Testing for Keynesian Labor Demand

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Abstract

According to the textbook sticky-price model, short-run demand for labor is driven by demand for goods. In this view, sellers deviate from setting the marginal product of labor equal to the real wage, if necessary, to satisfy the demand for goods. We test this prediction across U.S. industries in the two decades up through the Great Recession. To identify movements in goods demand, we exploit how durability varies across 70 categories of consumption and investment. We also take into account the flexibility of prices and capital-intensity of production across goods. We find evidence in support of Keynesian labor demand over a constant-markup version of flexible-price labor demand.

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1. Introduction

A leading (proximate) explanation for plunging employment during the Great Recession is price stickiness combined with plummeting demand for goods.[1] According to this Keynesian Labor Demand hypothesis, when producers face unexpectedly low demand for their goods they respond by laying off workers rather than lowering their output prices. Doing so should increase the marginal revenue product of labor and reduce the marginal cost of labor, driving a wedge between the two.

We test for this Keynesian Labor Demand wedge across U.S. industries in recent decades (1990-2011). To do so, we exploit how durability varies across 70 consumption and investment goods to construct an instrument for goods demand movements. We also incorporate information on the extent to which goods are luxuries vs. necessities, on how price flexibility differs across industries, and how the capital-intensity of production varies across industries.

According to consumer theory, durability should be a powerful determinant of the cyclical expenditures on a good. The more durable a good, the smaller is the average flow of expenditures on the good relative to the accumulated stock. For a good that lasts N years, increasing the stock by 1% requires an N% increase in *expenditures* on the good relative to replacement expenditures. Thus any common macro shock (such as to technology or monetary policy) should hit demand for durables more dramatically. Similarly, demand for luxuries should be more cyclical than demand for necessities.

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[1] Hall (2011) is a recent example. He emphasizes the Zero Lower Bound on interest rates as a constraint on goods demand, with the lower demand translating into lower employment because prices fail to adjust. Keynesian Labor Demand plays a central role in business cycle research more generally: see Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007).

Under sticky prices, firms should accommodate these shifts in demand by firing or hiring workers rather than adjusting their prices. Industries with more flexible pricing should be less susceptible to these Keynesian forces. If capital is less flexible than labor in the short run, firms in flexible-price industries should adjust their prices more and adjust their production less than do sticky-price industries – controlling for the size of the demand shift they face.

We implement our test using a variety of data. We use U.S. National Income and Product Accounts (NIPA) and insurance industry estimates of durability for 70 goods covering around 60% of GDP. These include most consumer and investment goods and services, but exclude government purchases and housing consumption. We estimate whether a good is a luxury or a necessity using cross-sectional Engel curves from the U.S. Consumer Expenditure Survey. We assess price flexibility using U.S. CPI and PPI micro data on the frequency of price changes by good.

We use quarterly NIPA data on consumption and investment from 1990 to 2011 to test whether our instruments succeed in predicting the cyclicality of expenditures. The first stage fit from the durability instrument alone is quite strong. And micro price flexibility is tightly related to the cyclicality of the price index for a good. Bringing in data from the U.S. Current Employment Survey, our demand instruments are also highly correlated with employment growth across industries – including in the Great Recession. Finally, we incorporate the U.S. Bureau of Labor Statistics KLEMS data on production, prices and inputs across detailed industries. This allows us to contrast movements in labor's productivity with its real wage, identifying whether producers move away from flexible-price labor demand in response to goods demand shocks.

We find evidence consistent with Keynesian Labor Demand, rejecting flexible-price labor demand with a constant markup. Firm behaves as if prices are even stickier than documented in the micro data. The wedges we find, however, could reflect intentional markup movements rather than just accidental byproducts of price stickiness. In particular, a model with countercyclical markups for durables but flexible pricing might explain the data equally well.

Despite its prominence in business cycle theorizing, there have been surprisingly few tests for Keynesian Labor Demand. Most have been based on aggregate time series, such as Galí and Rabanal (2004) and Basu, Fernald and Kimball (2006). More recently, a number of studies have exploited regional variation to test whether goods demand drives employment. Examples include Feyrer and Sacerdote (2011), Nakamura and Steinsson (2011), and Mian and Sufi (2012). Mulligan (2011) looks at seasonal movements in labor supply and employment. Our study complements these in looking at cross-industry evidence. Shea (1993) and Nekarda and Ramey (2011) examine the impact of an industry's downstream demand (Shea) and its share of government purchases (Nekarda and Ramey) on industry price and quantity. Our instruments are entirely different in nature. Chang et al. (2009) examine how employment responds to industry-specific productivity shocks, and how that response depends on the use of inventories and pricing frequency in the industry.

The rest of the paper is organized as follows: in Section 2, we lay out a DSGE model to illustrate the key forces that motivate our instrument set. Section 3 briefly describes the datasets we use. Section 4 presents the main results. Section 5 concludes.

2. Model

To illustrate the key forces that motivate our instruments for goods (and labor) demand, we build a multi-sector DSGE model in which firms differ along the following dimensions: the durability of the good they produce, the capital intensity of their production technology, and the frequency with which they change prices. We allow for both demand (i.e., monetary policy and government spending) and supply (i.e., TFP and investment-specific technology) shocks, and incorporate various forms of real rigidities including sticky wages and adjustment costs on durables expenditures (both consumption and investment). We will demonstrate how the model's implications for relative movements in quantities and prices across sectors differ depending on whether the model is (New) Keynesian or Classical (i.e., sticky or flexible prices).

Firms

There are two final goods, durables (Y_d) and nondurables (Y_n), which are produced from intermediates. For each final good, there are two types of intermediate goods producers: those with high- and low-capital-intensity technologies. Competitive final goods producers take prices as given and use the following production function

$$Y_{j,t} = \left(\sum_{f=h,l} Y_{jf,t}{}^{(\epsilon-1)/\epsilon} \right)^{\frac{\epsilon}{\epsilon-1}},$$

where $Y_{jf,t}$ are composite intermediate goods produced (by competitive firms) according to

$$Y_{jf,t} = \left(\int_0^1 y_{jf,t}(l)^{\frac{\epsilon-1}{\epsilon}} dl \right)^{\frac{\epsilon}{\epsilon-1}},$$

where $\epsilon > 1$. Individual intermediate goods producers are monopolistically competitive and produce using a constant-returns-to-scale (CRS) production function

$$y_{jf,t}(l) = A_{jf,t} k_{jf,t}(l)^{\alpha_f} n_{jf,t}(l)^{1-\alpha_f},$$

where $k_{jf,t}(l)$ and $n_{jf,t}(l)$ are capital and labor employed by firm l in sector jf at time t, $A_{jf,t}$ is sector-specific TFP, $j = \{d, n\}$ indexes the type of good produced, and $f = \{h, l\}$ denotes the technology used. Sectoral price indices, $P_{j,t}$ and $P_{jf,t}$, expressed as functions of individual prices $p_{jf,t}(l)$, can be derived via standard cost minimization.

We assume that capital and labor flow freely across firms within the same sector, and because firms' have CRS production functions, firms in the *same* sector will have the same nominal marginal cost and identical capital-labor ratios. Thus, $k_{jf,t}(l) / n_{jf,t}(l) = K_{jf,t} / N_{jf,t}$. However, as will become clear when we discuss households' supply of factor inputs, imperfect mobility of capital means that marginal costs can vary *across* sectors. Furthermore, different production technologies across sectors imply the slopes of the marginal cost curves will differ across sectors. In particular, greater reliance on fixed factors predicts that a given increase in production will require a greater increase in the flexible labor factor (i.e., marginal cost curve is steeper), thus motivating our use of capital intensity as an instrument for relative shifts in labor demand.

Finally, goods prices are sticky. We use the Calvo (1983) assumption where monopolistically competitive firms change prices with a constant probability of $(1-\theta_{jf})$, regardless of their history of price changes. We will allow θ_{jf} to vary by sector and will also consider the implications of perfect price flexibility $(\theta_{jf} = 0, \forall jf)$.

Households

Households get utility from nondurable and durable consumption and get disutility from working. Let $C_{n,t}$ be nondurable consumption, $C_{d,t}$ be durable consumption expenditures, D_t^c be the stock of the durable consumption goods, and N_t be labor supply. Household preferences are given by

$$\max E_t \sum_{s=0}^{\infty} \beta^s \left[u\left(C_{n,t+s}, D_{t+s}^c \right) - v(N_{t+s}) \right],$$

where the stock of the durable consumption good evolves according to

$$D_t^c = (1-\delta) D_{t-1}^c + C_{d,t} - \frac{S''}{2} \left(\frac{C_{d,t}}{D_{t-1}^c} - \delta \right)^2 D_{t-1}^c.$$

where $S'' > 0$ governs the strength of the adjustment costs for durables expenditures.

Greater durability of a good implies that any increase in consumption of that good requires a more dramatic increase in expenditure. To increase consumption of the durable good by 1%, from a steady state, requires an annual increase in expenditures of 1/δ%. For nondurables, a 1% increase in consumption of course requires only a 1% increase in expenditures. This motivates our use of durability as an instrument for goods demand, as well as labor demand since a larger increase in expenditures will also call forth a larger increase in hours worked in that sector.

The household also owns the economy's physical stock of capital (K^s), sets the utilization rate of capital (u), and rents the services of capital to firms in a competitive market. The relationship between capital services, utilization, and the physical capital stock is as follows

$$K_{jf,t} = u_{jf,t} K^s_{jf,t}.$$

The capital accumulation equation mirrors the accumulation equation for consumption durables

$$K^s_{jf,t} = (1-\delta)K^s_{jf,t-1} + I_{jf,t} - \frac{S''}{2}\left(\frac{I_{jf,t}}{K^s_{jf,t-1}} - \delta\right)^2 K^s_{jf,t-1},$$

where $I_{jf,t}$ denotes investment goods that add to the sector-*jf* capital stock. Note that $I_{jf,t}$ is distinct from investment expenditures, which are given by

$$\tilde{I}_{jf,t} = \frac{1}{\epsilon^i_t}\left(I_{jf,t} + a(u_{jf,t})K^s_{jf,t}\right).$$

That is, investment expenditures also include investment goods that cover maintenance costs arising from capital utilization, $a(u_{jf,t})K^s_{jf,t}$. The cost function $a(\cdot)$ is increasing, convex, and equals zero in steady state. In addition, investment expenditures are affected by the investment-specific technology, ϵ^i_t; higher technology means that fewer expenditures are needed to produce a given increase in the capital stock.

Importantly, we have assumed a separate capital stock for each sector, which means that capital is (partially) fixed in the short-run. Capital services can adjust immediately due to time-varying utilization, but the curvature of $a(\cdot)$ will govern their flexibility. The capital stock will adjust over time, with the speed depending on investment adjustment costs.

Households also supply labor services to firms. We incorporate Calvo-style wage setting frictions following Erceg et al (2000). In brief, households supply labor to each sector, but this process is intermediated by monopolistically competitive unions who have power to set wages. The unions face Calvo frictions in setting wages and change wages with a constant probability of $1-\theta_{jf}^{w}$. In the model specifications we consider, household labor supply across sectors is perfectly elastic, $N_t = \sum_{j,f} N_{jf,t}$, and wage stickiness does not vary by sector $\theta_{jf}^{w} = \theta^{w}$, so that (nominal) wages are equalized across sectors.

Government

The central bank conducts monetary policy using a Taylor rule of the form

$$\ln\left(\frac{R_t}{\bar{R}}\right) = b_r \ln\left(\frac{R_{t-1}}{\bar{R}}\right) + (1-b_r)\left[b_\pi \ln\left(\frac{\pi_t}{\bar{\pi}}\right) + b_y \ln\left(Y_t^{gap}\right)\right] + r_t,$$

where R_t is the nominal interest rate, b_r is the interest rate smoothing parameter and is strictly bounded between 0 and 1, b_π and b_y are non-negative parameters, $\bar{x}$ denotes the steady-state value of variable x, π_t is the gross inflation rate, Y_t^{gap} is the gap between total and potential output (defined as output in the flexible price and wage economy), and r_t is a monetary policy shock. Aggregate inflation and real output are constructed from sectoral prices and quantities by chain-weighting, consistent with the BLS's construction of the CPI.

Turning to fiscal policy, the government is subject to a standard intertemporal budget constraint and finances current expenditures by lump-sum taxes and changes in outstanding debt. Aggregate government spending G_t follows an exogenous stochastic process, and the government allocates spending between durable and nondurable goods to minimize (intertemporal) nominal expenditures subject to an aggregator function

$$H(G_{n,t}, D_t^g) \geq G_t,$$

and an accumulation equation for government durables, which takes the same form as that for the household's stock of durables.

Equilibrium Constraints

Finally, goods, labor, capital and bond markets must all be in equilibrium. In particular, for the goods markets this dictates that

$$Y_{n,t} = C_{n,t} + G_{n,t},$$

$$Y_{d,t} = C_{d,t} + G_{d,t} + \sum_{j,f} \tilde{I}_{jf,t}.$$

Functional Forms and Calibration

We use the same parametric functions as Barsky et al (2007) for u and v

$$u\left(C_{n,t}, D_t^c\right) = \frac{1}{1-\frac{1}{\sigma}}\left[\left[\psi^{\frac{1}{\eta}} C_{n,t}^{\frac{\eta-1}{\eta}} + (1-\psi)^{\frac{1}{\eta}} D_t^{c\,\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}\right]^{1-\frac{1}{\sigma}},$$

$$v(N_t) = \chi \frac{N_t^{1+\frac{1}{\phi}}}{1+\frac{1}{\phi}},$$

where σ is the intertemporal elasticity of substitution, ψ determines the relative preference for the nondurable vs. durable good, η is the elasticity of substitution between the two goods, ϕ is the Frisch labor supply elasticity, and χ governs the level of disutility from labor supply. We then specify a function for H that gives the government the same preferences over durables/nondurables as the households. That is,

$$H\left(G_{n,t}, D_t^g\right) = \left[\psi^{\frac{1}{\eta}} G_{n,t}^{\frac{\eta-1}{\eta}} + \left(1-\psi\right)^{\frac{1}{\eta}} D_t^{g\,\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}.$$

Table 1 describes our model calibration. Following Barsky et al (2007), the Frisch labor-supply elasticity (ϕ) is 1, and we consider log utility (σ and η are 1). ψ is set so that the steady-state ratio of nondurable to durable consumption is 2.96, and we set ε to generate a desired markup of 20 percent. We assume a 5 percent annual depreciation rate for the durable stocks, consistent with the weighted average life-span of 20 years exhibited by durables in our data. We set the household's annual discount rate (3.34 percent) to match an investment-to-output ratio of 0.16, given the depreciation rate and an empirical aggregate capital share of 0.322. For our simulations involving high- and low-capital share sectors, we consider equal-sized sectors with capital shares of $\alpha_h = 0.475$ and $\alpha_l = 0.169$, which are the weighted average capital shares for the top and bottom half of consumption categories when ordered by capital share.

Wages are assumed to change once a year ($1-\theta^w = 0.08$), while the average price changes every four months ($1-\theta = 0.24$).[2] When we consider high- and low-frequency

[2]The time period is a month in our model.

price-setting sectors, we consider equal-sized sectors with frequencies $1-\theta_h = 0.42$ and $1-\theta_l = 0.08$, consistent with the micro data underlying the U.S. CPI.

The parameters of the Taylor rule are set to standard values from the literature on Bayesian estimation of DSGE models, while the persistence of all shock processes and the volatility of the monetary policy, government spending, and investment-specific technology shocks are monthly transformations of the quarterly estimates of Smets-Wouters (2007).[3] We choose a somewhat larger volatility for the neutral technology shock to match the cyclicality of the aggregate labor share. Since our primary focus will be on conditional impulse response functions, however, alternative calibrations of the volatility of the shock processes will not change the lessons we draw from the model.

Finally, we must calibrate the curvature of the adjustment cost functions for utilization and durable expenditures. For utilization, our model dictates a precise mapping between relative utilization rates across sectors and relative labor-to-capital-stock ratios. Specifically,

$$\hat{u}_{j,t} - \hat{u}_{i,t} = \frac{1}{1+a''}\Big[(\hat{N}_{j,t} - \hat{K}^s_{j,t}) - (\hat{N}_{i,t} - \hat{K}^s_{i,t})\Big],$$

where a ^ denotes the log deviation of a variable from its steady-state level. As described in Appendix E, using data on 20 2-digit manufacturing sectors over the past 30 years, we regress Gorodnichenko-Shapiro (2011) utilization rates on labor-capital ratios (and time period effects) and estimate an elasticity of 0.30, corresponding to a''= 2.33. For durables expenditure adjustment costs we set $S'' = 0.455/\delta$ to match Cooper and Haltiwanger's (2006) estimate of the elasticity of the investment rate with respect to Tobin's Q.

Simulation Results

We simulate the model to demonstrate how differences in durability, price flexibility, and capital intensity across sectors affect relative movements in the following four variables: output, prices, labor and labor share. We begin by examining the economy's response to an expansionary monetary policy shock. Figure 1 shows the relative movement in durables to nondurables. For this exercise, the (average) capital intensity and price-change frequency in the two sectors are the same ($\alpha = 0.322, 1-\theta = 0.24$).[4] Theory predicts the demand for durables will respond more strongly than that for nondurables, as a larger increase in expenditures is needed to generate a similar increase in consumption. Although prices respond somewhat more for durables than nondurables, the relative price increase for durables (the green line) is not enough to preclude large relative movements in output (red line) and thus labor (blue line). The relative labor share (teal line) also increases on impact, reflecting two forces: first and most important, the price markup of durables firms is more countercyclical than that for nondurables; and second, within each sector the more labor-intensive subsector will gain market share (in terms of expenditures) because it has more flexibility to ramp up production. The labor share for both durables and nondurables will increase as a result of this composition effect, but the composition effect will be stronger for durables as their expenditures increase by more.

Note that these results do not depend qualitative on our calibration, but are instead implied by the shadow value of long-lived durables goods being nearly invariant to short-

[3] For the persistence parameters, we scaled down SW's "Great Moderation" estimates of 1- ρ by 1/3, while the standard deviations are 1/3 of SW's estimates. Note that the values reported in Table 1 also reflect differences in notation between the models.

lived shocks (Barsky et al 2007). In particular, for a sufficiently long-lived durable (and abstracting from adjustment costs on durables expenditures)[5], household optimizing requires

$$\frac{u_{C,t}}{u_{D,t}}\frac{P_{d,t}}{P_{n,t}} \approx cons\tan t,$$

where $u_{C,t}/u_{D,t} \propto D_t / C_{n,t}$ under our functional form assumptions. Also note that (i) an x% movement in D_t requires a x/δ% in $C_{d,t}$; (ii) prices are related to marginal costs through a standard Phillips curve relationship; (iii) marginal costs equal the (common) wage divided by the sector-specific marginal product of labor (MPL); and (iv) the MPL slopes downward because capital is imperfectly mobile. It is fairly straight-forward to show that an expansionary shock will cause the relative price, output, and labor of durables to increase. If the relative price does not increase, then $D_t / C_{n,t}$ must not decrease. But, this would imply by (i) that $C_{d,t} / C_{n,t}$ increases substantially, so that relative durables output, marginal cost (by iii and iv), and price (by ii) all increase. Thus, it must be the case that the relative price increases, reflecting an accompanying increase in relative marginal cost, output, and labor.

Figure 2 repeats the same exercise but with flexible prices in both sectors ($\theta = 0.00001$). Flexible prices means that the monetary shock has smaller real effects (i.e., the aggregate output response (black line) is smaller than it was in Figure 1), and as for cross-sector movements, the relative price of durables now increases by more, muting the shift in goods and labor demand towards durables. The labor-share response for durables and nondurables is similar, with the small difference solely reflecting the aforementioned

[4] Each sector has low- and high-capital intensity subsectors that are assumed to have identical price-change frequencies.

composition effect – i.e., expenditures are shifted to the high labor-share subsectors. Indeed, with flexible prices and under Cobb-Douglas technology, the labor share in all subsectors is constant, given by $(1-\alpha_f)/\mu$, where μ is a constant markup.

Figure 3 demonstrates the affect of price flexibility in another way. We once again allow for sticky prices, as in Figure 1, but consider low- and high-price flexibility subsectors ($1-\theta_l = 0.08$, $1-\theta_h = 0.42$) and focus on movements *within* the durables sector where most of the action takes place. Optimal demand of (competitive) final durable goods producers implies that

$$\frac{Y_{dl,t}}{Y_{dh,t}} = \left(\frac{P_{dl,t}}{P_{dh,t}}\right)^{-\varepsilon},$$

so that intermediate firms with less price flexibility and a smaller price response will experience a larger response in output and labor input. Because the marginal product of labor is downward sloping, these firms' marginal costs will also increase by more, implying a more countercyclical markup (i.e., higher labor share) for the less flexible subsector. That is, those firms that can respond to the monetary shock more quickly (on average) raise their prices by more and are thus able to maintain more of their price markup.

Finally, in Figure 4, we look across low- and high-capital-intensity subsectors ($\alpha_l = 0.169$ $\alpha_h = 0.475$) within the durables sectors, while keeping price frequency constant ($1-\theta_l = 1-\theta_h = 0.24$). In response to greater durable goods demand, firms with less capital-intensive technologies (i.e., fewer fixed factors) face a flatter marginal cost curve.

[5] Including adjustment costs requires multiplying the left-hand side of the subsequent expression by the relative price of installed durables. Adjustment costs effect the size of the impulse response of relative variables, but not their sign.

Thus, they do not face as much pressure to raise prices, and so their relative price (green line) falls, their relative output (red line) increases, and they are able to maintain a higher markup (i.e., relative labor share falls).[6] Given our calibration, the relative labor (blue line) of the low capital-intensity sector falls on impact before increasing, but the sign of the initial response is sensitive to the gap in capital intensities ($\alpha_h - \alpha_l$) and the fixity of the capital stock (i.e., strength of capital utilization and investment adjustment costs). At any rate, the relative labor response is much more muted than under flexible prices, where an even lower relative price for the low-capital-intensity sector would correspond to a larger increase in relative output and hours. Indeed, under flexible prices (not shown), relative labor increases by 0.56 percent on impact.

We next consider how the economy responds to a supply shock. Figures 5-8 are counterparts to Figures 1-4, but the initial shock is now to aggregate TFP rather than monetary policy. As can be seen from the response of aggregate output, the TFP shock is slightly smaller than the monetary shock, but also somewhat more persistent.

Figures 5 and 6 plot the relative responses of durables to nondurables under sticky and flexible prices, respectively. Both the movements of the variables and economic intuition are very similar to that provided for Figures 1 and 2. Demand shifts towards durables, both for consumption and investment purposes, calling forth more production and employment in this sector. Given the higher relative demand, the price of durables does not fall as much as that for nondurables. Under sticky prices, the relative labor share does rise, whereas with flexible prices (Figure 6), it is much more muted.

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[6] Note that the relative labor share maps one-to-one into the relative markup when we compare across subsectors. Under flexible prices, the relative labor share across subsectors will not fluctuate.

Figure 7 shows the results for low- and high-price flexibility subsectors within the durables sector. The subsector with less-flexible prices will have a more sluggish price response (i.e., its relative price increases), leading to smaller increase in output, hours, and labor share. Figure 8 plots the results for low- and high-capital-intensity subsectors within the durables sector. The flatter marginal-cost curve for the less capital-intensive firms leads them to reduce their price relatively more and produce relatively more output. Their labor share relative to that of high capital-intensity firms is reduced for the first several months.

In review, when comparing sticky and flexible-price economies (Figure 1 & 5 vs Figure 2 & 6), the variable that exhibits the clearest difference is the relative labor share. Whereas the *magnitudes* of the relative output, hours and price response differ across economies, the relative labor share is unresponsive (except for a small composition effect) to shocks under flexible prices, while responding noticeably due to fluctuating markups when prices are sticky. It also makes intuitive sense to think of this measure as a useful indicator of Keynesian labor demand. In a Keynesian world, firms deviate from (or are pushed off) the classical labor demand schedule that equates the marginal product of labor to the wage. Because, under Cobb-Douglas technology, the ratio of the (real) wage to the marginal product of labor is equivalent to the labor share, departures from the labor demand schedule are equivalent to fluctuations in the labor share. Our test does not hinge on Cobb-Douglas production, however, and in our empirical tests we will explicitly consider departures from it.

If this is the case, why not simply look to see if the aggregate labor share co-moves with the business cycle? The reason is that, even in a sticky-price model, the aggregate labor share can be uncorrelated with output. Indeed, this is exactly what is produced by both the Smets-Wouters (2007) model, which was estimated to US data, and our own model. The reason is that the aggregate labor share responds positively to some expansionary shocks and negatively to others. We demonstrate this in Figures 9 and 10, adding government spending and investment-specific technology shocks to the two we have already discussed. We scale the shocks to have the same initial effect on aggregate output (Figure 9), while Figure 10 demonstrates that aggregate labor share responds quite differently to the various shocks. Of course, one could address this by attempting to identify particular shocks (ala Gali (99)), but we pursue a different approach by making use of cross-industry evidence to construct instruments for labor demand. We focus on durability because, in an expansion, movements in the relative labor share across durable and nondurable goods do not depend on the identity of the underlying shock.

3. Evidence on the Cyclicality of Expenditures

Here we describe how we construct demand instruments for across industries. We start with the BLS's classification of goods in the CPI into 70 Expenditure Classes. (See Appendix 6 in http://www.bls.gov/opub/hom/pdf/homch17.pdf.) We combine four pairs of categories and drop five others due to missing NIPA data or overlap with NIPA investment categories, leaving us with 61 consumer goods.[7] We then add 9 categories of investment from the NIPA, leaving us with a total of 70 expenditure categories. Table 2 provides the full list, with the consumer goods first and the investment goods at the bottom.

[7] We combine the following pairs of categories to match more aggregated NIPA expenditure data: alcohol purchased for off-premises consumption and in purchased meals; prescription and non-prescription drugs; men's and boys' apparel; women's and girl's apparel. We dropped three categories due to no match with NIPA categories: personal care products; miscellaneous personal goods; and housekeeping supplies. We dropped rent and owner's equivalent rent of primary residence because investment in residential construction is one of our investment categories.

For each of these 70 categories, we create two demand instruments. The first instrument is based on the durability of the good, and the second is based on the extent to which the good is a luxury or necessity. We also construct two variables specific to each category that should determine how prices respond to demand: the frequency of price change and the importance of capital versus labor in producing the good.

Durability

The second column in Table 2 gives our estimates of durability by good. 28 of our 70 goods are durable (19 of the 61 consumer goods, and all 9 of the investment goods). We use two data sources to establish durability for the 28 categories. The primary source is life expectancy tables from a major property-casualty insurance company, which we use for 17 of the 28 goods. For autos, tires and the 9 investment categories, we use estimates from the U.S. Bureau of Economic Analysis (http://www.bea.gov/iTable/iTable.cfm?ReqID=10&step=1). Appropriately for our purposes, both sources try to incorporate both obsolescence and physical depreciation.

Among the 28 durable goods, the extent of durability varies widely. It is over 30 years for residential structures and three types of commercial buildings. For business equipment it ranges from 4 to 11 years (with information equipment and software at the less durable end, presumably due to obsolescence). Durability also varies among the 19 consumer durables. At the low end are clothing categories (less than 5 years) and at the upper end are appliances and electronics (closer to 10 years). We classify the remaining 42 consumption categories as nondurables, and as therefore having a service life of less than a year. These include perishables such as food, but also services.

Engel Curves

Whether a good is a luxury or necessity should also help predict cyclicality of demand. To estimate Engel Curves, we turn to the U.S. Consumer Expenditure Survey (CE) Interview Surveys. CPI categories are closely matched to questions in the CE, as the BLS uses the CE to determine expenditure weights for the CPI.

We pooled cross-sections from the 1982 to 2010 CE to estimate the Engel Curve elasticities for our 61 consumer categories as well as for housing services.[8] We restrict our sample to households that complete all four quarterly interview surveys. The CE Interview Survey lumps together all food for home consumption; so for these categories we estimate a common elasticity. We describe our estimation of these elasticities here. Appendix A provides more detail on our CE sample.

We estimate Engel elasticities by regressing the spending for each category from the household's second through fourth interviews on the sum of spending during those same three quarters. We omit the household's first quarter expenditures in order to use these to instrument for the household's total expenditures reported in its final three surveys. More exactly, we instrument for the log of the household's total expenditures in its final three interviews based on its (logged) total and nondurable expenditures from the first quarterly interview, as well as its (logged) before-tax annual income reported in both the first and final interviews. We instrument in order to avoid attenuation bias reflecting measurement error in household's total expenditures. We do not log expenditures for individual categories, the

[8] Housing services are measured by rent for renters. For home owners it is measured by household's estimate of the home's rental value.

dependent variables in the second stage, as these are zero in some cases. Instead we divide the household's spending on a category by mean spending on that category. So our elasticities must be interpreted as relative to mean household spending on that category.[9]

The CE do not address Engel curves for the NIPA investment categories. For these 9 categories we associate each with an Engel curve for the consumer goods that make use of that investment. For investment in residential structures we use our estimate for housing services; for investment in power and communication structures we use a weighted average of our estimates for household utilities. For the remaining investment categories we assign an elasticity that is a good-weighted average of the Engel elasticities for potentially all our NIPA goods. To construct the weights we employ the BEA's detailed commodity-by-commodity input-output matrix for 2002 (www.bea.gov/industry/io_benchmark.htm), with weights that reflect the relative importance of the goods as final users of that investment category.

The third column in Table 2 provides our point estimates for Engel Curve slopes. The slopes average right around unity, as one would expect. At the luxurious end are Household operations (over 2; think household help), lodging away from home (1.8), and recreation services (1.8). Necessities include tobacco (0.1), food for home consumption (0.4), and telephone services (0.6).

Frequency of Price Changes

The stickier the prices, the more Keynesian the Labor Demand (in theory). Thus we would like to control for the flexibility of prices in testing for Keynesian Labor Demand.

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[9] Both the first and second stage regressions include year and quarterly (seasonal dummies). They also include controls for household demographics on age, household size, urban status, marital status, and number of earners.

An advantage of using the BLS Expenditure Classes from the CPI is that estimates of price flexibility are readily available for these categories. From the micro price data underlying the CPI, we obtain price change frequencies from Klenow and Malin (2011). These are based on monthly prices from 1988 through 2009. We use their estimates for regular prices, i.e., excluding sale-related price changes, as suggested by Nakamura and Steinsson (2008).

For the four equipment investment categories, we use frequencies calculated by Nakamura and Steinsson on monthly PPI data from 1998-2005.[10] For the investment in structures we distinguish between structures built to order and those built speculatively. For 1988 to 2010, on average 61 percent of home sales occurred prior to completing the house (built to order), while 39 percent occurred after the house was built (spec homes built to stock). We treat built to order as selling at a negotiated price, assigning it a pricing frequency of one. For houses built to stock we err on the conservative side, and assume the home is priced only once when put on the market, setting frequency to one divided by median time on the market. Median time on the market for spec homes averaged 5 months for 1988 to 2010; so this yields a very conservative frequency of 0.2. But, since most homes are built by order, the overall frequency for residential investment remains high at over 0.7 per month. We assume that investment in business structures are essentially all produced to order, or at least priced subject to negotiation. So we assign a frequency of one to these categories.

The fourth column in Table 2 shows the monthly frequency of price change for our goods. As emphasized by Bils and Klenow (2004) and many others, price flexibility varies

[10] More exactly, we map 79 of their producer prices series to one of these 4 investment categories. The category is then assigned a weighted average of the frequencies of its associated producer prices, with weights reflecting a PPI relative importance for December 2009.

persistently and widely. It is lowest for services (such as health professionals and restaurant meals), where prices change less than once a year. It is highest for business structures (where we assume each price is newly negotiated) and for commodities such as gasoline and fresh produce (for which prices change every couple months).

Capital Shares

Our capital shares are taken from the U.S. KLEMS data on multifactor inputs and productivity for 18 manufacturing and 44 non-manufacturing sectors. This data is described in Section 4 below. The capital share for a NIPA category is assigned a weighted average of capital shares of value added in each of the KLEMS industries matched to that good. We map NIPA categories to the KLEMS based on the shares of employment assigned to corresponding KLEMS industries. This mapping is also described in detail in the next section.

Expenditure Shares and Employment Shares

To gauge whether our instruments predict cyclicality of expenditures, we matched our 70 goods to NIPA expenditure categories. (See http://bea.gov/iTable/index_UD.cfm for the consumption categories and both http://bea.gov/iTable/iTable.cfm?ReqID=9&step=1 and http://bea.gov/iTable/iTable.cfm?ReqID=21&step=1 for the investment categories.) The match was one-to-one for 44 consumer goods and for the 9 investment types. For 17 expenditure classes we had to combine two or more NIPA categories.

The sum total of nominal expenditures on our 70 goods averages 57% of nominal GDP from 1990:1 through 2011:2. The major components of GDP excluded from our set are rent and owner's implicit rent, government expenditures, inventory investment, and net exports. Of our 70 categories, 40% of spending is on durables, and 60% on nondurables.

We will use the expenditure shares to weight goods in the results that follow. The largest categories are hospital services (9.3%), residential structures (7.2%), professional services (7.2%), and food away from home (5.6%).

Based on data on employment by detailed industry from the BLS Current Employment Survey (CES), we also estimate the share of employment by industries producing each good.[11] Of our 70 categories, 32% of employment is in durables-producing industries, and 68% is in nondurables-producing industries. The largest employers are for food away from home (12.0%), hospital services (10.3%), and miscellaneous personal services (7.9%).

All of the results we report are for de-seasonalized series.

Relevance of the Durability Instrument

As illustrated in the previous model section, durability should be a powerful predictor for the cyclicality of expenditures and employment. In the next section we will test for Keynesian Labor Demand using production data across industries. The production data will be at a higher level of aggregation due to data limitations. So it is useful at this point to gauge whether durability is a good predictor of fluctuations in spending at our detailed level of 70 goods.

We first estimate the cyclicality of expenditures by good as follows. For each good, we regress quarterly HP-filtered log real expenditures on quarterly HP-filtered log real GDP from 1990:1 to 2011:2. The weighted mean coefficient is 1.62 and the weighted mean standard error is 0.24. (Our typical category is more cyclical than GDP because the largest excluded categories – rent and government expenditures – are less cyclical than GDP.) But the coefficients tend to be much bigger for durable goods (3.25) than for nondurable goods (0.54). Figure 11 plots these cyclicality coefficients against log durability of the good. The size of each ball represents its expenditure share. If one runs WLS on these 70 observations, the adjusted R2 is 0.54. The fit is not driven by the obvious outlier, business transportation equipment (mostly cars and trucks), which has a cyclicality coefficient over 10. The R2 rises to 0.77 if one excludes business transportation equipment. We obtain similar results if we look at growth rates and/or at annual data, though the standard errors are larger with annual data. In sum, durability looks highly relevant for cyclicality, as theory would predict.

Does the predictive power of durability carry over from expenditures to employment? Figure 12 answers this question with a resounding yes. The R2 from WLS here is a striking 0.85. The weighted mean coefficient for durables is 1.79 vs. only 0.19 for nondurables. In the Figure, the large maroon ball with cyclical response near 3 is residential construction. But this sector is far from driving the results. Without residential construction, the weighted mean cyclicality coefficient is still 1.52 for durables, and the R2 is still 0.63.

Our findings are robust to defining the cycle in terms of total nonfarm employment rather than GDP. Defined this way, the weighted mean cyclicality coefficient is 1.85 for durables vs. 0.34 for nondurables. The R2 from WLS is 0.70. See Figure 13. Residential construction actually reduces the fit here, as the R2 rises to 0.76 without it.

Figure 14 looks at the Great Recession in particular. Using the NBER Business Cycle dating, we calculate the peak-to-trough decline (log first difference in employment) for each

[11] Our matching of NIPA goods to CES employment industries is described in Section 4.

good from December 2007 to June 2009. The R2 from running WLS on log durability is 0.74. Residential construction is influential here, but not dominant. The R2 is still 0.41 without it. The outlier on the other side is manufacturing structures. Employment for industrial buildings inexplicably soared 38.5% during the Great Recession. The influence of this observation is limited by its small weight (0.5% of employment); the R2 rises modestly to 0.76 when we exclude it.

What about the time since the recovery began? Though famously jobless overall, it is worth examining the pattern of employment changes across goods. Figure 15 presents the log first difference of employment from June 2009 through June 2011. As has been widely discussed, residential construction employment fell another 8.5% in the two years of tepid recovery. But the Figure makes it clear that this failure to bounce back is not special to residential construction – it can be seen in almost all durables.

We can also look at how the cyclicality of final goods prices varies. Prices are relative to the GDP deflator. Figure 16 shows there virtually zero correlation between the cyclicality of prices and the cyclicality of quantities. The nondurables with highly procyclical prices are motor fuel (the large ball) and other fuels (the small one). If we exclude these the relationship becomes more positive (t-stat 2.4, adjusted R2 0.07). Of course, whether one should expect a positive or negative correlation depends on whether relative demand or supply shocks predominate. In Figure 17 we relate the cyclicality of prices to our durability instrument for demand cyclicality. A WLS regression does show a positive coefficient but it is statistically insignificant coefficient (0.11 with a standard error of 0.07). If we drop the energy outliers, the relationship becomes significantly positive with an adjusted R2 of 0.52.

4. Industry Results on Cyclical Wedge between Labor's Wage and Product

The results above show that durability is an important predictor of cyclical movements in employment and expenditures across goods. We now relate the information on our 70 NIPA goods for durability, Engel curves, and pricing frequencies to industry productivity data to see how industries differ cyclically depending on characteristics of the goods produced.

Measuring Cyclical Behavior by Industry

The productivity data we employ is the U.S. KLEMS data (http://www.bls.gov/mfp/). The KLEMS data provide annual values, both nominal and real, for gross output and inputs of intermediates, labor, and capital from 1987 to 2009. The data cover 18 manufacturing and 44 non-manufacturing sectors.

These data allow us to address several questions. For one, we can examine the cyclical behavior of output, as opposed to expenditures, for cyclical goods. In turn, we can see how the cyclicality of labor's share of output differs for these goods. From the model simulations, this is a key indicator of any cyclical wedge between the real wage and labor's marginal product. Related, with the industry data we can condition on industry movements in productivity, thereby seeing, for instance, whether the lack of procyclical prices for durables goods is driven by favorable productivity shocks skewed toward these goods. In addition, the industry data allow us to examine the impact of capital's share on fluctuations. Given that capital is relatively fixed in the short run, short-run marginal cost curves will be steeper in industries that are more capital intensive. Therefore, under flexible pricing, these industries should display more procyclical prices, but less cyclical quantities. With sticky prices, this role of capital's share will be muted.

We supplement the KLEMS data with series on employment, weekly hours, and wages from the BLS Current Employment Survey (CES). CES industries are matched to KLEMS by corresponding NAICS code. The CES reports hours and earnings for production related employees in goods-producing industries and for nonsupervisory employees in private service-providing industries. For our industries 81.8 percent of employees are production and non-supervisory. We follow the convention of referring to these employees collectively as production workers. Since March 2006 the BLS has presented earnings series for all employees. But for salaried workers it is especially difficult to justify the assumption that contemporaneous payments reflect their shadow wage. There is little reason for firms to contemporaneously increase salaries with hours worked, if it is understood that subsequently payments will increase or required hours will decrease. Importantly, under that scenario, any movement in hours for salaried workers will be misconstrued as associated with an opposite movement in the wage rate of the same percent.

We map the characteristics of the 70 NIPA goods to the KLEMS industries as follows. For 1990 forward, the CES provides data on employment for 210 distinct industries that can be mapped to our 70 NIPA goods.[12] Because each CES industry has, through NAICS, an associated KLEMS industry, we can then associate a relative importance of each NIPA category to a KLEMS industry in each year. This importance is measured by the KLEMS industry employment assigned to any good relative to the sum of that industry's employment assigned across all 70 NIPA goods. For instance, KLEMS industry NAICS 335 (electrical equipment, appliances, and components) is assigned for 2009 as 38% to consumer appliances

[12] For industries that map to more than one NIPA good category, we allocate CES employment in proportion to relative expenditures in the categories. For motor vehicles, computers, and computer software, we can make this allocation at a finer level of aggregation using NIPA data. Note also that the CES includes many more industries (beyond the 210) that cannot be mapped to NIPA goods.

and 62% to electrical equipment investment (part of other equipment). The characteristics assigned to NAICS 335 for 2009, in turn, are a weighted average of the characteristics for the two associated NIPA categories, with relative weights 0.38 and 0.62.

We achieve a mapping to NIPA categories for 41 of the KLEMS industries; for 40 of these, we have information on employment, hours, and wage rates. Table 3 lists these 40 industries together with their mapped characteristics. 13 are manufacturing industries; 27 reflect construction, trade, and services. We calculate that on average 44.4 percent of employment in a KLEMS industry is associated with one of the NIPA categories, weighting by value added. For eight of the industries, the NIPA goods account for less than 25 percent of that industry's employment. If goods produced by an industry are comparable in terms of durability, pricing frequency, and Engel curve elasticity, then this partial coverage is not problematic. But for robustness, below we also examine results restricting attention to industries where this fraction is 25 percent or higher.

We focus attention on how cyclicality differs across the KLEMS industries with respect to output, price, and production labor's share. Output and price are measured respectively by industry value added and its value-added deflator. These are constructed using the Divisia method from values and prices for gross output and intermediate inputs, as described by Basu and Fernald (1997).

The wedge between the real wage (deflating by producer price) and labor's marginal product is the inverse of the gross markup of price over marginal cost. Rotemberg and Woodfood (1999) refer to this as real marginal cost. In Appendix B, we illustrate that if (a) production is a power function in production workers (Cobb-Douglas), and (b) fluctuations in the marginal price of labor are captured by average hourly earnings, then fluctuations in real marginal cost are captured by movements in labor's share.[13] This is robust to adjustment costs for labor, provided there are no adjustment costs at the intensive, workweek margin. Appendix B expresses real marginal cost in terms of production labor's share of industry output. For salaried workers, the data do not provide a reliable measure of a worker's marginal price at the intensive, workweek margin; and it is not defensible to assume no adjustment costs for salaried workers at the extensive, employment margin.

Appendix B also generalizes labor share as a measure of real marginal cost if the elasticity of substitution between capital and labor differs from one. Below we show that our results are robust with respect to considerable variation in that elasticity.

Of more quantitative importance, in our view, is how the marginal price of labor is measured. In Appendices C and D, we discuss two alternatives to average hourly earnings as a measure of labor's marginal price. The first incorporates an estimate of the marginal impact of an increase in hours at the intensive margin. This suggests a marginal wage rate that increases relative to average hourly earnings if the workweek increases—so it is more procyclical assuming workweeks are procyclical. We refer to this as the marginal wage. Many of the KLEMS industries do not report data on overtime hours. For these industries we ignore any overtime premium, setting the marginal wage equal to average hourly earnings.

We also consider a variant in which we drop average hourly earnings entirely as a measure of labor's price. Instead, we calculate effective relative wage rates across industries based on assuming firms internalize workers' marginal disutility of an hour's work. We refer to this price of labor as the shadow wage. Our calculation of the shadow wage assumes a Frisch elasticity of labor supply at the intensive margin of 0.5. It assumes that the marginal

[13] This result has been illustrated often, for instance by Bils (1987), Sbordone (1996), Rotemberg and Woodford (1999), and Galí, Gertler and Lopez-Salido (2007).

utility of consumption does not vary cyclically for workers in one industry relative to another. These assumptions are consistent with the model's perfectly integrated labor market, as adjusting the shadow wage for hours worked can be viewed as the marginal compensating differential with respect to hours. To the extent consumption is more cyclical for workers in more cyclical industries (so that the marginal utility of consumption less cyclical), our assumptions will understate relative increases in the shadow wage for cyclical industries.

Results

Table 4 displays how cyclicality differs for industries that produce more, versus less, durable goods. Separate results are given for cyclicality in real value added, price (the deflator for value added), and labor share of value added. For instance, the first element in row one reflects a regression of real value added on a full set of year dummies (suppressed) as well as an interaction of industry-specific durability with the aggregate business cycle. We measure durability by Ln(1 + lifespan in years). The aggregate business cycle is measured by HP-filtered log real annual GDP. All dependent variables are logged and HP filtered as well.[14]

Consistent with results for NIPA goods in the previous section, durables show much greater cyclicality in quantities but not prices. Consider a good with lifespan of 12 years (appliances) versus a nondurable. The coefficient for quantity implies that a one percent increase in aggregate GDP is associated with a 1.7 percentage point greater increase in value added for an industry producing goods as durable as appliances relative to nondurables-

[14] Data are annual for 1990 to 2009 for each of the 40 industries, except Publishing, for which data on hours and wages are available beginning with 2003. The parameter for annual HP-filtering is 6.25, as suggested by Ravn and Uhlig (2002).

producing industry. (The standard error on that differential is 0.3 points.) Price is actually predicted to fall by 0.3 percentage points for the industry producing such a durable relative to those producing nondurables, though this relative price effect is not statistically significant.

As predicted by the sticky price model, labor share is more procyclical for more durable goods. The size of this effect is similar whether we measure the price of labor by average hourly earnings or by the marginal wage, in each case suggesting that each percentage point relative expansion in output for durables in a boom is associated with a relative increase in labor share of about one-third of a percentage point. This is actually somewhat larger than the response in labor share generated by the sticky-price model (see Figures 1 and 5).[15] If we measure labor's price by the shadow wage, then the magnitude of increase in labor share for more durable goods in booms is considerably larger. For instance, comparing goods with the durability of appliances (12 years) to nondurables, a one percent increase in GDP, which is associated with a 1.7 percentage point greater increase in value added for the durable, would be associated with a 1.1 percentage point greater increase in its labor share.

One possible explanation for the lack of a relative price increase for durables during expansions is that durable sectors experience more procyclical productivity shocks. Based on the KLEMS data, such an effect does not appear particularly important. Regressing value-added TFP on year dummies and the interaction of Ln(1 + lifespan) with the cycle yields a

[15] Aggregate, as opposed to relative, labor share is acyclical for these industries regardless of whether the wage is measured by average hourly earnings or the marginal wage. Pooling the industries, a one percent increase in GDP reduces labor share by 0.04 percent (std. error 0.10 percent) measuring with average hourly earnings and increases it by 0.002 percent (std. error 0.10 percent) measuring with the marginal wage. If we use the shadow wage, then labor share is clearly very procyclical, increasing by 0.41 percent (std. error 0.11 percent) for a one percent increase in GDP. But the assumptions we employed to motivate the shadow wage as a measure of relative wages across industries (no relative consumption movements) do not translate to measuring aggregate movements.

coefficient of only 0.10 (standard error 0.13). This is only one-seventh the size of the effect of durability on relative output. Of course, TFP is not necessarily an unbiased measure of productivity shocks. We calibrated model simulations to allow for capital utilization to be procyclical, responding with an elasticity of 0.3 with respect to movements in labor relative to the capital stock. (This adjustment is motivated by examining series on capital services constructed by Gorodnichenko and Shapiro, 2011, as described in Appendix E.) If we adjust TFP as a measure of productivity in this manner, we find that adjusted-TFP is slightly more procyclical for durables versus nondurables: its regression on Ln(1 + lifespan) interacted with the cycle yields a coefficient of 0.15 (standard error 0.13).

In the second panel of Table 4, we include adjusted-TFP as a regressor, in addition to the good's lifespan, in explaining relative cyclicality of output, price, and labor share. The impact of durability is largely unaffected. The estimated impact of durability on output is modestly reduced and that on price modestly increased, with the impact on cyclicality of price now very nearly zero. The impact of durability on relative cyclicality in labor share is modestly strengthened. Measuring labor share based on average hourly earnings or the marginal wage, relative labor share increases by an elasticity of about one-half with respect to the impact of durability on output. Measured by the shadow wage, the greater cyclicality in labor share for durables is nearly as great as its greater cyclicality in output.

The KLEMS data show the following for relative industry movements in adjusted-TFP: a one percent relative increase in industry productivity is associated with decline in price that is less than one-for-one, at 0.6 percent. Output increases nearly one-for-one with productivity, by 0.9 percent. This implies a small corresponding decrease in inputs. But, an estimate of the impact of adjusted-TFP on labor hours for production workers, conditioning on durability, is actually zero, with coefficient 0.01 and standard error of 0.01. An increase in adjusted-TFP is associated with a fall in labor share of about 0.3 percent, implying an increase in the gross price markup of that magnitude. This is true regardless of whether the wage measure is average hourly earnings, the marginal wage, or the shadow wage.

Our measure of cyclicality in labor share in Table 4 is based on assuming a substitution parameter of one between production labor and capital. In Table 5, we present alternative results, assuming first an elasticity of substitution equal to 0.5 and then equal to 2.0. The table shows that labor share becomes more procyclical if the elasticity is reduced from 1 to 0.5, and less procyclical if increased from 1 to 2. This is not surprising, given that the labor to capital ratio is more procyclical for durables. But the results for labor share are actually only very modestly affected relative to those in Table 4. This partly reflects that we allow for movements in capital utilization that partially offset movements in labor relative to the capital stock. Secondly, durables have a somewhat smaller capital share than nondurables. This makes marginal cost for durables less sensitive to movements in the labor-capital ratio than for nondurables.

The impact of durability on cyclicality in output, pricing, and labor share is potentially masked by the fact that durables display more frequent price changes. For our 40 KLEMS industries, the correlation between durability and frequency of price change is 0.67. Sticky price models, including that in Section 2, predict more cyclical price and less cyclical output and labor share for goods with more flexible price setting.

In Table 6 we add the sector's monthly frequency for price changes multiplied by cyclical movements in real GDP. We also include an interaction of this variable with the durability variable, allowing cyclical pricing of durables to differ for goods with frequent versus infrequent price changes.[16] As anticipated by what we saw across NIPA goods from Section 3, industries that produce goods with more frequent price changes display much more procyclical prices. They display less cyclical output. The coefficients for quantities and prices implies that a one-percent increase in aggregate GDP is associated with a 1.9 percentage point increase in the price deflator for an industry that produces goods with monthly frequency of 0.5 versus an industry that produces goods with frequency of 0.1, but a 0.7 percentage point smaller increase in output. Labor share is much more countercyclical for industries that produce goods with frequent price changes.

From Figure 16, energy prices are striking outliers in that they have displayed far more procyclical prices. For this reason, in the bottom panel table 6 we examine robustness to removing the two energy KLEMS industries, oil and gas extraction and petroleum and coal refining. The finding in the top panel, that frequent price changing predicts more cyclical prices, is not at all robust. Excluding the energy sectors, prices are no more or less cyclical for industries producing goods with frequent price changes, nor do they display less cyclical labor share. They do continue to show less procyclical output. For the balance of the paper, we show all results both with and without the energy industries.

Holding frequency of price change constant, durability continues to be associated with much more cyclical output and with much more procyclical labor share. These statements hold with or without the two energy industries. Again consider a good with lifespan of 12 years (appliances) versus a nondurable. A one percent increase in GDP would be associated with a 1.6 percentage point greater increase in value added for industries producing goods as

[16] This interaction is constructed with respect to the mean value of the durability and the mean frequency of price change; so the estimate for the durability variable can be interpreted as applying at the sector of mean frequency, and the estimate for the frequency variable applies at the sector with mean value for the durability variable.

durable as appliances compared to nondurables-producing industries (with standard error of 0.2 percentage points.) It is also associated with a 0.9 percentage point decrease in relative price for that durable industry (standard error 0.3 points.) Labor share is now shown to be extremely procyclical for more durable goods. Including the energy industries, relative labor share increases by about the same elasticity as does output with respect to durability—in fact, measured by the shadow wage, labor share increases by an even greater elasticity. Excluding energy, labor share increases with an elasticity of about 0.6 to 0.9 that in output, depending on the wage measure. Finally, prices continue to be no more procyclical for durable. If we include the two energy industries, they are actually significantly less procyclical.

Our findings conflict with modeling prices as flexible with constant markups. Labor share is much more procyclical for industries producing durables, implying sizable countercyclical movements in price markups for more durable sectors. These markup movements are actually larger than predicted by our sticky-price model with time-dependent pricing, as displayed in Figures 1 and 5. In addition, relative shifts in productivity, which have little effect on inputs, decrease labor share.

The regressions in Table 6 include interactions of durability and pricing frequency, to address whether countercyclical markups are more pronounced for durables with less frequent price changes, as predicted by the sticky price model. Here the results hinge on the energy industries. Including the energy industries, durable industries display especially countercyclical prices, and especially procyclical labor share, if producing goods with frequent price changes (e.g., construction industries). But in the bottom panel, dropping the energy industries, this result is gone. Procyclicality of labor share is most striking for durables with less frequent price changes.

In Table 7 we extend the regressions to include interactions of economy-wide GDP with the average Engel curve for goods produced in the industry and for the industry's (average) capital share in value added. Sticky-price models would suggest more cyclical expenditures but also more cyclical labor share (countercyclical markups) for industries producing luxuries. A higher capital share predicts that marginal cost will be more procyclical for an industry. Therefore, with sticky prices, it should be associated with a decline in the markup, manifested as an increase in labor share (see model Figures 4 and 8).

Turning to Table 7, note that results for cyclicality by durability and frequency of price change are essentially unchanged: Labor share remains highly procyclical for durables; more frequent price changes predicts much more procyclical prices and countercyclical labor share, but only if the energy industries are included. The estimated impact of an industry's Engel curve elasticity and capital share are not affected by excluding the energy industries, so we focus discussion on the top panel with them included.

As expected, output is more cyclical for industries producing luxuries. For instance, for an industry producing goods with an Engel curve elasticity of 1.6 (as estimated for jewelry) rather than one, a one percent increase in U.S. GDP would be associated with a 0.37 percentage point greater increase in output (with standard error of 0.08 points). But, in contrast to cyclicality for durables, prices for luxuries do rise in booms; and labor share for luxuries, if anything, is less cyclical than for necessities.

We see that higher capital share is associated with much less cyclical output, but not more cyclical prices. For instance, compare an industry with capital share of 0.7 (e.g., utilities) versus one with share of 0.2 (furniture manufacturing). The impact of that higher capital share for a one percent increase in GDP is that relative output decreases by 0.6

percentage points (standard error of 0.1 points), with no relative price effect. This pattern does not fit either a flexible price or simple sticky price story, as neither provides an explanation for output to depend on capital share except through more cyclical marginal cost and price. One possibility is that treating capital share as a supply-side instrument is mispecified, with cyclicality of demand correlated (negatively) with capital share. Alternatively, this might be taken as evidence against the standard assumption of most sticky price models, ours included, that firms stand ready to meet quantity demanded regardless of the markup. If the wage is measured by the average or marginal wage, higher capital share is associated with more procyclical marginal cost and a countercyclical markup. An increase in marginal cost can potentially discourage producing, without a price increase, in models with production to inventory. (See, for instance, Chang, Hornstein, and Sarte, 2009.).

For robustness, we repeated the estimation restricting the sample to those industries where the share of employment captured by its associated NIPA goods is at least 25 percent. The only important impact of imposing this restriction is that prices are now even more procyclical for industries producing luxuries. These industries also now display highly countercyclical labor share, implying price markups are more procyclical for luxuries. This reinforces the message from Table 7: if price stickiness exists, it does not prevent prices from responding more for luxuries with respect to the cycle.

To recap, the industry results violate predictions under flexible pricing and constant markups. Most notably, relative prices are not more procyclical for industries producing more durable goods, resulting in procyclical labor share for these industries. But the results do not all fit nicely with New-Keynesian sticky-price models. Labor share fails to increase cyclically for industries producing luxuries or producing under high capital shares. Both are predictions of the Keynesian sticky-price model. And, if we exclude the energy industries, more frequent price change does not translate into more procyclical prices.

Implications for Pass-through

Another way to view our results is through the prism of pass-through. That is, to what extent do movements in marginal cost produce increases in relative prices rather than markup declines? To predict movements in marginal cost we again use our demand instruments of durability and Engel curve interacted with the cycle, as well as our supply instrument of capital share interacted with the cycle.

Table 8 shows the response of price to instrumented fluctuations in marginal cost. The top panel shows the result of regressing *marginal cost* on our instruments, a full set of year dummies, and industry-specific TFP, corrected for movements in capital utilization. The last series is included as a control, given productivity shocks could be correlated with our instruments. Under Cobb-Douglas production, variations in marginal cost are captured by the wage relative to labor productivity. Columns 1 through 3 give results measuring the wage three ways – by the average, marginal, and shadow wage. Using the average or marginal wage, marginal cost is clearly more procyclical for industries producing durables, luxuries, or producing with high capital share. The impact of durability and capital share are particularly striking. For durability consider a good with lifespan of 12 years (appliances) versus a nondurable. Each percent increase in GDP is associated with a 0.8 percentage point increase in marginal cost (standard error 0.1) for the durable relative to nondurable.[17] If, alternatively,

[17] This impact on marginal cost mirrors labor productivity--a one percent increase in GDP is associated with a 0.7 percentage point decrease in labor productivity (standard error 0.1) for a good with lifespan of 12 years relative to a nondurable.

we employ the shadow wage, cyclicality in marginal cost projects even more strongly on durability, but now no longer depends on the Engel curve or capital share.

The bottom panel of Table 8 shows how *price* responds to cyclical movements in marginal cost, as instrumented by durability, Engel curve, and capital share of a sector. The second stage also includes corrected sector TFP as a regressor. This allows the price pass-through from marginal cost movements reflecting TFP to differ from the pass-through when marginal cost is predicted by our instruments. With marginal cost measured using either the average or marginal wage, pass-through is estimated at about 0.6 (standard error 0.2 to 0.3). By contrast, when the wage is measured by the shadow wage, pass-through is close to zero. This is not surprising. With the wage measured by the shadow wage, cyclicality of marginal cost is effectively driven by durability (see the top panel). And, from Tables 4-7, we know markups are highly countercyclical for durables.

In the last three columns of Table 8, we repeat the estimation, but drop the two energy sectors that have displayed such procyclical prices. The first-stage IV results are unaffected except marginal cost is modestly more procyclical for luxuries. But the 2nd stage estimates of pass-through, under either the average or marginal wage, are cut in half from 0.6 to 0.3 (standard error 0.2). Measuring labor's cost with the shadow wage, estimated pass-through actually increases when dropping the two energy sectors, but remains quite small at 0.2.

It is useful to compare our empirical pass-through of 0.3 to 0.6 with the properties of a conventional Keynesian DSGE model, such as the one we laid out in Section 2 above. We simulate this model, and time aggregate the simulated monthly series to create annual series on marginal cost and price for the durable and nondurable sector. We then calculate pass-through from a regression akin to what we run on the data. With all four shocks turned on, we obtain a model pass-through of around 0.6, just as in the data.[18] Thus our point estimates are consistent with a Keynesian sticky price model calibrated to the frequency of price changes in the micro data. From Table 8, if we drop the two energy sectors, pass-through is cut in half to about 0.3. To match this lower pass-through in the model, we have to cut the frequency of price changes by half relative to that observed in the micro data. That is, it requires calibrating to prices that change every 8 months, rather than every 4 months.

5. Conclusion

Employment's response to fluctuations in goods demand is exacerbated by price stickiness in many Keynesian models. This impact on employment is manifested through unintended countercyclical fluctuations in the markup of prices over marginal cost (Goodfriend and King, 1997). We test this prediction across U.S. industries. We identify movements in goods demand chiefly by exploiting differences in durability across 70 categories of consumer and investment goods--we show durability is a powerful predictor of relative fluctuations in expenditures and employment across sectors. We also map Engel curves to our goods, allowing us to treat an industry producing a luxury as a further instrument for cyclicality of goods demand. We stratify industries by the importance of capital in the production process and by the frequency of price changes for its goods: High capital share implies more cyclical marginal cost; and we anticipate that price will respond more with marginal cost if price changes are frequent.

[18] We use the shock processes estimated by Smets and Wouters (2007) for technology, government purchases, monetary policy, and investment-specific technology. Model pass-through does vary modestly with the shock: roughly 0.5 in response to monetary policy and investment-specific technology shocks, and 0.8 in response to general technology and government spending shocks.

We find evidence in support of Keynesian labor demand over a constant-markup version of flexible-price labor demand. First and foremost, we estimate that price markups decline considerably for durables relative to nondurables in expansions. This result is robust to measuring cyclicality of marginal cost under alternative measures of labor's price and under a broad range of assumed short-run substitutabilities of capital and labor. Because of countercyclical markups for durables, the cyclical movements in marginal cost predicted by industry durability, Engel-curve elasticity, and capital share are only modestly passed through to cyclical movements in price. In that regard, the evidence is consistent with a Calvo model calibrated to the frequency observed in the micro data, or even less frequent.

But not all the evidence aligns with sticky prices. Procyclical marginal cost, driven by producing a luxury or producing with a highly capital-intensive technology, does not generate a markup decline. And higher frequency of price change produces neither more cyclical prices nor price markups, beyond the extremely procyclical pricing of energy goods. The observed cyclical wedges between labor's marginal product and price might be better explained by intended pricing by firms, principally countercyclical markups for durables, rather than unintended markup movements that are the byproduct of price stickiness. That interpretation also allays the ostensible inconsistency of our findings with those of Shea (1993) and Nekarda and Ramey (2011), who find considerable price responses to their respective industry demand instruments. Targeted markups need not respond uniformly to a shift in goods demand, regardless of the source of that shift.

It is important to decipher whether departures of pricing from that implied by flexible pricing with constant markups reflect nominal price stickiness or firms targeting markups that are cyclical. Targeted markups also create a cyclical wedge that can exacerbate employment fluctuations. But, they do not support the same policy prescriptions often justified by assuming sticky prices, i.e, active monetary policy and fiscal policy that emphasizes spending, but not the marginal returns to working and consuming.

Appendix A: Consumer Expenditure Survey Sample

We estimate Engel curves for 60 of the 70 NIPA goods based on the U.S. Consumer Expenditure Survey (CE) Interview Surveys. These correspond to all our consumption categories except postage, which is not collected in the CE Interview Survey. We also estimate a unique elasticity for all food at home categories, as the Interview Survey does not provide separate categories for food at home. In addition, we estimate an Engel curve for housing services, which we employ for the category of investment in residential structures. (Housing services are measured by rent for renters. For home owners it is measured by household's estimate of the home's rental value.) The estimation is described in the text. Here we focus on describing our CE sample.

We pool the 1982 to 2010 CE surveys. The survey became annual in 1980, but home owner estimates of their home's rental value become available only in 1982. The CE is fairly large, with samples of 5,000 or more households in most years. Each household is assigned a "replicate" weight that maps the CE sample into a representative sample of the national population. We use that weight in all calculations. A household is interviewed about their expenditures for up to four consecutive quarters. Each interview records a household's expenditures by category over the previous three months. In the first and fourth interviews, the household is asked its income over the preceding 12 months, including all transfer income received. As stated in the text, we use these responses, as well as spending information from the first interview, to instrument for the sum of a household's expenditures from surveys two through four.

We restrict our sample to households that complete all four quarterly interview surveys. We also restrict the sample to those with household heads between ages 20 and 64.

We exclude households that report annual before-tax income (including transfers) of less than \$100, in 1983 dollars, in either the first or fourth interviews. We exclude households that report less than \$100 of spending on nondurables for their first quarterly interview, or less than \$300 over the subsequent three quarters (again in 1983 dollars). Our resulting sample includes 70,518 households.

Appendix B: Measuring the Gap between Real Wage and Labor's Marginal Product

Marginal cost can be measured by the price of any input relative to its marginal physical product. We consider hours of production labor as the input for measuring marginal cost. An advantage of considering production labor, rather than capital or non-production labor, is that hours are readily measured and costs of adjustment are arguably smaller. We focus on variations at the intensive, workweek margin for production workers. In doing so, we assume no adjustment costs in varying production workers' weekly hours. But we put no restrictions on employment adjustment costs, even for production workers.

We let value added reflect production and non-production inputs of capital and labor according to

$$y = f(k_{pr}, n_{pr})g(k_{np}, n_{np}) .$$

The variables k, n denote services of capital and labor, including any variations in services due to utilization rates. Variables with subscript *pr* refer to factors classified as engaged in physical production. (We map n_{pr} to hours of production and nonsupervisory labor in the data.) Variables with subscript *np* refer to factors not engaged in production.

We assume $f(k_{pr}, n_{pr})$ is CES,

$$f(k,n) = a\left((1-\alpha)(\phi_n n)^{\frac{\sigma-1}{\sigma}} + \alpha(\phi_k k)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\eta\sigma}{(\sigma-1)}}.$$

n and k refer to production labor hours (employment times workweek) and the capital engaged in production. ϕ_n and ϕ_k are respective utilization rates for production labor and capital (i.e, ϕ_n is effort per hour). We have dropped the subscripts to denote production. η equals the multiple of returns to scale and the share of production inputs in value added. σ is the elasticity of substitution between k and n.

The required increase in labor for a marginal increase in output (labor's marginal product inverted) can be written

$$\frac{\partial n}{\partial y} = \frac{1}{\eta(1-\alpha)}\frac{n}{y}\left((1-\alpha)+\alpha\left(\frac{\phi_k k}{\phi_n n}\right)^{\frac{\sigma-1}{\sigma}}\right).$$

Multiplying $\frac{\partial n}{\partial y}$ by the cost of an extra hour of labor, w, gives nominal marginal cost, mc.

Dividing nominal marginal cost by the firm's price yields the inverse of the gross price markup over marginal cost

$$\frac{mc}{p} = \frac{1}{\eta(1-\alpha)}\frac{wn}{py}\left((1-\alpha)+\alpha\left(\frac{\phi_k k}{\phi_n n}\right)^{\frac{\sigma-1}{\sigma}}\right).$$

The inverse price markup also represents the wedge (as ratio) between the real wage and labor's marginal product. Taking logs and ignoring constants,

$$\ln\left(\frac{mc}{p}\right) \approx \ln\frac{wn}{py} + \ln\left((1-\alpha)+\alpha\left(\frac{\phi_k k}{\phi_n n}\right)^{\frac{\sigma-1}{\sigma}}\right).$$

Under Cobb-Douglas ($\sigma = 1$) and a marginal price of labor, w, given by average hourly earnings, movements in the wedge are given by movements in production labor's share of output. This is one estimate of the wedge between the real wage and labor's marginal product that we consider.

We examine the robustness of our results to allowing less, or more, substitutability of production labor and capital in the short run, presenting results for $\sigma = 0.5$ and $\sigma = 2$. For Cobb-Douglas, there is no need to adjust for rates of utilization ϕ_n and ϕ_k. For $\sigma = 0.5$ and $\sigma = 2$, we assume that the rate of capital utilization varies with an elasticity of 0.3 with respect to the ratio of production labor to capital. We treat ϕ_n as unchanging. This elasticity is based on estimation using series on capital utilization from Gorodnichencko and Shapiro (2011), as outlined in Appendix E.

In addition to measuring the price of labor by the average hourly wage, we consider two other measures. One is based on an estimate of the marginal increase in straight and overtime payments for a marginal increase in the workweek. We refer to this as the marginal wage. The other is based on measuring the wage that would be dictated by worker indifference curves. We refer to this as the shadow wage. Discussions of these two measures follow.

Appendix C: Measuring the Marginal Wage

Our estimate of the marginal wage follows work by Bils (1987) and Nekarda and Ramey (2010). The starting point is allowing that labor may be quasi-fixed, with costs of adjusting employment. Such costs suggest that average hourly earnings may understate the cyclicality of the cost of labor. For example, in an expansion, the marginal adjustment cost would reflect finding and training an additional employee, whereas in a recession, this might reflect laying off one less employee. By considering the workweek as the margin of adjustment, we can avoid measuring marginal costs of adjusting employment. But average hourly earnings may also poorly capture variations in the price of labor at the hours margin. (In fact, if it poorly captures labor's marginal cost at the employment margin, it must poorly capture it at the hours margin, assuming firms are equating the effective marginal costs of labor at the employment and hours margins.) For example, a marginal increase in hours will more likely require premium payments (e.g., overtime) during a period when hours are high. Such overtime payments have little impact on average hourly earnings, as that measure divides those payments by all hours worked.

Let h denote a firm's average hours per worker and v denote its average overtime hours. Then the marginal wage for the firm, equaling the increase in wage bill per worker for an increase in h, is given by

$$w_m = w_{st}\left(1+0.5\frac{\partial v}{\partial h}\right).$$

w_{st} is the straight-time wage rate. Here we assume a fifty percent overtime premium, as dictated by legislation. Average hourly earnings are given by replacing the term $\frac{\partial v}{\partial h}$ in the marginal wage with $\frac{v}{h}$; so average hourly earnings would only capture the marginal wage in the peculiar case that overtime hours are a constant share of hours regardless of the workweek.

We posit the following functional form for estimating $\frac{\partial v}{\partial h}$:

$$\frac{\partial v}{\partial h} = a + b\left(h - 40\right) \ .$$

This is a special case of those estimated by Bils (1987) and Nekarda and Ramey (2010), which allow for higher-order terms in the workweek. But we did not find those terms matter for our estimates for 1990 to 2009.

We estimate this equation for the KLEMS industries to which we could map overtime hours from the BLS CES data. This is 13 of the 40 industries. The estimates are $a = 0.596$ (with standard error 0.041) and $b = 0.057$ (with standard error 0.017). These estimates imply a marginal wage that increases by about 2.2% if the workweek increases from 40 to 41, which implies an elasticity of a little less than 0.9 with respect to the workweek. For the 27 KLEMS industries without series on overtime hours, we assume overtime premia are irrelevant, setting the marginal wage to average hourly earnings.

Appendix D: Measuring the Shadow Wage

Here we drop any pretext that measured wages capture the effective price of labor. The implicit contracting literature provides one strong rationale for basing the perceived price of labor to firms as separated from observed variations in wage rate. Consider an alternative measure of wage rates that allows that employers internalize workers' indifference curves. This suggests that the effective wage is given by workers marginal rates of substitution: $u_h(c,h)/u_c(c,h)$. In turn, letting the marginal utility of consumption be equated to the shadow value of wealth (λ), we have

$$\frac{w}{p_c} = \frac{u_h(c,h)}{\lambda} \ .$$

where p_c is the price index for consumer goods, and h is hours worked. (Individual subscripts are implicit.)

To measure aggregate cyclicality of w/p_c requires measuring the cyclicality of λ. But we need only measure relative cyclicality, e.g., cyclicality of the wage for workers who produce durables goods relative to nondurables. If we assume that cyclical movements in λ are comparable across sectors, then relative wage movements across sectors will simplify to calibrating movements in the compensating differentials to those workers who experience a greater increase in hours worked than on average. If we further assume that preferences are separable with $u_h \approx h^{1/\gamma}$, then relative movements in wage rates are captured as

$$\ln\left(\frac{w}{\overline{w}}\right) = \frac{1}{\gamma}\Delta\ln\left(\frac{h}{\overline{h}}\right),$$

where variables with bars denote aggregates and γ is the Frisch elasticity.

In employing this measure, we use a Frisch elasticity of one half--so relative movements in wages across sectors simply equal two times the relative movements in hours (workweeks). To the extent workers in more cyclical industries, such as durables, exhibit greater cyclicality in consumption (and more counter-cyclical λ's) we will understate the relative cyclicality of wages and relative labor share for more cyclical industries.

Appendix E: Calibrating Cyclical Movements in Capital Utilization

We calibrate movements in capital's utilization rate to utilization rates constructed by Gorodnichenko and Shapiro (2011), largely from the U.S. Census Survey of Plant Capacity. The Gorodnichenko-Shapiro series are available annually for manufacturing series for the years 1974 to 2004, with the exception of 1998. We match their series at the two-digit SIC level (available on Shapiro's web page) to annual series on employment and hours for production and non-supervisor workers drawn from the NBER Productivity Database for manufacturing. For each manufacturing industry, we construct measures of the labor to capital stock ratio from the Productivity Database. We then regress movements in the Gorodnicheko and Shapiro utilization rates on industry movements in labor to capital. All series are HP-filtered with industry-specific filters.

We find that a one-percent increase in the labor to capital stock ratio is associated with a 0.3 percent increase in the utilization rate of capital. When the labor-capital ratio is measured by production hours to capital, the precise estimate is 0.30 with a standard error of 0.03. (When labor is measured by all worker hours, the estimate is 0.29 if we assume a constant 40-hour workweek for supervisory/non-production workers, and 0.30 if we assume nonproduction workers exhibit the same workweek movements as production workers.).

Table 1

Model Parameters

Discount Factor (β)	$0.966^{1/12}$	Utilization Cost Curvature (a'')	2.33
Intertemporal Elasticity (σ)	1	Durables Adj Cost Curvature (S'')	0.46/δ
Nondur-Dur Elasticitiy (η)	1	Steady-state G/Y	0.19
Frisch Labor-Supply Elasticity (ϕ)	1	Taylor interest-rate smoothing (b_r)	0.95
Elasticity across Varieties (ε)	6	Taylor-rule inflation (b_π)	1.8
Relative Nondur Pref (ψ)	0.639	Taylor-rule output gap (b_y)	0.12
Depreciation Rate (δ)	$1\text{-}0.95^{1/12}$	AR(1) of monetary shock (ρ_r)	0.76
Aggregate Capital Share (α)	0.322	AR(1) of TFP shock (ρ_a)	0.98
Low-Intensity Capital Share (α_l)	0.169	AR(1) of Govt spending shock (ρ_g)	0.99
High-Intensity Capital Share (α_h)	0.475	AR(1) of Investment shock (ρ_i)	0.88
Avg Price-Change Freq ($1-\theta$)	0.24	SD of monetary innovation (σ_r)	0.04
Low Flexibility ($1-\theta_l$)	0.08	SD of TFP innovation (σ_a)	0.72
High Flexibility ($1-\theta_h$)	0.42	SD of Govt spend innovation (σ_g)	0.72
Avg Wage-Change Freq ($1-\theta^w$)	0.08	SD of Investment innovation (σ_i)	0.06

Notes: Model is monthly. The disutility of labor χ is set so that steady-state aggregate labor supply is 1, and the relative steady-state TFP levels are set to produce equal-sized subsectors within the durables and nondurables sectors.

Table 2

NIPA Expenditure Categories (Goods)

Good	Dur. (years)	Engel Curve	Price Freq.	Capital Share	Exp. Share	Emp. Share
Men's and Boys' Apparel	2.78	1.090	0.0841	0.2371	1.468%	0.832%
Women's and Girls' Apparel	2.54	1.216	0.1262	0.2324	2.339%	1.370%
Footwear	2.56	0.945	0.0841	0.2311	0.809%	0.362%
Infants' and Toddlers' Apparel	2.30	0.554	0.1096	0.2321	0.197%	0.161%
Jewelry and Watches	6.90	1.590	0.0921	0.2631	0.834%	0.398%
Educational Books and Supplies	11.00	1.173	0.1105	0.3229	0.159%	
Tuition and Childcare	0.00	1.742	0.0879	0.3786	1.755%	2.358%
Postage and Delivery Services	0.00	1.000	0.0560	0.2199	0.167%	0.807%
Telephone Services	0.00	0.584	0.2525	0.5513	2.067%	2.239%
Information and Info. Processing	7.10	1.325	0.2812	0.2353	0.603%	0.543%
Cereals and Cereal Products	0.00	0.410	0.1462	0.3227	0.519%	0.411%
Bakery Products	0.00	0.410	0.1234	0.3790	0.891%	0.988%
Beef and Veal	0.00	0.410	0.2383	0.3492	0.518%	0.507%
Pork	0.00	0.410	0.2182	0.3492	0.362%	0.355%
Other Meats	0.00	0.410	0.1533	0.3492	0.310%	0.308%
Poultry	0.00	0.410	0.1990	0.3850	0.570%	0.721%
Fish and Seafood	0.00	0.410	0.1911	0.3643	0.168%	0.181%
Eggs	0.00	0.410	0.3723	0.3499	0.089%	0.081%
Dairy and Related Products	0.00	0.410	0.1942	0.3499	0.378%	0.344%
Fresh Fruit	0.00	0.410	0.3974	0.2402	0.313%	0.215%
Fresh Vegetables	0.00	0.410	0.4368	0.2402	0.467%	0.322%
Processed Fruits and Vegetables	0.00	0.410	0.1334	0.4383	0.330%	0.722%
Juice and Nonalcoholic Drinks	0.00	0.410	0.1196	0.3156	0.967%	0.740%
Beverages Including Coffee and Tea	0.00	0.410	0.1472	0.2418	0.140%	0.084%
Sugar and Sweets	0.00	0.410	0.0932	0.3357	0.558%	0.470%
Fats and Oils	0.00	0.410	0.1342	0.3499	0.199%	0.181%
Other Foods	0.00	0.410	0.1108	0.3136	1.422%	1.089%
Food Away From Home	0.00	1.206	0.0714	0.2030	5.557%	12.035%
Alcoholic Beverages	0.00	1.295	0.1019	0.2614	2.099%	1.067%
Tobacco and Smoking Products	0.00	0.083	0.2128	0.4872	1.130%	0.051%
Personal Care Services	0.00	1.038	0.0363	0.1184	1.094%	0.667%
Miscellaneous Personal Services	0.00	1.439	0.0540	0.3277	3.266%	7.932%
Lodging Away from Home	0.00	1.804	0.3689	0.3360	0.947%	2.629%
Tenants' and Household Insurance	0.00	1.105	0.0950	0.2126	0.075%	0.893%
Fuel Oil and Other Fuels	0.00	0.777	0.4290	0.4136	0.289%	0.181%

Table 2 continued

NIPA Expenditure Categories (Goods)

Good	Dur. (years)	Engel Curve	Price Freq.	Capital Share	Exp. Share	Emp. Share
Gas (piped) and Electricity	0.00	0.456	0.6613	0.7253	2.680%	1.002%
Water and Sewer and Trash Collections	0.00	0.688	0.1045	0.5519	0.910%	0.231%
Window and Floor Coverings and Linens	8.68	1.617	0.0785	0.2294	0.297%	0.143%
Furniture and Bedding	8.97	1.257	0.0969	0.2207	1.182%	1.004%
Appliances	12.09	0.964	0.1310	0.3143	0.596%	0.274%
Other Household Equipment, Furnishings	7.65	1.668	0.0857	0.2411	0.478%	0.480%
Tools, Hardware, Outdoor Equipment	7.50	1.085	0.0823	0.2469	0.293%	0.722%
Household Operations	0.00	2.018	0.0856	0.2472	0.771%	1.126%
Drugs and Medical Supplies	0.00	0.904	0.1388	0.3447	1.558%	1.698%
Professional Services	0.00	1.248	0.0472	0.1535	7.211%	6.939%
Hospital and Related Services	0.00	0.881	0.0991	0.2156	9.268%	10.289%
Health Insurance	0.00	0.919	0.0833	0.2126	1.540%	0.508%
Video and Audio	10.39	0.791	0.1330	0.5777	1.131%	1.042%
Pets, Pet Products and Services	0.00	1.454	0.0862	0.2819	0.380%	1.593%
Sporting Goods	9.60	1.587	0.0989	0.2611	0.602%	0.553%
Photography	2.93	1.401	0.0897	0.1842	0.092%	0.404%
Other Recreational Goods	6.15	1.119	0.0867	0.2454	0.501%	0.459%
Recreation Services	0.00	1.787	0.0894	0.2533	1.611%	2.452%
Recreational Reading Material	2.38	1.305	0.0780	0.2294	0.482%	0.215%
New and Used Motor Vehicles	9.00	0.846	0.3814	0.4133	2.155%	2.501%
Motor Fuel	0.00	0.650	0.8626	0.4428	3.215%	1.625%
Motor Vehicle Parts and Equipment	2.55	0.797	0.1383	0.2572	0.586%	1.821%
Motor Vehicle Maintenance and Repair	0.00	1.094	0.1571	0.1184	2.121%	1.240%
Motor Vehicle Insurance	0.00	0.895	0.1330	0.2126	0.768%	
Motor Vehicle Fees	0.00	1.127	0.0241	0.1184	0.197%	0.140%
Public Transportation	0.00	1.414	0.3651	0.2093	1.117%	0.560%
Commercial and health care structures	42.15	1.145	1.0000	0.1554	1.994%	1.967%
Manufacturing structures	32.01	1.154	1.0000	0.1654	0.651%	0.514%
Power and communication structures	45.22	0.540	1.0000	0.1509	0.824%	1.029%
Mining exploration, shafts, and wells	13.78	0.971	1.0000	0.1655	0.755%	0.584%
Information equipment and software	4.27	1.032	0.0749	0.2699	6.562%	2.647%
Industrial equipment	10.73	0.938	0.0840	0.2768	2.542%	2.114%
Transportation equipment	7.03	0.983	0.1707	0.2588	2.353%	2.758%
Other equipment	6.83	0.987	0.0752	0.2956	2.291%	2.045%
Residential structures	68.15	0.817	0.7340	0.1535	7.237%	5.081%

Notes to Table 2:

Dur. = durability (years of expected life).

Engel Curve = the cross-household elasticity of expenditures on the good with respect to overall nondurables and services expenditures. Estimated using the U.S. Consumer Expenditure Survey from 1982-2010.

Price Freq. = the monthly frequency of regular price changes in the CPI for consumption goods from 1988-2009, and in the PPI for investment goods.

Capital Share = capital's share of value added in producing industries (1 minus labor's share) from 1987-2009.

Exp. Share = NIPA expenditures on the good relative to expenditures on all 70 goods, averaged over 1990-2011.

Emp. Share = CES employment in producing industries relative to employment for all 68 categories, averaged over 1990-2011.

Table 3

KLEMS Industries

INDUSTRY	NAICS Code	Log Dur.	Engel Curve	Price Freq.	Cap. Sh.	VA Wt.
Oil and Gas Extraction	211	0.00	0.57	0.75	0.76	1.26
Utilities	22	0.00	0.49	0.59	0.72	2.91
Construction	23	3.90	0.89	0.89	0.14	7.15
Food, Beverage, and Tobacco	311,312	0.00	0.44	0.15	0.49	2.36
Apparel and Leather products	315,316	1.28	1.10	0.10	0.23	0.40
Wood products	321	4.24	0.82	0.73	0.22	0.44
Petroleum and Coal products	324	0.00	0.66	0.83	0.78	1.07
Chemical products	325	0.00	0.90	0.14	0.54	2.67
Plastics and Rubber products	326	1.27	0.80	0.14	0.36	0.98
Fabricated Metal products	332	2.97	1.04	0.62	0.30	1.84
Machinery	333	2.27	0.96	0.08	0.27	1.76
Computer and Electronic products	334	1.80	1.03	0.10	0.24	2.44
Electrical Equipment and Appliances	335	2.28	0.98	0.10	0.37	0.77
Transportation Equipment	336	1.63	0.89	0.18	0.26	2.82
Furniture and related products	337	2.23	1.18	0.09	0.21	0.48
Miscellaneous Manufacturing	339	1.82	1.19	0.08	0.34	0.88
Wholesale Trade	42	0.96	0.85	0.14	0.28	7.64
Retail Trade	44,45	0.95	0.83	0.26	0.23	9.08
Truck Transportation	484	0.00	2.02	0.09	0.21	1.50
Transit and Ground Passenger Transportation	485	0.00	1.41	0.37	0.21	0.28
Other Transportation	487,488, 492	0.00	1.00	0.06	0.22	1.12
Publishing Industries	511,516	0.48	1.35	0.09	0.41	1.81
Broadcasting and Telecommunications	515,517	0.20	0.60	0.24	0.59	3.60
Information and Data Processing Services	518,519	0.00	0.58	0.25	0.33	0.70
Credit Intermediation and Related Activities	521,522	0.00	1.44	0.05	0.45	4.29
Securities, Commodity Contracts, and Investments	523	0.00	1.44	0.05	0.16	2.47

Insurance Carriers and Related Activities	524	0.00	1.04	0.09	0.21	3.05
Real Estate	531	0.00	2.02	0.09	0.83	5.62
Rental and Leasing Services	532,533	2.36	0.82	0.27	0.79	2.01
Legal Services	5411	0.00	1.44	0.05	0.09	2.23
Miscellaneous Professional, Scientific and Technical Services	5412-5414, 5416-5419	0.83	1.35	0.19	0.15	6.58
Administrative and Support Services	561	0.00	2.02	0.09	0.11	3.78
Waste Management and Remediation Services	562	0.00	0.69	0.10	0.41	0.43
Ambulatory Health Care Services	621	0.00	1.25	0.05	0.15	4.52
Hospitals and Nursing and Residential Care Facilities	622,623	0.00	0.88	0.10	0.22	1.61
Performing Arts, Spectator Sports, Museums, and Related Activities	711,712	0.00	1.79	0.09	0.15	0.50
Amusements, Gambling, and Recreation Industries	713	0.00	1.79	0.09	0.28	0.55
Accommodation	721	0.00	1.80	0.37	0.34	1.06
Food Services and Drinking Places	722	0.00	1.22	0.08	0.20	2.35
Other Services, except Government	81	0.10	1.18	0.11	0.12	2.98

Table 4

Durability and Cyclicality

	Quantity	Price	Marginal Labor Share, Using: Average Wage	Marginal Wage	Shadow Wage
Ln (1 + lifespan)*GDP	0.67 (0.13)	−0.13 (0.12)	0.20 (0.09)	0.24 (0.09)	0.42 (0.09)
Ln (1 + lifespan)*GDP	0.53 (0.04)	−0.04 (0.09)	0.25 (0.08)	0.28 (0.08)	0.46 (0.09)
Adjusted-TFP	0.90 (0.01)	−0.60 (0.02)	−0.30 (0.02)	−0.29 (0.02)	−0.28 (0.02)

Notes: Sample = 787 in all panels. This reflects 20 annual observations, 1990-2009, for each of 40 industries with the exception of Publishing (NAICS 511,516), for which data on hours and wages are only available for 2003-2009. Quantity refers to real value added, price to the value added deflator. Marginal labor share is the effective price of labor times labor hours for production and nonsupervisory employees as a share of nominal value added. Regressions include full set of year dummies.

Table 5

Durability and Cyclicality without Cobb-Douglas

	Short-run Cap./Labor Subst = 0.5			Short-run Cap./Labor Subst = 2		
	Marginal Labor Share, Using:			Marginal Labor Share, Using:		
	Average Wage	Marginal Wage	Shadow Wage	Average Wage	Marginal Wage	Shadow Wage
Ln (1 + lifespan)*GDP	0.25 (0.09)	0.28 (0.09)	0.47 (0.10)	0.18 (0.09)	0.21 (0.09)	0.39 (0.09)
Ln (1 + lifespan)*GDP	0.30 (0.08)	0.33 (0.08)	0.51 (0.09)	0.22 (0.08)	0.25 (0.08)	0.44 (0.08)
Adjusted-TFP	−0.29 (0.02)	−0.28 (0.02)	−0.30 (0.03)	−0.30 (0.03)	−0.29 (0.02)	−0.29 (0.02)

Notes: Sample = 787 in all panels. Quantity refers to real value added, price to the value added deflator. Marginal labor share is the effective price of labor times labor hours for production and nonsupervisory employees as a share of nominal value added. Regressions include full set of year dummies.

Table 6

Cyclicality Interacting with Price-Change Frequency

	Quantity	Price	Marginal Labor Share, Using: Average Wage	Marginal Wage	Shadow Wage
Ln (1 + lifespan)*GDP	0.64 (0.07)	−0.36 (0.13)	0.57 (0.13)	0.65 (0.13)	0.79 (0.14)
Price Change Freq*GDP	−1.76 (0.27)	4.78 (0.58)	−3.64 (0.52)	−3.64 (0.52)	−3.41 (0.57)
Freq*Durability*GDP	0.42 (0.13)	−1.05 (0.28)	0.55 (0.26)	0.41 (0.26)	0.46 (0.28)
Adjusted TFP	0.89 (0.01)	−0.57 (0.02)	−0.32 (0.02)	−0.31 (0.02)	−0.30 (0.02)
Drop two energy industries					
Ln (1 + lifespan)*GDP	0.61 (0.07)	−0.04 (0.11)	0.34 (0.10)	0.43 (0.10)	0.55 (0.12)
Price Change Freq*GDP	−1.29 (0.39)	−0.11 (0.61)	0.22 (0.57)	0.08 (0.58)	0.48 (0.67)
Freq*Durability*GDP	0.28 (0.16)	0.33 (0.24)	−0.56 (0.23)	−0.66 (0.23)	−0.66 (0.27)
Adjusted TFP	0.89 (0.01)	−0.54 (0.02)	−0.36 (0.02)	−0.35 (0.02)	−0.35 (0.02)

Notes: Sample = 787 in top panel, = 747 in lower. Capital share measured by industry HP trend in capital's share of value added. Regressions include full set of year dummies. Frequency and durability are demeaned in variable Freq*Durability*GDP.

Table 7
Cyclicality with Engel Curves and Capital Shares

	Quantity	Price	Marginal Labor Share, Using: Average Wage	Marginal Wage	Shadow Wage
Ln (1 + lifespan)*GDP	0.67 (0.07)	−0.24 (0.15)	0.57 (0.13)	0.65 (0.13)	0.70 (0.14)
Price Change Freq*GDP	−0.45 (0.33)	5.65 (0.71)	−4.37 (0.64)	−4.39 (0.64)	−3.74 (0.70)
Freq*Durability*GDP	−0.16 (0.16)	−1.47 (0.33)	0.87 (0.31)	0.74 (0.31)	0.63 (0.33)
Engel Curve*GDP	0.62 (0.13)	0.85 (0.28)	−0.31 (0.26)	−0.32 (0.26)	−0.48 (0.28)
Capital Share*GDP	−1.29 (0.24)	−0.01 (0.51)	0.80 (0.46)	0.81 (0.47)	−0.29 (0.51)
Adjusted TFP	0.90 (0.01)	−0.57 (0.02)	−0.32 (0.02)	−0.31 (0.02)	−0.30 (0.02)
Drop two energy industries					
Ln (1 + lifespan)*GDP	0.64 (0.07)	0.01 (0.11)	0.38 (0.11)	0.46 (0.11)	0.52 (0.12)
Price Change Freq*GDP	0.30 (0.44)	0.58 (0.72)	−0.17 (0.67)	−0.35 (0.68)	0.37 (0.78)
Freq*Dur*GDP	−0.39 (0.18)	0.04 (0.29)	−0.40 (0.27)	−0.48 (0.28)	−0.61 (0.31)
Engel Curve*GDP	0.68 (0.13)	0.46 (0.21)	0.04 (0.20)	0.01 (0.20)	−0.16 (0.23)
Capital Share*GDP	−1.28 (0.24)	−0.11 (0.38)	0.87 (0.36)	0.89 (0.36)	−0.22 (0.41)
Adjusted TFP	0.89 (0.01)	−0.54 (0.02)	−0.36 (0.02)	−0.36 (0.02)	−0.35 (0.02)

Notes: Sample = 787 in top panel, = 747 in lower. Regressions include full set of year dummies. Frequency and durability are demeaned in variable Freq*Durability*GDP.

Table 8

Marginal Cost and its Pass-through to Prices

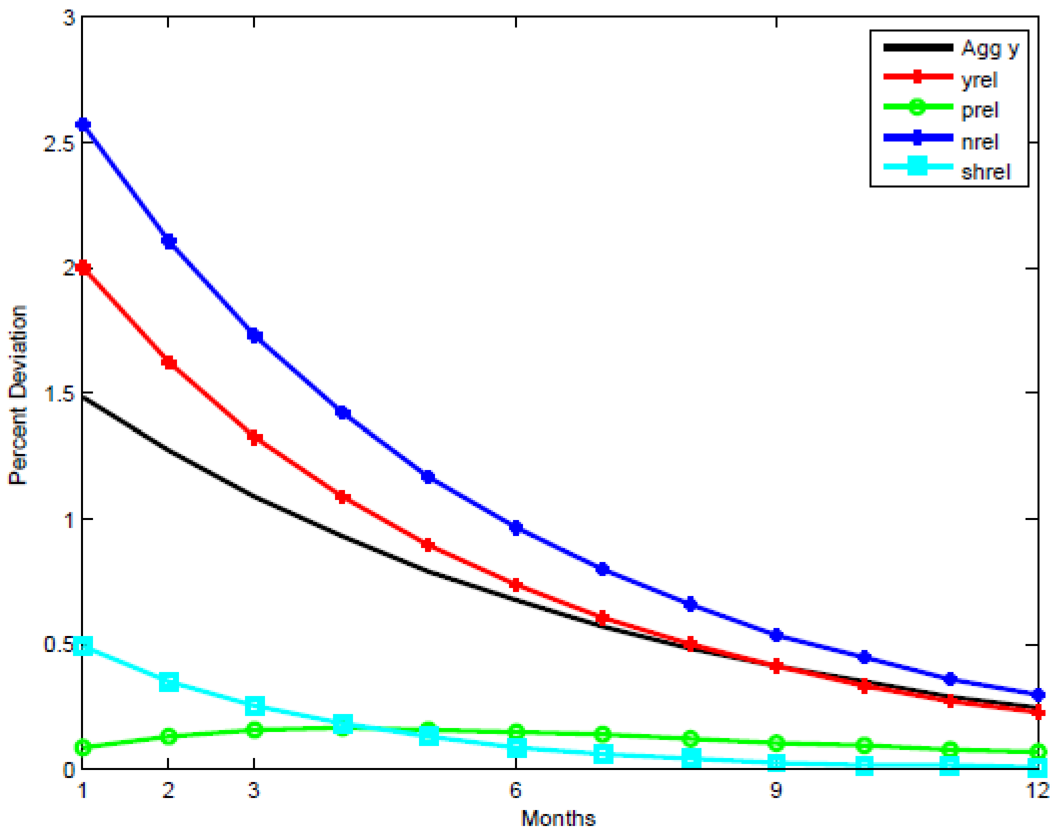
	All Industries			Dropping two Energy Industries		
	Wage measure: Average	Marginal	Shadow	Wage measure: Average	Marginal	Shadow
	1st Stage—Marginal Cost as Dependent Variable					
Ln (1 + lifespan)*GDP	0.29 (0.05)	0.32 (0.05)	0.43 (0.06)	0.31 (0.04)	0.34 (0.04)	0.45 (0.06)
Engel Curve*GDP	0.26 (0.12)	0.21 (0.13)	−0.05 (0.16)	0.39 (0.11)	0.35 (0.11)	0.11 (0.15)
Capital Share*GDP	1.25 (0.22)	1.30 (0.23)	0.39 (0.29)	0.89 (0.22)	0.92 (0.23)	−0.09 (0.22)
Adjusted TFP	−0.90 (0.01)	−0.88 (0.01)	−0.88 (0.02)	-0.90 (0.01)	-0.88 (0.01)	-0.88 (0.02)
	2nd Stage—Price as Dependent Variable					
Marginal Cost	0.62 (0.26)	0.56 (0.24)	0.05 (0.21)	0.32 (0.20)	0.28 (0.19)	0.17 (0.14)
Adjusted TFP	−0.04 (0.23)	−0.10 (0.21)	−0.56 (0.19)	−0.25 (0.18)	−0.29 (0.17)	−0.39 (0.12)

Notes: Sample = 787 in left panels, = 747 in right. Capital share measured by industry HP trend in capital's share of value added. Regressions include full set of year dummies.

Figure 1

Relative **Durables/Nondurables** Response to *Monetary Policy Shock*

Sticky Prices

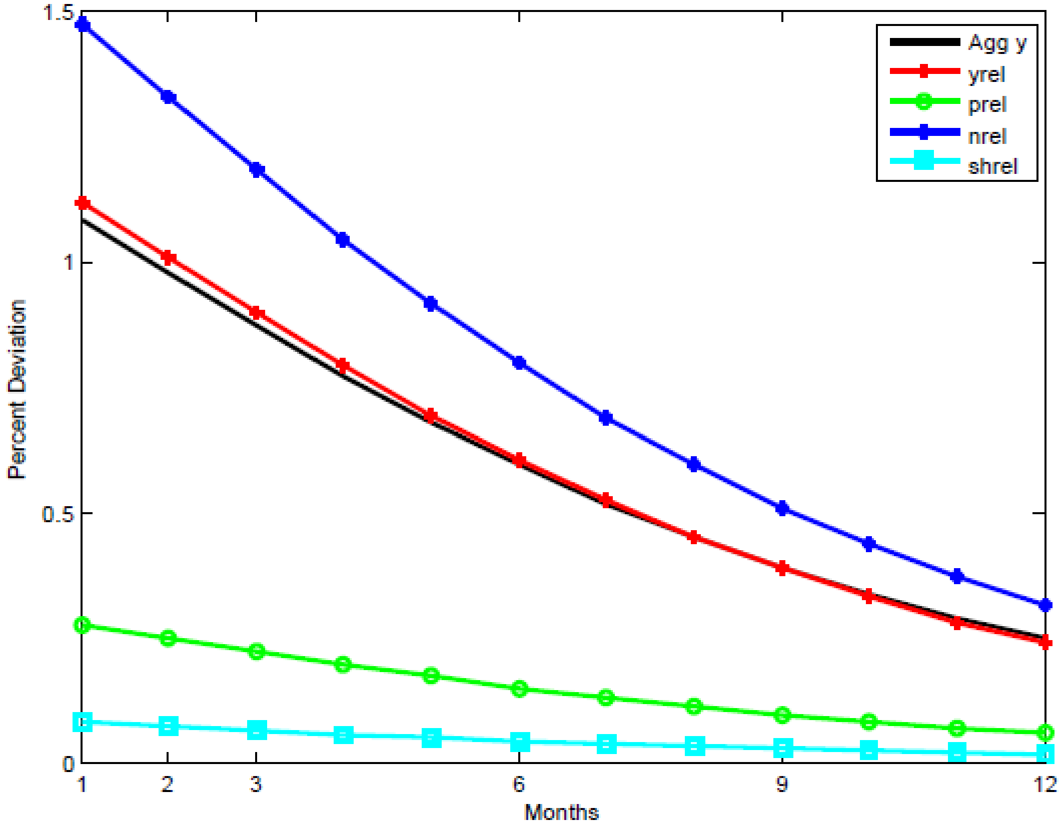


Notes for Figure 1: "Yrel" is relative output. "Prel" is relative price level. "Nrel" is relative labor. "Shrel" is relative labor share. "Agg Y" is aggregate output. Impluse response is to 1 s.d. monetary policy shock in period 1.

Figure 2

Relative **Durables/Nondurables** Response to *Monetary Policy Shock*

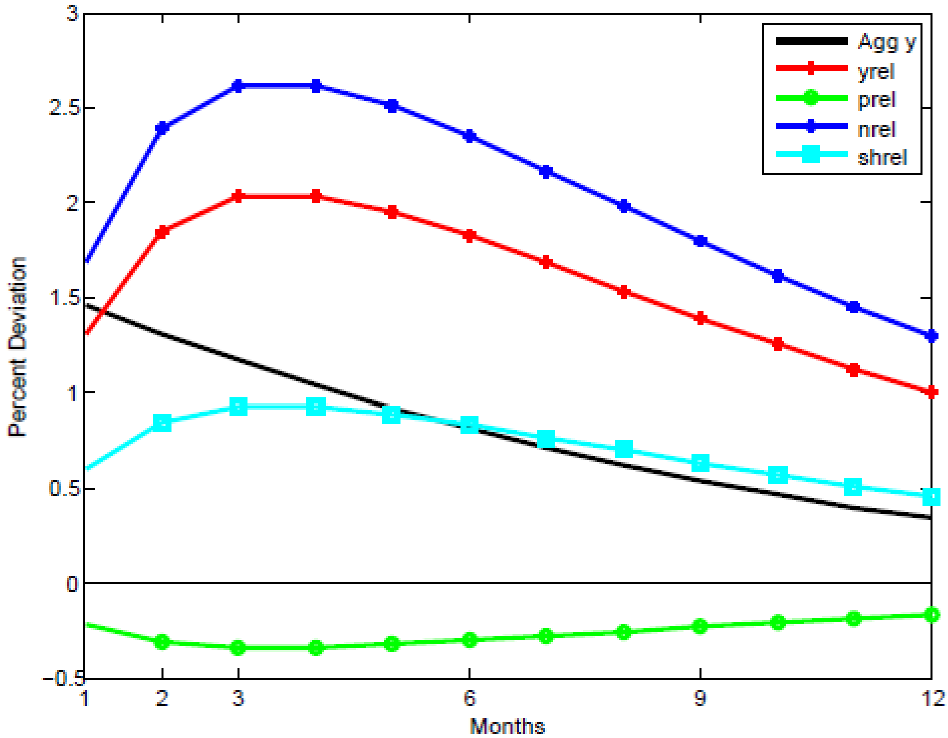
Flexible Prices



Notes for Figure 2: "Yrel" is relative output. "Prel" is relative price level. "Nrel" is relative labor. "Shrel" is relative labor share. "Agg Y" is aggregate output. Impluse response is to 1 s.d. monetary policy shock in period 1. Prices are almost perfectly flexible.

Figure 3

Relative **Low/High Price Flexibility** Response to *Monetary Policy Shock*

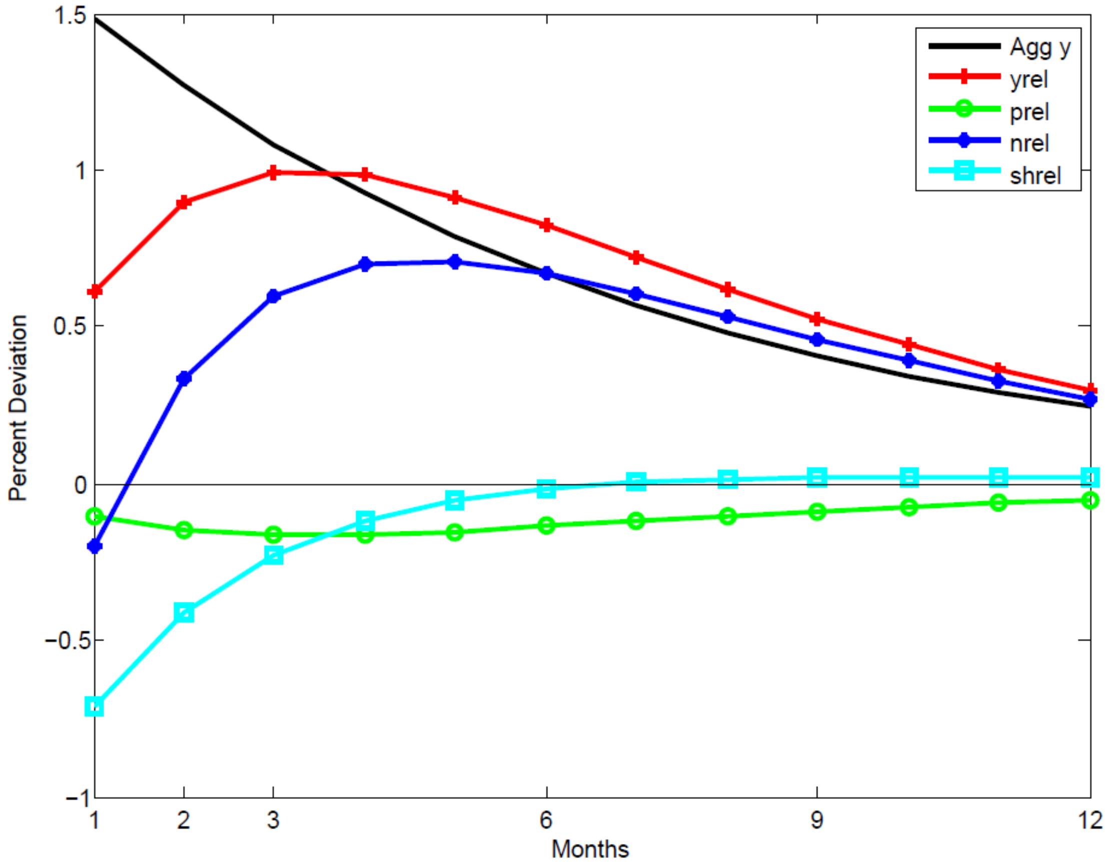


Notes for Figure 3: "Yrel" is relative output. "Prel" is relative price level. "Nrel" is relative labor. "Shrel" is relative labor share. "Agg Y" is aggregate output. Impluse response is to 1 s.d. monetary policy shock in period 1.

Figure 4

Relative **Low/High Capital Intensity** Response to *Monetary Policy Shock*

Sticky Prices

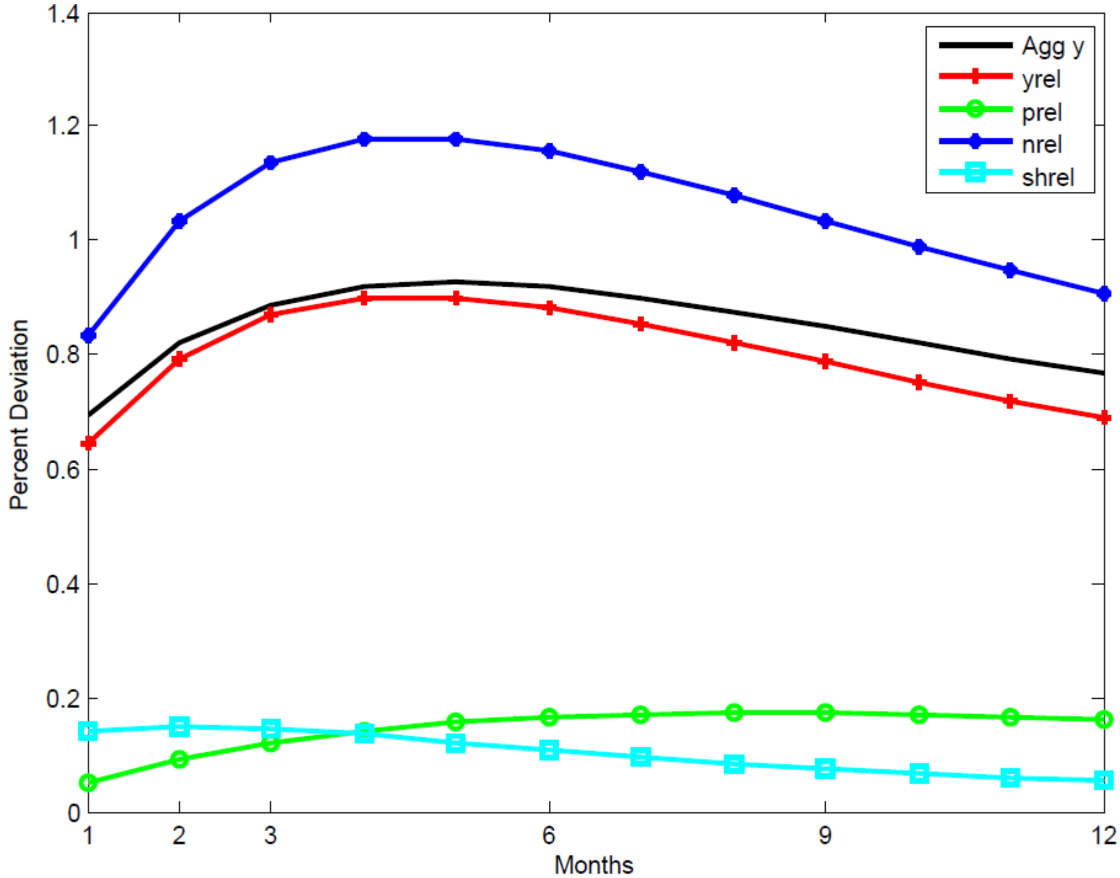


Notes for Figure 4: "Yrel" is relative output. "Prel" is relative price level. "Nrel" is relative labor. "Shrel" is relative labor share. "Agg Y" is aggregate output. Impluse response is to 1 s.d. monetary policy shock in period 1.

Figure 5

Relative **Durables/Nondurables** Response to *TFP Shock*

Sticky Prices

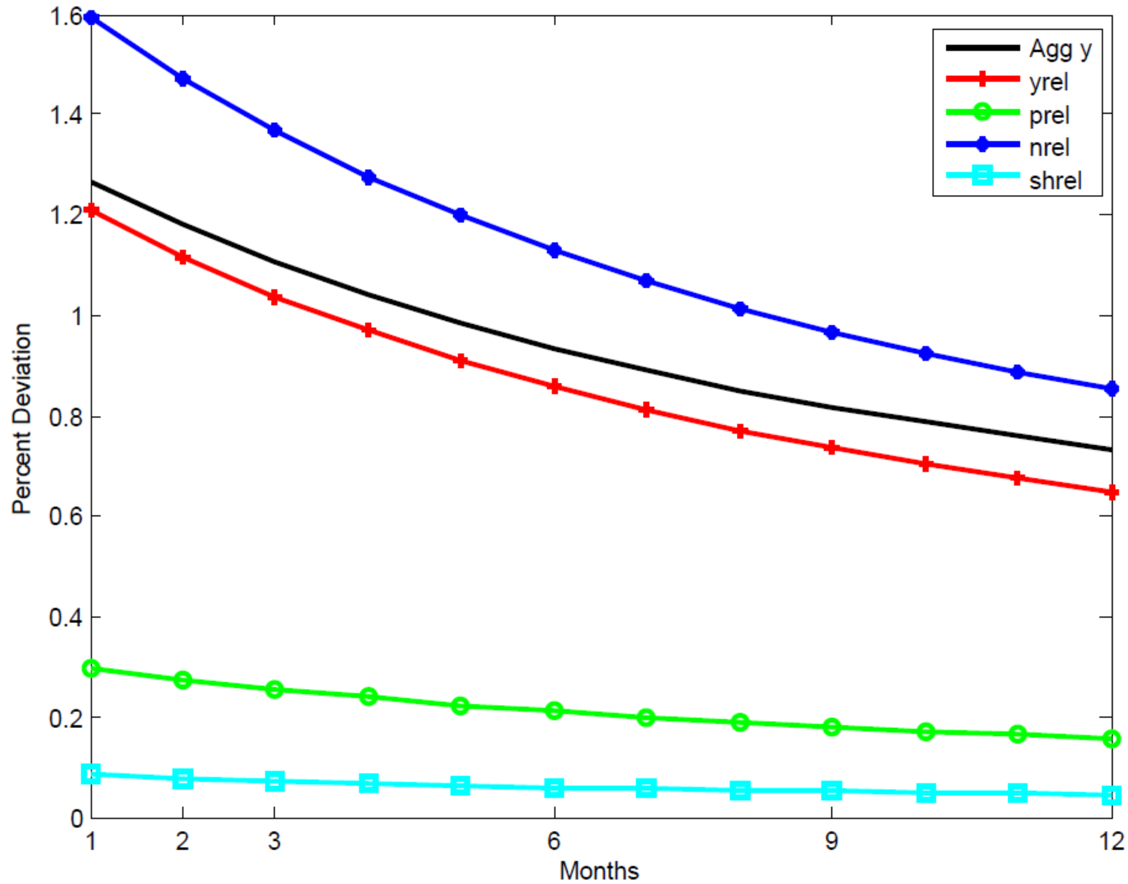


Notes for Figure 5: "Yrel" is relative output. "Prel" is relative price level. "Nrel" is relative labor. "Shrel" is relative labor share. "Agg Y" is aggregate output. Impluse response is to 1 s.d. TFP shock in period 1.

Figure 6

Relative **Durables/Nondurables** Response to *TFP Shock*

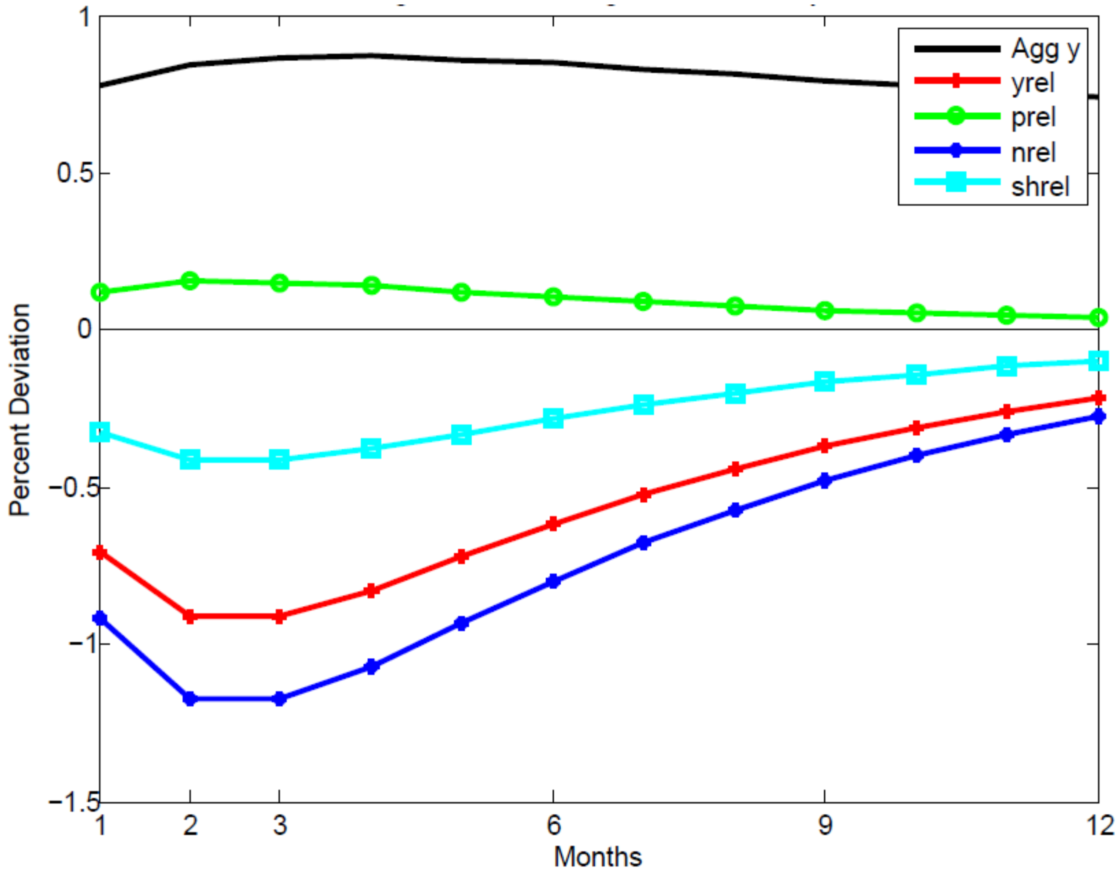
Flexible Prices



Notes for Figure 6: "Yrel" is relative output. "Prel" is relative price level. "Nrel" is relative labor. "Shrel" is relative labor share. "Agg Y" is aggregate output. Impluse response is to 1 s.d. TFP shock in period 1. Prices are almost perfectly flexible.

Figure 7

Relative **Low/High Price Flexibility** Response to *TFP Shock*

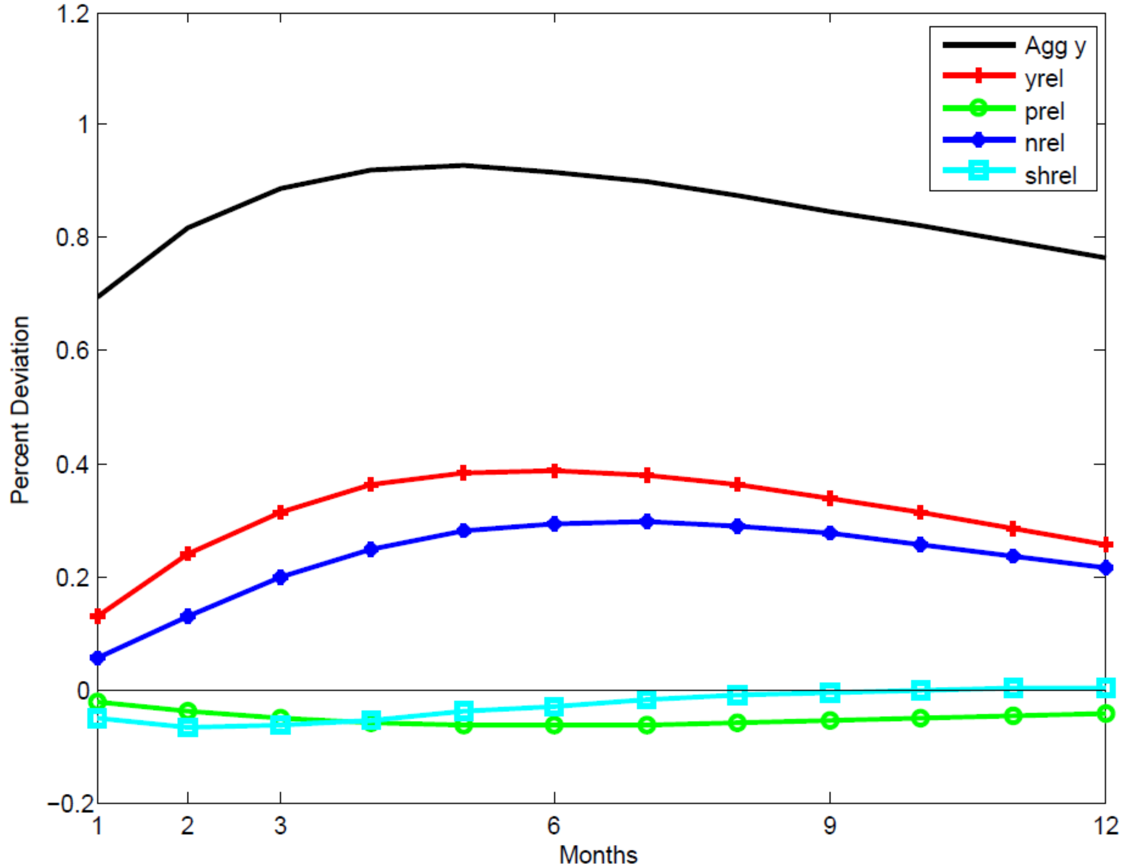


Notes for Figure 7: "Yrel" is relative output. "Prel" is relative price level. "Nrel" is relative labor. "Shrel" is relative labor share. "Agg Y" is aggregate output. Impluse response is to 1 s.d. TFP shock in period 1.

Figure 8

Relative **Low/High Capital Intensity** Response to *TFP Shock*

Sticky Prices

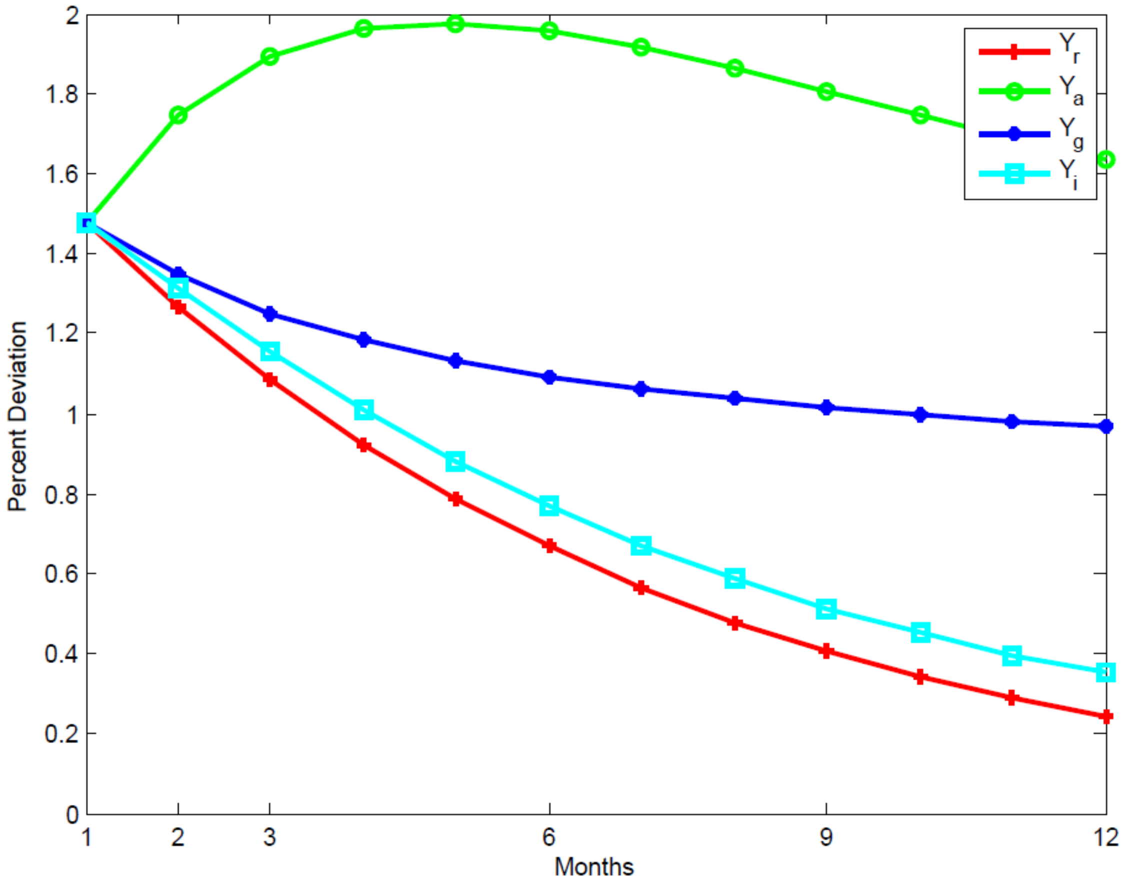


Notes for Figure 8: "Yrel" is relative output. "Prel" is relative price level. "Nrel" is relative labor. "Shrel" is relative labor share. "Agg Y" is aggregate output. Impluse response is to 1 s.d. TFP shock in period 1.

Figure 9

Aggregate Output Response to Various Shocks

Sticky Prices

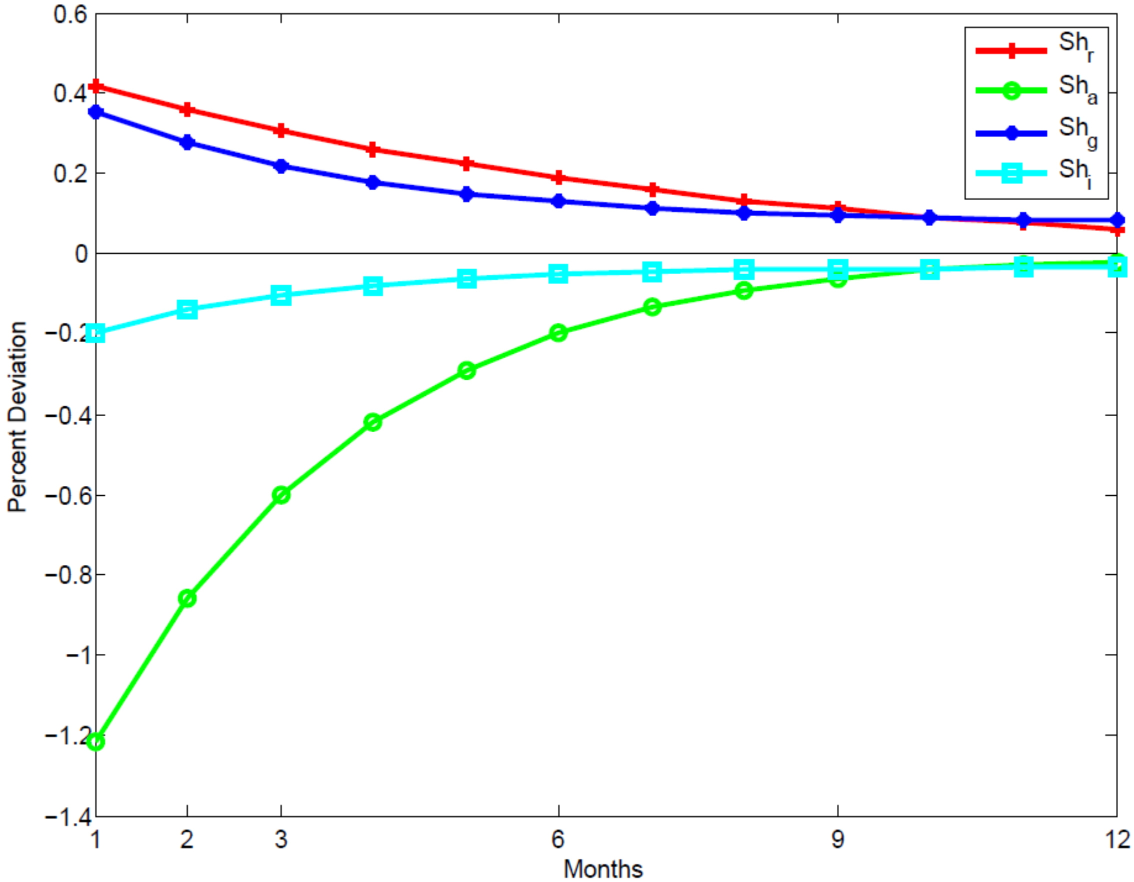


Notes for Figure 9: "Y_r" is aggregate output response to a monetary policy shock; "Y_a" to a TFP shock; "Y_g" to a government spending shock; and "Y_i" to an investment-specific technology shock. The shocks have been scaled to produce the same movement in aggregate output on impact.

Figure 10

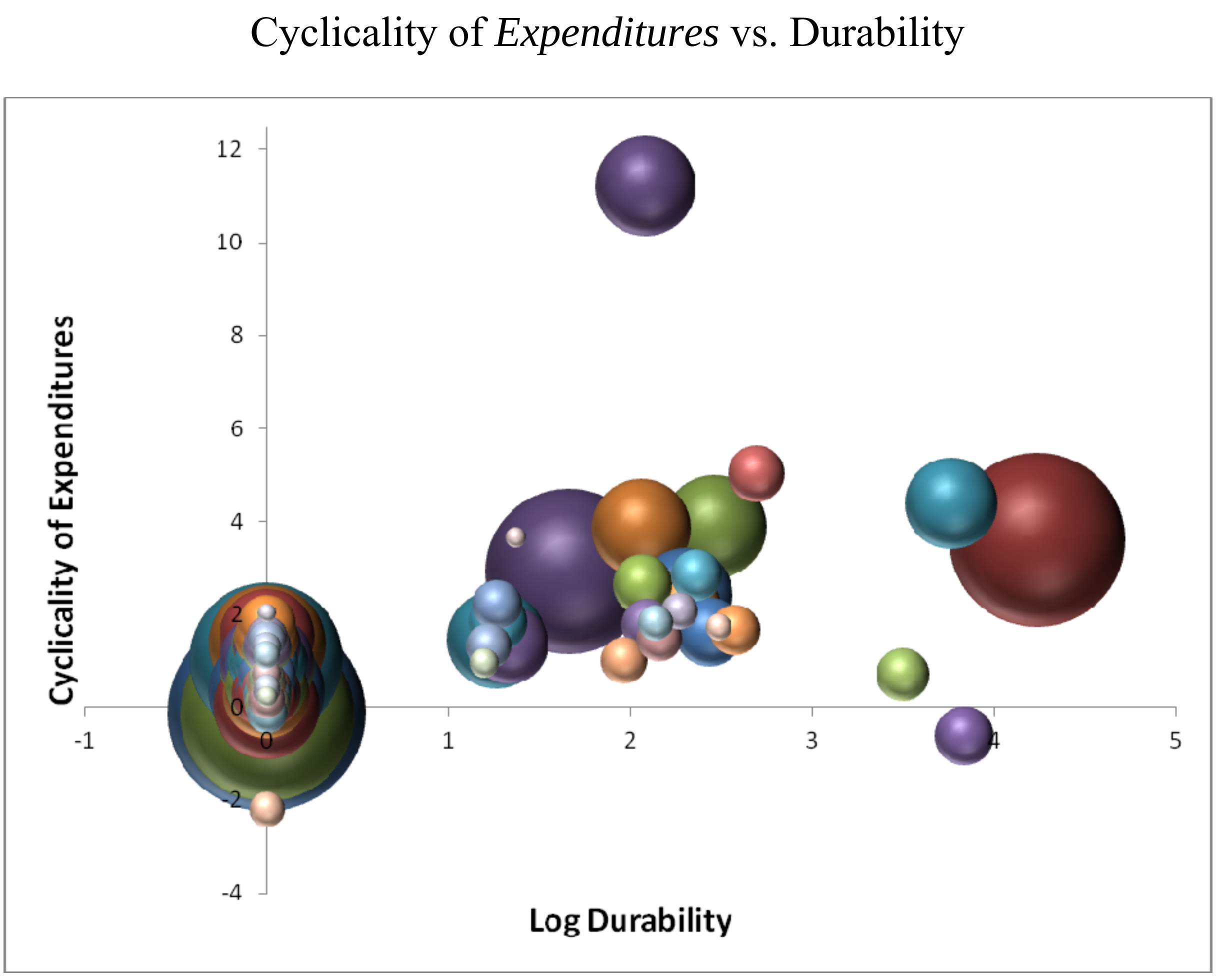
Aggregate Labor Share Response to Various Shocks

Sticky Prices



Notes for Figure 10: "Sh_r" is aggregate output response to a monetary policy shock; "Sh_a" to a TFP shock; "Sh_g" to a government spending shock; and "Sh_i" to an investment-specific technology shock. The shocks have been scaled to produce the same movement in aggregate output on impact.

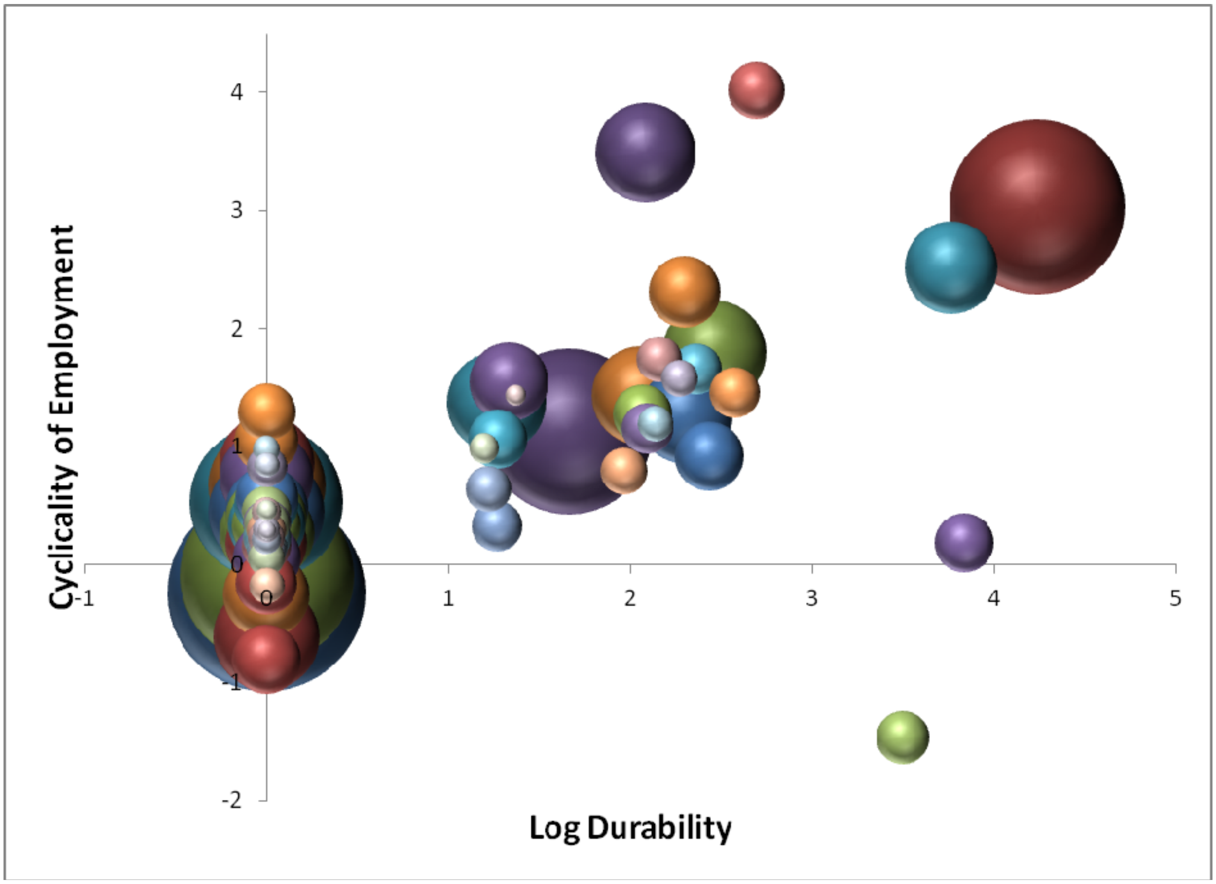
Figure 11



Notes for Figure 11: Each ball is one of 70 goods, with the size of the ball giving the average expenditure share over 1990-2011. For each good, cyclicality is obtained from regressing quarterly HP-filtered log real expenditures for a good on quarterly HP-filtered log real GDP. Durability is defined as 1 + Expected Life in Years.

Figure 12

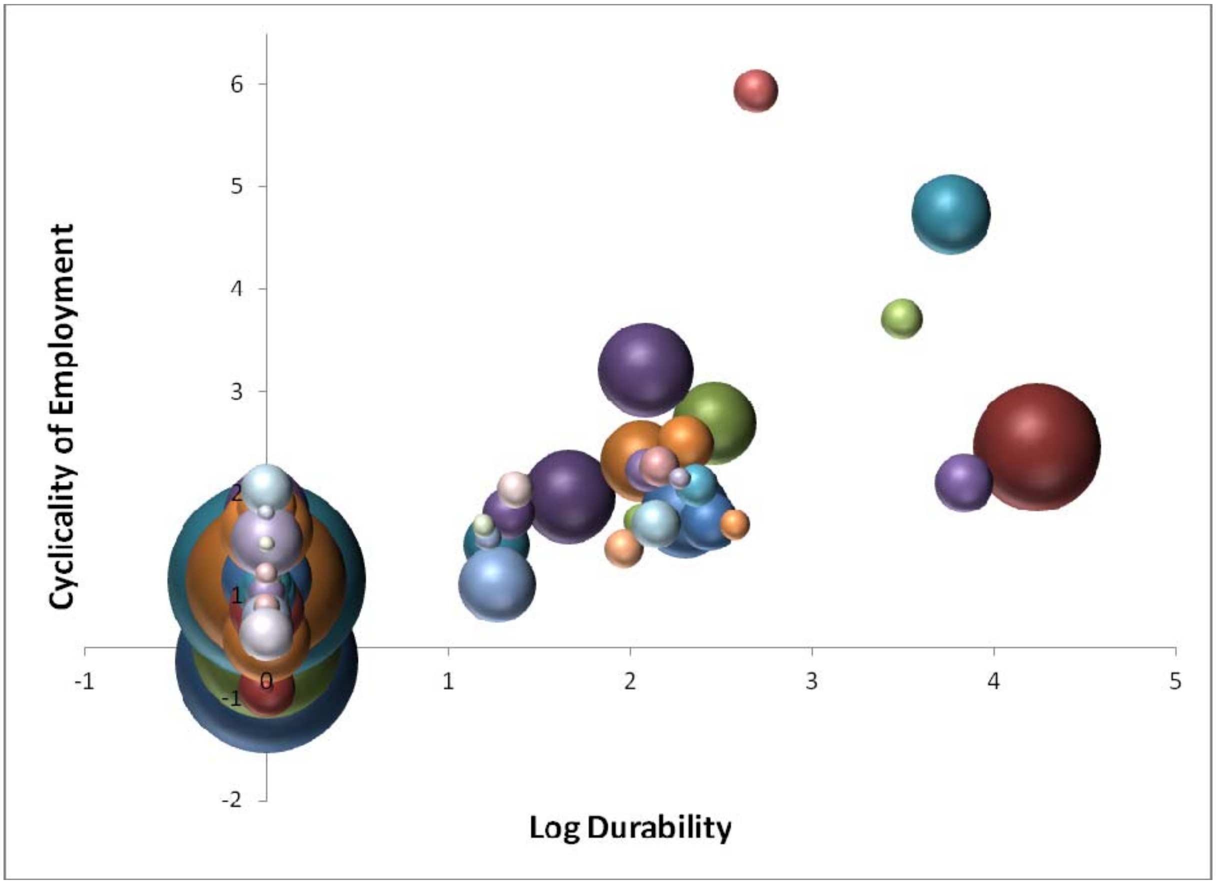
Cyclicality of *Employment* vs. Durability



Notes for Figure 12: Each ball is one of 68 industries, with the size of the ball giving the average expenditure share over 1990-2011. Cyclicality is obtained from regressing quarterly HP-filtered log industry employment on quarterly HP-filtered log real GDP. Durability is defined as 1 + Expected Life in Years.

Figure 13

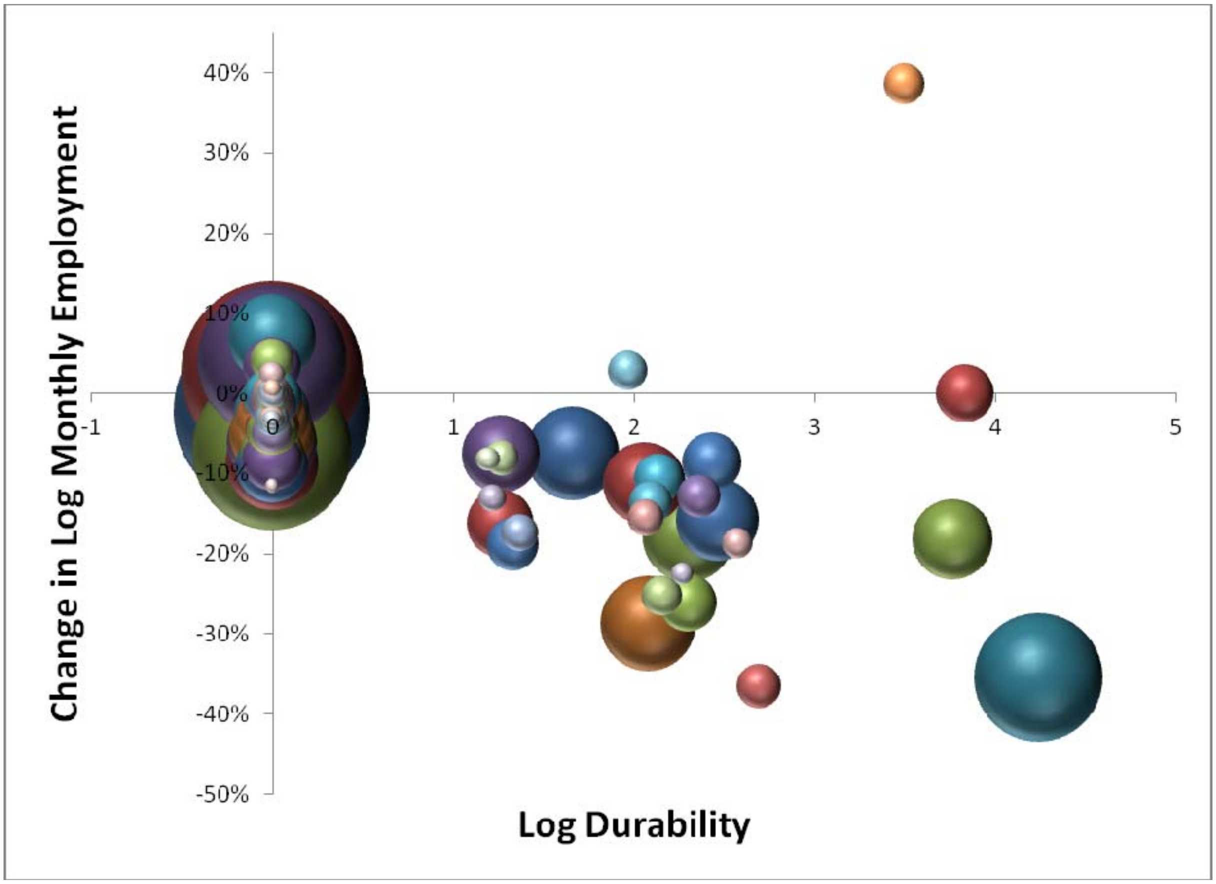
Cyclicality of Employment vs. Durability,
based on the cycle in *Aggregate Employment*



Notes for Figure 13: Each ball is one of 68 industries, with the size of the ball giving the average expenditure share over 1990-2011. Cyclicality is obtained from regressing quarterly HP-filtered log indsutry employment on quarterly HP-filtered log total nonfarm employment. Durability is defined as 1 + Expected Life in Years.

Figure 14

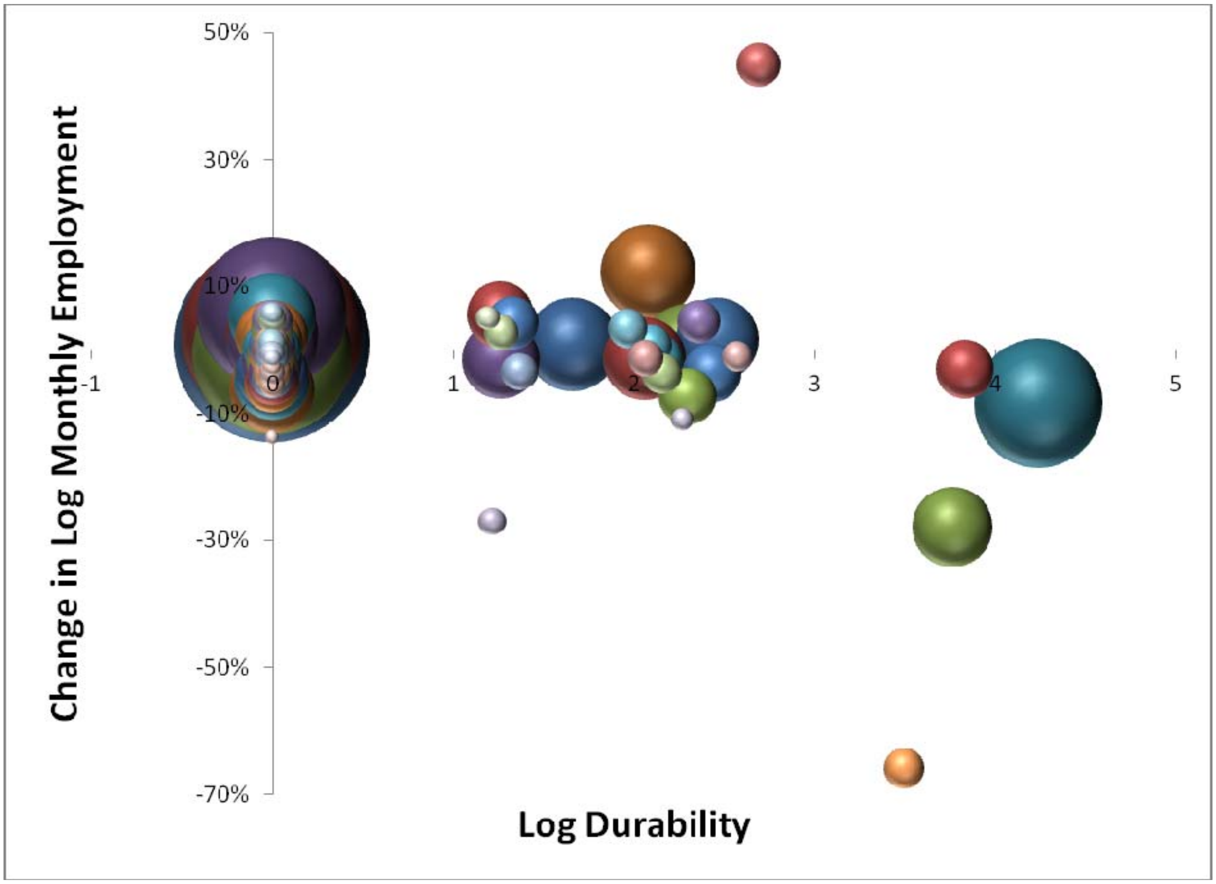
Employment Declines in the Great Recession vs. Durability



Notes for Figure 14: Each ball is one of 68 industries, with the size of the ball giving the average employment share over 1990-2011. The Great Recession is defined using the NBER peak-to-trough dates. The vertical axis plots the log first difference of industry employment in June 2009 vs. December 2007. Durability is defined as 1 + Expected Life in Years.

Figure 15

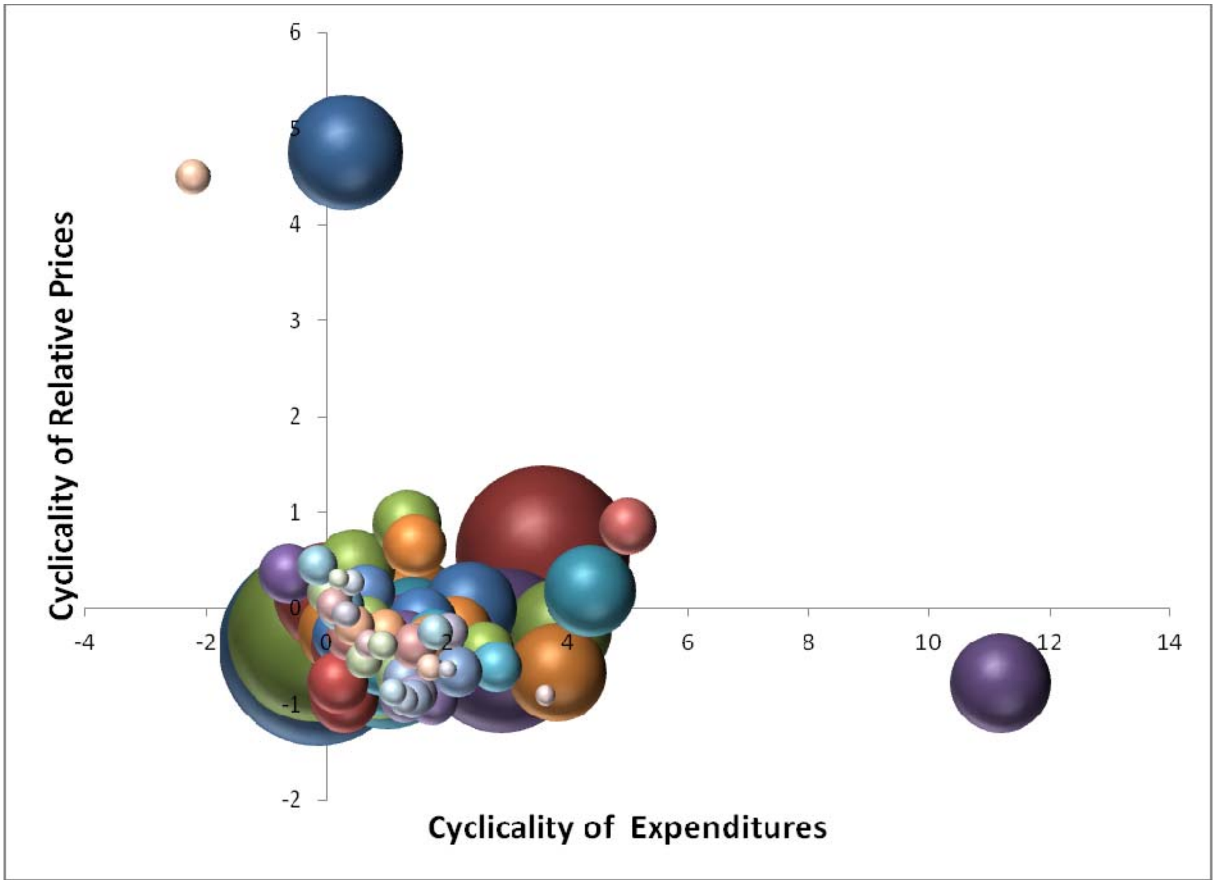
The Jobless Recovery and Durability



Notes for Figure 15: Each ball is one of 68 industries, with the size of the ball giving the average employment share over 1990-2011. The vertical axis plots the log first difference of industry employment in June 2011 vs. June 2009. Durability is defined as 1 + Expected Life in Years.

Figure 16

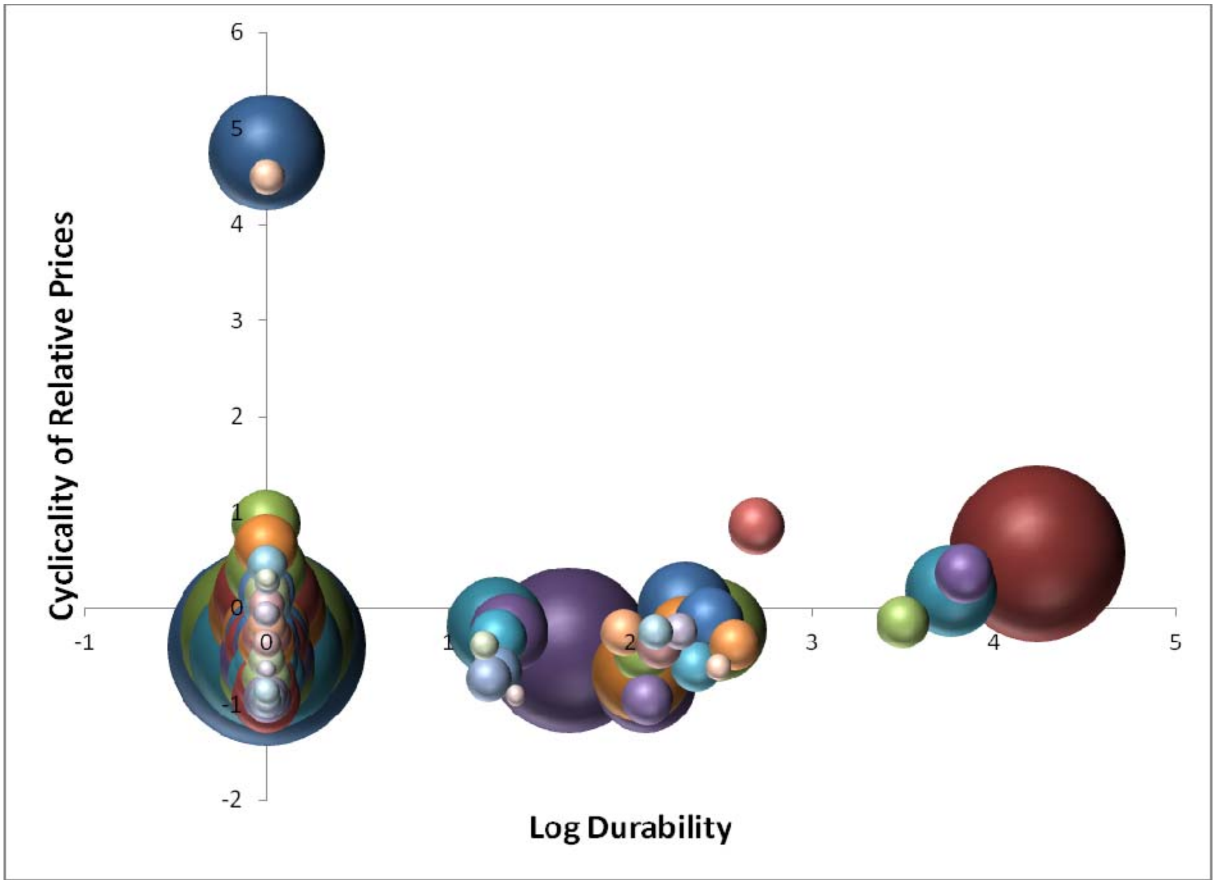
Cyclicality of Prices vs. Quantities



Notes for Figure 16: Each ball is one of 70 goods, with the size of the ball giving the average expenditure share over 1990-2011. For each good, cyclicality is obtained from regressing its quarterly HP-filtered log price index (relative to that for GDP) or log quantity on quarterly HP-filtered log real GDP.

Figure 17

Cyclicality of Prices vs. Durability



Notes for Figure 17: Each ball is one of 70 goods, with the size of the ball giving the average expenditure share over 1990-2011. For each good, cyclicality is obtained from regressing its quarterly HP-filtered log price index (relative to that for GDP) on quarterly HP-filtered log real GDP. Durability is defined as 1 + Expected Life in Years.

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