Cyclical Demand Shifts and Cost of Living Inequality

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Abstract

This paper examines the cyclical behavior of low-income versus high-income household price indices and documents two new facts: (1) during recessions prices rise more for products purchased relatively more by low-income households (necessities); (2) the aggregate share of spending devoted to necessities is counter-cyclical. I present a mechanism where adverse macroeconomic shocks cause households to shift expenditure away from luxuries toward necessities, which leads to higher relative prices for necessities. I embed this mechanism into a quantitative macroeconomic model which explains 72 percent of the cyclical variation in necessity prices and 57 percent of the cyclical variation in necessity shares. My results suggest that low-income households are hit twice by recessions: once by the recession itself and again as their price index increases relative to other households.

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KEYWORDS: inflation, non-homotheticity, real income inequality, business cycle, monetary policy

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1 Introduction

This paper studies income-level differences in cost-of-living over the course of the business cycle and makes three main contributions. First, I show that while consumption falls during recessions, it does not fall equally for all products; specifically, consumption falls more for luxury products than necessities. Second, I show that the relative price of necessities is counter-cyclical. Third, I present a theoretical framework that incorporates non-homothetic consumption preferences into a standard business cycle model. This model is able to explain a large fraction of the cyclical behavior of relative necessity prices and consumption, and estimates sizable increases in the relative cost-of-living for low-income households during recessions.

Since the 2008 financial crisis, a flurry of research has shown that recessionary shocks have heterogeneous effects on households and can exacerbate society inequities (Heathcote et al. 2020, Feiveson et al. 2020, Krueger et al. 2016, Meyer and Sullivan 2013, Hoynes et al. 2012). Much of the past literature have focused on the cyclical behavior of nominal consumption and income inequality and has ignored the denominator of real inequality: cost-of-living differences across households. In my project, I show that failing to include differential changes in the cost-of-living can dramatically understate the true welfare cost of recessions. For example Krueger et al. (2016) find that during the Great Recession, consumption growth fell by 0.3 percent more for households in the lowest wealth quintile compared to the highest. A back of the envelope calculation incorporating this paper's cost-of-living inequality estimates suggests that the actual difference in the fall of *real* consumption is almost four times as high at 1.18 percent.[1]

Is this unequal change in cost-of-living a fluke unique to the Great Recession, or is it a feature of all recessions? This study argues that it is the latter: recessions cause the products that poor households buy more intensively to increase in price relative to other households. I present a novel mechanism where contractionary shocks lead households to cut back on luxury goods (e.g. vacations and pet services), but households continue to buy necessities (e.g. groceries). This shift in relative demand increases the relative price of necessities,

[1] Krueger et al. (2016) classify households based on wealth levels, where this paper sorts households based on income.

which disproportionately affects poorer households since a larger share of their consumption basket is devoted to necessities. My mechanism implies that poor households are hit twice by recessions: once by the recession itself and again when the price of their basket increases relative to other households.

In order to study differences in household level price indices across time, I create 119 product sectors in the Consumer Expenditure Survey (CEX) that consistently represent the same type of spending from (1990-2019). I then sort households into 5 different income quintiles, and construct a measure of the relative importance of a product in a low-income household's consumption basket (expenditure ratio) by dividing the pooled average of the products expenditure share for households in the first income quintile by the average expenditure for that product of households in the highest income quintile. I define necessities as products purchased more by low-income households (expenditure ratio greater than one) and luxuries as products purchased more by high income households. Next, I match these 119 product sectors with publicly available price data from the CPI.

Based on this categorization, I examine the cyclical behavior of prices for necessity products. Since I have price data for a subset of products from 1967-2020, I am able to observe the cyclical behavior of necessity and luxury prices over 7 different recessionary periods. I construct composite price indices for necessities and luxuries and I find that the price index for necessities relative to luxuries has increased during 5 out of the last 7 recessions. Separately, in a panel regression using all 119 product sectors I find that a one percent increase in the unemployment rate is associated with a 1.3-1.8 percent increase in the relative price of necessity goods. This relationship still holds when controlling for whether products are services, durables, or in the energy sector.

While my CEX derived data on consumption shares is shorter, (1990-2019), I do find a very large increase in the share of aggregate spending on necessities during the Great Recession and subsequent slow recovery. This aggregate increase was driven by all income groups: for example, households in the lowest income group increased their share of necessity spending from 70 to 72 percent, while households in the highest income group increased from 50 to 52. In a panel regression using all 119 product sectors, I find a strong relationship between the aggregate share spent on necessities and the unemployment rate. To show that

this relationship is not just mechanically related to higher necessity prices, I also show that this cyclical relationship still holds when I regress a product's real aggregate expenditure (nominal expenditure divided by the product specific price index) on unemployment.

Having documented that both necessity relative prices and aggregate shares increase during recessions, I formally introduce a static model that can rationalize these facts. The key components of this model are non-homothetic preferences at the aggregate level and a concave production possibilities frontier. The non-homothetic preferences lead to cyclical demand shifts between necessities and luxuries that track the evolution of aggregate consumption expenditure. The concave production possibilities frontier leads to higher relative costs for the expanding sector. These components are sufficient for an aggregate decrease in expenditure to lead to a relative expansion in the necessity sector and higher relative necessity prices.

This model has testable conclusions: (1) does aggregate consumption shift towards necessities following a shock that lowers expenditure and (2) does this shift in demand lead to higher prices in the expanding sector? This presents a difficult identification problem as many shocks that affect household expenditure also directly affect relative marginal cost between industries. To get around these issues, I use surprise monetary policy news shocks derived from the change in asset prices in a thirty minute window around Federal Open Market Committee (FOMC) announcements (Swanson 2021). I find that 24 months after a 25 basis point contractionary monetary policy shock, aggregate expenditure falls by approximately 2 percent, while the aggregate share devoted to necessity products increases by approximately 5 percent and relative necessity prices increase by around 2.5 percent. Results are similar when conditioning on whether the product is a durable good or a service: sectors which typically have high interest rate elasiticities or sticky prices.

Next, I present a quantitative New Keynesian model that incorporates non-homothetic preferences and can be calibrated to the US economy. Household preferences are represented by the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer 1980). While these preferences have been widely used in the trade literature, to my knowledge this is the first paper to incorporate these preferences into a business cycle model. The AIDS inherits well behaved aggregation properties from the Generalized Linear class of demand systems

(Muellbauer 1975), which allows me to solve for aggregate necessity shares and relative necessity prices using a representative agent framework. I calibrate the model to match key features of the US economy in 2005-2006 right before the Great Recession.

My quantitative model is able to explain a large fraction of the cyclical variation in relative necessity prices and shares. In a validation exercise, I shock my model with a series of interest wedge shocks so that expenditure in the model exactly matches the cyclical component of real Personal Consumption Expenditures (PCE) from 1994-2019. The model's predicted necessity prices and shares can explain 72 percent of the cyclical variation in necessity prices and 57 percent of the variation in necessity shares over this period.

With my model in hand, I examine the welfare consequences of the Great Recession when households have different price indices. [2] Using the non-homothetic price index implied by the AIDS, I estimate that the price index for poor households increased by 0.88 percentage points relative to the price index of rich households over the course of the Great Recession (2007Q3-2009Q2). This large relative increase in cost-of-living can have considerable welfare consequences. I perform a test of the expenditure equivalent welfare loss due to the Great Recession and I find that the Great Recession was 19 percent more costly for poor households than rich households.

Taken together, my results suggest that income level differences in the cost-of-living vary systematically over the course of the business cycle; increasing during recessions and subsiding during expansions. This cost-of-living channel is yet another reason why recessions are particularly costly for poor households.

My paper is most closely related to a small, but fast growing literature examining changes in the cost-of-living across household groups. Early research by–Amble and Stewart (1994), Garner et al. (1996), Hobijn and Lagakos (2005), and McGranahan and Paulson (2005) – found only limited differences in inflation rates across demographic groups;[3] however, more recent work has leveraged detailed product categories as well as barcode level data to document substantial differences in inflation-rates across households (Kaplan and Schulhofer-

[2]Since my model abstracts from differences in employment loss or ability to borrow during the recession, these results are due only to differences in relative prices

[3]An exception in this early-period is work by Crawford and Oldfield (2002) who found that few households in Britain have inflation close to the official Retail Price Index

Wohl 2017, Jaravel 2019, Cavallo 2020, Gürer and Weichenrieder 2020, Argente and Lee 2021, Orchard 2021, Lauper and Mangiante 2021) This literature has focused on either trends in inflation rate disparities (Jaravel 2019, Gürer and Weichenrieder 2020) or particular events such as the Great Recession (Argente and Lee 2021) and the Covid-19 Pandemic (Cavallo 2020, Jaravel and O'Connell 2020). In contrast, this paper examines the cyclical response of inflation inequality to any shock that affects aggregate consumption expenditure.[4]

Jaravel (2019) studies income-group inflation rates from 2004-2015 using linked CEX and CPI data. He finds that the inflation rate for the lowest income quintile averaged 0.35 percentage points more than the highest. He argues that increases in income inequality and aggregate productivity over that period has led aggregate expenditure to become more concentrated in luxury sectors, which has induced increased product entry and competition. His paper argues that the expanding sector will have lower prices, while my paper focuses on short-term shifts in demand that cause higher prices in the expanding sector since levers such as innovation or capital reallocation are less available to firms in the short term.

Cravino et al. (2020) also study how relative prices for different income groups respond to cyclical shocks (monetary in their paper). Their focus is on the middle and highest income groups and they find that the price index of the highest income group is less responsive to monetary policy shocks than the median income group. They hypothesize that this difference emerges since the highest income group buys goods that are relatively more sticky than goods bought by the median income group. My paper proposes an alternate mechanism through which income groups inflation rates will respond differently to monetary policy shocks that still holds even when controlling for goods with notoriously sticky prices (services) or volatile prices (energy).

This paper also contributes to a literature on endogenous demand shifts. For example, Jaimovich et al. (2019) show that households switched from high- to low-quality products during the great recession and this shift in demand led to lower labor demand since low-quality products use less labor in production. Over a longer horizon, Boppart (2014) and

[4]Inflation inequality may be a confusing term since price inflation traditionally has been defined as a general increase in the prices of goods and services in an economy or a decrease in the purchasing power of a particular currency. In the emerging literature on changes in the cost-of-living across income groups, "Inflation Inequality" is generally defined as differences in the change of the cost of achieving a particular level of utility across household groups (Jaravel 2021).

Comin et al. (2021), show that non-homothetic demand can explain the shift from agriculture, to manufacturing and services in advanced economies. Comin et al. (2020) show how this long-term shift has contributed to labor-market polarization by shifting demand to high-expenditure elasticity industries that have more low- and high-skilled labor inputs.

The remainder of the paper proceeds as follows: Section 2 details the data I use in my analysis, Section 3 presents my twin motivating facts (counter-cyclical necessity prices and aggregate shares), Section 4 formally presents the cyclical demand shift mechanism, Section 5 tests the conclusions of my mechanism empirically via monetary policy news shocks, Section 6 presents my quantitative model, and Section 7 concludes.

2 Data

My primary data sources are the Consumer Expenditure Survey (CEX) and publicly available product-level Consumer Price Index (CPI) series, both from the Bureau of Labor Statistics (BLS). The BLS uses the CEX and micro-level price data to construct the CPI-U. In doing so, they aggregate micro-price data into 243 different item strata and construct weights using the CEX (U.S. BLS, 2020). Price time series for the 243 item-strata are not publicly available, instead the BLS publishes CPI price series for a variety of more aggregated products, which I use in my analysis.

I create a cross-walk by hand between the publicly available item level CPI categories and CEX MTBI micro-data. In this cross-walk, I create CEX products from base level UCC codes that were consistent across the 1991-2019 survey waves.[5] While some categories simply did not exist in earlier years (e.g. internet expenditures were not recorded prior to 1995 in the CEX), the categories are created so that comparison between years is possible and represent the same breadth of spending in each year. I matched these CEX categories to CPI item level price data. Where this was not possible (for example, CPI has separate price series for premium and regular gasoline) I created broader CEX products to match with the CPI or used a broader CPI category (e.g. gasoline). The result is 121 distinct products that represent the same types of spending from 1991-2019 (119 excluding housing). Taken

[5] A UCC code is the most disaggregated expenditure category in the CEX.

together, these product categories represent approximately 97.5 percent of all consumption spending in the CEX.

The CPI price series for these categories is not available across the entire sample period, as there was an expansion in published categories in 1967, 1977,1987, and 1997. For my analysis, I use either a balanced sample of products with continuous price information over some period (for example 1987-2019) or an unbalanced sample. Results are similar using either method.

I exclude housing in my analysis since most high-income households are homeowners while low-income households generally rent their home. While the BLS constructs an imputed owners equivalent rent series, homeowners do not actually pay this price. When rent prices change, homeowners can still consume at their initial endowment point and are shielded from increases in home prices. While studying the impacts of owning versus renting on real income and wealth inequality is an interesting area of research, it is not the focus of this article.

I follow Aguiar and Bils (2015) when creating my household sample and dividing these households into five different income groups. Namely, I keep only households that participate in all four CE interviews and that are complete income reporters. I also include only urban households and households whose household head is between 25 and 64. This leaves me with 76,448 distinct households from 1991-2019.

I divide households into 5 different income groups based on their pre-tax income. In addition to pre-tax income reported in the CEX, I add in income from alimony, gifts, gambling winnings, inheritance, and any other payments from persons outside the household; similarly I subtract from income the alimony, child support, etc. paid by the household. I regress this income measure on dummies of the household size, age, and the number of income earners in the household; I group households into groups based on their income percentile in the quarter they report their income (which would be the fourth interview). Similar to Aguiar and Bils (2015), the top income group are households in the 80-95 percentile of income (this lessens the degree to which changes in top-coding and outliers can change the composition of the top group). The bottom income group are households in the 5-20 percentile of income. Groups 2, 3 and 4 are households in the 20-40 percentile, 40-60 percentile and 60-80

percentile respectfully.

Households are interviewed four times three months apart and are asked about their spending in each of the previous three months in small categories (UCCs). These interview times do not necessarily correspond to calendar quarters, for example, a household interviewed in May would be asked about their spending in April, March, and February. In principle, I should be able to use the CEX data to create monthly expenditure variables for each household or quarterly expenditure based on each household's reported expenditure in that quarter, however, there is wide spread expenditure smoothing across months within an interview (Coibion, Gorodnichenko, Kueng, Silva 2017). This means that reported expenditure in UCC u for a household interviewed in May would be relatively smooth from February to April, but would have a much larger change when compared to January spending (which would come from the previous survey). For this reason, I base household spending at time t based on the quarter or month they were interviewed rather than the quarter or month for which they report their spending (Coibion et al. 2017). In my main analysis, my measure of aggregate spending share in a category j in month t is smoothed across the three proceeding months to capture all households surveyed in the quarter.

I create quarterly expenditure shares for the 121 product groups for each household by dividing expenditure in category j by total consumption expenditure. Total consumption expenditure is defined as quarterly household expenditure minus savings in pension plans, life insurance, health insurance rebates, and cash contributions to those outside the household.

I create income group expenditure shares as the weighted average of household expenditure shares for all households in the income group. I use the household survey weights computed by the BLS. Note that this is different from how the BLS creates expenditure shares for the CPI, since they also base their shares on the contribution of the household to total spending, which puts more weight on higher spending households. Since this paper is focused on non-homotheticities in consumption shares, weighting based on expenditure is problematic since it would give more weight to households at the upper-end of an income group (say those nearer to the 20th percentile vs. those nearer the 5th percentile). This could also be a problem when some household report more of their expenditure than other households (see Aguiar and Bils (2015) for under-reporting in the CEX).

I pool the quarterly expenditure shares across quarters to create a single expenditure share for each income-group and product. I define R_j, as the ratio of the share of consumer spending in the lowest income quintile to the share of spending in the highest quintile:

$$R_j = \frac{\sum_t \frac{1}{N_{t,Q1}} \sum_{h \in Q1} s_{jth}}{\sum_t \frac{1}{N_{t,Q5}} \sum_{h \in Q5} s_{jth}}. \tag{2.1}$$

R_j is equal to one if on average, poor and rich households spend the same percentage of their expenditure on product j. I define products as necessity goods if poor households have a higher expenditure share on these goods relative to rich households ($R_j > 1$) and luxury goods as products with $R_j < 1$. Note that this approach is similar to comparing the level of the Engel curve at the top and bottom of the income distribution. If the Engel curve is linear, than the "necessity" rank of the good using my method would be the same as the rank derived from the slope of the Engel curve (where a slope of zero would correspond to an expenditure share ratio of 1). If the underlying Engel curve is non-linear (as suggested by Atkin, Faber, Fally, and Gonzalez-Navarro (2020)) then my method ranks goods by their importance in the consumption basket of poor and rich households, which is key to understanding differences in relative price indices across these two groups.

Table 1 Panel A shows the top 10 luxury goods. The consumption category that has the highest comparative expenditure by those in the top income group is "Club memberships for shopping clubs, fraternal, or other organizations", which has an expenditure ratio, R_j, of .3. This means that on average, households in the highest income group spend 3.3 times a percentage of their total expenditure on this category compared to households in the lowest income group. Other top luxury goods include Airline flights, Day care, Hotels, Private Lessons, and alcoholic beverages away from home.

Panel B shows the top 10 necessity goods. These include tobacco products, food at home, electricity, and intracity transportation (e.g. bus or subway). Table 2 shows that luxuries tend to be more concentrated in services and durable goods, while necessities are more concentrated in energy and transportation.

3 Two Facts

In this section, I use the combined CEX-CPI data to examine the consumption and pricing behavior of luxuries and necessities. To this end, I begin by creating composite necessity and luxury products, so the reader can visualize the relationship between relative prices/shares and the business cycle. I also perform panel regressions to show that there is a strong positive correlation between the unemployment rate and the relative price/aggregate share of necessities.

3.1 Fact 1: Counter-cyclical Necessity Prices

Visual Evidence

I begin by showing a visualization of the relative prices of necessities and luxuries over the business cycle. I create a geometric-price index for a representative necessity (luxury) good as:

$$P_t^K = \prod_j \left(\frac{p_{j,t}}{p_{j,b}} \right)^{\omega_j}, \tag{3.1}$$

where $K = \{N, L\}$ for necessity and luxury respectively, and ω_j is the pooled aggregate share of product j in total necessity or luxury spending. Note that b refers to the prices in some base period, which I define as the first period in the sample. I then construct the relative necessity price as the log difference of prices between the composite necessity and luxury goods:

$$RP_t^N = \log \left(\frac{P_t^N}{P_t^L} \right). \tag{3.2}$$

Figure 1 shows the results of this visualization. For some products, I have price data since 1967, while for others the publicly available series is much shorter. I construct multiple different versions of equation (3.2) corresponding to more inclusive balanced samples of

products. For example, the series in blue comes from a balanced sample of 22 products with continuous price data from 1967-2020, while the series in red contains a much higher number of products (107) over a shorter time period (1997-2020). For visualization purposes, I remove the volatile energy and transportation sectors from this graph (appendix figure A8 shows the results with energy and transportation).

Panel A shows the unfiltered series with NBER recession dates shown in gray, while panel B removes the trend component to produce a cyclical series following Hamilton (2018). There are some large differences between the balanced samples in the unfiltered series, but each of the filtered series track each other quite closely. Two patterns are apparent: 1) there is a large increase in the relative price of necessities during and around NBER recessions. For example, the relative price of necessities increased by approximately 5 percent during the Great Recession relative to trend. Relative necessity prices have increased in every recession since 1970 with the exception of the Volcker Recessions in the early 1980s. The second pattern 2) is that there is an increase over-time in the relative price of necessities, which might be picking up the innovation in luxuries mechanism explained in Jaravel (2019). However, this second pattern is not robust and depends on the balanced sample series used, as well as the definition of necessity. For example, if I define products as necessities or luxuries based on the consumption pattern of a particular decade (say 2010-2020) rather than pooling data from 1991-2019 together, then the cyclical pattern of relative necessity prices and recessions holds, but the trend of increasing necessity prices does not (see figures A9, A10, and A11 in the appendix).

Regression Evidence

The visual evidence in the previous subsection shows that generally relative necessity prices increase during recessions and there was a large increase in the share of aggregate expenditure devoted to necessities during the Great Recession and the subsequent slow recovery. Now I formally test the relationship between relative necessity prices/shares and aggregate economic activity using a simple regression:

$$x_{j,t} = \beta_0 + \beta_1 \mathit{Unemployment} \times R_j + \delta_t + \gamma_j + \varepsilon_{j,t}. \tag{3.3}$$

Here, the dependent variable, $x_{j,t}$ is either the log-relative price [6] of products in sector j at time t or the log-aggregate share (presented in the next subsection). [7] The dependent variable is regressed on the interaction of the unemployment rate with R_j the relative expenditure ratio, which is increasing for necessities. I also include time δ_t and sector γ_j fixed effects (which absorb the level effect in the interaction).

My regression results have several advantages over the visual evidence. For example, I no longer have to rely on a binary definition of the necessity good, since R_j is a continous variable. Also, in the regression I can control for a variety of confounding factors that may be correlated with a products income elasticity and cyclicality; For example, services have stickier prices than goods (Nakamura and Steinsson 2008) and high-income households also buy more services. Also, durable purchases are particularly sensitive to interest rates (McKay and Wieland 2021, Barsky et al. 2007) and could be another confounding factor.

Results showing the correlation between relative necessity prices and the unemployment rate are shown in table 3. Panel A replaces R_j with a binary definition of necessity, while panel B shows the results of the regression in equation (3.3). Column 1 shows the baseline results. In column 2, in order to determine that my results are not dependent on some arbitrary classification of spending into my 121 categories, I weigh each observation by the sector's share in aggregate spending. Column 3 shows the results with a balanced sample. In columns 4-6 I add in controls of the interaction of the unemployment rate with various aspects of the product j that may confound my results including whether the product is directly related to oil prices (energy and transportation), whether the product is durable, or if the product is a service. Results are highly statistically significant and around the same size in all specifications. Overall, I find that when the unemployment rate goes up by one percentage point, necessity prices increase by $1.4 - 1.8$ percent relative to other products.

3.2 Fact 2: Relative Spending on Necessities is Counter-Cyclical

Visual Evidence

[6] Relative price is defined as the BLS price series of sector j divided by the CPI.

[7] The aggregate share is defined as: $p_{j,t}q_{j,t}/X_t$ where p is the price of sector j, q is quantity purchased of sector j, and X is aggregate expenditure

Next I show how the share of aggregate expenditure for the composite necessity good changes overtime. I construct the aggregate necessity share as:

$$s_{N,t} = \frac{\sum_{j \in Necessity} x_{jt}}{X_t}. \tag{3.4}$$

In the above expression, x_j is the total aggregate expenditure in the CEX on necessity sector j and X is total non-housing expenditure in the CEX. Figure 2 shows how the aggregate necessity share changes overtime. The necessity share is fairly flat through much of the 1990s and early 2000s, with the exception of a slight increase during the mild recession of 2001. Then there is a drastic increase in the necessity share starting in 2007, the beginning of the great recession, which peaks between 2013 and 2014. It is important to point out that the unemployment rate following the financial crisis peaked after the official end of the NBER recession, and it remained above 8 percent in January 2013. Real per-capita GDP did not recover from its pre-recession peak until Q1 of 2013.

The increase in the aggregate necessity share during the Great Recession was precipitated by all income groups. Figure3 shows the percentage point increase in the average necessity share for each income quintile during the Great Recession, 2007Q3-2009Q2, and the subsequent slow recovery (2009Q2-2012Q4). All income groups increased their share of necessity consumption expenditure by at least 2.5 percentage points during this period. The increase does vary by income group, for example the lowest income quintile had the lowest increase in necessity share especially during the official NBER recession, which may indicate a lack of an ability to substitute towards more luxuries (Argente and Lee 2021). It is important to note that while the shift in necessity expenditure varied by income group, the income group ranking of necessity shares does not change; the lowest income group has the highest necessity share of expenditure during the Great Recession (around 72 percent) and the highest income quintile had the lowest (around 52 percent).

Regression Evidence

Table 4 panel A shows the correlation between the log-aggregate share of necessities and the unemployment rate. The pattern here is quite similar to the results with prices. Aggre-

gate spending shifts towards products with a higher relative expenditure ratio (necessities) when unemployment increases. This result is both statistically and economically significant, as a one percentage point increase in the unemployment rate is correlated with a 2.1-2.7 percent increase in the aggregate share devoted to products with an expenditure ratio 1-point higher than average. Panel B replaces the log-share with the log-real expenditure of a sector to show that this result is not driven mechanically via higher prices.

To summarize, I find a statistical and economic significant correlation between relative necessity prices and shares with the unemployment rate. This result is not driven by differences in the service, energy, or durability composition of necessities. In the next section, I present a mechanism that can explain these two facts.

4 A Static Model of Relative Supply and Demand

In this section, I formalize the intuition behind the cyclical demand shift mechanism. I present a static model with a necessity and a luxury sector represented by perfectly competitive firms with decreasing returns to scale. Households have non-homothetic preferences over these two sectors. This model is presented in partial equilibrium and I abstract from household labor market and savings decisions. Instead, the level of household expenditure, X, is exogenous. I show that a decline in the expenditure level, X, leads to higher equilibrium consumption shares and prices for the necessity sector.

4.1 Firms

There are two sectors $\{N, L\}$. Each sector is competitive and is represented by a firm with a homogeneous production function over labor:

$$Y_i = F(H_i). \tag{4.1}$$

I assume that F$(\cdot)$ is strictly increasing in it's first derivative $F' > 0$ and homogeneous of degree $k < 1$, which implies that the firm has decreasing returns to scale in labor. Firms

can hire labor at an exogenous fixed wage rate w. Profit maximization implies that the ratio of the wage and the sector price is equal to the marginal productivity of labor:

$$\frac{w}{p_i} = F_H(H_i). \tag{4.2}$$

Lemma 1 (see appendix), shows that the Marginal Rate of Transformation (MRT) between the two sectors is increasing (i.e. the production possibilities frontier (PPF) between the two sectors is concave). Since markets are competitive, this is akin to saying that:

$$\frac{p_i}{p_j} = \frac{F_{j,H}(H_j)}{F_{i,H}(H_i)} = \frac{F_{j,H}(F_j^{-1}(Y_j))}{F_{i,H}(F_i^{-1}(Y_i))} \tag{4.3}$$

is sloping upward in $\frac{Y_i}{Y_j}, \frac{p_i}{p_j}$ space over some range Y. Intuitively, in the short term firms can only expand by changing their labor input. If one sector expands relative to the other, they must expand by increasing their relative share of labor. An example of this type of production function pair would be $F_i(H_i) = A_i H_i^{\alpha}$ where $\alpha \in (0, 1)$ and is common across sectors (decreasing returns to scale). If both sectors are constant returns to scale then the relative marginal cost curve would be flat (and the PPF would be linear), while increasing returns to scale would lead to a downward sloping curve.

4.2 Households and Intratemporal Substitution

The representative household is given an exogenous endowment of expenditure, X. They have non-homoethetic preferences over consumption in the necessity and luxury sectors $U(c_N, c_L)$ such that for prices p_N, p_L and nominal expenditure X over some interval around X, the ordinary demand of the luxury good $C^L(\cdot)$ increases in relation to that of the necessity good with an increase in X:

$$\frac{\partial}{\partial X}\frac{C^L(X, p_N, p_L)}{C^N(X, p_N, p_L)} > 0. \tag{4.4}$$

Since we only have two goods, this implies that when X increases, the share spent on the necessity good s_N decreases.

Figure 4 shows a representation of how the relative marginal cost curves (relative supply) and relative demand could look in $(s_N, \frac{p_N}{p_L})$ space. The relative supply curve slopes upward by assumption, while the relative demand curve can slope upward or downward (as pictured, the downward sloping relative demand implies that the goods are gross substitutes). If there is a decrease in expenditure X, then relative demand for necessities will rise and the relative demand curve will shift to the right. Equilibrium necessity expenditure share and relative price will both increase.

The intuition behind figure 4 is stated formally in the following proposition (the proof is included in the appendix).

Proposition 1 *In a two-sector competitive economy with a representative household that has preferences satisfying equation* (4.4)*, strictly increasing production function in each sector both homogeneous of degree* $k < 1$ *and standard market clearing conditions, then an decrease/increase in household expenditure will lead to an increase/decrease in the relative price of necessities.* [8]

In the above proposition, the representative household is assumed to have non-homothetic consumption preferences. This is not always the same assumption as the micro-level households having non-homothetic consumption preferences. I discuss this issue in more detail in the appendix.

5 Empirical Strategy

My empirical approach centers around: (1) testing how the aggregate relative demand curve shifts in response to a macroeconomic shock and (2) measuring the slope of the relative marginal cost curve. These two questions are directly related to the assumption that the representative consumer has non-homothetic preferences and that the relative supply curve is upward sloping. In order to address both of these questions, I need a macroeconomic shock

[8] Competitiveness is a sufficient, but not a necessary condition. What is important is that firm markups do not decrease with increases in demand.

that will shift *only* the relative demand curve and leave the relative supply curve unchanged. This is important as any shock that directly affects the slope/position of the relative supply curve will obscure efforts to test its slope.

I use monetary policy shocks to test the non-homotheticity of aggregate demand and the corresponding effect on relative prices. Interest rate shocks are typically treated as demand rather than supply shocks, as they directly affect households expenditure and savings, but not relative costs across sectors.[9] This ignores the potential cost channel of monetary policy (Barth III and Ramey 2001), as well as changes in household preferences for sector products that are correlated with my necessity/luxury classification. I partially address these latter concerns in my robustness section.

Since central banks respond to macroeconomic events, making interest rate changes endogenous, there is a large literature using monetary policy news as an external shock on interest rates (Gürkaynak et al. 2004, Swanson 2021, Bauer and Swanson 2020). As my proxy for a monetary policy shock, I use the estimated monetary policy news shock from Swanson (2021). This news shock is computed by looking at the change in a variety of asset-prices in a 30-minute window around each FOMC meeting from July 1991-June 2019. I use the first principle component of changes in this vector of asset prices, which corresponds to a change in the interest rate (rather than changes to forward guidance or Quantitative Easing).

In order to test the differential response of interest changes on necessity and luxury product shares and prices, I estimate a local projection of the dependent variable (x_j) on the interaction between the monetary policy shock and the product's expenditure ratio (Jordà 2005):

$$x_{j,t+h} = \beta_0 + \sum_{k=0}^{K} \beta^k x_{j,t-k} + \gamma^h i_t \times R_j + \delta_t + \psi_j + \varepsilon_{j,t+h} \tag{5.1}$$

In the above equation, the dependent variable ($x_{j,t+h}$) is either the log-aggregate share of product j at time $t+h$ or the log-price. The coefficient of interest γ^h (the coefficient of

[9] In the textbook New Keynesian model, the interest rate appears only in the household side of the model and operates through the Euler Equation (Galí 2015)

the interaction of the monetary policy shock i_t and expenditure ratio R_J) is the differential response of sector shares/prices based on expenditure ratio, which corresponds to the Blinder-Oaxaca extension to the local projection framework discussed in Cloyne et al. (2020). I include a year of lags of the dependent variable, $\sum_{k=0}^{K} \beta^k x_{j,t-k}$, so $K = 12$. I also include time fixed effects, δ_t, which absorb the direct affect of monetary policy on shares/prices, as well as any other macroeconomic events occurring at time t. Finally, I include product fixed effects, ψ_j which control for the average level of share/prices for product j. I compute these local projections on monthly share and price series for the panel of products in my data. In the appendix, I consider alternate specifications: including lags of the interaction of the shock i_t and the expenditure ratio R_j (Ramey 2021), limiting the shock data to pre-2008 to avoid the zero-lower bound period, and including sector specific time trends. Results for these alternate specifications are shown in figure A12.

If aggregate demand responds non-homothetically to monetary policy shocks, then I would expect γ^h to be positive when the dependent variable is log-share; a positive coefficient means that products that are bought more by poor households (the expenditure ratio R_j is higher) increase in price following a contractionary monetary policy shock compared to other products (which is what my model in the previous section predicts). Furthermore, an upward sloping relative supply curve implies that γ^h in the price regression should have the same sign as γ^h in the demand regression: i.e. if γ^h is positive when the dependent variable is log-share this implies that demand shifts towards necessities (away from luxuries) after a contractionary monetary policy shock and an upward sloping relative supply curve would require γ^h to also be positive in the price-regression.

In my model presented in the proceeding section, a fall in expenditure is what causes households to shift their demand to necessities due to non-homothetic preferences. Accordingly, I test directly how the monetary news shocks affect aggregate expenditure using a simple local projection of Log-real personal consumption expenditure (PCE) on the monetary policy shock (Jordà 2005). I follow Ramey (2016) and include lags of the monetary instrument and lags of the dependent variable. I also include lags of the price level (CPI), one-year treasury yield, the unemployment rate (Leahy and Thapar 2019).

All regressions use standard errors that are clustered at the time level and are robust

to serial correlation. Results are scaled so that a one-unit monetary shock corresponds to a 25-basis point increase in the one-year treasury bill. Regressions are weighted by the pooled aggregate share of sector j in consumer spending.

5.1 Results

Figure 5 shows the impulse response functions estimated following equation (5.1). Panel (a) shows the response of the One-Year treasury yield to the monetary policy news proxy. This result was scaled so that on impact the one-year treasury increases by 25 basis points. Panel (b) shows the response of log-real consumption; consumption falls by approximately 2 percent following the monetary shock. Panel (c) shows that aggregate expenditure shifts towards necessity products following a contractionary monetary shock. The IRF peaks at around 0.1 20 months following the shock, which means that products with an expenditure ratio of 1-point higher than average increase their aggregate share by approximately 10-percent relative to other products. Finally, panel (d) shows how the relative price of necessity goods increases following the monetary contraction. A product with expenditure ratio 1 point higher than average increases in price by around 3-percent, compared to other products, 20 months following the shock. My empirical results provide evidence for the mechanism presented in my model. Following shocks that lower aggregate expenditure, aggregate spending shifts towards necessities raising their prices.

5.2 Robustness

My identifying assumption in my empirical work is that monetary shocks affect product prices differently only to the extent that they shift demand through non-homothetic preferences. However, demand for durables can be more sensitive to interest rate changes than non-durables (McKay and Wieland 2021, Barsky et al. 2007), services tend to have stickier prices (Nakamura and Steinsson 2008), and the central bank can react to oil shocks directly. As a robustness check, I perform a similar local projection to equation (5.1), but I include an interaction between the monetary policy shock and dummies for whether the product is a durable, a service, or in the energy or transportation sector (energy). Estimates of γ^h,

the differential response of necessities, with these additional controls are shown in figure 6. Results are similar to the baseline for both shares and prices, with the exception of the price response when the energy interaction is included. Here necessity prices respond slower, but more persistently compared to the baseline set of local projections.

6 New Keynesian Model with Non-homothetic consumption preferences

I have already formally presented my cyclical demand shift mechanism, and shown that this mechanism is qualitatively consistent with my empirical results. In this section, I show that my theoretical results also quantitatively match the cyclical behavior of necessity prices and aggregate shares in the data. I include non-homothetic consumption preferences in a two-sector New Keynesian model with sticky wages and calibrate this model to the U.S. economy in 2005-2006. I then use my model to examine the welfare consequences of the cost-of-living channel of recessions for low- and high-income households.

6.1 Households

Household preferences follow the Almost Ideal Demand System (AIDS) first introduced by Deaton and Muellbauer (1980). I choose AIDS for two reasons: (1) my model relies on aggregate demand shifts and since AIDS is a form of PIG-Log preferences, they are within the Generalized Linear Class of preferences and can be aggregated (Muellbauer 1975). Aggregation is a clear advantage over other types of non-homomthetic demand systems, such as the Non-homothetic CES system presented in Comin et al. (2021). AIDS aggregation properties allows me to estimate aggregate parameters using micro-data, since the parameters for the representative household and the micro-level households are the same. The second reason, (2) is because the Almost Ideal Demand System was originally designed to be extremely flexible, in fact it is a first-order approximation to any demand system (Deaton and Muellbauer 1980).[10]

[10]A disadvantage is that the AIDS is not generally regular. There are levels of expenditure and prices for which AIDS is not a valid utility function. However, this is not an issue for the calibration and expenditure

The functional form for the household level indirect utility function is:

$$V(X^h, \mathbf{p}) = \left(\frac{X}{a(\mathbf{p})}\right)^{1/b(\mathbf{p})} \tag{6.1}$$

where $a(\mathbf{p})$ and $b(\mathbf{p})$ are price aggregators over a vector of sector level prices $\mathbf{p}$ defined by:

$$log(a(\mathbf{p})) = a_0 + \sum_k a_k \log(p_k) + \frac{1}{2}\sum_j \sum_k \gamma_{jk} \log(p_j) \log(p_k) \tag{6.2}$$

$$\log(b(\mathbf{p})) = \sum_j \beta_j \log(p_j) \tag{6.3}$$

Where γ_{jk} are cross-price semi-elasticities and β_j are expenditure semi-elasticites. Parameters have the following restrictions: $\sum_{j=1}^{N} a_j = 1, \sum_{j=1}^{N} \beta_j = \sum_{j=1}^{N} \gamma_{jk} = 0$ and $\gamma ij = \gamma ji \ \forall i, j$.

The indirect utility function equation (6.1) has a corresponding cost function:[11]

$$\log c(u_h^0, \mathbf{p}) = log(a(\mathbf{p})) + (b(\mathbf{p})) \log(u_h). \tag{6.4}$$

The cost function shows that households must pay some cost for subsistence level consumption $\log(a(\mathbf{p}))$, where $a(\mathbf{p})$ is a homothetic translog price aggregator. The second aggregator, $b(\mathbf{p})$ introduces non-homotheticities into the cost-function. A household's cost to reach a higher level of utility (expenditure) increases with $b(\mathbf{p})$. This allows me to construct the theoretically consistent non-homothetic price index for a household with fixed utility u_h :

$$\log P\left(\mathbf{p}^1, \mathbf{p}^0, u_h^0\right) = \log\left(\frac{a(\mathbf{p}^1)}{a(\mathbf{p}^0)}\right) + \log\left(u_h^{b(\mathbf{p}^1) - b(\mathbf{p}^0)}\right) \tag{6.5}$$

levels that I study.

[11] This functional form differs from the cost function in Deaton and Muellbauer (1980) due to a slight change in the definition of b(p). If written out fully, the two cost functions are identical

The greater the household's utility (expenditure) x^h the higher the welfare gain from reductions in $b(\mathbf{p})$. Similarly, households with low-expenditure level have changes in the cost of living closer to changes in the subsistence price index $a(\mathbf{p})$.

Roy's identity applied to equation (6.1) yields the following Marshallian demand share for products in sector j:

$$s_j = a_j + \sum_k \gamma_{jk} \log(p_k) + \beta_j \left(\frac{x^h}{a(\mathbf{p})} \right). \tag{6.6}$$

A households share of expenditure on a particular product j is dependent on prices and real expenditure level. The demand share increases with real expenditure if $\beta_j > 0$ (luxuries). The households expenditure elasticity for good j is $1 + \frac{\beta_j}{s_j}$, while the cross price elasticity is $\delta_{jk} + \frac{\gamma_{jk} - \beta_j(\alpha_j + \sum_k \gamma_{jk} \log(p_k))}{s_j}$ where δ_{jk} is the Kronecker delta term.

As shown in (Muellbauer 1975, Deaton and Muellbauer 1980) a collection of households with PIG-Log preferences can be represented by a household with income $X^r = X^{mean} exp\left(\sum \frac{x^h}{X^{mean}} \ln \left(\frac{x^h}{X^{mean}} \right) \right)$ where the term on the right $\left(\sum \frac{x^h}{X^{mean}} \ln \left(\frac{x^h}{X^{mean}} \right) \right)$ is the Theil index of the expenditure distribution. This index increases with inequality.

Household intratemporal aggregate demand can be represented completely by the representative household. Intertemporal decisions can also be represented by a representative household assuming that shocks do not affect expenditure inequality. While there has been extensive work showing that households intertemporal responses vary based on income level (see Kaplan, Moll, Violante (2018) for an example), heterogeneous intertemporal responses is not the key feature of this paper.[12] In practice, I solve for equilibrium prices and aggregate shares using the representative household. I can then back out household level price indices given aggregate prices. This approach has the advantage of being able to study welfare effects with heterogeneous consumption bundles using the large toolbox of solution methods for representative agent models.

[12]Some macroeconomic policies such as the 2020 and 2021 stimulus checks could have first order effects on relative prices, as only low to moderate income individuals were given checks. If low-income household expenditure increases sufficiently after such a policy then the Theil Index could rise enough to partially offset aggregate increases in expenditure.

The representative household chooses consumption expenditures to maximize their sum of discounted indirect utility over time.

$$\mathbb{E}_0 \sum_{t=0} \beta^t \left[V(X_t, \mathbf{p}_t) - g(H_t) \right]. \tag{6.7}$$

where $g()$ is the disutility of labor and H is hours worked.

The representative household works for wages W_t and can invest in a one-period nominally riskless bond B_t that pays one monetary unit in the next period at price Q_t. The resulting household budget constraint and the no-ponzi scheme condition are shown below:

$$\begin{aligned} X_t + Q_t B_t &\leq Z_t B_{t-1} + W_t H_t + D_t \\ \lim_{T \to \infty} \mathbb{E}_t \left(\Lambda_{t,T} B_t \right) &\geq 0. \end{aligned} \tag{6.8}$$

In the above expression, D_t is a dividend from firm profits and $\Lambda_{t,T} = \beta^{T-t} \frac{V_{X,T}}{V_{X,t}}$ where β is the discount factor. Z_t, is an interest rate wedge shock that is distributed $i.i.d$ and acts to dampen or increase a household's per-period expenditure.

The household's optimization problem and budget constraint yield the following Euler Equation:

$$Q = \beta \mathbb{E}_t \left[\frac{a(\mathbf{p}) b(\mathbf{p})}{a(\mathbf{p'}) b(\mathbf{p'})} \frac{\left(\frac{X'}{a(\mathbf{p'})} \right)^{\frac{1}{b(\mathbf{p'})} - 1}}{\left(\frac{X}{a(\mathbf{p})} \right)^{\frac{1}{b(\mathbf{p})} - 1}} \right] Z. \tag{6.9}$$

I assume that the disutilty of labor takes the familiar form (with ϕ the inverse of the Frisch elasticity of labor supply):

$$g(H_t) = \frac{H_t^{1+\phi}}{1+\phi}. \tag{6.10}$$

However, households do not decide how much labor to provide. Rather, they allow a labor

union to bundle and sell their labor, which introduces sticky wages and nominal rigidity (see Erceg et al. (2000) , Auclert et al. (2018), Auclert et al. (2020) , Broer et al. (2020), Ramey (2020)). The appendix shows that the Wage-Phillips curve is:

$$\begin{aligned}(1+\pi_t^w)\pi_t^w =& \beta \mathbb{E}_t\left[(1+\pi_{t+1}^w)\pi_{t+1}^w\right] \\ &+ \left(\frac{\epsilon_w}{\psi_w}\right)\left(H_t^\phi - \left(\frac{\epsilon_w - 1}{\epsilon_w}\right)\frac{W_t}{a(\mathbf{p}_t)b(\mathbf{p}_t)}\left(\frac{X_t}{a(\mathbf{p}_t)}\right)^{(1/b(\mathbf{p}_t))-1)}\right)\end{aligned} \tag{6.11}$$

6.2 Firms

There is a necessity and a luxury sector. Each sector has flexible prices and perfect competition. Firms take only labor as an input and has decreasing returns to scale; firms can scale up labor in the short run, but other factors of production are constrained. The production function for the representative firm in sector i is:

$$Y_t(i) = A_{it} H_t(i)^{(1-\alpha)} \ \alpha \in (0,1). \tag{6.12}$$

Firms sell their good for price $p_t(i)$ in a competitive market. Firms take prices and wages as given. Firm optimization implies that:

$$p_t(i) = \frac{W_t}{(1-\alpha)\, A_{it} H_t(i)^{\alpha}}. \tag{6.13}$$

This yields a relative supply curve, that is upward sloping:

$$\frac{p_t(i)}{p_t(j)} = \frac{A_{jt} H_t(j)^{\alpha}}{A_{it} H_t(i)^{\alpha}}. \tag{6.14}$$

The elasticity of marginal cost to an increase in output, which governs the slope of the relative supply curve, is $\frac{\alpha}{1-\alpha}$.

6.3 Equilibrium

An equilibrium for this model is defined as as series of prices $\{W_t, \mathbf{p}_t\}$ and quantities $\{Y_{N,t}, Y_{L,t}, H_t, \mathbf{h}_{j,t}, X_t, D_t, \mathbf{s}_{j,t}\}$ such that households optimize intertemporally and intratemporally given prices, the union chooses labor to maximize household utility, firms maximize profits given prices, and markets clear.[13]

6.4 Calibration

The two most important parameters for my results are $\beta_L = -\beta_N$ the degree of non-homotheticity, and α, which is one minus the labor share. The first is important since it governs the degree to which representative household spending shifts between sectors over the course of the business cycle. A value of $\beta_L = -\beta_N = 0$ would imply that the household has homothetic preferences and macroeconomic shocks would not affect the relative demand for necessities or luxuries. The second, α, controls the price response of the expanding sector.

In my baseline calibration, I choose β_L so that the steady state necessity share for low and high income households in the model match that of low- and high-income households in the data. In an alternate calibration, I estimate β_L and the other (AIDs) parameters directly from the micro data; the results of this alternate calibration are in the appendix.

There are a variety of estimates of α, the capital share, in the literature. These can range from as low as 0.16, the implied value based on the estimated elasticity of marginal cost to quantity produced from Feenstra and Weinstein (2017), to as high as 0.37 estimated directly in Fernald (2014). For my baseline specification, I choose α as the midpoint of these extreme values ($\alpha = 0.26$). Alternate calibrations with other values of α are included in the appendix.

The remaining parameters I either take from the literature, or from targeting the steady-state expenditure and necessity share of the representative agent to match representative expenditure and aggregate necessity shares in the period immediately preceding the great

[13]There is also a central bank that uses a Taylor rule to set interest rates:

$$-\log(Q_t) = i_t = F(\pi_t^w) \tag{6.15}$$

where $F(\cdot)$ is increasing in wage inflation.

recession (2005-2006).[14] Table 5 shows my chosen calibration.

6.5 Results

How well is my calibrated model able to explain the distribution of household consumption and historical changes in necessity shares and prices? I start by comparing the steady state necessity shares in the model, with those in the data. While I targeted the aggregate steady state share of necessities and those from the top and bottom income groups, the necessity share of the other income groups were not targeted. Figure 7 shows the model implied necessity shares for my five different income groups alongside their actual values in the data (2005-2006). In the data, low-income households spend around 70 percent of their budget on necessities compared to around 50 percent for high income households, which by design the model matches quite well (within one percentage point). The model also matches the necessity shares for the non-targeted income groups within 1.5 percentage points.

6.5.1 Historical Simulation

How well does my model predict necessity prices and shares overtime? As a validation exercise, I shock the model with a series of i.i.d. interest wedge shocks, so that the expenditure series in the model exactly matches the filtered real personal consumption series from the BEA. I then compare the necessity share and price series in the simulated model with their filtered counterparts in the data. Figure 8 shows the results of this simulation. The data series of prices and shares exclude the volatile energy and transportation sectors.

The top panel shows the path of both model and data expenditure from 1994-2019. The second panel shows the untargeted model necessity share series compared to the data. Similar to the data, the model necessity share series falls during the 1990s, rises around the time of the 2001 recession, falls again during the housing boom and then increases drastically during the great recession. The time series in the model and data are highly correlated (0.57) and a simple regression of the data series on the model series yields a coefficient of 0.6 (R^2 of 0.32).

[14] Representative expenditure in the data is average expenditure multiplied by the calculated Theil index.

The bottom panel compares relative necessity prices in the data with the cyclical component of the composite necessity price in the data. I use a balanced sample of products with continuous price data from 1997-2019 (this is the red series in figure 1).[15] The data and the model series match each other quite closely. In fact, a simple regression of the data series on the model series yields a coefficient of 0.56 and an R-squared of 0.57.[16] I conclude that the model is highly effective at predicting the cyclical path of relative necessity shares and prices.

Next I simulate the response of the model to a monetary policy shock. Households are hit with a series of i.i.d monetary shocks so that the IRF of expenditure in the model matches the IRF of expenditure in section 5. I then compare the response of the aggregate necessity share and relative price of necessities in the model, with their counterparts in the data. I slightly adjust my baseline empirical specification in section 5, so that the main coefficient is that of the interaction of the monetary shock with a binary variable equal to zero if the product is a necessity (rather than the continuous expenditure ratio used in section 5), so that both the model and the empirical section can be interpreted as the relative share/price response of a single necessity good.

Figure 9 shows the results of the monetary policy shock analysis. In this figure, the confidence intervals for the model are constructed by shocking the model with i.i.d shocks so that expenditure in the model matches the top or bottom confidence interval of expenditure in the empirical IRF. The model does a good job at matching the IRF of relative prices; the confidence intervals for the model and the data overlap throughout the entire horizon. The model does poorly at matching the IRF of necessity shares for the center part of the horizon, as it is not able to replicate the large shift in necessity shares that happens about four to seven quarters after the shock; however, the model does a good job at matching the early and late part of the IRF.

[15] Filtering requires dropping early years so the cyclical series begins in 2001

[16] Correlation coefficient is 0.72.

6.5.2 Welfare Implications

What are the welfare implications of this model? In this model, the expenditure inequality of households is fixed at the steady state level. However, households price indices can diverge since low-expenditure households spend more of their budget in the necessity sector. How much can this matter? Table 6 shows the difference in the non-homothetic price index (equation (6.5)) between households with expenditure matching expenditure in the bottom income quintile with expenditure in the top quintile. During the great recession, the price index of poor households increased by 0.88 percent more than rich households. This result actually closely matches the difference in the change in core inflation in the data over this same period (0.86 see figure A6). Failing to incorporate changes in the price index could lead to large underestimates of the change in consumption inequality over the Great Recession. For example, Krueger et al. (2016) use the PSID and find that household consumption in the first wealth quintile fell by approximately 0.3 percent more than consumption in the highest quintile from 2006-2010. A back of the envelope calculation suggests that the change in real consumption is $\Delta \ln\left(\frac{c}{p}\right) = \Delta \ln(c) - \Delta \ln(p) = 0.0118$ or 1.18 percent, which is a fourfold increase compared to Krueger et al. (2016).

While the model predicts that this price index gap will eventually close (as the model returns to steady state), the price index of the lowest income quintile remains elevated during the slow recovery (GDP per-capita did not return to pre-great recession levels until 2013Q1). The average difference in the cost of living from the beginning of the great recession until GDP per-capita recovered is 0.5 percentage points.

Next, I calculate the expenditure equivalent welfare loss of the Great Recession for both poor and rich households. This measure is the present discounted value of all future expenditure streams that the household would relinquish in order to avoid the Great Recession:

$$\mathbb{E}^{No\ Recession}\left[\sum_{t=0}^{\infty}\beta^t\left(V((1-\xi)X_t,\mathbf{p}_t)-g(H_t)\right)\right]=\mathbb{E}^{Recession}\left[\sum_{t=0}^{\infty}\beta^t\left(V(X_t,\mathbf{p}_t)-g(H_t)\right)\right] \tag{6.16}$$

where ξ is the share of all future expenditure the household would relinquish so that the

present discounted value of all future utility streams is equal in the counter-factual world where the Great Recession never happens. Table 6 shows that poor households would be willing to give up 0.62% of all future expenditure, while rich households would relinquish only 0.52%, a difference of nearly 20%!

7 Conclusion

In this project, I present new evidence on the cyclical behavior of necessity and luxury prices. I create a new dataset combining dis-aggregated CPI price indices with micro-level CEX data and I find that the prices and aggregate shares of products bought relatively more by low-income households are counter-cyclical. I show that these facts likely come via demand shifts by testing how aggregate necessity prices and shares respond to monetary policy shocks. I show that these empirical facts can jointly be reconciled by a model with non-homothetic preferences and an upward sloping relative supply curve. My calibrated model is able to explain over 70 percent of the cyclical variation of necessity prices. My results imply that the standard disinflation seen in most recessions, actually may only hold for wealthier households.

It is important to note, that my project studies changes in sector-level prices rather than prices within a sector; e.g. furniture is a category made up of many different micro-products with their own quality and prices. My project also ignores product entry and exit, which could also impact income-level cost-of-living (Feenstra 1994). To the extent that cyclical demand shifts occur within product categories, causing price increases for low-quality products or changes in product variety (at the business cycle frequency) is a topic for future research.

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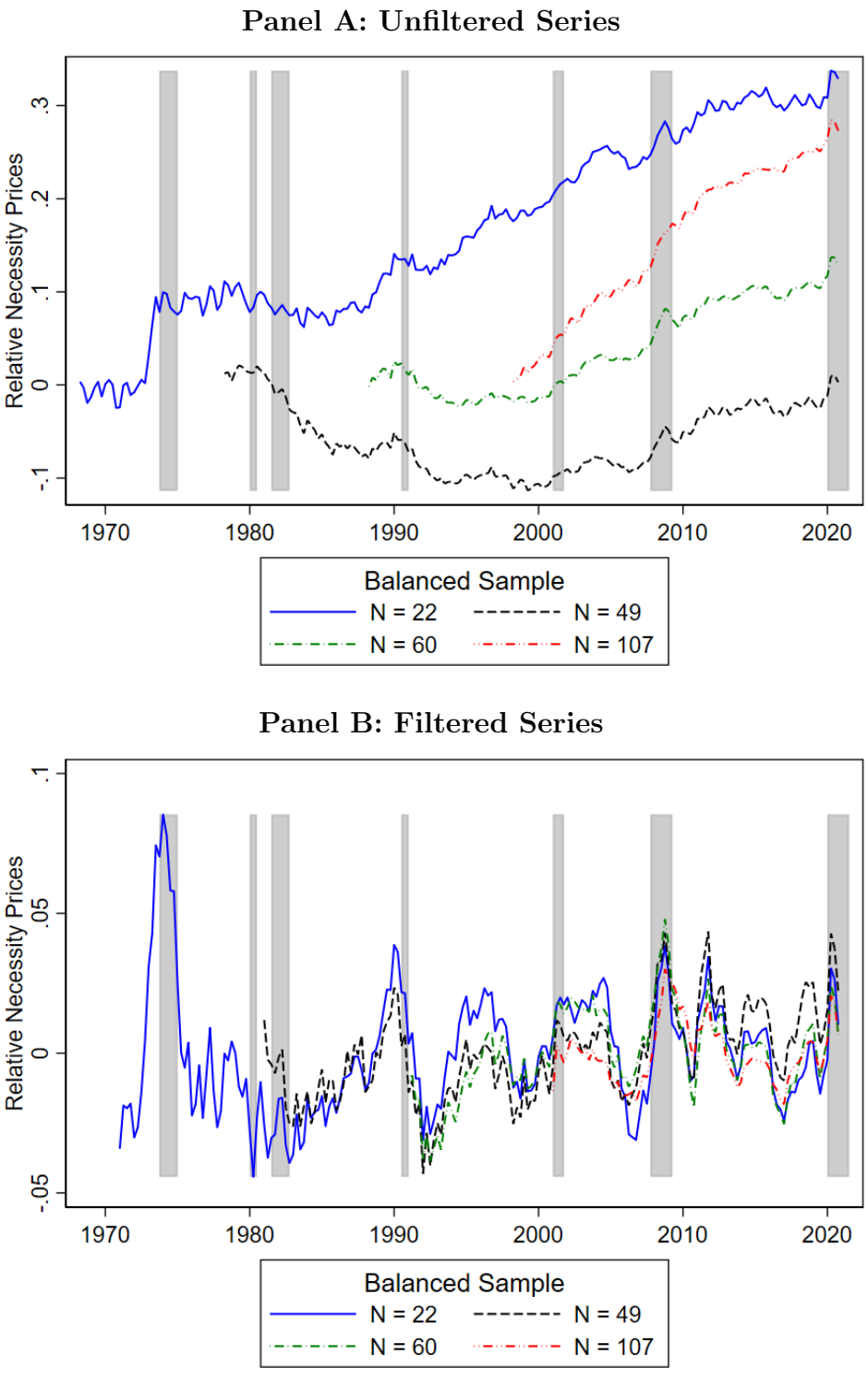
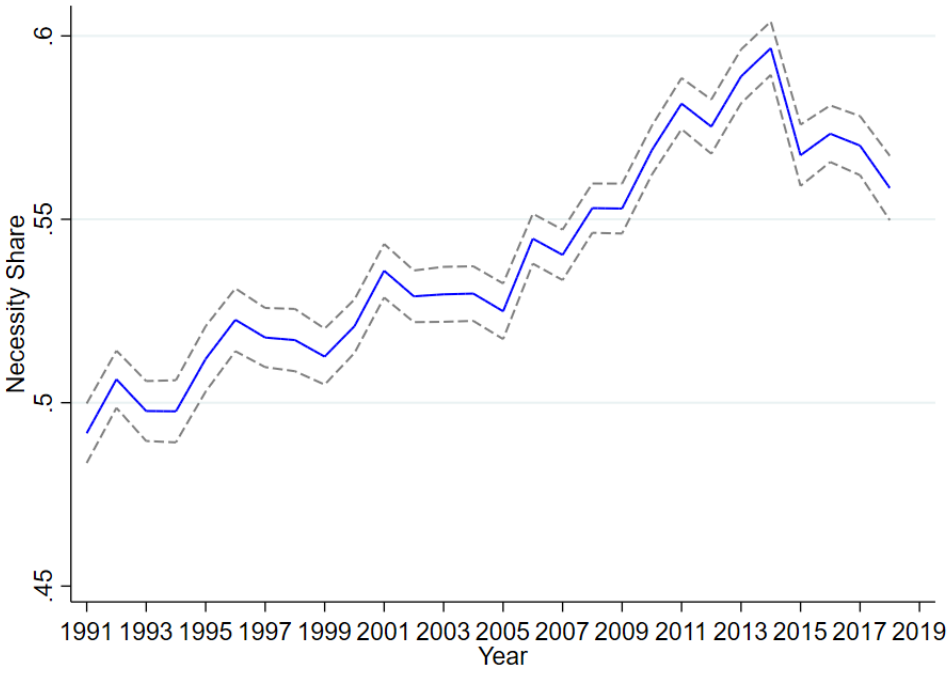
Figure 1: Relative Necessity Prices



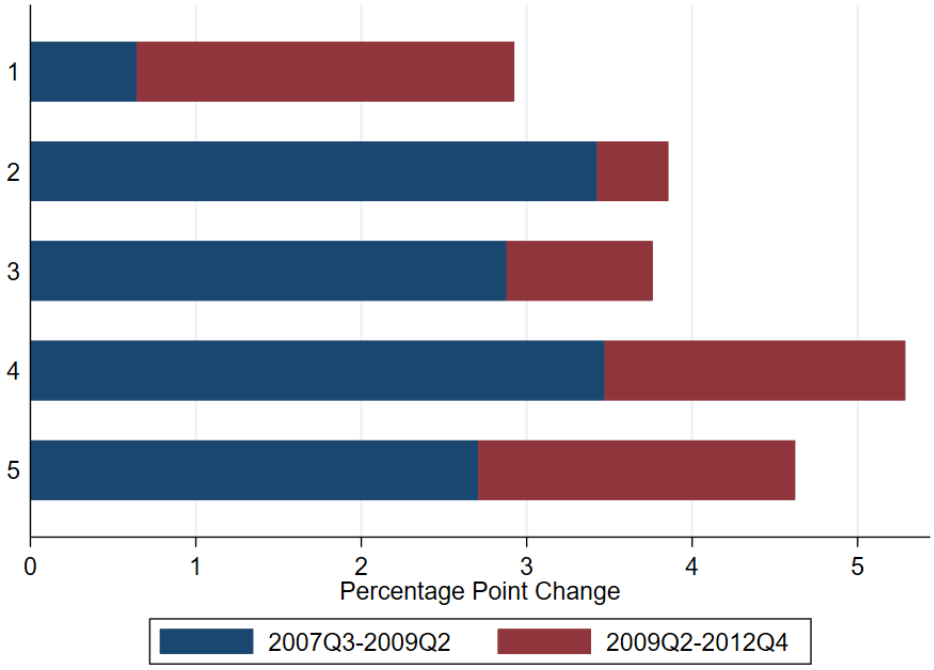
Source: Bureau of Labor Statistics and Author's own calculations. Excludes housing and energy. Data filtered following Hamilton (2018). Shaded area indicates NBER Recessions.

Figure 2: Necessities: Share of Aggregate Expenditure



Source: Consumer Expenditure Survey and Author's own calculations. Excludes housing.
Note: Shaded lines indicate bootstrapped 90-percent confidence interval.

Figure 3: Great Recession: Change in Necessity Share by Income Quintile



Source: Consumer Expenditure Survey and Author's own calculations. Excludes housing.

Figure 4: Relative supply and relative demand

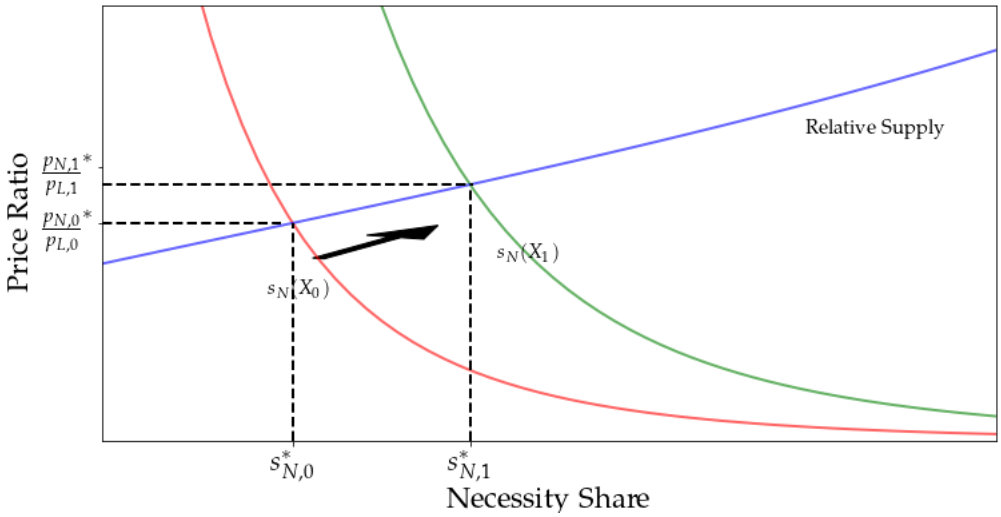
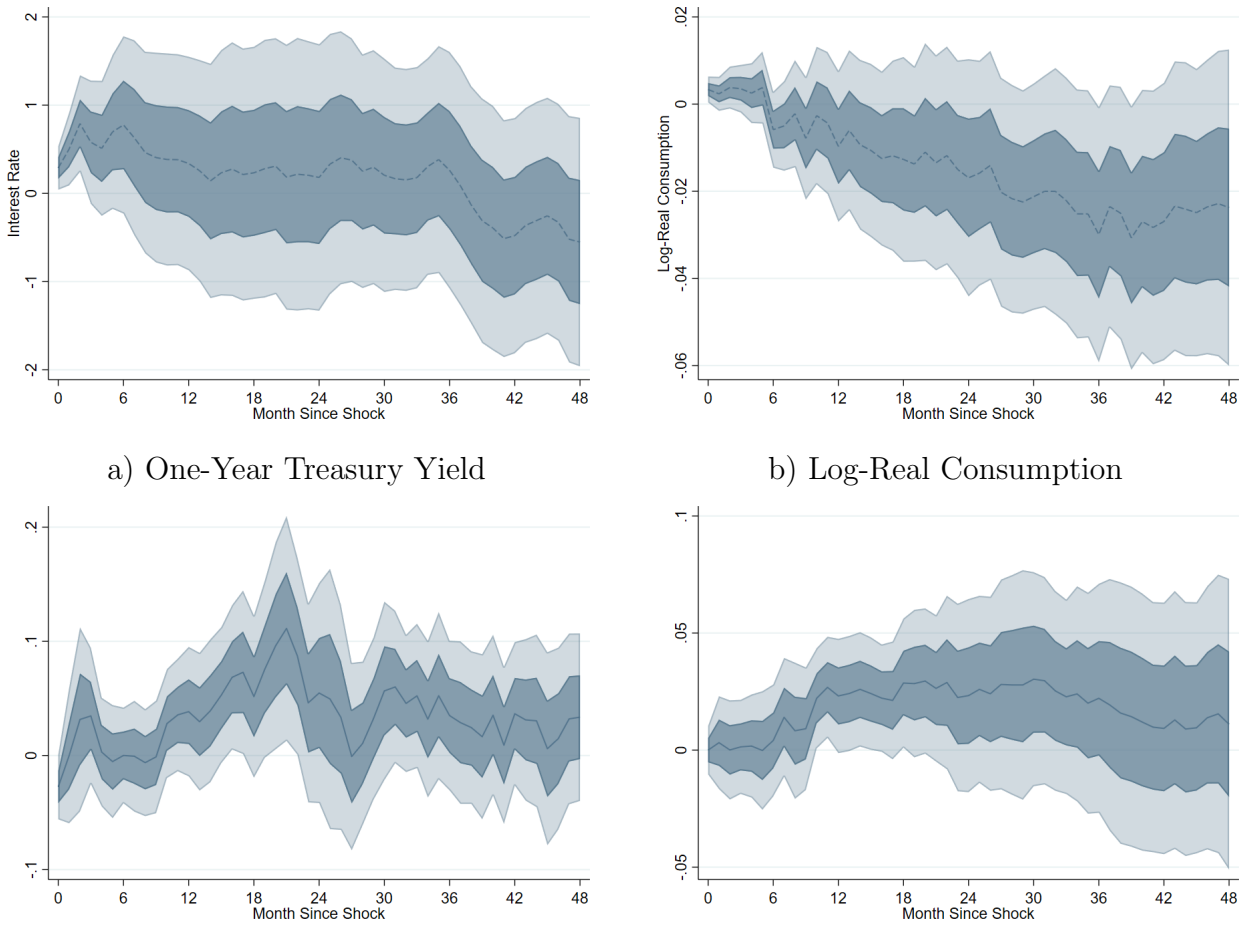


Figure 5: IRFs: Response to Monetary Policy Shock



a) One-Year Treasury Yield

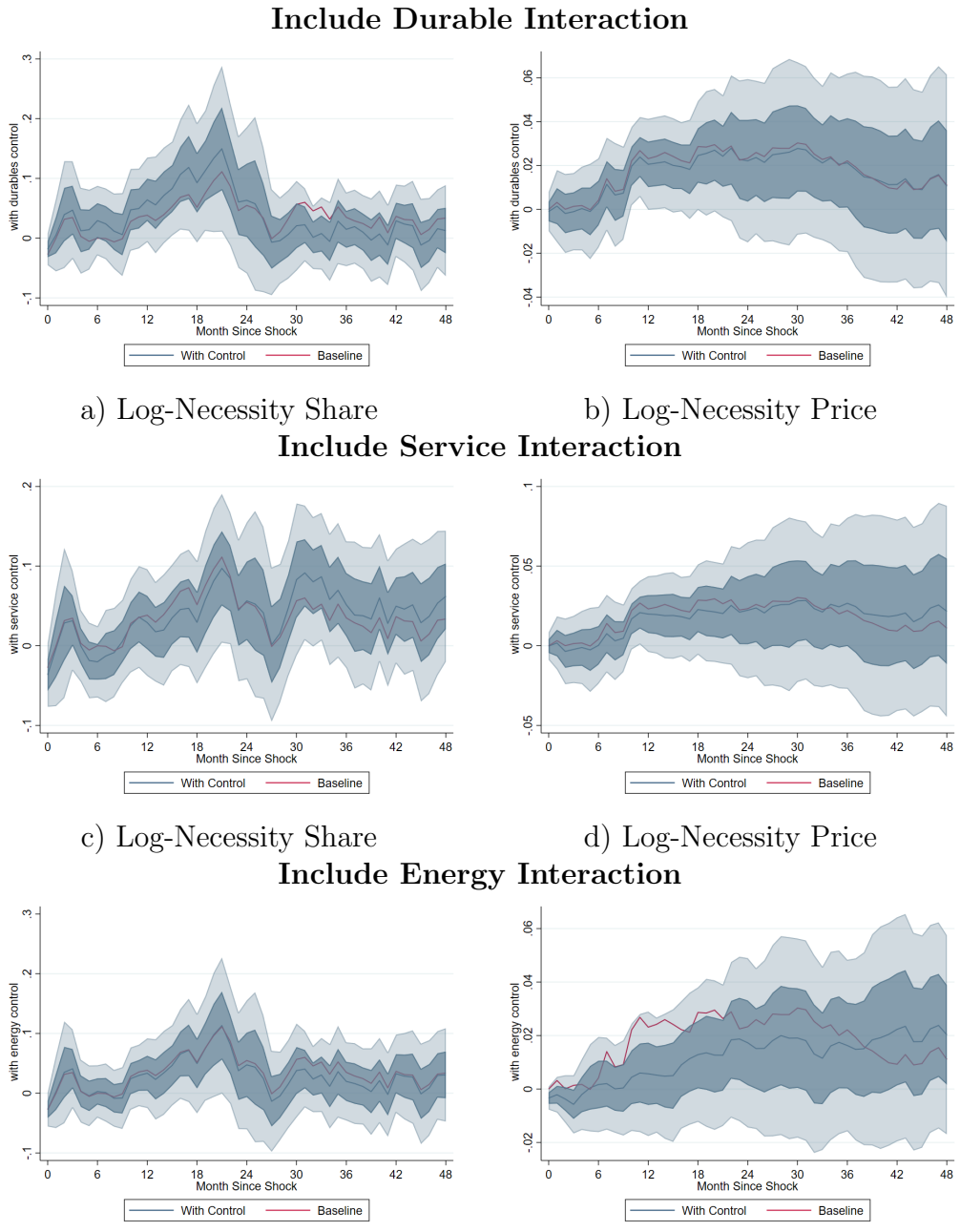
b) Log-Real Consumption

c) Log-Necessity Share

d) Relative Log-Necessity Price

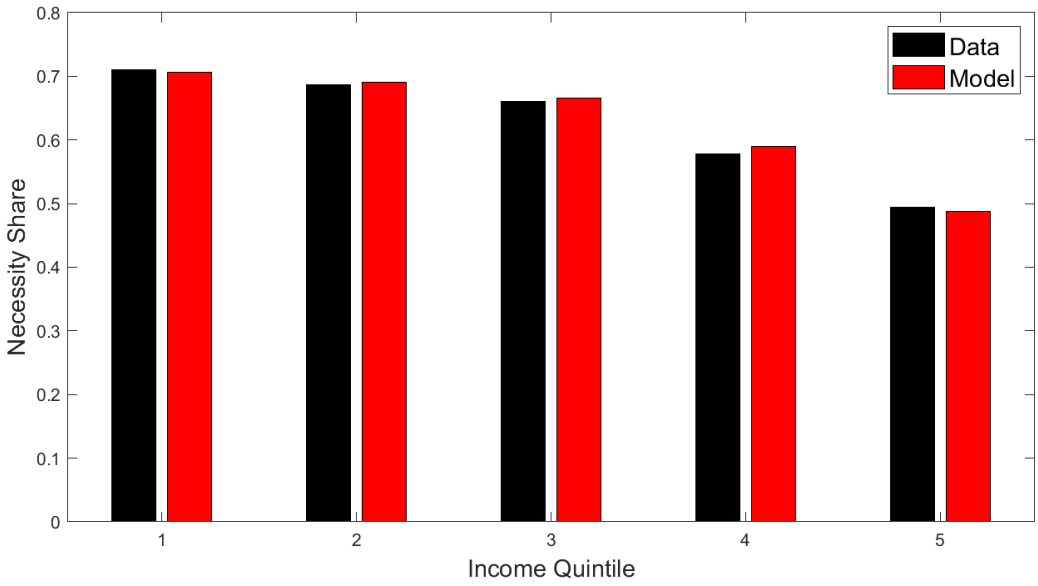
Note: Data from 1991-2019. Estimated coefficients from Local Projections explained in section 5. The unit of observation is the month in panels a) and b), and the sector-month in c) and d). Robust standard errors are shown by one- and two- standard error confidence bands indicated by the dark and light shaded areas respectively. Standard errors clustered at the monthly level for panels c) and d). Sectors weighted by their share in pooled aggregate expenditure. Monetary Policy shock normalized to 25-basis point increase in 1-year treasury in month $t = 0$. Figure d) uses a balanced sample of 60 sectors with price data available for the entire period.

Figure 6: IRF Robustness Checks: Response to Monetary Policy Shock



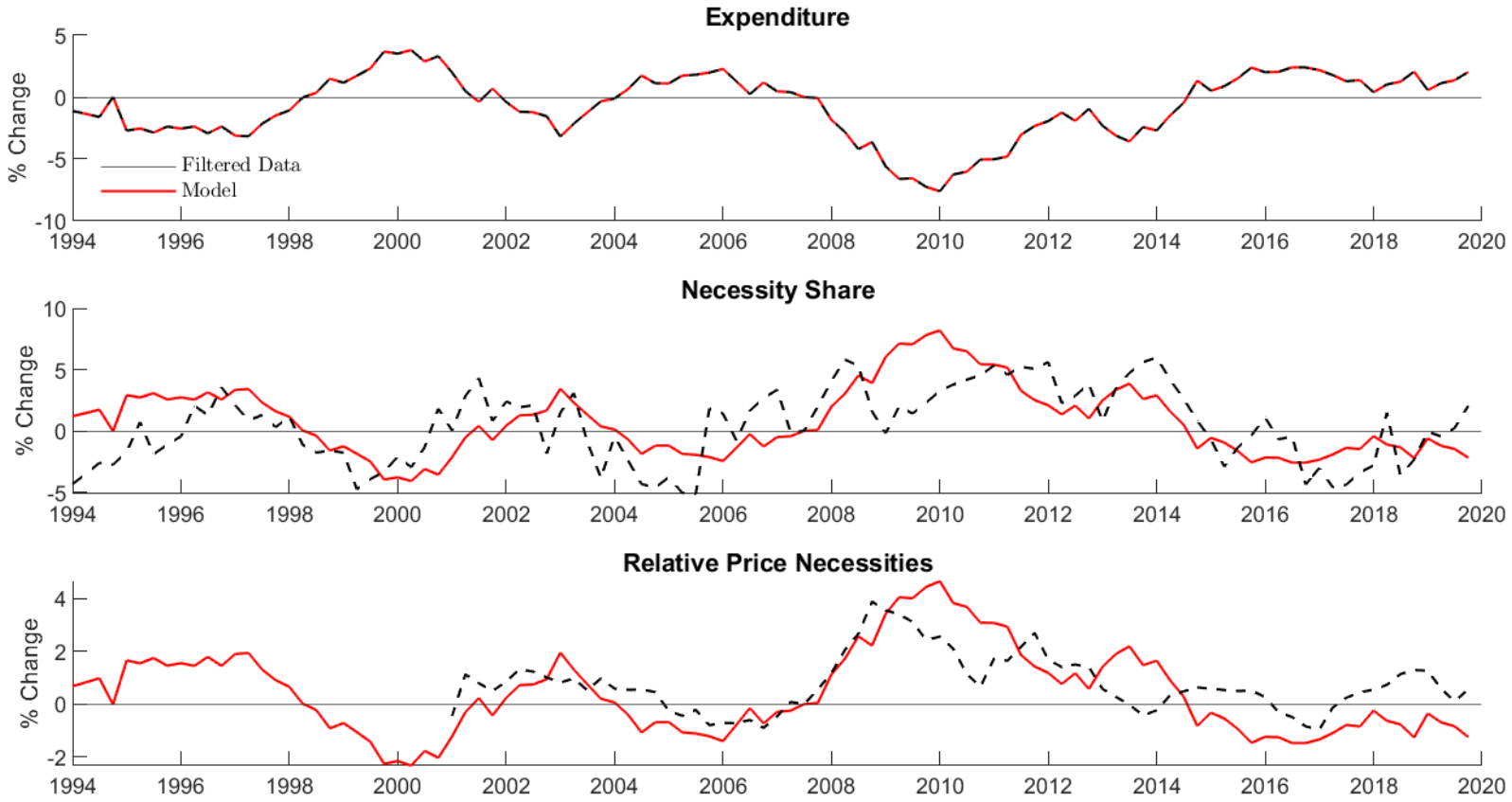
Note: Data from 1991-2019. Estimated coefficients from Local Projections explained in section 5. The unit of observation is the sector-month. Robust standard errors clustered at the monthly level are shown by one- and two- standard error confidence bands indicated by the dark and light shaded areas respectively. Sectors weighted by their share in pooled aggregate expenditure. Monetary Policy shock normalized to 25-basis point increase in 1-year treasury in month $t = 0$. When the dependent variable is log-price a balanced sample is used of 60 sectors with price data available for the entire period.

Figure 7: Model and Data: Necessity Shares by Income Group



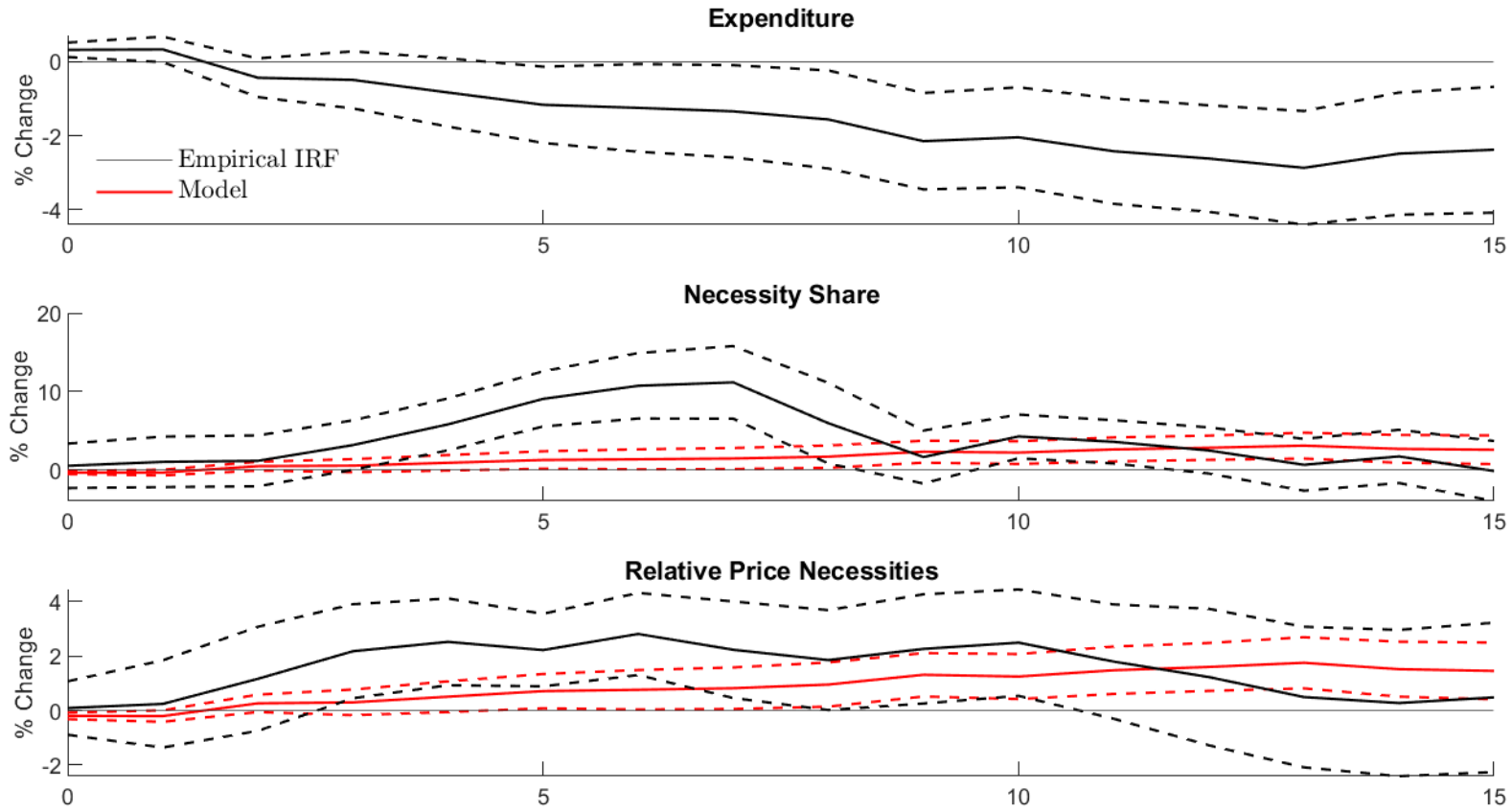
Note: Data from 2005-06. Model income-group shares at steady state. Author targeted calibration so model necessity shares for the top and bottom income quintiles would match empirical necessity shares. Necessity shares for the middle income quintiles are untargeted.

Figure 8: Model v. Data: Historical Simulation



Author targeted shock to match expenditure data (top panel). Necessity share and relative necessity price are untargeted. Data is filtered following Hamilton (2018) and excludes energy.

Figure 9: Model v. Data IRF to Monetary Policy Shock



Author targeted monetary shock so simulated model matched expenditure data (top panel). Necessity share and relative necessity price are untargeted. Empircal IRF displays estimates of the coefficient on the interaction between the monetary shock and a dummy for necessities. The one standard error confidence intervals are denoted by shaded black lines. The confidence intervals for the model estimates are constructed by targeting the monetary shock so the model's expenditure matched the low/high empirical confidence bands.

Tables

Table 1: Top luxury and necessity products

Panel A: Top Luxury Goods		
CPI Category	**Expenditure Ratio**	**Aggregate Share**
Club memberships for shopping clubs, fraternal, or other organizations	0.30	0.0033
Other Lodging away from home including hotels, and motels	0.33	0.0080
Day care and preschool	0.33	0.0075
Pet services	0.35	0.0081
Other intercity transportation	0.35	0.0021
Fees for lessons or instruction	0.35	0.0059
Airline Fares	0.36	0.0083
Other Furniture	0.38	0.0019
College tuition and fees	0.40	0.0130
Nursing homes and adult day services	0.40	0.0003
Panel B: Top Necessity Goods		
CPI Category	**Expenditure Ratio**	**Aggregate Share**
Cigarettes	3.35	0.0085
Tobacco products other than cigarettes	1.74	0.0083
Electricity	1.70	0.0312
Intracity transportation	1.59	0.0020
Food at Home	1.53	0.1202
Water and sewerage maintenance	1.46	0.0010
Prescription drugs	1.44	0.0054
Telephone services	1.41	0.0003
Boys' and girls' footwear	1.39	0.0012
Gasoline (all types)	1.38	0.0477

Source: Consumer expenditure survey and author's own calculations.
Note: Expenditure ratio is defined as the average expenditure share of households in the bottom income group divided by the average expenditure share of households in the top income group.

Table 2: Descriptive statistics for luxuries and necessities

Descriptive Stats		
	Necessity	**Luxury**
Number	30	89
Number Durables	2	34
Number Services	17	34
Number Energy	5	4
Average Share Aggregate Expenditure	0.013	0.004
Percent Expenditure Durables	12%	30%
Percent Expenditure Services	36%	58%
Percent Expenditure Energy	22%	3 %

Note: These 119 products exclude the two housing products: rent and owners equivalent rent. Energy: denotes that the product is part of the energy or transportation sectors.

Table 3: Relationship Unemployment and Relative Necessity Prices

Panel A: Binary Necessity Good

	Log-Relative Price					
	(1)	(2)	(3)	(4)	(5)	(6)
Right hand side variables:						
UR × Necessity	0.017	0.016	0.014	0.013	0.016	0.018
	(.0097)	(.0040)	(.0091)	(.0090)	(.0047)	(.0081)
UR × Energy				0.027		
				(.0087)		
UR × Durable					−.0061	
					(.0021)	
UR × Service						−.0065
						(.0019)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	No	Yes	No	No	No	No
Balanced Sample	No	No	Yes	No	No	No
Observations	48,802	48,802	23,760	48,802	48,802	48,802

Panel B: Scale by expenditure ratio

	Log-Relative Price					
	(1)	(2)	(3)	(4)	(5)	(6)
Right hand side variables:						
UR × Rel. Exp. Ratio	0.019	0.021	0.015	0.016	0.018	0.019
	(.0008)	(.0004)	(.0009)	(.0007)	(.0004)	(.0009)
UR × Energy				0.028		
				(.0010)		
UR × Durable					−.0065	
					(.0022)	
UR × Service						−.0041
						(.0020)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	No	Yes	No	No	No	No
Balanced Sample	No	No	Yes	No	No	No
Observations	48,802	48,802	23,760	48,802	48,802	48,802

Notes: The unit of observation is the sector-month. Rel. Exp. ratio is the ratio of expenditure shares of poor over rich households for the sector. Necessity good is defined as a sector with an expenditure share over one. Relative prices are the sector level CPI divided by the CPI-U. Standard errors, in parentheses, are clustered at the time level and are robust to auto-correlation. The balanced sample are 59 sectors with continuous price data from 1987-2020.

Table 4: Relationship Unemployment and Relative Necessity Shares

Panel A: Relative Necessity Shares and UR

	Log-Share				
	(1)	(2)	(3)	(4)	(5)
Right hand side variables:					
UR × Rel. Exp. Ratio	0.027	0.027	0.026	0.021	0.028
	(.0060)	(.0036)	(.0052)	(.0044)	(.0065)
UR × Energy			0.018		
			(.012)		
UR × Durable				−.021	
				(.0081)	
UR × Service					0.015
					(.012)
Sector FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Weighted	No	Yes	No	No	No
Observations	41,324	41,324	41,324	41,324	41,324

Panel B: Relative Necessity Real Expenditure and UR

	Log-Real Expenditure				
	(1)	(2)	(3)	(4)	(5)
Right hand side variables:					
UR × Rel. Exp. Ratio	0.013	0.010	0.014	0.012	0.013
	(.0061)	(.0044)	(.0063)	(.0050)	(.0063)
UR × Energy			−.0070		
			(.0043)		
UR × Durable				−.0050	
				(.0015)	
UR × Service					0.0080
					(.0083)
Sector FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Weighted	No	Yes	No	No	No
Observations	35,274	35,274	35,274	35,274	35,274

Notes: The unit of observation is the sector-month. Exp. ratio is the ratio of expenditure shares of poor over rich households for the sector.Standard errors, in parentheses, are clustered at the time level and are robust to auto-correlation. Share is defined as the aggregate expenditure on sector j divided by total aggregate expenditure. Real Expenditure is aggregate expenditure on sector j normalized by the sector specific price index.

Table 5: Baseline Calibration

Parameter	Desc.	Value	Source
α	Capital Share	0.26	(mean Fernald (2014) and Feenstra and Weinstein (2017))
β	Discount Rate	.99	
ϕ	Inverse Frisch Elasticity	1	
ψ_w	Wage Adjustment Penalty	20.7	(Wage Phillips Slope 0.29 Galí and Gambetti (2019))
ϵ_w	Substitutability of labor	6	(Colciago 2011)
β_L	Degree of non-homotheticity	0.29	(Target High- and Low- income steady state necessit
γ_{LN}	Cross-price semi-elasticity	0.95	(Feenstra and Weinstein 2017)
α_N		2.9	(Target necessity share 0.53)

Table 6: Welfare Difference Low v. High Income Households

Difference in Price Index		
Time Period	**End Period**	**Average**
Great Recession (2007Q3-2009Q2)	0.88	0.41
Recession to Recovery (2007Q3-2012Q4)	0.12	0.51
Expenditure Equivalent Welfare Loss		
	Low Income	**High Income**
Expenditure Equivalent Welfare	0.62 %	0.52 %
Ratio		1.187

Note: Price Index difference is defined as the percentage point difference in the change of the cost-of-living for Q1 v. Q5 households as calculated in the model. Expenditure equivalent welfare is the present discounted value of *all* future expenditure the household would be willing to forgo in exchange for avoiding shocks lead

A Mathematical Appendix

A.1 Proof of Proposition 1

Lemma 1 *If $F(H)$ is a strictly increasing function $F' > 0 \ \forall H$, and homogeneous of degree $k < 1$ then $\frac{\partial \frac{F'(H_j)}{F'(H_i)}}{\partial \frac{F(H_i)}{F(H_j)}} > 0$.*

For notational convenience, let $Y_i := F(H_i)$. By Euler's Homogeneous Function Theorem, $F(H_i) = F'(H_i)H_i$, which implies that:

$$\begin{aligned}\frac{F'(H_j)}{F'(H_i)} &= \frac{Y_j}{Y_i}\left(\frac{H_i}{H_j}\right) \\ &= \frac{Y_j}{Y_i}\left(\frac{F^{-1}(Y_i)}{F^{-1}(Y_j)}\right),\end{aligned}$$

where the inverse function must exist since F is strictly increasing. Next, I take the derivative with respect to the output ratio:

$$\frac{\partial}{\partial \frac{F(H_i)}{F(H_j)}}\frac{F'(H_j)}{F'(H_i)} = \frac{Y_j}{Y_i}\frac{\partial}{\partial \frac{F(H_i)}{F(H_j)}}\left(\frac{F^{-1}(Y_i)}{F^{-1}(Y_j)}\right) - \frac{F^{-1}(Y_i)}{F^{-1}(Y_j)} \tag{A.1}$$

Since the inverse of a homogeneous function of degree k, is a homogeneous function of degree $1/k$ it follows that:

$$\frac{\partial}{\partial \frac{Y_i}{Y_j}}\left(\frac{F^{-1}(Y_i)}{F^{-1}(Y_j)}\right) = \frac{\partial}{\partial \frac{Y_i}{Y_j}}\left(\left(\frac{Y_i}{Y_j}\right)^{1/k}\frac{F^{-1}(1)}{F^{-1}(1)}\right) \tag{A.2}$$

$$= \frac{1}{k}\left(\frac{Y_i}{Y_j}\right)^{(1-k)/k}. \tag{A.3}$$

By substituting equation (A.3) into equation (A.1) I find that:

$$\frac{\partial}{\partial \frac{F(H_i)}{F(H_j)}} \frac{F'(H_j)}{F'(H_i)} = \frac{Y_j}{Y_i}\frac{1}{k}\left(\frac{Y_i}{Y_j}\right)^{(1-k)/k} - \left(\frac{Y_i}{Y_j}\right)^{1/k}$$
$$= \left(\frac{Y_i}{Y_j}\right)^{1/k}\left(\frac{1}{k}-1\right),$$

which is > 0 if and only if $k < 1$. ■

Corrollary 1 *If $F(H)$ and $G(H)$ are positive strictly increasing functions $F', G' > 0\ \forall H > 0$, and both homogeneous of degree $k < 1$ then $\frac{\partial \frac{G'(H_j)}{F'(H_i)}}{\partial \frac{F(H_i)}{G(H_j)}} > 0$.*

This proof follows from the proof above, except replace $\frac{F^{-1}(1)}{F^{-1}(1)}$ in equation (A.2) with $\frac{F^{-1}(1)}{G^{-1}(1)}$, which implies that:

$$= \frac{F^{-1}(1)}{G^{-1}(1)}\left(\frac{Y_i}{Y_j}\right)^{1/k}\left(\frac{1}{k}-1\right),$$

■

Proposition 1 *In a two-sector competitive economy with a representative household that has preferences satisfying equation (4.4), strictly increasing production function in each sector both homogeneous of degree $k < 1$ and standard market clearing conditions, then an decrease/increase in household expenditure will lead to an increase/decrease in the relative price of necessities.*

Due to market clearing, it follows that

$$C^i(X, p_N, p_L) = F_i(H_i)\ \forall i$$

From equation (4.4) we know that

$$\frac{\partial}{\partial X}\frac{C^L(X, p_N, p_L)}{C^N(X, p_N, p_L)} > 0.$$

This implies that:

$$\frac{\partial}{\partial X}\frac{F_L(H_L)}{F_N(H_N)} = \frac{\partial}{\partial X}\frac{Y_L}{Y_N} > 0. \tag{A.4}$$

Relative prices can be expressed as:

$$\frac{p_L}{p_N} = \frac{F_{N,H}(H_N)}{F_{L,H}(H_L)}$$

From lemma and corollary 1, we get that:

$$\frac{\partial}{\partial \frac{Y_L}{Y_N}}\frac{F_{N,H}(H_N)}{F_{L,H}(H_L)} > 0. \tag{A.5}$$

Combining equation (A.4) with equation (A.5) and the chain-rule implies that:

$$\frac{\partial}{\partial X}\frac{p_L}{p_N} > 0$$

So the price of the expanding sector (luxuries in this case) must increase. ■

A.2 Derivation of Wage-Phillips Curve

I add sticky wages by following the convention in the literature and creating market power in the labor market via a labor union (see Erceg et. al. 2000, Auclert et. al. 2018, Auclert et. al. 2020, Broer et. al. 2020, Ramey 2020).

Specifically, each worker (i) in the economy provides h_{ikt} hours of labor to each of a continuum of unions indexed by $k \in (0, 1)$. Total labor for person (i) is then:

$$h_{it} = \int_k h_{ikt} dk. \tag{A.6}$$

Each union k aggregates units of work into a union specific task $H_{kt} - \int_i h_{ikt} di$.

There is a competitive labor packer that takes labor from unions and packages it into one unit of "usable" labor following a CES function. Aggregate labor is then:

$$H_t = \left(\int_k H_{kt}^{\frac{\epsilon_w - 1}{\epsilon_w}} \right)^{\epsilon_w/(\epsilon_w - 1)}, \tag{A.7}$$

where ϵ_w is the elasticity of substitution between different types of labor.

Unions set a common wage w_{kt} for all members and require each member household to supply uniform hours: $h_{ikt} = H_{kt}$.

Following (Auclert et al. 2018,2020) I add an extra disutility term for households, so that households dislike adjusting wages:

$$\frac{\psi_w}{2} \int_k (\frac{w_{kt}}{w_{kt-1}} - 1)^2 dk, \tag{A.8}$$

where ψ_w scales the degree of wage stickiness.

At time t, union k sets wage w_{kt} to maximize (on behalf of all union workers):

$$\begin{aligned} \max_{w_k t} \mathbb{E}_t \sum_{\tau > 0} \beta^{t+\tau} \left(\int \left[V(X_{it+\tau}, \mathbf{p}_{t+\tau}) - g(h_{i,t+\tau}) \right] d\psi_{it+\tau} - \frac{\psi_w}{2} \int_k (\frac{w_{kt}}{w_{kt-1}} - 1)^2 dk \right) \\ s.t.\ H_{kt} = \left(\frac{w_{kt}}{W_t} \right)^{-\epsilon_w} H_t \end{aligned} \tag{A.9}$$

The union takes as given the distribution ψ_{it} of workers (in this version of the model, all workers are identical) and all prices excluding w_{kt} (note that $W_t = \left(\int_k w_{kt}^{1-\epsilon_w} dk \right)^{1/(1-\epsilon_w)}$.)

The envelope theorem allows me to ignore both the intertemporal reoptimization of saving or spending in response to a marginal change in wages, along with the intratemporal

reoptimization of spending across sectors. I treat any change in income as a change in consumption expenditure:

$$\begin{aligned}\frac{\partial X_{it}}{\partial w_{kt}} &= \frac{\partial}{\partial w_{kt}} \int_0^1 w_{kt} h_{ikt} dk \\ &= \int_0^1 \frac{\partial}{\partial w_{kt}} w_{kt} \left(\frac{w_{kt}}{W_t}\right)^{-\epsilon_w} H_t dk \\ &= (1-\epsilon_w) \left(\frac{w_{kt}}{W_t}\right)^{-\epsilon_w}.\end{aligned}$$

I next derive the change in hours worked to a change in wages for household (i) using the labor rule that $H_{kt} = h_{ikt} \forall i$ and the demand constraint:

$$\begin{aligned}\frac{\partial h_{it}}{\partial w_{kt}} &= -\epsilon_w \left(\frac{w_{kt}^{-\epsilon_w - 1}}{W_t^{-\epsilon_w}}\right) \\ &= -\epsilon_w \frac{H_{kt}}{w_{kt}}.\end{aligned}$$

It follows that the first order condition of the union's maximization problem equation (A.9) becomes:

$$\begin{aligned}\int H_{kt} \left[V_X(X_i t, \mathbf{p}_t)(1-\epsilon_w) \left(\frac{w_{kt}}{W_t}\right)^{-\epsilon_w} + \frac{\epsilon_w}{w_{kt}} g'(h_{it}) \right] d\psi_{it} - \psi_w \left(\frac{w_{kt}}{w_{kt-1}} - 1\right) \frac{1}{w_{kt-1}} \\ + \beta \psi_w \mathbb{E}_t \left[\left(\frac{w_{k,t+1}}{w_{k,t}} - 1\right) \left(\frac{w_{k_t+1}}{w_{kt}^2}\right) \right] = 0.\end{aligned}$$

This simplifies when we note that the maximization problem for all unions is identical, so in equilibrium $w_{kt} = w_t$. Denoting $\pi_t^w \equiv \left(\frac{w_t}{w_{t-1}} - 1\right)$ and using the functional forms for $V[\cdot]$ and $g(\cdot)$ provided in section 6 yields:

$$\psi_w \pi_t^w (1+\pi_t^w) =$$
$$\beta \mathbb{E}_t \left(\psi_w \pi_{t+1}^w (1+\pi_{t+1}^w) \right) + H_t w_t \int \left[\frac{1}{a(\mathbf{p}_t) b(\mathbf{p}_t)} \left(\frac{X_t}{a(\mathbf{p}_t)} \right)^{(1/b(\mathbf{p}_t))-1} (1-\epsilon_w) + \frac{\epsilon_w}{W_t} H_{it}^{\phi} \right] d\psi_{it}.$$

In the representative agent model that I am considering here, this further simplifies to:

$$\begin{aligned} (1+\pi_t^w)\pi_t^w =& \beta \mathbb{E}_t \left[(1+\pi_{t+1}^w)\pi_{t+1}^w \right] \\ &+ \left(\frac{\epsilon_w}{\psi_w} \right) \left(H_t^{\phi} - \left(\frac{\epsilon_w - 1}{\epsilon_w} \right) \frac{W_t}{a(\mathbf{p}_t) b(\mathbf{p}_t)} \left(\frac{X_t}{a(\mathbf{p}_t)} \right)^{(1/b(\mathbf{p}_t))-1} \right) \end{aligned} \tag{A.10}$$

It follows that the union will adjust wages in expectations of future wage inflation or when the marginal disutility of labor is higher than the product of marginal utility of expenditure and the optimal wage.

A.3 A Note on Aggregation

In general, it is not true that if micro-households have non-homothetic preferences then the aggregate household will also have non-homoethetic preferences of the same form. Very few types of non-homoethetic preferences are Gorman-Polar (Stone-Geary is a notable exception), so these type of preferences cannot simply be added up across households to create an aggregate household with the same preference structure and parameters as the micro households (Muellbauer 1975).

Muellbauer (1975) shows that a necessary and sufficient condition for there to exist an income/expenditure level such that a representative household with that income/expenditure level to have preferences identical to the average of all households is that households must have Generalized Linear (GL) preferences. The expenditure/income of a slightly less general version of these preferences, Price Independent Generalized Linear (PIGL) is shown to depend positively on both aggregate income/expenditure and the inequality of the income/expenditure distribution. Intuitively, this is because in a more unequal economy, all

else equal, will have a higher portion of aggregate income/expenditure concentrated in a few hands, which means that more luxuries will be consumed. Hence, the representative household should have higher income/expenditure than that implied by the aggregate expenditure in the economy.

If the representative household proceeds to purchase relatively more necessity goods, then this will cause necessity prices to increase. Since poorer households have lower expenditure than rich households, these households will have a larger percentage of their basket devoted to the necessity good. This increase in necessity prices will increase their price index relative to rich households.

It has been documented that both recessions (Heathcote et al. 2020) and contractionary monetary policy (Coibion, Gorodnichenko, Kueng, Silvia 2018) increase inequality. Since demand for the necessity good depends both on aggregate expenditure (decreasing) and inequality (decreasing), a shock that simultaneously lowers aggregate expenditure and raises inequality would have ambiguous effects on relative necessity demand. To fix ideas, if representative expenditure x^r is a function $\mathrm{F}(\cdot)$ of aggregate expenditure $\bar{x}$ and expenditure inequality Σ_x then the elasticity of representative expenditure to a macroeconomic shock, $\mathcal{E}_{x^r,shock}$, would be:

$$\mathcal{E}_{x^r,shock} = \mathcal{E}_{x^r,\bar{x}}\mathcal{E}_{\bar{x},shock} + \mathcal{E}_{x^r,\Sigma_x}\mathcal{E}_{\Sigma_x,shock}. \tag{A.11}$$

In equation (A.11), the elasticity of representative expenditure to a shock depends both on the elasticity of aggregate expenditure to the shock and the elasticity of inequality to the shock, where each term is scaled by the elasticity of representative expenditure to either aggregate expenditure or inequality.[17] In the empirical section, I show that following a monetary policy shock the effect coming through aggregate expenditure dominates.

[17]In the PIG-Log (AIDS) specification I adopt in the main text, the elasticity of x^r with respect to both aggregate expenditure and inequality (as measured by the Theil Index) is one, so equation (A.11) reduces to just $\mathcal{E}_{\bar{x},shock} + \mathcal{E}_{\Sigma_x,shock}$. Coibion et al. (2017) finds that the elasticity of the standard deviation of expenditure increases by .03 four months after a one-s.d. monetary policy shock, while consumption falls by approximately 0.5 percent. Given that the Theil Coefficient for a log-normal distribution is $\sigma^2/2$ it follows that the aggregate expenditure elasticity dominates the inequality elasticity.

B Alternate Calibrations

As mentioned in the main text, I consider several alternative calibrations. I consider three different values for α; (1) $\alpha = 0.366$ from Fernald (2014), (2) $\alpha = 0.3$, which is implied by letting the marginal elasticity of marginal cost to quantity supplied in the model equal the median estimated value in Hottman and Monarch (2020), and (3) $\alpha = 0.16$, which is implied by the median results for ω in Feenstra and Weinstein (2017). I also directly estimate β_L and γ_{LN} from the micro-data, and use these values. My method of estimation is described in the next subsection.

B.1 Demand Parameter Estimation

I follow Deaton and Muellbauer (1980) and Fajgelbaum and Khandelwal (2016) when estimating the parameters in the AIDs. Specifically, I estimate equation (6.6) directly from the micro data by replacing $a(\mathbf{p})$ with a known price index (I use the CPI) so that the coefficient β_j represents changes in the share of expenditure on product j with changes in real expenditure, so that equation (6.6) becomes:

$$s_j = a_j^* + \sum_k \gamma_{jk} \log(p_k) + \beta_j \left(x_h^*\right). \tag{B.1}$$

Where x_h^* is real household expenditure, and a_j^* is a transformation of a^j.[18] Since there are only two sectors, I can estimate equation (B.1) directly via OLS by treating the price of one sector (necessities) as the numeraire and following the parameter restrictions defined earlier: $\sum_{j=1}^N a_j = 1, \sum_{j=1}^N \beta_j = \sum_{j=1}^N \gamma_{jk} = 0$ and $\gamma ij = \gamma ji \ \forall i, j$. Similar to the rest of my analysis, I control for household size, age of the household head, and the number of wage earners. I use the full household sample (1991-2019) and define the necessity good as the composite good of products with relative expenditure ratio greater than one.

Results from this estimation are shown in table **??**. Column one reports the results I show here in the paper. I estimate that $\beta^N = -0.18$, which implies a luxury sector expendi-

[18] In this framework, the a^j cannot be separately identified.

Table A.1: Almost Ideal Demand System Parameter Estimation

	OLS	IV − Income
	$s^h_{n,t}$	$s^h_{n,t}$
	(1)	(2)
Parameter Estimates:		
γ_{NL}	9.5×10^{-6}	1.1×10^{-5}
	$(.17)\times10^{-6}$	$(018)\times10^{-5}$
β^N	−.18	−.24
	(.00075)	(.00013)
Luxury Expenditure Elasticity	1.39	1.52
Necessity Expenditure Elasticity	.66	.55
Luxury Own Price Elasticity	-1.86	-2.45
Necessity Own Price Elasticity	-1.41	-1.8
Luxury Cross-Price Elasticity	-.86	-1.45
Necessity Cross-Price Elasticity	-.41	-.8
Observations	273,545	273,537

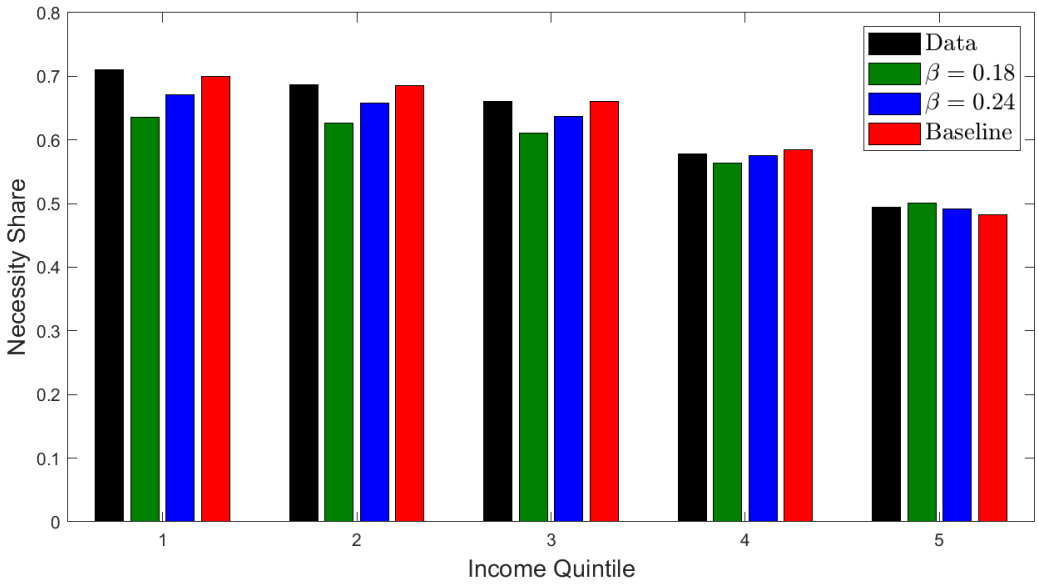
Notes: The unit of observation is the household-quarter. Robust standard errors in parentheses.

ture elasticity for the representative household of 1.4. I also estimate a positive cross-price elasticity, implying that necessities and luxuries are gross-complements. Column 2 shows an alternate estimation using household log-income and income quintiles as instruments for expenditure (Aguiar and Bils (2015) estimate expenditure elasticities using income as an instrument to correct for large under-reporting in the CEX).

B.2 Results

Here I show similar figures as those in the main text, but the the alternate 6 calibrations alongside the baseline calibration.

Figure A1: Model and Data: Necessity Shares by Income Group



Note: Data from 2005-06. Model income-group shares at steady state. The baseline calibration is described in the main text.

Figure A2: Model v. Data: Necessity Share

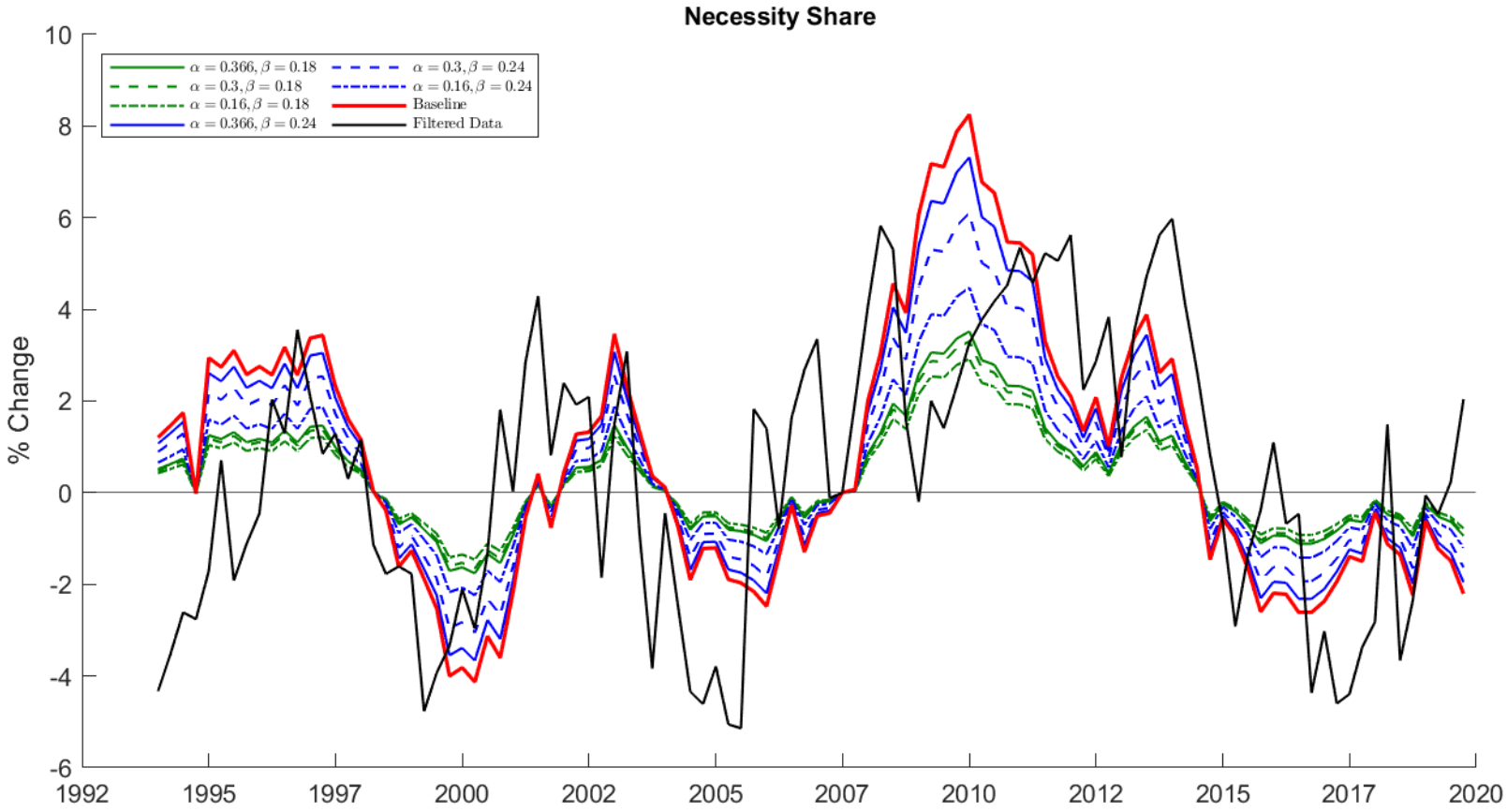


Figure A3: Model v. Data: Relative Necessity Prices

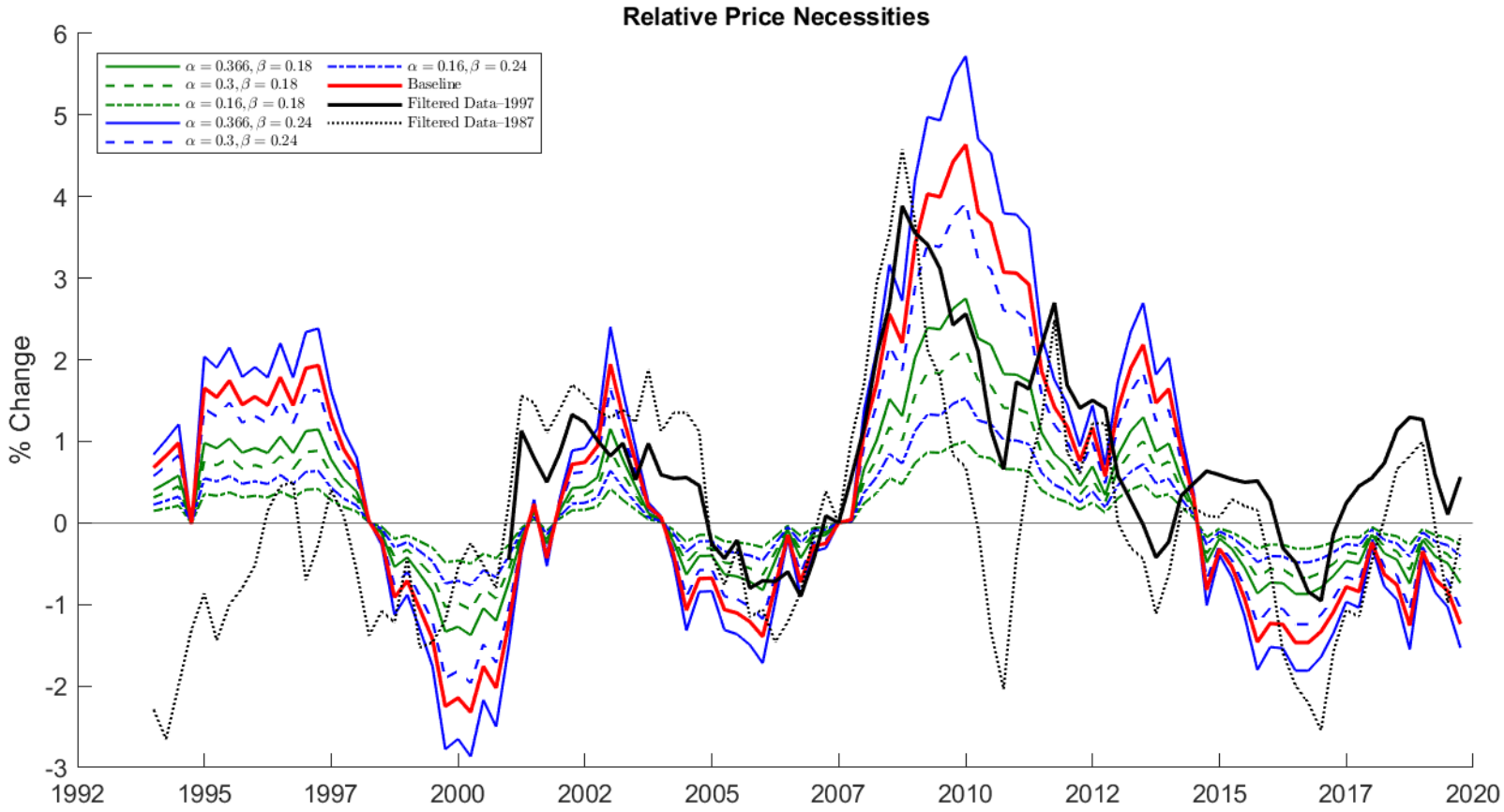


Figure A4: IRF: Relative Necessity Shares

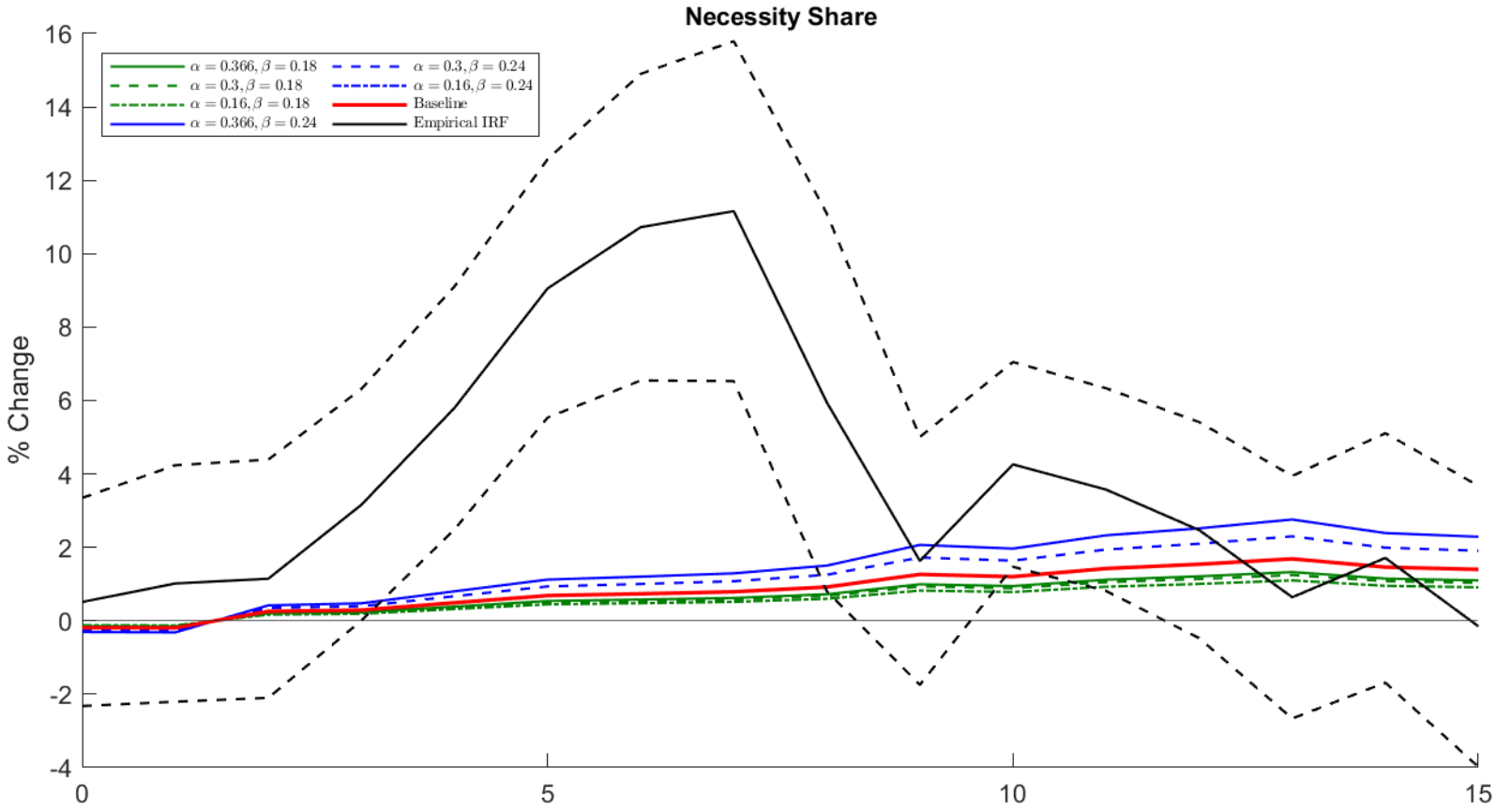
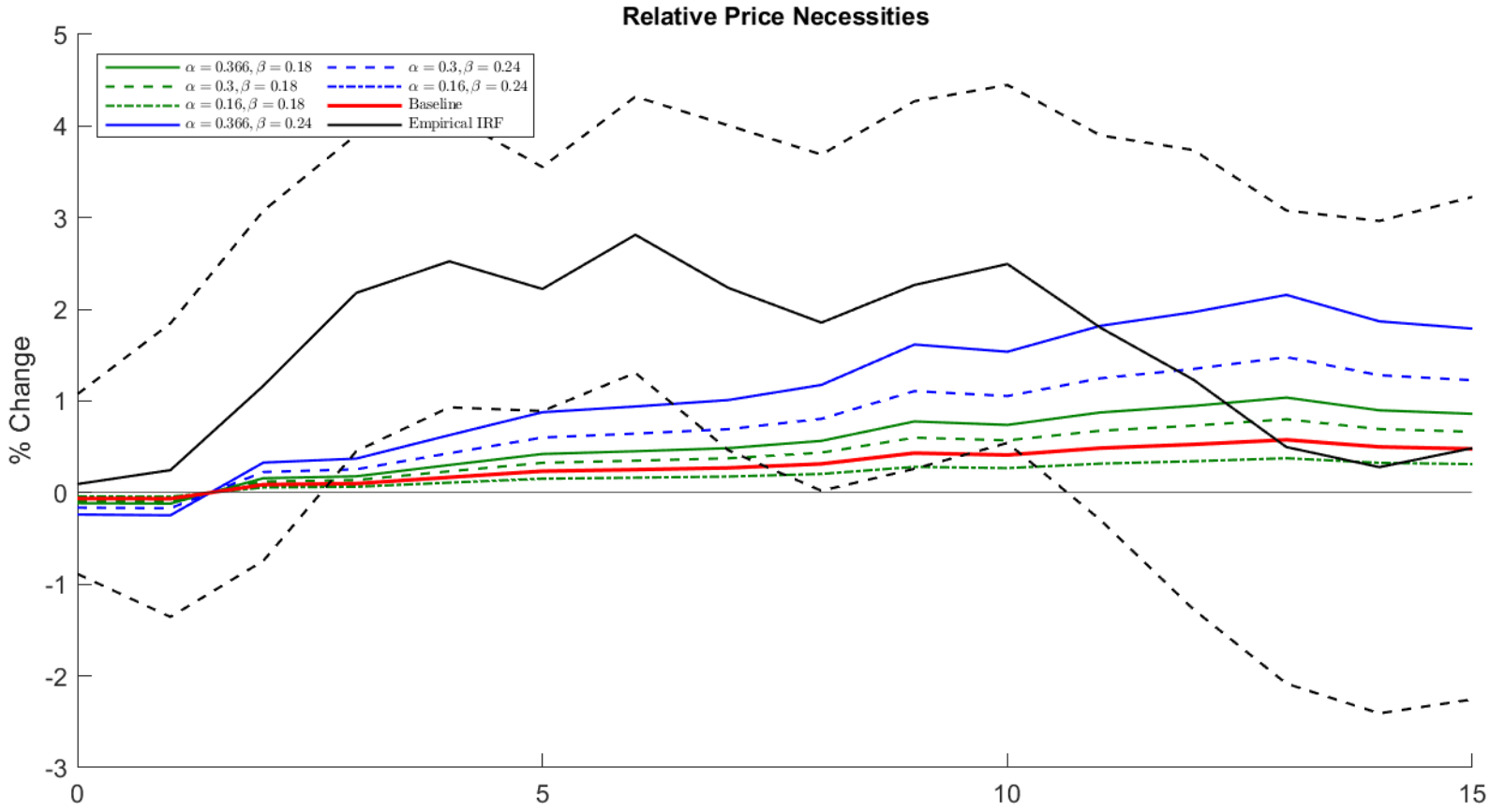
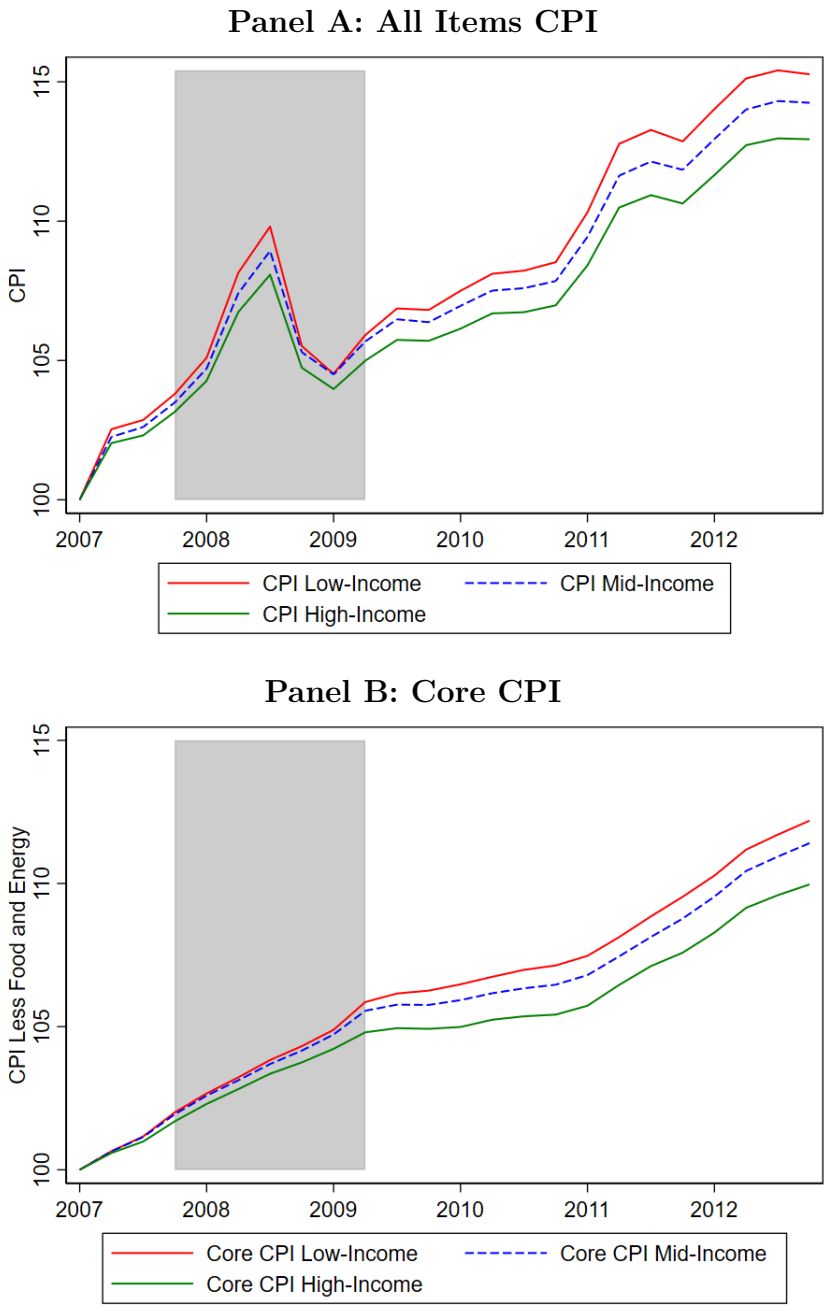


Figure A5: Model v. Data: Relative Necessity Prices



C Additional Figures

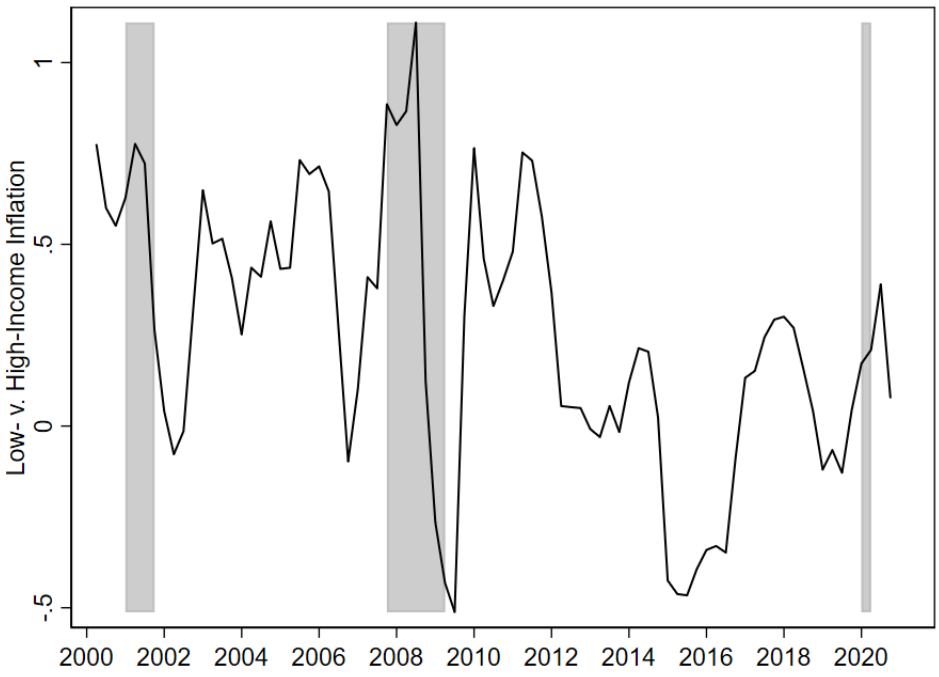
Figure A6: Income Level CPI's during the Great Recession and Slow Recovery



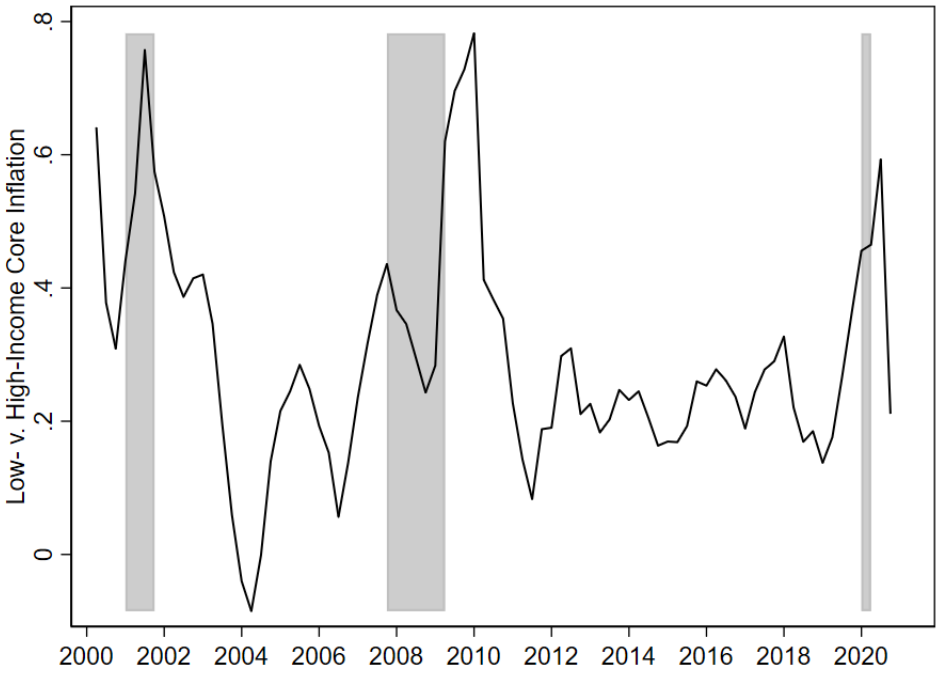
Source: Bureau of Labor Statistics and Author's own calculations.
Notes: NBER recession indicated by shaded area. Weights are democratic and based on 2005-06 consumption patterns. The base period is 2007Q1.

Figure A7: Inflation Inequality 2000-2020

Panel A: All Items CPI

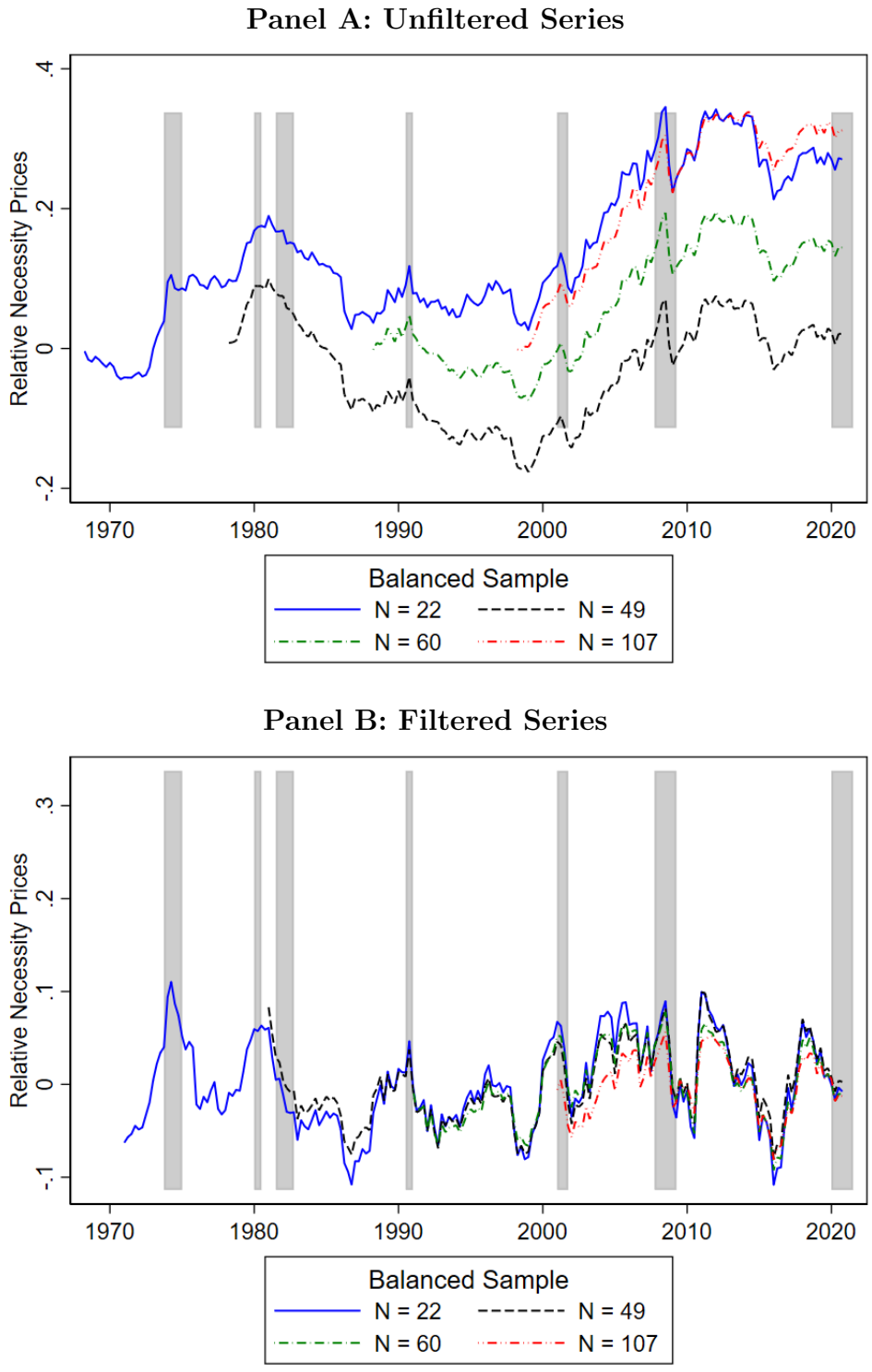


Panel B: Core CPI



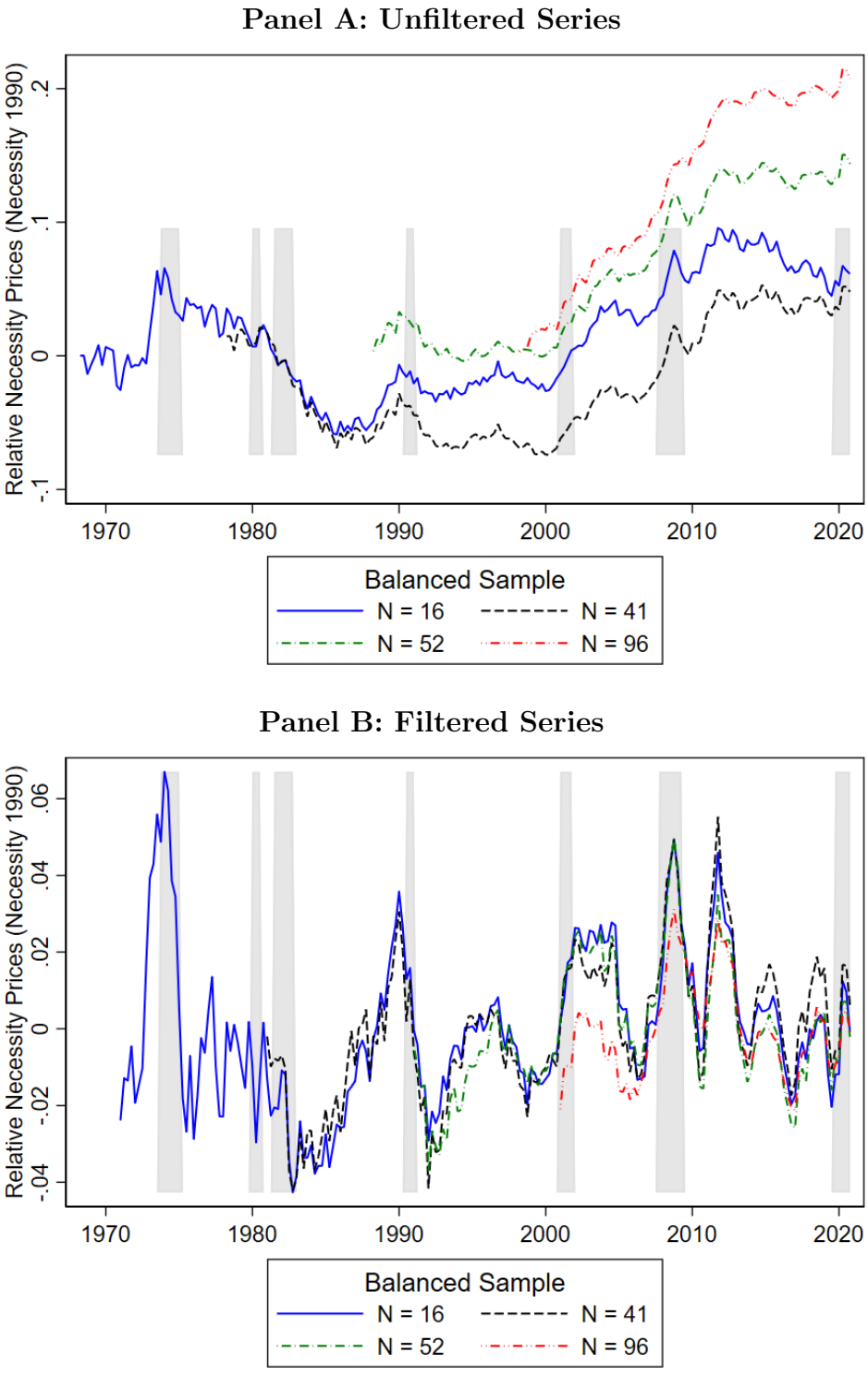
Source: Bureau of Labor Statistics and Author's own calculations.
Notes: NBER recessions indicated by shaded areas. Year over year inflation rate. Inflation inequality calculated as difference between the lowest and highest income quantile inflation rate. Weights are democratic and based on 2005-06 consumption patterns.

Figure A8: Relative Necessity Prices including energy



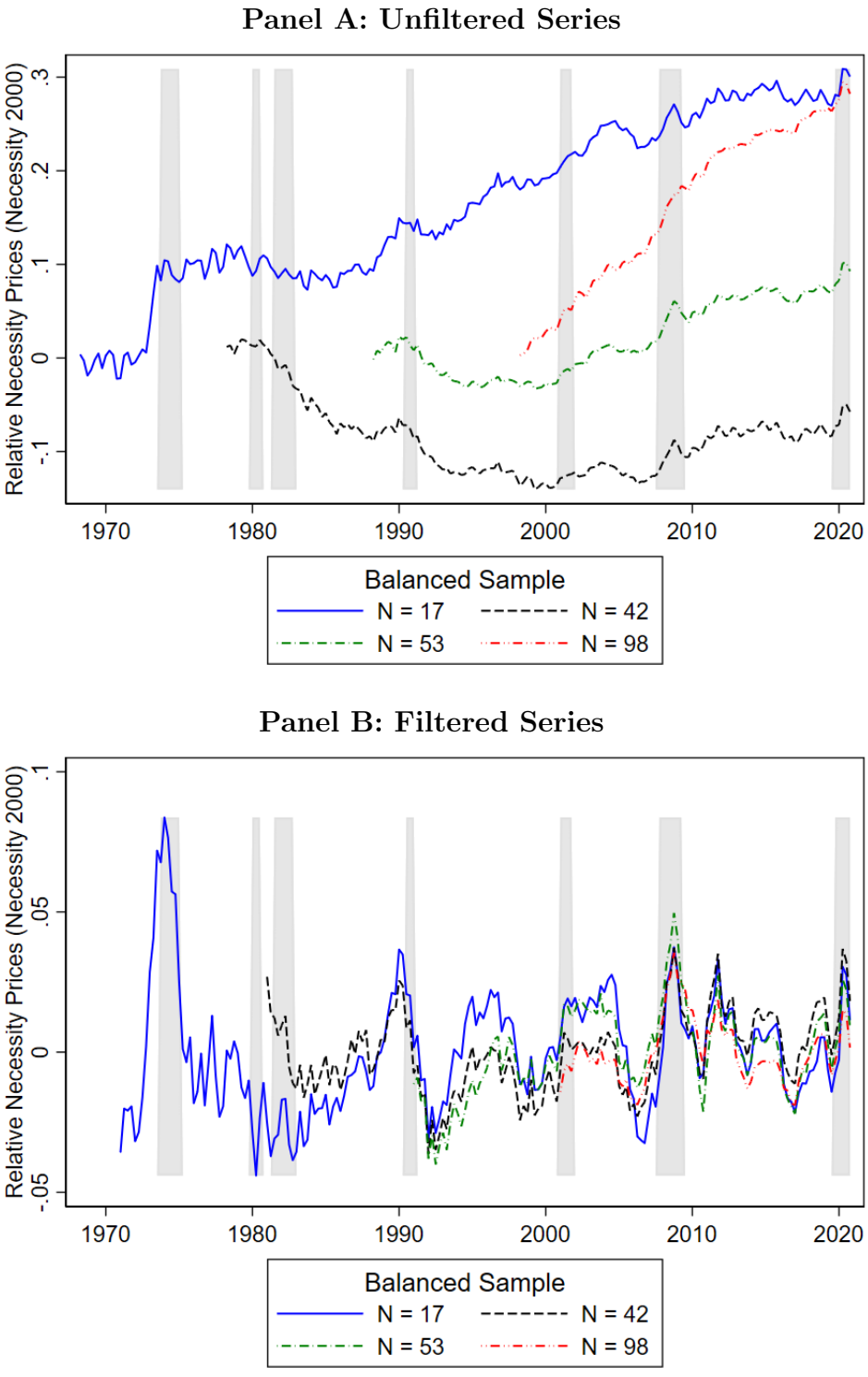
Source: Bureau of Labor Statistics and Author's own calculations. Excludes housing. Data filtered following Hamilton (2018). Shaded area indicates NBER Recessions.

Figure A9: Relative Necessity Prices 1990-2000 Consumption Patterns



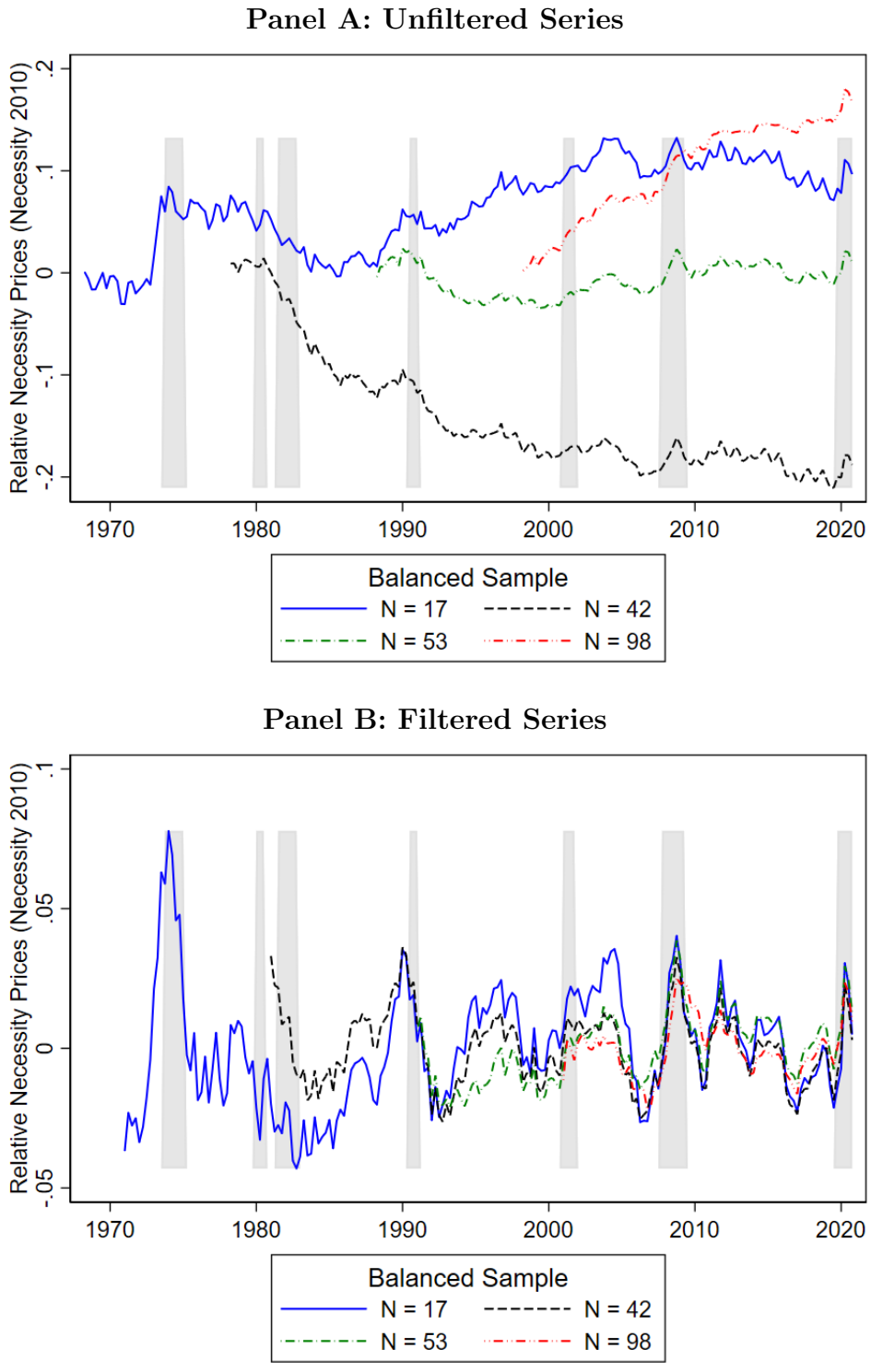
Source: Bureau of Labor Statistics and Author's own calculations. Excludes housing and energy. Data filtered following Hamilton (2018). Shaded area indicates NBER Recessions. Uses consumption shares data from 1990-2000 only when defining products as luxuries or necessities.

Figure A10: Relative Necessity Prices 2000-2010 Consumption Patterns



Source: Bureau of Labor Statistics and Author's own calculations. Excludes housing and energy. Data filtered following Hamilton (2018). Shaded area indicates NBER Recessions. Uses consumption shares data from 2000-2010 only when defining products as luxuries or necessities.

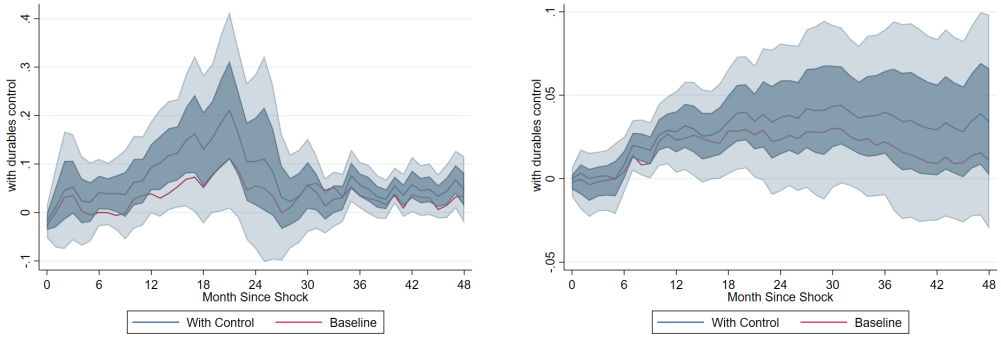
Figure A11: Relative Necessity Prices 2010-2020 Consumption Patterns



Source: Bureau of Labor Statistics and Author's own calculations. Excludes housing and energy. Data filtered following Hamilton (2018). Shaded area indicates NBER Recessions. Uses consumption shares data from 2010-2019 only when defining products as luxuries or necessities.

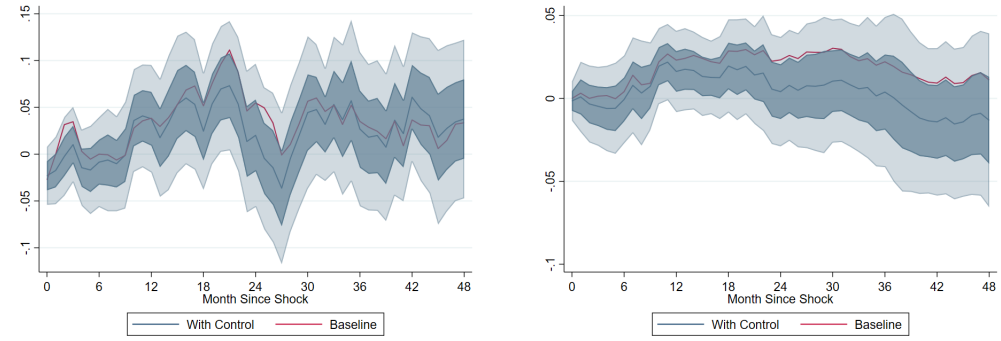
Figure A12: Additional IRF Robustness Checks

Pre-2008 Shock Data



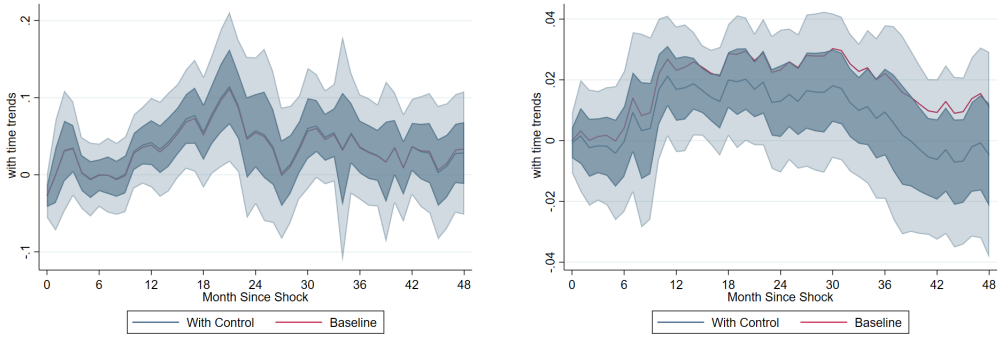
a) Log-Necessity Share b) Log-Necessity Price

Include 6 lags of $i \times R$



c) Log-Necessity Share d) Log-Necessity Price

Include Sector Specific Time-trends



e) Log-Necessity Share f) Log-Necessity Price

Note: Data from 1991-2019. Estimated coefficients from Local Projections explained in section 5. The unit of observation is the sector-month. Robust standard errors clustered at the monthly level are shown by one- and two- standard error confidence bands indicated by the dark and light shaded areas respectively. Sectors weighted by their share in pooled aggregate expenditure. Monetary Policy shock normalized to 25-basis point increase in 1-year treasury in month $t = 0$. When the dependent variable is log-price a balanced sample is used of 60 sectors with price data available for the entire period.