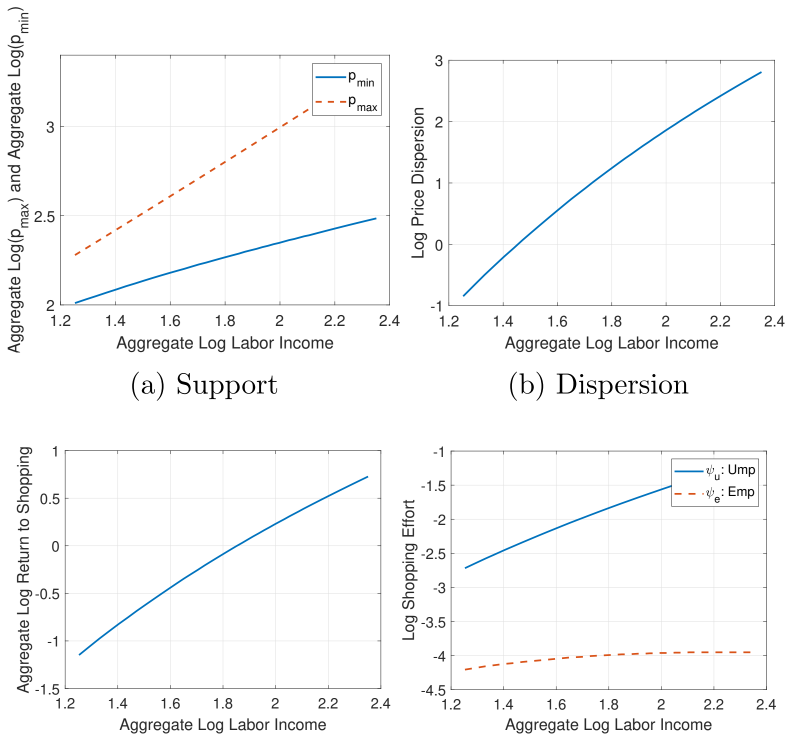
where $\mu(\sigma) = N(b,s)/s$ is the probability that an individual seller can meet buyers, $\nu(\sigma) = N(b,s)/b$ is the probability that an individual buyer can meet sellers, $\sigma = s/b$ is the product market tightness, and c is the marginal cost of producing goods in the BJ market.[9]

First, with probability $u(1+\psi_u)/b$, sellers meet unemployed buyers. Conditional on meeting unemployed buyers, unemployed buyers can find a price lower than p with probability $2\psi_u \nu(\sigma)G(p)/(1+\psi_u)$. Thus, as a complement to 1, unemployed buyers are captivated by the price p. Obviously, they are less likely to be captivated as sellers post the higher price p. The dynamics are symmetric for employed buyers. The size of the purchasing basket by the employed buyer is w/p, and by the unemployed buyer, it is z/p.

The equation (12) represents the analytical representation of the equilibrium quoted price distribution. In equilibrium, $R(p; w, u) = R$ for all $p \in [\underline{p}(w; u), \bar{p}(w; u)]$ where $G(p) = 0$ for all $p \leq \underline{p}$ and $G(p) = 1$ for all $p \geq \bar{p}$ as a result of an optimal pricing strategy given w and

[8] In the fully characterized dynamic model, the unemployment rate u also endogenously changes over the business cycle. Since there are more employed buyers in the boom and less in a recession, these effects on the price dispersion will be amplified once labor market decisions become endogenous.

[9] The crucial assumption here is that sellers cannot direct the type of buyers. That is, when sellers post prices, they do not know if they meet employed or unemployed buyers in ex-ante. Thus, this can be interpreted as the case of pooling equilibrium.



(a) Support (b) Dispersion

(c) Return (d) Equilibrium Search

Figure 3: Figure 3a represents elasticities of the upper support (red-dotted) and the lower support (blue solid), Figure 3b represents the price dispersion, Figure 3c represents the return to shopping, and Figure 3d represents shopping effort of employed (red-dotted) and unemployed buyers (blue solid) in response to aggregate labor income in equilibrium.

u. The equilibrium quoted price distribution $G(p)$ results in $R(\bar{p}) = R(p)$.

$$\begin{aligned} G(p; w, u) = &\left(u(1+\psi_u)z \left\{ 1 - \left[1 - \frac{2\psi_u \nu(\sigma)}{1+\psi_u} \right] \frac{(\bar{p}-c)}{(p-c)} \frac{p}{\bar{p}} \right\} \right. \\ &\left. + (1-u)(1+\psi_e)w \left\{ 1 - \left[1 - \frac{2\psi_e \nu(\sigma)}{1+\psi_e} \right] \frac{(\bar{p}-c)}{(p-c)} \frac{p}{\bar{p}} \right\} \right) \\ &\div \left[2\nu(\sigma) \left(zu\psi_u + (1-u)\psi_e w \right) \right] \end{aligned} \tag{12}$$

Thus, the equilibrium in the BJ market consists of the equilibrium price distribution $G(p)$ and policy functions ψ_e and ψ_u such that

1. Given the $G(p)$, each ψ_e and ψ_u is the solution of (1) for each $i \in \{e, u\}$.

2. Given the optimal policy functions ψ_e and ψ_u, sellers post price p first to maximize the revenue. In equilibrium, $G(p)$ makes $R(\bar{p}) = R(p) = R$ for all $p \in [\underline{p}, \bar{p}]$.

Figure 3 includes all equilibrium results. Figure 3a shows that the upper support $\bar{p}$ (red-

Figure 4: Timing of events

dotted line) is more procyclical than the lower support $\underline{p}$ (blue-solid line). As the result, in Figure 3b, the price dispersion increases in response to higher aggregate labor income. It leads to Figure 3c: the return to shopping increases. In equilibrium, unemployed buyers show much greater procyclicality in shopping effort than employed buyers as in Figure 3d.

3 Fully Characterized Dynamic Model

In this section, I build an infinite-horizon model of endogenous price hunting in decentralized labor and product markets to explore the aggregate implications of procyclical shopping effort in equilibrium. Compared to the static model in Section 2, the fully characterized dynamic model considers two further ingredients: the random search model of the labor market and wage rigidity. That is, I study how wage contracts affect prices in the full dynamic model.

3.1 Environment

Time is infinite and discrete, and there are labor and product markets. Figure 4 shows the timing of events. For each period, the labor market opens first. As in Diamond - Mortensen - Pissarides (DMP) model, firms post vacancies to hire workers and unemployed workers search for jobs. I call the labor market as DMP market. In the DMP market, workers and firms bargain over wages through the Nash bargaining, and both newly matched and existing firm-worker pairs should bargain over wages as they cannot commit contracts. After the DMP market, the decentralized product market opens. As in the static model, I call this market as BJ market. In the BJ market, sellers (firm-worker pairs) post prices optimally to maximize revenue, and each employed and unemployed workers choose shopping effort optimally given the price distribution posted by sellers. And then the frictionless centralized product market opens. As in Kaplan and Menzio (2016), I call this market the Arrow - Debreu (AD) market. In the AD market, all remained trades such as paying wages are implemented. Even though this paper focuses on only the DMP and BJ markets, the AD market is theoretically crucial for closing the model.

DMP Market In the DMP market, unemployed workers and firms search for each other.

Firms post vacancies to hire workers by paying fixed cost κ. The total number of matching in the DMP market M_t at period t is determined by the reduced form matching function $M_t = M(u_{t-1}, v_t)$, where u_{t-1} is a predetermined unemployment rate from the previous period $t-1$, and v_t is the number of posted vacancies by firms at time t. As in other studies in the literature, I consider a specific class of function M that satisfies a constant return to scale (CRS) and $M_t \leq \min\{u_{t-1}, v_t\}$. Each unemployed worker can meet firms with the probability $\lambda(\theta_t) = M(u_{t-1}, v_t)/u_{t-1}$, where $\theta_t = v_t/u_{t-1}$ is the job market tightness and each firm can meet unemployed workers with the probability $q(\theta_t) = M(u_{t-1}, v_t)/v_t$.

Matched workers provide labor services to produce y_t units of AD goods, which follows the first-order Markov process, and firms pay as wages w_t units of AD goods. Since firms should pay the wages before the revenues are realized, they have a liquidity issue in the labor market. To resolve it, firms issue IOU documents, which have the value of w_t for workers for wage payments in the DMP market. Workers can use the IOU in the product market as credit. Thus, the role of AD goods is a medium of exchange for both firms and workers.[10] After the meeting, the unemployment at time t is a function of the following law of motion:

$$u_t = \delta(1 - u_{t-1}) + (1 - \lambda(\theta_t))u_{t-1} \tag{13}$$

where δ is the exogenous job separation rate. Unemployed workers produce constant z units of AD goods at their home, as the home-production. They use z to trade with BJ goods in the BJ market. With expected revenues in the product market, firms post vacancies optimally based on expected gains from trade in the labor market.

To study how the wage dynamics affect price dynamics and other equilibrium variables, I consider both the flexible wage and rigid wage models. For each period, all newly matched and existing firm-worker pairs negotiate over wages through Nash bargaining. If wages are fully flexible, the Nash bargained wage for each period t is a function of only u_{t-1}, y_t, and exogenous parameters. If wages are rigid, that is, if they are too low compared to the previous wage w_{t-1}, firms should pay the weighted average of Nash bargained wages w_t^*, which is a desirable level of wage at period t, and w_{t-1}. Thus, it becomes also a function of w_{t-1}, too.[11]

[10] See Kaplan and Menzio (2016) for more theoretical details. I also assume that firms are owned by third parties; thus, we do not consider profit dividends to workers/buyers.

[11] Gertler and Trigari (2009), Bils et al. (2016) and Gertler et al. (2016) consider the Calvo (1983) type of wage stickiness. I do not consider this, as there is a technical issue of solving the model if wages are dispersed because of Calvo friction. If there are wage dispersions, since the BJ market is not fully directed, sellers should know the distribution of wages for each aggregate state in order to compute ex-ante revenues. This makes the problem unnecessarily complicated, and since the goal of this paper is to understand the dynamics of labor and product markets in a parsimonious way, I consider the case of downward wage rigidity, which requires us to consider only one more state variable, w_{t-1}, compared to the flexible wage model.

BJ Market In the BJ market, sellers, worker-firm pairs, post prices p first to sell goods produced in the DMP market. Each employed and unemployed buyer exert effort to find cheaper prices optimally given the quoted price distribution $G(p; \mathbf{S})$ and the purchasing power w_t and z, where $\mathbf{S}$ is a set of aggregate state variables. The buyer's flow utility function here is specified by $u(c, x, \psi)$ where c is the level of BJ goods, x is the level of AD goods and ψ represents shopping effort of buyers, which is the probability of drawing two price samples in the BJ market. For simplicity, I assume that buyers value the BJ good c only.[12] Then it converges to the utility function (4). And I also assume that firms value only AD goods. To the extent that they do so, firms' value functions are measured by AD goods, and this makes the representation of a firm's value function easier.

As in the DMP market, the total number of meetings is determined by a reduced-form function of the measure of sellers s_t and buyers b_t, $N(b_t, s_t)$. The measure of sellers is worker-firm pairs, $s_t = 1 - u_t$ where u_t is the equilibrium unemployment rate as a result of the law of motion in (13). And the measure of buyers is $b_t = 1 + \psi_{e,t} + u_t(\psi_{u,t} - \psi_{e,t})$, as in the static model. Following Kaplan and Menzio (2016), I also consider $N(b, s) = \min\{b_t, s_t\}$. Since the function satisfies the CRS property, the probability of meeting, that is, for each buyer to meet sellers and each seller to meet buyers, is also specified by the product market tightness $\sigma_t = s_t/b_t$. Let $\nu(\sigma_t) = N(b_t, s_t)/b_t$ be the probability of meeting for each buyer meeting sellers, and $\mu(\sigma_t) = N(b_t, s_t)/s_t$ to be a probability of meeting for each seller to meet buyers.

The crucial difference between this paper and Kaplan and Menzio (2016) is that, while price search intensities in their work are fixed as *parameters*, in this paper these intensities are buyers' *endogenous* choice variables. As the result, the procyclical shopping effort in equilibrium in this paper implies that macro aggregates are dampened compared to the model of fixed effort. Since sellers have greater room to enjoy relatively higher markups in a recession, as buyers search for lower prices less intensively, they can post greater vacancies and pay higher wages. If shopping effort is fixed, prices, markups, and thus labor market tightness drop more in a recession.

AD Market The last market to consider is the AD market. Since the AD market is perfectly competitive and frictionless, all remaining trades are completed. First, firms pay wages in AD goods for workers. If buyers could not trade in the BJ market[13], they can still consume BJ goods in the AD market through exchanges. That is, buyers can buy BJ goods freely using AD goods by paying the captive price, $\bar{p}$. The reason why we need the AD market

[12]The periodical utility function in Kaplan and Menzio (2016) with different notation is $u(c, x) = c^a x^{1-a}$ and $a = 1$ in their calibration. The utility function here can be considered as $u(c, x, \psi) = f(c)^a g(x)^{1-a} - h(\psi)$ under $a = 1$. In Section 3.2, I discuss this in more detail.

[13]While all individual sellers meet buyers in the BJ market, but there are some buyers they do not meet due to the matching technology, as given by $N(b, s) = \min\{b, s\}$.

is that the AD good is a medium of exchange in this model. Since revenues are realized after the DMP market, firms cannot pay wages when goods are produced. Thus, firms issue IOUs to workers in order to pay wages, with AD goods as units. In the BJ market, they collect IOUs used to purchase BJ goods, and they repay the IOUs to workers. If there is no AD market, we need to keep track of each seller's historical credit/debit position. As in the monetary search literature, the AD goods can be interpreted as a fiat money.[14] Thus, the AD market theoretically plays an important role, although it is not the main interest of this paper. As in Kaplan and Menzio (2016), I assume that excess profits are shared by the third party.

Production Technology With the concept of AD goods, let me revisit each firm's production technology in the DMP market. Given the matched worker's productivity y, each firm can produce any combination of BJ goods c and AD goods y with $c + x = y$. The implicit assumption here is that the opportunity cost of producing one unit of BJ goods is one unit of AD goods, which is a standard assumption in the literature. This implies that if a seller who posts a price p meets and *attracts* a buyer who has a purchasing power of m as measured by AD goods, the seller's net revenue measured by AD goods is $m - m/p = (m/p)(p-1)$.

3.2 Model

There are value functions of employed buyers, unemployed buyers, and sellers. From here, since I consider each agent's value function in a recursive way, I drop the time subscript $t-1$, t or $t+1$. Instead, I consider functional equations. Thus, for a variable k for each period $t-1$, t, or $t+1$, I denote these as k_{-1}, k and k' respectively.

Employed Buyer Under the assumption that buyers value BJ goods c only, I denote the utility function u as a function of BJ goods c and price search intensities ψ only. Given the quoted price $G(p;\mathbf{S})$, an individual employed buyer in a set of aggregate states $\mathbf{S} \equiv (w_{-1}, u_{-1}, y)$ maximizes her utility by solving following value function $W(\mathbf{S})$ optimally[15]

$$W(\mathbf{S}) = \max_{c_e,\psi_e} \{u(c_e, \psi_e) + \beta \mathbb{E}\left[(1-\delta)W(\mathbf{S}') + \delta U(\mathbf{S}')|\mathbf{S}\right]\}$$

[14]Instead of IOUs, firms can use fiat money for working capital. Buyers also have an incentive to use fiat money as a medium of exchange. I will be taking this up separately in the near future.

[15]Note that $\mathbf{S} \equiv (u_{-1}, y)$ in the flexible wage model.

subject to[16]

$$\text{Budget Constraint: } \mathbb{E}[p|\psi_e(\mathbf{S})]c_e(\mathbf{S}) = w(\mathbf{S}) \tag{14}$$

$$\text{Conditional Expected Paid Price: } \mathbb{E}[p|\psi_e(\mathbf{S})] = p^0(\mathbf{S}) - \psi_e(\mathbf{S}) \times MPB(\mathbf{S}) \tag{15}$$

$$\text{Unconditional Expected Posted Price: } p^0(\mathbf{S}) = \int p dG(p;\mathbf{S}) \tag{16}$$

$$\text{Marginal Price Benefit (MPB): } MPB(\mathbf{S}) = \int G(p;\mathbf{S})(1 - G(p;\mathbf{S}))dp \tag{17}$$

and the law of motion for unemployment (13), where β is the time discount rate and U is the unemployed buyer's value function. The natural log of productivity y follows the first order Markov process such that

$$\text{log}y' = \rho \text{log}y + \sigma_y \varepsilon \tag{18}$$

where ρ is an AR(1) coefficient and $\varepsilon \sim \mathbb{N}(0,1)$ is a structural innovation of (18).

Unemployed Buyer The unemployed buyer's problem is similar to the employed buyer's. Given the quoted price distribution $G(p;\mathbf{S})$, each individual unemployed buyer in a set of aggregate states $\mathbf{S}$ maximizes her utility by solving following value function $U(\mathbf{S})$ optimally.

$$U(\mathbf{S}) = \max_{c_u,\psi_u} \{u(c_u,\psi_u) + \beta \mathbb{E}\left[\lambda\left(\theta(\mathbf{S}')\right)W(\mathbf{S}') + \left(1 - \lambda\left(\theta(\mathbf{S}')\right)\right)U(\mathbf{S}')|\mathbf{S}\right]\} \tag{19}$$

subject to

$$\text{Budget Constraint: } \mathbb{E}[p|\psi_u(\mathbf{S})]c_u(\mathbf{S}) = z \tag{20}$$

$$\text{Conditional Expected Paid Price: } \mathbb{E}[p|\psi_u(\mathbf{S})] = p^0(\mathbf{S}) - \psi_u(\mathbf{S}) \times MPB(\mathbf{S}) \tag{21}$$

and the aggregate unconditional expected posted price (16), the return to shopping (17), and the law of motion for unemployment (13).

Preferences The periodical utility function $u(c_i,\psi_i)$ is an additively separable utility function

$$u(c_i,\psi_i) = \frac{c_i^{1-\alpha}}{1-\alpha} - \varphi_i \frac{\psi_i^{1+\xi}}{1+\xi} \tag{22}$$

where α is a curvature of the consumption, φ_i is a weight of disutility on price hunting for buyer $i \in \{e,u\}$, and ξ is a pseudo-inverse elasticity of price hunting. As shown in the budget

[16]See Section 2 and Appendix A.1 for derivations of (15), (16) and (17).

constraint, this paper does not consider the savings problem even though the utility function for consumption is concave. It can be justified with three reasons. First, as pointed out by other studies in the literature, such as Aguiar and Hurst (2005) and Aguiar and Hurst (2007), the shopping effort in macroeconomics is another important tool of consumption smoothing. Given this conceptual background, it can be justified considering the shopping effort only under the concave utility function. Secondly, technically, the budget set is not convex since the paid prices are not constant unlike in the problem of the perfect competitive market. Thus, if the utility function is linear, the model admits corner solutions regardless of the income and the return to shopping. Lastly, not only it is hard to solve the problem of Nash bargaining with a consumption-saving choice; it also requires us to know the cross-sectional distribution of the economy for each state. For example, since each buyer could have a different wealth within her employed group, depending on the history of her labor status, firms and sellers should know the distribution of assets (and thus also wages) to solve the problem.[17]

Matching Technology The reduced form matching function in the DMP market is[18]

$$M(u_{-1}, v) = u_{-1}v\left(u_{-1}^{\phi} + v^{\phi}\right)^{-1/\phi} \tag{23}$$

This implies the probability that each worker can meet firms $\lambda(\theta)$ and the probability that each firm can meet workers $q(\theta)$ are

$$\lambda(\theta) = \theta\left(1 + \theta^{\phi}\right)^{-1/\phi} \tag{24}$$

$$q(\theta) = \lambda(\theta)/\theta = \left(1 + \theta^{\phi}\right)^{-1/\phi} \tag{25}$$

Seller As the first mover in the BJ market, each individual seller posts the relative price of BJ goods p in the BJ market given the employed and unemployed optimal price hunting policy functions ψ_e and ψ_u to maximize the ex-ante net revenue $R(p; \mathbf{S})$ is

$$R(p; \mathbf{S}) = \max_{p}\left\{\mu\left(\sigma(\mathbf{S})\right)\left[\Phi_e(\mathbf{S}) \times \frac{w(\mathbf{S})}{p} + \Phi_u(\mathbf{S}) \times \frac{z}{p}\right](p-1)\right\} \tag{26}$$

where Φ_e is the probability of meeting captive employed buyers, and Φ_u is the probability

[17] Also, I consider different values of weights in assessing the disutility of shopping effort. I calibrate $\varphi_e > \varphi_u$ to explain the empirical differences between employed and unemployed buyers' shopping time. This potentially captures employed workers' working effort at the job.

[18] As discussed in den Haan et al. (2000) and Michaillat and Saez (2015), this function always guarantees $M \leq \min\{u_{-1}, v\}$ if $\phi > 0$.

of meeting captive unemployed buyers, such that

$$\Phi_e(\mathbf{S}) = \underbrace{\frac{(1-u(\mathbf{S}))(1+\psi_e(\mathbf{S}))}{b}}_{\text{Prob. of Meeting Emp. Buyer}} \underbrace{\left[1 - \frac{2\psi_e(\mathbf{S})\nu(\sigma(\mathbf{S}))G(p;\mathbf{S})}{1+\psi_e(\mathbf{S})}\right]}_{\text{Prob. of Making Emp Buyer be Captive}} \tag{27}$$

$$\Phi_u(\mathbf{S}) = \underbrace{\frac{u(\mathbf{S})(1+\psi_u(\mathbf{S}))}{b}}_{\text{Prob. of Meeting Ump. Buyer}} \underbrace{\left[1 - \frac{2\psi_u(\mathbf{S})\nu(\sigma(\mathbf{S}))G(p;\mathbf{S})}{1+\psi_u(\mathbf{S})}\right]}_{\text{Prob. of Making Ump Buyer be Captive}} \tag{28}$$

As discussed in Section 2, if $0 < \psi_i < 1$ for $i \in \{e, u\}$, there exists a non-degenerated quoted price distribution $G(p;\mathbf{S})$ for each $\mathbf{S}$ in equilibrium which makes $R(p;\mathbf{S}) = R(\mathbf{S})$ for all $p \in [\underline{p}(\mathbf{S}), \bar{p}(\mathbf{S})]$. Using the equilibrium condition, we have $R(\bar{p};\mathbf{S}) = R(p;\mathbf{S})$ with $G(\bar{p};\mathbf{S}) = 1$ and we can find $G(p;\mathbf{S})$ for each $\mathbf{S}$ as in (30).

To compute $G(p;\mathbf{S})$ completely, we should know values of $\bar{p}(\mathbf{S})$ and $\underline{p}(\mathbf{S})$ for each S. However, theoretically, there is no unique set of $(\underline{p}, \bar{p})$ for each aggregate state. More specifically, as (30) shows, $G(\bar{p}(\mathbf{S})) = 1$ for any $p = \bar{p}(\mathbf{S})$. This implies that there exists $\underline{p}(\mathbf{S})$ which satisfy $G(\underline{p}(\mathbf{S})) = 0$ *for any* $p = \bar{p}(\mathbf{S})$. To handle this, I assume ad-hoc rule of posting the highest prices as[19]

$$\bar{p}(\mathbf{S}) = \chi\left[(1-u(\mathbf{S}))\, w(\mathbf{S}) + u(\mathbf{S})z\right] \tag{29}$$

Given $\bar{p}(\mathbf{S})$ in (29), we can find $\underline{p}(\mathbf{S})$ for each $\mathbf{S}$.

$$\begin{aligned} G(p;\mathbf{S}) = \Bigg(& u(\mathbf{S})(1+\psi_u(\mathbf{S}))z\left\{1 - \left[1 - \frac{2\psi_u(\mathbf{S})\nu(\sigma(\mathbf{S}))}{1+\psi_u(\mathbf{S})}\right]\frac{(\bar{p}(\mathbf{S})-1)}{(p-1)}\frac{p}{\bar{p}(\mathbf{S})}\right\} \\ & + (1-u(\mathbf{S}))(1+\psi_e(\mathbf{S}))w(\mathbf{S})\left\{1 - \left[1 - \frac{2\psi_e(\mathbf{S})\nu(\sigma(\mathbf{S}))}{1+\psi_e(\mathbf{S})}\right]\frac{(\bar{p}(\mathbf{S})-1)}{(p-1)}\frac{p}{\bar{p}(\mathbf{S})}\right\}\Bigg) \\ & \div \left\{2\nu(\sigma(\mathbf{S}))\left[zu(\mathbf{S})\psi_u(\mathbf{S}) + (1-u(\mathbf{S}))\psi_e(\mathbf{S})w(\mathbf{S})\right]\right\} \end{aligned} \tag{30}$$

Firm Now we can define the matched firm's value function. The matched firm's value function $J(\mathbf{S})$ in a set of aggregate states $\mathbf{S}$ is

$$J(\mathbf{S}) = \max_p\{R(p,\mathbf{S}) + y\} - w(\mathbf{S}) + \beta\mathbb{E}\left[(1-\delta)J(\mathbf{S}')|\mathbf{S}\right] \tag{31}$$

With the value of filled jobs, each firm posts vacant jobs optimally. The value of posting vacancies is

$$V = -\kappa + q(\theta(\mathbf{S}))J(\mathbf{S}) \tag{32}$$

[19] Kaplan and Menzio (2016) and Pytka (2018) calibrate $\bar{p}$ to match an empirical moment of $\bar{p}/\underline{p}$. That is, the upper support of price in their works is an exogenous parameter. In this paper, I allow $\bar{p}$ is changed over the business cycle and calibrate χ to match the same empirical moment $\bar{p}/\underline{p}$.

By the free entry condition, the value of posting vacancies in equilibrium should be zero. Thus, the equilibrium job market tightness $\theta(\mathbf{S})$ is

$$\theta(\mathbf{S}) = \begin{cases} q^{-1}\left(\frac{\kappa}{J(\mathbf{S})}\right), & \text{if } J(\mathbf{S}) > \kappa \\ 0, & \text{otherwise} \end{cases} \tag{33}$$

Wage Determination and Downward Wage Rigidity For each state, since contracts are not fully committed, both newly hired and existing workers and firms negotiate over wages in fashion of the Nash bargaining such that

$$w^*(\mathbf{S}) = \underset{w}{\operatorname{argmax}}\, H(\mathbf{S})^{\gamma} J(\mathbf{S})^{1-\gamma} \tag{34}$$

where γ is a worker's bargaining power and $H = W - U$ is a net value of being employed such that[20]

$$H(\mathbf{S}) = u(c_e, \psi_e) - u(c_u, \psi_u) + \beta \mathbb{E}\left[(1 - \delta - \lambda(\theta(\mathbf{S}')))H(\mathbf{S}')|\mathbf{S}\right] \tag{35}$$

However, if wages are stuck at a too low level compared to previous wages, firms must pay a convex combination of bargained wages w^* and previous wages w_{-1} as in Eggertsson et al. (2017). Thus, equilibrium wages w are determined by

$$w(\mathbf{S}) = \max\{w^*(\mathbf{S}), \eta w_{-1} + (1-\eta)w^*(\mathbf{S})\} \tag{36}$$

where η is a weight on previous wages. See Appendix A.3 for the computational algorithm.

3.3 Calibration

Table 1 shows the calibrated parameters in the paper. Many of the values here are similar to those in Kaplan and Menzio (2016).

Deep Parameter and Time Discount There are two deep parameters, the curvature in consumption α and the elasticity of shopping ξ. In literature, the curvature or the relative risk aversion parameter α is used between one and five. Based on the discussion in Appendix A.2, I choose $\alpha = 3$, ξ, which can be interpreted as an inverse elasticity of shopping. Since the frequency of the model is monthly, I set $\beta = (1/1.035)^{12}$ based on an annual risk-

[20]Since unemployed buyers pay lower prices and the employed buyer's disutility from shopping effort is higher than that of unemployed buyer, there is no theoretical guarantee that $H > 0$. However, in the calibration, $H > 0$ for all $\mathbf{S}$.

Parameter	Value	Description	Targets/Reference	Model
α	3.000	Curvature in Consumption	Size of Income Effect	
β	0.997	Time Discount	Monthly Frequency	$(1.035)^{1/12}$
η	0.740	Degree of Downward Wage Rigidity	Ma (2017)	
ξ	2.500	Elasticity of Shopping	Literature	
φ_e	570.0	Disutility Weight on Employed Buyer	$\mathbb{E}(1+\psi_u)/(1+\psi_e) = 1.25$	1.2541
φ_u	10.00	Disutility Weight on Unemployed Buyer	$\mathbb{E}[\psi_u] = 0.25$	0.29
z	3.200	Home Production	Replacement ratio 70%	61.16%
γ	0.400	Worker's Bargaining Power	Profit Margin 0.05	0.056
δ	0.024	Exogenous Job Separation	Kaplan and Menzio (2016)	
ϕ	1.240	Elasticity in the Matching Function	Kaplan and Menzio (2016)	
κ	6.300	Fixed Cost of Posting Vacancies	$\mathbb{E}[u] = 5.7\%$	4.68%
χ	2.800	Pricing Rule of Upper Support	$\mathbb{E}[\bar{p}/\underline{p}] = 1.7$	1.7568
ρ	0.983	Persistence of Productivity	Gertler et al. (2016)	
σ_y	0.0075	Standard Deviation of Productivity	Gertler et al. (2016)	

Table 1: Baseline Calibration. Moments in the model are results in the flexible wage model.

free interest rate of 3.5%.

Downward Real Wage Rigidity The degree of wage rigidity here is governed by the parameter η. Note that while the most of literature focuses on nominal downward wage rigidity, this paper considers downward rigidity for real wages. However, unfortunately, since there is little literature studying downward real wage rigidity, I choose the conservative value 0.74, which is the lowest positive value in Ma (2017) in terms of monthly frequency.[21]

Disutility on Shopping I calibrate the disutility of shopping for employed and unemployed buyers ψ_e and ψ_u to match the average ratio between total price search intensities by employed and unemployed buyers 1.25, as in Kaplan and Menzio (2016). Simulated results of $\mathbb{E}[(1+\psi_u)/(1+\psi_u)]$ are 1.2451 and 1.2604 in the flexible and rigid wage models, respectively. As the result, in both rigid and flexible wage models, the effective price paid by unemployed buyers is 2% lower than the one by employed buyers on average, as in Kaplan and Menzio (2015, 2016)[22].

Home Production and Bargaining Power I calibrate jointly each unemployed worker's home production and worker's bargaining power to match the replacement ratio 70% and the profit margin $\mathbb{E}[(R+y-w)/(R+y)] = 0.05$. The simulated result of the average replacement ratio, $\mathbb{E}[z/w]$, is 64.26%, and that of the average profit margin is 5.6% in the rigid wage model. In the flexible wage model, they are 61.16% and 5.60%, respectively. Results

[21] Ma (2017) considers 0.3, 0.5 and 0.7 in the quarterly frequency model. I here use $0.3^{1/4} \approx 0.74$.

[22] $\mathbb{E}[p_e/p_u] = 0.9814$ in the rigid model and $\mathbb{E}[p_e/p_u] = 0.9792$ in the flexible wage model.

imply that the long-run average wage in the rigid wage model is lower than in the flexible wage model due to the Nash bargaining. That is, since firms expect that they should pay high wages even in a recession, they want to pay lower wages even in a boom. This leads to an even lower long-run unemployment rate in the rigid wage model, but the welfare is also lower there since aggregate consumption is much lower.

Job Separation, Matching Technology and Fixed Cost As in Kaplan and Menzio (2016), I target the monthly transition rate from employment to unemployment, 0.024. Thus, the monthly exogenous job separation rate δ is calibrated to 0.024. Also, I use the parameter value $\phi = 1.24$, the elasticity of matching function from the Kaplan and Menzio (2016) calibration. Related to this, the simulated value of the monthly transition rate from unemployment to employment (UE), that is, the job finding rate in the model $\mathbb{E}[\lambda(\theta)]$ is 0.4868 in the flexible wage model, which is slightly higher than the UE rate 0.433 in Kaplan and Menzio (2016). The fixed cost of posting vacancies $\kappa = 6.30$ to match the average unemployment rate 5.7% in the data from January 1948 to July 2018.[23] The simulated result of the average unemployment rate is 4.68% in the flexible wage model.

3.4 Results

In this section, I report quantitative results of the full model. Since the shopping effort is procyclical, sellers can post relatively higher prices in the recession, and need to post relatively lower prices in the boom. Thus, prices adjust sluggishly over the business cycle. The mechanism in the model suggests that wages are crucial not only as a factor price for sellers but also as an income effect for the shopping effort of buyers. That is, prices are more rigid as wages are rigid. Moreover, I show that the rigid prices imply smoothed business cycle. In decentralized labor and product markets, the price rigidity implies rigid revenues over the business cycle. For example, if sellers can enjoy relatively higher markups in recession by posting higher prices, they can post more vacancies and pay higher wages in the labor market. To see these dynamics more explicitly, I implement a counter-factual study. That is, I consider the counter-cyclical shopping effort in the model and compare the equilibrium dynamics of the model with those of the benchmark model. As I predicted, prices and aggregate variables such as labor market tightness and unemployment are more volatile if the shopping effort is counter-cyclical.

Additionally, I investigate the extensive margin of price adjustment, which is usually considered as price stickiness, and how wages and prices are related quantitatively. In the

[23] If we exclude the financial crisis by considering the period from January 1948 until December 2006, it becomes 5.61%.

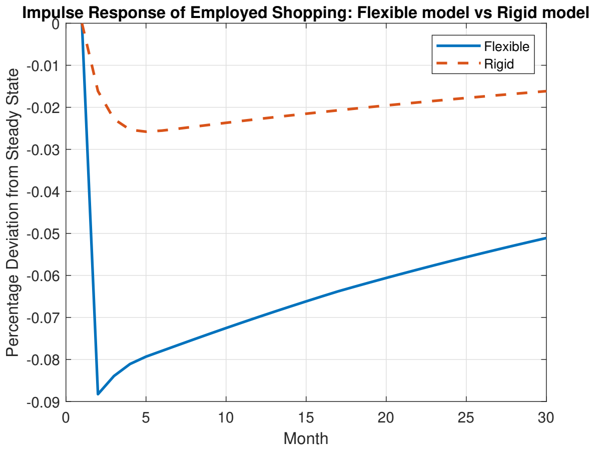


Figure 5: Negative 1% Labor Productivity Shock: Employed Shopping Effort

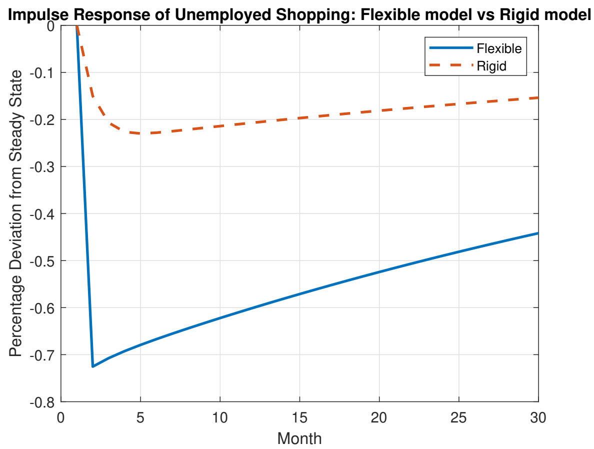


Figure 6: Negative 1% Labor Productivity Shock: Unemployed Shopping Effort

model, even though sellers do not need to pay any cost to change prices as in the menu-cost model, considerable fractions of sellers stay at the same prices. To implement this study, I use the methodology used in Head et al. (2012). Furthermore, using the simulated data from the model, I show that while the wage changes lead to price changes, the opposite direction does not hold.

Shopping and Price Dynamics Shopping and Price Dynamics Figure 5 and Figure 6 represent impulse response functions of shopping effort by employed and unemployed buyers, respectively, in response to the negative 1% labor productivity shock. In each graph, the blue-solid line represents the shopping effort in the flexible wage model, and the red-dotted line represents the shopping effort in the rigid wage model. Those graphs imply that the price search intensities of both employed and unemployed buyer are procyclical and those of unemployed buyers are much more elastic than employed buyers, as predicted in the static model.

Since buyers devote less effort in recession, sellers who are the first movers can enjoy relatively higher markup by posting relatively higher prices. As a result, prices are rigid in equilibrium. Figure 7 and Figure 8 represent the impulse response functions of posted prices in response to the negative and positive 1% labor productivity shock, respectively. Even in the flexible wage model (blue-solid line), posted prices change only around 0.5% in response to 1% labor productivity shock. In the rigid wage model, they change only 0.15 % and 0.3 % in response to the negative and positive 1 % shocks, respectively. The asymmetry in the rigid wage model is the result of the *downward* wage rigidity.

Smoothed Aggregate Dynamics with Counter-Factual Study In the imperfect de-

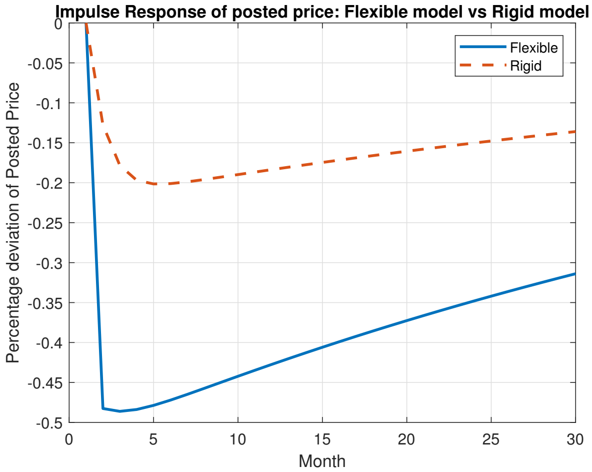


Figure 7: Negative 1% Labor Productivity Shock: Posted Prices

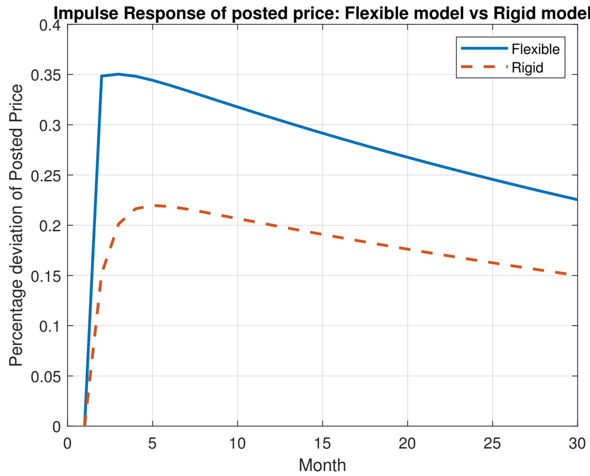


Figure 8: Positive 1% Labor Productivity Shock: Posted Prices

centralized product market, the rigid price implies rigid revenues. Moreover, the ex-ante revenue affects the job posting decision of firms. Since firms enjoy relatively higher (lower) markups in recession (boom), they can post relatively more vacant jobs and can pay higher wages. Thus, aggregate variables even in the labor market behave smoothly over the business cycle.

To study explicitly what aggregate implications the endogenous procyclical shopping effort has, I study various type of model. First, to study the role of decentralized product market, I compute the standard Diamond - Mortensen - Pissarides (DMP) and the DMP model with the downward wage rigidity.[24] Also, I compute the model of fixed shopping to investigate the role of endogenous procyclical shopping effort.

Lastly, I compute the model of the counter-cyclcial shopping effort as the counter-factual study. The technical issue here is that the procyclical shopping effort in the model is an endogenous equilibrium outcome. Thus, in order to explore the counter-cyclcial shopping effort, I consider the following ad-hoc policy functions of shopping effort.

1. From the original model, we can obtain simulated time-series values of shopping effort, unemployment rate, and labor productivity. Let us denote them as $\psi_i(t)$, $u(t)$, and $y(t)$ where $i \in \{e, u\}$, e=employed and u=unemployed.

2. Run the regression

$$\log \psi_i(t) = \beta_0 + \beta_1 \log u(t-1) + \beta_2 \log y(t)$$

[24]In order to compare in a fair way, I re-calibrate the fixed cost κ and the value of unemployment z, and fix other variables such as parameter in the matching technology ϕ, worker's bargaining power γ, and the consumption curvature parameter α.

	DMP	DMP +Rigid Wage	Fixed Shop +Flex. Wage	Endo. Shop + Flex. Wage	Endo. Shop + Rigid Wage	Counter-Factual + Flex. Wage
Output	0.0648	0.0650	0.0669	0.0668	0.0678	0.0664
Unemployment	0.0071	0.0133	0.0447	0.0406	0.0557	0.0488
Job Mkt. Tightness	0.0441	0.0628	0.1125	0.1022	0.1147	0.1232
Cons. Employed	0.0569	0.0481	0.0060	0.0090	0.0015	0.0028
Cons. Unemp	0	0	0.0314	0.0259	0.0126	0.0362
Posted Price	.	.	0.0317	0.0277	0.0135	0.0357
Wage	0.0569	0.0469	0.0372	0.0364	0.0145	0.0382

Table 2: Each value represents the standard deviation of each variable in each model. Output is calculated by $Y = (1-u)y$. Cons. Employed represents the consumption level of employed buyers and Cons. Unemployed represents that of unemployed buyers. The standard deviations are calculated by log variables filtered by the Hodrick - Prescott (HP) method with the penalty parameter 10^5. I simulate 5,000 months with 500 economies and burn out the first 1,000 periods.

Note that the state variables of the model are u_{t-1} and y_t in the flexible wage model[25]

3. The signs of $\hat{\beta}_1$ and $\hat{\beta}_2$ represent the cyclicality of the shopping effort. Thus, by considering the opposite signs of β_1 and β_2[26], we can consider the counter-cyclcical shopping effort.

4. Thus, in the counter-factual study, for each state-variable u_{t-1} and y_t, I consider the hypothetical counter-cyclical shopping effort by using the above ad-hoc rule. Thus, the counter-cyclical shopping effort is evaluated by

$$\log \psi_i(u_{t-1}, y_t) = \hat{\beta}_0 - \hat{\beta}_1 \log u_{t-1} - \hat{\beta}_2 \log y_t$$

Using the above policy functions, I solve the model again and get equilibrium dynamics.

Table 2 represents variabilities of aggregate variables for each model. First, as discussed in Kaplan and Menzio (2016), by considering decentralized and imperfect product market, labor market variables such as unemployment rate and the labor market tightness are more variable than the standard DMP model and the DMP model with downward rigid wages. Since prices and revenues do not flexibly adjust with respect to labor productivity shocks unlike in the DMP model, the job market tightness in decentralized labor and product market is not a jump variable anymore.

Second, the procyclical shopping effort has a quantitatively crucial effect. We can check

[25] We can consider various specifications. I choose the log-linear form since 1) it generates counter-cyclical shopping effort and 2) the mean value of fitted value is close to the mean value of original time-series values. The mean-squared error (MSE) in the log-linear function is smaller than that in the linear function.

[26] To keep the same average, β_0 should be fixed without changing the sign.

this by comparing it with the fixed shopping model and the counter-cyclical shopping model in counter-factual studies. From the endogenous shopping model to the fixed shopping model[27], both quantities (output, unemployment, and labor market tightness) and prices (posted prices and wages) become more volatile. And from the fixed shopping effort model to the counter-cyclical shopping effort model, we can again see that both quantities and prices in later models become more volatile. Figure 12 in the appendix represents the impulse response functions of average posted prices, the job market tightness, and the unemployment rate for the negative 1% labor productivity shock.

This aspect appears more pronounced by comparing equilibrium dynamics between the counter-cyclical shopping model and the rigid wage model. Even though wages are flexible in the counter-cyclical shopping model, both quantities and prices are more volatile than those of the rigid wage model. Thus, the procyclical shopping effort has crucial aggregate implications quantitatively.

Overall, the one crucial implication of the analysis here is that the cyclical behavior of shopping effort has a crucial channel as prices are not absorbing variables any more in decentralized labor and product markets. This explains why the variability of the job market tightness in the endogenous shopping - rigid wage model does increase very much compared to the endogenous shopping - flexible wage model as predicted by Shimer (2005), Hall (2005) and Gertler and Trigari (2009).

We can also consider various other interesting features. For example, not only posted prices, but also even wages are smoothed over the business cycle by studying the endogenous shopping model. Since revenues adjust sluggishly as shopping effort is procyclical and firms consider this when they negotiate over wages. In recession, since sellers can have relatively higher revenues and markups by running firms, they can post relatively greater vacant jobs with relatively higher wages. Furthermore, in the rigid wage model, since a higher purchasing power (wages) is beneficial to sellers in the product market as the second order effect, this would be one reason why the job market tightness decreases not so drastically.

Rigid Wages and Rigid Prices As a by-product, we can study how the wage dynamics affect the price dynamics. From Figure 7 and Figure 7, posted prices are less elastic in the rigid wage model.[28] Furthermore, I argue that all prices in the rigid wage model are more rigid than those in the flexible wage model, as prices are less variable and more persistent as the income effect in the rigid wage model decreases.

[27]In the fixed shopping model, as in Kaplan and Menzio (2016), I fix the price search intensities of employed and unemployed buyers as exogenous parameters.

[28]This holds for all other prices. Figures of impulse response functions are provided upon request.

Std. Deviation	Rigid Wage Endo. Shop	Flex. Wage Endo. Shop.	Flex. Wage Fixed Shop.
Posted Price	**0.0135**	0.0277	0.0317
Eff. Price by Emp	**0.0132**	0.0276	0.0316
Eff. Price by Ump	**0.0127**	0.0261	0.0315
Agg. Consumer Price	**0.0132**	0.0276	0.0316
Minimum Price	**0.0116**	0.0208	0.0273
Maximum Price	**0.0151**	0.0363	0.0371

Table 3: Simulation results, Standard Deviation. All variables are logged for 4,000 months in 300 economies with HP filter penalty parameter 10^5. The aggregate consumer price (Agg. Consumer Price) is artificially generated by $p_c = u \times \mathbb{E}[p|\psi_u] + (1-u) \times \mathbb{E}[p|\psi_e]$

Persistence	Rigid Wage Endo. Shop	Flex. Wage Endo. Shop.	Flex. Wage Fixed Shop.
Posted Price	**0.8743**	0.8421	0.8416
	(0.0101)	(0.0125)	(0.0124)
Eff. Price by Emp	**0.9078**	0.8421	0.8418
	(0.0076)	(0.0125)	(0.0124)
Eff. Price by Ump	**0.9086**	0.8431	0.8419
	(0.0075)	(0.0124)	(0.0124)
Agg. Consumer Price	**0.9079**	0.8423	0.8418
	(0.0075)	(0.0125)	(0.0124)
Minimum Price	**0.9079**	0.8423	0.8418
	(0.0076)	(0.0125)	(0.0124)
Maximum Price	**0.9079**	0.8423	0.8418
	(0.0076)	(0.0125)	(0.0124)

Standard deviations are in parenthesis.

Table 4: Simulation results, AR(1) coefficients. All variables are logged for 4,000 months with HP filter penalty parameter 10^5 in 300 economies. The aggregate consumer price (Agg. Consumer Price) is artificially generated by $p_c = u \times \mathbb{E}[p|\psi_u] + (1-u) \times \mathbb{E}[p|\psi_e]$

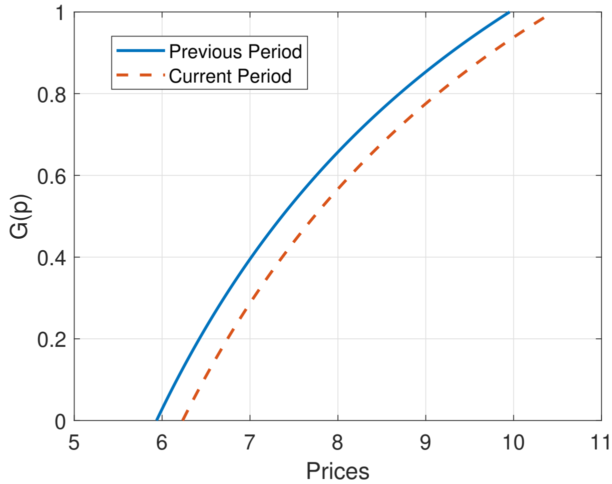


Figure 9: Quoted Price Distribution G(p) from the bad state to the good state

Table 3 represents the standard deviations of prices for each of the models, the rigid wage/endogenous shopping, flexible wage/endogenous shopping, and flexible wage/fixed shopping models. Due to the richness of the model, we can consider various prices such as those posted by sellers, paid by each employed and unemployed buyer, those in the aggregate consumer price index, or the minimum and maximum prices in the quoted price distribution. For all prices, the standard deviations in the rigid wage model are smaller than all of those in the flexible wage model. That is, prices behave more sluggishly over the business cycle if wages are rigid.

The rigid wage model also implies higher persistences of prices than those in the flexible wage model. If prices are more persistent, prices have tendencies to stay in the same level of prices. Table 4 represents AR (1) coefficients of prices for each model. Thus, in both variabilities and persistence, prices are more rigid if wages are rigid. Figure 13 and Figure 14 represent the impulse response functions for each posted price, effective paid prices by employed and unemployed buyers in the flexible and rigid wage model. For all of prices, the rigid wage model shows a sluggish adjustment of prices over the business cycle.

Sticky Prices: Extensive margin of price adjustments The above study of price rigidity is largely related to the total margin, and the intensive margin, of price adjustments. Since the model gives us a full price distribution function for each aggregate state, we can compute the fraction of sellers who adjust/keep their prices over the business cycle. To do so, I follow the methodology used in Head et al. (2012).

To better understand, let us see the Figure 9. The blue solid line represents the quoted price distribution at the previous period and the red dotted line represents the distribution

	Mean	Median
Rigid Wage	7.01%	6.77%
Flexible Wage	8.62%	8.51%

Table 5: Fractions of sellers who adjust prices

in the current period. We can interpret this as the transition of the quoted price distribution from a bad to a good state. If a seller has posted prices lower than the lowest support in the current period, she should adjust the prices. If she was in the overlapped region, that is, $p_{t-1} \in \{\underline{p}_t, \bar{p}_{t-1}\}$, she can either stay at the same price p_{t-1} or she can adjust her price to p', which is drawn from the adjusted price distribution $p' \in Q_t(p)$. As in Head et al. (2012), sellers adjust prices randomly with the probability $1-\rho$. That is, with probability ρ, she stays at the same price p_{t-1}; while, with the probability $1-\rho$, she draws the new price $p' \in Q_t(p)$, which is consistent with $G_t(p)$[29].

I calibrate the random probability ρ to match the average duration of the price, 11.6 months, as in Head et al. (2012).[30] For the same target, the calibrated ρ in the flexible wage model is $\rho_{\text{flex}} = 0.9381$, and that in the rigid wage model is $\rho_{\text{rigid}} = 0.9219$. Using the calibrated parameter, we can find how many sellers adjust their prices over the business cycle. Table 5 represents the result. In the rigid wage model, the average fractions of sellers who adjust prices over the business cycle are 7.01% in the rigid wage model and 8.62% in the flexible wage model. This implies that significant fractions of sellers do not adjust prices over the business cycle and that prices are rigid with an extensive margin, also.

Linkages: Wage Changes lead to Price Changes? Or the Opposite? As the last quantitative exercise, I study if wage changes lead to price changes or price changes lead to wage changes. This investigation is related to Druant et al. (2009) which empirically show that sticky wages lead to sticky prices in the firm-level Europe data.[31]

To implement this study, I implement the Granger Causality test using the simulated data from the model. Table 6 represents its result in the rigid wage model[32] and it implies that wage changes lead to price changes.

[29] See Head et al. (2012) for more technical details

[30] Note that there is no money in the model. Thus, all prices here are relative prices not nominal prices. Thus, it is hard to match directly with data moments from nominal price data. Furthermore, the shock here is not a nominal/monetary shock but a real labor productivity shock.

[31] Christiano et al. (2016) studies how sticky prices affect wage stickiness in the New Keynesian model.

[32] In the VAR analysis before implementing the test, I include all crucial endogenous and exogenous variables. Fully specified versions of tables will be provided upon request.

$\rightarrow$	ΔWages	ΔPrices
ΔWages		310.91^{***}
ΔPrices	17.04	

Table 6: Granger Causality Test based on VAR with 12 lags. Statistics are Chi-Square statistics. Simulated data with 3000 months and all variables are first differenced in the rigid wage model. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Empirical Evidence: Shopping Time, and Income and Return Effects over the Business Cycle

In this section, I study the cyclical dynamics of shopping effort, price dispersion, and the return to shopping over the business cycle empirically based on theoretically identified channels in Section 2. Thus, the main focus of this section is to test empirically how employed and unemployed buyers adjust their time to find cheaper prices over the business cycle with the return to shopping and the price dispersion.

Section 4.1 introduces the datasets used in this paper, the American Time Use Survey (ATUS) and the Kilts-Nielsen Consumer Panel Data (KNCPD). In Section 4.2, I study the dynamics of shopping time in both cross-sectional and time series perspectives. In Section 4.3, I explore the empirical relationships between shopping intensities, price dispersion, and the return to shopping over the business cycle.

4.1 Data

ATUS The ATUS is conducted by the Bureau of Labor Statistics (BLS) and individuals in the data are drawn from the exiting sample of the Current Population Survey (CPS). The sample periods of ATUS in this paper are between 2003 to 2017. Survey respondents are sampled approximately three months after completion of their final CPS survey on average. Each wave is based on 24-hour time diaries where respondents report the activities from the previous day in detailed time intervals. For more information on the types of activities that are recorded in the ATUS, see Hamermesh et al. (2005) and Aguiar et al. (2013).

To measure the shopping effort in the ATUS, I follow the time categories used in Petrosky-Nadeau et al. (2016). The total shopping time includes time spent shopping for consumer goods, researching goods and services, waiting time associated with shopping, traveling, and for groceries, gas and food (GGF). See Appendix B.1 for more details with codes.

I consider only working-age ($25 \sim 55$) survey respondents, similarly to the study in Petrosky-Nadeau et al. (2016). For the reason discussed in Petrosky-Nadeau et al. (2016), excluding samples of persons aged under 25 and above 55 can be justified, since one of the main focuses is to compare the shopping efforts of employed and unemployed buyers. To study the dynamics of shopping time, I combine the ATUS with the CPS. Note that the ATUS-CPS does not include information on wealth, and unemployed respondents' incomes are recorded as zero.[33]

KNCPD The KNCPD is a panel data set that includes the shopping behavior of households over the period 2004-2016.[34] Households in the sample are drawn from 49 states. Demographic information on households is collected at the time of entry into the panel survey and then updated annually through a written survey during the fourth quarter of each year.

Households in the panel provide information about each of their shopping trips using a universal product code (UPC), or barcode, scanning device provided by Nielsen. When a panelist returns from a shopping trip, he uses the device to enter details about the trip, including the date and store where the purchases were made. The panelist then scans the barcode of each purchased good and enters the number of units purchased. The price of the good is recorded in one of two ways, depending on the store where the purchase took place. If the good was purchased at a store that Nielsen covers, the price is set automatically to the average price of the good at the store during the week when the purchase was made. If the good was purchased at a store that Nielsen does not cover, the price is entered directly by the panelist. Panelists are also asked to record whether the good was purchased using one of four types of deal: (i) store feature, (ii) store coupon, (iii) manufacturer coupon, or (iv) other deal. If the deal involved a coupon, the panelist is prompted to input its value.

Nielsen offers households incentives to join and stay active in the panel. These contain monthly prize drawings, gift points, and regular sweepstakes. For the quality of data, Nielsen filters out households that do not regularly report, and adds new households to the panel data if some households leave. Furthermore, the KNCPD contains only actively reporting households that meet this threshold over a 12-month period. This yields an annual panelist retention rate of approximately 80%. As in other survey data, Nielsen provides the sample weight that is called a projection factor to make the sample representative of the U.S. population. I use the projection factor in empirical studies here.

4.2 ATUS: Cyclicality and Income Effect

In order to reexamine procylicality of shopping time and income effect with longer time span, in this section, I study empirical dynamics of shopping time in both time-series and cross-

[33]To be strict, they are coded as a negative unity, -1.

[34]Kaplan and Menzio (2015) use the KNCPD over the period 2004-2009 and Nevo and Wong (2018) use it over the period 2004-2010. The KNCPD at 2016 is the recent available dataset on August 2018.

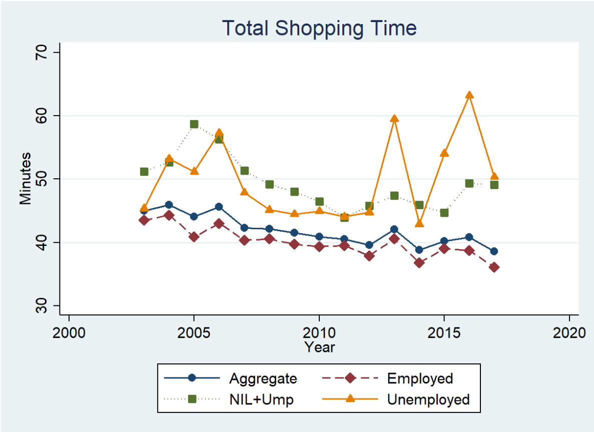


Figure 10: Total Shopping Time (Not Detrended): 2003 $\sim$ 2017

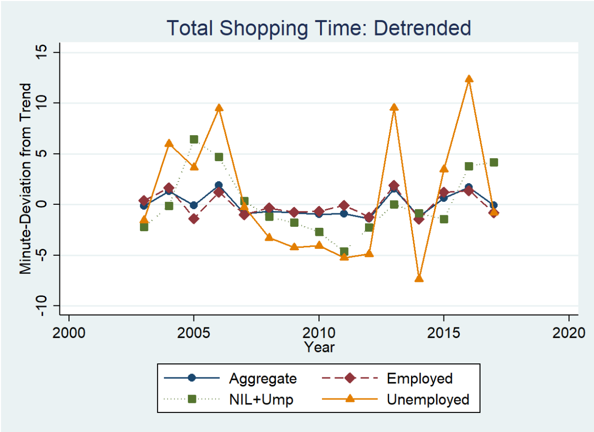


Figure 11: Total Shopping Time (Detrended): 2003 $\sim$ 2017

sectional perspectives. Through the time-series analysis, I explore 1) if the shopping effort is pro/counter/a-cyclical and 2) if unemployed buyers are elastic than employed buyers in adjusting shopping effort over the business cycle. Since the frequency of samples in the ATUS is annual, that is, the number of samples in the time-series perspective is only 15, I study them in the state-level variations as in Aguiar et al. (2013). In the cross-sectional analysis, I investigate a various determinants on shopping effort such as labor-status, earnings, wages, hours work, home-production and etc.

First, I consider the averages of total shopping time for each year and each labor status. Figure 10 is the result of OLS estimates $\hat{\beta}_{jt}$

$$\tau^c_{jt} = \beta_{jt} D_t + \varepsilon_{jt} \tag{37}$$

where

$$\tau^c_{jt} = \sum_{i=1}^{N_{jt}} \left(\frac{\omega_{ijt}}{\sum_{i=1}^{N_{jt}} \omega_{ijt}} \right) \tau^c_{ijt} \tag{38}$$

where D_t is the time dummy from 2003 to 2017, τ^c_{ijt} represents minutes per day on time use category c by individual i in labor status j during the year t, ω_{ijt} is the ATUS sampling weight, and N_{jt} is the total number of individuals i in labor status j in year t. The category c includes total time, goods, and services (GS), and grocery, gas, and food (GGF); and labor status j is an aggregate of the employed, unemployed, and not working statuses (NIL+unemployed). NIL stands for *Not-In-Labor Force*. Figure 11 is the detrended version of Figure 10.[35]

[35]In Figure 11, I run the regression for the shopping time on the time trend and extract the residuals. Since the time span is short and the sample frequency is annual, I do not report the results from alternative

Figure 10 and Figure 11 are helpful for understanding the cyclical dynamics of shopping time roughly, even though we cannot judge whose shopping time is more elastic or variable over the business cycle.[36] First, we can conjecture that there exist decreasing trends, except for the shopping time of unemployed buyers, from Figure 10. Secondly, shopping intensities by both unemployed and non-working (NIL+unemployed) buyers seem to be more variable than for employed buyers. Further, they seem roughly to be procyclical. However, since the standard deviation of $\hat{\beta}_{jt}$ for unemployed buyers is too large in an aggregate time-series analysis, we cannot say that the shopping effort of unemployed buyers is more elastic or variable than that of employed buyers. This result is consistent with the regression result on annual averages of unemployment rates. See Appendix B.1 ATUS codes to measure the shopping time in detail and Appendix B.3 for various categories and gender differences in the shopping time in aggregate time-series analysis.

Cross-State Variations To overcome the short time spans of ATUS samples, as in Aguiar et al. (2013) and Petrosky-Nadeau et al. (2016), let us consider the state-level aggregates of shopping time. Similarly to (38), we can define τ^c_{sjt} for each state s as

$$\tau^c_{sjt} = \sum_{i=1}^{N_{sjt}} \left(\frac{\omega_{isjt}}{\sum_{i=1}^{N_{sjt}} \omega_{isjt}} \right) \tau^c_{isjt} \tag{39}$$

Then, we can construct the panel shopping time with state s and year t. The ATUS includes samples for 50 states and the District of Columbia. To investigate whether the shopping effort is procyclical and the shopping time of unemployed or not-working (NIL+unemployed) buyers is more elastic than that for employed buyers, I run fixed-effect regressions for the shopping time on the state-level unemployment rate provided by the BLS.

In order to handle potential non-stationarity, I also consider regressions with raw and de-trended variables with trend and recession dummies.[37] First, I run the regression as the benchmark case

$$\log(Shopping)^c_{jst} = \alpha^c_j \text{Trend} + \beta^c_j \log(u_{st}) + \lambda^{\text{recession},c}_t + \lambda^c_s + \varepsilon^c_{st} \tag{40}$$

where $\lambda^{\text{recession},c}_t$ is the recession dummy for $t = 2008$ and 2009, and λ^c_s captures the state-

de-trend methods such as the Hodrick-Prescott (HP) filter. But all of the results from the different methods of filtering are consistent. The sample weights are applied for all analysis in this section.

[36]There are only 15 time-series samples and the ATUS sample period includes only one recession. The KNCPD also includes only the financial crisis.

[37]I also conduct several unit-root tests for all variables. However, because of short time samples with low frequency, the power would be low and thus, results would not be highly reliable.

	(1) Aggregate	(2) Employed	(3) Unemployed	(4) Not-Working
Trend	-0.0116***	-0.0116***	0.00530***	-0.0135***
	(-74.21)	(-79.16)	(9.52)	(-23.14)
$\log(u_{st})$	-0.0356***	-0.0111***	-0.249***	-0.157***
	(-27.46)	(-12.27)	(-11.49)	(-20.77)
Recession	-0.0120***	-0.0119***	-0.0850***	-0.00493
	(-19.99)	(-42.03)	(-13.51)	(-1.99)
_cons	26.86***	26.90***	-7.569***	30.45***
	(86.22)	(91.68)	(-6.65)	(26.37)
State Fixed Effect	Yes	Yes	Yes	Yes
# of Obs.	765	765	765	765

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Baseline regression. The shopping time here is the total shopping time, the sum of all categories. All state-level shopping time and unemployment rates are logged. Shopping time in the regression (1) is the total shopping time by aggregate buyers. (2) is the total shopping time by employed buyers, (3) is by unemployed buyers and (4) is by not-working buyers. t-values are calculated with robust standard errors clustered at the standard level

level fixed effect. In all regressions here include state-level fixed effects.

Table 7 represents results of (40). Table 7 clearly shows that (1) the shopping time is procyclical and (2) the shopping time of unemployed and non-working buyers is more elastic than that of employed buyers with respect to business cycle fluctuations. In particular, unemployed buyers reduce the shopping effort more than employed buyers during a financial crisis. Thus, the results of the empirical analysis are consistent with Petrosky-Nadeau et al. (2016).[38] As discussed in Section 2, this can be explained by the income effect which makes the shopping effort counter-cyclical and the return effect which makes it procyclical. See Appendix B.4 for more details related to categorical shopping time, such as goods and services (GS), and grocery, gas, and foods (GGF), and for alternative specifications.

Individual Level Analysis Now, let us consider determinants of the shopping effort at the individual level. To conduct the individual level analysis, I use the ATUS multi-year microdata files, which include the period over $2003-2017$. The ATUS multi-year microdata

[38] Nevo and Wong (2018) argue that the shopping intensity is counter-cyclical using the KNCPD. Nevo and Wong (2018) measure shopping intensities as the fraction of discounts by coupon or deals in each shopping trip. In Section 4.3, I measure the shopping effort as the number of trips, and it is procyclical. I discuss this in Section 4.3 in more detail.

is provided by the BLS, and combines the ATUS microdata files for each year from 2003 to 2017. Also, since the BLS provides the ATUS-CPS dataset, which is easily linked with the ATUS, I combine the ATUS with ATUS-CPS for a richer analysis.

As the first step, we can check if unemployed buyers devote more time for shopping than employed buyers at the individual level, as shown in Kaplan and Menzio (2015) and Kaplan and Menzio (2016). To see the differences between employed and unemployed buyers' shopping time I run the regression (41) and Table 12 shows results.[39]

$$\log(\text{Shopping})^c_{ijst} = \beta D_{ijst} + \delta X_{ijst} + \lambda_s + \lambda_t + \varepsilon_{ijst} \tag{41}$$

where $D = 1$ if the buyer is employed, X includes control variables of age, sex, marital status, number of children, employed spouses, and race, λ_s is a state dummy and λ_t is the year dummy. Table 12 implies that employed buyers devote less time to shopping than unemployed buyers, and almost of them are significant at the 1% level except for waiting and researching, which have relatively small observations.

As the next step, I study the income effect on the shopping effort. Table 13 represents the effects of weekly earnings and Table 14 represents the effects of weekly wages on the shopping time for each category. As shown in Section 2, buyers devote less effort if they have less income. Since the ATUS-CPS provides the information related to labor earnings, we can consider the regression with labor earnings. However, since unemployed/not-in-labor force workers do not have labor earnings nor hours of work, we can consider the income effect only for employed buyers. The ATUS reports weekly earnings and weekly hours at all jobs.

Even though the income effect in Table 13 and Table 14 does not hold for all categories in terms of statistical significance, we can still see that higher earnings reduce the shopping time in terms of total goods and services, and GGF, which takes into account most of the fractions in the shopping time. And the effect of earnings on shopping time is relatively more significant than the effect of wages. Also, the results of the empirical study here are consistent with other studies in the literature. For example, the results show that buyers devote more time to shopping over the life-cycle, as shown by Aguiar and Hurst (2007). The results also imply that female buyers devote more effort to shopping than male buyers.

4.3 Shopping Effort, Price Dispersion and Return to Shopping

In this section, I explore the price dispersion and the return to shopping with decomposed shopping intensities over the business cycle using the KNCPD. One important empirical result of this paper is that it can explain results in both Petrosky-Nadeau et al. (2016) and

[39] Table 12, Table 13 and Table 14 are in Appendix B.5.

Nevo and Wong (2018). In Section 4.2, I show that unemployed buyers' shopping effort is more cyclical than employed buyers' and buyers who have higher income exert spend less time on shopping. To test predictions of the model empirically, remained part is to investigate how the price dispersion and the return to shopping behave over the business cycle. Let first define a few important variables in the KNCPD.

Shopping Intensity Let us define a shopping intensity. Unlike the ATUS, the KNCPD does not report actual minutes for each shopping. Instead, survey respondents report the number of shopping trips, and each shopping trip is uniquely identified by the trips code for each week. For example, if the respondent visited Target twice and the Kroger once during the survey week, the total number of shopping trips is 3. As in other studies in the literature, I define the total shopping intensity as the total number of trips. Also, as in Aguiar and Hurst (2007) and Kaplan and Menzio (2015), we can decompose it as two margins. That is, the total shopping intensity is decomposed by the number of trips to different stores and the number of trips to the same store. I take the first one as an extensive margin of the shopping intensity, and the later one as an intensive margin of it.

This paper is consistent with Petrosky-Nadeau et al. (2016) in explaining the cyclical behavior of shopping and is also consistent with Nevo and Wong (2018) in explaining the procyclical return to shopping.[40] Related to this, I show that the returns to shopping from extensive and intensive margins are different, and more interestingly, that responsiveness to price dispersion or the coefficient of variation (CV) are also different for each of them.

Household Price Index To measure the return to shopping for each household, we first need to define the price index for each household. Like in Kaplan and Menzio (2015) and Nevo and Wong (2018), I follow the methodology in Aguiar and Hurst (2007) to measure the household level price index. Note that I use the projection factor provided by the Nielsen as the sample weight for all empirical analysis in this section.[41]

Let $p_{i,k,t}$ be the price of good k on shopping trip t purchased by household i where $i \in \{1, 2, \ldots, I\}, k \in \{1, 2, \ldots, K\}$ and $t \in \{1, \ldots, m\}$. The frequency of sampling in the KNCPD, i.e., the frequency of t is roughly weekly. As in Aguiar and Hurst (2007), I aggregate them at the monthly frequency. Then, the household i's total expenditure during month m

[40] Kaplan and Menzio (2015) also show that the return from the extensive margin is larger than that from the intensive margin of shopping. Note that Nevo and Wong (2018) defines shopping intensity as the fraction of: purchasing sale items/ using coupons/ buying generic goods/ purchasing large-size items /shopping at discount stores. I conjecture that this is the main reason that Petrosky-Nadeau et al. (2016) and Nevo and Wong (2018) have different conclusions.

[41] I exclude samples which do not have the projection factor even though the KNCPD also report information on magnet transactions, for goods without barcodes as in Kaplan and Menzio (2015).

$\tilde{X}_{i,m}$ is

$$\tilde{X}_{i,m} = \sum_{k \in K, t \in m} p_{i,k,t} q_{i,k,t} \tag{42}$$

where $q_{i,k,t}$ is the quantity of good k purchased on shopping trip t by household i. Since there could be another household purchasing the same good at a different price, take the average price paid for each good k during the month m to obtain the price index *for good* k, where the average is weighted by quantity purchased:

$$\bar{p}_{k,m} = \sum_{i \in I, t \in m} p_{k,t} \left(\frac{q_{i,k,t}}{\bar{q}_{k,m}} \right) \tag{43}$$

where

$$\bar{q}_{k,m} = \sum_{i \in I, t \in m} q_{i,k,t} \tag{44}$$

Then aggregate individual prices into an index. By doing this, we can see how much more or less than the average is the household paying for its chosen basket of goods. If the household paid the average price for the same basket of goods, the cost of bundle is:

$$Q_{i,m=} \sum_{k \in K, t \in m} \bar{p}_{k,m} q_{i,k,t} \tag{45}$$

Then define the price index for the household as the ratio of expenditures at actual prices divided by the cost of the bundle tat the average price, $\bar{p}_{i,m}$:

$$\tilde{p}_{i,m} = \frac{\tilde{X}_{i,m}}{Q_{i,m}} \tag{46}$$

Finally, let normalize the index. By doing this, the average price index for each month becomes one. In this paper, I use this price index (47) when I study the return to shopping.

$$p_{i,m} = \frac{\tilde{p}_{i,m}}{\sum_i \tilde{p}_{i,m}/I} \tag{47}$$

Price Dispersion and Coefficient of Variation (CV) We can consider two versions of the price dispersion. First, we can calculate the standard deviation of prices for all UPC level at the given time. That is, the price dispersion can be measured by the standard deviation of $p_{i,j,t}|_{t \in m}$. Secondly, we can consider the standard deviation of the household price index $p^{i,m}$ for each month. It is symmetric to measuring the coefficient of variation (CV). The CV could be a better measure as a determinant of the return to shopping since it controls for the average. For both of them, to implement the empirical analysis more efficiently, I compute them at the state level.

For both measures of the price dispersion, there exists an endogeneity issue when we investigate the empirical relationship between the shopping intensity and the price dispersion/CV. As discussed in Section 2, the higher price dispersion in the equilibrium price distribution in the mean-preserving sense increases the shopping intensities. Also, by the standard theory of price search in Burdett and Judd (1983), the dispersion is shrunk to the competitive price as consumers search for cheaper prices more intensively, $\psi \to 1$. Thus, I consider both regressions with and without instrument variables (IV).

Structural Break and Seasonality Nielsen introduced a new method using new devices to incoming panelists starting in 2007 and continuing to 2008-2009. To deal with this issue, I include time dummies for those periods. In particular, for the study using the panel data at the household level, I use household fixed effects as in Nevo and Wong (2018). For potential seasonality, I include quarterly dummy variables to handle it in the simplest way.

Cyclical Dynamics of Price Dispersion/CV and Shopping Intensity Now, let consider the cyclical dynamics of price dispersion and CV to test the model prediction of procyclical price dispersion and CV (and return to shopping) empirically. Using monthly state-level first-differenced unemployment rates and those variables, I run the linear panel regression with state-level fixed effects. Table 17 shows the result. It shows that both of them are procyclical, even though they do not move exactly in the same direction.

And since the CV and the shopping intensity can affect each other, we can consider the simultaneous equation model in the panel data with fixed effects. Table 18 shows the result and it implies that 1) the higher CV increases shopping effort, 2) the higher shopping intensities decrease the CV but its size is much smaller than the effect in 1), and 3) the CV is procyclical.

Furthermore, by decomposing the shopping intensity into extensive and intensive margins, we can see an interesting feature. That is, the effect of the CV on the extensive margin is much larger than it is on the intensive margin. Table 19 shows the case of the extensive margin and Table 20 shows the case of the intensive margin. Also, as rough analysis, the marginal effect of CV on the intensive margin is lower than the marginal effect of the intensive margin on the CV. We can also see these dynamics from Table 21 in the household-level study. In Table 21, using the linear panel regression with household-level fixed effects, I show that (1) the decrement of the extensive margin of the shopping intensity is greater than the increment of the intensive margin of the shopping intensity in a recession, and (2) the increment of the extensive margin of the shopping intensity is greater than the decrement of the intensive margin of the shopping intensity for higher price dispersion.

Return to Shopping over the Business Cycle Lastly, I investigate the empirical dynamics of the return to shopping. To study this, I consider the following regression:

$$\log p_{i,m} = \beta_0 \text{Shopping}_{i,m} + \beta_1 \text{Recession} \times \text{Shopping}_{i,m} + \beta_2 \text{Recession} + \delta X_{i,m} + \lambda_i + \lambda_s + \varepsilon_{i,m} \tag{48}$$

where a Recession is a dummy variable which is 1 if the samples are taken from December 2007 to June 2009, and X includes control variables such as shopping needs (the number of children, the size of the family, the number of product-categories, the cost of bundle in (45))[42], age, type of residence, time dummies to control structural breaks, etc. λ_i captures each household's fixed effects, and λ_s is a dummy variable for each state. For the shopping effort, I consider the total shopping intensity and its extensive and intensive margins separately.

The main interest variable is a β_1, which represents the return to shopping in a recession. If β_1 is positive, given a negative value of $\beta_0 + \beta_1$ which represents the return to shopping, this implies that the return to shopping declines in a recession. Table 22 represents the results. The results are partially consistent with the discussion in this paper in the sense that while the return to shopping from the extensive margin is low, the return from the intensive margin is high. However, these are all are not statistically significant.

5 Conclusion

In this paper, I build a model of endogenous price hunting under decentralized labor and product markets to investigate how we can understand the cyclical dynamics of price search intensities by employed and unemployed buyers, as well as the aggregate implications of the theory. The interaction between buyers and sellers through the endogenous shopping effort is a key mechanism for understanding the empirical findings on employed and unemployed buyers' shopping efforts. In this paper, I propose the two main theoretical effects, the income and return effects, and provide empirical evidence using the ATUS and KNCPD. In equilibrium, prices are rigid and the rigid wage makes prices more rigid in the model.

There are various extended studies that use the model of endogenous price hunting under decentralized labor and product markets. We can extend the model to analyze the effects of minimum wages in richer dimensions. For example, what Card and Krueger (1994) shows is that there was little change in employment and a small increase in inflation. The extended

[42] I use similar variables to those used in Aguiar and Hurst (2007) to control shopping needs. These variables are also used in Table 21 to control them.

version of the model here could partially explain the case study in New Jersey and Pennsylvania, since the distortion of job postings from higher minimum wages can be compensated by buyers' higher purchasing power and (slightly) lower price search intensities. Similarly, we can study the policy implications of unemployment insurance benefits. Even though they call for deeper consideration since they are normative studies, the theory used in this paper would be useful for studying them in a different perspective.

References

Aguiar, Mark and Erik Hurst, "Consumption versus Expenditure," *Journal of Political Economy*, 2005, *113* (5), 919–948.

_ and _ , "Life-Cycle Prices and Production," *American Economic Review*, 2007, *97* (5), 1533–1559.

_ , _ , and Loukas Karabarbounis, "Time Use during the Great Recession," *American Economic Review*, August 2013, *103* (5), 1664–96.

Arslan, Yavuz, Bulent Guler, and Temel Taskin, "Price Search, Consumption Inequality, and Expenditure Inequality over the Life Cycle," 2014 Meeting Papers 819 2016.

Bils, Mark, Yongsung Chang, and Sun-Bin Kim, "How Sticky Wages In Existing Jobs Can Affect Hiring," Working papers 2016rwp-91, Yonsei University, Yonsei Economics Research Institute October 2016.

Burdett, Kenneth and Kenneth L. Judd, "Equilibrium Price Dispersion," *Econometrica*, 1983, *51* (4), 955–969.

Calvo, Guillermo, "Staggered prices in a utility-maximizing framework," *Journal of Monetary Economics*, 1983, *12* (3), 383–398.

Card, David and Alan Krueger, "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania," *American Economic Review*, 1994, *84* (4), 772–93.

Christiano, Lawrence J., Martin S. Eichenbaum, and Mathias Trabandt, "Unemployment and Business Cycles," *Econometrica*, 2016, *84* (4), 1523–1569.

den Haan, Wouter J., Garey Ramey, and Joel Watson, "Job Destruction and Propagation of Shocks," *American Economic Review*, June 2000, *90* (3), 482–498.

Druant, Martine, Silvia Fabiani, Gabor Kezdig, Ana Lamo, Fernando Martins, and Roberto Sabbatini, "How are firms' wages and prices linked: survey evidence in Europe," Temi di discussione (Economic working papers) 725, Bank of Italy, Economic Research and International Relations Area October 2009.

Eggertsson, Gauti B., Neil R. Mehrotra, and Jacob A. Robbins, "A Model of Secular Stagnation: Theory and Quantitative Evaluation," Working Paper 23093, National Bureau of Economic Research January 2017.

Gertler, Mark and Antonella Trigari, "Unemployment Fluctuations with Staggered Nash Wage Bargaining," *Journal of Political Economy*, 2009, *117* (1), 38–86.

_ **, Christopher Huckfeldt, and Antonella Trigari**, "Unemployment Fluctuations, Match Quality, and the Wage Cyclicality of New Hires," Working Paper 22341, National Bureau of Economic Research June 2016.

Hall, Robert E., "Employment Fluctuations with Equilibrium Wage Stickiness," *American Economic Review*, March 2005, *95* (1), 50–65.

Hamermesh, Daniel S., Harley Frazis, and Jay Stewart, "Data Watch: The American Time Use Survey," *Journal of Economic Perspectives*, March 2005, *19* (1), 221–232.

Head, Allen, Lucy Qian Liu, Guido Menzio, and Randall Wright, "STICKY PRICES: A NEW MONETARIST APPROACH," *Journal of the European Economic Association*, 2012, *10* (5), 939–973.

Kaplan, Greg and Guido Menzio, "The Morphology Of Price Dispersion," *International Economic Review*, November 2015, *56*, 1165–1206.

_ **and** _ , "Shopping Externalities and Self-Fulfilling Unemployment Fluctuations," *Journal of Political Economy*, 2016, *124* (3), 771–825.

Ma, Eunseong, "Real Wage Rigidity, Heterogeneity, and the Business Cycles," *Working Paper*, 2017.

Michaillat, Pascal and Emmanuel Saez, "Aggregate Demand, Idle Time, and Unemployment," *The Quarterly Journal of Economics*, 2015, *130* (2), 507–569.

Nevo, Aviv and Arlene Wong, "The Elasticity of Substitution Between Time and Market Goods Evidence from the Great Recession," *International Economic Review (Forthcoming)*, 2018.

Petrosky-Nadeau, Nicolas, Etienne Wasmer, and Shutian Zeng, "Shopping time," *Economics Letters*, 2016, *143*, 52 – 60.

Pytka, Krzysztof, "Shopping Effort in Self-Insurance Economies," *Working paper*, 2018.

Shimer, Robert, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, March 2005, *95* (1), 25–49.

Appendices

A Theoretical Supplements

A.1 Linearity of Effective Price

I introduce a simple derivation of (6) in the way discussed in Pytka (2018). From (5), we have

$$
\begin{aligned}
\mathbb{E}[p|\psi] &= \int_{\underline{p}}^{\bar{p}} p dF(p;\psi) \\
&= [pF(p;\psi)]_{\underline{p}}^{\bar{p}} - \int_{\underline{p}}^{\bar{p}} F(p;\psi)dp \\
&= \bar{p} - \int_{\underline{p}}^{\bar{p}} (1-\psi)G(p) + \psi\left(1-(1-G(p))^2\right)dp \\
&= \bar{p} - \int_{\underline{p}}^{\bar{p}} G(p)dp - \psi\int_{\underline{p}}^{\bar{p}} G(p)\left(1-G(p)\right) \\
&= \int_{\underline{p}}^{\bar{p}} pdG(p) - \psi\int_{\underline{p}}^{\bar{p}} G(p)\left(1-G(p)\right) \\
&= p^0 - \psi \times MPB
\end{aligned}
$$

A.2 Analytical Study of Endogenous Price Hunting

Even though the first order condition (FOC) itself is not used when I actually solve the model, and we can have closed form solution, it is beneficial to study it to understand the optimal price hunting intuitively. Given the additively separable utility function (4), the FOC is

$$
\left(\frac{m}{p^0-\psi MPB}\right)^{1-\alpha}\frac{MPB}{p^0-\psi MPB} = \varphi\psi^{\xi} \tag{49}
$$

We can easily see that there is no income effect if $\alpha = 1$, that is, the log utility function. To analyze it more intuitively, let take natural logs on both sides and take a total differentiation. Then we have

$$
\varepsilon_{\psi} = \frac{1}{\xi}\left[(1-\alpha)\varepsilon_m - (2-\alpha)\varepsilon_{p(\psi)}\times MPB + \varepsilon_{MPB}\right] \tag{50}
$$

where $\epsilon_x = dx/x$, the elasticity of x and $p(\psi) = p^0 - \psi MPB$, the effective paid prices. Note that since the right-hand side also includes ψ, the implied elasticity of ψ in (50) is not true value. The elasticity of the effective paid price $\epsilon_{p(\psi)}$ is

$$\begin{aligned}
\frac{dp(\psi)}{p(\psi)} &= \frac{1}{p^0 - \psi MPB}\left[p^0\varepsilon_{p^0} - \psi MPB\left(\varepsilon_\psi + \varepsilon_{MPB}\right)\right] \\
&= \underbrace{\frac{p^0}{p^0 - \psi MPB}}_{\text{Posted/Effective}}\varepsilon_{p^0} - \underbrace{\frac{\psi MPB}{p^0 - \psi MPB}}_{\text{Posted/Return to Shopping}}\left(\varepsilon_\psi + \varepsilon_{MPB}\right) \\
&= \Phi_s\varepsilon_{p^0} - \Phi_b\left(\varepsilon_\psi + \varepsilon_{MPB}\right)
\end{aligned} \tag{51}$$

Thus, we have

$$\left(1 + \frac{MPB(2-\alpha)\Phi_b}{\xi}\right)\varepsilon_\psi = \frac{1}{\xi}\left\{(1-\alpha)\varepsilon_m - (2-\alpha)MPB(\Phi_s\varepsilon_{p^0} - \Phi_b\varepsilon_{MPB}) + \varepsilon_{MPB}\right\} \tag{52}$$

Thus, the implication is as follows. First, the absolute size of shopping elasticity depends on the inverse of ξ, as in other standard macro-labor literature. Second, To have the income effect as in empirical findings, we need to have $\alpha > 1$. Also, to make buyers be more elastic with respect to the level of MPB, we need to have $\alpha > 2$ with large ξ where $\xi > MPB(2-\alpha)$. Numerically, under the calibration in this paper, it holds $\Phi_s\varepsilon_{p^0} - \Phi_b\varepsilon_{MPB} > 0$.

A.3 Computational Algorithm

To solve the model, I use following algorithm.

1. Solving the flexible wage model first. In this case, the state variables are the unemployment rate u_{t-1} and labor productivity y. When I solve it, I follow these steps.
   Step 1 Guess labor market tightness θ, employed and unemployed buyer's price search ψ_e and ψ_u, the net value of being employed $H = W - U$, the value of filling vacancies J, and desirable level of wage w for each state (u, y).
   Step 2 Solve the product market problem first as the backward induction. To solve the product market, we need to know the unemployment rate at the product market, i.e., u_t. Using guessed labor market tightness, we can evaluate it from each state u_{t-1}. Once we have the unemployment after the labor market matching, we can evaluate the measure of buyers and sellers in the product market.
   Step 3 Using evaluated measures of product market variables[43], guessed price search and wages, we can find implied the equilibrium quoted price distribution $G(p)$ and ex-ante expected revenues. In particular, since we know the equilibrium price distribution

[43] Measure of buyers is $b(u, y) = 1 + \psi_e + u_t(\psi_u - \psi_e)$ and measure of sellers is $1 - u_t$. And thus product market tightness σ, the probability that buyers can meet sellers $\nu(\sigma)$ and sellers can meet $\mu(\sigma)$.

which makes ex-ante revenues are identical for all supported price $p \in [\underline{p}, \bar{p}]$ such that

$$\begin{aligned} G(p,u,y) = &\Bigg(u(1+\psi_u)z \left\{ 1 - \left[1 - \frac{2\psi_u \nu(\sigma)}{1+\psi_u} \right] \frac{\bar{p}-c)}{(p-c)} \frac{p}{\bar{p}} \right\} \\ &+ (1-u)(1+\psi_e) \left\{ 1 - \left[1 - \frac{2\psi_e \nu(\sigma)}{1+\psi_e} \right] \frac{(\bar{p}-c)}{(p-c)} \frac{p}{\bar{p}} \right\} w \Bigg) \\ &\div 2\nu(\sigma) \left[zu\psi_u + (1-u)\psi_e w \right] \end{aligned} \tag{53}$$

where $G(\underline{p}) = 0$ and $G(\bar{p}) = 1$ for each state.

Step 4 Using $G(p)$, we can find implied optimal price search ψ_u and ψ_e. In order to do so, we need to compute the unconditional average price $p^0 = \int p dG(p)$ and the marginal price benefit $MPB = \int G(p)(1-G(p))dp$. Using implied p^0 and MPB, solve buyers' optimal price search problem

$$\psi = \underset{\psi}{\operatorname{argmax}}\, u(c, \psi) \tag{54}$$

subject to

$$\mathbb{E}[p|\psi]c = m, m : \text{income} \tag{55}$$

$$\mathbb{E}[p|\psi] = p^0 - \psi MPB \tag{56}$$

Because there is no closed solution, I find it numerically using the simplex method.

Step 5 Now, solve the labor market problem. Using implied product market variables, solve the Nash bargaining

$$w(u_{t-1}, y) = \underset{w}{\operatorname{argmax}}\, H(u_{t-1}, y)^{\gamma} J(u_{t-1}, y)^{1-\gamma} \tag{57}$$

Again, since there is no closed form solution, I find the maximizer w numerically.

Step 6 Using implied wages and product market variables, compute implied value functions H and J.

Step 7 Using updated J and free entry condition, compute the implied labor market tightness θ. That is,

$$\theta(u_{t-1}, y) = q^{-1} \left(\frac{\kappa}{J(u_{t-1}, y)} \right) \tag{58}$$

where q is the probability that firms can meet workers and κ is fixed cost of posting vacancies.

Step 8 Check the distances between guessed and implied labor market tightness θ, employed and unemployed buyer's price search ψ_e and ψ_u, the net value of being employed $H = W - U$, the value of filling vacancies J, and desirable level of wage w. If not converged, update all of them with speed of adjustment. At this stage, I'm using it with 0.6 (60% weight on implied results).

2. Once the flexible wage model is solved, we now solve the rigid wage model using results of flexible wage model. Logic is the same except wage determination.
   Step 1 Under the downward wage rigidity, we have one more state variable, which is w_{t-1}, the previous wage level. I construct the wage grid using Nash bargained wages in the flexible wage model. We can construct the wage grid as a support of $[(1-t)\min w^*, (1+t)\max w^*]$ where t is an arbitrary positive constant and w^* is the solution of Nash bargaining in the flexible wage model. To be simple, I set $t = 0$[44].
   Step 2 Guess for same variables as in the flexible wage model. Now, we have one additional state variable, w_{t-1}. For the first stage of guess, for all w_{t-1}, I import results from the flexible wage model for each u_{t-1} and y.
   Step 3 Solve the model in the same way except wage determination. Now wages are determined through two stages. At the first stage, workers and firms negotiate over wages given aggregates states (w_{t-1}, u_{t-1}, y_t). And if the bargained wages are too small compared to the previous wages w_{t-1}, wages are choosen by the convex combination of Nash bargained wages and previous wages. That is,

$$w_t(w_{t-1}, u_{t-1}, y_t) = \max\{\eta w_{t-1} + (1-\eta) w^*(w_{t-1}, u_{t-1}, y_t), w^*(w_{t-1}, u_{t-1}, y_t)\} \quad (59)$$

   where $w^*(w_{t-1}, u_{t-1}, y_t)$ is the solution of Nash bargaining and η is the degree of downward wage rigidity.

[44] Computation results are robust to values of t. Also, conceptually, wages are more likely binding to the downward rigid contract when wages are high. In this sense, we could consider finder grids on the high level of wages similar to the consumption-saving choice problem. Results are robust to for both uniform distance grid and selectively higher grid.

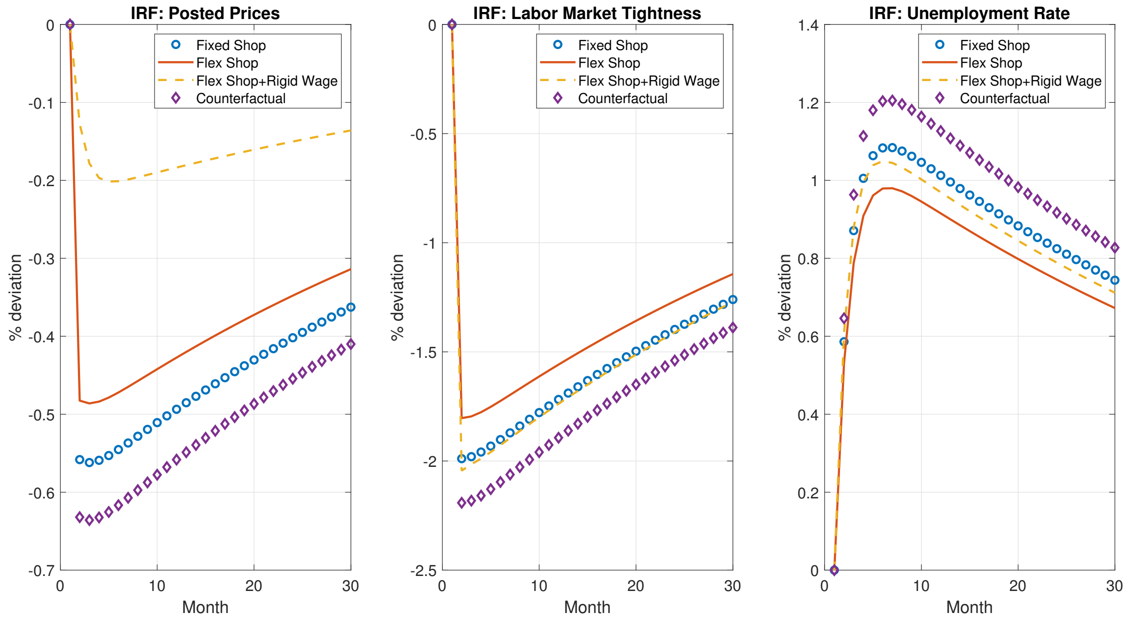


Figure 12: Impulse Response Functions: Negative 1% Shock

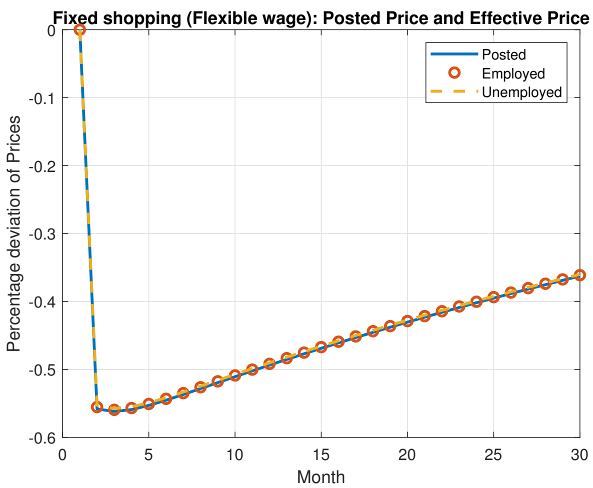


Figure 13: IRF in Flexible Wage - Posted Price, Effective Prices paid by Emp and Ump Buyers (Neg. 1% Shock)

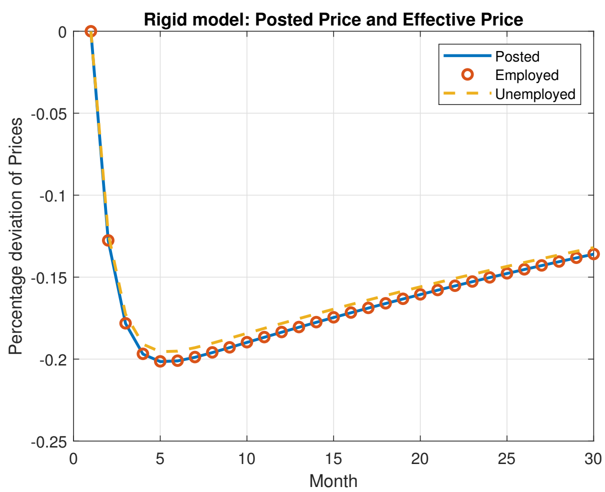


Figure 14: IRF in Rigid Wage - Posted Price, Effective Prices paid by Emp and Ump Buyers (Neg. 1% Shock)

A.4 Impulse Response Functions

This section includes various other impulse response functions.

B Data

B.1 Codes to Measure Shopping Time in the ATUS

According to Petrosky-Nadeau et al. (2016), I use following categories to measure the shopping time in the ATUS.

1. Shopping for consumer goods: Grocery shopping (t070101), Purchasing gas (t070102), Purchasing food (not groceries, t070103), Shopping except Grocery, Gas and Food (t070104), Waiting associated with shopping (t070105), Shopping, n.e.c (t070199), Comparison shopping (t070201), Researching purchases, n.e.c (t070299), Security procedures related to consumer purchases (t070301), Security procedures related to consumer purchases (t070301), Security procedures related to consumer purchases, n.e.c (t070399), and Consumer purchases, n.e.c (t079999)

2. Waiting associated with shopping: Waiting associated with purchasing childcare services (t080102), Waiting associated with banking/financial services (t080203), Waiting associated with legal services (t080302), Waiting associated with medical services (t080403), Waiting associated with personal care services (t080502), Waiting associated with purchasing/selling real estate (t080602), Waiting associated with veterinary (t080702), Waiting associated with using household services (t090104), Waiting associated with home main/repair/decoration/construction (t090202), Waiting associated with pet services (t090302), Waiting associated with using lawn/garden services (t090402), and Waiting associated with vehicle main or repair services (t090502), Waiting associated with arts & entertainment (t120504)

3. Traveling related to shopping (t18-07) : Travel related to grocery shopping (t180701) and Travel related to shopping except grocery shopping (t180782)

4. Travel related to using services (t18-08, t18-09 and t18-12): Travel related to using childcare services (t180801), Travel related to financial services and banking (t180802), Travel related to legal services (t180803), Travel related to medical services (t180804), Travel related to personal care services (t180805), Travel related to using real estate services (t180806), Travel related to using veterinary services (t180807), Travel related to using professional & personal care services, n.e.c (t180899), Travel related to using household services (t180901), Travel related to using home main/ repair/ decoration/ construction (t180902), Travel related to using pet services (t180903), Travel related to using lawn/garden services (t180904), Travel related to using vehicle main or repair

services (t180905), Travel related to using household services, n.e.c (t180999), and Travel related to using arts & entertainment (t181204)

B.2 Codes to Measure Home Production in the ATUS

According to Aguiar et al. (2013), I use following categories to measure the time spent on home production in the ATUS. I consider only the core home production in Aguiar et al. (2013). It includes 02-01, 02-02, 02-03 excluding 02-03-01, 02-07, 02-08, 02-09 excluding 02-09-03 and 02-09-04, 02-99, 18-02-01, 18-02-02, 18-02-03, 18-02-07, 18-02-08, 18-02-09, and 18-02-99.

Specifically, Interior cleaning (t020101), Laundry (t020102), Sewing, Repairing and Maintaining textiles (t020103), Storing interior hh items, including foods (t020104), Housework, n.e.c. (t020199), Food and drink preparation (t020201), Food presentation (t020202), Kitchen and food clean up (t020203), Food and drink preparation & Clean up, n.e.c. (t020299), Building and repairing furniture (t020302), Heating and cooling (t020303), Interior maintenance, repair & decoration, n.e.c., (t020399), Vehicle repair and maintenance by self (t020701), Vehicles, n.e.c. (t020799), Appliance, tool, and toy set-up, repair & maintenance by self (t020801), Appliance and tool, n.e.c. (t020899), Financial management (t020901), Household & personal mail & messages except e-mail (t020903), Home security (t020905), and Travel related to household activity (t180280)

B.3 ATUS: Aggregate Time-Series for a various categories

Figure 15 and Figure 16 represent the time spent on shopping for goods and services, for each year by each aggregate, employed, unemployed and not-working (NIL+unemployed) buyer. Figure 17 and Figure 18 represent the time spent on shopping for grocery, gas and food, for each year by each aggregate, employed, unemployed and not-working (NIL+unemployed) buyer. Figure 19 and Figure 20 represent the total shopping time by aggregate, male and female buyers. Lastly, Figure 19 and Figure 20 represent the total shopping time by employed male and female and not-working male and female buyers.

B.4 ATUS: Cross-State Variations: Additional analysis

I study alternative specifications and a various categories of the shopping time at the state level. Firstly, I consider the regression analysis when I take first differences to both shopping effort and unemployment rate at the state-level. The result is still consistent with the main result in the paper in the sense that unemployed buyer's shopping time is more cyclical than

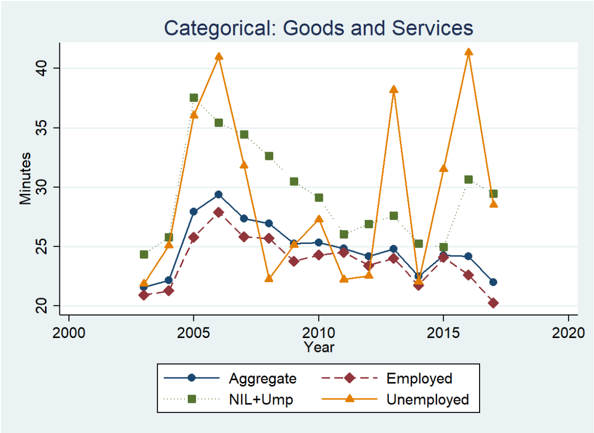


Figure 15: Goods and Services (Not Detrended): 2003 ∼ 2017

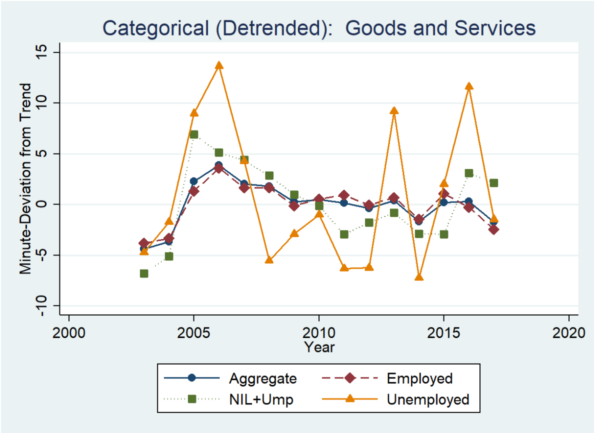


Figure 16: Goods and Services (Detrended): 2003 ∼ 2017

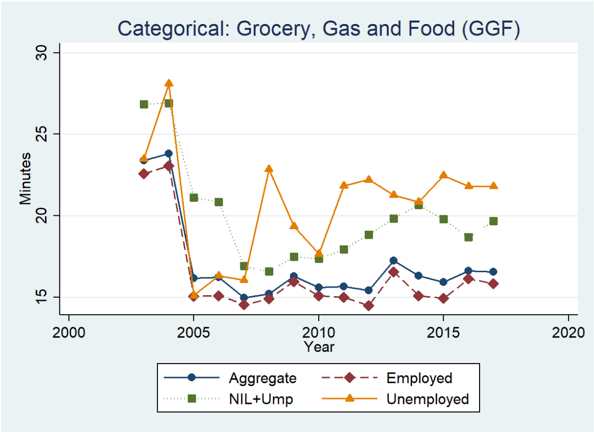


Figure 17: Grocery, Gas and Food (GGF, Not Detrended): 2003 ∼ 2017

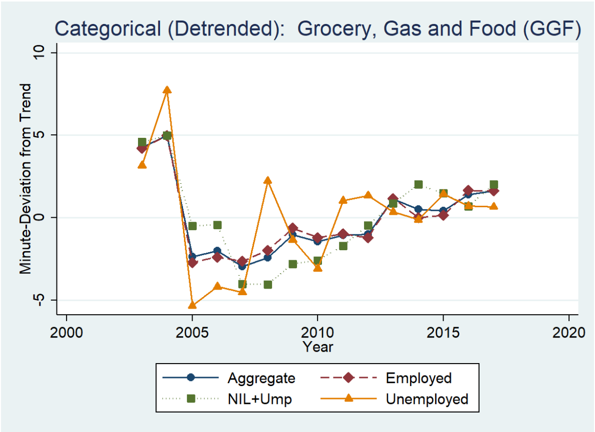


Figure 18: Grocery, Gas and Food (GGF, Detrended): 2003 ∼ 2017

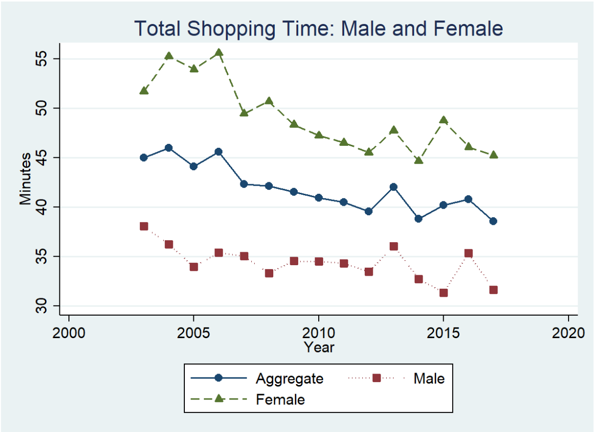


Figure 19: Total Shopping Time (Not Detrended): Male vs Female

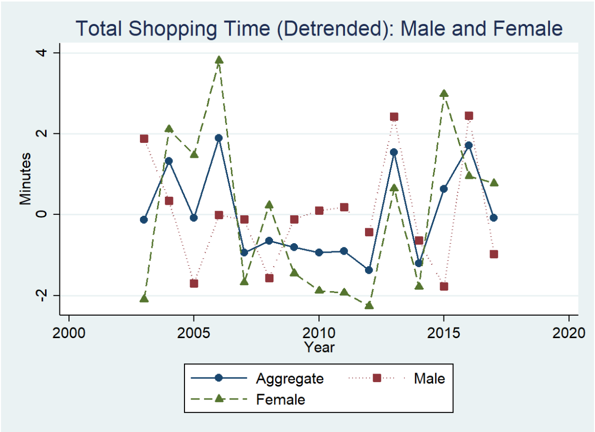


Figure 20: Total Shopping Time (Detrended): Male vs Female

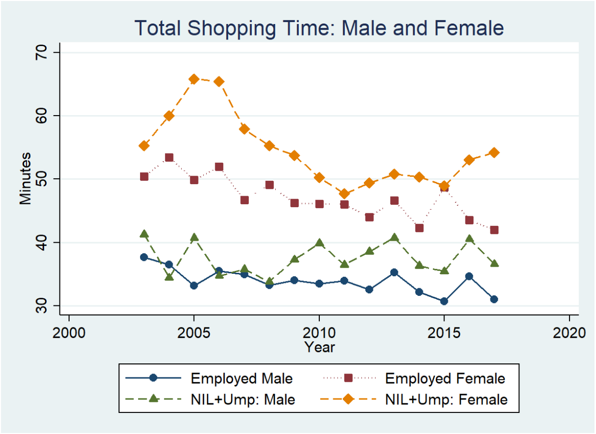


Figure 21: Total Shopping Time (Not Detrended): Employed Male vs Female

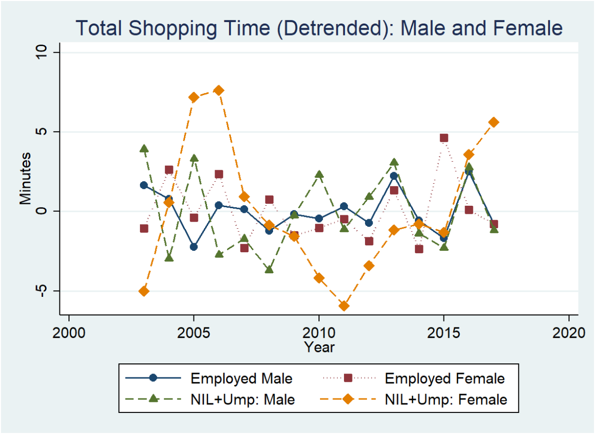


Figure 22: Total Shopping Time (Detrended): Employed Male vs Female

employed buyer's shopping time. Table 8 is the result of following regression:

$$\Delta \log(\text{Shopping})^c_{jst} = \beta^c_j \Delta \log u_{st} + \varepsilon^c_{st} \tag{60}$$

Another alternative specification is to consider detrended variables in the regression analysis. For this case, since I already consider the time trend in the base regression (40), this regression here is conceptually similar to it. Table 9 represents results of following regression:

$$\widetilde{\log(\text{Shopping})}^c_{jst} = \beta^c_j \widetilde{\log u}_{st} + \lambda^{\text{recession},c}_t + \varepsilon^c_{st} \tag{61}$$

where $\tilde{x} = \log x - \hat{x}$ where $\hat{x}$ is the fitted value of the regression $\log x = \delta \times \text{time} + e$. As expected, all results are almost the same with Table 7. For the remained part of this section, let consider the cyclical dynamics of the shopping in the cross-state variations for other categories, such as goods and services (GS) and grocery, gas and foods (GGF). Similar to the case of total shopping time in the benchmark case, I consider the regression with the base specification (40) for $c \in \{\text{GS,GGF}\}$.

Other Categories Table 10 shows the result for the time spent on shopping for general goods and services except GGF (GS) and Table 11 shows the result for GGF.

	(1)	(2)	(3)	(4)
	ΔAggregate	ΔEmployed	ΔUnemployed	ΔNot-Working
$\Delta\log u_{st}$	-0.00295	0.0000109	-0.0592**	-0.0514***
	(-1.00)	(0.00)	(-2.79)	(-7.59)
_cons	-0.0115***	-0.0138***	0.00880***	-0.00495***
	(-184.66)	(-187.17)	(19.62)	(-34.61)
State Fixed Effect	Yes	Yes	Yes	Yes
# of Obs	714	714	714	714

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: First Differenced. The shopping time here is the total shopping time, the sum of all categories. All state-level shopping time and unemployment rates are natural-logarithm variables. Shopping time in the regression (1) is the total shopping time by aggregate buyers. (2) is the total shopping time by employed buyers, (3) is by unemployed buyers and (4) is by not-working buyers. t-values are calculated with robust standard errors clustered at the standard level.

	(1)	(2)	(3)	(4)
	$\widetilde{\text{Aggregate}}$	$\widetilde{\text{Employed}}$	$\widetilde{\text{Unemployed}}$	$\widetilde{\text{Not-Working}}$
$\widetilde{\log u_{st}}$	-0.0356***	-0.0112***	-0.250***	-0.157***
	(-27.20)	(-12.35)	(-11.59)	(-20.21)
Recession	-0.0118***	-0.0116***	-0.0834***	-0.00484
	(-19.38)	(-41.93)	(-12.43)	(-1.83)
_cons	0.00157***	0.00155***	0.0111***	0.000645
	(19.38)	(41.93)	(12.43)	(1.83)
State Fixed Effect	Yes	Yes	Yes	Yes
# of Obs	714	714	714	714

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Time Detrended. $\tilde{x} = \log x - \hat{x}$ where $\hat{x}$ is the fitted value of the regression $\log x = \delta \times \text{time} + e$. The shopping time here is the total shopping time, the sum of all categories. Shopping time in the regression (1) is the total shopping time by aggregate buyers. (2) is the total shopping time by employed buyers, (3) is by unemployed buyers and (4) is by not-working buyers. t-values are calculated with robust standard errors clustered at the standard level

	(1)	(2)	(3)	(4)
	GS	GS by Emp	GS by Ump	GS by Not-Working
Trend	-0.00552***	-0.00548***	0.00883***	-0.00760***
	(-42.18)	(-54.53)	(4.67)	(-14.52)
$\log u_{st}$	-0.0412***	-0.00467	-0.462***	-0.208***
	(-6.88)	(-0.76)	(-9.11)	(-15.89)
Recession	0.0616***	0.0453***	-0.150***	0.142***
	(43.15)	(29.01)	(-12.35)	(9.72)
_cons	14.15***	14.14***	-15.90***	17.96***
	(53.41)	(69.65)	(-4.11)	(17.30)
State Fixed Effect	Yes	Yes	Yes	Yes
# of Obs.	765	765	742	765

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: The shopping time here is the time spent shopping on goods and services (GS), except grocery, gas and food (GGF). All state-level shopping time and unemployment rates are natural-logarithm variables. Shopping time in the regression (1) is the GS by aggregate buyers. (2) is the GS by employed buyers, (3) is by unemployed buyers and (4) is by not-working buyers. t-values are calculated with robust standard errors clustered at the standard level

	(1) GGF	(2) GGF	(3) GGF by Ump	(4) GGF by Not-Working
Trend	-0.0169***	-0.0171***	0.00718***	-0.0185***
	(-70.50)	(-60.60)	(3.69)	(-22.60)
logu_{st}	-0.0186*	-0.0121	0.0117	-0.0680***
	(-2.18)	(-1.38)	(0.62)	(-4.72)
Recession	-0.109***	-0.0811***	0.0138	-0.227***
	(-46.33)	(-37.29)	(0.56)	(-9.65)
_cons	36.72***	37.17***	-11.47**	39.90***
	(76.06)	(65.12)	(-2.95)	(24.08)
State Fixed Effect	Yes	Yes	Yes	Yes
# of Obs.	765	765	742	765

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: The shopping time here is the time spent shopping on grocery, gas and food (GGF). All state-level shopping time and unemployment rates are natural-logarithm variables. Shopping time in the regression (1) is the GGF by aggregate buyers. (2) is the GGF by employed buyers, (3) is by unemployed buyers and (4) is by not-working buyers. t-values are calculated with robust standard errors clustered at the standard level

	(1) Total	(2) GS	(3) GGF	(4) Waiting	(5) Traveling	(6) Researching
Employment	-0.217***	-0.225***	-0.415***	-0.0743	-0.0937***	-0.0507
	(-13.58)	(-10.09)	(-15.94)	(-1.01)	(-5.69)	(-0.14)
Age	0.00273**	0.00392***	0.00513***	0.00582	0.00452***	0.0124
	(3.22)	(3.41)	(3.90)	(1.46)	(5.21)	(0.78)
Gender	-0.157***	-0.142***	-0.368***	0.197**	-0.0353*	0.00160
	(-10.79)	(-7.18)	(-16.38)	(2.92)	(-2.40)	(0.01)
Married	0.0326	0.0399	-0.0234	-0.214	0.0419	-0.977
	(1.17)	(1.00)	(-0.57)	(-1.55)	(1.45)	(-0.99)
# of Children	0.00213	-0.00144	0.00447	0.0126	-0.0135*	0.0934
	(0.37)	(-0.18)	(0.52)	(0.48)	(-2.27)	(0.80)
Employed Spouse	-0.0249	-0.0283	-0.0940***	-0.0205	-0.0432*	-0.732*
	(-1.37)	(-1.13)	(-3.35)	(-0.24)	(-2.37)	(-2.03)
Race	-0.0247	-0.0232	-0.0723	-0.132	0.0505	0.641
	(-0.93)	(-0.67)	(-1.81)	(-1.10)	(1.95)	(1.59)
State & Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs	34901	28682	21226	1312	34186	95

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Employed vs Unemployed at the individual level. I take the natural logarithm for the shopping time in all categories. Employment, Gender, Married, Employed Spouse, and Race variables are dummy variables and each variable takes unity if the buyer is employed, male, married, has an employed spouse, and black respectively. I include state level and time dummies but I do not report their estimates.

B.5 ATUS: Individual Level Study

	(1) Total	(2) GS	(3) GGF	(4) Waiting	(5) Traveling	(6) Researching
Earnings	-0.297**	-0.189*	-0.635*	-0.583	-0.0926	0.0786
	(-3.25)	(-2.22)	(-2.25)	(-1.55)	(-1.67)	(0.04)
Age	0.00335***	0.00396**	0.00805***	0.00439	0.00470***	0.0374
	(3.29)	(2.88)	(5.10)	(0.90)	(4.56)	(1.49)
Gender	-0.119***	-0.114***	-0.337***	0.248**	-0.00365	-0.116
	(-6.77)	(-4.91)	(-10.70)	(2.98)	(-0.21)	(-0.36)
Married	0.0267	0.0111	0.00813	0.0267	0.0138	-0.814
	(0.81)	(0.24)	(0.17)	(0.16)	(0.42)	(-0.96)
# of Children	0.00230	0.00314	0.00795	-0.0198	-0.0134	0.243
	(0.32)	(0.32)	(0.73)	(-0.56)	(-1.81)	(1.49)
Employed Spouse	-0.0370	-0.0404	-0.117***	0.0252	-0.0447*	-0.779
	(-1.75)	(-1.40)	(-3.62)	(0.25)	(-2.09)	(-1.41)
Race	-0.0156	-0.00810	-0.0936*	-0.127	0.0517	0.877*
	(-0.50)	(-0.20)	(-2.02)	(-1.00)	(1.70)	(2.19)
State & Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	24734	20527	15074	870	24206	71

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Income Effect - Earnings. I use weekly earnings at all jobs. I take natural logarithms to the shopping time for all categories and earnings. This is the conditional sample on working buyers. Gender, Married, Employed Spouse, and Race variables are dummy variables and each variable takes unity if the buyer is employed, male, married, has an employed spouse, and black respectively. I include state level and time dummies but I do not report their estimates.

	(1) Total	(2) GS	(3) GGF	(4) Waiting	(5) Traveling	(6) Researching
Wage	-0.0158	0.0196	-0.141***	-0.0149	0.0350	1.627
	(-0.73)	(0.66)	(-4.04)	(-0.14)	(1.59)	(.)
Age	0.00324*	0.00409*	0.00889***	0.00910	0.00306*	0.0472
	(2.27)	(2.05)	(3.98)	(1.42)	(2.10)	(.)
Gender	-0.140***	-0.152***	-0.364***	0.301*	-0.0260	-3.240
	(-5.98)	(-4.70)	(-9.97)	(2.34)	(-1.09)	(.)
Married	0.0445	0.0309	0.0129	-0.130	0.0239	0
	(1.03)	(0.51)	(0.21)	(-0.68)	(0.57)	(.)
# of Children	0.00327	0.00298	0.00789	-0.0287	-0.0134	0.183
	(0.33)	(0.22)	(0.51)	(-0.64)	(-1.34)	(.)
Employed Spouse	-0.0370	-0.0596	-0.142**	0.0616	-0.0658*	3.290
	(-1.21)	(-1.44)	(-3.07)	(0.47)	(-2.17)	(.)
Race	-0.0799	-0.0826	-0.147*	0.0113	0.0345	-0.0512
	(-1.89)	(-1.50)	(-2.30)	(0.06)	(0.87)	(.)
State & Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	11998	9868	7437	402	11755	27

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Income Effect - Wage. Wage is calculated by weekly earnings/weekly hours work. I take natural logarithms to the shopping time for all categories and wages. This is the conditional sample on working buyers. Gender, Married, Employed Spouse, and Race variables are dummy variables and each variable takes unity if the buyer is employed, male, married, has an employed spouse, and black respectively. I include state level and time dummies but I do not report their estimates.

	(1) Total	(2) GS	(3) GGF	(4) Waiting	(5) Traveling	(6) Researching
Wage	-0.00987	0.0232	-0.120***	-0.0146	0.0362	-0.475
	(-0.46)	(0.79)	(-3.51)	(-0.13)	(1.64)	(.)
Home Prod.	0.000781***	0.000607***	0.00233***	0.0000564	0.000160	0.0170
	(7.27)	(4.18)	(13.10)	(0.10)	(1.60)	(.)
Age	0.00259	0.00355	0.00683**	0.00908	0.00293*	-0.650
	(1.81)	(1.78)	(3.12)	(1.41)	(2.00)	(.)
Gender	-0.0963***	-0.121***	-0.228***	0.304*	-0.0169	4.068
	(-3.97)	(-3.66)	(-6.06)	(2.32)	(-0.69)	(.)
Married	0.0435	0.0293	0.0116	-0.130	0.0238	0
	(1.02)	(0.48)	(0.20)	(-0.68)	(0.56)	(.)
# of Children	-0.00169	-0.000562	-0.00347	-0.0287	-0.0144	-4.062
	(-0.17)	(-0.04)	(-0.23)	(-0.64)	(-1.44)	(.)
Employed Spouse	-0.0439	-0.0653	-0.162***	0.0616	-0.0671*	-4.705
	(-1.44)	(-1.58)	(-3.57)	(0.47)	(-2.21)	(.)
Race	-0.0701	-0.0766	-0.113	0.0117	0.0365	-2.640
	(-1.66)	(-1.40)	(-1.78)	(0.06)	(0.92)	(.)
State & Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	11998	9868	7437	402	11755	27

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Income Effect - Wage with home production. Wage is calculated by weekly earnings/weekly hours work. I take natural logarithms to the shopping time for all categories and wages. This is the conditional sample on working buyers. Gender, Married, Employed Spouse, and Race variables are dummy variables and each variable takes unity if the buyer is employed, male, married, has an employed spouse, and black respectively. I include state level and time dummies but I do not report their estimates. See Appendix B.2 about the ATUS codes to measure the core home production in detail.

	(1) Total	(2) GS	(3) GGF	(4) Waiting	(5) Traveling	(6) Researching
Earnings	-0.215**	-0.105	-0.391	-0.527	-0.0523	-0.0667
	(-2.59)	(-1.31)	(-1.75)	(-1.31)	(-0.88)	(-0.03)
Hours Work	-0.000623	-0.00116	-0.00238*	-0.00132	-0.000694	-0.00364
	(-0.92)	(-1.36)	(-2.18)	(-0.49)	(-1.06)	(-0.24)
Home Prod	0.000960***	0.000781***	0.00280***	-0.000240	0.000227**	-0.000578
	(12.24)	(7.37)	(22.38)	(-0.62)	(3.07)	(-0.22)
Age	0.00253*	0.00326*	0.00552***	0.00435	0.00449***	0.0348
	(2.50)	(2.37)	(3.61)	(0.89)	(4.35)	(1.28)
Gender	-0.0706***	-0.0744**	-0.185***	0.246**	0.0106	-0.0986
	(-3.96)	(-3.13)	(-6.59)	(2.89)	(0.59)	(-0.27)
Married	0.0242	0.00818	0.00314	0.0256	0.0131	-0.786
	(0.74)	(0.18)	(0.07)	(0.16)	(0.39)	(-0.88)
# of Children	-0.00444	-0.00247	-0.00993	-0.0201	-0.0152*	0.253
	(-0.62)	(-0.25)	(-0.94)	(-0.57)	(-2.06)	(1.38)
Employed Spouse	-0.0450*	-0.0481	-0.137***	0.0278	-0.0469*	-0.837
	(-2.12)	(-1.67)	(-4.35)	(0.27)	(-2.19)	(-1.40)
Race	-0.00577	-0.000800	-0.0612	-0.127	0.0542	0.789
	(-0.18)	(-0.02)	(-1.34)	(-0.99)	(1.78)	(1.62)
State & Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	24734	20527	15074	870	24206	71

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Income Effect - Earnings with home production and hours work. I use weekly earnings at all jobs. I take natural logarithms to the shopping time for all categories and wages. This is the conditional sample on working buyers. Gender, Married, Employed Spouse, and Race variables are dummy variables and each variable takes unity if the buyer is employed, male, married, has an employed spouse, and black respectively. I include state level and time dummies but I do not report their estimates. See Appendix B.2 about the ATUS codes to measure the core home production in detail.

	(1) CV	(2) Price Dispersion
Δ Unemployment	-0.302**	-0.0901***
	(-3.00)	(-3.52)
Trend	-0.00236***	-0.000206**
	(-23.01)	(-3.43)
Recession	-0.0361***	-0.00468
	(-3.90)	(-1.16)
λ_{2007}	-0.110***	0.0276***
	(-8.56)	(5.61)
λ_{2010}	0.0375**	0.0153**
	(3.18)	(2.83)
State Fixed Effect	Yes	Yes
# of Obs.	7595	7595

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Cyclical Behavior of Price Dispersion and CV: The regression captures the state-level fixed effect. I take natural logarithms on the state-level unemployment rate, CV and price dispersion. The unemployment rate is first-differenced. Recession is a dummy variable to capture the financial crisis from December 2007 to June 2009. λ_{2007} and λ_{2010} are dummy variables to capture structural breaks.

B.6 Tables: Analysis in the KNCPD

	(1) CV	(2) Total Shopping
Total Shopping	-0.599***	
	(-16.99)	
Trend	-0.00171***	0.00849***
	(-22.93)	(22.58)
ΔUnemployment	-0.550***	
	(-8.16)	
Recession	-0.206***	
	(-25.78)	
CV		3.713***
		(18.38)
ΔEarnings		-1.053
		(-0.70)
λ_{2007}		0.531***
		(17.09)
# of Obs.	7595	7595

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Cyclical Behavior of CV in the 2SLS with Total Shopping Intensity: The simultaneous equation model captures the state-level fixed effect. I take natural logarithms on the state-level unemployment rate, the state-level earnings, CV and total shopping intensities. The unemployment rate and earnings are first-differenced. Recession is a dummy variable to capture the financial crisis from December 2007 to June 2009. λ_{2007} us a dummy variable to capture structural breaks.

	(1) CV	(2) Extensive
Extensive	-0.935***	
	(-15.40)	
Trend	-0.00155***	0.00724***
	(-16.94)	(23.20)
ΔUnemployment	-0.657***	
	(-8.70)	
Recession	-0.255***	
	(-22.06)	
CV		3.157***
		(18.82)
ΔEarnings		-0.532
		(-0.42)
λ_{2007}		0.417***
		(16.16)
# of Obs.	7595	7595

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Cyclical Behavior of CV in the 2SLS with Extensive Shopping: The simultaneous equation model captures the state-level fixed effect. I take natural logarithms on the state-level unemployment rate, the state-level earnings, CV and extensive shopping intensities. The unemployment rate and earnings are first-differenced. Recession is a dummy variable to capture the financial crisis from December 2007 to June 2009. λ_{2007} us a dummy variable to capture structural breaks.

	(1) CV	(2) Intensive
Intensive	-1.785***	
	(-11.96)	
Trend	-0.00182***	0.00139***
	(-18.70)	(12.60)
ΔUnemployment	-0.290**	
	(-3.02)	
Recession	-0.132***	
	(-18.22)	
CV		0.582***
		(9.84)
ΔEarnings		-0.444
		(-1.01)
λ_{2007}		0.112***
		(12.35)
# of Obs.	7595	7595

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Cyclical Behavior of CV in the 2SLS with Intensive Shopping: The simultaneous equation model captures the state-level fixed effect. I take natural logarithms on the state-level unemployment rate, the state-level earnings, CV and intensive shopping intensities. The unemployment rate and earnings are first-differenced. Recession is a dummy variable to capture the financial crisis from December 2007 to June 2009. λ_{2007} us a dummy variable to capture structural breaks.

	(1) Total Shopping	(2) Extensive Margin	(3) Intensive Margin
Recession	-0.0034414***	-0.1318934***	0.0767142***
	(-22.19)	(-60.15)	(39.21)
Price Dispersion	7.746897***	15.07506***	-7.328167***
	(17.67)	(39.15)	(-21.95)
Unemployment	0.0090053*	-0.0124569***	0.0214621***
	(1.90)	(-2.92)	(5.72)
# of Product	0.4649599***	0.2240378***	0.2409221***
	(319.96)	(197.92)	(226.09)
Log$Q$	.0660672***	0.027364***	0.0387032***
	(67.44)	(33.24)	(52.08)
Size of Household	-.0141969***	-0.0077027***	-0.0064942***
	(-9.95)	(-6.02)	(-5.91)
Trend	-.0034414***	-0.003251***	-0.0001904*
	(-22.19)	(-26.32)	(-1.87)
Age	0.0143588***	0.0071127***	0.0072461***
	(9.25)	(5.97)	(7.60)
Income	-0.0045278***	-0.0011743***	-0.0033534***
	(-11.41)	(-3.43)	(-11.08)
HH Fixed Effect	Yes	Yes	Yes
State Dummy	Yes	Yes	Yes
# of Obs.	2,548,212	2,548,212	2,548,212

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Dispersion, Recession and Shopping: I take natural logarithms to the total shopping, extensive shopping and intensive shopping intensities, the state-level unemployment rate (Unemployment), the price dispersion, # of Product, the cost of bundle (45) (Log$Q$). To avoid endogeneity problem, I use IV with previous period unemployment rate, the inflation rate by the consumer price index (CPI), and Log$Q$ at the state level. Income is categorical data for each household's annual income. I do not report results of estimates for state dummies, time dummies to handle structural breaks and other control variables such as type of residence and education. They are available upon request.

	(1) HH Price	(2) HH Price	(3) HH Price
Recession	-0.0057301***	-0.0060851***	-0.0054972***
	(-6.58)	(-8.96)	(-8.68)
Total Shopping	-0.006587***	.	.
	(-3.51)	.	.
Recession×Total	0.0090053	.	.
	(1.90)	.	.
Extensive Shopping	.	-0.0109436***	.
	.	(-5.10)	.
Recession×Extensive	.	0.0001816	.
	.	(0.33)	.
Intensive Shopping	.	.	-0.0055744***
	.	.	(-8.96)
Recession×Intensive	.	.	-0.00034
	.	.	(-0.65)
Income	0.0003238***	.000334***	0.0003234***
	(4.44)	(4.57)	(4.43)
HH Fixed Effect	Yes	Yes	Yes
State Dummy	Yes	Yes	Yes
# of Obs.	2,548,212	2,548,212	2,548,212

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22: Return to Shopping: I take natural logarithms to the household price index (HH Price), the total shopping, extensive shopping and intensive shopping intensities, the state-level unemployment rate (Unemployment), the price dispersion, # of Product, the cost of bundle (45) (Log$Q$). To avoid endogeneity problem, I use IV with previous period unemployment rate, the inflation rate by the consumer price index (CPI), and Log$Q$ at the state level. I do not report results of estimates for state dummies, time dummies to handle structural breaks and other minor control variables. They are available upon request.