

Demand Shocks as Technology Shocks*

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Abstract

We provide a macroeconomic theory where *demand* for goods has a productive role. A search friction prevents perfect matching between producers and potential customers. Larger demand induces more search, which in turn increases GDP. We embed the product-market friction in a standard neoclassical model and estimate it using Bayesian techniques. Business cycles are driven by preference shocks, true technology shocks, and investment-specific shocks. Preference shocks account for a large share of the fluctuations in consumption, GDP, and the Solow residual. The dynamics of the model's implied search effort matches the empirical fall in U.S. shopping time during the Great Recession.

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1 Introduction

In the standard neoclassical model, output is a function of inputs such as labor and capital. There is no explicit role for demand because potential consumers are always available and Walrasian prices adjust so that all produced goods become used. In reality, customers and producers must meet in order for the produced good to be consumed, so value added depends on how well they are matched. As an example, consider a restaurant. According to the neoclassical view, the value added of a restaurant should be a function of its inputs (employees, tables, etc.), irrespective of the number of patrons and how hungry they are. Moreover, the restaurant owner would set prices so that all tables were in use. However, actual production takes place only when customers show up. The more customers demand the restaurant's meals, the larger the value added will be. The idea that the demand for goods plays a direct role extends to many forms of production: dentists need patients, car dealers need shoppers, all producers need buyers.

This paper provides a theory where search for goods—which we with some abuse of terminology refer to as *demand*—has a productive role. The starting point is that customers search for producers, and a standard matching friction prevents Walrasian market clearing, in the sense that all potential productive capacity necessarily translates into actual value added.¹

Allowing an explicit role for demand has implications for business cycle analysis, especially for our understanding of the driving factors for business cycles. In our model, changes in search effort affect output even if conventional inputs, and the intensity with which they are used, remain constant. A key purpose of this paper is to investigate how our notion of demand shocks works in terms of driving the Solow residual and to quantify how important this mechanism is for aggregate fluctuations, compared to more standard shocks in the business cycle literature.

To clarify our main argument, we start by analyzing a simple endowment economy with search for goods and show that preference shocks generate fluctuations in measured TFP in this economy. Technically, we resolve the search friction by building on the competitive search model (Moen (1997)). To find goods for consumption, consumers have to exert costly search effort. Firms post prices and customers trade off good prices versus congestion when searching for goods. In equilibrium, firms charge higher prices in markets where they have a lower chance of realizing a sale, and it is easier for customers to find goods. Search effort is determined by a familiar condition: the marginal rate of substitution between search costs and consumption (i.e., the ratio of marginal disutility of search to the marginal utility of consumption) must equal the marginal transformation of search, i.e., the marginal increase in the probability

¹The National Income and Product Accounts (NIPA) measures consumption expenditure as value added only when goods are purchased by consumers. Indeed, a lost opportunity, such as an empty seat on a bus, is not value added. In the neoclassical model the true value of consumption—in money units—is the price times the quantity of consumption goods, consistent with the way value added is measured in NIPA. Note, however, that in the presence of a goods market search friction, a notion of value added that captures the benefits for the consumer would be different because obtaining goods requires a search cost. Therefore, price times quantity will underestimate such notion of value added.

that a match will occur when search effort is increased marginally.

We then embed the search friction for consumption goods in an otherwise standard stochastic neoclassical growth model. To study the role of shocks to consumption demand—modeled as shopping effort preference shocks—we allow for the possibility that business cycles can also be driven by other shocks that are standard in the business cycle literature. In particular, we consider shocks that affect the marginal rate of substitution (MRS) between consumption and leisure, a standard economy-wide technology shock, and an investment-specific productivity shock (see e.g., [Justiniano et al. \(2010\)](#) and references therein).

Ceteris paribus, a preference shock that increases shopping effort will increase both consumption and the Solow residual. Firms respond in a similar way to a preference shock and to a true technology shock. Thus, if one ignores changes in the search effort, consumption demand appears as if it were a positive externality in the economy. This mechanism reverses the direction of causation relative to the neoclassical model: there, a positive true technology shock would increase TFP and, in turn, consumption. Interestingly, aggregate data for the United States suggest that it is factors influencing consumption that drives TFP, rather than TFP driving consumption. In particular, a simple Granger test reveals that aggregate consumption turns out to Granger cause TFP, while TFP does not Granger cause aggregate consumption.²

The central mechanism of our model is that fluctuations in shopping effort are manifested in the measured TFP in the consumption sector. One way to verify that this mechanism is reasonable is to consider the empirical relationship between TFP in consumption production and some measure of shopping effort. Using data on shopping time from the American Time Use Survey (ATUS) as a stand-in for search effort, we find that shopping time and TFP in consumption are strongly positively related, with a correlation coefficient of 0.74.³

The model is estimated using Bayesian estimation techniques targeting time series for output, labor productivity, investment, and the relative price of investment goods. This allows us to quantify the contribution of each shock to the variance of aggregate variables. The Bayesian estimation chooses shocks to maximize the probability of observing the realized aggregate time series. One of our main findings is that it is necessary to attribute a large role to demand shocks in order to match the data: preference shock to shopping account for about half the variance of the Solow residual, 69 percent of the variance of consumption, and 29 percent of the variance of output. Moreover, the preference shock

²The Granger test was done with HP-filtered quarterly U.S. data, Q1:1967 to Q4:2013, with the Solow residual calculated by assuming a Cobb-Douglas production function with a labor share of $2/3$. The p-value of TFP causing consumption is 0.34, while the p-value for consumption causing TFP is 0.002.

³TFP in consumption production is constructed using the approach proposed by [Herrendorf et al. \(2013\)](#), which involves using the input-output matrix and sectoral data on inputs and value added to impute aggregate inputs to consumption production. Data on shopping time is from ATUS from 2003 to 2014 (see Section 5.2.1 for details). Both series are logged and detrended with a linear trend. Note also that the correlation between TFP and shopping time is very similar when measuring TFP as the standard Solow residual using annual aggregate data from NIPA.

to shopping accounts for 42 percent of the variance of the relative price of investment goods, which is substantially larger than the role of the investment-specific productivity shock for this variable. Thus, what may appear as technology shocks from the perspective of a standard neoclassical growth model do—according to our estimated model—to a large extent reflect fluctuations in resource utilization arising from consumers varying their shopping efforts for goods.

Our benchmark model features just-in-time production in line with the restaurant example above. We pursue two important extensions to this framework in order to show that our findings are robust. First, note that if firms could store produced goods as inventories, then demand shocks might—*ceteris paribus*—be expected to matter less for business cycles. However, one countervailing force is that households may also store these goods. To address this issue, we extend the baseline model to incorporate storable goods in the form of firm inventories and a stock of consumer durables. Our main results hold up: demand shocks continue to be a major driving force for consumption, TFP, and GDP, even when goods can be stored.⁴ Moreover, our model replicates the empirical facts that purchases of durables are much more volatile than services and non-durable consumption goods and that the ratio of inventories-to-sales is countercyclical. These findings hinge on the assumption that goods can be stored by both households and firms.

The second extension pertains to the capacity utilization of capital. Our exercise documenting how preference shocks can influence aggregate measured productivity is related to the well-known fact that any mismeasurement of factor inputs will manifest itself as movements in the Solow residual. Indeed, in quantitative business cycle analysis, it is standard to allow for varying capacity utilization of capital and labor.⁵ For example, [Wen \(2004\)](#) and [Nakajima \(2005\)](#) argue that with variable capacity utilization, preference shocks that change the desired timing of consumption will cause changes in the utilization of input factors and, hence, generate fluctuations and cause changes in the measured Solow residual. This begs the question of whether the significant role our estimation assigns to demand shocks through shopping utility preference shocks is simply a stand-in for varying capacity utilization. To address this issue, we extend our benchmark production model to allow for variable capacity utilization of capital along the lines of [King and Rebelo \(1999\)](#). We find that the quantitative role of the shopping preference shocks is robust to extending our model to allow for varying capacity utilization of capital in the sense that the demand shocks we consider continue to account for a significant share of the aggregate fluctuations.⁶ Thus, we conclude that the mechanism for generating endogenous fluctuations in the variable capacity

⁴When firms can store consumer durables, demand shocks account for one third of the variance of the Solow residual, half of the variance of consumption, and 20 percent of the variance of output.

⁵For example, [Greenwood et al. \(1988\)](#), [Kydland and Prescott \(1988\)](#), [Bils and Cho \(1994\)](#), [Basu \(1996\)](#), [King and Rebelo \(1999\)](#), [Licandro and Puch \(2000\)](#), and [Francis and Ramey \(2005\)](#) study variable capital utilization, and [Burnside et al. \(1993\)](#) introduce variable worker utilization in the form of labor hoarding during periods of low aggregate activity. In periods during which productivity and/or profits are high, firms will use the input factors more intensively, causing movements in the Solow residual that do not reflect true technology shocks.

⁶In the presence of variable capacity utilization we find that demand shocks account for half of the variance of the Solow residual, about two thirds of the variance of consumption, and 21 percent of the variance of output.

utilization literature is fundamentally different from that of the search-based theory we explore in this paper.

Our theory of matching frictions in product markets has far-reaching implications over and above the novel mechanism for how preference shocks generate productivity movements and propagate to the aggregate economy. In particular, our model provides a new theory of the relative prices of investment and consumption goods that is not based exclusively on exogenous technology shocks.⁷ The model also embeds a theory of endogenous capacity utilization, based on lost goods and omitted factor inputs where the notion of utilization is the share of potential goods that are found. This is different from the earlier capacity utilization literature, where inputs are not being used at full capacity. We also provide an efficiency result: in our competitive search model where consumers search for firms and productions is endogenous, the equilibrium requires indexing markets not only by price and market tightness but also by the quantity of the good traded. Finally, our model provides a mechanism through which movements in search intensity affects asset prices.

Summing up, we see our paper as an implementation of Keynes' central idea that shocks to demand can give rise to business cycle fluctuations. This is done by extending a standard neoclassical framework with a search friction for goods. The role for demand is intrinsic to the process of production and is not arbitrarily imposed: markets clear, and no agent has incentives to deviate. There is a long tradition of attributing a role for demand in business cycle analysis, starting with Keynes' seminal contributions. However, in none of the earlier approaches has demand had a direct productive role.⁸ We pursue neither the fixed-price tradition of the New Keynesian literature nor the coordination-problem tradition that sees a recession as a bad outcome within environments susceptible to multiple equilibria. Instead, we follow a tradition where a fall in demand generates a recession via infra-utilization of productive capacity.

Our paper is also related to [Petrosky-Nadeau and Wasmer \(2015\)](#), which is developed independently from our paper. They also model costly search for goods in final goods markets although their focus is on how this search interacts with search in the labor market and influences the business cycle properties of the model. In particular, they do not focus on aggregate demand effects. [Rudanko and Gourio \(2014\)](#) study a business cycle model with a search friction in the market for consumption goods. Firms form long-lasting relationships with customers, and the authors focus on the role of customers as capital. Our contribution is also related to several papers emphasizing the effects of search frictions in shaping TFP ([Alessandria \(2005\)](#), [Faig and Jerez \(2005\)](#), and [Lagos \(2006\)](#)), although none of these focus on business

⁷See, for example, [Greenwood et al. \(1997\)](#), [Krusell et al. \(2000\)](#) and [Fisher \(2006\)](#) for papers that rely on exogenous technological shocks to derive changes in the relative price of investment.

⁸[Michaillat and Saez \(2015\)](#) also study a model where aggregate demand can increase output and employment through a search friction in product markets. Their model relies on predetermined (i.e., exogenous) prices and wages as their equilibrium abstracts from a mechanism that can determine search intensity. Moreover, their model is static and the equilibrium is inefficient. In contrast, our dynamic model is embedded in a standard business cycle framework, it assumes flexible prices, and poses a theory of determination of search effort that yields a unique and efficient equilibrium as in [Moen \(1997\)](#).

cycles.

Some papers examine, as we do, how demand changes affect productivity and capacity utilization, although through very different mechanisms. In [Fagnart et al. \(1999\)](#), monopolistic firms with putty-clay technology are subject to idiosyncratic demand shocks, which causes fluctuations in capacity utilization. In [Floetotto and Jaimovich \(2008\)](#), changes in the number of firms cause changes in markups and, hence, changes in the measured Solow residual. [Swanson \(2006\)](#) shows that government expenditure shocks can increase aggregate output, consumption, and investment in a model with heterogeneous sectors. Finally, a number of papers build directly on our approach of consumption demand shocks in models with a search friction in product markets, including [Huo and Ríos-Rull \(2013\)](#), [Duras \(2015, 2016\)](#), and [Bai and Ríos-Rull \(2015\)](#).

The paper is organized as follows. Section 2 lays out the main mechanism in a simple endowment economy where we show how preference shocks that increases demand are partially accommodated by an increase in productivity via more search. The full production economy is presented in Section 3. We then map the model to data in Section 4. In Section 5 we estimate the model and document that movements in the shopping effort implied by the model is consistent with dynamics of empirical shopping time in the U.S. since 2003. In Section 6 we extend the model to allow for varying capacity utilization of capital, as well as storable goods and firm inventories. Section 7 concludes. Appendices A-G provide proofs, computational and data details, and some additional tables and figures.

2 Competitive search for goods in an endowment model

We start by illustrating the mechanism of the model in an endowment model with competitive search for goods. We show that search affects aggregate output and TFP in a way that can be interpreted as being due to a technology shock. In particular, a shift in preferences can influence aggregate consumption.

Consider a static economy where a measure one of identical households have preferences $u(c, d)$ over consumption c and shopping effort d . There is a continuum of suppliers with measure $T = 1$. The suppliers are owned by the representative household. Each supplier is endowed with Z pieces of the consumption good. A standard search friction makes it difficult for consumers to find suppliers and the household makes search effort $d \in [0, 1]$ to overcome this friction.

Following [Moen \(1997\)](#), we assume a competitive search protocol where households search in markets indexed by price and market tightness.⁹ The number of matches are given by the matching function $M(D, T) \rightarrow [0, T]$. M is increasing and strictly concave in both arguments and is constant returns to scale. Moreover, M satisfies the Inada conditions. Market tightness q is defined as shopping effort per supplier, $q = D/T$, where D is shopping effort and T is the measure of suppliers in the specific market.

⁹Here, shoppers are searching for suppliers. In related work ([Duras \(2015, 2016\)](#)) matches occur between household search units and goods. There, more goods per supplier would reduce the tightness in the market.

The rate at which shoppers finds suppliers is then $M/D \equiv \Psi_d(q)$ and the probability that a supplier is matched is $M/T \equiv \Psi_T(q) = q \cdot \Psi_d(q)$. Once a match is formed, goods are traded at the posted price p per unit. The real quantity of consumption goods purchased by the household is $c = d\Psi_d(q)Z$.

Consider first the problem of a household who has an endowment y and who shops at a market offering a pair (\hat{p}, \hat{q}) . The budget constraint for this household is then given by

$$y \geq \hat{p} d\Psi_d(\hat{q})Z. \quad (1)$$

Using the budget constraint (1), search effort, d can be expressed as $d = y/[\hat{p}\Psi_d(\hat{q})Z]$. Moreover, given expenditure y and price \hat{p} , the the real consumption purchased is $c = y/\hat{p}$ in equilibrium.¹⁰

Let $\hat{V}(y, \hat{p}, \hat{q})$ denote the indirect utility for this household. Given the expressions for c and d , \hat{V} can be defined as

$$\hat{V}(y, \hat{p}, \hat{q}) \equiv u\left(\frac{y}{\hat{p}}, \frac{y}{\hat{p}\Psi_d(\hat{q})Z}\right). \quad (2)$$

Let $V(y)$ be the indirect utility for the household once it has incorporated the optimal market choice. V is determined by the best market; $V(y) = \max_{(p,q) \in \Phi} \hat{V}(y, p, q)$, where Φ is the set of available markets in equilibrium, yet to be determined.

Consider now the problem for the suppliers. Each supplier offers a market bundle (\hat{p}, \hat{q}) . To attract shoppers, it must offer bundles no worse than the most attractive one available to shoppers. Let Y denote the endowment of the representative household. The firm's objective is to maximize profits, $\max\{\hat{p}\Psi_T(\hat{q})Z\}$, subject to the participation constraint for shoppers, i.e., subject to (\hat{p}, \hat{q}) satisfying

$$\hat{V}(Y, \hat{p}, \hat{q}) \geq V(Y). \quad (3)$$

The solution to the firm's problem is characterized by the first-order condition

$$-\frac{u_d}{u_c} = Z \frac{\partial \Psi_T(q)}{\partial q}, \quad (4)$$

where u_c and u_d are marginal utilities.¹¹

A *competitive search equilibrium* is defined by indirect utility functions (V, \hat{V}) , individual decision rules (c, d) , aggregate allocations (D, C, Y) , and a set of markets $\Phi = \{(p_i, q_i)\}_{i \in I}$ so that (i) the individual decision rules and value functions solve the household's problems of choosing the best market and maximizing u subject to equation (1); (ii) for every active market $i \in I$, the price and market tightness

¹⁰We consider economies where the disutility of search effort is sufficiently low that the entire budget is spent in equilibrium.

¹¹To see this, take first-order conditions w.r.t. \hat{p} and \hat{q} in the constrained supplier problem and exploit that $\Psi_T(q) = q \cdot \Psi_d(q)$. See Appendix A for details.

pair $(p_i, q_i) \in \Phi$ satisfies the firms' first-order condition (4); (iii) the household endowment Y equals the aggregate profits of firms, and (iv) individual decisions and market tightness are consistent with aggregate allocations.

For convenience, we let the consumption good be the numéraire good. The competitive search equilibrium and its efficiency properties can be characterized by the following proposition.

Proposition 1. *There exists a unique competitive search equilibrium with a unique active market featuring $p = 1$ and $q = D$. Equilibrium allocations are given by $C = Y = Z\Psi_T(D)$, where the aggregate search D is determined by the functional equation*

$$-\frac{u_d(Z\Psi_T(D), D)}{u_c(Z\Psi_T(D), D)} = Z\frac{\partial\Psi_T(D)}{\partial D}. \quad (5)$$

The competitive equilibrium is efficient.

The proof follows from the first-order condition (4) and the equilibrium conditions. The efficiency result follows from considering the planning problem $\max_{C,D} \{u(C, D)\}$ subject to the aggregate resource constraint $C = Z\Psi_T(D)$. The solution to equation (5) solves this planning problem, which establishes efficiency.

Intuitively, the equilibrium condition (5) states that the marginal rate of substitution between shopping and consumption equals the marginal rate of transformation of shopping, i.e., the marginal increase in the probability that the suppliers are matched times the amount of goods per supplier.

The reason why there can only be one active market in equilibrium is that households are identical and the equilibrium is unique.¹² It follows that the set of available markets Φ is a singleton. Note also that the household endowment is the average profits per firm because $T = 1$.

In this economy, *potential* output is always Z . However, the *realized* output is smaller than Z . Some units are not found, and hence some potential output is lost due to insufficient search. Nevertheless, the economy is efficient: finding additional goods is not worth the additional search effort. Total factor productivity is a function of both search effort D and Z , $TFP = Z\Psi_T(D)$, and will, as we shall see, respond to changes in preferences.

Note that we measure realized consumption consistently with the way value added is measured in NIPA: a lost opportunity does not contribute to value added and it is only when it is purchased that potential production translates into consumption. In our model search effort can be interpreted as an input to production. Note that when constructing measures for factor inputs in NIPA, the national statistical offices do not include search effort as an input. The reason why fluctuations in search can give

¹²In Section 4.2.1 we analyze the case of cross-sectional heterogeneity in consumption expenditures.

rise to fluctuations in measured TFP is precisely because we (mis-)measure inputs in the same way as in NIPA. Indeed, if search effort were properly accounted for as an input factor, then TFP would be just Z .

We close this section with a simple example to illustrate how preference shocks that increase the desire to consume are partly accommodated by an increase in search effort that squeezes more output out of the economy, thereby making it more productive. Let the number of matches between suppliers and consumers be given by a standard Cobb-Douglas matching function

$$M = D^\varphi T^{1-\varphi}, \quad (6)$$

where φ is a matching technology parameter. This implies $\Psi_d(q) = q^{\varphi-1}$ and $\Psi_T(q) = q^\varphi$. Moreover, let the utility function be

$$u(c, d) = \frac{1}{1-\gamma} \left(c - \theta \frac{d^{1+1/\eta}}{1+1/\eta} \right)^{1-\gamma}, \quad (7)$$

where the preference parameter $\theta \geq \varphi Z$.

Given the preferences and matching technology, the equilibrium allocation are given by

$$D = \left(\frac{\varphi Z}{\theta} \right)^{\frac{1}{1/\eta+1-\varphi}}, \quad C = \left(\frac{\varphi}{\theta} \right)^{\frac{\varphi}{1/\eta+1-\varphi}} (Z)^{\frac{1/\eta+1}{1/\eta+1-\varphi}}.$$

A decrease in the disutility of search θ (or, equivalently, a crave for consumption) translates into an increase in search effort and, hence, increased consumption. The elasticity of consumption to changes in θ is increasing in the share of search in the matching function, φ . As φ goes to zero, the shopping economy converges to the standard endowment economy, where aggregate consumption is entirely determined by the endowment Z and invariant to the preference shock.

3 The stochastic growth model version of the economy

We now embed the matching frictions in product markets into an otherwise standard growth model suitable for quantitative business cycle analysis. We focus on matching frictions in consumption good markets and abstract from matching frictions in firms' purchases, including the investment goods market. While matching frictions must exist also for firm-to-firm transactions, these are presumably less severe than for households since firms buy most of their output from related parties and in larger quantities.¹³ Consequently, there are two sectors: one producing consumption goods and the other investment goods. Production uses capital and labor as inputs. We start by describing technology and preferences. We then

¹³This assumption mitigates the role of shopping effort for business cycle fluctuations. In a previous version of this paper we assumed a search friction also for investment goods.

analyze the problems faced by households and firms, and study price determination in the presence of the search friction.

3.1 Technology and Markets

There are two types of firms, a unit measure of firms producing consumption and a unit measure of firms producing investment goods. Each firm resides in a location, equivalent to a supplier in Section 2. Consumption firms have a technology for transforming capital k and labor n into the consumption good via a standard production function $zf(k, n)$, where f is differentiable and strictly concave. Investment firms are subject to an additional aggregate investment shock z_i , so their production function is $z_i zf(k, n)$.

As in Section 2, we assume a competitive search protocol for consumption goods. Note that since production is endogenous, the equilibrium requires indexing markets not only by price and market tightness (p, q) but also by the quantity of the good offered for sale by the firm, F . The quantity F is in turn a function of the firm's labor and pre-installed capital stock.¹⁴ In Appendix B we show that with endogenous production optimality requires that markets are indexed by the triplet (p, q, F) of price, market tightness, and the quantity of the good produced. We conjecture that this property applies to all competitive search models where consumers search for firms and firms can decide the magnitude of the available goods.

The aggregate state vector is $\Lambda \equiv (\theta, Z, K)$, comprising a vector of preference shocks θ , a vector of technology shocks $Z = (z, z_i)$, and a vector of capital stocks $K = (K_c, K_i)$ installed in consumption and investment firms, respectively. As in Section 2, the matching technology for shoppers and firms is given by $M = D^\varphi T^{1-\varphi}$.

To simplify the description of equilibrium we formulate the problem so that all dynamic choices are made by the household: it chooses how much capital to accumulate of each type. Moreover, households receive the net profits from the firm as dividends. It would be straightforward to extend the model to explicitly incorporate trade in shares in the firms and let the firms carry out dynamic choices. The equilibrium allocation would not be affected by such extension.

3.2 Households

There is a measure one of households who have preferences over consumption c , shopping effort d , and labor supply n . Preferences are subject to a shock θ , perfectly correlated across households. The utility function is $u(c, d, n, \theta)$. The household owns k_c and k_i units of capital installed in consumption- and investment-firms, respectively and is entitled to the dividends of firms. The household's state vector includes the state of the economy Λ and individual holdings of (k_c, k_i) .

¹⁴Recall that the quantity produced was not part of the variables indexing markets in the simple endowment economy. There, the amount of goods per supplier was exogenous and identical across suppliers by assumption.

Households take aggregate variables as given, including the price p , market tightness q , and quantity F in the active consumption-good market, the rental rates on capital invested in consumption- and investment-producing firms, R_c and R_i respectively, aggregate dividends π , the price of new capital P_i , the wage W , and the laws of motion of aggregate capital $K'_c = G_c(\Lambda)$ and $K'_i = G_i(\Lambda)$. These aggregate equilibrium objects are functions of the state vector Λ .

We denote by $V(\Lambda, k_c, k_i)$ the value of a representative household and by $\widehat{V}(\Lambda, k_c, k_i, \widehat{p}, \widehat{q}, \widehat{F})$ the value that it would obtain if it went shopping in a $(\widehat{p}, \widehat{q}, \widehat{F})$ market. Specifically, households in market $(\widehat{p}, \widehat{q}, \widehat{F})$ choose consumption c , shopping effort d , labor supply n , and future capital k'_c and k'_i so as to maximize

$$\widehat{V}(\Lambda, k_c, k_i, \widehat{p}, \widehat{q}, \widehat{F}) = \max_{d, n, c, k'_c, k'_i} u(c, d, n, \theta) + \beta E\{V(\Lambda', k'_c, k'_i) \mid \Lambda\} \quad (8)$$

subject to the shopping constraint, the budget constraint, the capital accumulation, and the aggregate laws of motion of capital,

$$c = d \Psi_d[\widehat{q}] \widehat{F}, \quad (9)$$

$$\widehat{p} c + P_i i = \pi + k_c R_c + k_i R_i + n W, \quad (10)$$

$$i = k'_c + k'_i - (1 - \delta)(k_i + k_c), \quad (11)$$

$$K'_c = G_c(\Lambda), \quad K'_i = G_i(\Lambda). \quad (12)$$

The value function V is determined by the best market;

$V(\Lambda, k_c, k_i) = \max_{(p, q, F) \in \Phi} \widehat{V}(\Lambda, k_c, k_i, p, q, F)$, where Φ is the set of available markets.

3.3 Firms

Representative firms rent capital and hire labor in spot markets. Given the state of the economy Λ , consumption firms make two choices: how much labor and consumption-specific capital to rent for producing output, and what market bundle (p, q, F) to offer. The problem for the consumption firms is

$$\pi_c(\Lambda) = \max_{k, n, \widehat{p}, \widehat{q}, \widehat{F}} \widehat{p} \widehat{F} \Psi_T(\widehat{q}) - W(\Lambda) n - R_c(\Lambda) k, \quad (13)$$

$$\text{subject to } \widehat{V}(\Lambda, K, \widehat{p}, \widehat{q}, \widehat{F}) \geq V(\Lambda, K),$$

$$z f(k, n) \geq \widehat{F}.$$

Note that the firm's problem (13) is static in the sense that current decisions do not influence the future value of the firm, and future dividends and prices do not matter for the firm's current problem. The problem determines the dividends π_c , the factor demands n_c and k_c , and the triplet (p, q, F) , all

expressed as functions of Λ .

The corresponding static problem for the investment firms is standard and is given by

$$\pi_i(\Lambda) = \max_{k,n} P_i z_i z f(k, n) - W n - R_i k, \quad (14)$$

which determines π_i , n_i , k_i , and aggregate investment.

3.4 Equilibrium

The competitive search equilibrium of the production economy consists of value functions and decision rules $\{V, \widehat{V}, c, d, n, k'_c, k'_i\}$, all expressed as functions of the individual state (Λ, k) , and a set of aggregate allocations $\{C, D, I, N, G_c, G_i, N_c, N_i, K'_c, K'_i\}$, prices $\{p, W, R_c, R_i, P_i\}$, market tightness q , consumption capacity F , dividends π , and profits π_i, π_c , where all aggregate variables are expressed as functions of Λ , such that

1. The consumption good is the numéraire, $p = 1$.
2. The decision rules $c(\Lambda, k_c, k_i)$, $d(\Lambda, k_c, k_i)$, $n(\Lambda, k_c, k_i)$, $k'_c(\Lambda, k_c, k_i)$, $k'_i(\Lambda, k_c, k_i)$, and the associated value functions $\widehat{V}(\Lambda, k_c, k_i, p, q, f)$ and $V(\Lambda, k_c, k_i)$ solve the household problem (8-12), taking as given prices $\{W, R_c, R_i, P_i\}$ and dividend income π . Moreover, $V(\Lambda, K_c, K_i) = \widehat{V}(\Lambda, K_c, K_i, 1, q(\Lambda), F(\Lambda))$.
3. The triplet $p = 1$, $q(\Lambda)$, and $F(\Lambda)$, factor demands $N_c(\Lambda)$ and K_c , and profit $\pi_c(\Lambda)$ solve the problem of the producers of the consumption good (13), taking as given $\{W, R_c, V, \widehat{V}\}$, where $F(\Lambda) = z f(K_c, N_c(\Lambda))$.
4. Factor demands $N_i(\Lambda)$ and K_i , and profit $\pi_i(\Lambda)$ solve the investment producers' problem (14), taking as given $\{W, R_i, P_i\}$.
5. Individual decision rules are consistent with the aggregate functions; $C(\Lambda) = c(\Lambda, K)$, $D(\Lambda) = d(\Lambda, K)$, and $N(\Lambda) = n(\Lambda, K)$.
6. Market clearing conditions are satisfied,

$$\begin{aligned} C(\Lambda) &= \Psi_T(q(\Lambda)) F(\Lambda), & q(\Lambda) &= D(\Lambda), \\ I(\Lambda) &= z_i z f(K_i, N_i(\Lambda)) = G_c(\Lambda) + G_i(\Lambda) - (1 - \delta)(K_c + K_i), \\ N(\Lambda) &= N_i(\Lambda) + N_c(\Lambda), & \pi(\Lambda) &= \pi_i(\Lambda) + \pi_c(\Lambda). \end{aligned}$$

7. Aggregate laws of motion of capital are consistent with individual behavior, $K'_c = G_c(\Lambda) = k'_c(\Lambda, K)$ and $K'_i = G_i(\Lambda) = k'_i(\Lambda, K)$.

As we show in Appendix B, the welfare theorems apply so the competitive equilibrium is efficient. It is therefore convenient to solve for the equilibrium using a standard social planner approach where the planner faces the same search friction in the consumption goods market. Given an aggregate state variable Λ , the social planner's problem is

$$\mathcal{W}(\Lambda) = \max_{D, N_c, N_i, K'_c, K'_i} \left\{ u(D, \Psi_d[D] z f(K_c, N_c), D, N_c + N_i, \theta) + \beta E\{\mathcal{W}(\Lambda') \mid \Lambda\} \right\} \quad (15)$$

$$\text{subject to } z_i z f(K_i, N_i) = K'_c + K'_i - (1 - \delta)(K_c + K_i) \text{ and } \Lambda' = (\theta', Z', K'_c, K'_i).$$

The first-order conditions yield four optimality conditions (see Appendix B for derivations). First, an intra-temporal first-order condition equating the marginal cost and the marginal gain of consumption search. Equation (16) equates the marginal rate of substitution between search and consumption to the marginal rate of transformation, i.e., the marginal increase in aggregate consumption from searching slightly harder,

$$-\frac{u_d}{u_c} = \frac{\partial M[D, 1]}{\partial D} z f(K_c, N_c). \quad (16)$$

This corresponds to the optimality condition (5) in the endowment economy with the only difference that capacity, $z f$, is now endogenous. The second optimality condition is a standard intra-temporal first-order condition for labor supply, equating the marginal utility cost of working one additional hour to the marginal utility gain of the increased consumption production due to the additional hour worked,

$$-\frac{u_n}{u_c} = \Psi_T[D] z \frac{\partial f(K_c, N_c)}{\partial N_c}. \quad (17)$$

The third optimality condition equalizes the marginal gain of investing in each sector,

$$0 = E \left\{ u_{n'} \left(\frac{\partial f(K'_i, N'_i) / \partial K'_i}{\partial f(K'_i, N'_i) / \partial N'_i} - \frac{\partial f(K'_c, N'_c) / \partial K'_c}{\partial f(K'_c, N'_c) / \partial N'_c} \right) \mid \Lambda \right\}. \quad (18)$$

Finally, the planner program implies an Euler equation,

$$\frac{u_n}{z_i z \frac{\partial f(K_i, N_i)}{\partial N_i}} = \beta E \left\{ \frac{u'_n}{z'_i z'_i \frac{\partial f(K'_i, N'_i)}{\partial N'_i}} \left(z'_i z'_i \frac{\partial f(K'_i, N'_i)}{\partial K'_i} + 1 - \delta \right) \mid \Lambda \right\}. \quad (19)$$

The left-hand side is the utility cost of producing one more unit of the investment good by working $1 / (z_i z \partial f(K_i, N_i) / \partial N_i)$ more hours. The right-hand side is the equivalent next-period utility gain of a marginal increase in K'_i . Note that if consumption and investment were the same good, as in the standard growth model, the term on the left-hand side of the equation would just be the marginal utility

of consumption u_c and equation (19) would simplify to the familiar Euler equation.

Given the equilibrium allocations it is straightforward to back out the prices that would obtain in a decentralized competitive equilibrium. It is instructive to consider the implied relative price of investment goods (in terms of consumption goods), P_i ,

$$P_i = \frac{1}{1-\varphi} \frac{\Psi_T(D)}{z_i} \frac{\partial f(K_c, N_c) / \partial N_c}{\partial f(K_i, N_i) / \partial N_i}. \quad (20)$$

The investment price is declining in the investment technology shock z_i since a higher investment productivity increases investment production and lowers the relative value of investment goods. Similarly, P_i is increasing in consumption market tightness $\Psi_T(D)$ and, hence, search effort. The reason is that with higher search effort the relative price of consumption falls.

4 Mapping the Model to Data

We now choose the functional forms for preferences and technology. We then follow the business cycle literature to calibrate the standard parameters. The parameters associated with shopping frictions are identified by using cross-sectional household data.

4.1 Functional forms

We assume a so-called Greenwood-Hercowitz-Huffman formulation for preferences over consumption and shopping search effort. This specification rules out wealth effects in search effort. As we shall see below, such a property is necessary to account for the cross-sectional aspects of shopping effort. This feature will also ensure that the model generates a procyclical shopping effort, in line with the empirical evidence on shopping time documented by [Petrosky-Nadeau et al. \(2016\)](#). We assume that preferences are additively separable between labor and the composite of consumption and search effort. The period utility function is then,

$$u(c, n, d) = \frac{1}{1-\gamma} \left(c - \chi_d \frac{d^{1+1/\eta}}{1+1/\eta} \right)^{1-\gamma} - \chi_n \frac{n^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}. \quad (21)$$

The parameters are the discount rate β , the inverse of the intertemporal elasticity of substitution, γ , the Frisch elasticity of labor supply ν , and the parameters that determine average hours worked and average search effort, χ_n and χ_d , respectively. The parameter η determines the elasticity of shopping effort with respect to variation in the return to search.

Firms have decreasing returns to scale. This is a natural assumption in a model with frictions in the

matching between consumers and firms.¹⁵ The production function is Cobb-Douglas,

$$f(k, n) = k^{\alpha_k} n^{\alpha_n}. \quad (22)$$

4.2 Calibration

As far as possible, the calibration targets for the steady state are standard in business cycle research. Table 1 reports the targets and the parameters most closely associated with each target. The targets are defined in yearly terms even though the model period is a quarter.

Table 1: Calibration Targets, Implied Aggregates, and (Quarterly) Parameter Values

Targets	Value	Parameter	Value
First Group: Parameters Set Exogenously			
Risk aversion	2	γ	2
Real interest rate	4%	β	0.99
Frisch elasticity	0.72	ν	0.72
Second Group: Standard Targets			
Investment share of output	0.20	δ	1.78%
Physical capital to output ratio	2.75	α_k	0.25
Labor share of output	0.67	α_n	0.54
Third Group: Normalizations			
Steady-state output	1	$E(z)$	1.20
Relative price of investment	1	$E(z_i)$	0.74
Fraction of time spent working	30%	χ_n	14.91
Capacity utilization of consumption sector	81%	χ_d	1905
Fourth Group: Targets Specific to This Economy			
Cross-sectional st. dev. of cons. good prices	9%	φ	0.23
Shopping time expenditure elasticity	7.5%	η	0.11

The first group of parameters does not need the computation of the steady state to be determined: the intertemporal elasticity of substitution is 0.5, and the rate of return is 4 percent. The Frisch elasticity is more controversial. We choose a value of 0.72 based on [Heathcote et al. \(2010b\)](#), who take into account the response of hours worked for both men and women in a model that explicitly incorporates households with husbands and wives.

¹⁵Note that if production were constant return to scale in capital and labor then the search friction would become irrelevant as one firm would produce all goods and all search would focus on finding the firm with available goods.

The second group of parameters are determined simultaneously through specified steady-state targets. The physical capital to output ratio, the investment share of output, and the labor share allow us to identify the depreciation rate and the shares of capital and labor, α_k and α_n . In particular, the quarterly capital depreciation rate δ is set to 1.78% so as to generate an annual investment-output ratio of 20%.¹⁶ A labor share of output of 0.67 implies a labor share parameter $\alpha_n = 0.54$. A capital-output ratio of 2.75 generates a capital share parameter $\alpha_k = 0.25$ (see Appendix C for derivations). The third group of parameters are normalizations that are immaterial to the cyclical behavior of the economy. Nevertheless we target values that have a direct interpretation. The average adult works about 1600 hours per year, so 30% of available time is spent working. Moreover, the share of potential goods that are found is set equal to the average capital utilization in the U.S. Capacity Utilization series published by the Board of Governors (81%).

4.2.1 Identifying Shopping Parameters with Cross-sectional Shopping Data

The last group of parameters, specific to our shopping theory, are the elasticity of shopping effort η and the weight of shopping in the matching function, φ .

Our model is formulated with a representative agent. However, to calibrate the parameters φ and η it is useful to study the cross-sectional implications of our shopping model. To this end, consider a version of our economy where J types of households differ in their household wealth. Let y_j and μ_j denote the consumption expenditure of households of type $j \in \{1, \dots, J\}$ and the measure of type j households, respectively. The equilibrium can be characterized as follows (proof in Appendix D.)

Proposition 2. *The competitive equilibrium in the stochastic growth model with cross-sectional heterogeneity is a vector of prices and allocations where all firms offer the same capacity F and the posted price of the consumption good in the market targeting type j households is*

$$p_j = \frac{C^{1-\varphi}}{F} \cdot (y_j)^\varphi (D_j)^{-\varphi}, \quad (23)$$

where C is aggregate consumption (in physical units). The measure of firms selling to type j households is equal to the households' expenditure share, $T_j = \mu_j y_j / C$, the real consumption of type j households is $c_j = D_j^\varphi (y_j / C)^{1-\varphi} F$, and the search effort is given by the solution to the first-order condition

$$-u_d = \varphi (D_j)^{\varphi-1} (y_j)^{1-\varphi} u_c F. \quad (24)$$

Consider now the utility function in equation (21). From equation (24) the shopping effort for type j households is given by $D_j = (\varphi F / \chi_d)^{\eta / [\eta(1-\varphi)+1]} y_j^{\eta(1-\varphi) / [\eta(1-\varphi)+1]}$. Taking the difference of logs across

¹⁶Note that investment in our model is strictly business investment. Consumption durables are excluded since the markets for business investments are frictionless while consumer goods by assumption are subject to search frictions.

households of different types yields

$$\Delta \log(D_j) = \frac{\eta(1-\varphi)}{\eta(1-\varphi)+1} \Delta \log(y_j). \quad (25)$$

Consider now the price equation (23) in log form and take the standard deviation on each side of the equation. This yields

$$\text{std}(\log(p_j)) = \frac{\varphi}{\eta(1-\varphi)+1} \text{std}(\log(y_j)). \quad (26)$$

Kaplan and Menzio (2016) report that the cross-sectional standard deviation of household price indexes is 9% when using standardized bar codes to identify goods. With a standard deviation of log consumption expenditures on services and non-durables of 42.4% (cf. Heathcote et al. (2010a)), we get $\text{std}(\log(p_j))/\text{std}(\log(y_j)) = 0.212$. Petrosky-Nadeau et al. (2016) report that in the cross section of individual households, shopping time is *increasing* in household income when controlling for observable household characteristics. For example, households with income between \$100,000 and \$150,000 spend 3.6 minutes more on shopping per day than households with income between \$25,000 and \$50,000. With an average of 42 minutes shopping per day, this difference amounts to $3.6/42 = 8.6\%$ of average shopping time. The difference in income between these groups is roughly a factor of three. This implies an elasticity $\Delta \log(D_j)/\Delta \log(y_j) \approx 0.075$. Applying these moments in equations (25)-(26) imply $\varphi = 0.23$ and $\eta = 0.11$.

5 Quantitative results

We now estimate the model with Bayesian methods to assess the role of demand shocks in accounting for aggregate fluctuations in the U.S. (Section 5.1). We then explore the implications of our model for the Great Recession which, as we shall see, was characterized by a sharp decline in shopping time. Our model imputes a decline in shopping effort so as to account for the sustained fall in consumption and the weak response of the price of investment (Section 5.2).

5.1 Estimating the model with U.S. data

We estimate the process for the shocks that affect the model using U.S. quarterly data (1967I-2013IV). We consider four types of shocks, two preference shocks and two technology shocks. The preference shocks are the disutility to shopping θ_d and the disutility to work θ_n , so preferences are

$$u(c, n, d; \theta_d, \theta_n) = \frac{1}{1-\gamma} \left(c - \theta_d \chi_d \frac{d^{1+1/\eta}}{1+1/\eta} \right)^{1-\gamma} - \theta_n \chi_n \frac{n^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}.$$

There are two types of technology shocks: a shock to total factor productivity z and a shock to investment specific technology z_i . We assume that all four shocks follow AR(1) processes with respective persistence $\{\rho_d, \rho_n, \rho_z, \rho_i\}$. The innovations to the shocks are independent and normally distributed with standard deviations denoted by $\{\sigma_d, \sigma_n, \sigma_z, \sigma_i\}$.

We estimate jointly the autocorrelations $\{\rho_d, \rho_n, \rho_z, \rho_i\}$ and the standard deviation of innovations $\{\sigma_d, \sigma_n, \sigma_z, \sigma_i\}$ using Bayesian methods. We use four logged and linearly detrended data series in the estimation: output, investment, labor productivity and the relative price of investment to consumption. All data are real and from the National Income and Product Accounts for the period of 1967 to 2013 at a quarterly frequency. Since our model is a closed economy without a government sector, we measure investment as private investment and construct output from the sum of private consumption and private investment. Labor productivity is the ratio of our measure of output to total working hours.

The upper panel of Table 2 shows the priors and posteriors for all shock parameters. We assume that autocorrelations follow a Beta distribution and that standard deviation of innovations follow an inverse Gamma distribution. We assume an initial prior of equal autocorrelation for all shocks and let the estimation tell us which one is more persistent. The 90th percentile intervals show that our estimation is tight. The estimated autocorrelations of the preference shocks θ_d and θ_n are close to unity.

The variance decompositions of the major aggregate variables are reported in the lower panel of Table 2. The preference shock to the disutility of shopping, θ_d accounts for about 30 percent of the variance of output and labor.¹⁷ It is also the main driving force for consumption (69%), labor productivity (53%), and the relative price of investment (42%). Combined, the two shocks θ_d and the neutral productivity shock z account for almost the entire variation in consumption, labor productivity, and the Solow residual. The two shocks account for an equal share of the variance of TFP. The shock to z accounts for roughly half of the fluctuations in output and investment. The investment-specific technology shock accounts for a significant share of the investment and investment price dynamics —50 and 26 percent respectively— but has a negligible role for other variables. The shock to θ_n matters mainly for labor dynamics and contributes little to other variables. Finally, while the previous business cycle literature has usually treated fluctuations in the relative investment price P_i as reflecting investment-specific technology shocks (cf. Greenwood et al. (1997)), we find that θ_d accounts for a larger share of the variance in the relative price of investment goods than does z_i —42% versus 26%, respectively. The Bayesian estimation procedure chooses shocks so as to maximize the probability of the observed aggregate time series. We conclude that to match the data —especially the consumption dynamics— it is necessary to attribute a

¹⁷As a robustness exercise we explore alternative formulations for the technology shocks on goods and investment relative to that of the benchmark economy. This includes (i) assuming independent shocks for consumption and investment production, and (ii) assuming a joint shock z and a relative shock z_x so TFP for consumption and investment production are zz_x and z/z_x , respectively. When estimated, these alternative formulations imply a larger role for θ_d than in Table 2. The benchmark formulation yields a somewhat larger likelihood than the alternative models (2172 versus 2130 or less). See Table 7 for details.

Table 2: Bayesian Estimation: Benchmark Model

Priors and Posteriors for the Shock Parameters likelihood = 2172.07					
Parameter	Density	Para(1)	Para(2)	Mean	90% Intv.
ρ_d	Beta	0.930	0.05	0.9995	[0.9989, 0.9999]
ρ_z	Beta	0.930	0.05	0.7894	[0.7782, 0.7994]
ρ_i	Beta	0.930	0.05	0.9849	[0.9807, 0.9883]
ρ_n	Beta	0.930	0.05	0.9986	[0.9974, 0.9999]
σ_d	Inv Gamma	0.150	Inf	0.6099	[0.5542, 0.6749]
σ_z	Inv Gamma	0.002	Inf	0.0120	[0.0107, 0.0131]
σ_i	Inv Gamma	0.002	Inf	0.0164	[0.0148, 0.0179]
σ_n	Inv Gamma	0.010	Inf	0.0193	[0.0176, 0.0207]

	Variance Decomp			
	θ_d	z	z_i	θ_n
Y	28.61	54.03	11.31	6.05
Labor	31.25	1.55	7.76	59.45
Consumption	69.00	23.34	1.95	5.71
Investment	0.78	47.24	50.31	1.67
TFP	47.07	48.02	4.74	0.17
Y/N	53.15	41.60	2.54	2.71
P_i	41.81	32.32	25.58	0.30
Capacity	99.98	0.01	0.00	0.00
Shopping	99.98	0.01	0.00	0.00

The estimation targets the data series of GDP, labor productivity, investment, and investment price. Quarterly U.S. data, 1967:I to 2013:IV.

significant role to θ_d .

5.2 Verifying the model over the Great Recession

The key departure of our model from the existing literature is the role of shoppers in shaping productivity via their endogenous choice of shopping effort. One way to verify that the mechanism of our model is reasonable is to investigate the model's predictions about the shopping effort. Unfortunately, shopping effort in the model does not have an immediate empirical counterpart. However, it seems reasonable that the *time* households devote to shopping should be correlated with the shopping effort.

This section compares the empirical time spent shopping in the U.S. over the Great Recession with the behavior of shopping effort implied by our model over the same period (Section 5.2.1). We then investigate the mechanism responsible for the shopping effort over that period (Section 5.2.2).

5.2.1 The Behavior of Shopping Effort

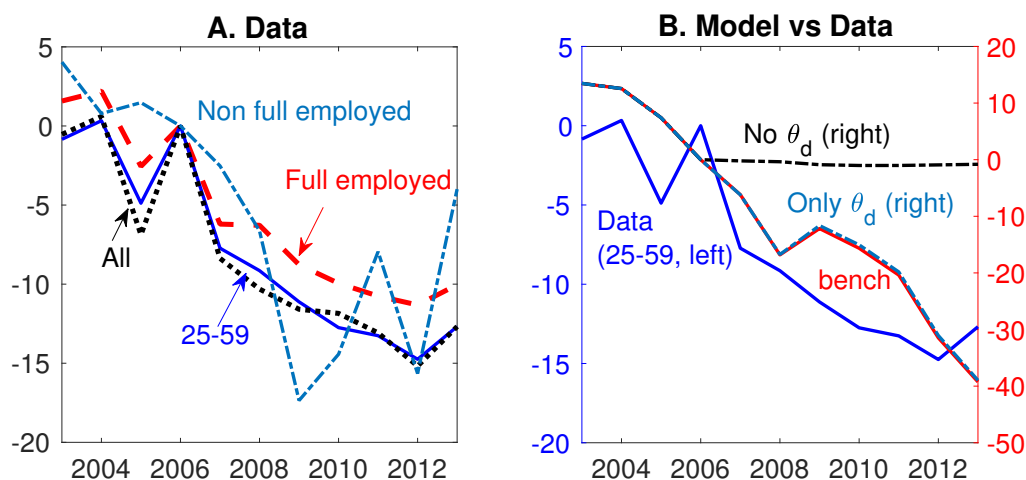
To measure shopping time we use the American Time Use Survey (ATUS), which provide annual data from 2003 and onward. We measure shopping time as the average time spent shopping for goods, professional and personal care services, and household services, plus the travel time associated with this shopping.

Panel A of Figure 1 shows the percentage change in average shopping time for various groups, relative to 2003. Shopping time for the working age population (25-59) fell by about 12.5 percent over the sample period. Most of the fall in shopping time occurred between 2006 and 2010, and shopping time is roughly stationary before 2006 and after 2010. This fall in shopping time during the Great Recession is consistent with the evidence documented by [Aguiar et al. \(2013\)](#) and [Petrosky-Nadeau et al. \(2016\)](#). As is clear from the figure, shopping time fell by similar magnitudes also for various subgroups of the population, including the full-time employed and those not full-time employed (11.8 percent and 14.4 percent, respectively, between 2006 and 2010). [Aguiar et al. \(2013\)](#) interpret the decline in shopping time during the Great Recession as reflecting an aggregate trend toward less shopping time. [Petrosky-Nadeau et al. \(2016\)](#) use cross-state and individual regressions analysis and argue that the recent decline in aggregate shopping time reflects that consumer search in the goods market is procyclical.¹⁸

¹⁸Note that even when allowing for a linear trend in shopping time between 2003 and 2014, there is a sharp decline in aggregate shopping time during the Great Recession, with the trough in shopping time (relative to the linear trend) occurring during 2009-2010. [Aguiar et al. \(2013\)](#) use data for a shorter time period —up until 2010— and find that if a linear trend were applied for this shorter period, then the 2009-2010 period would appear as years with shopping time above trend (cf. Table 1 in their paper). [Petrosky-Nadeau et al. \(2016\)](#) argue that the fact that shopping time declined during the Great Recession —a period during which unemployment increased sharply— runs counter to the perception that shopping time tends to increase during recessions. Since people who are less than full time employed spend about 12 percent more time on shopping than do the full-time employed, one might expect that a reduction in employment should be a force for increasing the average shopping time during recessions (cf. [Kaplan and Menzio \(2016\)](#)). However, this compositional effect has only a minor impact on aggregate shopping time: if shopping time for all groups were held constant, then a fall in employment rate for full time workers of six percentage points— equivalent to the change over the 2006-2010 period— should increase

We now compare the dynamics of the empirical shopping time with the theoretical shopping effort implied by our estimated model. Given the empirical facts documented above—including the procyclical nature of shopping time (cf. [Petrosky-Nadeau et al. \(2016\)](#))—it seems natural to require that a theory of shopping effort be consistent with a large empirical drop in shopping time since 2003. To infer the shopping effort predicted by our theory, we first back out the shock innovations using the four observed data series, output, labor productivity, investment, and the relative investment price for the period of 2003 to 2013. The implied annualized shopping effort is shown by the solid line in Panel B of Figure 1. The key observation is that our model generates dynamics of shopping effort qualitatively similar to those of our measure of the empirical shopping time. In particular, the estimated model implies a sharp decline in shopping effort during the sample period, including a decline during the Great Recession.¹⁹

Figure 1: Shopping



Panel A shows the percentage change in shopping time between 2003 and 2013 for various groups. Shopping time is measured as the average time spent shopping for goods, professional and personal care services, and household services, plus the travel time associated with this shopping. Data source: American Time Use Survey (ATUS).

Panel B shows the evolution of average shopping time for the group 25-59 years old (blue solid line) plotted against the shopping effort implied by our estimated benchmark model (red solid line) over the ATUS sample period. The panel also displays shopping effort under two alternative scenarios—one where the θ_d shock follows its estimated path while the remaining shocks (θ_n, z, z_i) are fixed after 2006 (green dashed line), and one where θ_d is constant after 2006 while the remaining shocks (θ_n, z, z_i) follow their estimated paths (black dash-dot line).

average shopping time by merely one half of a percent. This compositional effect is dwarfed by the massive empirical declines in shopping time across groups over this period, documented in Figure 1.

¹⁹An alternative way to verify our model's predictions of lower search effort after 2006 is to consider the frequency of stockouts of goods. Our model abstracts from the possibility of stockouts. Nevertheless, we conjecture that if our model were extended to incorporate such inventory stockouts, then these would be more likely during periods with surprisingly large search effort. Thus, an increase in search effort should manifest itself as an increase in the probability of observing episodes of stockout. [Bils \(2016\)](#) documents stockouts using micro-CPI data. He finds that the occurrence of stockouts tend to fall during recessions, and especially so during the Great Recession (cf. his Figure 1). This is broadly consistent with Figure 1.

One additional dimension of the data that may shed light on the model’s mechanism is the distinction between goods that are purchased often such as for example groceries, for which the search frictions presumably are smaller than for other goods. If search frictions were to matter for business cycles then one would expect that shopping time for goods with more frictions —i.e., goods other than groceries— should be tighter correlated to the business cycle than is shopping time for goods with less matching frictions. To investigate this issue we split the total shopping time in Figure 1 into shopping for groceries and shopping for everything else. The main finding is that there is no clear trend in shopping time for groceries —it is essentially constant between 2006 and 2013, while shopping time for other goods essentially follows the same pattern as in Figure 1 (cf. Figure 3 in Appendix E). Moreover, while shopping time for other goods is procyclical, the shopping time for groceries is acyclical.²⁰

5.2.2 Inspecting the mechanism

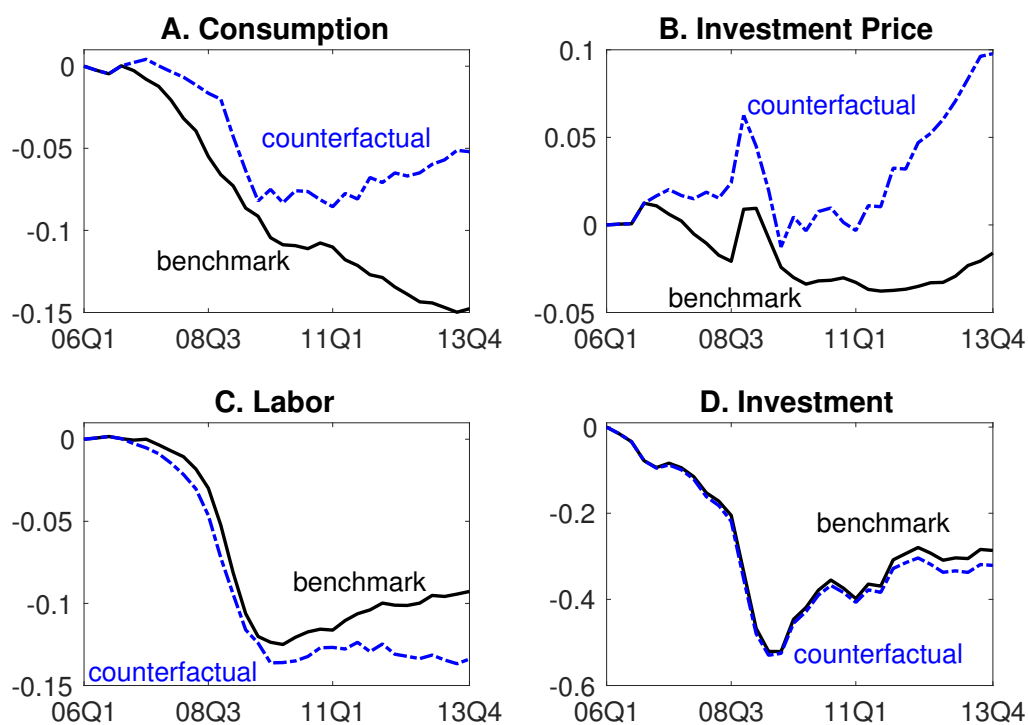
We now investigate why the estimated model implies a large decline in shopping effort after 2006. We start by documenting which of the four shocks of the estimated model $(\theta_d, \theta_n, z, z_i)$ is the main driver of the implied endogenous shopping effort. To this end we show how the shopping effort predicted by the model would have evolved from 2006 and onward under two counterfactual scenarios: one where the θ_d shock follows its estimated path after 2006 while the remaining shocks (θ_n, z, z_i) are held constant at their 2006 levels, and one where the shocks (θ_n, z, z_i) follow their estimated paths after 2006 while the θ_d shock is held constant at its 2006 levels. The implied counterfactual paths for shopping effort are displayed in Panel B of Figure 1. As is clear from the figure, the shopping effort in the model is entirely driven by the dynamics of θ_d : the scenario where only θ_d moves is visually indistinguishable from the benchmark scenario involving all the shocks.

Given this insight, we investigate why our Bayesian estimation predicts such a large fall in θ_d after 2006. Recall that the model is estimated by targeting the aggregate time series of C_t , I_t , N_t , and P_{it} . We now investigate what aspects of these empirical observations identify the implied dynamics of θ_d . To this end we perform a series of counterfactual analyses, asking what the evolution of each of these aggregate variables would have been —according to the model— if the shopping shock θ_d had remained fixed from 2006 and onward.

Panel A of Figure 2 shows that the large and sustained fall in aggregate consumption (relative to trend) during the Great Recession is an important reason why the model implies a sustained fall in shopping effort. As can be seen from the figure, aggregate consumption would —in the absence of the decline in shopping effort— have risen by ten percent relative to its actual path over the 2007-2014 period. This effect is especially large after 2009. The larger disutility of search effort makes the households search

²⁰The correlation of grocery shopping time with HP-filtered annual GDP is -0.056, while the correlation of shopping time for other goods with GDP over the 2003-2014 period is 0.53. To calculate these correlations, we HP-filter yearly GDP from 1967 to 2014 and use the cyclical values from 2003 to 2014.

Figure 2: Counterfactual Series for Aggregate Variables under Fixed θ_d .



The four panels display the aggregate time series of C_t , P_{it} , N_t , and I_t after 2006, plotted against their respective counterfactual series predicted by the estimated model under the assumption that the *search shock* θ_d remains constant after 2006. Panel A displays consumption C_t , Panel B displays the relative investment good price P_{it} , Panel C displays labor supply N_t , and Panel D displays investment I_t .

less for consumption goods —consistent with the observed fall in shopping time. This in turn makes consumption more expensive. The behavioral response in the model is to reduce consumption and, to a lesser extent, increase labor supply (we discuss this in detail below).

Panel B of Figure 2 shows that the fall in the relative price of investment goods is also a factor pushing for a decline in the implied shopping effort, especially after 2009. The empirical investment price fell slightly during the Great Recession and remained low after 2009. In the absence of the decline in shopping effort the investment price should have risen by twelve percent relative to its actual path. To understand this point, note that given the assumed Cobb-Douglas production function we can rewrite the investment price expression in equation (20) as

$$P_i = \frac{1}{1-\varphi} \frac{D^\varphi}{z_i} \left(\frac{k_c}{k_i}\right)^{\alpha_k} \left(\frac{n_c}{n_i}\right)^{\alpha_n-1}. \quad (27)$$

Clearly, a fall in search effort D should be associated with a lower investment price P_i .²¹

Panel C of Figure 2 illustrates how aggregate labor supply would have evolved —according to the model— if shopping effort had not fallen after 2006. Between 2006 and 2009 the effect is small. After 2009, labor supply would have fallen more if θ_d had remained constant. Ceteris paribus, a lower search effort lowers the tightness in the goods market and, hence the probability that a firm will be matched, $\Psi_T[D]$. From the intra-temporal first-order condition for labor supply (17), a lower $\Psi_T[D]$ will in turn lower the marginal disutility of labor supply, inducing a lower n . Finally, Panel D shows that aggregate investment is hardly affected by the dynamics of θ_d .

We conclude that the culprits for the large and sustained fall in shopping effort during and after the Great Recession are the unusually large and sustained fall in consumption (relative to output) and the weak development of the relative investment price observed during this period.

6 Extensions: Variable capacity utilization and Storable Goods

We now extend the model in two directions. The first is to allow variable capacity utilization. The aim of this extension is to separate our mechanism from that of variable capacity utilization and mismeasured inputs (Section 6.1). The second studies environments where goods can be stored by both households and firms (Section 6.2).

²¹Note that the ratio $(k_c/k_i)^{\alpha_k} (n_c/n_i)^{\alpha_n-1}$ is approximately constant. This ratio would be exactly constant under perfect foresight or if capital could be reallocated between K_i and K_c within the period. It follows that the dynamics of P_i is mainly driven by fluctuations in θ_d and the technology shocks.

6.1 Varying capacity utilization

In our model demand shocks—in the form of for example a crave for consumption or a change in the disutility of search effort—induce an endogenous change in search effort and, hence, a change in the share of the consumption capacity that is realized as consumption. Thus, shopping effort is a factor of production. However, since this factor is unmeasured, fluctuations in search influence the measured Solow residual, as illustrated in Section 2.

This point is related to the well known measurement concern that any mismeasurement of factor inputs will show up as movements in the Solow residual. It is a common practice in DSGE models to allow for varying capacity utilization, i.e., changes in the intensity of factors of production, which in turn can induce movements in the Solow residual, possibly independently from the true movements in technology (see for instance [King and Rebelo \(1999\)](#) and [Francis and Ramey \(2005\)](#)).

The purpose of this section is to demonstrate that the significant role our estimation attributes to (shopping utility) preference shocks—see Table 2—is robust to allowing for varying capacity utilization of capital and shocks to this utilization. To this end we extend our benchmark model to allow for varying capacity utilization of capital along the lines of [Christiano et al. \(2005\)](#).²² In particular, we assume that to utilize a fraction h of pre-installed capital, households have to pay the variable cost $\psi(h)$, given by

$$\psi(h) = \xi \frac{h^{1+\sigma_a} - 1}{1 + \sigma_a}, \quad (28)$$

where $1/\sigma_a$ captures the elasticity of depreciation of capital with respect to how intensively it is used. Households can choose a separate capacity utilization for each capital stock, denoted h_c and h_x for utilization of capital for consumption and investment sector, respectively. The budget constraint—the equivalent to equation (10) with consumption as the numéraire good—becomes

$$c + P_i i = \pi + (h_c k_c) R_c + (h_i k_i) R_i + n W,$$

where the expression for investment i —the equivalent to equation (11)—now incorporates the additional cost of using capital more intensively,

$$i = k'_c + k'_i - (1 - \delta - \psi(h_c)) k_c - (1 - \delta - \psi(h_i)) k_i.$$

We first estimate this version of model with the same shocks and data series as in the benchmark model, but allowing the value for σ_a to be estimated. We assume that σ_a follows an inverse Gamma distribution. [Christiano et al. \(2005\)](#) calibrate σ_a to be 0.1. We therefore use this value as the prior

²²Since wages are not very pro-cyclical, we ignore the possibility of varying capacity utilization of labor.

for σ_a . Table 3 presents the estimated results. In line with the findings of [Christiano et al. \(2005\)](#) the estimated value for σ_a implies a large elasticity.

Table 3: Bayesian Estimation: with Capacity Utilization on Capital

Priors and Posteriors for the Shock Parameters likelihood = 2274.84					
Parameter	Density	Para(1)	Para(2)	Mean	90% Intv.
ρ_d	Beta	0.930	0.05	0.9998	[0.9996, 0.9999]
ρ_z	Beta	0.930	0.05	0.8135	[0.8120, 0.8156]
ρ_i	Beta	0.930	0.05	0.9992	[0.9986, 0.9998]
ρ_n	Beta	0.930	0.05	0.9988	[0.9982, 0.9995]
σ_d	Inv Gamma	0.150	Inf	0.4122	[0.3862, 0.4469]
σ_z	Inv Gamma	0.002	Inf	0.0080	[0.0074, 0.0085]
σ_i	Inv Gamma	0.002	Inf	0.0076	[0.0068, 0.0084]
σ_n	Inv Gamma	0.010	Inf	0.0189	[0.0173, 0.0202]
σ_a	Inv Gamma	0.100	Inf	0.0390	[0.0226, 0.0558]

	Var Decomp			
	θ_d	z	z_i	θ_n
Y	19.29	57.54	8.91	14.26
Labor	19.28	0.65	0.01	80.06
Consumption	62.93	18.26	1.21	17.59
Investment	0.81	77.81	16.89	4.48
TFP	50.47	42.89	6.06	0.58
Y/N	44.45	45.53	7.74	2.28
P_i	49.58	31.11	18.72	0.60
Capacity	99.98	0.01	0.00	0.01
Shopping	99.98	0.01	0.00	0.01

The estimation targets the data series of GDP, labor productivity, investment, and investment price. Quarterly U.S. data, 1967:I to 2013:IV. The inverse of σ_a is the elasticity of capital depreciation rate to capital usage.

Capacity utilization on capital gives the model an additional channel for labor productivity and Solow residual movements. This in turn generates smaller estimated fluctuations for the demand shock θ_d and productivity shock z . The standard deviation of θ_d drops from 0.6 to 0.4 and the standard deviation of z drops from 0.012 to 0.008. The variance decomposition, however, shows that even when allowing for a standard mechanism of capital capacity utilization, our shopping mechanism is still quantitatively important (cf. Table 3). In particular, the demand shock θ_d accounts for about 19 percent of GDP variability, about 50 percent of TFP variability, and almost 2/3 of consumption variability (versus 29, 47,

and 69 percent, respectively, in the benchmark economy).

Ideally we would like to measure the role of varying capacity utilization versus the varying shopping effort. Fortunately, there exists aggregate measurements of capital capacity utilization—for example the series Total Capacity Utilization in Manufacturing—that allows us to undertake such a comparison by incorporating a quarterly version of such data explicitly in the estimation of the model. Since we target an additional data series we must introduce an additional shock. In a way parallel to the shock to the disutility of shopping effort we introduce a shock θ_h to the cost of varying capacity utilization, affecting both capital stocks. The cost of capacity utilization h then becomes

$$\psi(h, \theta_h) = \theta_h \xi \frac{h^{1+\sigma_a} - 1}{1 + \sigma_a}, \quad (29)$$

We assume that the shock θ_h follows an AR(1) process with an autocorrelation of ρ_h and a standard deviation of innovation of σ_h . We estimate this shock together with the four shocks of the benchmark model using the same data series as before plus the aggregate Total Capacity Utilization series from the Federal Reserve Bank of St. Louis. Table 4 provides the results. The estimation, variance decomposition, and the business cycle statistics are similar to the previous estimation without the extra shock. The main finding is that the role of the shopping preference shock θ_d in the capacity utilization model is unaffected by the existence of the new shock. It still contributes to over 20 percent of the variance of output, to 64 percent of consumption, and over half of the variation of TFP. Moreover, the capacity utilization shock plays a small role in accounting for the aggregate variables, including the Solow residual—less than a third of the contribution of the shopping shock.

We conclude that varying capital capacity utilization is a mechanism fundamentally different from our shopping friction mechanism, and that our shopping effort mechanism remains important regardless of whether or not we also allow for varying capacity utilization and shocks to capacity utilization costs in the model.

6.2 Storable Goods

In our benchmark model newly produced consumption goods can either be found by a shopper (and consumed instantly) or not found, in which case the goods are permanently lost. This property seems a good description of services, which are consumed the moment they are produced. However, for a large number of goods—especially for durables—producers have a third alternative: goods that are not instantly found can be stored as inventories and offered for sale again later. As it turns out, inventories are large. For example, the ratio of inventories to annual sales for total business (i.e., manufacturing, retail, and wholesale) is 11.5% (source: Bureau of Labor Statistics (BLS)).

The possibility to store goods could in principle change the mechanism for how shocks to shopping

Table 4: Bayesian Estimation: with Capacity Utilization Shock

Priors and Posteriors for the Shock Parameters likelihood = 2843.28					
Parameter	Density	Para(1)	Para(2)	Mean	90% Intv.
ρ_d	Beta	0.930	0.05	0.9997	[0.9994, 1.0000]
ρ_z	Beta	0.930	0.05	0.8325	[0.8136, 0.8513]
ρ_i	Beta	0.930	0.05	0.9985	[0.9973, 0.9996]
ρ_n	Beta	0.930	0.05	0.9983	[0.9971, 0.9997]
ρ_h	Beta	0.930	0.05	0.9091	[0.8985, 0.9220]
σ_d	Inv Gamma	0.150	Inf	0.4497	[0.4071, 0.4804]
σ_z	Inv Gamma	0.002	Inf	0.0076	[0.0071, 0.0082]
σ_i	Inv Gamma	0.002	Inf	0.0082	[0.0074, 0.0092]
σ_n	Inv Gamma	0.010	Inf	0.0194	[0.0181, 0.0208]
σ_h	Inv Gamma	0.005	Inf	0.0120	[0.0108, 0.0132]
σ_a	Inv Gamma	0.100	Inf	0.0743	[0.0314, 0.1165]

	Var Decomp				
	θ_d	z	z_i	θ_n	θ_h
Y	20.70	49.59	9.79	13.31	6.60
Labor	21.40	0.47	0.07	77.86	0.20
Consumption	64.49	15.53	0.95	14.86	4.16
Investment	0.94	68.12	20.75	4.79	5.40
TFP	53.42	34.95	5.93	0.75	4.94
Y/N	45.57	37.85	7.58	2.15	6.86
P_i	52.42	26.37	18.90	0.71	1.61
Capacity	99.98	0.01	0.00	0.01	0.00
Shopping	99.98	0.01	0.00	0.01	0.00

The estimation targets the data series of GDP, labor productivity, investment, investment price, and total capacity utilization. Quarterly U.S. data, 1967:I to 2013:IV. The inverse of σ_a is the elasticity of capital depreciation to capital usage. ρ_h and σ_h are the autocorrelation and standard deviation of innovation of the cost for capacity utilization of capital.

utility propagates to the aggregate economy, relative to the mechanism in our benchmark model. To investigate this possibility, we extend our shopping environment to model explicitly the distinction between services and consumer goods, allowing goods to be stored as inventories for firms and as a stock of consumer goods for households. Since a good can be stored by firms, it is natural to allow it to be stored also by households. As we shall see, this property is important. Investment goods and services are modeled exactly as in the benchmark model in Section 3.

6.2.1 A Shopping Model with Storable Goods

There are search frictions for both consumption goods and services but not for investment. An unmatched service location produces zero output. Goods, however, can be stored by both households and firms. Consumer goods are produced in two stages. First, there is a manufacturing stage where a physical object is produced using capital and labor. This object is then added to the firm's stock of inventories and these goods become available in a location that may or may not be matched with a shopper. If there is a match, a sale is produced that adds to output. If there is no match, the goods become inventories that may in turn be traded across firms in a secondary frictionless market.

Output is the sum of the sales of goods, services, and investment, plus the change in inventories. This procedure for measuring output is consistent with the way GDP is measured in NIPA. The aggregate state of the economy is $\Lambda = (\theta, G, X, K)$ where G denotes households' stocks of consumer goods, X denotes firms' inventories and K is a vector of the capital stocks, $K = (K_g, K_s, K_i)$, with K_g for goods sector, K_s for service sector, and K_i for investment sector.

Markets are differentiated by what is traded, and by price, tightness, and quantity. The triplets offered in consumer goods markets and in service markets are (p_g, q_g, F_g) and (p_s, q_s, F_s) , respectively, where p_j is the price, $q_j = D_j/T_j$ is market tightness, and F_j is the capacity in market $j \in \{s, g\}$. The price of consumer good inventories is given by p_x . The measure of service firms is normalized to $T_s = 1$.

Households Let g be the stock of consumer goods the household carries over from the previous period and let c be the new purchases. The stored goods depreciate at rate δ_h . The current stock of consumer goods is therefore $c + (1 - \delta_h)g$. Households have preferences over services from their stock of consumer goods, services s , total shopping effort on goods d_g and services d_s , and hours worked n . Current utility is given by $u(c + (1 - \delta_h)g, s, d_g + d_s, n; \theta)$ where $\theta = (\theta_d, \theta_n)$ is the same vector of preference shocks as in the benchmark model.

Each period, households start with an initial holding of consumer goods g , and capital in each sector $k = (k_g, k_s, k_i)$. Households choose consumption goods, services, shopping efforts, hours worked, and investments in each sector $i = (i_g, i_s, i_i)$, taking as given the aggregate state Λ , the wage W , and rental

returns $R = (R_g, R_s, R_i)$, to maximize

$$V(\Lambda, g, k) = \max_{c, s, d_g, d_s, n, i, k'} u(c + (1 - \delta_h)g, s, d_g + d_s, n; \theta) + \beta E\{V(\Lambda', c + (1 - \delta_h)g, k')\}$$

subject to the budget constraint

$$\begin{aligned} c p_g(\Lambda) + s p_s(\Lambda) + p_i(\Lambda)(j_g + i_s + i_i) \\ \leq \pi(\Lambda) + n w(\Lambda) + R_g(\Lambda)K_g + R_s(\Lambda)k_s + R_i(\Lambda)k_i, \end{aligned}$$

the shopping constraints for goods and services, $c = d_g \Psi_d[q_g(\Lambda)] F_g(\Lambda)$ and $s = d_s \Psi_d[q_s(\Lambda)] F_s(\Lambda)$, and capital accumulations for each sector $m = \{g, s, i\}$, $k'_m = (1 - \delta)k_m + i_m$.

Let the temporary value functions $\widehat{V}^g(\Lambda, g, k, \hat{p}_g, \hat{q}_g, \hat{F}_g)$, $\widehat{V}^s(\Lambda, g, k, \hat{p}_s, \hat{q}_s, \hat{F}_s)$ denote the utility attained by the household if the market for consumption goods and services were given by the triplets $(\hat{p}_g, \hat{q}_g, \hat{F}_g)$ and $(\hat{p}_s, \hat{q}_s, \hat{F}_s)$ as opposed to the equilibrium triplets $(p_g(\Lambda), q_g(\Lambda), F_g(\Lambda))$ and $(p_s(\Lambda), q_s(\Lambda), F_s(\Lambda))$, respectively.

Firms As in the benchmark model, each sector has a fixed measure of firms and a production function f as in equation (22). Moreover, service production is subject to a neutral technology shock z , while consumption goods production and investment production have sector-specific TFP shocks given by $z_g * z$ and $z_i * z$, respectively, where z , z_g , and z_i are independent.²³ Firms in the services sector and in the investment good sector solve the same problem as in the benchmark model (cf. equations (13)-(14)) with the participation constraints in the service sector given by $\widehat{V}^s(\Lambda, G, K, \hat{p}_s, \hat{q}_s, \hat{F}_s) \geq V(\Lambda, G, K)$.

Consider now the problem of consumer goods producers. Firms carry inventories x from last period that depreciate at rate δ_f . Firms then choose inputs of labor n_g and capital k_g for production and add the current production $z_g z f(k_g, n_g)$ to their net inventories $(1 - \delta_f)x$. This sum yields current capacity F_g . Firms also choose which triplet (p_g, q_g, F_g) to offer to customers. After the matching process, firms choose how much extra investment of inventory to purchase or to sell in the frictionless market for inventories. The unmatched firms purchase $i_{x,u}$ units of inventory and the matched firms purchase $i_{x,m}$. This in turn gives the next period's inventories x'_u and x'_m for the unmatched and matched firms,

²³We also experimented with a range of different specifications for the productivity and preference shocks, including (i) a joint productivity shock for consumption goods and services plus a relative productivity shock that increases productivity for goods relative to services, (ii) independent sector-specific TFP shocks z_s , z_g , and z_i , and (iii) a model where the search effort preference shock is allowed to differ for services and for consumption goods, while TFP for goods and services are identical. Our benchmark specification is the one that yields the highest likelihood in the Bayesian estimation. See Table 7 in Appendix G for details.

respectively,

$$x'_n = z_g z f(n_g, k_g) + (1 - \delta_f)x + i_{x,u}, \quad (30)$$

$$x'_m = z_g z f(n_g, k_g) + (1 - \delta_f)x - F_g + i_{x,m}. \quad (31)$$

To summarize, a consumer goods producer chooses $\{n_g, k_g, p_g, q_g, F_g, i_{x,u}, i_{x,m}, x'_m, x'_n\}$ to solve the following recursive problem, where $\Psi_{T,g}(q_g)$ is the probability that the firm will be matched with a shopper, $\Omega(\Lambda, x)$ is the value of the firm, and $\Upsilon(\Lambda, \Lambda')$ is the stochastic discount factor.

$$\begin{aligned} \Omega(\Lambda, x) = & \max_{n_g, k_g, i_{x,m}, i_{x,u}, p_g, q_g, F_g} -W(\Lambda)n_g - R_g(\Lambda)k_g \\ & + \Psi_{T,g}(q_g) \{p_g F_g - p_x(\Lambda)i_{x,m} + E[\Upsilon(\Lambda, \Lambda') \Omega(\Lambda', x'_m) | \Lambda]\} \\ & + (1 - \Psi_{T,g}(q_g)) \{-p_x(\Lambda)i_{x,u} + E[\Upsilon(\Lambda, \Lambda') \Omega(\Lambda', x'_n) | \Lambda]\} \end{aligned}$$

subject to the capacity constraint

$$F_g \leq z f(n_g, k_g) + (1 - \delta_f)x,$$

the dynamics of inventories for non-matched (30) and matched state (31), and the participation constraint for shoppers $\hat{V}_g(\Lambda, G, K, \hat{p}_g, \hat{q}_g, \hat{F}_g) \geq V(\Lambda, G, K)$.

Average dividends of consumption good producers are

$$\pi_g(\Lambda) = \Psi_{T,g}(q_g)p_g F_g - W(\Lambda)n_g - R_g(\Lambda)k_g - \Psi(q_g)p_x(\Lambda)i_{x,m} - (1 - \Psi(q_g))p_x(\Lambda)i_{x,u}.$$

Finally, in Appendix F we show that firms with identical initial inventories choose the same inventory holdings for the following period, i.e., $x'_n(\Lambda, x) = x'_m(\Lambda, x)$.

Equilibrium Let the consumption good be the numéraire, so $p_g = 1$. The competitive equilibrium consists of allocations $\{S, C, D_g, D_s, I_g, I_s, I_i, N, N_g, N_s, N_i, G, K'_g, K'_s, K'_i, X', x'_m, x'_n, i_{x,u}, i_{x,m}\}$, dividend and profits $\{\pi, \pi_g, \pi_i, \pi_s\}$, values V and Ω , prices $\{W, R_g, R_s, R_i, p_x, p_i, \Upsilon\}$, market tightness and capacity $p_g, p_s, q_g, q_s, F_g, F_s$ such that

1. Households choose $\{C, S, D_g, D_s, I_g, I_s, I_i, N, \pi, G', K'_g, K'_s, K'_i, V, a'\}$ to solve their problem taking as given prices $\{W, R_g, R_s, R_i, p_i, P_a\}$ and dividends π . The stochastic discount factor Υ satisfies $\Upsilon(\Lambda, \Lambda') = \beta u_s(\Lambda')/u_s(\Lambda)$.
2. The allocation $\{p_g, q_g, F_g, N_g/T_g, K_g/T_g\}$, profit π_g , inventory choices $X'/T_g = x'_m = x'_n$, $i_{x,u}, i_{x,m}$, and value function Ω solve the problem of the consumption goods producers, taking

as given $\{\Upsilon, W, R_g, p_x\}$.

3. The allocation $\{N_i, K_i\}$ and the profit π_i solve the problem of the investment producers, taking as given $\{W, R_i, p_i\}$.
4. The allocation $\{p_s, q_s, F_s, N_s, K_s\}$ and the profit π_s solve the problem of the consumption service producers, taking as given $\{W, R_s\}$.
5. Market clearing conditions are satisfied

$$\begin{aligned}
C &= T_g \Psi_{T,g}(q_g) F_g & S &= \Psi_{T,s}(q_s) z f(N_s, K_s) \\
zz_i f(N_i, K_i) &= I_g + I_s + I_i & N &= N_g + N_s + N_i \\
X' &= T_g [1 - \Psi_{T,g}(q_g)] F_g & \pi &= \pi_g + \pi_i + \pi_s \\
F_g &= (1 - \delta) X / T_g + zz_g f(K_g / T_g, N_g / T_g).
\end{aligned}$$

The equilibrium is optimal (we omit the proof since it is similar to the one in Section 3).

6.2.2 Calibration and Quantitative Analysis

We assume that consumption is a constant-elasticity-of-substitution (CES) composite of services and consumption goods. Households' preferences are otherwise similar to those in the benchmark model and are given by

$$u(c, s, d_c, d_s, n) = \frac{1}{1 - \gamma} \left\{ \left[\mu c^{\frac{\omega-1}{\omega}} + (1 - \mu) s^{\frac{\omega-1}{\omega}} \right]^{\frac{\omega}{\omega-1}} - \chi_d \frac{(d_c + d_s)^{1+1/\eta}}{1 + 1/\eta} \right\}^{1-\gamma} - \chi_n \frac{n^{1+1/\nu}}{1 + 1/\nu},$$

where μ is the share of storable consumption goods and ω is the elasticity of substitution between services and the consumption good.

Most parameters are calibrated using the same moments as in the benchmark (the parameter values and targets are summarized in Table 6 in Appendix G). We set μ so the model matches the empirical share of consumer durables in total consumption expenditures, i.e., 8 percent. BEA defines consumer durables as goods which are storable and last for at least a year. This corresponds well to our notion of storable consumption goods. Similarly, the empirical counterpart to services in the model is the sum of non-durable consumption and services. In the robustness analysis we investigate the effect of opting for a wider notion of storable goods. According to the BEA, the average annualized depreciation rate of durable consumption goods (held by consumers) is 18.5 percent. Richardson (1995) argues that the annual cost of holding inventories is between 25 percent and 55 percent of the value of the stored goods. Taking out interest rate costs, the cost of holding inventories is between 19 percent to 43 percent per year. Thus, the depreciation rates of goods does not seem to be higher for households than for firms. For

simplicity we equate these rates and set them to $\delta_h = \delta_f = 19$ percent. We set the elasticity between goods and services to $\omega = 0.85$, as in [Herrendorf et al. \(2013\)](#).

The measure of service and investment producing firms are each normalized to unity. To calibrate the measure of goods producing firms T_g we consider the ratio of inventories to sales since the market tightness D_g/T_g pins down the relative size of inventory to sales. The average annual real inventories to sales ratio for total business (manufacturing, wholesale and retail trade) is 11.5 percent (Source: BLS). We also normalize the steady-state investment goods price to 1 as in the benchmark calibration and equalize the steady-state productivity of goods and service production. These normalizations pin down the steady state productivities z_s , z_g , and z_i .

As in the benchmark, we estimate the model using Bayesian methods. The model has five shocks: the disutility shock of shopping θ_d , the disutility shock of labor θ_n , and the technology shocks for three sectors, z , z_g , and z_i . In addition to the four data series in the benchmark, we introduce an extra time-series to do the Bayesian estimation, namely the ratio of consumption goods to consumption services. This data series helps us identify the relative productivity of goods versus services. The priors and distributions are the same as in the benchmark estimation.

Table 5 reports the estimated results together with business cycle statistics and variance decomposition. The variance decomposition shows that the demand shock θ_d still plays a significant role in accounting for business cycle fluctuations – about 20 percent of the variance of output, 35 percent of TFP, and more than half of the the variance of consumption. Note that the role of θ_d is sensitive to the specification of the technology and preference shocks. Estimating the model with different specifications of the technology shocks and preference shocks we found that the share of output accounted for by search-related preference shocks range from 18 to 35 percent. See Table 7 in Appendix G for details.²⁴ Note also that the shopping friction is quantitatively more relevant for services than for durable consumption goods: according to the variance decomposition the “demand shock” θ_d accounts for 65 percent of the variance of services and just two percent of the variance of durables (cf. Table 5).

The extended model has richer predictions than the benchmark model. In particular, we study the dynamics of goods, services, and the inventories-to-sales ratio. In the data, aggregate purchases of durable goods are much more volatile than services and non-durable goods, and the model has similar predictions. Note that this empirical success of the model hinges on the assumption that both firms and households can store durables. To see this, compare the relative variance of goods to services in economy BM5 relative to the benchmark (BM1) in Table 7. If only firms could store goods (BM5), then the variance of goods relative to the variance of services in the reestimated model would be just one tenth of the ratio in the benchmark economy.²⁵ Moreover, the inventories-to-sales ratio in the model is countercyclical as

²⁴For example, if we were to assume independent productivity shocks for each good, then θ_d would account for a larger share of aggregate fluctuations —34.5 and 44.2 percent of output and TFP, respectively.

²⁵The low relative volatility of services in the benchmark model also depends on the way the technology shocks are

Table 5: Bayesian Estimation: Model with Storable Goods

Priors and Posteriors for the Shock Parameters (Likelihood = 2570.6)
Data used: $Y, Y/N, Inv, P_i, C/S$

Parameter	Density	Para(1)	Para(2)	Mean	90% Intv.
ρ_d	Beta	0.930	0.05	0.9958	[0.9918, 0.9995]
ρ_{z^g}	Beta	0.930	0.05	0.5634	[0.5327, 0.6001]
ρ_{z^i}	Beta	0.930	0.05	0.9946	[0.9909, 0.9988]
ρ_{z^s}	Beta	0.930	0.05	0.8799	[0.8569, 0.8996]
ρ_n	Beta	0.930	0.05	0.9825	[0.9742, 0.9899]
σ_d	Inv Gamma	0.150	Inf	0.5631	[0.5152, 0.6179]
σ_{z^g}	Inv Gamma	0.002	Inf	0.0274	[0.0250, 0.0302]
σ_{z^i}	Inv Gamma	0.002	Inf	0.0111	[0.0100, 0.0122]
σ_{z^s}	Inv Gamma	0.002	Inf	0.0125	[0.0114, 0.0137]
σ_n	Inv Gamma	0.020	Inf	0.0176	[0.0162, 0.0189]

	Variance Decomposition				
	θ_d	z^g	z^i	z	θ_n
Y	19.71	2.09	3.61	68.51	6.08
Labor	25.26	2.04	2.05	2.14	68.51
Consumption	51.67	7.32	0.89	35.61	4.51
Investment	1.43	2.05	23.13	69.45	3.93
Goods	2.15	81.06	0.81	15.17	0.81
Services	65.15	0.41	0.53	29.47	4.44
TFP	35.04	0.86	1.92	62.07	0.11
Y/N	41.26	0.46	1.22	54.45	2.62
P_i	0.02	21.76	62.69	14.70	0.83
Goods/service	2.89	87.31	0.60	8.94	0.26
$\frac{Inventory}{P_{sale}}$	29.13	59.16	0.49	10.66	0.57
$\frac{P_{goods}}{P_{service}}$	62.02	9.95	0.51	26.81	0.72

The table shows the Bayesian estimation for the shopping model with storable goods and services. The service share of consumption is 0.92. The estimation targets the data series of output, labor productivity, investment, investment price, and the ratio of consumption durables to nondurables. *goods* to services. *Durable goods* (labeled *consumption goods* in the theory) are measured as durable consumption goods expenditures in NIPA, and *nondurables* (labeled as *services* in the theory) are measured as consumption services plus non-durable consumption goods. The sample is quarterly U.S. data, from Q1 in 1967 to Q4 in 2013.

in the data, although it is more volatile in the model than that in the data.

In our benchmark analysis we have used durable consumption goods as the empirical counterpart to our notion of consumption goods. However, many so-called non-durable goods can be stored a limited period of time and might be perceived as being part of storable consumption goods. As a sensitivity analysis we assume that the empirical counterpart to goods in the model is durable goods plus non-durable goods. The series used for consumption goods and services in the Bayesian estimation are redefined accordingly. In this case the share of storable goods in consumption expenditures is 40 percent. When reestimating the model the empirical time series for goods and services are modified accordingly. With a larger share of storable goods the preference shocks generally play a smaller role: across various specifications for the technology shocks and preference shocks, the preference shocks account for between 6.5 percent and 18 percent of output, see Table 7 in Appendix G for details.

Summing up, the main results from the benchmark model are robust to allowing firms to hold inventories of consumer durables and to let households store such goods: demand shocks are a major driver of aggregate consumption, TFP, and output. In addition, the extension with inventories is consistent with a number of stylized facts on cyclical properties of services, consumption goods, and inventories. In particular, the model replicates the correlation between the inventory to sales ratio and output, and services is substantially less volatile than consumption durables.

7 Conclusion

This paper provides a business cycle theory with an explicit productive role for the demand for goods. A search friction prevents perfect matching between producers and potential consumers. A larger consumer demand for consumption is associated with more intense search for goods and, hence, a larger utilization of the potential production. Shocks that cause changes in search effort will therefore induce changes in aggregate output even if standard factors such as capital and labor are fixed. Thus, when applying a neoclassical production function that ignores search effort as an input, changes in demand and search effort generate procyclical movements in measured TFP.

A competitive search protocol resolves the matching friction and the equilibrium outcome is efficient and unique. The framework is otherwise a standard neoclassical model with flexible prices.

Our main quantitative exercise is to estimate the model using standard Bayesian techniques. Business

specified. As it turns out, it is only in the benchmark specification —when the TFP shock on service production is the *neutral* technology shock— that the model generates a variance of durable good expenditure which is 20-25 times larger than the variance of service consumption, similar to the difference in the U.S. data. For example, if the neutral technology shock were to apply to goods production and TFP of service production were $z z_s$, then services become almost as volatile as consumption goods (see Economy BM3 in Table 5). In this case the estimation assigns a very volatile neutral technology shock and volatile θ_d shock in order to make consumption goods sufficiently volatile. This in turn makes services substantially more volatile.

cycles are driven by preference shocks to search effort and labor supply, true technology shocks, and investment-specific shocks. Preference shocks affecting search effort account for a large share of the fluctuations in consumption, GDP, and the Solow residual. This finding is robust to extending the model to allow for varying capacity utilization of capital and to allow firms and households to store consumption goods as inventories and durables.

While our notion of search effort for consumption goods is unobservable, we note that the shopping effort implied by our estimated model turns out to be correlated with the measured *time* U.S. households devote to shopping. Interestingly, both the shopping effort in our model and the average empirical shopping time for U.S. households experienced a sharp decline during the Great Recession. According to our model, this fall is needed to account for the large and persistent fall in consumption as well as the suppressed relative price of investment after 2006 in the U.S.

Our paper is consistent with Keynes' idea that consumer demand can have real effects. We show that this holds true even in a neoclassical model with flexible prices, amended with a product market matching friction.

In future work, we plan to extend this environment to contexts where the demand shocks are generated by financial frictions, government expenditures, or foreign demand shocks. It would also be interesting to consider additional frictions that could break the efficient outcome of the competitive search model, such as coordination failures or additional labor market frictions. Finally, it is straightforward to embed our search friction for goods within the New Keynesian and Mortensen-Pissarides approaches to fluctuations, which assume frictions in either price setting or labor markets to generate large fluctuations in output and hours worked. Ultimately, these two traditions build on technology shocks as a major source of fluctuations, and our findings provide a rationale for substituting productivity shocks for demand shocks in these models.

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Appendix

A Proof of Proposition 1

Write the Lagrangian problem as $\mathcal{L} = p\Psi_T(q)Z - \lambda \left(u\left(\frac{Y}{p}, \frac{Y}{p\Psi_d(q)Z}\right) - \bar{u} \right)$. The first-order conditions are then

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial q} &= \Psi_T(q)Z - \lambda \left(-u_c \frac{Y}{(p)^2} - u_d \frac{Y}{(p)^2} \frac{1}{\Psi_d(q)Z} \right) = 0 \\ \frac{\partial \mathcal{L}}{\partial p} &= -pZ \frac{d\Psi_T(q)}{dq} - \lambda u_d \frac{Y}{pZ} \frac{1}{(\Psi_d(q))^2} \frac{d\Psi_d(q)}{dq} = 0\end{aligned}$$

Substituting out λ and simplifying yields the following condition:

$$u_c Z = u_d \frac{1}{\Psi_d(q)} \left(\frac{\Psi_T(q)}{\Psi_d(q)} \frac{\frac{d\Psi_d(q)}{dq}}{\frac{d\Psi_T(q)}{dq}} - 1 \right)$$

Exploiting that $q^{-1}\Psi_T(q) = \Psi_d(q)$ and $\frac{d\Psi_d(q)}{dq} = -\frac{1}{q^2}\Psi_T(q) + \frac{1}{q}\frac{d\Psi_T(q)}{dq}$, we can rewrite the first-order conditions as

$$u_c Z = -u_d \frac{1}{\Psi_d(q)} \frac{1}{q} \frac{\Psi_T(q)}{\frac{d\Psi_T(q)}{dq}} = -u_d \frac{1}{\frac{d\Psi_T(q)}{dq}}.$$

With $T = 1$ and $q = D$ in equilibrium, equation (5) follows. QED

B Planner Problem, Competitive Equilibrium, and the First Welfare Theorem in the Production Economy

In the text we appeal to a version of the First Welfare Theorem and focus on the planner problem. This Appendix characterizes the planner problem and the competitive equilibrium, and proves that the allocation implied by the decentralized competitive equilibrium is equivalent to the planner allocation.

B.1 Derivations of optimality condition for the planner

The optimality conditions follow from the first-order conditions of the planner problem (15), rewritten as

$$\begin{aligned}\max_{D, N_c, N_i, K'_c} & u(D, \Psi_d[D], z f(K_c, N_c), D, N_c + N_i, \Lambda) \\ & + \beta E\{W(\theta', K'_c, z_i z f(K_i, N_i) + (1 - \delta)(K_c + K_i) - K'_c) \mid \Lambda\}.\end{aligned}$$

The first-order conditions over D , N_c , N_i , and K'_c are given by

$$u_c \frac{\partial \Psi_T [D]}{\partial D} z f(K_c, N_c) + u_d = 0 \quad (\text{B.1})$$

$$u_n + u_c \Psi_T [D] z \frac{f(K_c, N_c)}{\partial N_c} = 0 \quad (\text{B.2})$$

$$u_n + z_i z \frac{\partial f(K_i, N_i)}{\partial N_i} \beta E \left\{ \frac{\partial W(\Lambda')}{\partial K'_i} \middle| \Lambda \right\} = 0 \quad (\text{B.3})$$

$$\beta E \left\{ \frac{\partial W(\Lambda')}{\partial K'_c} - \frac{\partial W(\Lambda')}{\partial K'_i} \middle| \Lambda \right\} = 0. \quad (\text{B.4})$$

And the envelope conditions are

$$\frac{\partial W(\Lambda)}{\partial K_c} = u_c \Psi_T [D] z \frac{\partial f(K_c, N_c)}{\partial K_c} - \frac{(1 - \delta) u_n}{z_i z \frac{\partial f(K_i, N_i)}{\partial N_i}} \quad (\text{B.5})$$

$$\frac{\partial W(\Lambda)}{\partial K_i} = - \left(z_i z \frac{\partial f(K_i, N_i)}{\partial K_i} + 1 - \delta \right) \frac{u_n}{z_i z \frac{\partial f(K_i, N_i)}{\partial N_i}}. \quad (\text{B.6})$$

Optimality conditions (16)-(17) follow directly from equations (B.1)-(B.2). Combining equations (B.4)-(B.5)-(B.6) with (B.2) yields equation (18):

$$0 = E \left\{ \frac{\partial W(\Lambda')}{\partial K'_c} - \frac{\partial W(\Lambda')}{\partial K'_i} \middle| \Lambda \right\} = E \left\{ u_{n'} \left(\frac{\frac{\partial f(K'_i, N'_i)}{\partial K'_i}}{\frac{\partial f(K'_i, N'_i)}{\partial N'_i}} - \frac{\frac{\partial f(K'_c, N'_c)}{\partial K'_c}}{\frac{\partial f(K'_c, N'_c)}{\partial N'_c}} \right) \middle| \Lambda \right\}.$$

Euler equation (19) follows from plugging (B.6) into equation (B.3).

B.2 Competitive Equilibrium

Consider the household problem in the benchmark economy, equations (8)-(11) in the text. Let the multiplier on the household's budget constraint (10) be denoted λ . The first-order conditions for the

households can then be expressed as,

$$\begin{aligned}
\lambda \hat{p} &= u_c + \frac{u_d}{\Psi_d(\hat{q})\hat{f}} & (B.7) \\
\lambda p_i &= \beta E \lambda' [R_c(\Lambda') + p_i(\Lambda')(1 - \delta) | \Lambda] \\
\lambda p_i &= \beta E \lambda' [R_i(\Lambda') + p_i(\Lambda')(1 - \delta) | \Lambda] \\
\lambda W &= u_n \\
V_{\hat{p}} &= -\lambda d A \hat{q}^{\varphi-1} \hat{f} \\
V_{\hat{q}} &= (\varphi - 1) d A \hat{q}^{\varphi-2} \hat{f} (u_c - \lambda \hat{p}) \\
V_{\hat{f}} &= u_c d A \hat{q}^{\varphi-1} (u_c - \lambda \hat{p}).
\end{aligned}$$

Now let's consider the problem of a consumption-producing firm (13). Let the multiplier for the participation constraint be γ and for the production constraint be μ . We can write the firm's first-order conditions as

$$\begin{aligned}
A \hat{q}^\varphi \hat{f} + \gamma V_{\hat{p}} &= 0 \\
\varphi A \hat{q}^{\varphi-1} \hat{p} \hat{f} + \gamma V_{\hat{q}} &= 0 \\
\hat{p} A \hat{q}^\varphi - \mu + \gamma V_{\hat{f}} &= 0 \\
W &= \mu z \frac{\partial f(k, n)}{\partial n} \\
R_c &= \mu z \frac{\partial f(k, n)}{\partial k}
\end{aligned}$$

The first-order conditions for the investment-producing firms are standard and are given by

$$\begin{aligned}
W &= p_{iZZ_i} \frac{\partial f(k, n)}{\partial n} \\
R_i &= p_{iZZ_i} \frac{\partial f(k, n)}{\partial k}.
\end{aligned} \tag{B.8}$$

Equilibrium In equilibrium, $p = \hat{p} = 1$, $q = \hat{q}$, and $F = \hat{f}$. The competitive equilibrium consists of 15 functions, three functions from the households' problem, $\{C, D, N\}$, five functions from the firms' problems, $\{K'_c, K'_i, N_c, N_i, \pi\}$, one function from competitive search problem, $\{q\}$, and six price functions, $\{W, p, P_a, p_i, R_c, R_i\}$, which simultaneously satisfy the following functional equations.

First, the household problem yields the following functional equations,

$$u_c = \beta \mathbb{E} \left\{ \frac{R_c(\Lambda') + p_i(\Lambda')(1 - \delta)}{p_i(\Lambda')} u'_c \mid \Lambda \right\} \quad (\text{B.9})$$

$$u_c = \beta \mathbb{E} \left\{ \frac{R_i(\Lambda') + p_i(\Lambda')(1 - \delta)}{p_i(\Lambda')} u'_c \mid \Lambda \right\} \quad (\text{B.10})$$

$$(1 - \varphi)u_c = \frac{u_n}{W} \quad (\text{B.11})$$

$$-u_d = \varphi u_c D^{\varphi-1} f(K_c, N_c). \quad (\text{B.12})$$

Second, the firms' problems yield four functional equations,

$$(1 - \varphi)W = \Psi_T(q)z \frac{\partial f(K_c, N_c)}{\partial N_c} \quad (\text{B.13})$$

$$\frac{W}{R_c} = \frac{\partial f(K_c, N_c)/\partial N_c}{\partial f(K_c, N_c)/\partial K_c} \quad (\text{B.14})$$

$$\frac{W}{p_i} = z z_i \frac{\partial f(K_i, N_i)}{\partial N_i} \quad (\text{B.15})$$

$$\frac{W}{R_i} = \frac{\partial f(K_i, N_i)/\partial N_i}{\partial f(K_i, N_i)/\partial K_i}. \quad (\text{B.16})$$

Finally, market clearing yields

$$q = D$$

$$C = \Psi_T(q)z f(K_c, N_c)$$

$$z_i z f(K_i, N_i) = K'_c + K'_i - (1 - \delta)(K_c + K_i)$$

$$N = N_c + N_i.$$

Incidentally, by combining equations (B.13) and (B.15) we obtain the expression for the relative price of investment, equation (20) in the text.

B.3 A First Welfare Theorem in the Production Economy

We now show that the competitive equilibrium corresponds to the planner allocation. To this end, we show that the first-order conditions of the competitive equilibrium are the same as the ones in the planner problem.

First, equation (B.12) in the equilibrium is identical to equation (16) in the planner problem. Second, combining equation (B.11) and (B.13) yields the first-order condition on labor (17) in the planner problem. Finally, equation (18) in the planner problem holds in equilibrium. To see this, take the difference between

(B.9) and (B.10) from the household's problem, and get

$$0 = E \left\{ (R_i(\Lambda') - R_c(\Lambda')) \frac{u'_c}{p(\Lambda')} \mid \Lambda \right\}$$

Now we replace u_c with u_n/W using equation (B.11) and obtain

$$0 = E \left\{ (R_i(\Lambda') - R_c(\Lambda')) \frac{u'_n}{W(\Lambda')} \mid \Lambda \right\}.$$

Then replace R/W with firms' first-order conditions (B.14) and (B.16) to obtain the planner's Euler equation.

C Details about the Calibration of the Production Economy

Depreciation δ . Let the investment share of output be $\kappa = p_I I/Y = 20\%$ and the size of the aggregate capital-output ratio $p_I K/Y = 2.75$. This allows us to pin down the depreciation rate from the steady-state relation $\delta K = I$, so

$$\delta = \frac{p_I I/Y}{p_I K/Y} = \frac{0.2}{2.75} = 7.3\%$$

Labor's share θ_n : for an investment firm the labor's share of output is simply θ_n (proof omitted). Consider now the share of output for a consumption-producing firm that is paid to labor. Note that the equilibrium price of the consumption good is given by

$$\hat{p} = (1 - \varphi) \frac{W}{\Psi_T(q) z \frac{\partial f(K_c, N_c)}{\partial N_c}}, \quad (\text{C.1})$$

where $\hat{p} \equiv 1$ since consumption is the numéraire good. The wage bill is WN_c . Total (measured) value added is the sales $\Psi_T(q) F$, where $F = zf(K_c, N_c)$, so labor's share of output in consumption firms is

$$\frac{WN_c}{C} = \frac{WN_c}{\Psi_T(q) z f(K_c, N_c)} \cdot \frac{\partial f}{\partial N_c} = \frac{WN_c}{(1 - \varphi) W} \cdot \frac{\partial f}{\partial N_c} = \frac{\theta_n}{1 - \varphi},$$

where the second equality follows from equation (C.1) and the third equation from the assumption that f is Cobb-Douglas so $\theta_n f(K_c, N_c) = N_c \frac{\partial f}{\partial N_c}$. The aggregate labor share is then given by,

$$\frac{WN}{Y} = \theta_n \frac{1 - \kappa\varphi}{1 - \varphi}.$$

With an aggregate share of output that goes to labor $WN/Y = 0.67$ and $\kappa = 0.2$, we have $\theta_n = 0.54$.

Capital's share θ_k . The share of output that goes to reproducible capital is

$$\frac{RK}{Y} = \theta_k \frac{1 - \kappa\varphi}{1 - \varphi}.$$

From households' first order conditions, we know that in steady state

$$\frac{R}{p_I} = \frac{1 - \beta(1 - \delta)}{\beta},$$

and $\beta = 1/(1 + r)$. In addition, in steady state $R/W = (\partial f(N_c, K_c)/\partial K_c) / (\partial f(N_c, K_c)/\partial N_c)$. With $\varphi = 0.23$, $\delta = 7.3\%$, $r = 4\%$, $\kappa = 0.2$, and $p_I K/Y = 2.75$, this implies $\theta_k = 0.25$.

Weight on search effort χ_d . The capacity utilization in consumption is defined as the probability that a production unit gets matched, i.e., $\Psi_T[D] = D^\varphi$. A capacity utilization of 81% then implies $D = (0.81)^{1/0.23} = 0.4$. Given the expressions for u , Ψ_T and F , the intra-temporal first-order condition (16) imply

$$\chi_d = \varphi C(D)^{-\left(\frac{1}{\eta}+1\right)} = 0.23 * 0.8 * (0.4)^{-\left(\frac{1}{0.11}+1\right)} = 1905.$$

Mean TFP $Z = E(z)$ and $Z_I = E(z_I)$. To compute average TFPs, we first obtain the share of labor and capital in each sector. In steady state, the two sectors, consumption and investment, have the same ratio of wage to rental. Under the assumption of Cobb-Douglas of f , this implies $\frac{N_i}{K_i} = \frac{N_c}{K_c} = \frac{N}{K}$. In addition, we divided equation (B.13) by equation (B.15) and get

$$(1 - \varphi)p_I = \frac{\Psi_T(q)z\partial f(K_c, N_c)/\partial N_c}{z z_i \partial f(K_i, N_i)/\partial N_i} = \frac{C N_i}{I N_c},$$

which implies

$$\frac{N_i}{N_c} = \frac{(1 - \varphi)\kappa}{1 - \kappa}. \quad (\text{C.2})$$

Note that we choose $p_I = 1$ in steady state, thus $I = \kappa$. Under our quarterly model, capital used for production $K = 4I/\delta = 11$. Taking the ratio of consumption over investment, we have

$$\frac{C}{I} = \frac{1 - \kappa}{\kappa} = \Psi_T(q) \frac{1}{Z_I} \left(\frac{(1 - \varphi)\kappa}{1 - \kappa} \right)^{\alpha_k + \alpha_n}.$$

We can therefore calibrate Z_I ,

$$Z_I = \frac{\kappa}{1 - \kappa} \Psi_T(q) \left(\frac{(1 - \varphi)\kappa}{1 - \kappa} \right)^{-\alpha_k - \alpha_n} = \frac{0.2}{0.8} * 0.81 * \left(\frac{(1 - 0.23) * 0.2}{0.8} \right)^{-0.25 - 0.54} = 0.74.$$

From equation (C.2) and the fraction of time spent on working in steady state $N = .3$, we know that $N_c = 0.25$ and $N_i = 0.05$. Similarly, $K_c = 0.83 * K$ and $K_i = 0.17 * K$. We can now back up the neutral technology in steady state

$$Z = \frac{C}{\Psi_T(D)f(K_c, N_c)} = \frac{0.8}{0.81K_c^{\alpha_k} N_c^{\alpha_n}} = 1.2.$$

D Proof of Proposition 2

Consider a static economy with J types of agents who differ in their consumption expenditure y_j , $j \in \{1, \dots, J\}$. With a price level of $P = 1$, the aggregate expenditure must equal $\sum_j y_j \mu_j = C$, where μ_j is the population share of type j households, and C is aggregate consumption. There is a unit measure of firms, each of whom has a production function $f(k, n) = (k)^{\alpha_k} (n)^{\alpha_n}$. We start by showing that in equilibrium all firms supply the same capacity F .

Lemma 1. *All firms supply the same capacity of consumption goods, given by $F = zf(K_c, N_c)$.*

Proof. Since there are no externalities or distortions, it is straightforward that the welfare theorems apply. Accordingly, we formulate the problem as a planner problem,

$$\begin{aligned} & \max \sum_j \xi_j u(C_j, D_j) \\ \text{s.t. } & K_C = \sum_j K_j \quad N_C = \sum_j N_j \quad 1 = \sum_j T_j, \quad C_j = D_j^\varphi T_j^{1-\varphi} z f(K_j, N_j), \end{aligned}$$

where ξ_j denotes the planner weight on households of type j and K_j , N_j , and T_j denote the capital, labor, and share of firms allocated to production intended for group j . D_j and T_j represent the aggregate search effort in market j and the aggregate measure of firms catering to market j . We rewrite the problem as a Lagrange problem

$$\Theta = \sum_j \xi_j u \left(D_j^\varphi (T_j)^{1-\varphi} z f(K_j, N_j), D_j \right) - \lambda_K \left(\sum_j K_j - K_C \right) - \lambda_N \left(\sum_j N_j - N_C \right) - \Gamma \left(\sum_j T_j - 1 \right)$$

Taking the first-order conditions yields,

$$\begin{aligned}
-u_{d,j} &= u_{c,j} \cdot \varphi \left(\frac{D_j}{T_j} \right)^{\varphi-1} z f(K_j, N_j) \\
\frac{\Gamma}{\lambda_K} &= \frac{\xi_j u_{c,j} \cdot (1-\varphi) \left(\frac{D_j}{T_j} \right)^\varphi f(K_j, N_j)}{\xi_j u_{c,j} \cdot \left(\frac{D_j}{T_j} \right)^\varphi T_j \frac{\partial f(K_j, N_j)}{\partial K_j}} = (1-\varphi) \frac{f(K_j, N_j)}{T_j \frac{\partial f(K_j, N_j)}{\partial K_j}} \\
\frac{\lambda_K}{\lambda_N} &= \frac{\xi_j u_{c,j} \cdot \left(\frac{D_j}{T_j} \right)^\varphi T_j \frac{\partial f(K_j, N_j)}{\partial K_j}}{\xi_j u_{c,j} \cdot \left(\frac{D_j}{T_j} \right)^\varphi T_j \frac{\partial f(K_j, N_j)}{\partial N_j}} = \frac{\frac{\partial f(K_j, N_j)}{\partial K_j}}{\frac{\partial f(K_j, N_j)}{\partial N_j}}.
\end{aligned}$$

When f is Cobb-Douglas, the last two conditions imply

$$\begin{aligned}
\frac{\Gamma}{\lambda_K} &= (1-\varphi) \frac{(K_j)^{\alpha_k} (N_j)^{\alpha_n}}{T_j \alpha_k (K_j)^{\alpha_k-1} (N_j)^{\alpha_n}} = \frac{1-\varphi}{\alpha_k} \frac{K_j}{T_j} \\
\frac{\lambda_K}{\lambda_N} &= \frac{\alpha_k (K_j)^{\alpha_k-1} (N_j)^{\alpha_n}}{\alpha_n (K_j)^{\alpha_k} (N_j)^{\alpha_n-1}} = \frac{\alpha_k}{\alpha_n} \frac{N_j}{K_j}.
\end{aligned}$$

It follows that all firms have the same capital-labor ratio, equal to K_c/N_c , and all firms have the same output per location, $F = z f(K_c, N_c)$. \square

We now solve the decentralized problem. Conjecture that there will be J different markets open, which all provide F but differ in the offered pair (p_j, q_j) . Let $\bar{\pi}$ represent the expected revenue for a firm operating in the most profitable market. Profit maximization then imposes the following arbitrage condition on any offered (p_j, q_j) ,

$$p_j = \frac{\bar{\pi}}{F} \cdot (q_j)^{-\varphi} = \frac{\bar{\pi}}{F} \cdot \left(\frac{D_j}{T_j} \right)^{-\varphi}.$$

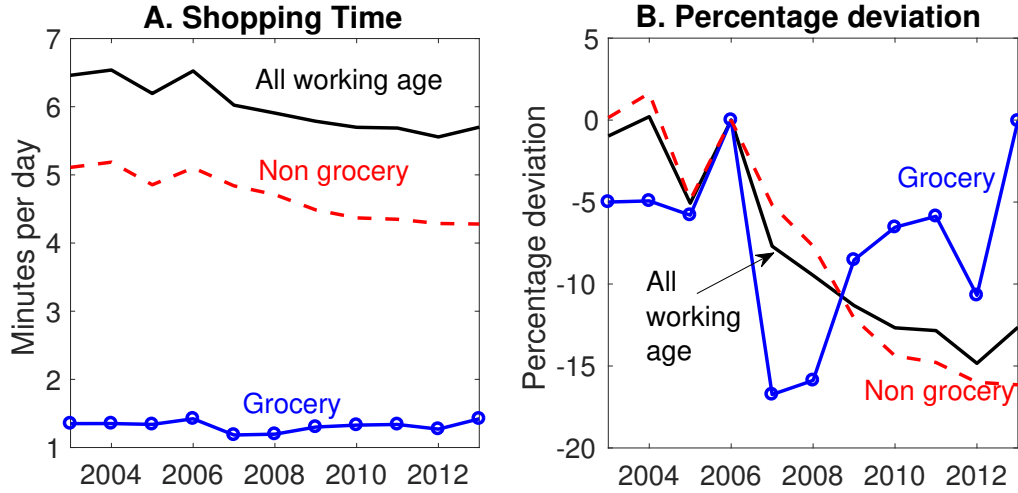
The search technology implies that for households of type j , $c_j = D_j^\varphi (T_j)^{1-\varphi} F$. We can thus obtain income of a household $y_j = p_j c_j = \bar{\pi} T_j$. Thus, since $\int T_j dj = 1$, aggregate revenue equals aggregate expenditure, $\bar{\pi} = \int y_j dj = C$. It follows that the measure of firms catering to type j households is equal to j 's expenditure share $T_j = \mu_j y_j / C$. This in turn implies equation (23). Finally, the intra-temporal first-order condition yields equation (24).

E Grocery and Non-Grocery Shopping

Figure 3 shows the shopping time between 2003 and 2013 for the working age group (25-59 years old). The data source is American Time Use Survey (ATUS). Panel A shows the level for all shopping time (black-solid line), grocery shopping time (blue-circled line), and others shopping time (red-dashed line)

of the working-age group. Panel B shows the percentage deviation of these categories.

Figure 3: Shopping



This figures shows the level and percentage deviation in shopping time between 2003 and 2013 for the working age group (25-59 years old). The data source is American Time Use Survey (ATUS). Panel A shows the level for all shopping time (black solid line), grocery shopping time (blue circled line), and other shopping time (red dashed line) of the working-age group. Panel B shows the percentage deviation of these categories.

F Identical inventory choice at the storable good model

In this subsection, we show that consumption goods producers with identical initial inventory choose the same holdings of next period's inventory, i.e.

$$x'_n(\Lambda, x) = x'_m(\Lambda, x). \quad (\text{F.1})$$

A consumption good producer chooses $\{n_g, k_g, p_g, q_g, F_g, i_{x,u}, i_{x,m}, x'_m, x'_n\}$ to maximize

$$\begin{aligned} \Omega(\Lambda, x) = \max \quad & -W(\Lambda)n_g - R_g(\Lambda)k_g \\ & + \Psi_{T,g}(q_g) \{p_g F_g - p_x(\Lambda)i_{x,m} + E [M(\Lambda, \Lambda') \Omega(\Lambda', x'_m) | \Lambda]\} \\ & + (1 - \Psi_{T,g}(q_g)) \{-p_x(\Lambda)i_{x,u} + E [M(\Lambda, \Lambda') \Omega(\Lambda', x'_n) | \Lambda]\} \end{aligned}$$

subject to the capacity constraint

$$F_g \leq zf(n_g, k_g) + (1 - \delta_f)x,$$

the inventory accumulation constraint for the unmatched state and for the matched state,

$$x'_n = zf(n_g, k_g) + (1 - \delta_f)x + i_{x,u}, \quad (\text{F.2})$$

$$x'_m = zf(n_g, k_g) + (1 - \delta_f)x - F_g + i_{x,m}, \quad (\text{F.3})$$

and the participation constraint of households. Let μ_n and μ_m be the multipliers on the unmatched constraint (F.2) and the matched inventory constraint (F.3) respectively. Taking the first order conditions on $i_{x,u}, i_{x,m}, x'_m, x'_n$, we have

$$\begin{aligned} \Psi_{T,g}(q_g)p_x(\Lambda) &= \mu_m, & (1 - \Psi_{T,g}(q_g))p_x(\Lambda) &= \mu_n \\ \Psi_{T,g}(q_g)E[M(\Lambda, \Lambda')\Omega_x(\Lambda', x'_m)] &= \mu_m, & (1 - \Psi_{T,g}(q_g))E[M(\Lambda, \Lambda')\Omega_x(\Lambda', x'_n)] &= \mu_n \end{aligned}$$

Combining these four equations, we have

$$\frac{\Psi_{T,g}(q_g)E[M(\Lambda, \Lambda')\Omega_x(\Lambda', x'_m)]}{(1 - \Psi_{T,g}(q_g))E[M(\Lambda, \Lambda')\Omega_x(\Lambda', x'_n)]} = \frac{\mu_m}{\mu_n} = \frac{\Psi_{T,g}(q_g)p_x(\Lambda)}{(1 - \Psi_{T,g}(q_g))p_x(\Lambda)}$$

which implies

$$\frac{E[[M(\Lambda, \Lambda')\Omega_x(\Lambda', x'_m)]]}{E[[M(\Lambda, \Lambda')\Omega_x(\Lambda', x'_n)]]} = 1.$$

It is therefore $x'_m = x'_n$.

G Robustness estimation on the storable good model

In this section, we report the robustness check over the estimation of the storable good model for alternative shock specifications and alternative definitions of storable goods. Table 6 reports the calibrated targets and parameter values, Table 7 presents the likelihood for the estimated models, the contribution of the θ_d shock on output, TFP, and consumption (according to the variance decomposition), as well as two moments unique to the storable good model. These moments are the relative variance of storable consumption goods to services and the correlation of the inventory-to-sale ratio with output. A Supplementary Appendix available in <https://www.sas.upenn.edu/~vr0j/papers/BRSSupplAppSept19.pdf> reports the details of the various estimated models, including business cycle statistics and the complete variance decompositions for all variables.

We consider four alternative specifications for the technology and preference shocks. Economy 1 has the benchmark specification where service production is subject to a neutral productivity shock (labeled z_s), consumption good production has a TFP given by the neutral TFP shock times a good-specific shock so that TFP is $z_s z_g$, and investment production has TFP $z_s z_i$ as in the benchmark model in Sections 3-5.

Table 6: Calibration of the Shopping Model with Storable Goods

Targets	Value	Parameter	Value
First Group: Parameters Set Exogenously			
Risk aversion	2.	γ	2
Real interest rate	4%	β	0.99
Frisch elasticity	0.72	ν	0.72
Elasticity of substitution	0.85	ω	0.85
Households depreciation	0.185	δ_h	0.185
Firm depreciation	0.185	δ_f	0.185
Second Group: Standard Targets			
Fraction of time spent working	30%	χ_n	10.68
Labor share of output	0.67	α_n	0.55
Consumption share	0.80	α_k	0.25
Capital-output ratio	2.75	δ	0.07
Storable goods share in cons.	0.08	μ	0.07
Inventory-sale ratio	11.5%	T_g	0.018
Third Group: Normalization			
Steady-state output	1	$E(z)$	1.74
Relative price of investment	1	$E(z_i)$	0.09
Capacity utilization of services	0.81	χ_d	2339
Fourth Group: Targets Specific to This Economy			
Cross-sectional st. dev. of cons. good prices	9%	φ	0.23
Shopping time expenditure elasticity	7.5%	η_d	0.11

Economy 2 has two types of shopping disutility shocks, one applying to search for storable goods, θ_d^g , and one applying to search for services, θ_d^s . With some abuse of notation we record the sum of variance contribution attributable to θ_d^g and θ_d^s in the column labeled θ_d . Moreover that economy has only two productivity shocks: a neutral TFP shock z_s applying to both consumption goods and services and the standard specification $z_s z_i$ for investment production. Economy 3 has z_g as the neutral technology shock, so TFP for service production becomes $z_s z_g$. Finally, Economy 4 assumes that TFP for the three production functions are independent, i.e., z_s on service production, z_g on goods production, and z_i on investment production.

The upper panel of Table 7, “Benchmark definition of storable goods: Durable goods”, reports the statistics for the benchmark calibration where the empirical counterpart to storable goods is durable consumption goods and the consumption expenditure share of these goods is calibrated to eight percent. Our benchmark specification – Economy BM1 – has the highest likelihood and matches best the observed relative variance of goods to service. Across specifications the θ_d shock(s) account for 18 to 35 percent of output variation, at least one third of TFP variation, and more than 50 percent of consumption variation. All specifications feature countercyclical inventory to sales ratios.

Economy BM5 considers a version of the storage economy where the quarterly depreciation rate of consumption goods is set to 99 percent. The specification of shocks is the same shock specification as BM1. This economy is intended to capture a counterfactual economy where firms can store goods but households are effectively prevented from storing goods.

Economies BM6 and BM7 reestimates the storage model but with just four shocks, similar to the benchmark model in Sections 3, and targets the same data series as in 5 (GDP, labor productivity, aggregate consumption and the relative price of investment to goods). Economy BM6 allows households to store the storable good (and with $\delta_h = 0.05$) while Economy BM7 effectively rules out storage (with $\delta_h = 0.99$).

The lower panel of Table 7, “Alternative definition of storable goods: Durable plus non-durable goods”, reports the statistics for an alternative calibration where the empirical counterpart to storable goods is non-durable plus durable consumption goods. In this case the expenditure share of these goods is calibrated to 40 percent, equal to the NIPA expenditure share on non-durable plus durable consumption goods. Note that the data series used in the estimation are adjusted accordingly. Therefore, the likelihood is not comparable across the upper and lower panels.

We conduct four different shock specifications also under this alternative calibration. Clearly, with a large expenditure share of storable goods, the θ_d shock plays a smaller role. The contribution varies from 7 percent to 18 percent for output, 16 percent to 33 percent for TFP, and 22 percent to 45 percent for consumption. With goods including nondurable consumption, the relative goods volatility reduces from

27 times to 7 times of service volatility. The benchmark shock specification still has the highest likelihood and a relative variance of consumption goods to services closest to the data.

Table 7: Robustness Estimation on Storable Good Model

Economy	Shocks	Likelihood	contribution of θ_d			$\frac{Var(\text{goods})}{Var(\text{services})}$	Corr(Y , $\frac{\text{inventories}}{\text{sales}}$)
			Y	TFP	Con.		
Benchmark definition of storable goods: Durable goods							
Data						27.33	-0.42
BM1	$z_s, z_s z_g, z_s z_i, \theta_d, \theta_n$	2570.57	19.71	35.04	51.67	23.41	-0.58
BM2	$z_s, z_s, z_s z_i, \theta_d^g, \theta_d^s, \theta_n$	2553.36	18.88	33.85	55.52	19.36	-0.13
BM3	$z_g z_s, z_g, z_g z_i, \theta_d, \theta_n$	2511.71	21.57	29.63	38.75	1.31	-0.62
BM4	$z_s, z_g, z_i, \theta_d, \theta_n$	2452.48	34.46	44.15	49.78	3.68	-0.49
BM5	$\delta_h = 0.99$, BM1 shocks	2023.96	18.31	33.02	61.37	2.50	-0.03
BM6	$z_s, z_s, z_i, \theta_n, \theta_d$	2335.44	18.34	33.96	52.39	4.50	-0.66
BM7	$\delta_h = 0.99$, BM6 shocks	2322.48	20.61	41.04	60.71	0.31	-0.19
Alternative definition of storable goods: Durable plus non-durable goods							
Data				7.12	-0.42		
ND1	$z_s, z_s z_g, z_s z_i, \theta_d, \theta_n$	2835.17	6.51	16.07	22.18	8.02	-0.63
ND2	$z_s, z_s, z_s z_i, \theta_d^g, \theta_d^s, \theta_n$	2820.89	7.11	17.15	45.02	5.84	-0.21
ND3	$z_g z_s, z_g, z_g z_i, \theta_d, \theta_n$	2680.90	7.97	19.28	31.88	1.42	-0.57
ND4	$z_s, z_g, z_i, \theta_d, \theta_n$	2699.52	18.03	32.89	38.04	1.80	-0.49

The table summarizes key statistics for the storable good model for different specifications of productivity and preference shocks and for different calibrations of the share of storable goods. The upper panel reports the results for the benchmark calibration where the empirical counterpart to storable goods is durable consumption goods. The lower panel, "Alternative definition of storable goods: Durable plus non-durable goods" reports the results for an alternative calibration where the empirical counterpart to the storable good is durable plus non-durable consumption goods. The specifications of the technology and preference shocks are reported in the following sequence: (1) TFP shock for service production, (2) TFP shock for storable consumption good production, (3) TFP shock for investment production, (4) shock(s) to the disutility of shopping, and (5) preference shock for leisure. Economies BM3 and ND3 have two shopping disutility shocks, θ_d^g and θ_d^s . In this case the column labeled θ_d records the sum of variance contribution attributable to θ_d^g and θ_d^s . Economy BM5 has the same shock specification as BM1 but prevents households from storing goods (with $\delta_h = 0.99$). Economy BM6 and BM7 has the same shock specification as our benchmark (non-storage) economy and estimates the model with the four data series used in the benchmark non-storage economy (Y , Y/N , P_i , and C).