

NBER WORKING PAPER SERIES

TRADING DOWN AND THE BUSINESS CYCLE

Nir Jaimovich
Sergio Rebelo
Arlene Wong

Working Paper 21539
<http://www.nber.org/papers/w21539>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2015, Revised September 2017

This research was conducted with restricted access to the Bureau of Labor Statistics (BLS) data. The views expressed here are those of the authors and do not necessarily reflect the views of the BLS, the Federal Reserve Bank of Minneapolis, the Federal Reserve System, or the National Bureau of Economic Research. We thank our project coordinator at the BLS, Ryan Ogden, for help with the data, and Yuriy Gorodnichenko and Michael Weber for making their data and code available to us. We are grateful for comments from David Berger, Guido Menzio, Emi Nakamura, Aviv Nevo, Raphael Schoenle, Henry Siu, and Jon Steinsson.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

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NBER Working Paper No. 21539
September 2015, Revised September 2017
JEL No. E1,E2,E3

ABSTRACT

We document two facts. First, during the Great Recession, consumers traded down in the quality of the goods and services they consumed. Second, the production of low-quality goods is less labor intensive than that of high-quality goods. When households traded down, labor demand fell, increasing the severity of the recession. We find that the trading-down phenomenon accounts for a substantial fraction of the fall in U.S. employment in the recent recession. We show that embedding quality choice in a business cycle model improves the model's amplification and comovement properties.

Nir Jaimovich
Department of Finance and Business Economics
Marshall Business School
University of Southern California
Los Angeles, CA 90089-0804
and NBER
nir.jaimovich@marshall.usc.edu

Arlene Wong
Department of Economics
Princeton University
192A Julis Romo Rabinowitz Building
Princeton, NJ 08544
and NBER
arlenewong@princeton.edu

Sergio Rebelo
Northwestern University
Kellogg School of Management
Department of Finance
Leverone Hall
Evanston, IL 60208-2001
and CEPR
and also NBER
s-rebelo@northwestern.edu

1 Introduction

One of the classic research areas in macroeconomics is the study of how households make consumption choices and how these choices impact the economy. There is a large empirical literature on this topic going as far back as the work of Burns and Mitchell (1946). This literature has received renewed attention after the Great Recession.¹

In this paper, we contribute to this line of research as follows. First, we show that during the Great Recession, consumers traded down in the quality of the goods and services they consumed. Second, we show that the production of low-quality goods is generally less labor intensive than that of high-quality goods. These two facts imply that when households traded down, labor demand fell, increasing the severity of the Great Recession.

To quantify the implications of “trading down” for employment during the Great Recession, we combine various data sources to construct a data set with firm-level measures of product quality, labor intensity, and market share. For most of our analysis, we use prices as a proxy for quality. Our assumption is that, if consumers are willing to pay more for an item, they perceive it to be of higher quality. We corroborate the plausibility of this assumption using data with independent measures of quality and price.

We obtain price measures from two sources: data scraped from the Yelp!, a website where consumers post information about different goods and services, and the confidential micro data set used to construct the Producer Price Index (PPI). We merge these data with Compustat data to measure labor intensity and market share for each firm in our sample. We estimate that around half of the decline in employment in the Great Recession is accounted for by consumers trading down in the quality of the goods and services they purchased.

¹Recent contributions to this literature include Aguiar, Hurst, and Karabarbounis (2013), Kaplan and Menzio (2015), Stroebel and Vavra (2015), and Nevo and Wong (2015).

To study the effects of trading down from a theoretical perspective, we embed quality choice into an otherwise standard business cycle model. We find that the presence of quality choice magnifies the response of these economies to shocks, generating larger booms and deeper recessions. The reason for this amplification is as follows. Consider for example, the case of a negative shock that reduces the household's income. This fall in income, leads the household to trade down in the quality of the goods it consumes. Since lower quality goods use less labor, the trade down in quality reduces the demand for labor.

The quality-augmented model has two other interesting properties. First, it can generate comovement between employment in the consumption and investment sectors, a property that is generally difficult to obtain (see Christiano and Fitzgerald (1998)). Second, the model produces an endogenous, countercyclical labor wedge. As Shimer (2009) emphasises, this type of wedge is necessary in order to reconcile business-cycle models with the empirical behavior of hours worked.

Our paper is organized as follows. In Section 2, we describe our data and present our empirical results. We study the quantitative properties of two models with quality choice in Section 3. The first model has a representative agent while the second has heterogenous agents. Section 4 concludes.

2 Empirical findings

In this section, we analyze the impact of trading down on labor demand. By trading down we mean shifts in the composition of consumption across firms *within* narrowly defined sectors towards lower quality goods. To study the effect of trading down on employment, we estimate the labor intensity of different quality levels within each sector. We then study how shifts in the market share of the different quality levels affects employment. This within-sector trading-down channel differs from other channels through which demand can affect employment, such as shifts in spending *across* sectors (e.g.

from restaurants to the grocery sector) or declines in total spending.²

Our empirical approach to study the effects of trading down is as follows. We denote by M the number of sectors in the economy. Total aggregate employment across these sectors is:

$$H_t = \sum_{m=1}^M H_{m,t}, \quad (1)$$

where $H_{m,t}$ denotes employment at time t in sector m .

In each sector, goods can belong to one of J levels of quality. The market share of quality tier j in sector m ($S_{j,m,t}$) is the ratio of sales of goods in quality tier j ($Y_{j,m,t}$) to total sales in sector m ($Y_{m,t}$):

$$S_{j,m,t} = \frac{Y_{j,m,t}}{Y_{m,t}}.$$

The measure of labor intensity ($LI_{j,m,t}$) that we construct is the ratio of employees ($H_{j,m,t}$) to sales ($Y_{j,m,t}$):

$$LI_{j,m,t} = \frac{H_{j,m,t}}{Y_{j,m,t}}.$$

Using this notation, we can write total employment in sector m in period t as:

$$H_{m,t} = Y_{m,t} \sum_{j=1}^J S_{j,m,t} LI_{j,m,t}, \quad (2)$$

where $Y_{m,t}$ denotes total sales in sector m , $Y_{m,t} = \sum_{j=1}^J Y_{j,m,t}$. Combining equations (1) and (2), we can write aggregate employment as:

$$H_t = Y_t \sum_{m=1}^M \frac{Y_{m,t}}{Y_t} \sum_{j=1}^J S_{j,m,t} LI_{j,m,t}, \quad (3)$$

where Y_t denotes aggregate sales across the M sectors. Using equation (3), we can write

²See Section 2.5 for a discussion of shifts in spending across sectors.

the log-percentage change in employment, $\log(H_{t+1}/H_t)$ as:

$$\begin{aligned} \log(H_{t+1}/H_t) &= \log(Y_{t+1}/Y_t) + \log\left(\sum_{m=1}^M \frac{Y_{m,t+1}}{Y_{t+1}} \sum_{j=1}^J S_{j,m,t+1} LI_{j,m,t+1}\right) \\ &\quad - \log\left(\sum_{m=1}^M \frac{Y_{m,t}}{Y_t} \sum_{j=1}^J S_{j,m,t} LI_{j,m,t}\right). \end{aligned} \quad (4)$$

In order to quantify the effect of trading down on employment, we calculate a counterfactual value for employment in period $t + 1$:

$$H_{t+1}^{CF} = Y_{t+1} \sum_{m=1}^M \left(\frac{Y_{m,t+1}}{Y_{t+1}} \sum_{j=1}^J S_{j,m,t} LI_{j,m,t+1} \right). \quad (5)$$

This counterfactual level of employment is the one that would have occurred in the absence of trading down, that is, if the market shares of each quality tier were the same at time t and $t + 1$. Hence, in the absence of trading down, the change in employment would have been:

$$\begin{aligned} \log(H_{t+1}^{CF}/H_t) &= \log(Y_{t+1}/Y_t) + \log\left(\sum_{m=1}^M \frac{Y_{m,t+1}}{Y_{t+1}} \sum_{j=1}^J S_{j,m,t} LI_{j,m,t+1}\right) \\ &\quad - \log\left(\sum_{m=1}^M \frac{Y_{m,t}}{Y_t} \sum_{j=1}^J S_{j,m,t} LI_{j,m,t}\right). \end{aligned} \quad (6)$$

The difference between the actual change in employment and the counterfactual change in employment if no trading down occurred, gives us an estimate of the importance of the trading down phenomenon for employment. Below, we produce this estimate using our data.

2.1 Empirical measures

We start by using a data set that merges data from Yelp!, the Census of Retail Trade, and Compustat. We then extend our analysis to the manufacturing sector by using

the micro data gathered by the BLS to construct the PPI. Finally, we consider several other data sets.

We define the relative quality of goods and services as encompassing anything that consumers are willing to pay for. This notion of quality encompasses both the item itself, and the service or convenience of the product. For example, in restaurants, it includes both the meal and the ambience of the place. For grocery stores, it is not only the item sold but also the convenience and service of the store.

We measure quality using the price distribution of firms within each sector. This measure is the most comprehensive in terms of sectoral coverage, making our analysis consistent across all of the sectors that we consider.

2.2 Results obtained with Yelp! and Census of Retail Trade data

In this section, we discuss the results we obtain using data from Yelp! and from the Census of Retail Trade. The combined data set covers five North American Industry Classification System (NAICS) sectors: apparel, grocery stores, restaurants, home furnishing, and general merchandise. These sectors represent 17 percent of private non-farm employment. As we discuss below, our analysis includes the effects of trading down on the demand for intermediate inputs from all sectors in the economy computed using the BLS input-output data.

We focus on two main time periods. Our recession period covers 2007-2012 period, while our pre-recession period covers 2004-2007.³ The data for the period 2004-2007 allows us to control for trends in trading down so that we can isolate the cyclical component of trading down that is associated with the Great Recession.

³Even though the NBER determined that the recession ended in June 2009, average and median household income continued to fall until 2012. In addition, employment recovered very slowly: in December 2012 employment was still 3 percent below its December 2007 level. In Appendix E, we report results when we use 2007-2009 as the recession period.

Yelp! data

For sectors other than General Merchandise, we collect information on prices by scraping data from Yelp!, a website where consumers share reviews about different goods and services. For each store and location pair, Yelp! asks its users to classify the price of the goods and services they purchased into one of four categories: \$ (low), \$\$ (middle), \$\$\$ (high), and \$\$\$\$ (very high). Since there are few observations in the very-high category, we merge the last two categories into a single high-price category.

We construct the Yelp! data set as follows (see Appendix A for more details). We first associate each firm (for example, Cost Plus, Inc.) with its brand names and retail chains (for example, Cost Plus owns the retail chain World Market). We find the Yelp! profile for each retail chain and brand in the 18 largest U.S. cities and collect the first match (for example, the first match for World Market in Chicago is the store on 1623 N. Sheffield Av.). We then compute the average price category across the first match for each of the 18 cities (to compute this average, we assign 1 to category low, 2 to middle and 3 to high).⁴

Consistent with the assumption that prices proxy for quality, we find that there is a positive correlation between the average rating and the average price in the Yelp! data.

U.S. Census of Retail Trade data

For General merchandise, the U.S. Census of Retail Trade splits firms into three price tiers that correspond to three different levels of quality: non-discount stores (high quality), discount department stores (middle quality), other general merchandise stores, including family dollar stores (low quality). For each of these three tiers, the Census provides information about employment and sales. We use this information to construct labor intensity measures and market shares. The Census categorization in the general merchandise store sector aligns with the Yelp! categorization of Compustat firms into

⁴The dispersion in price categories across cities is relatively small; it is rare for firms to be included in different price categories in different cities.

price categories, highlighting the consistency of our quality categorization across the different data sources.

Compustat data

We merge the price information for each firm in our Yelp! data set with data from Compustat on the number of employees, sales, operating expenses, and cost of goods sold. Our measure of labor intensity is the ratio of employees to sales. We focus on this measure because of its availability. The SEC requires that firms report the number of employees and, as a result, these data are available for all companies in Compustat. In contrast, only less than 1/4 of the firms in Compustat of firms report labor costs.⁵

Findings

Tables 1 and 2 present our estimates of labor intensity and market share by quality tier. We use these estimates as inputs into equations (4) and (6). Labor intensity increases with quality in all five sectors. For example, in 2007, the number of employees per million dollar of sales is 6.33, 9.23 and 10.86 for low-, middle-, and high-quality apparel stores, respectively (Table 1). Overall, the middle quality uses 46 percent more workers per million dollar of sales than the low-quality producers. Similarly, the high-quality producers use 18 percent more workers per million dollar of sales than the middle-quality producers. Other things equal, a shift of one million dollar of sales from middle to a low quality stores reduces employment by roughly three jobs.

Between 2007 and 2012, firms that produce middle- and high-quality items lost market share relative to firms that produce low-quality items. In 2007, the low-, middle-

⁵For the sample of firms that report the labor share in cost, the correlation between labor share and the labor intensity measure of employees/sales is 0.94. The correlation between the labor share in cost and employees/gross margin is 0.97. As a robustness check, we also use the ratio of employees to gross margin as a measure of labor intensity (Appendix D). Gross margin, which is sales minus cost of goods sold, is a measure that is close to value added. Value added is equal to the gross margin minus energy and services purchased. We cannot compute value added because Compustat does not report data on energy and services purchased. The correlation between employees/gross margin and employees/sales is 0.72.

and high-price categories account for 42, 52 and 6 percent of sales, respectively. In contrast by 2012, high-quality producers lost about 0.5 percentage points in market share, middle-quality producers lost 6.5 percentage points, and low-quality producers gained 7 percentage points. This pattern is present in all the sectors we consider with one exception: the market share of high-quality grocery stores increased.⁶ This exception is driven by an outlier: WholeFoods, a high-quality supermarket that gained market share despite the recession.

With the information in Tables 1 and 2, we can implement the empirical approach described by equations (4) and (6). Overall employment in the sectors included in our data set fell by 3.39 percent. Using equation (6), we find that in the absence of trading down employment would have fallen by only 0.39 percent. This result implies that trading down accounts for $(3.39 - 0.39)/3.39 = 88$ percent of the fall in employment.⁷

Trend versus Cycle

Trading down was occurring before the recession, so there are both trend and cycle components of trading down. In order to disentangle these two components, we proceed as follows. We compute market shares by quality tier for each sector for the period 2004-2007. We use the change in these shares over this period to linearly extrapolate what the market shares of different quality tiers would have been in 2012. Using these market shares, we construct the 2012 employment implied by the extrapolated market shares

$$N_{2012}^{CF2} = Y_{2012} \sum_{m=1}^5 \left(\frac{Y_{m,2012}}{Y_{2012}} \sum_{j=1}^3 \left[S_{j,m,2007} + \frac{S_{j,m,2007} - S_{j,m,2004}}{(2007 - 2004)} \times (2012 - 2007) \right] [LI_{j,m,2012}] \right). \quad (7)$$

⁶Using the PPI data discussed below, we find that there is no correlation between the changes in prices that occurred during the recession and the quality tier of the firm. This fact suggests that changes in market shares are driven mostly by changes in quantities rather than by changes in prices or markups. This inference is consistent with the finding in Anderson, Rebelo and Wong (2017) that markups in the retail sector remained relatively stable during the Great Recession.

⁷Our calculations are based on Census estimates of sector expenditures. We are implicitly assuming that the market shares and labor intensities in our data are representative of each sector in a whole.

Table 1: Market shares and Labor Intensity: 2007

Industry	\$m Sales	Labor intensity			Market share		
		Low	Middle	High	Low	Middle	High
Home furnishing and appliances	654,535	4.40	4.97	7.10	1%	95%	5%
Grocery stores	547,837	3.37	4.68	7.58	39%	59%	2%
Food services and drinking places	444,551	15.63	24.02	22.43	52%	41%	7%
Clothing stores	221,205	7.55	9.43	16.49	11%	78%	11%
General merchandise stores	578,582	3.72	6.92	7.19	64%	23%	13%
Total	2,446,710	6.33	9.23	10.86	35%	58%	7%

Note: This table depicts the 2007 total sales, labor intensity and market share for different retail sectors. The last row is a sales-weighted measure. Sales are from the US Census of Retail Trade, and the labor intensities and market shares are from Compustat. Labor intensity is defined as the number of employees per million dollars of sales and the market share are the share of sales for each price tier within each sector. Price tiers are denoted by low, middle and high, and are based on Yelp! classifications of prices \$, \$\$, and \$\$\$, respectively. See text for more information.

Table 2: Market shares and Labor Intensity: 2012

Industry	\$m Sales Census	Labor intensity			Market share		
		Low	Middle	High	Low	Middle	High
Home furnishing and appliances	609,323	3.49	4.92	5.93	1%	94%	5%
Grocery stores	631,486	1.92	4.15	6.06	43%	53%	5%
Food services and drinking places	524,892	13.43	19.49	22.40	61%	33%	6%
Clothing stores	241,386	6.50	9.16	15.09	15%	77%	7%
General merchandise stores	649,754	3.72	6.92	7.19	72%	18%	10%
Total	2,656,841	5.41	8.49	10.36	42%	52%	6%

Note: This table depicts the 2012 total sales, labor intensity and market share for different retail sectors. The last row is a sales-weighted measure. Sales are from the US Census of Retail Trade, and the labor intensities and market shares are from Compustat. Labor intensity is defined as the number of employees per million dollars of sales and the market share are the share of sales for each price tier within each sector. Price tiers are denoted by low, middle and high, and are based on Yelp! classifications of prices \$, \$\$, and \$\$\$, respectively. See text for more information.

This counterfactual measure of employment is 2.38 percent lower than the level of employment in 2007. We conclude that $(3.39 - 2.38) / 3.39 = 30$ percent of the fall in employment is due to trend factors. Recall that trading down accounted for a 3 percentage points fall in employment, so the part of trading down associated with cyclical factors is: $[3 - (3.39 - 2.38)] = 1.99$. In other words, $1.99 / 3.39 = 58$ percent of the fall in employment is due to trading down associated with cyclical factors.

2.3 PPI data

In order to extend the analysis to the manufacturing sector, we use the confidential micro data collected by the Bureau of Labor Statistics (BLS) to construct the PPI.⁸ As with the Yelp! data, we merge the PPI data with Compustat to obtain price, labor intensity, and market share for each firm. This combined data set has 62,000 monthly observations for the period 2007-2012. Overall, the sectors covered by the merged PPI and Compustat data account for 15 percent of private non-farm employment.

We focus on the 2-digit NAICS manufacturing sectors 31, 32, and 33 because in these sectors we are able to merge the PPI and Compustat data for more than 10 firms per sector and span a range of quality tiers.⁹

Our quality measure for the product of a given firm is based on its price relative to the median price of that product across firms. We refer the reader to Appendix B for more details. Our analysis is based on products defined at a six-digit industry code level. For reporting purposes, we aggregate the results to the two-digit level using shipment revenue.

⁸Examples of other papers that use these data include Nakamura and Steinsson (2008), Gilchrist et al (2014), Gorodnichenko and Weber (2014), and Weber (2015).

⁹The three digit sectors included in our data are: 311 Food manufacturing, 312 Beverage & Tobacco Product Manufacturing, 315 Apparel Manufacturing, 321 Wood Product Manufacturing, 321 Wood Product Manufacturing, 325 Chemical Manufacturing, 326 Plastics & Rubber Products Manufacturing, 331 Primary Metal Manufacturing, 333 Machinery Manufacturing, 334 Computer & Electronic Product Manufacturing, 336 Transportation Equipment Manufacturing, 337 Furniture & Related Product Manufacturing, and 339 Miscellaneous Manufacturing.

One challenge with using the PPI data is that firms in the same industry report prices that correspond to different units of measurement, e.g. some firms report price per pound, others price per dozen. To address this problem we convert prices into a common metric whenever possible (for example, converting ounces to into pounds). The PPI provides information on the unit of measure for each item which we use to ensure that prices in our sample refer to the same unit of measurement (e.g. pounds). Unfortunately, there is a large number of observations on the unit of measure missing before 2007. This limitation restricts our ability to account for “pre-Great Recession” trend.

To make our results comparable with those obtained with Yelp! data, we proceed as follows. Once we rank establishments by their relative price, we assign the top 7 percent to the high-quality category, the middle 58 percent to the middle-quality category, and the bottom 35 percent to the low-quality category. Recall that this is the distribution of firms by quality tier that characterize the firms included in the Yelp! data set.

We aggregate the establishment quality tier assignment to firm level by taking a shipment-value weighted average of the quality tier and rounding to the closest quality tier. Finally, we merge the firm-level quality tier assignment from the PPI with the Compustat sample of firms.¹⁰ This merged data set allows us to compute labor intensity by quality tier.¹¹

Tables 3 and 4 shows that our two key facts hold in the PPI data. First, low-quality firms gained market share between 2007 and 2012 at the cost of middle and high-quality firms. Second, quality is correlated with labor intensity. High-quality producers have higher labor intensity than middle-quality producers and middle-quality producers have

¹⁰The aggregation of establishments up to firm level uses the matching done by Gorodnichenko and Weber (2014), who shared their code with us. In their work, they manually matched the names of establishments to the name of the firm. They also searched for names of subsidiaries and checked for any name changes of firms within the Compustat data set. See Gorodnichenko and Weber (2014) for more detail. A similar exercise of matching establishments to firms is used in Gilchrist et al (2014).

¹¹We use the entire sample of establishments within the PPI to rank the establishments, not just those that we are able to match with Compustat.

Table 3: PPI Sectors 2007

Industry	\$m Expenditure in 2007	Labor Intensity			Market share		
		Low	Middle	High	Low	Middle	High
31	811,751	0.74	3.41	n.a.	23%	77%	n.a.
32	1,434,885	2.73	2.99	4.62	26%	45%	29%
33	2,457,336	2.04	2.60	4.05	31%	63%	6%
Total	4,703,972	2.03	2.86	3.53	28%	58%	14%

Note: This table depicts the 2007 total sales, labor intensity and market share for different manufacturing sectors. The last row is a sales-weighted measure. Sales are from Census, and the labor intensities and market shares are from Compustat. Labor intensity is defined as the number of employees per million dollars of sales and the market share are the share of sales for each price tier within each sector. Price tiers are denoted by low, middle and high, and are based on firm-level producer price data. See text for more information.

higher labor intensity than low-quality producers.¹²

We now use the PPI data to implement our empirical approach. Overall employment in the sectors included in our data fell by approximately 8.6 percent. The counterfactual fall in employment that would have occurred without trading down is 3.9 percent. Hence, trading down accounts for 54 percent of the fall in employment.

In sum, our results using the PPI data are consistent with those obtained with Yelp! and Census of Retail Trade data. Higher priced stores, which are generally more labor intensive, lost market share during the recent recession. This loss of market share accounts for about half of the overall decline in employment.

2.4 NPD data

In this subsection, we discuss results obtained using data on the evolution of market shares in restaurants of different quality levels. This data set collected by the NPD Group (a marketing consulting firm) includes restaurant traffic (number of meals served) and consumer spending in restaurants broken into four categories of service: quick-

¹²We do not have any firms within the high-quality tier for Sector 31 (defined based the PPI data) that could be merged with the Compustat data.

Table 4: PPI Sectors 2012

Industry	\$m Expenditure in 2012	Labor Intensity			Market share		
		Low	Middle	High	Low	Middle	High
31	956,083	0.40	3.41	n.a.	34%	66%	n.a.
32	1,461,253	2.69	2.85	4.59	27%	47%	26%
33	2,494,959	1.40	2.41	3.32	38%	57%	5%
Total	4,912,295	1.59	2.74	3.06	33%	54%	13%

Note: This table depicts the 2012 total sales, labor intensity and market share for different manufacturing sectors. The last row is a sales-weighted measure. Sales are from Census, and the labor intensities and market shares are from Compustat. Labor intensity is defined as the number of employees per million dollars of sales and the market share are the share of sales for each price tier within each sector. Price tiers are denoted by low, middle and high, and are based on firm-level producer price data. See text for more information.

service restaurants, midscale restaurants, casual dining, and fine dining/upscale hotel. These categories are designed to represent different levels of quality.

These data can shed light on the appropriateness of our assumption that the price of a good or service is a good proxy for its quality. If we sort firms using the average price of a meal as a proxy for quality, we obtain a sorting by quality tiers similar to NPD's.¹³ The average price of dinner (lunch) is \$6.5 (\$5.8) in quick-service restaurants, \$11.2 (\$9.2) in midscale restaurants, and \$14.9 (\$11.7) in casual dining.¹⁴

We find clear evidence of trading down in the NPD data. Consider first the number of meals served. Table 5 shows that the percentage of meals served by quick-service restaurants increased from 76.1 percent in 2007 to 78.2 percent in 2012. At the same time, the fraction of meals served declined in all the other segments: midscale, casual

¹³There is a literature on the role of search frictions in generating price dispersion. While search frictions are clearly important, the price differences across categories in our dataset are clearly too large to be accounted for by these frictions alone. Aguiar and Hurst (2006) estimate that doubling of shopping frequency lowers the price paid for a given good by 7 to 10 percent. The price differences across different categories in our data are almost an order of magnitude larger than these estimates.

¹⁴These price data were collected in March 2013. We do not have average meal prices for fine-dining restaurants.

and fine-dining.¹⁵ Table 6 reports results for market share. We see that over the period 2007-2012 the market share of quick-service restaurants rose from 57.7 percent to 60 percent. At the same time, the market share declined in all the other segments.¹⁶

Unfortunately, we cannot do our accounting calculations directly with these data because we do not have the breakdown of labor intensities for the restaurant categories used by NPD. However, we can use the labor intensity estimates for Food services and drinking places reported in Tables 1 and 2, which are based on Yelp! data, as a proxy for the labor intensity in the NPD categories.¹⁷ To do so, we equate the low, middle and high quality categories in Yelp! to Quick Service, Mid-scale plus Casual Dining, and Fine Dining categories in NPD, respectively. We find that trading down accounts for 92 percent of the fall in employment. These results are similar to the total effect of trading down (including both trend and cycle) that we estimated using the Yelp! data (88 percent). Since we only have data from NPD since 2007, we cannot separate trend effects from cyclical effects.

2.5 Substitution across categories

In our analysis, we focus on the implications of trading down for employment. We also studied the employment implications of substitution across categories, for example from luxuries to necessities. Our analysis is based on CEX and NIPA PCE data (see Appendix C for more detail on the calculations).

It is well known that different categories of expenditure have different income elasticities. As a result they differ in their cyclical properties. For example, expenditure

¹⁵There is also some evidence in the NDP data that consumers traded down in terms of the meal they choose to eat at restaurants, eating out at breakfast and lunch instead of at dinner.

¹⁶Tables 5 and 6 show that after the worst of the recession was over in 2010, fine dining started to recover. But overall, the fraction of meals served and market share of fine dining are still lower in 2012 than in 2007.

¹⁷NPD provided us with a partial list of restaurants classified according to the NPD categories. Using this list, we concluded that their classification is almost identical to the one we obtain using Yelp!

Table 5: Percentages of Restaurant Traffic by Year and Quality Segment

Quality segment	2007	2008	2009	2010	2011	2012
Quick service restaurants	76.1	76.4	76.8	77.2	77.8	78.2
Midscale	11.4	11.1	11.0	10.7	10.3	10.0
Casual dining	11.2	11.1	11.1	10.9	10.7	10.4
Fine dining/upscale hotel	1.4	1.4	1.2	1.2	1.3	1.3

Note: The data is from NPD Group.

Table 6: Restaurant Market Share by Year and Quality Segment

Quality segment	2007	2008	2009	2010	2011	2012
Quick service restaurants	57.7	58.0	58.7	59.0	59.4	60.0
Midscale	15.4	15.2	15.1	14.8	14.5	14.1
Casual dining	21.5	21.4	21.4	21.3	20.9	20.5
Fine dining/upscale hotel	5.5	5.3	4.9	5.0	5.2	5.4

Note: The data is from NPD Group.

on food away from home falls during recessions by much more than expenditures on personal care.

We find that substitution across categories has a negligible effect on employment. This result is driven by the low correlation between income elasticities of different categories and labor intensity is quite low. For example, both food away from home and vehicle purchases fall during recessions. But food away from home has high labor intensity, while vehicle purchases has low labor intensity. We summarize our results in Appendix C.

3 Quality choice in a business-cycle model

In this section, we study a general-equilibrium model in which households choose the quality of the goods they consume. We show that this quality choice is a source of amplification and that it enables the model to successfully address some long-lasting challenges in the business-cycle literature.

We first study a representative-agent model and compare its cyclical properties with those of U.S. data. The model's simplicity allows us to highlight the new mechanism at work. It also facilitates the comparison of the model with other representative-agent models in the literature. We then extend our model to include heterogeneity in consumer quality choices. This extension allows us to draw a tighter connection between the model and our empirical work. As it turns out, the key results are consistent across the representative agent and heterogeneous agent models.

We focus our discussion on a flexible-price version of the model. We show in Appendix F that the same mechanism that amplifies real shocks also amplifies nominal shocks. We do so by embedding quality choice in an model with Calvo (1983)-style sticky prices.

3.1 A representative-agent model

Household The household derives utility (U) from both the quantity (C) and quality (q) of consumption and disutility from work (H),

$$U = U(C, q, H), \quad (8)$$

where

$$U_1(C, q, H) > 0, U_2(C, q, H) > 0, U_3(C, q, H) < 0. \quad (9)$$

The household's problem is:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t [U(C_t, q_t, H_t)], \quad (10)$$

s.t.

$$P_{q,t}C_t + I_t = W_tH_t + r_tK_t, \quad (11)$$

$$K_{t+1} = I_t + (1 - \delta)K_t, \quad (12)$$

where E_0 is the conditional expectation operator, W_t is the wage rate, r_t is the rental rate of capital, and I_t is the level of investment.¹⁸ $P_{q,t}$ is the price of one unit of consumption with quality q .

The first-order conditions for hours, consumption and quality imply that:

$$\frac{U_2(C_t, q_t, H_t)}{U_1(C_t, q_t, H_t)} = \frac{P'_{q,t}C_t}{P_{q,t}}, \quad (13)$$

$$\frac{U_3(C_t, q_t, H_t)}{U_1(C_t, q_t, H_t)} = -\frac{W_t}{P_{q,t}}. \quad (14)$$

The requirement that quality be a normal good, so that higher-income consumers choose to consume higher-quality goods, imposes restrictions on the utility function. Equations (13) and (14) imply that if U is homogeneous in C , quality is independent

¹⁸We choose the investment good to be the numeraire, so we set its price to one.

of income. So, in order for quality to be a normal good, U must be non-homothetic in C .

With this requirement in mind, we assume that the household's problem is to maximize

$$\max E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{q_t^{1-\theta}}{1-\theta} \log(C_t) - \phi \frac{H_{s,t}^{1+\nu}}{1+\nu} \right], \quad (15)$$

subject to equations (11)-(12). An advantage of this functional form is that it nests the usual separable logarithmic utility in consumption and power disutility in hours worked as a special case. This property simplifies the comparison of versions of the model with and without quality choice.

The first-order condition for C_t is:

$$\frac{q_t^{1-\theta}}{1-\theta} \frac{1}{P_{q,t} C_t} = \lambda_t, \quad (16)$$

where λ_t denotes the Lagrange multiplier associated with the budget constraint of the household in period t .

The first-order conditions for quality is:

$$q_t^{-\theta} \log(C_t) = \lambda_t C_t P'_{q,t}. \quad (17)$$

For future reference, we note that combining these last two equations implies that consumption comoves with the price elasticity with respect to quality,

$$\log(C_t) = \frac{1}{1-\theta} \frac{P'_{q,t} q_t}{P_{q,t}}. \quad (18)$$

The first-order conditions for hours worked and capital accumulation have the following familiar form

$$\chi H_{s,t}^{\nu} = \lambda_t W_t, \quad (19)$$

$$\lambda_t = \beta E_t \lambda_{t+1} (1 - \delta + r_{t+1}), \quad (20)$$

Production Consumption is produced by a continuum of measure one of competitive firms according to the following production function:

$$C_t = A_t \left[\alpha \left(\frac{H_t^C}{q_t} \right)^\rho + (1 - \alpha) (K_t^C)^\rho \right]^{\frac{1}{\rho}}, \quad (21)$$

where H_t^C and K_t^C denote labor and capital employed in the consumption sector, respectively.¹⁹ The consumption firms' problem is to maximize:

$$\max P_{q,t} C_t - W_t H_t^C - r_t K_t^C. \quad (22)$$

The solution to this problem implies that the equilibrium price of a consumption good with quality q is given by

$$P_{q,t} = \frac{1}{A_t} \left[\alpha^{\frac{1}{1-\rho}} (q_t W_t)^{\frac{\rho}{\rho-1}} + (1 - \alpha)^{\frac{1}{1-\rho}} r_t^{\frac{\rho}{\rho-1}} \right]^{\frac{\rho-1}{\rho}} \quad (23)$$

We assume that $\rho < 0$, so there is less substitution between capital and labor than in a Cobb-Douglas production function. It is easy to show that this assumption is necessary so that, consistent with our empirical results, higher-quality goods are more labor intensive. The assumption that $\rho < 0$ also implies that the price is an increasing function of quality. This property is consistent with our empirical approach which used price as a proxy for quality. Finally, $\rho < 0$ implies that the price elasticity with respect to quality is increasing with quality. This property ensures that there is comovement between the quantity and quality consumed (see equation (18)).

Investment is produced by a continuum of measure one of competitive firms according to:

$$I_t = A_t \left[\alpha (H_t^I)^\rho + (1 - \alpha) (K_t^I)^\rho \right]^{\frac{1}{\rho}}. \quad (24)$$

This production function is the same used in the consumption sector without quality as a variable. Since our evidence about trading down is only for consumption goods, we assume that investment goods are homogeneous in quality.

¹⁹We abstract from technical progress in both the consumption and investment sectors. A version of the model with labor-augmenting technical progress that is consistent with balanced growth is available upon request.

The problem of a producer of investment goods is

$$\max P_t^I I_t - W_t H_t^I - r_t K_t^I. \quad (25)$$

where H_t^I and K_t^I denote labor and capital employed in the investment sector, respectively.

Equilibrium The equilibrium definition is as follows. Households maximize utility taking the wage rate, the rental rate of capital, and the price-quality schedule as given. Since households are identical, they all choose the same level of quality and only this quality level is produced in equilibrium. Firms maximize profits taking the wage rate and the rental rate of capital as given. The labor and capital market clear, so total demand for labor and capital equals their supply:

$$K_t^C + K_t^I = K_t, \quad (26)$$

$$H_t^C + H_t^I = H_{s,t}. \quad (27)$$

Real output (Y_t) in the economy is given by:

$$Y_t = P_{q,t} C_t + I_t. \quad (28)$$

This expression assumes that real output is computed using hedonic adjustments: when the price of consumption rises, the statistical authorities recognize that this rise is solely due to an increase in the quality of the goods consumed.

Simulation We solve the model numerically, using the parameters described in Table 7, by linearizing the equilibrium conditions around the steady state. There are three parameters that cannot be directly calibrated from the existing literature: α , ρ , and θ . In the heterogeneous-agent model discussed in Section 3.2.1, we calibrate these parameters by matching the moments from the micro data presented in Section 2. To facilitate comparison, we set these parameters in the representative agent model to

be the same as in the heterogeneous model. For the remaining parameters we follow common choices used in the literature.²⁰

Table 7: Calibration

Parameter	Moment/Description	Value
β	Quarterly discount rate	0.985
ν	Inverse of Frisch elasticity	0.001
ϕ	Match steady state H	5.31
δ	Depreciation rate	0.025
κ	AR(1) coefficient of TFP	0.95
α	Production function share	0.6
ρ	EOS between K and N: $\frac{1}{1-\rho}$	-1.4
θ	Elasticity of utility to quality	0.75

Amplification

The top panel of Figure 1 shows the impulse response functions of labor and output for two versions of the model, with and without quality choice, in response to a negative TFP shock of the same magnitude. The model without quality choice is a benchmark one-sector Real Business Cycle (RBC) model with a CES production function.

Figure 1 shows that the model with quality choice produces much more amplification than the model without quality choice. The reason is that in response to a negative shock, consumers trade down in the quality of the good they consume (see bottom panel of Figure 1). Since lower quality goods are less labor intensive, trading down reduces the demand for labor. This property is reflected in the ratio of production

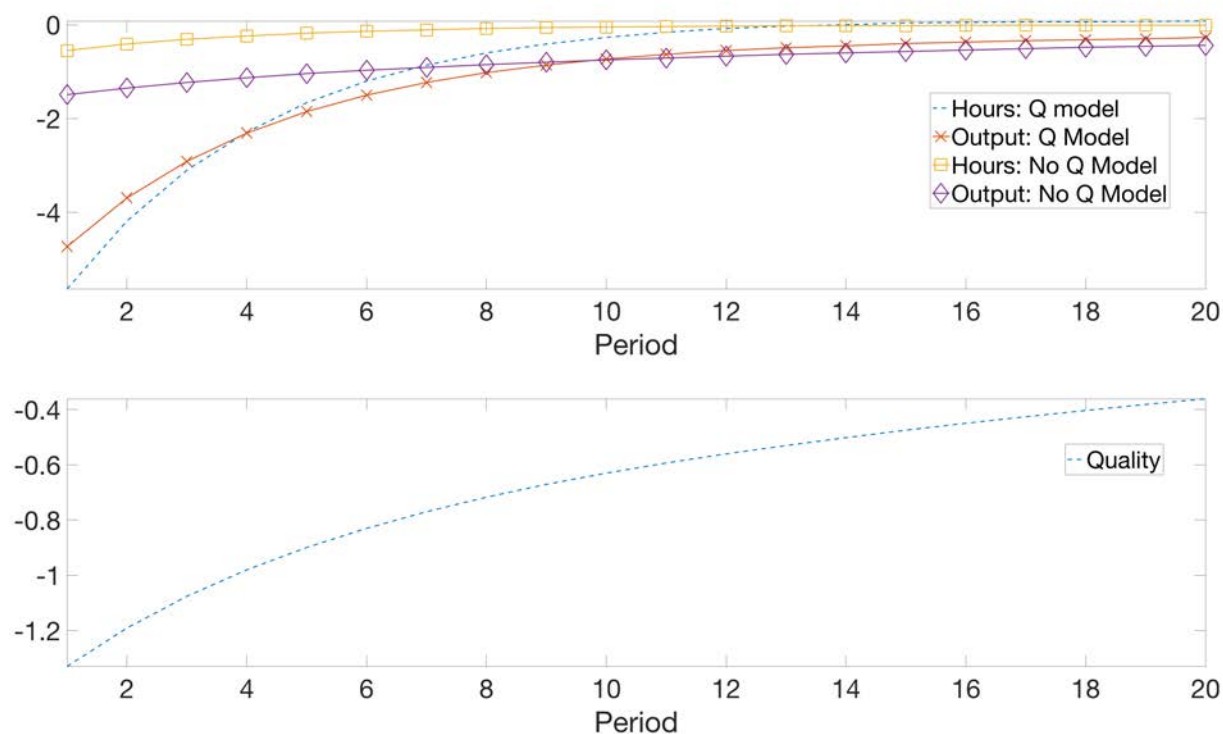
²⁰We choose a high elasticity of labor supply (the inverse of the Frisch elasticity is 0.001) so that the performance of the version of the model without quality choice is as good as possible.

factors chosen by a consumption good producer,

$$\frac{H_t^C}{K_t^C} = q_t^{\frac{\rho}{\rho-1}} \left(\frac{\alpha}{1-\alpha} \frac{r_t}{W_t} \right)^{\frac{1}{1-\rho}}. \quad (29)$$

Since $\rho < 0$, a fall in the optimal quality chosen by the household, acts as a negative demand shifter for hours worked. This amplification channel is absent in a model without quality choice.

Figure 1: Impulse Response Functions for a Fall in A



To study the model's business cycle implication, we simulate quarterly versions of the models with and without quality choice model driven by an AR(1) TFP shock. We HP-filter both the U.S. data and the time series generated by the models with a smoothing parameter of 1600.

Table 8 reports the standard deviation relative to aggregate output (denoted by σ_X/σ_{GDP}) and the correlation with aggregate output (denoted by $Cor^{X,GDP}$) with the

following variables: consumption, investment, total hours worked, hours worked in the consumption sector, hours worked in the investment sector, and the labor wedge. Columns 1-2, 3-4, and 5-6 present the results for U.S. data, our representative agent model with quality choice and the model without quality choice, respectively.

The table shows that the model with quality choice provides much more amplification of hours worked relative to output than a model without quality choice. In fact, the model generates a relative volatility of hours and output that is very close to the one observed in the U.S. data.

Table 8: Second Moments

Variable	Data		Rep. Agent with Quality		No Quality		Het Agents with Quality	
	$\frac{\sigma_X}{\sigma_{GDP}}$	$Cor^{X,GDP}$	$\frac{\sigma_X}{\sigma_{GDP}}$	$Cor^{X,GDP}$	$\frac{\sigma_X}{\sigma_{GDP}}$	$Cor^{X,GDP}$	$\frac{\sigma_X}{\sigma_{GDP}}$	$Cor^{X,GDP}$
Total Hours	1.1	0.78	1.21	0.99	0.34	0.92	0.96	0.99
Hours in C	0.80	0.48	0.17	0.41	0.08	-0.27	0.16	0.66
Hours in I	2.48	0.86	3.11	0.97	6.23	0.84	3.68	0.96
Consumption	0.80	0.85	0.29	0.84	0.69	0.95	0.39	0.88
Investment	3.16	0.87	3.28	0.98	6.76	0.88	3.91	0.97
Labor Wedge	1.1	-0.69	0.21	-0.94	NA	NA	0.11	-0.98

Sources of amplification We now discuss two sources of amplification embodied in our model: the effect of changes in quality on labor demand and the weaker income effects on the labor supply.

Consider first the effect of changes in quality on labor demand. Recall that high-quality goods are more labor intensive than low-quality goods. Since quality is procyclical, labor demand fluctuates by more in the model with quality choice.

One way to see the importance of this effect is to compare the volatility of hours in the models with and without quality choice when we keep λ_t (the marginal utility of income) constant.²¹ The labor supply equation (19) is the same in both models, so keeping λ_t constant ensures that differences in the volatility of hours do not come from the behavior of the labor supply. The volatility of hours in these λ_t -constant versions of the models is 92 percent higher in the model with quality choice. This result shows that the model with quality choice embodies sources of amplification that are not related to the behavior of the labor supply.²²

To understand these sources of amplification, it is useful to consider a static, partial equilibrium version of our model in which the household has an exogenous income, ξ_t . The household problem is

$$\max \frac{q_t^{1-\theta}}{1-\theta} \log(C_t), \quad (30)$$

subject to

$$P_{q,t}C_t = \xi_t, \quad (31)$$

The first-order conditions for this problem are equations (16)-(17). On the production side, we assume that firms produce the consumption good according to equation (21).

We compare the response of labor demand to exogenous changes in household income, for constant values of W and r in versions of the model with and without quality choice.²³ In the model without quality choice q is equal to one and the budget constraint is $C_t = \xi_t$. The following proposition, proved in Appendix H, summarizes the key result.

Proposition 1. *For given levels of W and r , the fall in hours worked employed by firms*

²¹To do so, we allow the disutility of labor, χ to be stochastic so that it perfectly cancels movement in λ_t .

²²For this experiment, the lowest value of ν we can consider is 0.15. For lower values of ν the Blanchard-Kahn conditions are not satisfied. The key properties of the model reported in Table 8 continue to hold in this alternative calibration.

²³In the model with quality choice, the price of consumption changes in respond to changes in the optimal quality chosen by the household.

in response to an exogenous fall in household income is always higher in the model with quality choice.

Figure 2: Response to an Income Shock

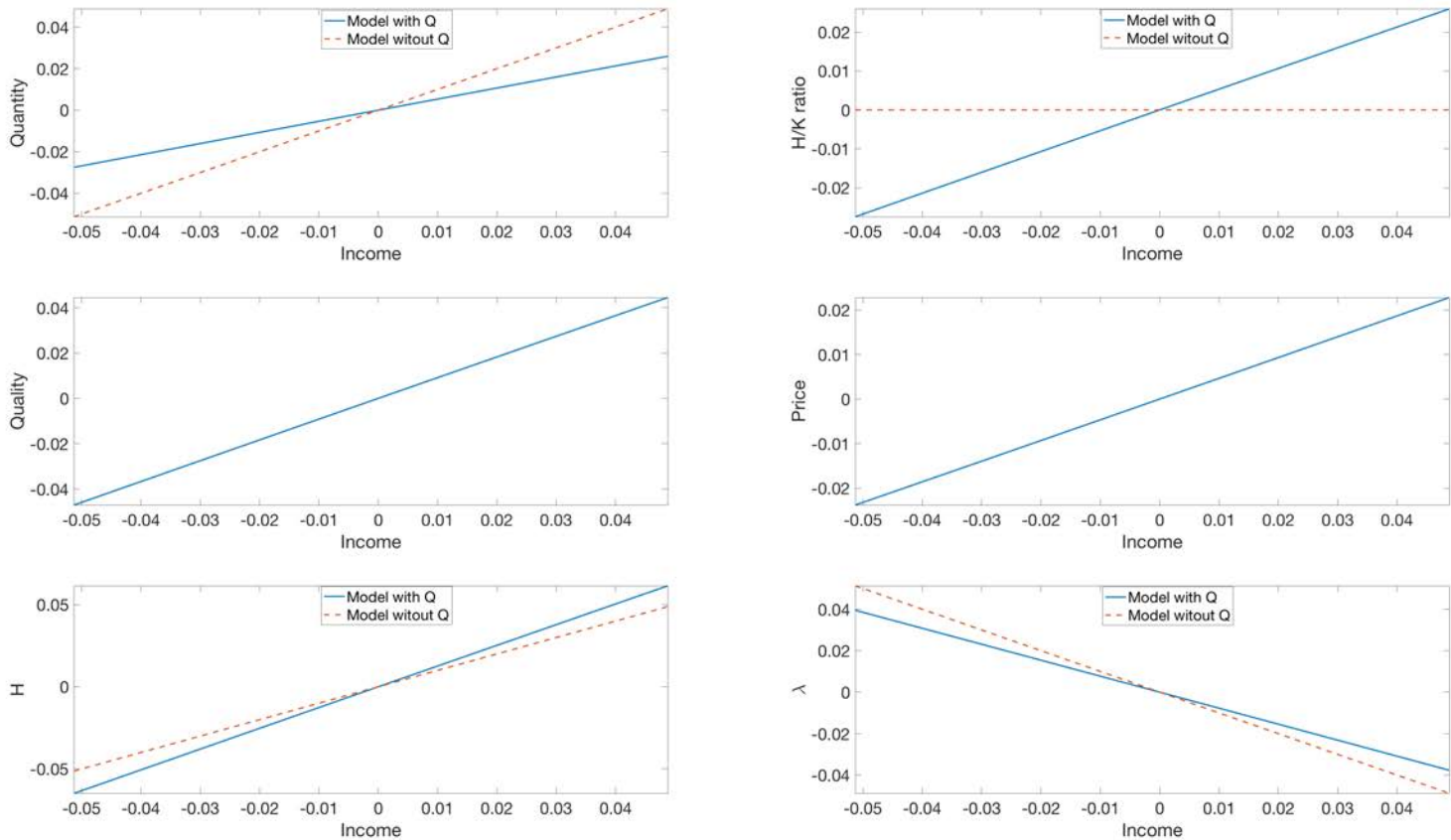


Figure 2 illustrates this result. The figure depicts the response of economies with and without quality choice to a shock in household income (depicted on the x-axis in terms of percentage deviations). All variables are expressed as percentage deviations from their steady state values in the general equilibrium model.

Consider first the model without quality choice. A drop in household income leads to a reduction in the quantity of consumption goods demanded (depicted by the hatched

line on the top left panel). Since the prices of the two production factors are constant, the firm reduces the demand for labor and capital in the same proportions (see equation (29) with $q = 1$). As a result, the capital-labor ratio remains constant (see the hatched line in the top right panel).

Consider now the model with quality choice. A fall in consumer income is associated with a fall in the quantity and quality consumed (see the left middle-row panel). The fall in quality leads firms to contract more the demand for labor than the demand for capital (top right panel). Hours worked change by more in the economy with quality choice (last row, left panel).

The second source of amplification is the relative weakness of income effects on the labor supply in the model with quality choice. Equation (19) shows that movements in λ_t reduce the volatility of hours worked. A rise in the real wage produces a negative income effect that induces workers to supply fewer hours (richer workers want to enjoy more leisure). This effect counters the substitution effect that induces workers to supply more hours in response to a rise in the real wage. A weaker income effect generates higher volatility in hours worked.

We compare the importance of income effects on the labor supply by simulating versions of the model with and without quality choice where λ_t is kept constant in equation (19). Keeping λ_t constant increases the volatility of hours worked by a factor of 7 in the model without quality choice. In contrast, keeping λ_t constant in the model with quality choice increases the volatility of hours worked by a factor of only 2.3. An alternative way to compare the importance of income effects on the labor supply in models with and without quality choice is to compare the volatility of λ_t in the two economies. This volatility is 24 percent lower in the model with quality choice.

The intuition for the lower volatility of λ_t in our model is as follows. In the model without quality choice, agents have only one margin to adjust their consumption in response to an exogenous income shock: to reduce the quantity they consume. In the model with quality choice agents can use two margins of adjustment: change the

quantity and the quality of what they consume. As a result, λ changes by less in response to an income shock. This weaker income effect leads to larger movements in hours worked.

The right panel in the third row of Figure 2 depicts the behavior of λ in the partial equilibrium model discussed above. The figure shows that changes in income have a smaller effect on λ in the model with quality than in the model without quality.

Comovement

The results reported in Table 8 show another interesting difference between the models with and without quality choice. As emphasized by Christiano and Fitzgerald (1998), hours worked in the consumption sector are procyclical in the data but countercyclical in the standard RBC model.²⁴ The model with quality choice generates procyclical hours worked in the consumption sector.

To understand this property, it is useful to write the first-order condition for labor choice for a standard RBC model with a Cobb-Douglas production function:

$$\phi(H_t^C + H_t^I)^\nu = \frac{\alpha}{H_t^C}.$$

It is clear that H_t^I and H_t^C are negatively correlated, so that H_t^I and H_t^C cannot be both positively correlated with aggregate output. Using a CES production function changes the form of the first-order condition but does not help generate comovement.

Consider the first-order condition for labor choice in the model with quality choice:

$$\phi(H_t^C + H_t^I)^\nu = \frac{q_t^{1-\theta-\rho}}{1-\theta} \frac{\alpha}{(H_t^C)^{1-\rho}} \left(\frac{A_t}{C_t}\right)^\rho.$$

This equation shows that H_t^C and H_t^I can be positively correlated, because quality is

²⁴To classify the sectors into “consumption” and “investment” we follow standard practice. We use the BEA’s 2002 benchmark I/O “use tables.” To compute the share of sectoral output used for private consumption vs. private investment, we assign a sector to the consumption (investment) sector if most of its final output is used for consumption (investment). For the hours/sectors data we use the Current Employment Statistics 1964:Q1 - 2012:Q4.

procyclical. The rise (fall) in quality increases (decreases) the demand for labor in the consumption sector, contributing to the comovement between H_t^C and H_t^I .

An endogenous labor wedge Shimer (2009) modifies the standard Euler equation for labor to allow for a “labor wedge,” τ_t , that acts like a tax on the labor supply:

$$\phi H_t^\nu = (1 - \tau_t) \frac{1}{C_t} w_t. \quad (32)$$

He then computes the labor wedge, using empirical measures of H_t , C_t , and w_t . Shimer (2009) finds that τ_t is volatile and counter-cyclical: workers behave as if they face higher taxes on labor income in recessions than in expansions.

The analogue of equation (32) in our model is

$$\phi H_t^\nu = \frac{q_t^{1-\theta}}{1-\theta} \frac{1}{C_t} \frac{w_t}{P_{q,t}}. \quad (33)$$

Since the quality consumed, q_t , is procyclical (see Table 8), our model generates a counter-cyclical labor wedge.

Summary We find that introducing quality choice into an otherwise standard model amplifies the response to real shocks, giving rise to higher fluctuations in hours worked. This property enables the model to match the overall relative variability of hours to output that is observed in U.S. data. Moreover, the model can also account for the sectoral comovement in hours worked in the consumption and investment sectors and generate a counter-cyclical labor wedge.

3.2 An heterogeneous-agent model

In the representative-agent model there’s a single level of quality consumed in equilibrium. In this subsection, we consider an extension of the model in which there are multiple quality levels produced in equilibrium. This distribution of quality facilitates the comparison of the model implications and our empirical findings. We show that

the key properties of the representative-agent model are preserved in the presence of heterogeneity.

We assume that individuals are endowed with different levels of efficiency units of labor, ϵ , distributed according to the cdf $\Gamma(\epsilon)$.

To reduce the dimension of the state space and make the problem more tractable, we model household decisions as made by families that contain a representative sample of the skill distribution in the economy. The family's objective is to maximize

$$V_\epsilon = \text{Max}_{\{C_{\epsilon,t}, q_{\epsilon,t}, H_{s,\epsilon,t}, K_{s,\epsilon,t+1}, I_{\epsilon,t}\}} \sum_{t=0}^{\infty} \beta^t \int_{\epsilon} \omega_\epsilon \left\{ \frac{q_{\epsilon,t}^{1-\theta}}{1-\theta} \log(C_{q_{\epsilon,t}}) - \phi \frac{H_{s,\epsilon,t}^{1+\nu}}{1+\nu} \right\} \Gamma'(\epsilon) d\epsilon. \quad (34)$$

The variable ω_ϵ denotes the weight attached by the family to an individual of ability ϵ . The variables $q_{\epsilon,t}$, $C_{q_{\epsilon,t}}$, and $H_{s,\epsilon,t}$ denote the quality and quantity of the good consumed and the labor supplied by an individual with ability ϵ in period t , respectively.

The family's budget constraint is:

$$K_{t+1} = \int_{\epsilon} [W_t \epsilon H_{\epsilon,t} - P_{q_{\epsilon,t}} C_{q_{\epsilon,t}}] \Gamma'(\epsilon) d\epsilon + r_t K_t + (1 - \delta) K_t, \quad (35)$$

where $P_{q_{\epsilon,t}}$ is the price of one unit of consumption of the quality consumed by an individual with ability ϵ in period t . The variable K_t denotes the family's stock of capital.

The first-order conditions for the quantity and quality of consumption and hours worked for each family member are the same as in the representative-agent model (equations (16)-(18)).

The goods consumed by agents with ability ϵ are produced by perfectly competitive producers according to the following CES production function:

$$Y_{\epsilon,t} = A_t \left[\alpha \left(\frac{H_{d,\epsilon,t}}{q_{\epsilon,t}} \right)^\rho + (1 - \alpha) (K_{d,\epsilon,t})^\rho \right]^{\frac{1}{\rho}}, \quad (36)$$

The variables $H_{d,\epsilon,t}$ and $K_{d,\epsilon,t}$ denote the labor and capital employed by the producer, respectively. As in our representative-agent model, we assume that $\rho < 0$.

The problem of a producer who sells its goods to consumers with ability ϵ is given by

$$\max P_{q_{\epsilon,t}} Y_{\epsilon,t} - W_t H_{d,\epsilon,t} - r_t K_{d,\epsilon,t}. \quad (37)$$

This solution to this problem implies that the price schedule, $P_{q_{\epsilon,t}}$, is

$$P_{q_{\epsilon,t}} = \frac{1}{A_t} \left[\alpha^{\frac{1}{1-\rho}} (q_{\epsilon,t} W_t)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{1}{1-\rho}} r_t^{\frac{\rho}{\rho-1}} \right]^{\frac{\rho-1}{\rho}}, \quad (38)$$

and that firm's optimal labor-capital ratio is

$$\frac{H_{d,\epsilon,t}}{K_{d,\epsilon,t}} = q_{\epsilon,t}^{\frac{\rho}{\rho-1}} \left(\frac{\alpha}{1-\alpha} \frac{r_t}{W_t} \right)^{\frac{1}{1-\rho}}. \quad (39)$$

Investment goods are produced by a continuum of measure one of competitive firms according to:

$$I_t = A_t \left[\alpha H_{d,inv,t}^{\rho} + (1-\alpha) K_{d,inv,t}^{\rho} \right]^{\frac{1}{\rho}}, \quad (40)$$

where $H_{d,inv,t}$ and $K_{d,inv,t}$ denote labor and capital employed in the investment sector, respectively. As in the representative-agent model, we assume that there is no quality choice in the investment sector.

Equilibrium The equilibrium definition is as follows. Households maximize utility taking the wage rate per efficiency unit of labor, the rental rate of capital, and the price-quality schedule as given. Firms maximize profits taking the wage rate per efficiency unit of labor and the rental rate of capital as given. The labor market clears, so total demand for labor equals total supply:

$$\int_{\epsilon} H_{d,\epsilon,t} d\epsilon + H_{d,inv,t} = \int_{\epsilon} H_{s,\epsilon,t} \epsilon \Gamma'(\epsilon) d(\epsilon). \quad (41)$$

The capital market clears, so total demand for capital equals total supply:

$$\int_{\epsilon} K_{d,\epsilon,t} d\epsilon + K_{d,inv,t} = K_t. \quad (42)$$

The goods market clear so, for each quality level, production equals consumption:

$$Y_{\epsilon,t} = \Gamma'(\epsilon)C_{q_{\epsilon,t}}. \quad (43)$$

Using investment as the numeraire, real output, Y_t , is given by:

$$Y_t = I_t + \int_{\epsilon} P_{q_{\epsilon,t}} C_{q_{\epsilon,t}} d\epsilon. \quad (44)$$

3.2.1 Calibration

Diamond and Saez (2011) argue that U.S. income follows approximately a Pareto distribution. For this reason, we assume that ability follows a Pareto distribution.

To solve the model numerically, we discretize the Pareto distribution using a support with n ability levels. The value of n needs to be large enough so that there are enough agents near the lower bounds of the high and medium quality bins. It is the trading down by these agents in response to a negative shock that leads to changes the market shares of the three quality categories. At the same time, since we solve for the optimal quality and quantity of the consumption good for each ability, we are limited in the number of types we can consider. We discretize the support of the ϵ distribution with $n = 100$ grid points.

We set the shape parameter of the Pareto distribution to 1.5, which is the value estimated by Diamond and Saez (2011). The ratio of the upper and lower bound of the support of the ϵ distribution, $\epsilon_{max}/\epsilon_{min}$, is chosen to match the income ratio of the top 5 percent to the second income quintile between 2010-2014. This ratio is equal to 4.9.²⁵ We choose the weights attached by the family to a worker of skill ϵ to be the ratio of ϵ to the average skill, $\epsilon/E(\epsilon)$.

The remaining three parameters, ρ , α , and θ are chosen so that in the steady state we match the empirical values of the following three moments: (i) the ratio

²⁵See the data in <http://www.taxpolicycenter.org/statistics/historical-income-distribution-all-households>

the labor intensity in the “middle quality” market to the labor intensity in the “low quality” market in 2007, (ii) the ratio of the labor intensity in the “high quality” market to the labor intensity in the “middle quality” market in 2007, and (iii) the share of capital income. We discuss the details of our calibration procedure in Appendix G. This procedure yields the following parameter values: $\alpha = 0.6$ and $\rho = -1.4$, and $\sigma = 0.75$. The remaining parameters are the same we used in our representative-agent model.

3.3 Results

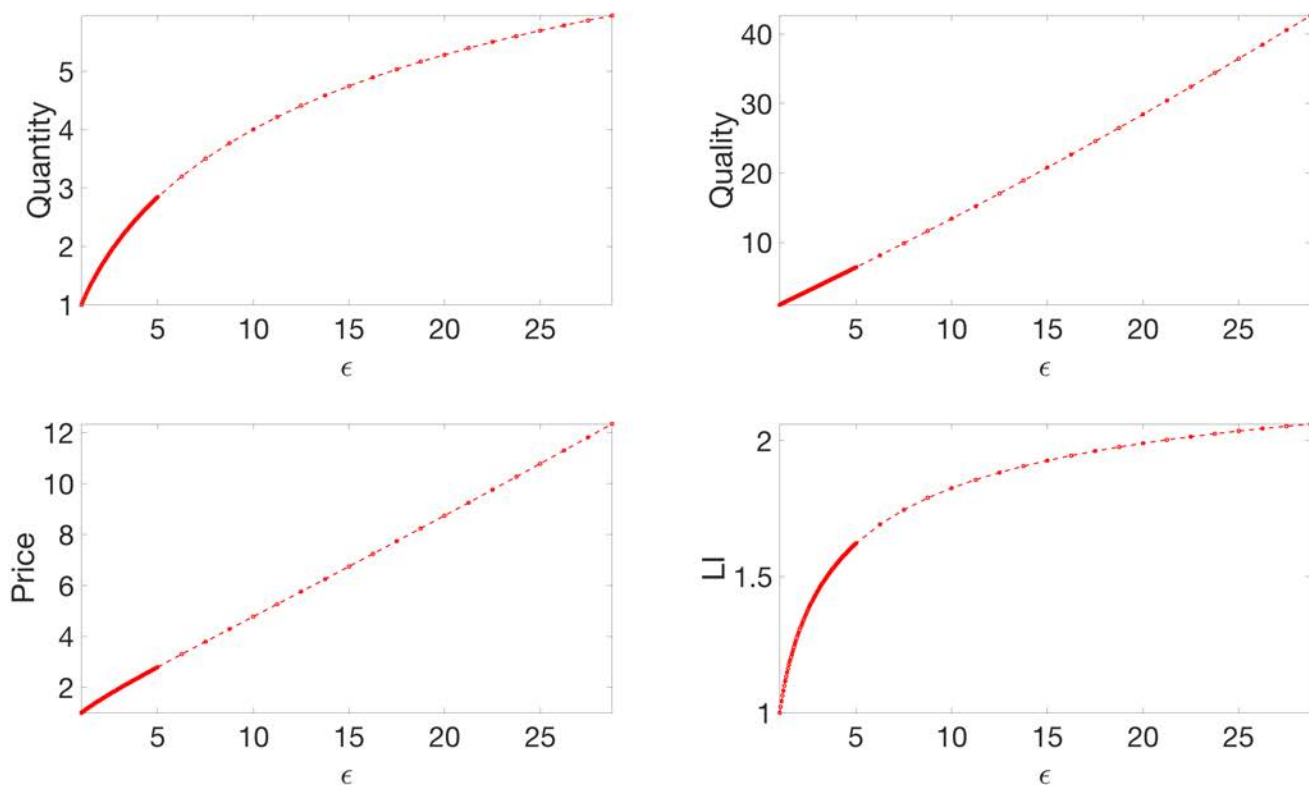
Steady State Figure 2 illustrates some key properties of the steady state that are consistent with our empirical facts. The first panel shows that higher-skilled individuals (those with a higher ϵ) consume more quantity and higher quality. The second panel shows that higher quality goods have higher prices and are produced with higher labor intensities.

The Effect of Trading Down Recall that around half of the observed fall in employment was due to cyclical trading down. We follow the empirical approach described in Section 2, summarized in equations (4)-(6), to compute the impact of trading down on employment in our model.

We subject the economy to a TFP shock that generates the same 7 percent increase in the share of the low-quality segment we estimate with Yelp! data. We then calculate the market share of the low, middle and high qualities markets, and the labor intensity in each of these three segments in the period when the shock occurs. We then use this information to compute the counterfactual change in hours worked that would have occurred in the absence of trading down.

Overall, we find that hours worked in the consumption sector fall on impact by 4.8 percent. We find that, absent trading down, hours worked would have fallen by only 1.9 percent. These results imply that trading down accounts for around 60 percent of

Figure 3: Optimal Choices and Implications



the observed changes in employment, which is roughly consistent with our empirical estimates.

Business Cycle Moments The last two columns in Table 8 reports the cyclical properties of the heterogeneous agent model. We see that the business-cycle properties of this model are very similar to those of the representative agent model. The heterogeneous-agent model generates amplification in hours worked, comovements of hours worked in the consumption and investment sectors, and a countercyclical labor wedge.

4 Conclusion

We document two facts. First, during the Great Recession consumers traded down in the quality of the goods and services they consumed. Second, lower quality products are generally less labor intensive, so trading down reduces the demand for labor. Our calculations suggest that trading down accounts for about half of the decline in employment during the Great Recession.

We study a general equilibrium model in which consumers choose both the quantity and quality of consumption. We show that in response to a fall in TFP the model generates trading down in quality and declines in employment that are broadly consistent with our empirical findings.

The presence of quality choice improves the performance of the model along two dimensions. First, cyclical changes in the quality of what is consumed amplifies the effects of shocks to the economy, resulting in higher variability in hours worked. Second, the model generates comovement between labor employed in the consumption and investment good sectors.

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Appendix

In this appendix, we accomplish four main tasks. First, we provide more details about the construction of the Yelp! and PPI data set. Second, we report additional robustness checks on the estimates presented in the main text regarding the effects of trading down on employment. Third, we discuss the algorithm used to calibrate the heterogeneous-agent model. Finally, we discuss a version of the representative model with Calvo-style price stickiness.

A Yelp! data

We scraped data for Yelp in April 2014. For firms that own more than one brand, we compute the average price category for each brand and then compute the average price category for the firm, weighting each brand by their sales volume. One concern about this procedure is that we might be averaging high-quality and low-quality brands. In practice, this situation is rare: 73 percent of the firms in our sample have a single brand. For multi-brand firms, 54 percent have all their brand in the same price category. For example, the firm Yum! Brands owns three brands (Taco Bell, KFC, and Pizza Hut), but they are all in the same price category (low price). For robustness, we redid our analysis including only firms that either have a single brand or have all their brands in the same price category. We obtain results that are very similar to those we obtain for the whole universe of firms.

In merging the data with Compustat we note that for companies with operations outside of the U.S., we use the information on sales by business region to compute U.S. sales. We also use the break down of employment by business region to compute labor intensity in the U.S. We exclude from our sample manufacturing firms for which this breakdown is not available. For retail firms, foreign operations are generally small, so we include companies with foreign operations in our sample. As we robustness check, we redo our analysis excluding these companies. The results are similar to those we

obtain for the full sample.

Table 9 presents some description of the data used to analyze quality shifts in expenditure in five retail sectors. It describes the data source (column I), the number of firms covered in the sample in 2007 (II), the average annual firm sales revenue (III), and the percent of the overall sector sales that our sample covers (IV).

Table 9: Data Sample Description

Sectors	Data Source (I)	Number of Firms (II)	2007 Annual Sales	
			of Average Firm (\$m) (III)	% of U.S. Sector (IV)
Apparel	Compustat and company reports	54	1,648	41%
Grocery stores	Compustat and company reports	9	34,348	56%
Restaurants	Compustat and company reports	74	1,012	19%
Home furnishing	Compustat	41	4,750	39%
General Merchandise	U.S. Census	n.a.	n.a.	100%

Note: This table describes for each sector the data source used (I), the number of firms within the sample (II), and the average annual sales of each firm (III). (IV) reports the share of the sales of the entire sector that our data set covers.

B PPI

Using the PPI data presents two challenges. First, firms in the same industry report prices that correspond to different units of measurement, e.g. some firms report price per pound, others price per dozen. To circumvent this problem, we first convert prices into a common metric whenever possible (for example, converting ounces to into pounds). We then compute the modal unit of measurement for each 6-digit NAICS

category and restrict the sample to the firms that report prices for this model unit. This filtering procedure preserves 2/3 of the original data, which is comprised of 16,491 establishments out of a sample of about 25,000 establishment surveyed by the PPI. Some establishments are excluded because we only include items that are recorded at the modal unit of measure within the 6-digit product category.

Second, some of the firms included in the PPI data offshore their production, so their reported employment does not generally include production workers. It includes primarily head-office workers and sales force in the U.S. Using information in the firms' annual reports, we exclude firms that have most of their production offshore. The resulting data set preserves over half of the merged PPI/Compustat data.

In order to construct a quality measure for each firm, we proceed as follows. For each product k that establishment e sells in year t , we calculate its price, p_{ket} , relative to the median price in the industry for product k in year t , \bar{p}_{kt} :

$$R_{ket} = p_{ket}/\bar{p}_{kt}.$$

Our analysis is based on products defined at a six-digit industry code level and then further disaggregated by product type. Therefore, although the results are presented at a 2-digit level, all relative prices are defined at a narrow 6-digit level for comparability. For details of this disaggregation, see Table 11 of the BLS PPI Detailed Report. The variable \bar{p}_{kt} is a shipment-value weighted average within the product category. For reporting purposes, we aggregate the results to the two-digit level. The aggregation is based on shipment revenue.

For single-product establishments, we use this relative price as the measure of the quality of the product produced by establishment e . For multi-product establishments, we compute the establishment's relative price as a weighted average of the relative price

of different products, weighted by shipment revenue in the base year (w_{ke}):²⁶

$$R_{et} = \sum_{k \in \Omega} w_{ke} R_{ket}.$$

where Ω denotes the set of all products in the PPI data set that we examined.

C Substitution across categories

Our main analysis focuses on trading-down behavior within categories. We also examined substitution across consumption categories and the effect on employment. We use data from the CEX Survey and NIPA personal consumption expenditures (PCE). We consider 31 different consumption categories (see Figure 4).

We examine the effect of across-category substitution on employment in two steps. First, we construct the labor intensity for each consumption category. We match CEX consumption categories with the NIPA PCE commodity definitions.²⁷ This allows us to use the Input/Output commodity-level data to construct labor intensity measures for each consumption category. Second, we compute the change in budget share for each consumption category over 2007-2012 for the average household. To isolate out the cyclical component of the budget reallocation across consumption categories, we estimate elasticities of the category budget shares to total household expenditure. We then multiply the elasticities by the actual change in household expenditure to obtain the change in budget allocation for each category.

We derive shifts in expenditure associated with the recessionary drop in household income by estimating the following Engel curve elasticities:

$$w_{ht}^k = \alpha^k + \beta^k \ln(X_{ht}) + \sum_j \gamma_j \ln(P_{jt}) + \theta_{ht}^k \cdot Z_{ht} + \epsilon_{ht}^k, \quad (45)$$

²⁶This approach for constructing firm-level price indices is similar to that used by Gorodnichenko and Weber (2014), and Gilchrist et al (2014). However, we compute relative prices using a much finer product definition than these authors. We refer the reader to Section II in Gorodnichenko and Weber (2014) for a discussion of how the BLS samples products and firms.

²⁷Further details of this matching process are available upon request.

where w_{ht}^k is the budget share allocated to category k by household h at time t ; X_{ht} is total household expenditure; and P_{jt} is the price index of each expenditure category j at time t . The variable Z_{ht} is a vector of household demographics variables, including the age and square of the age of the head of household, dummies based on the number of earners (<2,2+), and household size (<2,3-4,5+). The error term is denoted by ϵ_{ht}^k . We estimate equation (45) using household sample weights given in the CEX data based on the 1980-2012 waves of the CE Surveys. The coefficient β^k gives the fraction change in budget share allocation to expenditure category k , given a 100 percentage point change in total household expenditure.²⁸

²⁸There potential issues that arise in estimating equation (45). For instance, mismeasurement of individual goods may be cumulated into total expenditure, which would bias the estimated coefficients. Aguiar and Bils (2013) for a more detailed discussion of these measurement issues associated with using the CE Survey to estimate elasticities. Therefore for robustness, we also use the standard approach of instrumenting total expenditure with total income reported by the household. The estimated elasticities yield similar results to our base estimation without instrumenting.

Figure 4: Scatter plot of labor intensity and elasticities across sectors

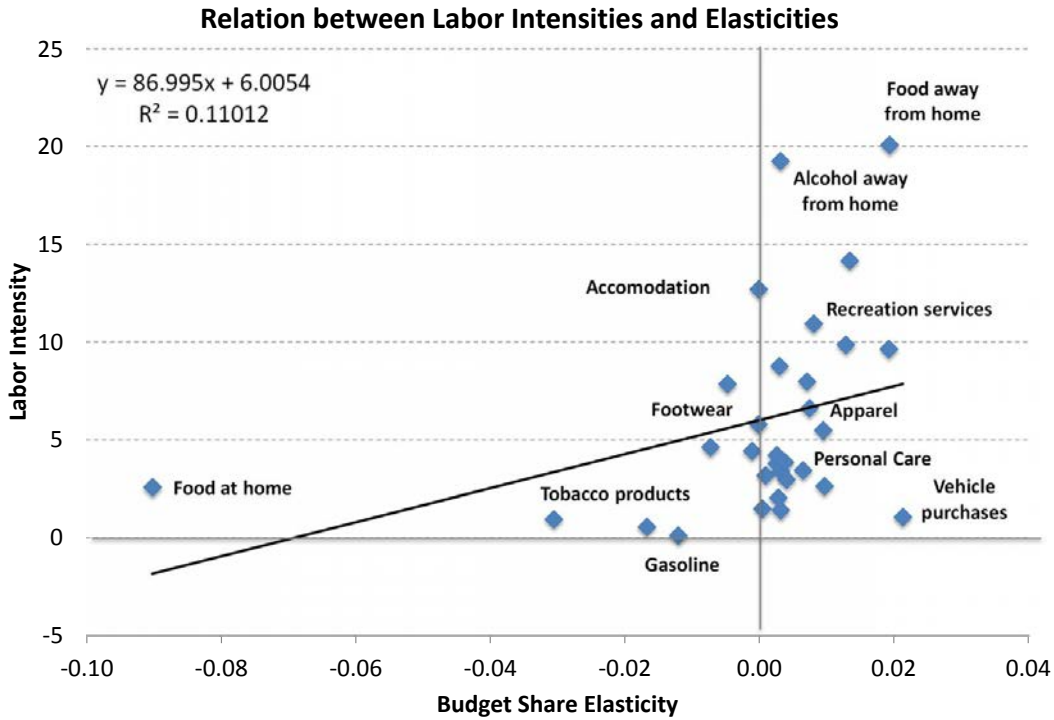


Figure 4 shows there is a low positive relation between a category expenditure elasticity and its labor intensity measure. To examine the effect of across-category substitution on employment, we perform a similar exercise as our trading-down calculation. We compute the change in the number of employed workers between 2007 and 2012 due to changes in the shares of the expenditures categories, holding fixed the measured labor intensity.²⁹ This exercise yields a negligible effect of the substitution across categories on aggregate employment, in contrast to our findings of large effects of quality trading-down within categories.

²⁹We also did the computation using actual observed change in expenditure allocations in the NIPA PCE data and found similar results.

D Results based on alternative labor intensities

As a robustness check, Tables 10 and Tables 11 reports our calculation using our second measure of labor intensity, employment/gross margin. For the period 2007-12, the change in employment accounted for by trading down represents 37 percent of the fall in employment. For the period 2007-09, this fraction represents 28 percent of the fall in employment.

Table 10: Market shares and Labor Intensity: 2007

Industry	\$m Sales - COGS	Labor intensity			Market share		
		Low	Middle	High	Low	Middle	High
Home furnishing and appliances	248,751	14.05	15.27	27.90	1%	95%	4%
Grocery stores	353,472	16.23	18.06	21.22	16%	80%	4%
Food services and drinking places	270,390	68.08	131.75	93.70	58%	36%	6%
Clothing stores	119,579	27.34	24.34	29.59	8%	76%	16%
General merchandise stores	425,163	16.23	24.26	19.49	56%	25%	19%
Total	1,417,355	26.68	41.65	36.41	33%	58%	10%

Note: This table depicts the 2007 sales less cost of goods sold, labor intensity and market share for different retail sectors. The last row is a value-added-weighted measure. Sales and cost of goods sold are from the US Census of Retail Trade, and the labor intensities and market shares are from Compustat. Labor intensity is defined the ratio the number of employees (thousands) per sales less cost of goods sold (millions), and the market share are the share of sales less cost of goods sold for each price tier within each sector. Price tiers are denoted by low, middle and high, and are based on Yelp! classifications of prices \$, \$\$, and \$\$\$, respectively. See text for more information.

Table 11: Market shares and Labor Intensity: 2012

Industry	\$m Sales - COGS	Labor intensity			Market share		
		Low	Middle	High	Low	Middle	High
Home furnishing and appliances	212,650	8.25	14.68	15.57	1%	93%	5%
Grocery stores	410,500	14.62	16.61	16.33	21%	72%	7%
Food services and drinking places	313,782	53.53	85.08	125.80	70%	26%	4%
Clothing stores	129,444	21.20	21.62	26.68	11%	79%	10%
General merchandise stores	473,441	16.23	24.26	19.49	65%	21%	14%
Total	1,539,817	22.72	33.07	40.37	41%	51%	8%

Note: This table depicts the 2012 sales less cost of goods sold, labor intensity and market share for different retail sectors. The last row is a value-added-weighted measure. Sales and cost of goods sold are from the US Census of Retail Trade, and the labor intensities and market shares are from Compustat. Labor intensity is defined the ratio the number of employees (thousands) per sales less cost of goods sold (millions), and the market share are the share of sales less cost of goods sold for each price tier within each sector. Price tiers are denoted by low, middle and high, and are based on Yelp! classifications of prices \$, \$\$, and \$\$\$, respectively. See text for more information.

E Results based on alternative definition of the recession

As a robustness check, Table 12 and 13 reports our calculation using for the period 2007-09 for the retail sector and manufacturing sectors, respectively. For the period 2007-09, the change in employment accounted for by trading down represents 20 percent and 16 percent of the fall in employment for the retail sector and manufacturing sectors, respectively.

Table 12: Market shares and Labor Intensity: 2009

Industry	\$m Sales in 2009	Labor intensity			Market share		
		Low	Middle	High	Low	Middle	High
Grocery stores	558,337	n.a.	4.40	4.83	n.a.	95%	5%
Food services and drinking places	690,225	1.83	4.01	5.91	44%	51%	5%
Clothing stores	621,902	12.34	21.67	21.97	43%	47%	10%
General merchandise stores	255,052	6.69	8.40	9.27	19%	71%	10%
Total	673,729	3.61	5.74	7.24	76%	16%	9%

Note: This table depicts the 2009 total sales, labor intensity and market share for different retail sectors. The last row is a sales-weighted measure. Sales are from the US Census of Retail Trade, and the labor intensities and market shares are from Compustat. Labor intensity is defined as the number of employees per million dollars of sales and the market share are the share of sales for each price tier within each sector. Price tiers are denoted by low, middle and high, and are based on Yelp! classifications of prices \$, \$\$, and \$\$\$, respectively. See text for more information.

Table 13: Market shares and Labor Intensity: 2009

Industry	\$m Sales in 2009	Labor Intensity			Market share		
		Low	Middle	High	Low	Middle	High
31	824,269	0.48	3.27	n.a.	34%	66%	n.a.
32	1,201,015	3.10	3.36	4.74	27%	47%	26%
33	1,902,289	1.98	2.96	3.86	38%	57%	5%
Total	3,927,573	2.01	3.15	3.32	33%	54%	13%

Note: This table depicts the 2009 total sales, labor intensity and market share for different manufacturing sectors. The last row is a sales-weighted measure. Sales are from Census, and the labor intensities and market shares are from Compustat. Labor intensity is defined as the number of employees per million dollars of sales and the market share are the share of sales for each price tier within each sector. Price tiers are denoted by low, middle and high, and are based on firm-level producer price data. See text for more information.

F A sticky-price model

In this appendix, we show that the same mechanism that amplifies real shocks also amplifies nominal shocks. We do so by embedding quality choice in an model with Calvo-style sticky prices. To highlight the role of quality choice in a parsimonious way, we abstract from capital accumulation.

F.1 The household problem

The representative household maximizes expected life-time utility defined in equation (15). The two constraints on the household problem are:

$$P_{q,t}C_t + B_{t+1} = B_t(1 + R_t) + W_tH_t, \quad (46)$$

and

$$E_0 \lim_{t \rightarrow \infty} B_{t+1} / [(1 + r_0)(1 + r_1) \dots (1 + r_t)] \geq 0.$$

Here, B_{t+1} the number of one-period nominal bonds purchased at time t , and R_t is the one period nominal interest rate.

The first-order conditions for the household are two equations associated with the static model (equations (16) and (17)), together with the following additional condition:

$$\lambda_t = E_t \beta \lambda_{t+1} (1 + R_{t+1}), \quad (47)$$

where λ_t is the Lagrange multiplier associated with the budget constraint (46).

Final good firms

The final good is produced by competitive firms using a continuum of intermediate goods, $Y_t^i(q_t)$:

$$Y(q_t) = \left(\int_0^1 [Y_t^i(q_t)]^{\frac{\varepsilon-1}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon-1}}, \quad \varepsilon > 1. \quad (48)$$

We assume that producing a final good of quality q_t requires that all intermediate inputs have quality q_t .

The problem of firms in the final-goods sector is:

$$\max P(q_t)Y(q_t) - \int_0^1 P_t^i(q_t) Y_t^i(q_t) di,$$

where $P_t^i(q_t)$ is the price of intermediate good i . The first-order conditions of the firms' problem imply:

$$P_t^i(q_t) = P(q_t) \left[\frac{Y(q_t)}{Y_t^i(q_t)} \right]^{\frac{1}{\varepsilon}}, \quad (49)$$

where P_t is the price of the homogeneous final good. Using the first-order conditions of the firms' problem we can express this price as:

$$P(q_t) = \left(\int_0^1 P_t^i(q_t)^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}}.$$

Intermediate Good Firms

The i th intermediate good is produced by a monopolist using a technology that is the limiting case of the flexible price model without capital:

$$Y_t^i(q_t) = \frac{A_t}{q_t} H_t^i(q_t). \quad (50)$$

Here, $H_t^i(q_t)$ denotes the labor employed by the i^{th} monopolist who is producing a product of quality q . If prices were flexible, the optimal price for the i th monopolist would be given by the usual mark-up formula:

$$P_t^i(q_t) = \frac{\varepsilon}{\varepsilon - 1} \frac{W_t}{A_t} q_t.$$

However, producers are subject to Calvo-style pricing frictions. We assume that monopolists post a pricing schedule that is linear in q_t :

$$P_t^i(q_t) = \mu_t^i q_t.$$

The monopolist can re-optimize the slope of the pricing schedule, μ_t^i , with probability $1 - \xi$. With probability ξ , the firm has to post the same price schedule as in the previous period:

$$P_t^i(q_t) = \mu_{t-1}^i q_t.$$

We denote by $\tilde{\mu}_t^i$ the optimal price-quality schedule for firms that have the opportunity to re-optimize μ_t^i at time t . Since only a fraction $1 - \xi$ of the firms have this opportunity, the aggregate price level is given by:

$$P(q_t) = \mu_t q_t, \tag{51}$$

where

$$\mu_t = \left[(1 - \xi) (\tilde{\mu}_t^i)^{1-\varepsilon} + \xi \mu_{t-1}^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}. \tag{52}$$

Firm i chooses $\tilde{\mu}_t^i$ to maximize its discounted profits, given by:

$$E_t \sum_{j=0}^{\infty} \beta^j \lambda_{t+j} \left[P_t^i(q_{t+j}) Y_t^i(q_{t+j}) - W_{t+j} H_t^i(q_{t+j}) \right], \tag{53}$$

subject to the Calvo price-setting friction, the production function, and the demand function for $Y_t^i(q_t)$.

Given that the price schedule is linear in quality, the demand function for $Y_t^i(q_t)$ can be written as:

$$\tilde{\mu}_t^i = \frac{P(q_t)}{q_t} \left[\frac{Y(q_t)}{Y^i(q_t)} \right]^{\frac{1}{\varepsilon}}. \tag{54}$$

Since the price schedule chosen in period t is only relevant along paths in which the firm cannot reoptimize its schedule, the firm's problem is given by:

$$E_t \sum_{j=0}^{\infty} \beta^j \xi^j \lambda_{t+j} q_{t+j}^{1-\varepsilon} \left[P(q_{t+j}) \right]^\varepsilon Y(q_{t+j}) \left[(\tilde{\mu}_t^i)^{1-\varepsilon} - W_{t+j} \frac{(\tilde{\mu}_t^i)^{-\varepsilon}}{A_{t+j}} \right].$$

Following the usual procedure to solve Calvo-style models, we obtain the following modified Phillips Curve:

$$\hat{\pi}_t = \frac{(1 - \beta\xi)(1 - \xi)}{\xi} \theta \hat{H}_t + \beta \hat{\pi}_{t+1}, \tag{55}$$

and the following intertemporal Euler condition:

$$\hat{H}_{t+1} - \hat{H}_t = \frac{-rr + r_{t+1} - \hat{\pi}_{t+1}}{\theta}. \quad (56)$$

It is useful to compare these two equations with those associated with a version of the model with no quality choice:

$$\hat{\pi}_t = \frac{(1 - \beta\xi)(1 - \xi)}{\xi} \hat{H}_t + \beta\hat{\pi}_{t+1}, \quad (57)$$

$$\hat{H}_{t+1} - \hat{H}_t = -rr + r_{t+1} - \hat{\pi}_{t+1}. \quad (58)$$

Comparing these two sets of equations we see that, since $\theta < 1$, the model with quality choice produces a higher response to monetary shocks than the standard model. This difference in amplification is illustrated in Figure 5.³⁰

To understand this difference, it is useful to consider first a flexible-price version of the model without quality choice. In this model, if the central bank raises the nominal interest rate, the price level falls and expected inflation rises, leaving the real interest rate unchanged. As a result, the change in the nominal interest rates has no effect on real variables.

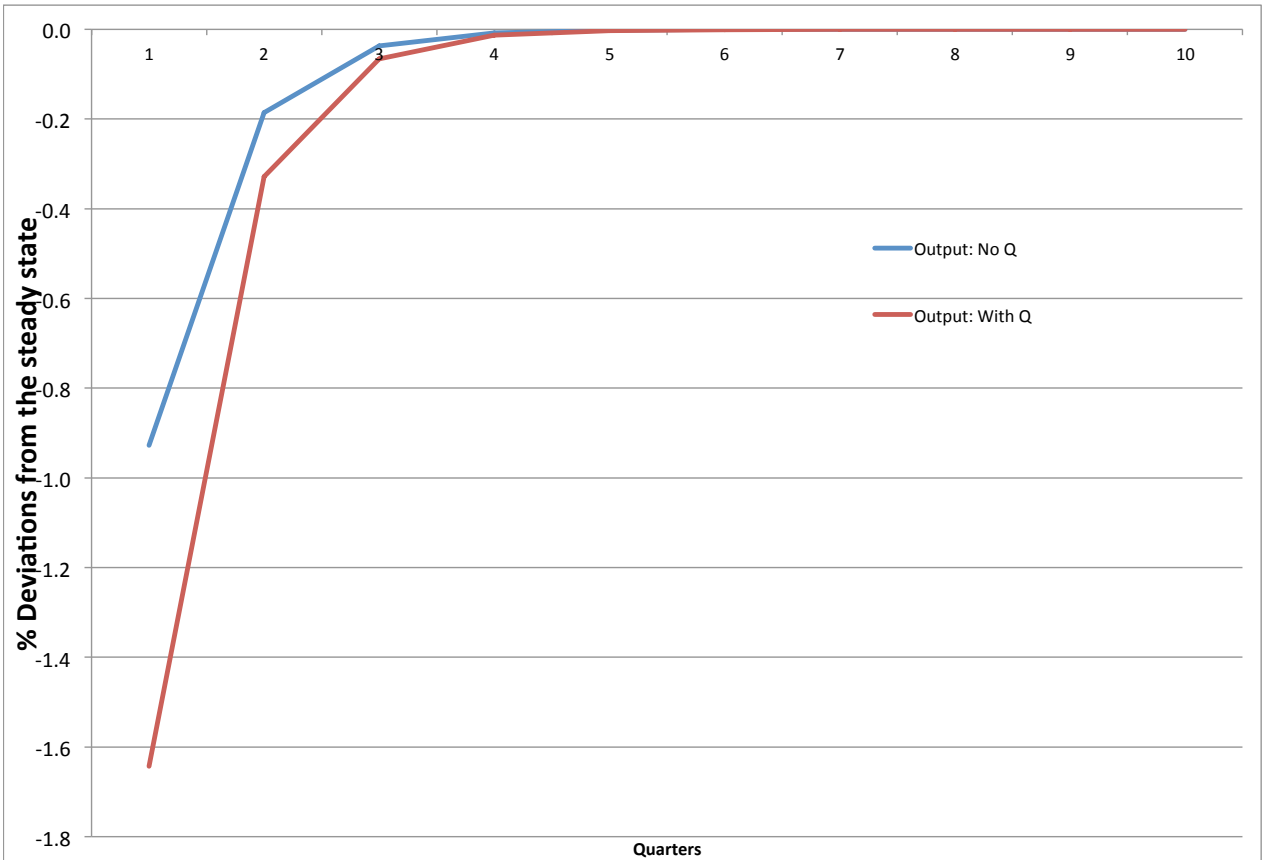
Now consider the model with sticky prices but no quality choice. When the central bank raises the nominal interest rate, only a few firms can lower prices and so the price decline is spread over time. As a result, the real interest rate rises. This rise in the real interest rate makes households want to consume less today and more in the future. The current demand for consumption falls and, since employment is demand determined, hours fall.

The key difference between the model with and without quality choice is that the former exhibits a stronger response of the labor supply to shocks. As a consequence, the wage rate has to fall more to clear the labor market than in the standard model.

³⁰We use the same parameter values for β , θ , and ν as in the flexible price model. We set $\varepsilon = 0.75$ so firms optimize their price schedule on average every four quarters. We use a Taylor rule with a 1.5 coefficient on inflation.

The rate of inflation becomes more negative than in the standard model, as firms lower prices in response to the lower labor costs. This higher rate of deflation implies that the real interest rate is higher in the model with quality choice than in the standard model. This higher real interest rate is associated with a larger fall in consumption, as households postpone consumption to take advantage of the high real interest rate. The result is a larger fall in employment in the quality-choice model than in the standard model.

Figure 5: Impulse Response Functions for a Negative Monetary Shock



G Calibration of Heterogeneous Agent Model

In this appendix we discuss the procedure used to calibrate α , ρ , and σ . Given an initial guess for these three parameters, we solve for the optimal conditions of the households and the firms, and check whether the market clearing condition for hours worked and capital (equations (41) and (42)) hold. Once we clear the two factor markets, we calculate the three moments discussed above. The construction of the share of capital income is straightforward. To compute the other two moments we first find the quality threshold, q_{low} , below which we have 35 percent of total consumption, i.e.

$$\sum_{j=q_{min}}^{q_{low}} \frac{P_{j\epsilon} Y_j}{\sum_{z=q_{min}}^{q_{max}} P_{z\epsilon} Y_z} = 0.35.$$

Similarly, we find the quality level q_{middle} such that consumption in the middle quality segment accounts for 58 percent of total consumption, i.e.,

$$\sum_{j=q_{low}}^{q_{middle}} \frac{P_{j\epsilon} Y_j}{\sum_{z=q_{min}}^{q_{max}} P_{z\epsilon} Y_z} = 0.58.$$

The remaining 7 percent correspond to the high-quality segment. These values are the market shares in our data.³¹ As in our empirical analysis, we calculate the revenue-weighted average of the labor intensity within each of the three quality categories, i.e.

$$LI_{low} = \sum_{j=q_{min}}^{q_{low}} \left(\frac{H_j}{P_{j\epsilon} Y_j} \right) \left(\frac{P_{j\epsilon} Y_j}{\sum_{z=q_{min}}^{q_{low}} P_{z\epsilon} Y_z} \right),$$

$$LI_{middle} = \sum_{j=q_{low}}^{q_{middle}} \left(\frac{H_j}{P_{j\epsilon} Y_j} \right) \left(\frac{P_{j\epsilon} Y_j}{\sum_{z=q_{low}}^{q_{middle}} P_{z\epsilon} Y_z} \right),$$

$$LI_{high} = \sum_{j=q_{middle}}^{q_{max}} \left(\frac{H_j}{P_{j\epsilon} Y_j} \right) \left(\frac{P_{j\epsilon} Y_j}{\sum_{z=q_{middle}}^{q_{max}} P_{z\epsilon} Y_z} \right).$$

³¹As with the ratios of the labor intensities, we match the 2007 weighted average numbers in Table 1.

We iterate on ρ , α and θ and repeat all the steps discussed above until we match the following two empirical moments

$$\log\left(\frac{LI_{middle}}{LI_{low}}\right) = 0.38,$$

$$\log\left(\frac{LI_{high}}{LI_{middle}}\right) = 0.16.$$

and the share of capital income.

H Proof of Proposition 1

Consider first the model without quality choice. The production function is given by

$$C = [\alpha (H)^\rho + (1 - \alpha)K^\rho]^{\frac{1}{\rho}} \quad (59)$$

The producer's problem implies that the ratio of the optimal demand for hours worked and capital is given by

$$\frac{H}{K} = \left(\frac{\alpha}{1 - \alpha} \frac{r}{W}\right)^{\frac{1}{1-\rho}} \quad (60)$$

and the optimal price is given by

$$P = \left[\alpha^{\frac{1}{1-\rho}} (W)^{\frac{\rho}{\rho-1}} + (1 - \alpha)^{\frac{1}{1-\rho}} (r)^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}} \quad (61)$$

Income is spent solely on consumption so

$$\xi = P \times C$$

Since this is a partial-equilibrium setting, where the rental price and the wage are constant, the price of the consumption good is also constant. As a result, consumption moves one-to-one with income. Substituting equation (60) into equation (59) we obtain

$$C = K \left[\alpha \left(\left(\frac{\alpha}{1 - \alpha} \frac{r}{W} \right)^{\frac{1}{1-\rho}} \right)^\rho + (1 - \alpha) \right]^{\frac{1}{\rho}}.$$

We proceed by log-linearizing the equilibrium conditions. Denoting the percentage deviations of a variable from steady state by a circumflex, it follows that

$$\hat{C} = \hat{K} = \hat{\xi}.$$

From equation (60) it follows that hours worked move one-to-one with consumption and thus with income, i.e.

$$\hat{H} = \hat{\xi}.$$

Thus, in the model without quality, the elasticity of hours worked with respect to income is 1. In what follows we show that this elasticity in the model with quality choice is always greater than 1.

Recall that the production function in the model with quality is given by

$$C = \left[\alpha \left(\frac{H}{q} \right)^\rho + (1 - \alpha) K^\rho \right]^{\frac{1}{\rho}} \quad (62)$$

and that the resulting factor maximization implies that the ratio of the optimal demand for hours worked and capital is given by

$$\frac{H}{K} = q^{\frac{\rho}{\rho-1}} \left(\frac{\alpha}{1 - \alpha} \frac{r}{W} \right)^{\frac{1}{1-\rho}} \quad (63)$$

The resulting optimal price is given by

$$P = \left[\alpha^{\frac{1}{1-\rho}} (qW)^{\frac{\rho}{\rho-1}} + (1 - \alpha)^{\frac{1}{1-\rho}} (r)^{\frac{\rho}{\rho-1}} \right]^{\frac{\rho-1}{\rho}} \quad (64)$$

For future reference it is useful to write this expression as

$$\begin{aligned} P &= \left[(r)^{\frac{\rho}{\rho-1}} \left\{ \alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r} \right)^{\frac{\rho}{\rho-1}} + (1 - \alpha)^{\frac{1}{1-\rho}} \right\} \right]^{\frac{\rho-1}{\rho}} \\ P &= r \left[\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r} \right)^{\frac{\rho}{\rho-1}} + (1 - \alpha)^{\frac{1}{1-\rho}} \right]^{\frac{\rho-1}{\rho}} \end{aligned} \quad (65)$$

From the household's first-order conditions for quality and quantity it follows that

$$C = \exp\left(\frac{1}{1-\theta} \frac{qP'_q}{P}\right) \quad (66)$$

The price elasticity is given by

$$\frac{P'_q}{P} = \eta_{P,q} = \frac{\alpha^{\frac{1}{1-\rho}} (qW)^{\frac{\rho}{\rho-1}}}{\left[\alpha^{\frac{1}{1-\rho}} (qW)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{1}{1-\rho}} (r)^{\frac{\rho}{\rho-1}}\right]} \quad (67)$$

Linearizing the above equilibrium condition results in the following five equations. First, a linearized the budget constraint

$$\widehat{\xi} = \widehat{P} + \widehat{C}. \quad (68)$$

Second, a linearized demand for the factors of production

$$\widehat{H} = \frac{\rho}{\rho-1} \widehat{q} + \widehat{K}. \quad (69)$$

Third, a linearization of the first-order condition for quality and quantity combined with the expression for the linearized price elasticity,

$$\widehat{C} = \left(\frac{1}{1-\theta}\right) \eta_{P,q} \widehat{\eta_{P,q}} = \left(\frac{1}{1-\theta}\right) \frac{\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} (1-\alpha)^{\frac{1}{1-\rho}}}{\left[\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{1}{1-\rho}}\right]^2} \frac{\rho}{\rho-1} (\widehat{q}). \quad (70)$$

Fourth, a linearized production function

$$\widehat{C} = \frac{\alpha \left(\frac{H}{q}\right)^\rho (\widehat{H} - \widehat{q}) + (1-\alpha) K^\rho \widehat{K}}{\alpha \left(\frac{H}{q}\right)^\rho + (1-\alpha) K^\rho}. \quad (71)$$

And finally, a linearized price function

$$\widehat{P} = \frac{\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}}}{\left[\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{1}{1-\rho}}\right]} \widehat{q}. \quad (72)$$

Combining equations (68), (70), and (72), we can relate changes in income to the optimal change in quality;

$$\hat{q} = \frac{1}{\frac{\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}}}{\left[\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{1}{1-\rho}}\right]} \left(1 + \frac{\left(\frac{1}{1-\theta}\right)(1-\alpha)^{\frac{1}{1-\rho}}}{\left[\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{1}{1-\rho}}\right]} \frac{\rho}{\rho-1}\right)} \widehat{\xi} \quad (73)$$

Equation (73) relates the exogenous change in income to a change in quality. Note that all the coefficients are positive; i.e. a positive (negative) change in income leads to quality increasing (decreasing).

Combining the remaining equations and doing some algebraic manipulations we obtain the following relation between the optimal number of hours demanded by the firm and the optimal quality choice of the consumer

$$\hat{H} = \frac{\hat{q} \left(\frac{\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} (1-\alpha)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{\rho}{\rho-1}}}{(1-\alpha)^{\frac{\rho}{\rho-1}}} + \left(\frac{1}{1-\theta}\right) \frac{\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} (1-\alpha)^{\frac{1}{1-\rho}}}{\left[\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{1}{1-\rho}}\right]} \frac{\rho}{\rho-1} \right)}{\left(\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{1}{1-\rho}}\right)} \quad (74)$$

Combining equation (73) and equation (74) results in the following relation between hours worked and income changes

$$\hat{H} = \widehat{\xi} \left(1 + \frac{\left(\frac{(1-\alpha)^{\frac{1}{1-\rho}}}{\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} \frac{\rho}{\rho-1}} \right)}{\left(1 + \frac{\left(\frac{1}{1-\theta}\right)(1-\alpha)^{\frac{1}{1-\rho}}}{\left[\alpha^{\frac{1}{1-\rho}} \left(\frac{qW}{r}\right)^{\frac{\rho}{\rho-1}} + (1-\alpha)^{\frac{1}{1-\rho}}\right]} \frac{\rho}{\rho-1} \right)} \right) \quad (75)$$

Recall that $\rho < 0$. This condition implies that the coefficient on the right hand side is always greater than 1. QED.