Computerizing Households and the Role of Investment-Specific Productivity in Business Cycles

Seunghoon Na and Hyunseung Oh

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Abstract

Advancements in computer technology have reshaped not only business operations but also household consumption. We estimate a business-cycle model disaggregating consumer IT and non-IT durable goods from the capital stock. We find that shocks to the supply of IT durables account for more than half of the variation in households' real expenditure on IT durables. Furthermore, investment-specific productivity shocks drove nearly half of the rapid growth in household durable expenditures during the 2000s. Nonetheless, they have small influence over output dynamics, because unlike business investment goods, consumer durables do not add to the productive capital of the economy. The shocks become important when household IT goods are complementary to firms' capital, such as when online services are provided through consumers' smartphones.

Keywords: Investment; Durables; Investment-specific productivity.
JEL Classification Numbers: E22, E32, E37.

1 Introduction

Studies on business cycles emphasize investment behavior as a key source of economic fluctuations. The recent literature has proposed that shocks to the demand and supply of investment goods are an important driver of busines cycles. A consensus has formed that disturbances to investment demand are crucial for investment and output dynamics. However, the importance of shocks to the supply of investment goods remains controversial (Fisher, 2006; Justiniano, Primiceri, and Tambalotti, 2011).

In this paper, we explore the business-cycle implications of investment-specific productivity (ISP) focusing on shocks, especially those to investment goods used by households (i.e. consumer durables). Existing approaches that study investment shocks pay less attention to consumer durables, as the standard practice in this literature is to treat consumer durables as a subset of productive capital in both model and data. We argue that a careful investigation of consumer durables provides us with a better understanding of the role of ISP shocks over the business cycle.

Figure 1 plots expenditures on the final use of computer goods by household and business, normalized by the GDP deflator.[1] Both series moved together and increased significantly during the 1990s investment boom, but they diverged since 2001. While business spending on computer goods sharply declined in 2001 and remained stagnant, households continued to computerize and their expenditures grew rapidly until 2007. Notably, 2001 is the year when Steve Jobs announced the opening of Apple Stores which has paved the way to Apple's success in the development and sales of consumer electronics.[2] Consumer durables based on information technology (IT), such as smartphones and tablets, are ubiquitous nowadays, which can be missed if one only looks at the total expenditure in the figure.

To understand the role that innovations to consumer IT products played in the U.S. business cycle, we first look into the aggregate and detailed goods-level series of consumption expenditures in Section 2. We document markedly different cyclical properties between IT and non-IT household durables and their relative prices. To study their business-cycle implications, we incorporate into a medium-scale real business cycle model both IT and non-IT durables in Section 3.

In Section 4, investment shocks are structurally estimated with Bayesian methods, using as observables the relative prices of IT and non-IT consumer durables as well as other key macroeconomic variables. The results are discussed in Section 5. We find

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[1] The series is commonly used to study the macro-level effect of computerizing industries, e.g. Aum, Lee, and Shin (2018).

[2] "How the Apple store took over the world." *The Washington Post*, July 21, 2015.

Figure 1: Computer goods expenditure by household and business
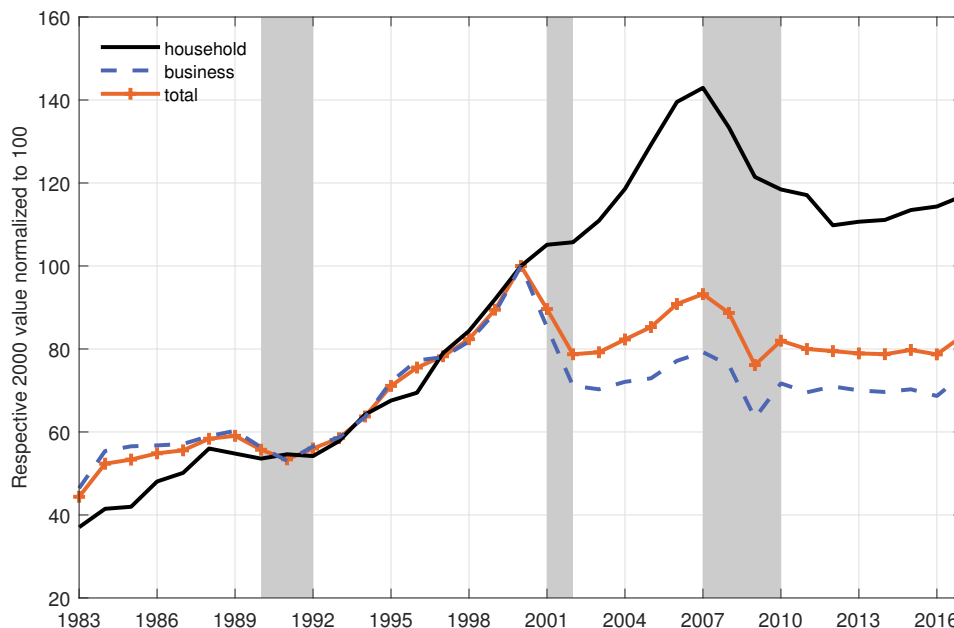
Note: Annual data from the Bureau of Economic Analysis input-output use table (before redefinition, at producer price), North American Industry Classification System (NAICS) code 334 "computer and electronic product manufacturing goods." The legends "household" and "business" indicate personal consumption expenditures and private equipment investment of goods shipped from industry 334. Each series is divided by the GDP deflator and normalized to 100 in 2000. Shaded area indicates NBER recessions.

that ISP shocks account for more than half of the dynamics of IT goods spending by households in the whole sample. Moreover, these shocks were a major driver of the 2000s boom in durable consumption expenditures. The estimated importance of ISP shocks on household spending hinges on the separation between IT and non-IT consumer durables. When estimating the model with an aggregate consumer durable good, ISP shocks are not relevant at all, consistent with Justiniano, Primiceri, and Tambalotti (2011).

However, ISP shocks are not the major sources of output and nondurable consumption fluctuations. This may be puzzling since a shock that mainly accounts for the dynamics of investment variables would usually affect other macroeconomic variables. A key intuition is that firms' capital is used in the production, whereas consumer durables only enter household utility. We conclude in Section 6 after discussing the potential channels that would amplify the macro-level importance of household IT goods.

Related literature. Seminal papers by Greenwood, Hercowitz, and Krusell (1997, 2000) and Cummins and Violante (2002) argue that productivity growth specific to investment goods can account for the majority of long-run growth, and is also important in accounting for business cycles. Fisher (2006) estimates a structural vector autoregression model and find that ISP shocks are key to output and investment dynamics. Nevertheless, estimation results in dynamic, stochastic, general equilibrium models find limited importance of these shocks, when data on the relative price of investment are taken into account (Justiniano, Primiceri, and Tambalotti, 2010, 2011; Schmitt-Grohe and Uribe, 2012; Moura, 2018).[3] This literature so far does not address the difference between household and business investment goods and their relative prices. Our contribution is to bring the relative price of consumer durables into the discussion of investment shocks, especially in recent periods where households are computerized and connected everywhere.

Our paper also fits into the literature on sectoral approaches to the business cycle. The focus on IT goods to understand consumer durable dynamics is related to studies on the 1990s investment boom that emphasizes a sectoral approach into the computer goods industry, such as Whelan (2003) and Tevlin and Whelan (2003). Our approach in taking a sectoral approach to the relative price of consumer durables is related to Reis and Watson (2010), where they look into the detailed consumer price data and quantify several relative price movements across consumer goods that contribute to the dynamics of aggregate inflation. In the model estimation, we show that the quantitative importance of investment shocks differ when taking a disaggregate approach on consumer durables. This point is somewhat related to Guerrieri, Henderson, and Kim (2014), as they analyze shocks to the marginal efficiency of investment in a single production function model and compare those to investment-specific productivity shocks in a model with a separate production functions for consumption and investment goods. Lastly, we argue that even if the sector share is small, sectoral shocks could potentially be important in the aggregate when complementarity in some form exists across goods. Complementarity in the production of goods across industries are widely studied in the literature, such as Atalay (2017). Fisher (2007) shows evidence that household capital is complementary to the production of business goods, although household capital in his data is housing rather than consumer durables. While complementarity arising from general purpose technology such as advances in computer goods is widely discussed in the literature (Jovanovic and Rousseau, 2005),

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[3]Recently, the price dynamics of investment goods are also studied in estimating international business cycles, e.g. Boileau and Normandin (2017) and Dogan (2019).

household to business complementarity based on IT goods is less studied as we discuss in the last part of the paper.

Of note, the measurement of ISP shocks through the relative price of investment goods is standard in the literature, as published in Fernald (2014). The goal of this paper is to understand the implications of the relative prices, and we analyze the NIPA price series as given without attempting to address their measurement issues. Nevertheless, as there might be concerns with earlier period data on quality characteristics, we begin our sample period from 1983.[4]

2 IT consumer durables in the business cycle

In this section, we provide several business-cycle statistics of consumer durables, focussing on the difference between IT and non-IT goods.

2.1 Data and definition of IT goods

The data are from the detailed category of personal consumption expenditures (PCE) in NIPA. We use quarterly series of both price indices and nominal spending of consumer durable goods from 1983q1 to 2018q4. The total number of consumer durable goods in PCE's finest category is 44.

We classify the 44 types of consumer durables into IT and non-IT goods in a standard manner. Ten goods are included in IT goods, which are (1) TV, (2) other video, (3) audio, (4) audio disc and permanent downloads, (5) video disc and permanent downloads, (6) photo equipment, (7) PC/tablet, (8) computer software, (9) other information processing equipment, (10) telephone and related communication equipment. Except for "telephone and related communications equipment," nine of these goods are classified under the parent category "video, audio, photographic, and information processing equipment and media." The remaining 34 goods are included in non-IT goods. Notable products in this classification are autos, furniture, and household appliances.

Using this classification, the chain-weighted per-capita quantity indexes of both IT and non-IT durables are constructed. The relative prices of IT and non-IT durables

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[4]Many studies find their measurement of the quality-adjusted prices to be consistent with NIPA estimates in several moments. As the NIPA price deflators for consumption goods are based on the consumer price index published by the Bureau of Labor Statistics, we find the relative price data to be highly reliable.

Figure 2: Relative prices of consumer durables (in growth rate)
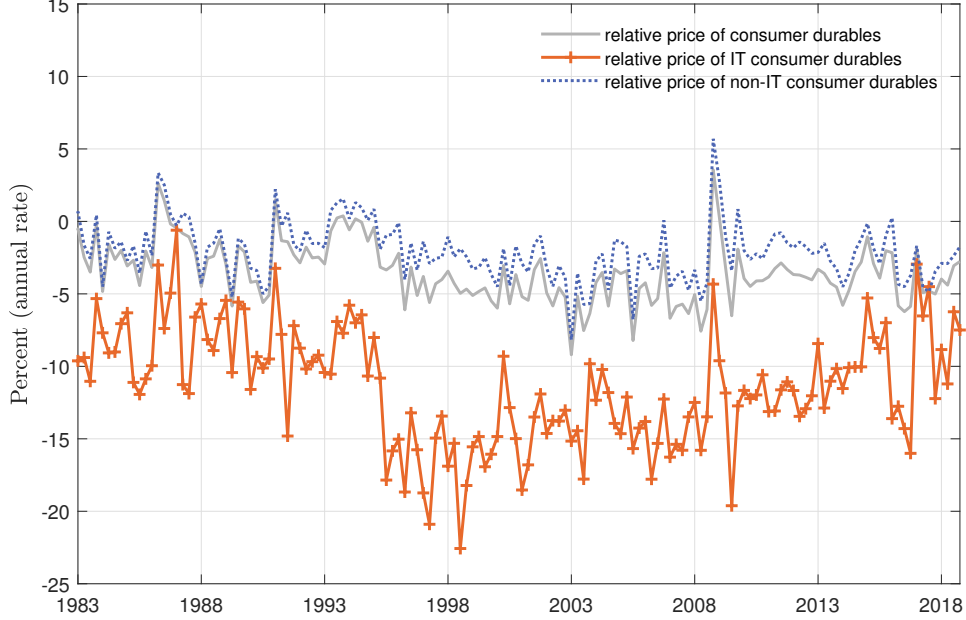
Note: Each time series plots the growth rate from the previous quarter in an annual rate. For reference, the average annual growth rates of the relative price of IT durables and that of non-IT durables in this period are -11.42 percent and -2.07 percent, respectively.

are the respective price indexes of the two durables divided by the price index of nondurables and service.

2.2 IT and non-IT consumer durables

Figure 2 plots the time series of the growth rates of the relative prices of IT and non-IT durables. Not surprisingly, the growth rate has been substantially lower for IT durables compared to non-IT durables, consistent with technology improvements concentrated in the IT sector. At the same time, the relative price of IT durables appears to be more volatile compared to that of non-IT durables, suggesting a business-cycle angle as well in distinguishing these two relative prices.

To better understand the difference in the dynamics between IT and non-IT durables, we display three business-cycle moments of consumer durables in Table 1. The first column, $\rho_{p,n}$, is the correlation between the growth rates of the relative price and the real expenditure for each durable good. This moment has been crucial in arguing for the importance of investment-specific productivity shocks (Greenwood, Hercowitz, and Krusell, 2000). The second and third columns are the standard deviations of the relative price and the real expenditure for each good. These three

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Table 1: Business-cycle moments of consumer durables

	Growth rate I			Growth rate II		
	$\rho_{p,n}$	σ_p	σ_n	$\rho_{p,n}$	σ_p	σ_n
Consumer durables:	-0.11	1.00	4.56	-0.14	1.00	4.87
• IT durables:	-0.44	1.92	3.90	-0.46	1.89	4.09
• Non-IT durables:	-0.11	0.96	5.03	-0.13	1.00	5.37

Note: Growth rate I refers to detrending by taking the quarterly growth rate of each series. Growth rate II fits a cubic trend of each log-level series between 1959Q1 and 2018Q4, then takes the quarterly difference of the detrended series. Data from 1983Q2 to 2018Q4 are used to compute the above moments. Correlation between the cyclical components of the relative price and the real quantity per capita of each series. Relative price is computed by dividing the price series by the price index of nondurables and services.

moments are computed for the aggregate consumer durable good category as well as its breakdown between IT and non-IT goods.

Using a growth rate filter, the correlation, $\rho_{p,n}$, is -0.11. Normalizing the standard deviation of the growth rate of the relative price of consumer durables, σ_p, to one, that of the growth rate of the real expenditure on consumer durables, σ_n, is 4.56.

However, when consumer durables are broken down into IT and non-IT durables, we find that the business-cycle features of IT durables are quite different from those of other consumer durables. The correlation between the relative price and quantity for IT durables are highly negative at -0.44 as opposed to that of non-IT durables which is the same as aggregate durables. The standard deviation of the relative price is 1.92 times higher for IT durables, while the standard deviation of the quantity of IT durables is lower than that of the aggregate.

Table 1 also displays the same statistics for an alternative growth rate filtering of the variables. The diffusion of IT goods is widely studied in the literature on general purpose technology, and the diffusion of these goods is typically S-shaped where the goods are slowly adopted initially, and accelerates in later periods (Jovanovic and Rousseau, 2005). One way to capture such pattern is to allow for a cubic deterministic trend in the level of the variables. Specifically, both a stochastic trend and a deterministic cubic trend in the log-level of each variable starting from 1959Q1 is assumed. In this case, the growth rate of each series is stationary up to a deterministic quadratic trend that we estimate. The growth rate that detrends the deterministic component is used in computing the moments under the category "Growth rate II." After allowing for this nonlinear detrending, the business-cycle properties of IT

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durables still remain and are actually reinforced. The negative correlation between the relative price and quantity is strong at -0.46, and the standard deviation of the relative price is high.

To sum up, the relative price of IT durables is much more volatile than other durables and the correlation between the relative price and quantity is strongly negative only for IT durables.

2.3 Detailed IT and non-IT consumer durables

Differences in the business-cycle properties between IT and non-IT durables also hold when we look into the detailed category of household durable expenditures. As noted, PCE data classifies consumer durables into 44 different goods, and we assign 10 goods to IT durables and 33 goods to non-IT durables. The series "employee reimbursement" under used autos is dropped because the series is reported with negative expenditure values.

2.3.1 Distribution of business-cycle moments

The distributions of each moment for IT and non-IT durables are shown in box-plots in Figure 3. The median correlation between the growth rates of the relative price and quantity is -0.62 for IT goods and is -0.35 for non-IT goods. The 25th-75th percentile boxes barely overlap with each other in the first and second columns, whereas they totally overlap in the third column. Visually, this implies that the distributions of the correlation between the relative price and quantity as well as the standard deviation of the relative price are quite different between IT and non-IT durables.

To formally discuss the statistical difference in the mean of the two distributions, we conduct a simple randomization test on the difference of the mean of the moments in the two samples. The computed p values (with 100,000 resampling) for both the correlation between the relative price and quantity and the standard deviation of the relative price are around or below 1 percent, rejecting the hypotheses that these two moments are equal between IT and non-IT durables at a 5 percent significance level. On the other hand, the p value for equality of the standard deviation of the quantity is above 10 percent.

By looking into the detailed category of consumer durables, we confirm that both the strong negative correlation between the relative price and quantity and the high variance of the relative price are pervasive features of IT consumer durables.

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Figure 3: Boxplot of the moments in IT and non-IT durables

(a) Growth rate I
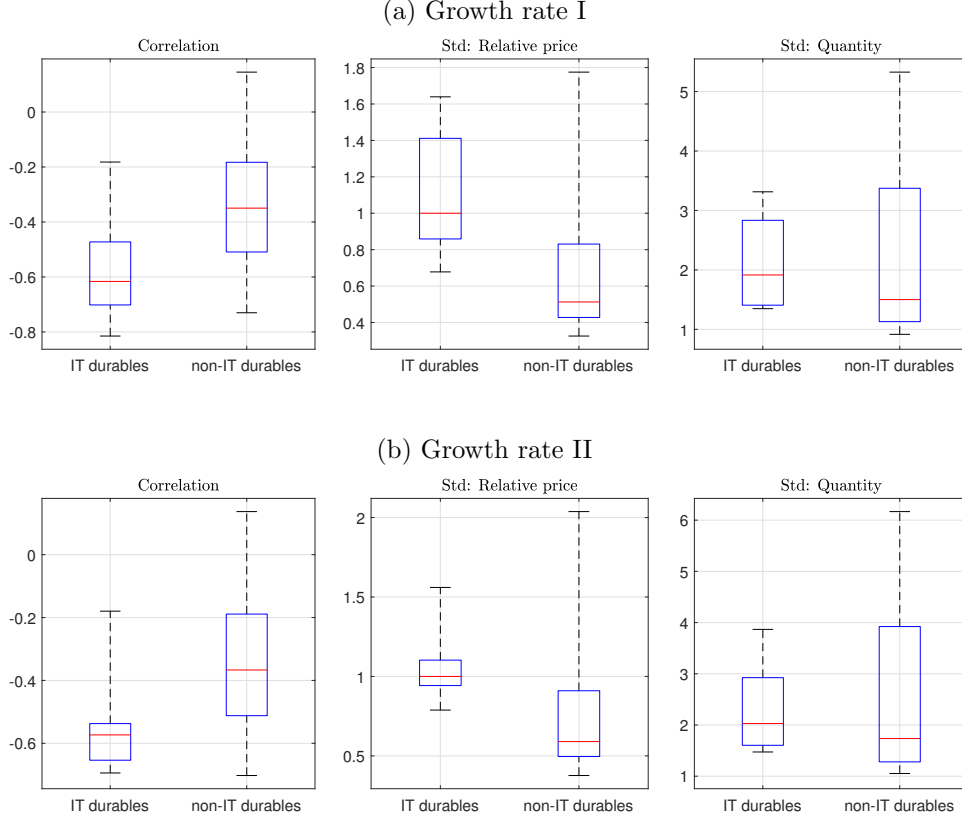
(b) Growth rate II

Note: Boxplot figures display the median (red line), 25 and 75 percentiles (the box), and the minimum and maximum values (black endpoints). Panel (a) uses growth rate detrending in computing the moments. Panel (b) uses variables that subtracts out both a deterministic cubic trend using the longest time series available and then takes the growth rate. The first column shows the correlation between the relative price and quantity. The next two columns show the standard deviations of the relative price and of the quantity, normalized by the median relative price for IT durables. The moments are computed based on data between 1983Q2 and 2018Q4.

2.3.2   Classification of IT durables

Our choice of IT goods is standard in the sense that we include the broad PCE classifications of information processing and communication goods. However, one might wonder where to draw the line between IT and non-IT goods, because IT, as general purpose technology, would also affect other devices such as "smart" household appliances.

If a good currently classified as non-IT is becoming more and more embedded with smart devices in the longer run, its relative price should also be quickly falling like a typical IT good. Hence the average relative price growth rate of each good is one

Table 2: Major consumer durables ranked by average relative price growth

Rank	Goods	IT/non-IT	μ_p	$\rho_{p,n}$	σ_p
1	Personal computers and tablets	IT	-20.55	-0.70	1.00
2	Computer software and accessories	IT	-14.40	-0.71	0.96
3	Televisions	IT	-14.05	-0.66	0.69
4	Other video equipment	IT	-11.75	-0.56	0.52
5	Telephone and related communication	IT	-8.52	-0.81	0.86
6	Video discs and digital downloads	IT	-7.89	-0.42	0.54
7	Audio equipment	IT	-6.59	-0.57	0.45
8	Photographic equipment	IT	-6.23	-0.68	0.58
9	Clocks, lamps, and lighting fixtures	non-IT	-5.76	-0.73	0.50
10	Calculators and other information	IT	-5.01	-0.47	0.64
11	Dishes and flatware	non-IT	-4.45	-0.64	0.59
12	Small electronic household appliances	non-IT	-4.40	-0.51	0.40
13	Window coverings	non-IT	-3.98	-0.56	0.52
14	Audio discs and digital downloads	IT	-3.80	-0.18	0.41
15	Sporting equipment, supplies and guns	non-IT	-3.55	-0.44	0.31
16	Major household appliances	non-IT	-3.18	-0.51	0.37
17	Outdoor equipment and supplies	non-IT	-3.00	-0.39	0.27
$\vdots$		$\vdots$	$\vdots$	$\vdots$	$\vdots$
21	Furniture	non-IT	-2.61	-0.31	0.27
$\vdots$		$\vdots$	$\vdots$	$\vdots$	$\vdots$
29	New domestic autos	non-IT	-1.71	-0.19	0.20
$\vdots$		$\vdots$	$\vdots$	$\vdots$	$\vdots$
43	Educational books	non-IT	$+2.70$	-0.37	0.26

Note: Data from 1983Q2 to 2018Q4 are used to compute the above moments. Relative price is computed by dividing the price series by the price index of nondurables and services. Annualized average realtive price growth (μ_p), correlation between the relative price and quantity ($\rho_{p,n}$), and the normalized standard deviation of the relative price (σ_p) are shown in the table.

measure to understand the pervasiveness of IT into other durables. Table 2 shows the detailed categories ordered by the average relative price growth rate. As expected, the steepest fall in the relative price occurred for personal computers and tablets at above 20 percent, followed by computer software and accessories. Out of the 10 goods that are classified as IT durables, 9 of them make it to the top 10 list of the highest price dropping series. The decline in the average relative price of household appliances is 4.40 percent for small goods and 3.18 percent for major goods, which are smaller in absolute value than most of the IT products.

Table 2 reveals a clear distinction between IT and non-IT goods in their long-run relative price growth path. Nevertheless, even if some of the marginal non-IT

goods are included into IT goods, the main business-cycle properties of IT goods would not change in a dramatic fashion. The correlation between the relative price and quantity is significantly negative for the higher ranked non-IT goods, and the standard deviation of the relative price for these goods is also high. The difference in the business-cycle properties of non-IT goods is only clear when looking into other major non-IT goods such as furniture and new autos. For these goods, the correlation between the relative price and quantity is not as negative, and the relative price series is not volatile. We verify that our classification of IT and non-IT goods is sensible based on the data we use and that small changes to the classification would not affect our description of the business-cycle properties of the two goods.

2.3.3 Factor approach to the relative price of durables

Our choice of taking IT and non-IT consumer good relative price series into a business-cycle model hinges on the presumption that both of these relative prices convey significant information about the aggregate series. Before estimating our business-cycle model, one might ask if there is any statistical guidance in selecting the number of time series variables relevant for macroeconomic analysis. A concern is that by separating out IT and non-IT durables and using both of these series, we could be injecting noise that contaminates the general equilibrium implications of our model.

Although not exact, the literature on factor models is highly relevant in this regard. In particular, using the same PCE price series as we do, but also including the detailed nondurable and service prices, Reis and Watson (2010) find that an aggregate "pure" inflation factor is not enough to account for the dynamics of the overall inflation data and that a low-dimensional index of aggregate relative price changes is also needed. Leaving the details in the Appendix, we estimate a factor model on the detailed series of relative price of consumer durables.[5] The number of factors selected by the Bai and Ng (2002) information criterion is two, and the second factor significantly accounts for the relative prices of IT consumer goods. When conducting the same analysis excluding the relative prices of IT consumer durable goods, the information criterion determines that only one factor is needed. Later, we also estimate our model in section 3 with an aggregate relative price of consumer durables and compare the results with our baseline model with two relative prices of consumer durables.

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[5]The Appendix is uploaded in the authors' personal webpage.

3 Model

The goal in the remaining part of the paper is to quantitatively understand whether innovations to household IT goods—evidenced by their relative price dynamics—played an important role over the business cycle. In this section, we set up a medium-scale real business cycles model with consumer durables. Following the practice in Justiniano, Primiceri, and Tambalotti (2010, 2011) as well as Schmitt-Grohe and Uribe (2011, 2012), the model incorporates shocks to investment-specific productivity directly linked to the observed relative price of investment goods. We extend the model by separating out household IT and non-IT durable goods from aggregate investment, and by allowing for distinct innovations to the productivity of each of these goods. The model allows for other disturbances that are standard in the quantitative real business cycle literature, such as shocks to labor augmenting productivity, marginal efficiency of investment, and household preference.

3.1 Households

The economy is populated by a large number of identical agents with preferences described over composite habit-adjusted consumption, $M_t(\theta)$, under a degree of habit persistence $\theta \in [0, 1)$ and hours worked, h_t:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t b_t \left[\log M_t(\theta) - \gamma_h \frac{h_t^{1+\nu}}{1+\nu} \right], \tag{1}$$

where β denotes the long-run household subjective discount factor, b_t captures any shift of the discount factor, ν is the inverse Frisch elasticity of labor supply, and γ_h is the labor supply disutility weight parameter.

The composite habit-adjusted consumption consists of nondurable (including service) consumption, C_t, stock of IT durables, $D_{1,t}$, as well as stock of non-IT durables, $D_{2,t}$, all subject to an internal habit persistence parameter θ, in the following manner:

$$M_t(\theta) = (C_t - \theta C_{t-1})^{1-\gamma_1-\gamma_2} (D_{1,t} - \theta D_{1,t-1})^{\gamma_1} (D_{2,t} - \theta D_{2,t-1})^{\gamma_2}. \tag{2}$$

The household sequential budget constraint is

$$C_t + P_{1,t}^d I_{1,t} + P_{2,t}^d I_{2,t} + P_t^k I_{k,t} = W_t h_t + R_t u_t K_t, \tag{3}$$

where $P_{1,t}^d$, $P_{2,t}^d$, P_t^k are the relative prices of IT and non-IT consumer durable goods as well as capital goods, respectively. IT durable, non-IT durable, and capital investment goods are denoted as $I_{1,t}$, $I_{2,t}$, and $I_{k,t}$. Real wage is W_t and the real rental rate of utilized capital is R_t, where u_t measures the rate of capital utilization in period t. Thus $u_t K_t$ is the amount of utilized capital in period t.

Each household's real stock of durables $D_{j,t}$ $(j = 1, 2)$ evolves over time according to

$$D_{j,t} = (1 - \delta_j)D_{j,t-1} + \mu_t^d I_{j,t} \left[1 - S_j \left(\frac{I_{j,t}}{I_{j,t-1}}\right)\right], \tag{4}$$

where $S_j(\cdot)$ is the flow adjustment cost of durable j and μ_t^d measures the marginal efficiency of investment for consumer durables. The parameter δ_j governs the depreciation rate of consumer durable j. The relation between the utility generating stock of durables and the real stock of durables will be stated after introducing the producers below.

Similarly, capital stock K_t evolves over time according to

$$K_{t+1} = (1 - \delta_k(u_t))K_t + \mu_t^k I_{k,t} \left[1 - S_k \left(\frac{I_{k,t}}{I_{k,t-1}}\right)\right]. \tag{5}$$

The flow adjustment cost of capital goods is $S_k(\cdot)$ and μ_t^k measures the marginal efficiency of investment for capital goods. We assume that higher utilization of capital yields faster rate of depreciation. Thus the depreciation rate of the capital is an increasing and convex function of capital utilization, $\delta_k(u_t)$.

3.2   Producers

Total output is produced by the effective stock of capital inputs $u_t K_t$ and effective labor inputs $X_t^z h_t$. The production function of the firm is given by the Cobb-Douglas form:

$$Y_t = (u_t K_t)^\alpha (X_t^z h_t)^{1-\alpha}, \tag{6}$$

where Y_t is total production, X_t^z is a nonstationary labor augmented productivity process, and α is the elasticity of production with respect to utilized capital.

Total output good producers maximize the following profit function:

$$\Pi_t = Y_t - R_t u_t K_t - W_t h_t, \tag{7}$$

by choosing utilized capital and labor inputs in competitive markets.

Investment good producers. Producers of capital and consumer durable investment goods are subject to a linear production function:

$$I_{k,t} = a_{k,t} X_t^a \tilde{I}_{k,t}, \qquad I_{j,t} = a_{j,t} X_t^a \tilde{I}_{j,t}, \quad (j = 1, 2) \tag{8}$$

where $\tilde{I}_{k,t}$ and $\tilde{I}_{j,t}$ are respective inputs for the production of capital and durable j, X_t^a denotes the nonstationary investment-specific productivity common across all investment goods, and $a_{k,t}$ and $a_{j,t}$ are stationary capital and durable j specific productivity processes, respectively. Following the literature on investment-specific productivity shocks, we assume a common stochastic trend to the production of business investment and consumer durable goods. At the same time, we introduce stationary shocks specific to the productivity of each investment good to allow for differences in their observed relative prices.[6]

Producers of investment goods maximize the following profit functions:

$$\Pi_{k,t} = P_t^k I_{k,t} - \tilde{I}_{k,t}, \qquad \Pi_{j,t} = P_{j,t}^d I_{j,t} - \tilde{I}_{j,t}, \quad (j = 1, 2), \tag{9}$$

by choosing their respective inputs $\tilde{I}_{k,t}$ or $\tilde{I}_{j,t}$ in competitive markets.

3.3 Market clearing and exogenous processes

Output in terms of consumption goods is spent by households either as consumption, or purchased by investment good firms as inputs for producing capital, IT and non-IT consumer durables:

$$Y_t = C_t + \tilde{I}_{k,t} + \tilde{I}_{1,t} + \tilde{I}_{2,t}. \tag{10}$$

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[6]Our model choice of investment-specific productivity is stylized as we abstract from both endogenous markup dynamics (Moura, 2018) and nonstationary shocks specific to each investment good. As we study a real model with three investment goods driving the dynamics, our judgement is that these extensions are beyond the scope of this project.

Labor and capital markets also clear.

The model has two nonstationary processes: labor augmented productivity X_t^z and common investment-specific productivity X_t^a. Their growth rates $g_t^z = X_t^z/X_{t-1}^z$ and $g_t^a = X_t^a/X_{t-1}^a$ are assumed the following stationary exogenous processes:

$$\hat{g}_t^z = \rho_g^z \hat{g}_{t-1}^z + \sigma_g^z \varepsilon_{g,t}^z, \tag{11}$$

$$\hat{g}_t^a = \rho_g^a \hat{g}_{t-1}^a + \sigma_g^a \varepsilon_{g,t}^a. \tag{12}$$

where a hatted variable indicates log-deviation from its deterministic steady state. The remaining stationary exogenous processes are

$$\hat{b}_t = \rho_b \hat{b}_{t-1} + \sigma_b \varepsilon_{b,t}, \tag{13}$$

$$\hat{\mu}_t^d = \rho_\mu^d \hat{\mu}_{t-1}^d + \sigma_\mu^d \varepsilon_{\mu,t}^d, \tag{14}$$

$$\hat{\mu}_t^k = \rho_\mu^k \hat{\mu}_{t-1}^k + \sigma_\mu^k \varepsilon_{\mu,t}^k, \tag{15}$$

$$\hat{a}_{k,t} = \rho_k \hat{a}_{k,t-1} + \sigma_k \varepsilon_{k,t}, \tag{16}$$

$$\hat{a}_{1,t} = \rho_1 \hat{a}_{1,t-1} + \sigma_1 \varepsilon_{1,t}, \tag{17}$$

$$\hat{a}_{2,t} = \rho_2 \hat{a}_{2,t-1} + \sigma_2 \varepsilon_{2,t}. \tag{18}$$

3.4 Competitive equilibrium

A competitive equilibrium of the model is where given exogenous processes (11)-(18), households maximize their utility (1)-(2) subject to their budget constraint (3) as well as durable (both IT and non-IT) and capital accumulation functions (4)-(5), output firm maximizes profit (7) given its production function (6) by choosing labor, capital, and capital utilization, each investment good firm (IT and non-IT consumer durables as well as capital) maximizes profit (9) by choosing input investment goods given its production function (8), goods market clears (10), and labor and capital markets also clear.

The full equilibrium conditions are stated in the Appendix. For reference, the relative price of investment goods are linked to investment-specific productivity in the following manner:

$$P_t^k = \frac{1}{a_{k,t} X_t^a}, \qquad P_{j,t}^d = \frac{1}{a_{j,t} X_t^a}, \quad (j = 1, 2).$$

4   Estimation

We estimate several structural parameters in our model, using Bayesian methods. We then investigate the fit of the estimated model.

4.1   Calibration

Table 3 summarizes parameters that are calibrated at quarterly frequency. Parameters that are directly related to consumer durables are the preference and depreciation rate parameters for both IT and non-IT consumer durables. The two preference parameters (γ_1, γ_2) are set such that (i) the steady state IT share in consumer durable spending is 0.125 and (ii) the steady state consumer durable spending share in total consumption spending is 0.25. The IT and non-IT consumer durable depreciation rates (δ_1, δ_2) are calculated based on the annual "Consumer Durable Goods Detailed Estimates" published by the Bureau of Economic Analysis. For each durable good category, we calculate its depreciation rate by taking the depreciation estimate over the sum of net stock and depreciation estimates for each year from 1983 to 2016. Using the average nominal weights of each category during this period, we calculate the IT and non-IT consumer durable good depreciation rates.

Other parameters are standard and mostly follow the practice in the literature. The steady state growth rate of the relative price of investment is calculated by the mean of the growth rate of the price index of nonresidential fixed investment including consumer durables between 1983 to 2018.[7]

4.2   Bayesian methods

The remaining parameters of the model are estimated using Bayesian methods. The prior distribution for all structural parameters is given in Table 4.[8] Notably, we set the prior mean of the two MEI innovations to be greater than other shocks. This is to make sure that we are not favoring ISP shocks to drive the dynamics of investment in our prior distribution.

To construct the likelihood function conditional on the model, we use eight observables: (i) real GDP per capita, (ii) real consumer nondurable and services spend-

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[7]Of note, we focus on the cyclical properties of different investment goods and abstract from addressing the difference in the mean growth rates of the relative prices across investment goods.

[8]Measurement errors are also estimated based on a uniform distribution with an upper bound that is 25 percent of the standard deviation of each observable. The Appendix contains its estimation results.

Table 3: Calibrated Parameters

Parameter	Value	Description
α	0.37	labor income share: 0.63
β	0.99	subjective discount factor
ν	1.45	inverse Frisch elasticity of labor supply
γ_h	22.6	hours worked: 0.3
δ_k	0.025	capital depreciation rate
γ_1	0.048	IT share in consumer durable spending: 0.125
γ_2	0.347	initial durable share in total household spending: 0.25
δ_1	0.054	consumer IT durable depreciation rate
δ_2	0.041	consumer non-IT durable depreciation rate
$\bar{g}^{PI}$	0.9912	growth rate of relative price of investment
$\bar{g}^Y$	1.0042	growth rate of output

ing per capita, (iii) real IT consumer durable spending per capita, (iv) real non-IT consumer durable spending per capita, (v) private business (nonresidential fixed) investment per capita, (vi) relative price of IT consumer durables, (vii) relative price of non-IT consumer durables, and (viii) relative price of business investment. The sample period is from 1983q2 to 2018q4, and all obervables are in demeaned growth rates. We allow for measurement errors in all of these observables. The likelihood evaluation is via Kalman filter iterations in the linear state space representation of the model.

Based on the priors and the likelihood function, 10 million chains are generated by Markov Chain Monte Carlo methods using the random walk Metropolis-Hastings sampler described in Herbst and Schorfheide (2016). The last two columns of Table 4 summarize the posterior median and 90 percent credible interval for each parameter.

4.3   Fit to the data

Table 5 compares unconditional second moments from the data and the estimated model. For most observables, the estimated model closely matches unconditional standard deviations and output growth correlations. Estimated correlations between investment goods and their relative prices tend to be on the negative side compared to their data counterparts, although their qualitative ordering matches the data and the difference is the smallest for IT consumer durables. First-order autocorrelations in the model are also overall reasonable, although the model shows some difficulty in

Table 4: Marginal prior and posterior distributions for structural parameters

Parameter	Prior (mean, std)	Posterior median	[5%, 95%]
θ	Beta $(0.5, 0.1)$	0.57	[0.50, 0.62]
κ_1	Gamma $(4, 1)$	0.10	[0.09, 0.12]
κ_2	Gamma $(4, 1)$	0.05	[0.04, 0.06]
κ_k	Gamma $(4, 1)$	0.17	[0.13, 0.21]
δ_k''/δ_k'	Gamma $(5, 1)$	8.23	[6.57, 10.19]
ρ_g^z	Beta $(0.5, 0.1)$	0.40	[0.32, 0.47]
ρ_g^a	Beta $(0.5, 0.1)$	0.38	[0.29, 0.46]
ρ_b	Beta $(0.5, 0.1)$	0.60	[0.36, 0.79]
ρ_μ^d	Beta $(0.5, 0.1)$	0.61	[0.45, 0.76]
ρ_μ^k	Beta $(0.5, 0.1)$	0.67	[0.40, 0.82]
ρ_1	Beta $(0.5, 0.1)$	0.99	[0.98, 0.99]
ρ_2	Beta $(0.5, 0.1)$	0.14	[0.08, 0.22]
ρ_k	Beta $(0.5, 0.1)$	0.98	[0.97, 0.99]
$\sigma_g^z \times 100$	Gamma $(0.5, 1)$	0.82	[0.73, 0.94]
$\sigma_g^a \times 100$	Gamma $(0.5, 1)$	0.44	[0.39, 0.50]
$\sigma_b \times 100$	Gamma $(0.5, 1)$	0.44	[0.00, 0.67]
$\sigma_\mu^d \times 100$	Gamma $(2, 1)$	0.52	[0.41, 0.69]
$\sigma_\mu^k \times 100$	Gamma $(2, 1)$	0.47	[0.19, 0.70]
$\sigma_1 \times 100$	Gamma $(0.5, 1)$	0.87	[0.78, 0.97]
$\sigma_2 \times 100$	Gamma $(0.5, 1)$	0.20	[0.17, 0.24]
$\sigma_k \times 100$	Gamma $(0.5, 1)$	0.57	[0.51, 0.64]

Note: Posterior distributions are based on draws from the last 1 million draws from a 10 million chain. Parameters $\kappa_1, \kappa_2, \kappa_k$ are investment adjustment costs for durable good 1, durable good 2, and capital good, respectively.

matching the high autocorrelation of the relative price of IT consumer durables. The performance of moment matching from the estimation is successful, which indicates that there is no misspecification in the estimation procedure.

5 IT goods and household spending

In this section, we study the business-cycle implications of consumer IT goods, by digging into the difference between IT and non-IT goods as well as their relative prices. We look into the drivers of consumer durable spending throughout the whole sample period, as well as the source of the consumption boom in early 2000s. We

Table 5: Unconditional second moments (data and model)

	Data	Model		Data	Model
Standard deviations			**Output growth correlations**		
$std(C)/std(Y)$	0.65	0.70	$corr(C,Y)$	0.63	0.57
$std(I_1)/std(Y)$	3.32	3.68	$corr(I_1,Y)$	0.44	0.47
$std(I_2)/std(Y)$	4.29	5.22	$corr(I_2,Y)$	0.41	0.60
$std(I_k)/std(Y)$	3.09	2.47	$corr(I_k,Y)$	0.58	0.43
$std(P_1^d)/std(Y)$	1.64	1.47	$corr(P_1^d,Y)$	-0.03	-0.03
$std(P_2^d)/std(Y)$	0.82	0.81	$corr(P_2^d,Y)$	-0.08	-0.08
$std(P^k)/std(Y)$	0.89	1.10	$corr(P^k,Y)$	-0.31	-0.09
Price-quantity correlations			**Autocorrelations**		
$corr(I_1,P_1^d)$	-0.44	-0.52	$corr(Y,Y_{-1})$	0.38	0.48
$corr(I_2,P_2^d)$	-0.11	-0.42	$corr(C,C_{-1})$	0.34	0.54
$corr(I_k,P_k)$	-0.23	-0.44	$corr(I_1^d,I_{1,-1}^d)$	0.38	0.53
			$corr(I_2^d,I_{2,-1}^d)$	-0.03	0.28
			$corr(I_k,I_{k,-1})$	0.61	0.59
			$corr(P_1^d,P_{1,-1}^d)$	0.59	0.08
			$corr(P_2^d,P_{2,-1}^d)$	0.40	0.19
			$corr(P^k,P_{-1}^k)$	0.32	0.15

Note: All moments are computed based on the growth rate of each variable. In the model, the parameters are set at their respective posterior median values.

also study whether the distinction between IT and non-IT goods and their relative prices matter when studying the dynamics of consumer durables.

5.1 ISP shocks, investment, and the macroeconomy

The first panel of Table 6 shows the unconditional variance decomposition of the estimated model, based on posterior median values. One starking result is the difference in the sources of shocks for IT and non-IT consumer durables. For IT goods (I_1), more than half of its movement is driven by ISP shocks whereas for non-IT goods (I_2), ISP shocks play a minimal role. Instead, labor augmented productivity and MEI shocks account for the majority of its dynamics. For capital goods (I_k), labor augmented productivity and ISP shocks account for more than half of its dynamics, with durable MEI playing a larger role than capital MEI. This result suggests a meaningful substitution channel between business capital and consumer durables, as capital investment declines with a durable MEI shock that increases consumer durable spending.

Table 6: Unconditional variance decomposition

		I_1	I_2	I_k	P_1^d	P_2^d	P^k	C	Y
	Posterior median								
μ^d	MEI (D)	11.9	36.8	24.4	0.0	0.0	0.0	1.1	2.1
μ^k	MEI (K)	1.3	4.7	4.0	0.0	0.0	0.0	3.2	3.1
a_1	ISP (IT)	57.7	0.1	0.1	92.2	0.0	0.0	0.0	0.0
a_2	ISP (non-IT)	0.6	2.5	0.9	0.0	5.9	0.0	0.0	0.1
a_k	ISP (K)	1.8	4.8	27.0	0.0	0.0	69.7	1.4	1.0
g^a	Common ISP	3.3	5.3	4.9	7.3	93.7	30.1	1.2	0.8
g^z	Productivity	21.3	39.5	29.2	0.0	0.0	0.0	88.3	91.9
b	Preference	0.3	1.5	4.3	0.0	0.0	0.0	4.8	0.9
	Measurement error	1.9	4.6	5.3	0.5	0.4	0.2	0.1	0.2
	Prior mean								
μ^d	MEI (D)	49.7	49.4	0.3	0.0	0.0	0.0	7.4	6.0
μ^k	MEI (K)	45.4	45.0	92.9	0.0	0.0	0.0	28.6	57.0
a_1	ISP (IT)	0.2	0.0	0.0	49.9	0.0	0.0	0.0	0.0
a_2	ISP (non-IT)	0.0	0.3	0.0	0.0	50.0	0.0	0.2	1.2
a_k	ISP (K)	0.0	0.0	0.8	0.0	0.0	50.0	0.6	4.3
g^a	Common ISP	2.9	2.8	3.6	49.9	50.0	50.0	14.1	6.5
g^z	Productivity	1.2	1.1	1.5	0.0	0.0	0.0	46.1	24.4
b	Preference	0.1	0.1	0.3	0.0	0.0	0.0	2.9	0.5
	Measurement error	0.4	1.2	0.6	0.1	0.0	0.0	0.0	0.0

Note: Variance decomposition is computed based on the growth rate of each variable. Productivity above indicates labor augmented productivity.

Notice that the above results are not driven by the prior distribution. The second panel of Table 6 displays the decomposition assuming parameters to be their prior mean values. In the prior distribution, we have set MEI shocks to effectively account for all variations of the three investment goods. Taking advantage of Bayesian methods, we can firmly argue for our result that ISP shocks are quantitatively more important than MEI shocks in accounting for the dynamics of consumer IT goods.

ISP shocks and other macroeconomic variables. Turning our focus to the relative prices, we find that common ISP shocks drive the relative price of non-IT goods, whereas the shock only accounts for a small portion of IT relative prices. This result is consistent with the factor analysis conducted in section 2, where we discuss that the detailed relative prices of non-IT consumer durables could be effectively summarized by a common factor, whereas the relative prices of all consumer durables are better represented with two factors instead of one. The common ISP shock also

Table 7: Growth accounting (annualized growth rate in percent)

	total	without ISP	ISP contribution
The 2000s boom (2001q4–2007q4)			
Consumer durables	5.62	2.88	2.74
Household spending	1.90	1.24	0.65
Business investment	3.01	4.46	−1.45
Output	1.37	1.44	−0.05
The 1990s boom (1991q1–2001q1)			
Consumer durables	5.53	5.47	0.06
Household spending	2.38	2.39	−0.01
Business investment	5.35	3.91	1.44
Output	2.58	2.29	0.29

Note: Column 'total' displays the model-implied growth rate during its respective period, which adds the average (trend) growth rate to the cyclical growth rate estimated by the model. Column 'without ISP' subtracts the contribution of ISP shocks in the estimated model from the 'total'. Column 'ISP contribution' is the growth rate of each variable due to ISP shocks. The growth rate is expressed in annualized percentage points.

accounts for about 30 percent of the relative price of capital goods.

We then look into other key macroeconomic variables such as nondurable consumption and output. As the business-cycle literature emphasizes investment dynamics as key to understanding aggregate fluctuations, shocks that mainly account for investment goods are expected to also matter for consumption and output dynamics. Looking into the last two columns of table 6, we find that this does not necessarily hold true. ISP shocks that account for consumer IT goods play no role in nondurable consumption and output dynamics. Even durable MEI shocks which matter for non-IT durables and capital goods do not matter, even less than capital MEI shocks which contribute only trivially to the variance of these investment goods.

We provide two explanations to this finding. First, consumer IT goods are only a small portion of total investment goods. Its average share in total consumer durables is below 15 percent, and spending on total consumer durables is less than two thirds of business capital spending. Therefore, consumer IT goods have been only around 5 percent of total investment spending on average, which limits its macroeconomic relevance. Second, the accumulation of consumer durables by households do not directly contribute to the production frontier of the economy, as opposed to the accumulation of business capital. As a result, even durable MEI shocks that matter for non-IT durables do not affect output dynamics as much.

Investment boom in the 2000s. While we find that ISP shocks only matter significantly for consumer IT goods during the whole sample period, they are likely to have played a crucial role for macroeconomic variables at least during the early 2000s when households were actively computerizing. To quantify the macroeconomic effects of ISP shocks during this period, we conduct a growth accounting exercise by taking the average growth rates of several aggregate variables between 2001q4 and 2007q4, the NBER trough and peak periods. The quarterly growth rate of consumer durables is computed as the weighted sum of the growth rates of IT and non-IT durables, and the quarterly growth rate of household spending is computed as the weighted sum of consumer durables and consumer nondurables. The weights are adjusted every quarter, based on the nominal spending of each good in the previous period. The approach is similar to the exercise in Tevlin and Whelan (2003), where they quantify the importance of the computer industry during the 1990s investment boom. Our approach is conservative in the sense that, if weights are instead based on real quantities, the growth accounting exercise will be dominated by computer-intensive goods as their real quantities have increased rapidly.

The first panel of Table 7 displays the average annualized growth rates of four macroeconomic variables during the 2000s boom. Expenditures on consumer durables have increased by about 5.6 percent during this period. Notice that about half of the increase in consumer durable spending could be attributed to productivity improvements specific to investment goods. This improvement also contributed to one third of the increase in total household spending. On the other hand, ISP shocks negatively affected business investment, as high-tech businesses may have suffered in the aftermath of the dot-com bubble. Notice that for output, the effect of ISP shocks remains minimal which suggests that the model does not favor ISP shocks that drive consumption goods as the main driver of output.

The second panel also shows growth rates during the 1990s boom. The average growth rate of consumer durables are similar to the 2000s, but growth due to ISP shocks is vastly lower. Even without ISP shocks, consumer durables increased by about 5.5 percent per year, as spending in non-IT consumer durables led the growth. Not surprisingly, ISP shocks did not matter household spending growth as well. On the other hand, ISP shocks left a positive imprint on business investment growth. Their contribution to output growth is more noticeable, at around 11 percent.[9]

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[9]A sectoral approach to the computer industry might also lead to a higher contribution of ISP shocks in business investment, as documented in Tevlin and Whelan (2003). As we focus on consumer durables, a sectoral approach also to business investment is beyond the scope of our paper.

Table 8: Unconditional variance decomposition (one durable good)

		I_d	I_k	P^d	P^k	C	Y
		Posterior median					
μ^d	MEI (D)	76.8	1.1	0.0	0.0	0.0	24.1
μ^k	MEI (K)	2.5	26.1	0.0	0.0	0.1	1.7
a_d	ISP (D)	0.0	0.0	0.0	0.0	0.0	0.0
a_k	ISP (K)	0.0	0.0	0.0	67.0	0.0	0.0
g^a	Common ISP	0.0	0.0	99.4	32.8	0.0	0.0
g^z	Productivity	19.7	61.1	0.0	0.0	95.4	74.1
b	Preference	1.1	11.6	0.0	0.0	4.5	0.1
	Measurement error	0.0	0.0	0.6	0.2	0.0	0.0
		Prior mean					
μ^d	MEI (D)	49.6	0.3	0.0	0.0	7.4	6.0
μ^k	MEI (K)	45.2	92.9	0.0	0.0	28.6	56.8
a_d	ISP (D)	0.3	0.0	50.0	0.0	0.2	1.6
a_k	ISP (K)	0.0	0.8	0.0	50.0	0.6	4.3
g^a	Common ISP	2.8	3.6	50.0	50.0	14.1	6.5
g^z	Productivity	1.1	1.5	0.0	0.0	46.1	24.3
b	Preference	0.1	0.3	0.0	0.0	2.9	0.5
	Measurement error	0.8	0.6	0.0	0.0	0.0	0.0

Note: Variance decomposition is computed based on the growth rate of each variable.

5.2   Estimation of a single consumer durable good model

Justiniano, Primiceri, and Tambalotti (2011) find in their estimated model that the observed relative price of investment series plays no role in even accounting for investment dynamics. This is likely due to aggregation of the relative price series, and we verify whether this result also holds when we only look into consumer durables as a whole. Table 8 shows the variance decomposition result with the model is estimated with only one consumer durable good. The contribution of ISP shocks are surprisingly similar to Justiniano, Primiceri, and Tambalotti (2011). None of these shocks matter at all for both consumer durables and business investment, and MEI shocks pick up its contribution on consumer durables. This shows that aggregation of the relative price series matter when studying ISP shocks, due to the widely different movement in these two price series which are smoothed out and become acyclical when aggregated.

5.3 Limited transmission of household ISP shocks

We find that investment-specific productivity shocks to IT consumer durables mainly account for the dynamics of consumer durables, but barely account for non-durable consumption. This is at odds with findings in the literature where investment shocks should also affect nondurable consumption dynamics. In the Appendix, we provide intuition to this result through a simple business-cycle model of consumer durables with durable-specific productivity shocks. The key argument is that productivity shocks specific to household investment but unrelated to business investment are weak in its transmission to output, as the production possibility frontier remains less affected. Unlike business capital, household durable stocks contribute to household welfare, but not to the production of nondurable goods. Therefore, when studying the transmission mechanism of investment-specific productivity shocks, the standard practice of aggregating both household and business investment spending together is no longer an innocuous assumption.

The limited transmission of consumer durable specific productivity shocks could be viewed as another version of the Barro-King curse (Barro and King, 1984) discussed with investment variables in Fisher (1997) or with investment shocks in Ascari, Phaneuf, and Sims (2019). However, it is possible that consumer IT goods are becoming increasingly complementary to business capital as firms benefit from household's broader usage of IT equipments, such as services provided by rideshare and online delivery companies. Data suggests that household internet usage by smartphones increased substantially in recent years. For example, the percent of U.S. households with mobile broadband internet access at home increased from 6.5 percent in 2010 to 67.1 percent in 2017 (OECD, 2020).

To explore this idea in a readily manner, we introduce complementarity in the production function by modifying equation (6) into

$$Y_t = [(u_t K_t)^{-\varepsilon} + (D_{1t}^*)^{-\varepsilon}]^{-\frac{\alpha}{\varepsilon}} (X_t^z h_t)^{1-\alpha}. \tag{19}$$

The variable D_{1t}^* is the total stock of household IT durables that the producer takes as given. The parameter $\varepsilon \geq -1$ controls for the degree of complementarity between household IT durable and business capital.[10] In equilibrium, the total stock satisfies $D_{1t}^* = D_{1t}$. Using the same calibration targets as well as the posterior median values,

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[10]When $\varepsilon = 0$, the production function is $Y_t = (u_t K_t D_{1t}^*)^{\alpha} (X_t^z h_t)^{1-\alpha}$. This approach broadly captures the idea in Fisher (1997), although we consider complementarity across household and business stocks rather than investment.

Figure 4: ISP contribution with a modified production function
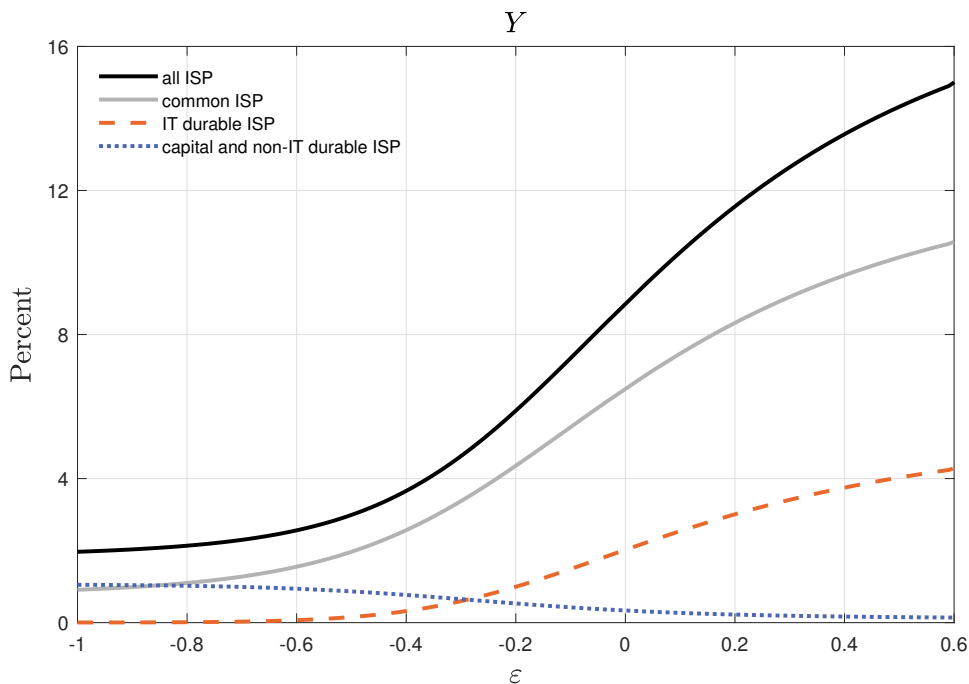
Note: Solution of the model with modified production function (19) in place of (6). All ISP denotes the total contribution of ISP shocks in the model.

we compute numerically the variance of output accounted for by ISP shocks.

Figure 4 plots the output growth contribution of ISP shocks as the degree of complementarity increases.[11] When the two goods are perfect substitutes ($\varepsilon = -1$), total ISP shocks contribute to output growth at a level similar to Table 6. However, as the degree of complementarity increases, the output growth contribution of ISP shocks rises significantly. Looking into the components, both common ISP and IT durable ISP shocks matter, with the contribution of IT durable specific ISP shocks growing from zero to four percent with higher complementarity. These results illustrate the potential macroeconomic importance of shocks to household investment goods.

6   Conclusion

In this paper, we study the dynamics of consumer durables and their relative prices through the lens of the business-cycle literature on ISP shocks. We analyze the cyclical difference between IT and non-IT durables, and estimate a medium-scale

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[11]The highest degree of complementarity that our estimated model allows within its determinacy area is around 0.67.

real business-cycle model with ISP shocks to understand the lessons that could be drawn by carefully dissecting investment goods. We find that ISP shocks are the main driver of consumer IT goods, and also have significantly pushed up growth of aggregate consumer durables during the economic boom in 2000s. These shocks nevertheless are limited in accounting for the dynamics of output and nondurable consumption in our estimated model, as these goods do not contribute to productive capital.

With the IT innovation of household equipment during the 2000s, we believe that there is a rich avenue of business cycle studies moving forward. The stock of consumer IT goods might have positive externality to businesses as more and more households are equipped with these goods. Macroeconomic studies on computer goods mainly focus on the direct industry effects, but household computerization and its impact on industry is also likely to become a key channel in the future. This paper serves as a stepping stone to study the business-cycle importance of household IT goods and their usage that will only become more relevant to the macroeconomy.

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