Testing for Keynesian Labor Demand

Mark Bils
University of Rochester and NBER

Peter J. Klenow
Stanford University and NBER

Benjamin A. Malin
Federal Reserve Bank of Minneapolis

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Abstract

According to the textbook Keynesian model, short-run demand for labor is sensitive to the demand for goods. In this view, sellers deviate from setting the marginal product of labor proportional to the real wage, instead enduring or choosing lower price markups when demand for goods is high. 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.

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1. Introduction

A leading proximate explanation for plunging employment during the Great Recession is plummeting demand for goods. 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. The underlying source of Keynesian Labor Demand could be nominal price stickiness and/or countercyclical desired markups. See Keynes (1939) for his embrace of both justifications.[1]

We test for Keynesian Labor Demand across U.S. industries in recent decades (1990-2011). To do so, we exploit how durability varies across 70 consumption and investment categories to predict relative goods demand movements over the business cycle. Relative demand shocks allow us to test whether markups move in the *direction* predicted by Keynesian Labor Demand.[2] We also exploit information on which goods are luxuries vs. necessities to predict relative demand, and take into account how price flexibility and capital-intensity of production vary 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

[1] Keynesian Labor Demand has played a central role in business cycle modeling. See, for example, Rotemberg and Woodford (1991), Christiano, Eichenbaum and Evans (2005), Smets and Wouters (2007) and Hall (2011).

[2] Under partially sticky prices, markups should actually move in the same direction as output in response to productivity shocks. For this reason, one cannot simply look at the cyclicality of the average economy-wide markup to test for Keynesian Labor Demand. One has to relate markups to demand and/or supply shocks. By using durability to predict relative demand, we sidestep the need to identify aggregate demand or supply shocks.

monetary policy) should hit demand for durables more dramatically. Similarly, demand for luxuries should be more cyclical than demand for necessities.

Under sticky prices, firms should accommodate shifts in relative demand by firing or hiring workers rather than adjusting their prices. 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. If target markups are countercyclical, however, then price stickiness may not be essential for a Keynesian Labor Demand response to goods demand shocks.

We test for Keynesian Labor Demand 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 durability and luxuriousness succeed in predicting the cyclicality of expenditures. Durability is a strong predictor. Bringing in data from the U.S. Current Employment Survey, we find that durability is 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 constant-markup labor demand in response to goods demand shocks.

We find that industries producing goods that are more durable, while displaying much more cyclical employment and output, exhibit countercyclical relative markups. This countercyclical increase in markups is sufficiently large that relative prices of durables do not fall in recessions. (By contrast, sectoral TFP movements play little role in explaining the lack of cyclicality in durables' relative prices.) Our evidence rejects flexible-price labor demand under a constant markup, but is consistent with Keynesian Labor Demand. This cyclical pricing for durables could reflect intentional markup movements, rather than being the byproduct of price stickiness. In fact, a model with countercyclical intended markups for durables, but flexible pricing in general, would arguably explain the data better than a sticky-price model.

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 by looking at cross-industry evidence. Thus, our approach is similar to Shea (1993) and Nekarda and Ramey (2011), who examine the impact of an industry's downstream demand (Shea) and its share of government purchases (Nekarda and Ramey) on industry price and quantity. 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 demand predictors. Section 3 briefly describes the datasets we use. Section 4 presents the main results. Section 5 concludes.

2. Model

In this section we use a multi-sector DSGE model to demonstrate how relative demand shocks affect markups under Keynesian vs. Classical Labor Demand. Here the source of Keynesian Labor Demand is sticky prices, rather than countercyclical intended markups. We incorporate heterogeneity in the durability of goods, the capital intensity of firms' production, and the frequency of price changes. After sketching the key model features,[3] we use a simplified version of the model to illustrate analytically how movements in relative quantities and prices across sectors differ depending on whether the model is Keynesian or Classical (i.e., sticky or flexible prices). We then calibrate and simulate the full-blown model to get some quantitative sense of these movements.

Firms

Durable (Y_d) and nondurable (Y_n) final goods are produced from intermediate goods, which are produced by two types of firms: those with high- and low-capital-intensity technologies. Competitive final goods producers use the following production function

[3] A complete specification of the model is provided in Online Appendix A.

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

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 services 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.

Capital and labor flow freely between firms in the same sector, which implies, under CRS production, that nominal marginal costs and capital-labor ratios will be equated across firms in the same sector. However, as will become clear when we discuss household supply of factor inputs, imperfect capital mobility will allow marginal costs to vary *across* sectors. Furthermore, different production technologies across sectors imply different slopes for sectoral marginal cost curves. In particular, firms that produce with more capital-intensive technologies (larger α_f) will require a greater increase in the flexible labor factor to effect a given short-run increase in production (i.e., their marginal cost curves are steeper).

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

Households

Households get utility from nondurable and durable consumption and disutility from working. Let $C_{n,t}$ denote nondurable consumption, $C_{d,t}$ durable consumption expenditures, D_t^c the stock of the durable consumption good, and N_t labor supply. Households maximize expected discounted utility

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

and 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 δ is the depreciation rate and S'' governs adjustment costs on durables expenditures. Following Barsky et al. (2007), the functional forms for household preferences are

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

where σ is the intertemporal elasticity of substitution, ψ determines the relative preference for nondurables vs. durables, 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.

Greater durability implies that any increase in consumption requires a more dramatic increase in expenditure. To increase consumption of the durable good by 1% from a steady state level requires an annual increase in expenditure of 1/δ%, whereas a 1% increase in nondurables consumption requires only a 1% increase in expenditure. This motivates our use of durability as a shifter of goods demand and, because a larger increase in expenditure will call forth a larger increase in hours worked, labor demand as well.

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

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

The accumulation equation for capital mirrors that for durables consumption:

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

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

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

Investment expenditures include maintenance costs arising from capital utilization, $a(u_{jf,t}) K^s_{jf,t}$. The cost function $a(\cdot)$ is increasing, convex, and zero in steady state. In addition, investment is affected by investment-specific productivity (ϵ_t^i); greater productivity means less expenditure is required to achieve a given increase in the capital stock.

Importantly, we have assumed each sector has a separate capital stock, which means that capital is (partially) fixed in the short-run. Capital services can adjust immediately due to time-varying utilization, but utilization costs make utilization less than perfectly flexible. Capital stocks adjust fully over time, but the speed depends on investment adjustment costs.

Households also supply labor to firms in each sector, and this process is intermediated by monopolistically competitive unions who have the power to set wages (Erceg et al., 2000). The unions face Calvo frictions, altering wages with a constant probability of $1-\theta^w$. Because wage stickiness does not vary by sector and labor supply across sectors is assumed to be perfectly elastic ($N_t = \sum_{j,f} N_{jf,t}$), (nominal) wages W_t will be equalized across sectors.

Analytical Discussion

Before presenting numerical simulations, we use a stripped down version of our model to analytically illustrate how cyclical movements in relative sector quantities, prices and markups behave under sticky vs. flexible prices. We assume the economy starts in steady state and evaluate the immediate response to an expansionary aggregate shock at time *t*. The stripped down model features a constant *aggregate* capital stock, with the *distribution* of capital services across sectors fixed at time *t* but perfectly mobile by *t+1* (fixed capital utilization and no investment adjustment costs). We also assume durables goods are very long-lived (δ sufficiently small that the shadow value of durables is nearly invariant to short-lived shocks, as in Barsky et al., 2007).

With sufficiently long-lived durables, household optimization requires

$$\frac{1}{\eta}\left[\hat{D}_t^c - \hat{C}_{n,t}\right] \approx \hat{P}_{n,t} - \hat{P}_{d,t}, \tag{1}$$

where hatted variables are log deviations from steady-state values. Furthermore, the law of motion for durables implies $\hat{D}_t^c = \delta \hat{C}_{d,t}$; all produced goods are consumed $\hat{C}_{j,t} = \hat{Y}_{j,t}$; the production functions are $\hat{Y}_{j,t} = \hat{A}_t + (1-\alpha_j)\hat{N}_{j,t}$; marginal costs are $\hat{M}_{j,t} = \hat{W}_t - \hat{A}_t + \alpha_j \hat{N}_{j,t}$; and markups are given by $\hat{\mu}_{j,t} = \hat{P}_{j,t} - \hat{M}_{j,t}$. Combining these expressions, we have

$$\left[\alpha_d + \frac{\delta(1-\alpha_d)}{\eta}\right]\hat{N}_{d,t} \approx \left[\alpha_n + \frac{1-\alpha_n}{\eta}\right]\hat{N}_{n,t} - (\hat{\mu}_{d,t} - \hat{\mu}_{n,t}) + \frac{1-\delta}{\eta}\hat{A}_t. \tag{2}$$

We first consider a flexible-price economy. Markups are constant at $\mu_j = \varepsilon/(\varepsilon-1)$. If sectors have the same capital intensities, equation (2) shows that labor will expand more in the durables sector. Thus, relative output, marginal costs, and prices also increase. Note that these relative movements do not depend on the underlying shock causing the expansion, but the movements are even larger if the source is a positive aggregate TFP shock.

The results differ under sticky prices. Take the extreme of fixed prices, so that relative prices do not move. Equation (1) implies an increase in relative durables output, and thus labor and marginal costs. Therefore, relative markups are countercyclical. If prices are not perfectly rigid but are equally sticky in the two sectors, one can show that relative output, labor and prices are procyclical, while relative markups are countercyclical.[4] So, the primary

[4] If firms have the same price-change frequency and (expected) marginal costs are equalized across firms from *t+1* onwards (which is true under CRS production and perfectly mobile factor inputs), then $\hat{P}_{d,t} - \hat{P}_{n,t} = \kappa\left(\hat{M}_{d,t} - \hat{M}_{n,t}\right)$, with $0 < \kappa < 1$. Combining this expression with equation (1) yields an expression, similar to equation (2), which shows relative durables labor is procyclical. Relative marginal costs are thus procyclical, while relative markups are countercyclical.

(qualitative) difference between flexible and sticky prices is the behavior of relative markups.

We have derived these predictions for relative movements in durables holding other characteristics – such as price flexibility, capital intensity, and TFP – fixed across sectors. This is important. For example, if durables prices were perfectly flexible and nondurables perfectly rigid, the relative durables markup would be *procyclical* and, under some parameters, relative labor could be countercyclical. Likewise, if the aggregate expansion was caused by a shock to durables TFP ($A_{d,t} > A_{n,t}$), one can show that, under sticky prices, the relative durables markup would again be *procyclical* (e.g., assuming η=1 and $\alpha_j = \alpha$). In our subsequent empirical analysis, therefore, we will control for variables that might be correlated with durability.

So far, we have analyzed the response of durables relative to nondurables, but the model also predicts relative movements across goods on other dimensions, holding durability constant. Optimal demand by final (durable or nondurable) goods producers implies

$$\hat{Y}_{h,t} - \hat{Y}_{l,t} = \varepsilon\left[\hat{P}_{l,t} - \hat{P}_{h,t}\right], \tag{3}$$

where *h* and *l* denote high- and low-capital-intensity firms. Assuming equally-sticky prices in the two subsectors, one can derive the following expression for relative markups

$$\hat{\mu}_{h,t} - \hat{\mu}_{l,t} = \left[(1-\theta)(1-\beta\theta)-1\right]\alpha_l \left[\frac{\alpha_h + \left[\varepsilon(1-\theta)(1-\beta\theta)-1\right]\alpha_h\alpha_l}{\alpha_l + \left[\varepsilon(1-\theta)(1-\beta\theta)-1\right]\alpha_h\alpha_l} - 1\right]\hat{N}_{l,t},$$

so that higher capital intensity production implies a countercyclical markup. The sign of the relative movements in other variables depends on parameter values, although the more capital-intensive good typically has higher marginal costs and prices, but lower output.

We can also use equation (3) to analyze how differences in price stickiness affect relative movements, now letting *h* and *l* denote firms with high and low price stickiness. We get the following relationship between relative labor and relative markups:

$$\hat{N}_{l,t} - \hat{N}_{h,t} = \frac{\varepsilon}{1+(\varepsilon-1)\alpha}\left[\hat{\mu}_{h,t} - \hat{\mu}_{l,t}\right].$$

That is, relative labor (and thus output and marginal costs) will move in the opposite direction of relative markups (and prices). Whether the relative markups are procyclical or countercyclical, however, depends on the nature of the underlying shock. Monetary (TFP) shocks which put upward (downward) pressure on prices will lead to countercyclical (procyclical) markups for the sector with stickier prices.

Quantitative Results

We now calibrate and simulate the full-blown model. This allows us to move away from stark assumptions, such as the complete short-run fixity of capital, and consider realistic features like capital utilization and investment adjustment costs. We consider an empirically relevant amount of durability, capital intensity, and price stickiness in order to get a quantitative sense of the size of movements of key variables across sectors.

Table 1 summarizes our model calibration. The parameters governing household preferences (σ, η, ϕ) and desired markups are set to standard values, and ψ is set to produce a steady-state nondurable-to-durable consumption ratio of 2.96. The annual depreciation rate of 5% matches the (weighted) average life-span of durables in our data (i.e., 20 years). 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. When we consider high- and low-capital intensity sectors, we use capital shares of $\alpha_h = 0.475$ and $\alpha_l = 0.169$, which are the weighted average capital shares for consumption categories above and below the median capital share, respectively. Consistent with the micro data underlying the U.S. CPI, the average price changes every four months, while high- and low-frequency firms set prices roughly every 2.5 and 12 months. Wages are assumed to change once a year.

The curvature of the utilization adjustment cost function is pinned down by the relationship between relative sector utilization rates and relative labor-to-capital ratios:

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

Using Gorodnichenko and Shapiro (2011) data on 20 2-digit manufacturing sectors over the past 30 years, we regress utilization rates on labor-capital ratios (and time effects) to estimate an elasticity of 0.33, corresponding to a'' = 2.0. Online Appendix C has details. 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.

Finally, we need to calibrate the exogenous shock processes and the Taylor Rule that governs monetary policy. With one exception, these parameters are monthly transformations of the quarterly estimates of Smets-Wouters (2007).[5] We choose a larger volatility for the neutral technology shock to match the cyclicality of the aggregate labor share (i.e., inverse markup), but since our primary focus is on conditional impulse response functions, alternative calibrations of the volatility do not change the insights we draw from the model.

[5] We consider four shocks: monetary policy, government spending, TFP, and investment-specific technology. For the persistence parameters ρ, we scaled down SW's "Great Moderation" estimates of 1- ρ by 1/3, and the standard deviations are 1/3 of SW's estimates. Note that the values reported in Table 1 also reflect differences in notation between our model and the SW model.

Figures 1 to 4 show impulse responses to an expansionary monetary policy shock.[6] We plot relative movements in output, labor, prices, and markups, where we measure markups using the inverse of the labor share. (Note that, under Cobb-Douglas production, fluctuations in markups are equivalent to fluctuations in the labor share. However, our test does not hinge on Cobb-Douglas production, and we will explicitly consider departures from it in our empirical analysis.) For scaling purposes, we also show the response of aggregate output (thin line). Figure 1 shows the relative durable-to-nondurable responses under sticky prices. For this exercise, the average capital intensity and price-change frequency in the two sectors are the same.[7] Relative output (thick solid line) and labor (dashed line) are strongly procyclical, while the relative price response (dashed-dotted line) is also positive but muted by sticky prices. Relative markups (dotted line) are countercyclical, reflecting two forces: first and most important, price markups are more countercyclical for durables firms than for nondurables firms; second, within each sector the more labor-intensive subsector will gain market share because it has more flexibility to ramp up production. This composition effect will cause the labor share of both sectors to increase (decreasing the measured markup), but will be stronger for durables as their expenditures increase more.

The immediate relative markup response is about 25 percent that of relative output, while the relative labor response is 25 percent greater than the output response. With wages equalized across sectors, $\hat{\mu}^{rel} = \hat{P}^{rel} + \hat{Y}^{rel} - \hat{N}^{rel}$. These magnitudes are, of course, dependent on our calibration. If the cost of varying capital utilization was zero (infinite), the relative

[6] Impulse responses to other shocks are available in Online Appendix A. As shown analytically, the (qualitative) results do not depend on the identity of the underlying shock, as long as private spending expands. However, a government spending shock that increases production but reduces private spending (i.e., fiscal multiplier < 1) will produce relative durables movements with opposite signs.

[7] Each sector has low- and high-capital-intensity subsectors that have equal price-change frequencies.

labor response would be the same as (50 percent greater than) the relative output response.

Figure 2 repeats the same exercise but with flexible prices in both sectors. (Note that wages are still sticky.) The monetary shock has smaller real effects under flexible prices; the aggregate output response is about 70 percent as big as the response under sticky prices. The relative price of durables now increases more, muting the shift in goods and labor demand towards durables. The relative markup response is nearly zero, with the small discrepancy solely reflecting the aforementioned composition effect.

Figure 3 demonstrates the effect 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. The subsector with less price flexibility will exhibit a more sluggish price response, decreasing its relative price and increasing its relative output, labor input, and marginal costs. Thus, firms whose prices respond more slowly (on average) to the monetary shock see their relative markups decline. The magnitude of the relative markup movement is almost half the magnitude of the relative output response.

Finally, Figure 4 compares high- and low-capital-intensity subsectors ($\alpha_h = 0.475$, $\alpha_l = 0.169$) within the durables sector, while keeping prices equally sticky. In response to an expansionary shock, firms with more capital-intensive technologies face steeper marginal cost curves. Although their relative markup decreases (as shown analytically), their higher marginal costs lead to a higher relative price and lower relative output. Note that the magnitude of the markup response is greater than the output response because the initial relative labor response is positive under our calibration, although this result is quite sensitive to the capital-intensity gap ($\alpha_h - \alpha_l$) and fixity of the capital stock. At any rate, the relative labor response is more muted than under flexible prices, where markups are constant and the higher marginal costs of high-capital-intensity firms are completely passed through into relative prices, resulting in a larger decrease in relative output and a decrease in relative hours.

To recap, the Keynesian Labor Demand hypothesis is that firms respond to unexpectedly low demand for their goods by laying off workers rather than lowering their output prices. Equivalently, if marginal cost curves are upward sloping, firms increase their markups. In this section we have considered one possible source of this behavior – nominal price stickiness – and have shown that the relative markups of more durable and more capital-intensive goods are (essentially) constant under flexible prices but countercyclical under sticky prices.[8] In our empirical analysis, we will exploit variation across different types of goods to test this prediction of Keynesian Labor Demand.

The model is also helpful for clarifying why we do not simply examine the cyclicality of the *aggregate* markup in the data. The reason is that, even under sticky prices, the aggregate markup can be uncorrelated with output. This is what happens, for example, in the Smets-Wouters (2007) model estimated on U.S. data. The reason is that the aggregate markup responds positively to some expansionary shocks but negatively to others. We demonstrate this in Figures 5 and 6, which show impulse responses to all four aggregate shocks in our DSGE model. We scale the shocks to have the same initial effect on aggregate output (Figure 5), while Figure 6 shows the different aggregate markup responses to the various shocks. Of course, one could address this by conditioning on particular aggregate

[8] As emphasized earlier, nominal stickiness is not the only source of countercyclical markups – see Rotemberg and Woodford (1991, 1999) for models in which flexible-price firms choose countercyclical markups.

shocks *a la* Gali (1999). But we pursue a different, complementary approach of examining how relative markups respond to relative demand shocks across industries.

3. Evidence on Durability and the Cyclicality of Expenditures

We now construct demand predictors across industries. We start with the BLS's classification of goods in the CPI into 70 Expenditure Classes (ECs). (See Appendix 6 in http://www.bls.gov/opub/hom/pdf/homch17.pdf.) We combine four pairs of ECs and drop five others due to missing NIPA data or overlap with NIPA investment categories, leaving us with 61 consumer goods.[9] We then add 9 categories of investment from NIPA, leaving us with a total of 70 expenditure categories. Online Appendix Table 1 provides the full list.

For each of these 70 categories, we create two demand predictors. The first is based on the good's durability, and the second is based on the Engel Curve slope for the good (i.e., the extent to which the good is a luxury or necessity). We also construct two variables specific to each category that should affect how prices and costs respond to demand: the frequency of price change and the importance of capital versus labor in producing the good.

Durability

Of our 70 goods, 28 are classified by NIPA as durable goods (19 of the 61 consumer goods are durables, and all 9 investment goods). We use two sources to quantify the durability of the durables. A primary source is life expectancy tables from a major property-casualty insurance company, which we use for 17 goods. For autos, tires and the 9 investment

[9] We drop three categories with no NIPA match (personal care products, miscellaneous personal goods and housekeeping supplies). We drop rent and owner's equivalent rent because investment in residential construction is already one of our investment categories.

categories we use estimates from the U.S. Bureau of Economic Analysis (http://www.bea.gov/iTable/iTable.cfm?ReqID=10&step=1).

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 (i.e., lasting less than a year). These include food and 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. We pool CE cross-sections from 1982 to 2010 to estimate Engel elasticities for our 61 consumer goods and for housing services.[10] The CE Interview Survey lumps together all food for home consumption, so for these categories we estimate a common elasticity.

Households are interviewed up to four consecutive quarters on their detailed expenditures. We estimate Engel elasticities by regressing spending on each category from the household's second through fourth interviews on the sum of its spending during those same three quarters. We instrument for the log of a household's total expenditures in its final three interviews based on its (logged) total and nondurable expenditures from the first

[10] Online Appendix B on our websites provides more detail on our CE sample. Housing services are measured by rent for renters. For home owners it is measured by household's estimate of the home's rental value.

quarterly interview, as well as its (logged) before-tax annual income reported in both the first and final interviews. We instrument to limit attenuation bias from measurement error in household total expenditures. We do not log expenditures for individual categories, the 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 across households. So our elasticities are relative to mean household spending on that category.[11]

For the 9 NIPA investment categories, we estimate Engel curves for 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 weighted average of the Engel elasticities for all of 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 reflecting the importance of the goods as final users of that investment category.

Online Appendix Table 1 provides our point estimates for Engel Curve slopes. The slopes average about one, as expected. 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) and food for home consumption (0.4).

[11] The regressions control for year and seasonal dummies, as well as household demographics (age, household size, urban status, marital status, and number of earners).

Frequency of Price Changes

The stickier the prices, the more Keynesian the Labor Demand if desired markups are constant. Thus we would like to incorporate information about the flexibility of prices in testing for Keynesian Labor Demand.

An advantage of using the BLS Expenditure Classes for the CPI is that estimates of price flexibility are readily available for these categories. From the micro 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.[12] For structures we distinguish between those built to order and those built speculatively. From 1988 to 2010, on average 61 percent of new homes were sold prior to completing the house (built to order), while 39 percent sold after the house was built (spec homes built to stock). We treat built to order homes as selling at a negotiated price, assigning it a pricing frequency of one. For houses built to stock we assume they are priced only when put on the market, setting frequency to one divided by the median time on the market, which averaged 5 months for 1988 to 2010. This yields an overall frequency for residential investment of 0.73 per month. We assume business structures are all produced to order, or at least priced subject to negotiation. So we assign a frequency of one to the business structure categories.

[12] We map 79 of their producer prices series to one of these 4 investment categories. We estimate a category's frequency from the weighted average of the frequencies of its associated producer prices.

Table A1 gives the monthly frequency of price change for our goods. As emphasized by Bils and Klenow (2004) and others, price flexibility varies widely. It is lowest for services (e.g. 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 (prices change every few 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 a weighted average of the capital shares of value added in each of the KLEMS industries matched to that good. We map NIPA categories to 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 durability (and Engel elasticities) predict cyclicality of expenditures, we match our 70 goods to NIPA expenditure categories.[13] Nominal expenditures on our 70 goods average 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. Among our 70 categories, 40% of spending is on durables, and 60% on nondurables. We will use expenditure shares to

[13] For consumption categories see http://bea.gov/iTable/index_UD.cfm and for investment categories see both http://bea.gov/iTable/iTable.cfm?ReqID=9&step=1 and http://bea.gov/iTable/iTable.cfm?ReqID=21&step=1 .

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.[14] 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 Section 2, durability should powerfully predict 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 are 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.) The coefficients tend to be much bigger for durable goods (3.25) than for nondurable goods (0.54).

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

Figure 7 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 R2 actually rises to 0.77 if one excludes the outlier of business transportation equipment (whose cyclicality coefficient is 10). We obtain similar results if we look at growth rates or annual data, though the standard errors are larger with annual data.

Figure 8 shows that durability predicts the cyclicality of employment even better. 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 ball with a cyclical response near 3 is residential construction. But this sector is far from driving the results. Without residential construction the mean cyclicality coefficient for durables is still 1.52 and the R2 is 0.63.[15]

Figure 9 looks at the Great Recession in particular. Using NBER Business Cycle dates, we calculate the peak-to-trough decline (log first difference in employment) for each good from December 2007 to June 2009. The R2 from running WLS on log durability is 0.74. Residential construction is influential, but not dominant. The R2 is still 0.41 without it. The outlier on the other side is manufacturing structures. Employment for industrial buildings soared 38% during the Great Recession. The influence of this observation is limited by its small weight (0.5% of employment); the R2 edges up to 0.76 when we exclude it.

In Figure 10 we relate the cyclicality of prices to durability. A WLS regression does show a positive coefficient but with an imprecise coefficient (0.11 with a standard error of 0.07). If we drop the energy outliers, the relationship becomes more positive and statistically significant (coefficient 0.18, s.e. 0.02). But economically the impact remains small – an order

[15] 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.

of magnitude smaller than the cyclical impact of durability on expenditures and employment. Finally, we note that the failure of durable goods to show (much) greater cyclicality in their prices does not reflect countercyclical prices for durable investment equipment (e.g., Greenwood, et al., 2000 or Fisher, 2006). These 4 categories are not especially durable and, if we drop them, the price of durables becomes only slightly more procyclical.

4. Industry Results on the Cyclicality of Markups

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 data to see how industries differ cyclically depending on characteristics of the goods produced.

Measuring Cyclical Behavior by Industry

The U.S. KLEMS data (http://www.bls.gov/mfp/) provide annual values, both nominal and real, for gross output and inputs of intermediates, labor, and capital from 1987 to 2009 for 18 manufacturing and 44 non-manufacturing sectors. These data allow us to examine the cyclical behavior of output, as opposed to expenditures, and to construct a measure of movements in price markups as discussed below. With the industry data we can also condition on industry movements in productivity, thereby seeing whether the lack of procyclical prices for durables goods is driven by favorable productivity shocks skewed toward these goods. The data also allow us to examine the impact of capital's share on fluctuations. Under flexible pricing, high-capital-share industries should display more procyclical prices but less cyclical quantities in response to relative demand shifts. 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). 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 provided earnings series for all employees. But for salaried workers it is especially difficult to justify the assumption that contemporaneous payments reflect their shadow wage.

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.[16] Because each CES industry has, through NAICS, an associated KLEMS industry, we can associate a relative importance of each NIPA category to an industry based on the KLEMS industry employment assigned to that category as a share of employment assigned across all 70 NIPA categories. For instance, employment for KLEMS industry NAICS 335 (electrical equipment and appliances) is assigned for 2009 as 38% to consumer appliances and 62% to electrical equipment investment. The characteristics assigned to NAICS 335 for 2009, in turn, are a weighted average of those for these two NIPA categories, with relative weights 0.38 and 0.62. We achieve a mapping for 40 KLEMS industries. Online Appendix Table 2 lists these industries along with their mapped characteristics. 13 are manufacturing; 27 are in construction, trade, or services.[17]

[16] 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.

[17] On average, we associate 44.4 percent of employment in a KLEMS industry with NIPA categories. For robustness, we also estimated for industries with at least 25 percent of employment covered. The only notable impact is that prices become more procyclical for industries producing luxuries.

We focus attention on how cyclicality differs across the KLEMS industries with respect to output, price, and the price markup. Output and price are measured by industry value added and its 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 markup of price over marginal cost can be expressed as a worker's marginal product relative to his real product wage. The Appendix illustrates that if (a) production is Cobb-Douglas, and (b) the marginal price of labor is captured by average hourly earnings, then fluctuations in the markup are captured by movements in the inverse of labor's share.[18] This is robust to adjustment costs for labor, provided there are no adjustment costs at the intensive, workweek margin. The markup is measured 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.

The Appendix generalizes this measure of real marginal cost for elasticities of substitution between capital and labor other than one. Below we show that our results are robust with respect to considerable variation in that elasticity.

Of more quantitative importance is how the marginal price of labor is measured. In the Appendix we discuss two alternatives to average hourly earnings. The first incorporates an estimate of the marginal impact of an increase in hours on overtime pay. This suggests a marginal wage rate that increases relative to average hourly earnings if the workweek increases. 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

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

the marginal wage equal to average hourly earnings. We also consider dropping average hourly earnings entirely as a measure of labor's price. In this variant we calculate relative wage rates across industries based on firms internalizing workers' marginal disutility of an hour's work. We refer to this price of labor as the shadow wage. Our calculated shadow wage assumes a Frisch elasticity of labor supply at the intensive margin of 0.5 (see Hall 2009 and Chetty 2012). It assumes, further, that the marginal 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.

We ask if markups are more countercyclical for durables. Under the null hypothesis of classical labor demand the markup is constant; so clearly the answer is no. That is

$$E\left[(\mu_{j,t}-\mu_t)\cdot\delta_j \mid Y_t\right]=0,$$

where $\mu_{j,t}-\mu_t$ is the markup for good *j*, relative to the average for all goods, δ_j is good *j*'s durability, and Y_t is aggregate output. We reject this hypothesis below, as markups are more countercyclical for durables. Given that rejection, we want to refine the alternative – that cyclicality of markups depends on durability – to condition out the effect of variables that might be correlated with durability and, under sticky prices, might affect the markup. The model presented in Section 2 highlighted three such variables: sector-specific technology shocks ($A_{j,t}-A_t$), sector frequency of price change (θ_j), and sector capital share (α_j). Thus our alternative hypothesis of countercyclical markups for durables can be expressed as

$$E\left[\left((\mu_{j,t}-\mu_t)-E[(\mu_{j,t}-\mu_t)\mid(A_{j,t}-A_j),\theta_j,\alpha_j]\right)\cdot\delta_j \mid Y_t\right] < 0.$$

Results

Table 2 displays how cyclicality differs by durability of an industry's good. Separate results are given for cyclicality in real value added, price (the deflator for value added), and the price markup. 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 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 (which also removes industry fixed effects).[19]

Consistent with results from the previous section, durables show greater cyclicality in quantities but not prices. Consider a good with lifespan of 12 years (appliances) versus a nondurable. The estimates imply 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 industries producing nondurables. 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.

The price markup is relatively countercyclical 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 a percentage point relative expansion in output for durables in a boom is associated with a relative decrease in the markup of about one-third of a percentage point. This is actually larger than the response generated by the

[19] 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 in 2003. The parameter for annual HP-filtering is 6.25 (Ravn and Uhlig, 2002).

sticky-price model we sketched above (see Figure 1).[20] If we measure labor's price by the shadow wage, then the decrease in markups for durable goods in booms is considerably larger. For instance, comparing a good 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 output for the durable, is associated with a 1.1 percentage point relative decrease in its markup.

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 important. Regressing TFP on year dummies and the interaction of Ln(1 + lifespan) with the cycle yields an insignificant coefficient of only 0.10. 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. Our model simulations allowed capital utilization to respond with an elasticity of one third to movements in the labor-capital ratio. (This adjustment was motivated by examining series on capital services constructed by Gorodnichenko and Shapiro, 2011.) If we empirically adjust TFP based on that elasticity response, we find that adjusted-TFP is slightly less procyclical for durables – its regression on Ln(1 + lifespan) interacted with the cycle yields a coefficient of −0.08 (standard error 0.27). In the second panel of Table 2, we include adjusted-TFP as a regressor, in addition to the good's lifespan, for explaining the relative cyclicality of output,

[20] The markup is acyclical overall for these industries if the wage is measured by average hourly earnings or the marginal wage. Pooling the industries, a one percent increase in GDP increases the markup by 0.04 percent using average hourly earnings and decreases it by 0.002 percent using the marginal wage. Using the shadow wage the markup is strongly countercyclical, decreasing by 0.41 percent (std. error 0.18 percent). But the assumptions motivating the shadow wage as a measure across industries (no relative consumption movements) do not extend to aggregates. Moreover, there remains the issue of whether demand or supply shocks drive the overall business cycle.

prices, and markups. The estimated cyclical impact of durability on an industry's output, price, and markup is not affected.

From the bottom panel of Table 2, we see the following effects for industry movements in adjusted-TFP. A one percent relative increase in industry productivity is associated with a decline in the industry's relative price of 0.7 percent. Output increases a little less than one-for-one with productivity, by 0.8 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 close to zero, with coefficient 0.03 (standard error 0.03). An increase in adjusted-TFP is associated with a rise in the markup of 0.1 percent. This is true whether the wage measure is average hourly earnings, the marginal wage, or the shadow wage. Although this effect is in the direction predicted by sticky-price models, the magnitude is quite small and statistically insignificant.

Our measure of cyclicality in markups in Table 2 assumes an elasticity of substitution of 1 between capital and labor. In Table 3 we present alternative results, assuming elasticities of 0.5 then 2.0. The markup becomes more countercyclical for durables if the elasticity is reduced to 0.5, and less countercyclical if increased to 2. This is not surprising given the labor to capital ratio is more procyclical for durables. But the impact of assuming non-Cobb-Douglas production is quite modest.

The impact of durability on cyclicality in output, pricing, and markups 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. In the top panel of Table 4 we control for the sector's monthly frequency of price changes multiplied by real GDP. We also include an interaction of this variable (demeaned) with the durability variable (demeaned), allowing cyclical pricing of durables to differ for goods with frequent versus infrequent price changes. Industries that produce goods with more frequent price changes display more procyclical prices, but also less cyclical output. Price markups are relatively procyclical for industries producing goods with frequent price changes.

From Section 3, energy prices are striking outliers, displaying far more procyclical prices. For this reason, in the bottom panel of Table 4 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 not more cyclical for industries producing goods with frequent price changes, nor do they display more cyclical price markups.

Durability continues to be associated with much more procyclical output and with relatively countercyclical markups. When all industries are considered, the estimated impact on markups becomes considerably larger holding frequency of price change constant (by a factor of 50 to 100 percent depending on the choice of wage measure.) Excluding energy, the negative impact on markups is again of the magnitude reported in Table 2, though estimated somewhat less precisely.

The regressions in Table 4 include interactions of durability and pricing frequency. These address whether countercyclical markups are more pronounced for durables with less frequent price changes, as predicted by the sticky-price model. The answer is affected by the energy industries. Including the energy industries, markups for durables are, if anything, more countercyclical for goods with frequent price changes. But in the bottom panel, dropping the energy industries, this result is gone. Countercyclical markups are more apparent for durables with less frequent price changes.

In Table 5 we extend the regressions to include interactions of economy-wide GDP with the Engel curve for goods produced in the industry and for the industry's (average) capital share in value added. Sticky-price models suggest more cyclical expenditures, but also more 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. The results for cyclicality by durability and frequency of price change are largely unchanged: in particular, markups remain countercyclical for durables. The estimated impact of an industry's Engel curve elasticity and capital share are not overly 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 0.5 percentage point greater increase in output. But, in contrast to durables, prices for luxuries do rise in booms; and markups for luxuries are at least as cyclical as for necessities.

A higher capital share is associated with much less cyclical output, but not more cyclical prices. 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 (though the standard error here is 0.4 points), with no relative price effect. This does not particularly fit a flexible price or sticky-price story, as neither explains why output should depend on the capital share except through cyclicality of marginal cost and price. Markups are, arguably, more countercyclical for industries with high capital share, as predicted by sticky-price models. But this impact on markups is not at all precisely estimated nor is it robust to employing the shadow wage as the price of labor.

To recap, our results conflict with the joint assumption of flexible pricing and constant markups. In particular, we find countercyclical markups for durable goods in booms relative to other goods. But the results do not entirely fit sticky price theories: adjusted-TFP movements are largely passed through to prices; markups do not fall in expansions for industries producing luxuries; and more frequent price changes only predict a more cyclical industry price if energy goods are included.

5. Conclusion

Employment's response to fluctuations in goods demand is exacerbated by countercyclical markups in Keynesian models. 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 that durability is a powerful predictor of cyclicality in expenditures and employment across sectors. We also map Engel curves to our goods, allowing us to treat an industry producing a luxury as facing more cyclical 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.

We find evidence in support of Keynesian Labor Demand over flexible prices with constant markups. 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 substitutability of capital and labor.

Not all of our evidence aligns with New-Keynesian, sticky-price models of labor demand. Procyclical marginal cost driven by producing a luxury does not generate a markup decline. And a higher frequency of price change does not result in more cyclical prices, 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. This interpretation would resolve the ostensible inconsistency between our findings and 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 shifts in goods demand regardless of the source of that shift. It is important to decipher whether departures from 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: Measuring the Cyclical Markup Wedge

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. In doing so, we assume no adjustment costs in varying production workers' weekly hours. But we put no restrictions on employment adjustment costs.

Let value added reflect production and non-production inputs according to

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

The variables k, n denote services of capital and labor. Variables with subscript *pr* refer to factors classified as engaged in physical production. Variables with subscript *np* refer to factors not engaged in production.

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

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

We have dropped the subscripts to denote production. ϕ_n and ϕ_k are utilization rates for production labor and capital (i.e, ϕ_n is effort per hour). η equals the multiple of returns to scale and production inputs' share in value added. σ is the elasticity of input substitution. The required increase in labor for a marginal increase in output is

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

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

Dividing price by mc yields the (gross) markup. Taking logs and ignoring constants,

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

Under Cobb-Douglas ($\sigma = 1$) and a marginal price of labor, w, given by average hourly earnings, movements in the markup equal inverse movements in production labor's share of output. This is one estimate of the markup we consider.

We examine the robustness of our results to allowing less, or more, substitutability of production labor and capital in the short run. For Cobb-Douglas, there is no need to adjust for rates of utilization ϕ_n and ϕ_k. For $\sigma \neq 1$, we assume capital utilization varies with an elasticity of one third with respect to the ratio of production labor to capital. (We treat ϕ_n as constant.) This elasticity is estimated using series on capital utilization from Gorodnichencko and Shapiro (2011), as outlined in online Appendix C.

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.

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. 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. We assume a fifty percent overtime premium, as dictated by legislation. Average hourly earnings are given by replacing the term $\frac{\partial v}{\partial h}$ here 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 industries without series on overtime hours, we assume overtime premia are irrelevant, setting the marginal wage to average hourly earnings.

The third wage measure we consider, the shadow wage, drops any pretext that measured wages capture the effective price of labor. The implicit contracting literature provides one strong rationale for separating the price of labor to firms from observed variations in wage rate. Consider an alternative wage measure that allows that employers internalize workers' indifference curves; so the effective wage is given by workers marginal rates of substitution: $u_h(c,h)/u_c(c,h)$. (Individual subscripts are implicit.) In turn, equating the marginal utility of consumption 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 for consumer goods, and h is hours worked.

To measure aggregate cyclicality of w/p_c requires knowing the cyclicality of λ. But our interest is only to measure relative cyclicality across industries. If we assume that cyclical movements in λ are comparable across industries, then relative wage movements simplifies 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 wage movements are

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

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

Table 1

Model Parameters

Discount Factor (β)	$0.966^{1/12}$	Utilization Cost Curvature (a'')	2.00
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 Durability and Cyclicality

	Quantity	Price	Price Markup Using: Average Wage	Marginal Wage	Shadow Wage
Ln (1 + lifespan)*GDP	0.67 (0.27)	−0.13 (0.25)	−0.20 (0.08)	−0.24 (0.08)	−0.42 (0.09)
Ln (1 + lifespan)*GDP	0.73 (0.09)	−0.19 (0.09)	−0.20 (0.09)	−0.23 (0.09)	−0.41 (0.10)
Adjusted-TFP	0.81 (0.05)	−0.73 (0.10)	0.07 (0.10)	0.07 (0.10)	0.10 (0.10)

Table 3 Durability and Cyclicality without Cobb-Douglas

	Short-run Cap./Labor Subst = 0.5			Short-run Cap./Labor Subst = 2		
	Price Markup Using:			Price Markup Using:		
	Average Wage	Marginal Wage	Shadow Wage	Average Wage	Marginal Wage	Shadow Wage
Ln (1 + lifespan)*GDP	−0.25 (0.08)	−0.28 (0.09)	−0.47 (0.10)	−0.18 (0.08)	−0.21 (0.08)	−0.39 (0.09)
Ln (1 + lifespan)*GDP	−0.25 (0.09)	−0.28 (0.11)	−0.46 (0.11)	−0.18 (0.09)	−0.21 (0.09)	−0.39 (0.10)
Adjusted-TFP	0.07 (0.10)	0.07 (0.10)	0.09 (0.10)	0.07 (0.10)	0.07 (0.10)	0.09 (0.10)

Notes to Tables 2 and 3: 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. Price markup is the inverse marginal labor share, which 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. Newey-West corrected standard errors in parentheses.

Table 4

Cyclicality Interacting with Price-Change Frequency

	Quantity	Price	Price Markup Using: Average Wage	Marginal Wage	Shadow Wage
Ln (1 + lifespan)*GDP	0.86 (0.20)	−0.40 (0.18)	−0.40 (0.15)	−0.49 (0.16)	−0.63 (0.21)
Price Change Freq*GDP	−1.22 (0.53)	3.56 (1.45)	2.98 (1.23)	3.00 (1.18)	2.88 (1.29)
Freq*Durability*GDP	0.13 (0.34)	−0.83 (0.48)	−0.62 (0.41)	−0.48 (0.41)	−0.53 (0.49)
Adjusted TFP	0.80 (0.06)	−0.71 (0.09)	0.10 (0.09)	0.09 (0.09)	0.11 (0.09)
Drop two energy industries					
Ln (1 + lifespan)*GDP	0.88 (0.19)	−0.17 (0.16)	−0.18 (0.13)	−0.28 (0.14)	−0.41 (0.21)
Price Change Freq*GDP	−1.50 (0.79)	−0.15 (0.67)	−0.47 (0.67)	−0.33 (0.66)	−0.69 (0.72)
Freq*Durability*GDP	0.18 (0.41)	0.28 (0.32)	0.41 (0.26)	0.52 (0.27)	0.53 (0.38)
Adjusted TFP	0.77 (0.06)	−0.61 (0.07)	0.17 (0.08)	0.17 (0.08)	0.19 (0.08)

Notes: Sample = 787 in top panel, 747 in lower. Regressions include full set of year dummies. Frequency and durability demeaned in variable Freq*Durability*GDP. Newey-West corrected standard errors in parentheses.

Table 5
Cyclicality with Engel Curves and Capital Shares

	Quantity	Price	Price Markup Using: Average Wage	Marginal Wage	Shadow Wage
Ln (1 + lifespan)*GDP	0.92 (0.18)	−0.31 (0.18)	−0.39 (0.16)	−0.47 (0.16)	−0.55 (0.22)
Price Change Freq*GDP	0.22 (0.65)	4.21 (1.38)	3.61 (1.29)	3.67 (1.24)	3.14 (1.41)
Freq*Durability*GDP	−0.51 (0.37)	−1.14 (0.46)	−0.90 (0.46)	−0.77 (0.46)	−0.67 (0.56)
Engel Curve*GDP	0.83 (0.35)	0.63 (0.35)	0.30 (0.38)	0.31 (0.40)	0.48 (0.53)
Capital Share*GDP	−1.13 (0.66)	−0.01 (0.46)	−0.63 (0.52)	−0.65 (0.53)	0.43 (0.65)
Adjusted TFP	0.80 (0.06)	−0.71 (0.09)	0.10 (0.09)	0.10 (0.09)	0.12 (0.09)

Drop two energy industries

	Quantity	Price	Average Wage	Marginal Wage	Shadow Wage
Ln (1 + lifespan)*GDP	0.94 (0.18)	−0.13 (0.16)	−0.21 (0.14)	−0.31 (0.16)	−0.37 (0.22)
Price Change Freq*GDP	0.20 (0.89)	0.40 (0.77)	−0.12 (0.79)	0.08 (0.80)	−0.60 (1.00)
Freq*Dur*GDP	−0.54 (0.45)	0.05 (0.33)	0.26 (0.30)	0.35 (0.32)	0.50 (0.48)
Engel Curve*GDP	0.83 (0.35)	0.35 (0.32)	−0.002 (0.31)	0.03 (0.34)	0.19 (0.49)
Capital Share*GDP	−1.10 (0.66)	−0.13 (0.42)	−0.71 (0.42)	−0.73 (0.45)	0.36 (0.64)
Adjusted TFP	0.78 (0.06)	−0.61 (0.07)	0.17 (0.08)	0.17 (0.08)	0.1935 (0.07)

Notes: Sample = 787 in top panel, 747 in lower. Full set of year dummies included. Frequency and durability demeaned in Freq*Durability*GDP. Newey-West corrected standard errors in parentheses.

Figure 1

Relative **Durables/Nondurables** Response, Sticky Prices

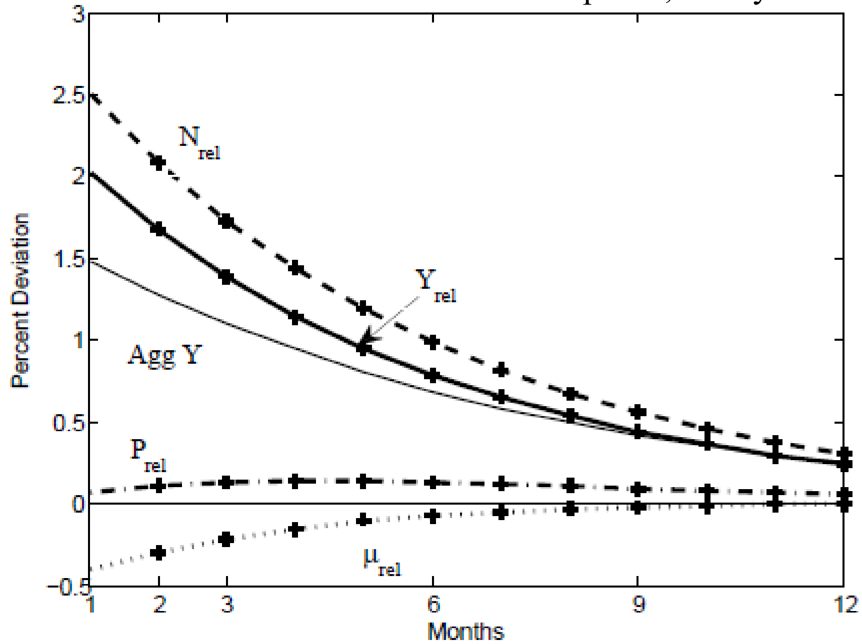
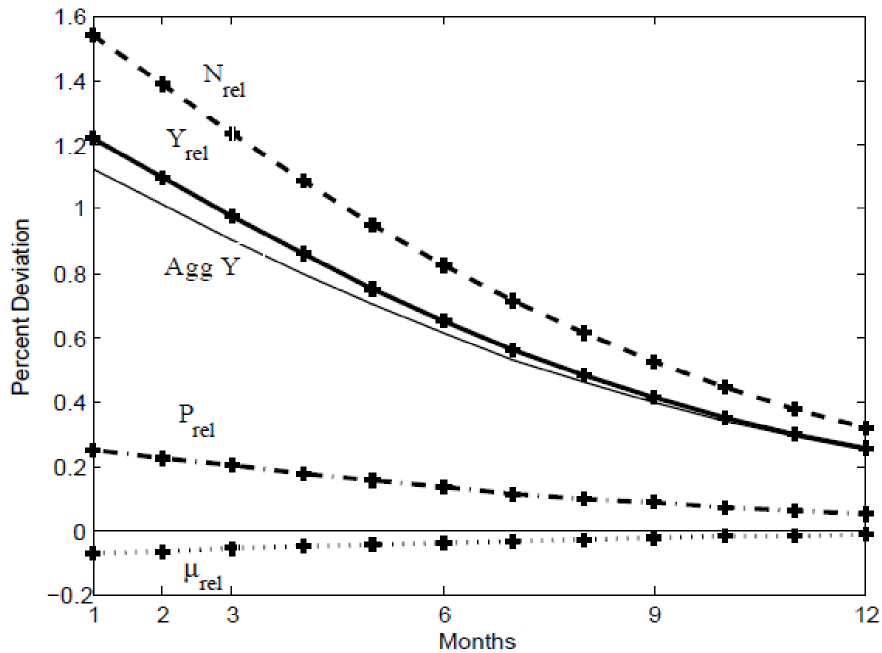


Figure 2

Relative **Durables/Nondurables** Response, Flexible Prices



<u>Notes for Figures 1 & 2</u>: Impulse response to monetary policy shock. Y is output, N labor, P prices and μ markups.

Figure 3

Relative **Low/High Price Flexibility** Response

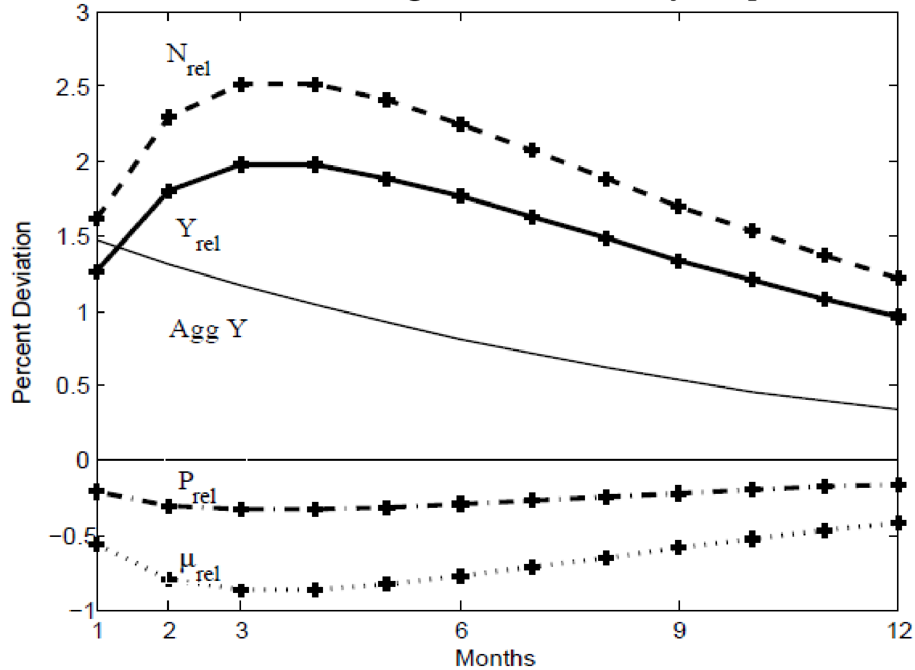
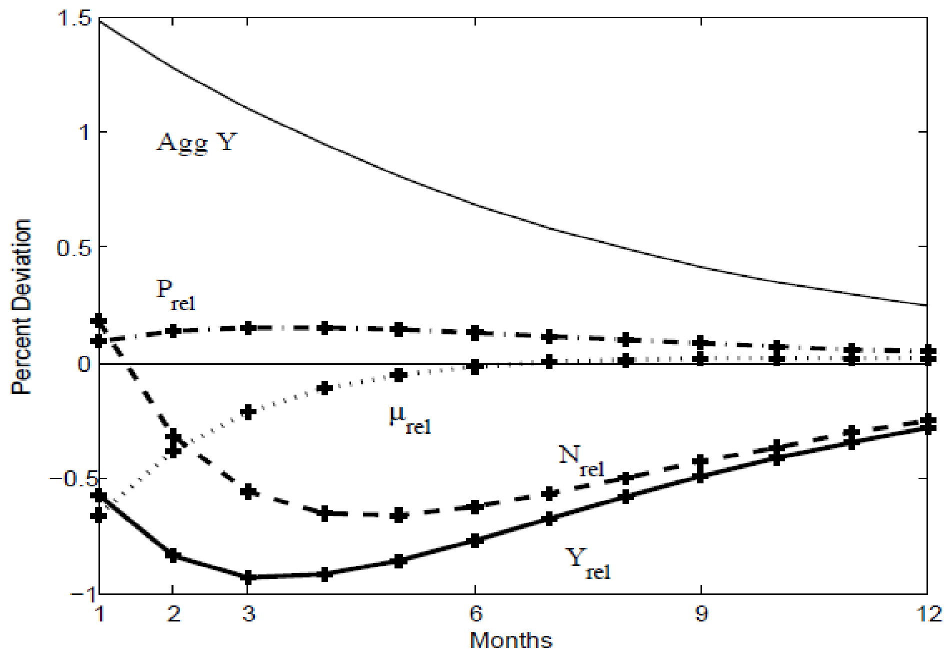


Figure 4

Relative **High/Low Capital Intensity** Response, Sticky Prices



<u>Notes for Figures 3 & 4</u>: Impulse response to monetary policy shock. Y is output, N labor, P prices and μ markups.

Figure 5

Response of **Aggregate Output** to Various Shocks

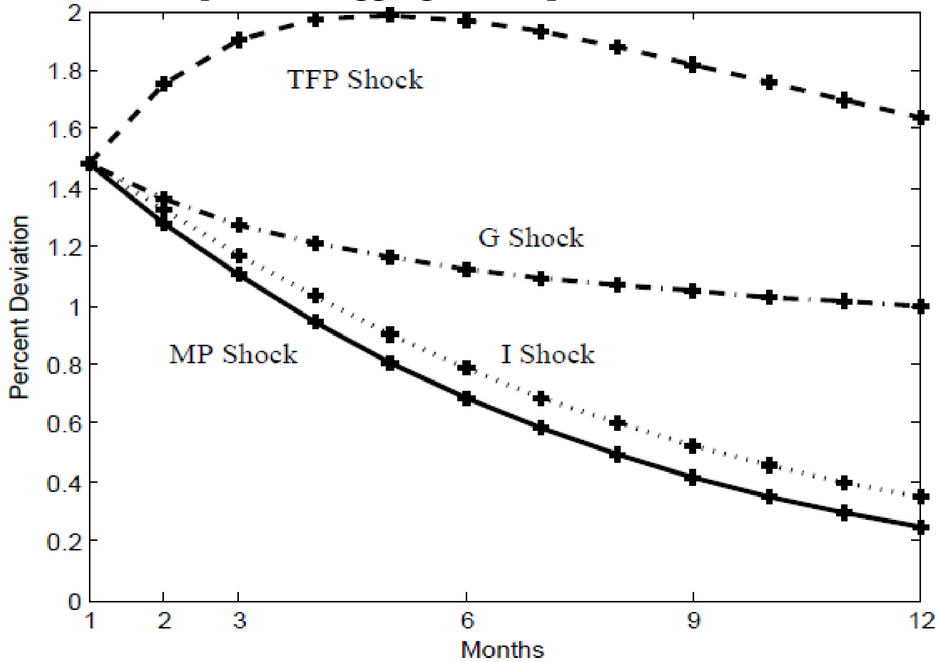
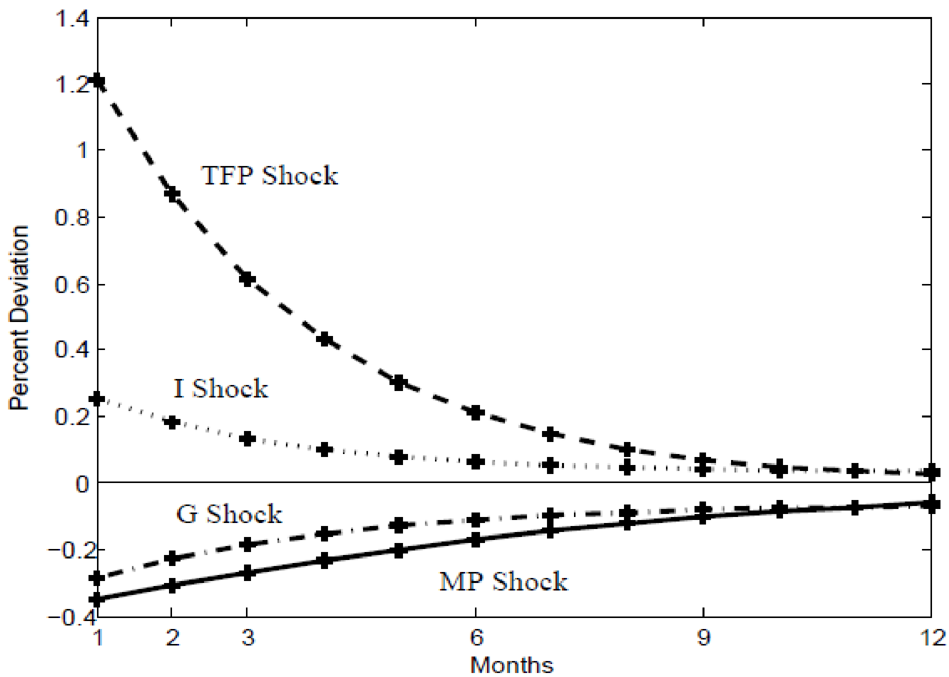


Figure 6

Response of **Aggregate Markup** to Various Shocks



<u>Notes for Figures 5 & 6</u>: MP stands for monetary policy, G for government spending, I for investment-specific technology, and TFP for neutral technology. The shocks have been scaled to produce the same movement in aggregate output on impact.

Figure 7 Cyclicality of *Expenditures* vs. Durability

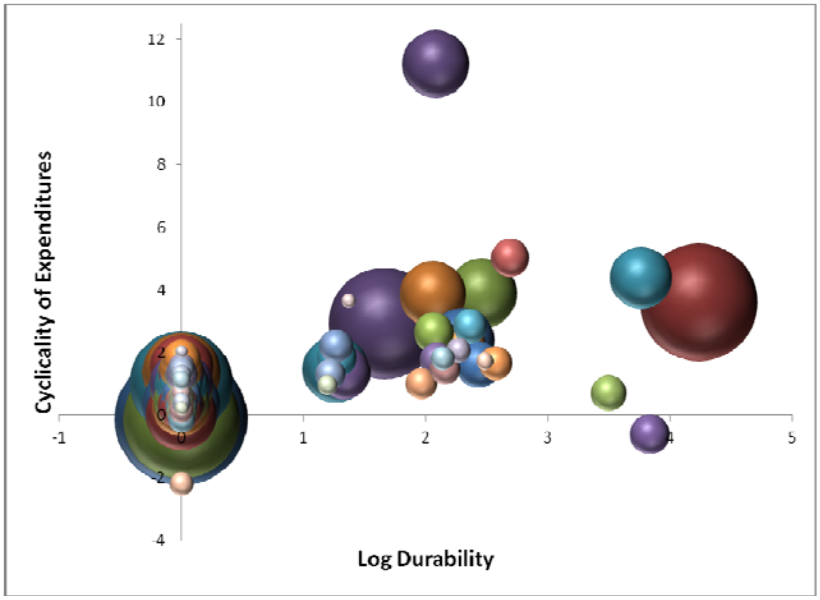
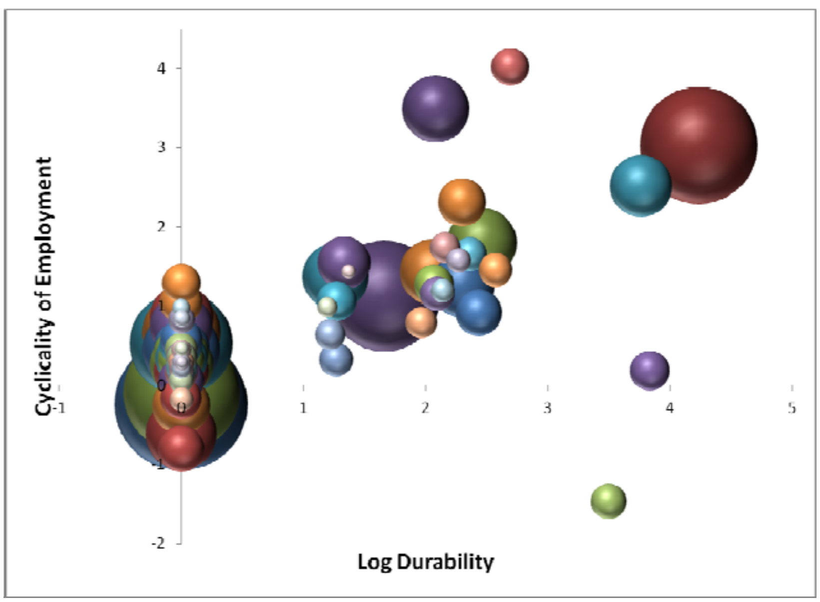


Figure 8 Cyclicality of *Employment* vs. Durability



<u>Notes for Figures 7 and 8</u>: Each ball is one good out of 70 in Figure 7, out of 68 in Figure 8. The ball size gives the average expenditure share over 1990-2011. Each good's cyclicality reflects regressing quarterly HP-filtered log real expenditures (or log industrial employment) on quarterly HP-filtered log real GDP. Durability is defined as 1 + Expected Life in Years.

Figure 9 Employment Declines in the Great Recession vs. Durability

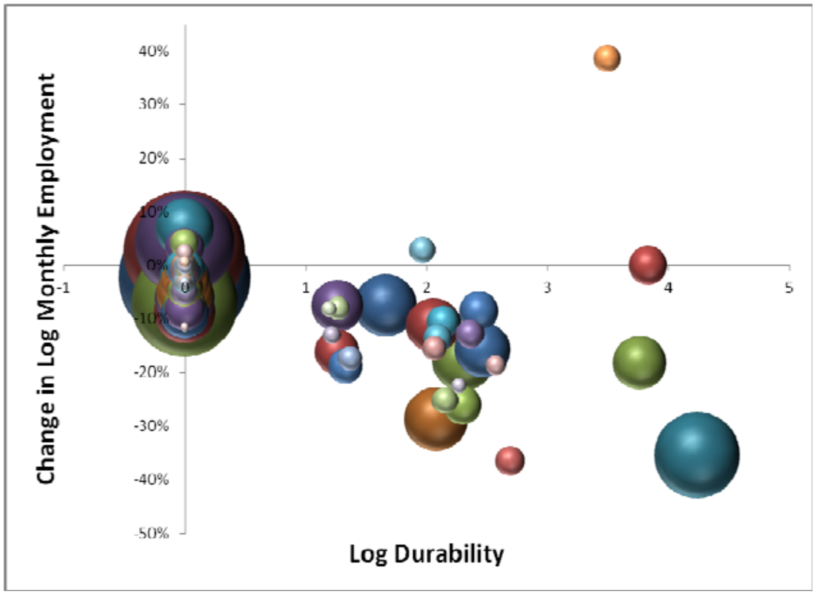
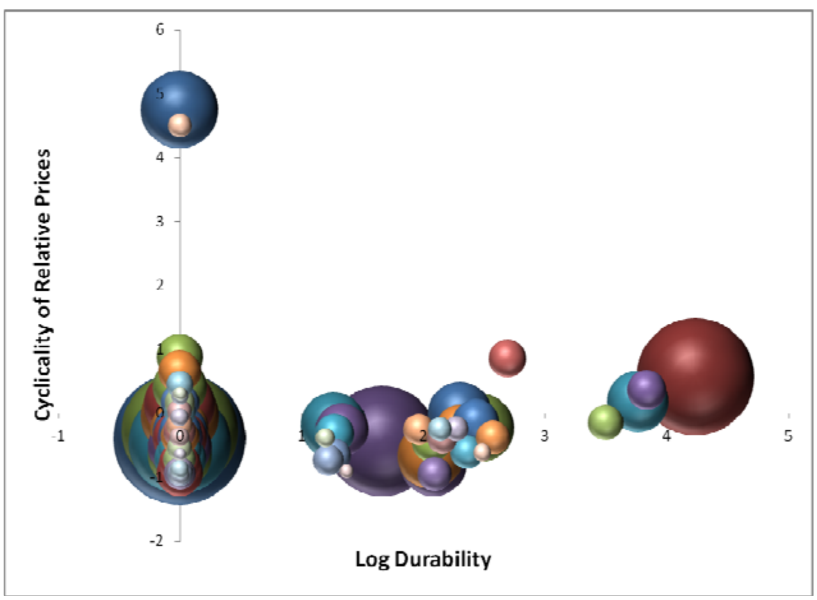


Figure 10 Cyclicality of Prices vs. Durability



Notes: Each ball is one of 68 (70) industries (goods), the size of the ball giving the average employment (expenditure) share over 1990-2011. The Great Recession is defined using the NBER peak-to-trough dates. The vertical axis in Figure 9 plots the log first difference of industry employment in June 2009 vs. December 2007. In Figure 10 cyclicality is obtained from regressing a good's 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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