ESSAYS ON THE MACROECONOMIC EFFECTS OF
CONSUMPTION HETEROGENEITY

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Abstract

This dissertation seeks to advance our understanding of the macroeconomic effects of heterogeneity in consumption.

In the first chapter, I study quantitatively how a credit crunch affects aggregate consumption when households are heterogeneous in their wealth levels. I model credit conditions through either a “hard constraint”, where households are allowed to borrow at the risk free rate only up to an exogenous amount, or a “soft constraint”, where households can borrow as much as they want but the borrowing interest rate is greater than the savings interest rate. I find that a tightening of borrowing conditions delivers a much more severe drop in aggregate consumption in the hard constraint economy. I conclude that the quantitative effects of a credit crunch largely depend on the modeling approach.

In the second chapter, I assess whether the minimum wage could increase aggregate consumption through redistribution towards poor, high-marginal propensity to consume workers. I use retail sales data by county and I exploit heterogeneity in minimum wage rates across states and over time to estimate the causal effect of the minimum wage on nondurable consumption in a panel data research design. I find that an increase of 10% in the minimum wage rate increases nominal sales by 1.1% and real sales by 0.7%. The response to minimum wage hikes is stronger in counties where the policy is more binding. I show that my results are explained by positive spillovers benefiting the bottom quarter of the labor income distribution.

In the third chapter, I study the labor intensity of the expenditure response to unemployment. First, I show that different consumption goods are produced with very different labor shares. While communications, housing, and utilities have a labor share lower than 0.4, the labor share of domestic services, education, and health care is greater than 0.7. Second, I find that upon unemployment, households disproportionately cut back expenditures on labor-intensive goods. I explore the implications for fiscal stimulus in a heterogeneous agent New
Keynesian model. The model suggests that targeting fiscal policy towards labor-intensive goods can be significantly more effective than capital-intensive government purchases.
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To my parents.
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Chapter 1

Hard vs. Soft Financial Constraints: Implications for the Effects of a Credit Crunch

1.1 Introduction

After the Great Recession, research has flourished in an attempt to enhance our understanding of the effects of a credit crunch (i.e., a decrease in the availability of credit in the economy) on real variables such as consumption and employment.\(^1\) Most recent work has modeled credit conditions as a hard borrowing constraint, that is an exogenous limit on the amount that households can borrow. In this context, a credit crunch is defined as a reduction in the borrowing limit, which forces households to reduce their consumption until they satisfy the new, lower limit. An alternative approach is to assume what I will call a soft borrowing constraint. In this setup, households can borrow as much as they want, up to their natural borrowing limit, but at an interest rate that is higher than the saving rate and that potentially increases with the amount borrowed. In this context, a credit crunch is

modeled as an increase in the borrowing interest rate. Both models can easily accommodate loose financial conditions (loose borrowing limit, low borrowing rate) as well as tight ones (tight borrowing limit, high borrowing rate). In this chapter, I demonstrate that the choice to describe credit market conditions in terms of hard or soft constraints is not inconsequential. Rather it has important implications for inference on the effects of a credit crunch in the macroeconomy.

I compare these two alternative specifications of the financial constraints in a life-cycle Standard Incomplete Markets framework with heterogeneous agents in partial equilibrium. Consumers receive a stochastic and idiosyncratic income shock every period and decide how much to consume and how much to save or borrow of a risk-free asset given the credit constraints in place, i.e., a borrowing limit in the hard constraint economy and a borrowing interest spread in the soft constraint case. The setting is deliberately simple. I abstract away from many important aspects of debt accumulation such as mortgages, default, and endogenous labor market decisions, because the goal of this exercise is to explore the implications of financial conditions in the simplest, but still realistic, framework for consumption. I calibrate the discount factor and borrowing parameters in these two economies using the Method of Simulated Moments to match the levels of aggregate wealth and debt in the U.S. economy in 2006 according to the Survey of Consumer Finances.

While the two models predict very similar life-cycle patterns for asset accumulation, the soft constraint model matches the empirical debt distribution better than the hard constraint model in the baseline specification. Because the income profile grows with age, households have incentives to borrow early in life to smooth consumption. Debt is also useful to smooth transitory shocks to income, but as households grow older and richer, this role vanishes. Relative to the data, both models overstate the amount of debt contracted early in life and predict no borrowing after middle age. But in terms of assets and debt distributions, the soft constraint model obtains a significantly better fit to the empirical evidence in the Survey of Consumer Finances. The debt distribution, i.e., the distribution of assets conditional on
being negative, is better captured by the soft constraint model since the hard constraint model misses all the households with debt levels above the calibrated borrowing limit and predicts a counterfactual mass point at that amount. Nevertheless, this better fit is not an intrinsic characteristic of the model and alternative specifications of the soft constraint, a convex borrowing cost for instance, yield a debt distribution closer to the one derived from the hard constraint model.²

My main quantitative result is that a tightening of borrowing conditions induces a much more severe drop in consumption in the hard constraint economy than in the soft constraint economy. I follow Guerrieri and Lorenzoni (2015) in the definition of a credit crunch: a change in the borrowing parameter (i.e., a decrease in the borrowing limit in the hard constraint model or an increase in the borrowing spread in the soft constraint model) that produces a decrease of the debt to GDP ratio of 56% in the new long run equilibrium of the economy. Following a credit crunch, the drop in consumption in the hard constraint economy is more than double the drop in consumption in the soft constraint economy. The reason for this difference is that in the hard constraint economy, the credit crunch induces a large drop in consumption by forcing households to deleverage immediately or soon after, whereas in the soft constraint economy, the incentives to deleverage are provided through the interest rates, in response to which households choose to optimally reduce their debt at a lower pace. A number of robustness exercises regarding the calibration targets, elasticity of intertemporal substitution, and initial distribution of assets, confirm that the milder response in the soft constraint setting is a very general result.

In this chapter, I adopt the most basic form of the soft constraint, a constant spread between the saving and the borrowing rate. The assumption is driven by its simplicity and parsimony, because it reduces the calibration to only one parameter. In Section 1.6, I introduce some heterogeneity by allowing the borrowing spread to differ across households. I choose to model such heterogeneity as a fixed financial type to be consistent with the lack

²This case is shown in Appendix A.3.
of life-cycle features of the reported borrowing interest rate. I take the borrowing spreads directly from the data and I use the discount factor to match the amount of debt in the economy. In this context, I find that a sevenfold increase in the borrowing spread is required for the soft constraint model to deliver drops in consumption similar to those in the hard constraint model. An alternative approach would have been to estimate the soft constraint directly in the data using information on interest rates and debt levels. Unfortunately, the Survey of Consumer Finances does not include data on credit scores and so, a regression of interest rates on debt levels would suffer from omitted variable bias. In Appendix A.3, I also consider the case of a convex borrowing cost and show that the soft constraint still exhibits a milder consumption response.

The idea of a soft constraint, a setting in which the interest rate that borrowers have to pay depends on the amount they want to borrow, has already been explored in the literature but not in the context of a credit crunch. An early study of an increasing and convex interest rate schedule on assets emerging from the default risk is found in Eaton and Gersovitz (1981) in the context of sovereign debt. More recently, Chatterjee et al. (2007) and Livshits, MacGee, and Tertilt (2007) incorporate default in a life-cycle model with incomplete markets and endogenously derive the price of consumer loans in equilibrium.\footnote{Athreya, Tam, and Young (2012) is also concerned with unsecured debt, although not in a life-cycle framework.} Even in the absence of default, a positive borrowing spread can be understood as an intermediation cost in the spirit of Bernanke (1983). Since I do not model default explicitly, I prefer the latter interpretation of the borrowing spread. Finally, agnostic about the origin of the constraint, Fernández-Corugedo (2002) studies the consumption-savings problem and finds that precautionary savings are higher in the hard constraint model than in the soft constraint. However, since I calibrate impatience and borrowing parameters to match the same amounts of wealth and debt in equilibrium, such difference will be absorbed by the discount factor.

The main contribution of this chapter is to the literature on consumption and credit conditions. Building on the influential work by Guerrieri and Lorenzoni (2015), I show that
the magnitude of the macroeconomic consequences of a credit crunch largely depends on the modeling strategy employed. If the tightening of credit market conditions occurs through interest rates rather than borrowing limits, my results cast doubts on the quantitative importance of this mechanism to explain the drop in consumption during the Great Recession. Other mechanisms such as the increase in the risk of unemployment or the negative wealth effect of lower housing prices are then more likely explanations of the last recession. But the question of whether the credit crunch affected households via borrowing limits or spreads is ultimately an empirical question that this chapter cannot address because of data limitations. An ideal dataset to answer such question will include households’ borrowing conditions before and after the credit crunch. To the best of my knowledge there is not public dataset with that information.4

The rest of the chapter proceeds as follows. Section 1.2 describes the model, which is calibrated in Section 1.3. Section 1.4 presents the main results in the initial steady state of each economy and Section 1.5 explores the consumption response to a worsening of the financial conditions. Section 1.6 extends the basic framework to allow for heterogeneous financial conditions and provides additional robustness checks. Finally, Section 1.7 concludes.

1.2 Model

In this section, I describe the model that I use to study the differences between a hard constraint and a soft constraint economy.

I compare the aggregate implications of the different models of credit conditions in a Standard Incomplete Markets framework with heterogeneous agents in the tradition of Aiyagari (1994). Agents in this model are consumers/households who receive an stochastic income every period and decide how much to spend that period and how much to save or borrow in a risk-free asset. The stochastic income is idiosyncratic and cannot be insured against

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4 The 2007-09 Panel Survey of Consumer Finances provides information on households’ changes in wealth during the Great Recession, but the dataset does not include interest rates on unsecured debt, nor credit scores.
because financial markets are incomplete. In this framework, financial conditions are introduced as limits to the agent’s borrowing ability. In the hard constraint economy, the agent can borrow at the risk-free rate only up to an exogenous amount. There is no such limit in the soft constraint economy so that the consumer can borrow as much as she wants up to the natural borrowing limit, but the interest rate she will have to pay on her debt is higher than the rate she would received if she had positive assets.

Time is discrete. The economy is populated by a continuum of households of measure one. Each household is an agent who works and consumes for a finite but uncertain number of periods. The agent starts working immediately after she is born and retires at age $T_w$. After retiring from the workforce, the agent starts facing a risk of death. An agent of age $t$ survives the period with probability $\zeta_t$ and no agent grows older than $\bar{T}$, i.e., $\zeta_\bar{T} = 0$. New agents are born every period to replace the ones who die keeping the population size constant.

The agent has preferences over consumption in different periods and states of the world. These preferences are represented by the utility function:

$$E \left[ \sum_{t=1}^{T} \beta^t U(C_t) \right]$$

with

$$U(C) = \begin{cases} \frac{C^{1-\gamma}}{1-\gamma} & \text{if } \gamma \neq 1 \\ \ln C & \text{if } \gamma = 1 \end{cases}$$

where $C_t$ is the consumption level when the agent is $t$ periods old, $\beta$ is the discount factor, $\gamma$ is the inverse of the elasticity of intertemporal substitution and $E[\cdot]$ is the expectation operator.

During her working life, when the agent is younger than $T_w$, she receives stochastic earnings every period in compensation for her work, which she supplies inelastically. Let $Y_{i,t}$ be earnings before taxes for agent $i$ of age $t$. Log earnings, $y_{i,t}$, are assumed to be decomposed
into a common deterministic experience profile, $\kappa_i$; an individual fixed effect, $\mu_i$; a persistent shock, $z_{i,t}$; and a transitory shock, $\epsilon_{i,t}$.

$$y_{i,t} = \ln(Y_{i,t}) = \kappa_t + \mu_i + z_{i,t} + \epsilon_{i,t}$$

$$z_{i,t} = z_{i,t-1} + \eta_{i,t}$$

where $\{\eta_{i,t}\}_{t=1}^{T_w}$ is a sequence of independent random variables with normal distribution, zero mean, variance $\sigma^2_\eta$, and $z_0 = 0$. $\{\epsilon_{i,t}\}_{t=1}^{T_w}$ is a sequence of independent random variables with normal distribution, zero mean and variance $\sigma^2_{\epsilon}$. The individual fixed effect exhibits also a normal distribution across agents with zero mean and variance $\sigma^2_{\mu}$. All these shocks are independent across agents in the economy. Then, the Law of Large Numbers applies in this economy and there is no aggregate risk. To solve the model by simulation, the income process is discretized and so, the Natural Borrowing Limit is not zero.

During retirement, the agent receives a constant pension benefit per period until her death. This benefit is a function of all the history of individual earnings before taxes during her working life, i.e., $P(Y_{i,g,1}, \ldots, Y_{i,g,T_w}, Y_{i,g,T_w-1})$, which I approximate keeping track of average individual gross earnings.

Both earnings and pension benefits are taxed using a non-linear schedule on pre-tax income, $\tau(\cdot)$. After-tax income $\bar{Y}_{i,g,t}$ is then given by $\bar{Y}_{i,g,t} = Y_{i,g,t} - \tau(Y_{i,g,t})$.

Unsecured debt is more prevalent among young households, but also retired agents borrow in the data, as shown in Figure 1.5. Since in the model retired agents face death risk, their natural borrowing limit in absence of life insurance would be zero, and so they would be unable to borrow. To match the empirical fact that even old households borrow, I assume that there exist perfect, actuary-fair, annuities markets that allow retired agents to purchase insurance against the death shock and so, to borrow.
Other than life insurance, markets are incomplete. Households are allowed to borrow and save only through a risk-free, one period asset. This asset pays a deterministic interest rate given by the function \( R(A) \), where \( A \) is the level of assets held by the agent. Also, there is a limit \( \bar{A}_t \) on the amount that can be borrowed as in Aiyagari (1994). There is no default option in the model. Certainly allowing for agents to default would be an interesting extension, but it is beyond the scope of this chapter.

Therefore, the agent’s budget constraint per period can be summarized as follows:

\[
C_{i,t} + A_{i,t+1} = R(A_{i,t}) A_{i,t} + \bar{Y}_{i,t} + TR_{i,t} \quad \text{if} \quad t \leq T_w
\]

\[
C_{i,t} + \frac{1}{\zeta_{t+1}} A_{i,t+1} = R(A_{i,t}) A_{i,t} + \bar{P}(Y_{i,1}, ..., Y_{i,T_w-1}) + TR_{i,t} \quad \text{if} \quad t > T_w
\]

where \( TR_{i,t} \) is a government transfer to ensure a consumption floor \( \bar{c} \) for all households. \( \bar{c} \) will be calibrated to a very small level and no positive transfers will take place in these economies at the initial steady state. However, after the impact of a credit crunch, some households could be forced into negative consumption if their income is not enough to cover the required deleverage, and in those cases positive transfers will emerge. These transfers can then be thought as a rudimentary safety net.

Finally, initial assets are drawn from a distribution \( H(A_0) \).

**Financial Conditions in the Hard Constraint Model.** Agents can borrow only up to a certain level at a constant interest rate. There is no spread between the borrowing and saving rates. The borrowing limit \( \bar{A}_t \) in period \( t \) is the minimum of the natural borrowing limit for that period (\( NBL_t \), the maximum amount that could be fully repaid with probability one) and an exogenous amount \( \bar{\phi} \), assumed constant over the life-cycle. Then, \( \bar{A}_t = \min \{ \bar{\phi}, NBL_t \} \). The interest rate function is simply \( R(A) = R^f \) where \( R^f \) denotes the gross risk-free rate. In Section 1.6, heterogeneity in the borrowing limit will be allowed and the distribution will be inferred from the data, but for the rest of the chapter all the households will face the same borrowing limit regardless of their income. In Appendix A.2,
I study an alternative specification for the hard constraint, where the borrowing limit is a fraction of the natural borrowing limit, i.e., $\bar{A}_t = \bar{\phi}_{\text{NBL}}NBL_t$. The results do not vary significantly.

**Financial Conditions in the Soft Constraint Model.** Agents can borrow as much as they want up to the natural borrowing limit ($\bar{A}_t = NBL_t$), but the interest rate is no longer constant. In particular, a constant borrowing spread is assumed such that:

$$R(A) = \begin{cases} R^f & \text{if } A \geq 0 \\ R^f + \phi & \text{if } A < 0 \end{cases}$$

For parsimony, the constant borrowing spread assumption is maintained in the baseline specification. Heterogeneity in the borrowing spread will be allowed in Section 1.6. In Appendix A.3, I consider the case of a convex function for the borrowing spread.

Figure 1.1 illustrates the difference between these two alternative approaches to modeling financial conditions in terms of the shape of the resulting budget constraint in a simple two-period model. Both can accommodate very loose and very tight borrowing conditions, although the soft constraint seems more realistic as we do observe borrowing spreads in the data, whereas borrowing limits are more difficult to identify.

### 1.3 Calibration

In this section I discuss the calibration of the model. The strategy largely follows Kaplan and Violante (2010), although my calibration is at the quarterly level and theirs is annual. I match aggregate moments of the U.S. economy in 2006, before the beginning of the Great Recession, using the 2007 Survey of Consumer Finances (SCF 2007 henceforth).

Assets are defined as net liquid financial wealth. This definition follows Guerrieri and Lorenzoni (2015) not only for comparability of the results, but also to give unsecured debt a

---

5 Checkings, savings and money market accounts, stocks, bonds, and certificates of deposits minus revolving credit card debt, consumer and educational loans.
Consumption possibilities differ only for borrowers

\( y_1 \) and \( y_2 \) are income in the present and future respectively, i.e., \((y_1, y_2)\) is the autarky point. Households whose optimal consumption bundle is to the left of \( y_1 \) are saving and those to the right of \( y_1 \) are borrowing.

In Panel A the slope of the budget constraint is \( R^f \) until the hard borrowing constraint starts to bind and the slope becomes infinite. In Panel B, the slope is \( R^f \) to the left of the autarky point (household saving) and \( R^f + \phi \) to the right (household borrowing).

meaningful role as an instrument to smooth consumption. The definition excludes housing, mortgages, and other types of secured debt because the model does not capture the main features of these assets.

**Demographics.** Households join the labor market at age 25 (\( t = 1 \) in the model) and retire at age 65 (\( T_w = 160 \)). Survival probabilities are obtained from population data from the 2010 Census. Agents die with certainty after they turn 95 (\( T = 280 \)). Therefore, households work for 40 years (160 quarters) and live on their pension benefits and accumulated assets for, at most, 30 years (120 quarters).

**Initial Assets Distribution.** All agents start their economic life with zero assets. In Section 1.6, results are shown to be robust to including a non-degenerate initial distribution.
of assets, $H(A_0)$, estimated from the SCF 2007 as the distribution of financial wealth for households younger than 25.

**Earnings Before Tax.** The age profile of labor income is estimated using data from the Panel Study of Income Dynamics (PSID henceforth) between 1967 and 2002 as suggested in Heathcote, Perri, and Violante (2010). The deterministic experience profile, $\{\kappa_t\}_{t=1}^{T_w}$, is computed with a fourth-order polynomial on potential experience (Mincer, 1958) over log earnings for households with age between 25 and 64. For comparability between assets data obtained from the SCF and earnings figures obtained from the PSID, the intercept is then adjusted to match average pre-tax annual earnings before retirement in the SCF 2007: $\$61,521$.

The variance of the residuals of earnings after subtracting the deterministic component and controlling by time fixed effects$^6$ rises almost linearly, a point previously noted by Kaplan and Violante (2014), which justifies the assumption of a unit root earnings process. Following Kaplan and Violante (2014), I set the variance of the individual fixed effect to 0.18 to match the initial dispersion in earnings and the variance of the permanent shock to 0.003 to replicate the rise in dispersion over the life-cycle. The quarterly variance of the transitory shock is set equal to 0.19 to reproduce an annual variance of 0.05 as used in Kaplan and Violante (2010). In Appendix A.1, I show that my results are robust to an annual specification of the transitory shock instead of a quarterly one.

**Pension Benefits and Tax System.** Following Kaplan and Violante (2010), pension benefits and the tax schedule are computed such that they resemble the actual U.S. systems. Social security payments are equal to 90% of average individual gross earnings up to a first bend point (18% of cross-sectional average), 32% up to a second bend point (110%) and 15% from there on. Then, the payments are scaled to get an average replacement rate of 45%.

Gross earnings are taxed through the nonlinear function estimated by Gouveia and Strauss (1994):

$^6$Similar results are obtained after controlling for cohort fixed effects.
\[
\tau(Y) = \tau^b \left[ Y - (Y - \tau^p - \tau^s)^{-\frac{1}{\gamma}} \right]
\]

with \(\tau^b = 0.258\), \(\tau^p = 0.768\) and \(\tau^s\) chosen to match the ratio of personal current tax receipts on labor income to total labor income in the U.S. economy, 25%. As in the data, 85% of the social security benefits are taxed in the model.

The consumption floor is defined as the quarterly average SNAP benefit per person in 2007.

**Preferences.** For the baseline specification, logarithmic preferences, \(\gamma = 1\), are assumed. Section 1.6 shows that results are robust to other sensible values of \(\gamma \in [0.5, 4]\). The calibration of the discount factor is described below.

**Saving Interest Rate.** As in Telyukova (2013) and because of the lack of other high-yield assets in the model, the annual interest rate of financial assets is set to 4%.

**Discount Factor and Borrowing Parameters.** The discount factor \(\beta\) and the borrowing parameters (the exogenous borrowing limit in the hard constraint version and the borrowing spread in the soft constraint) are jointly estimated to match two significant moments of the data through the Method of Simulated Moments. Since I am interested in studying the dynamics of unsecured debt over the life-cycle, I match the ratios of aggregate gross financial wealth and debt to income from the SCF 2007. Guerrieri and Lorenzoni (2015) also target these moments, but they compute them from national accounts data. Instead, I compute them from micro data from where the age profiles can also be recovered. In the SCF 2007, the ratio of aggregate financial wealth to income is 1.4654, whereas the debt to income ratio is 0.0556. In Section 1.6, I show that my results are even stronger when calibrating the models to match the moments as computed from the national accounts data.

For the hard constraint, this approach results on \(\beta = 0.9874\) (equivalent to an annual discount factor of 0.9505) and a borrowing limit of \(\bar{\phi} = -20,952\). For the soft constraint, I obtain \(\beta = 0.9873\) (equivalent to an annual discount factor of 0.9503) and a borrowing wedge of \(\phi = 0.0079\), which implies an annual borrowing interest rate of 7.3%.
The interest rates and discount factors are reported in annual levels. Discount factor and borrowing parameters chosen to match aggregate debt and aggregate wealth to GDP ratios in each economy. Refer to the text for details on the calibration of the remaining parameters.

The calibration is summarized in Table 1.1. The discount factor, $\beta$, is identical for agents in both economies and it is not implausible low. The borrowing limit, 20,952, does not seem unreasonable considering I am matching only unsecured debt. According to the SCF 2007, less than a quarter of the debtors had unsecured debt for amounts greater than this borrowing limit. Also, in terms of self-reported borrowing limit on credit cards, around 75% of the households indicated a limit below my calibrated amount. In the model, 0.5% of the households are borrowing at the limit. On the other hand, the borrowing spread is below what is observed in the data by implying an annual borrowing interest rate of 7.3%. The median annual interest rate on unsecured debt in the SCF 2007 was 8.0%, whereas the mean was 9.4%. Certainly a limitation of the baseline model is the assumption that the

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>Coefficient of relative risk aversion</td>
<td>1</td>
</tr>
<tr>
<td>$R_f$</td>
<td>Annual net risk-free rate</td>
<td>4%</td>
</tr>
<tr>
<td>$\sigma^2_{\eta}$</td>
<td>Quarterly variance of the persistent shock</td>
<td>0.003</td>
</tr>
<tr>
<td>$\sigma^2_{\mu}$</td>
<td>Variance of the individual fixed effect</td>
<td>0.18</td>
</tr>
<tr>
<td>$\sigma^2_{\epsilon}$</td>
<td>Quarterly variance of the transitory shock</td>
<td>0.19</td>
</tr>
<tr>
<td>$\bar{c}$</td>
<td>Consumption Floor</td>
<td>289</td>
</tr>
</tbody>
</table>

**Hard Constraint Economy**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Annual discount factor</td>
<td>0.9505</td>
</tr>
<tr>
<td>$\bar{\phi}$</td>
<td>Borrowing limit</td>
<td>20,952</td>
</tr>
</tbody>
</table>

**Soft Constraint Economy**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Annual discount factor</td>
<td>0.9503</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Annual borrowing interest rate</td>
<td>7.3%</td>
</tr>
</tbody>
</table>
same financial conditions apply to everyone. This issue is addressed in Section 1.6, where the distribution of borrowing rates and credit limits are taken directly from the data.

1.4 Steady State Results

The model is solved numerically. I use Carroll (2005)'s Endogenous Grid Points Method\(^7\) to find the policy functions for each model and then I simulate economies with 100,000 households. In this section, I compare the long run equilibrium outcomes of the hard constraint and soft constraint economies, in particular, the household policy functions, life-cycle paths, and asset distributions.

The credit conditions affect consumption decisions only when the level of assets is low. Figure 1.2 plots the consumption policy functions resulting from the models calibrated as indicated in the previous section for agents at two different ages (29 and 62, very early and very late in their working life). As noted in the consumption literature,\(^8\) consumption is linear in wealth (or cash-in-hand) provided the amount of assets held by the household is positive and large enough, as the financial constraints are then irrelevant. In fact, the policy functions for the soft and hard constraint versions are very similar in this area of the state space.

As the amount of wealth decreases and becomes close to zero, the policy functions start to differ significantly. For the hard constraint, the well-known concave shape emerges from the combination of the borrowing limit and the stochastic earnings process. Uncertainty vanishes for an agent close to retirement and so, the policy function is almost linear for all the domain for the older agent. On the other hand, the soft constraint allows for an extended domain as households can borrow greater amounts. Around the Natural Borrowing Limit, the consumption policy function is concave for the young agent. When the amount of debt.

\(^7\)I use 62 grid points for assets, 30 for negative values and 32 for positive. I space the points with a polynomial of exponent 0.4 such that more grid points are obtained close to the borrowing limit and to zero. I use 11 grid points for the permanent component, 5 for the transitory shock, 5 for the individual fixed effect, and 5 for lifetime average earnings.

Consumption decisions only differ significantly between the two economies when the agent is borrowing or has a positive but small stock of assets. Quarterly consumption level as a function of the assets held by an agent of age 29 and 62 (15 and 150 in the model) with average earnings history, average permanent shock, average individual fixed effect, and average transitory shock. Consumption and assets are expressed in thousands of U.S. dollars. HC: Hard Constraint Model. SC: Soft Constraint Model.

is large but far from the limit, the policy function is again linear as the savings rate does not factor into the problem in the short and medium term. Around zero, the discontinuity in the interest rate induces another non-linearity in the consumption function. The household chooses a level of consumption below the hard constraint amount acknowledging the greater borrowing cost. A different non-linearity emerges in the policy function of the old agent in the soft constraint model. When the amount of debt is large enough, the agent chooses to default into the consumption floor and so, the policy function is flat in that region.

The two models predict a similar evolution of mean consumption and wealth over the life-cycle. Figure 1.3 summarizes them. The combination of financial constraints and a stochastic labor income produces a hump-shaped consumption profile. Mean consumption attains a maximum at age 45 in the hard constraint model and 46 in the soft constraint. The timing of the peak is consistent with the empirical evidence documented by Fernández-Villaverde.
On average, consumption and assets show a similar evolution over the life-cycle in both models. Means computed from the simulation of two economies with 100,000 households each. Consumption and income are annualized. HC: Hard Constraint Model. SC: Soft Constraint Model.

and Krueger (2007), who find that both total and non-durable consumption peak in the late forties. The soft constraint presents a slightly steeper consumption growth early in life, with consumption at the peak being 48% higher than at age 25, versus 45% in the hard constraint. In both cases, consumption grows over the first years of the working life as the household moves away from the financial constraints, and then it decreases as retirement approaches because the household is more impatient than the market and the stochastic component of income starts to vanish. Other features traditionally associated with the hump-shape of consumption such as changes in family demographics, housing and other durable goods, and non-separability between consumption and leisure,\(^9\) are absent in my model.

The degree of consumption smoothing is similar in the aggregate for the two models, but there are life-cycle differences early in life. Following Kaplan and Violante (2010), I

compute the insurance coefficients\(^{10}\) in both economies using the observed permanent and transitory shocks. On the one hand, the insurance coefficient for the permanent shock is 0.21 in the hard constraint economy and 0.18 in the soft constraint economy. As in Kaplan and Violante (2010), both models underestimate the amount of insurance with respect to what Blundell, Pistaferri, and Preston (2008) find in the data, 0.36, and they yield a U-shaped profile over the life-cycle (Figure 1.4). However, the soft constraint economy exhibits less insurance early in life against the permanent shock because of the higher borrowing interest rate. On the other hand, both models predict high insurance for transitory shocks: 0.95 in the hard constraint and 0.97 in the soft constraint, consistent with Blundell, Pistaferri, and Preston (2008)’s empirical finding of 0.95. In the soft constraint version, the age profile of the transitory insurance coefficient is fairly flat around 0.97. In contrast, in the hard constraint the insurance coefficient decreases early in life as households accumulating debt are less able to self-insure against the shock when they approach the borrowing limit. As households age and save, the insurance coefficient grows and converges to the level in the soft constraint economy.

The predictions of both models in terms of the ratios of debt and wealth to income over the life-cycle are fairly similar. Relative to the data, both models overstate the amount of borrowing early in life, while they are unable to explain any borrowing between age 45 and retirement. In a similar fashion, the two models miss the continuously increasing wealth to income ratio, especially after retirement.\(^{11}\) The failure of the models in those dimensions could be corrected by extending them to include durable consumption, changes in family size, or altruistic inheritances which would enhance the use of unsecured debt late in the working life and provide incentives to keep accumulating wealth after retirement. However, an insurance coefficient of 1 implies that consumption does not react to the shock at all (full insurance), whereas an insurance coefficient of 0 indicates complete absence of insurance.

\(^{10}\phi^x = 1 - \frac{\text{cov}(\Delta c_{it}, x_{it})}{\text{var}(x_{it})}\) where \(x_{it}\) is either the transitory or the permanent shock. With this definition, note that the sharp increment in the gross wealth to income ratio at retirement is generated in both models mechanically by the sudden (but predictable and expected) decrease in labor income associated with the end of the working life, rather than by additional savings.
The models differ on the insurance options early in life. In the soft constraint economy it is easier to insure transitory shocks, but it is more difficult to insure permanent shocks. Insurance coefficients are computed following the procedure described in Kaplan and Violante (2010) and employing the true values of the permanent and transitory shocks. HC: Hard Constraint Model. SC: Soft Constraint Model. Refer to the text for further details.

The goal of this chapter is to study the implications of financial conditions in the simplest consumption framework. To that extent, the present model offers a reasonable first pass.

By construction, both models produce the same amount of aggregate wealth and debt. However, the distributions differ. In the hard constraint version, 30.7% of the households are borrowing, with 1.6% of them borrowing at the limit. In the soft constraint, the fraction of households borrowing is 25.3%, closer to the fraction observed in the data, 25.7%.

It is a well established fact that this class of models struggles to match the entire wealth distribution, even when targeting multiple moments of the distribution.\textsuperscript{12} It is then no surprise that none of the models does a great job at matching the wealth or debt distributions, although the soft constraint version does better as shown in Figure 1.6. In terms of the distribution of assets, both models fail to replicate the large proportion of households with

Both models predict a similar pattern for the ratios of wealth and debt to income, overstating the amount of debt early in life and understating it in middle age. Debt to income is the ratio of the absolute value of aggregate negative assets to aggregate annual income. Gross wealth to income is the ratio of aggregate positive assets to aggregate annual income.


In terms of the debt distribution, it is clear that the soft constraint produces a better match. The Jensen-Shannon divergence\textsuperscript{13} between the model-derived debt distribution and

\textsuperscript{13}The Jensen-Shannon divergence is a measure of the similarity between two probability distributions. It is symmetric and bounded between 0 and \( \log(2) \). In this chapter, I discretize the model and empirical distributions using the same 500 bins in both and I use the natural logarithm when computing the Jensen-Shannon divergence.
The soft constraint model produces assets and debt distributions closer to the data

Assets and debt are in thousands of U.S. dollars. The axis have been truncated to facilitate visualization.


its empirical counterpart is 0.1556 in the hard constraint economy, whereas it is 0.0718 in the soft constraint economy. By unrealistically offering cheap credit, a significant number of households end up at the borrowing limit and so, the distribution is not monotonically decreasing in the amount of debt, but actually has a mass point at the exogenous borrowing limit. As it will be discussed in the next section, these households borrowing at the limit will be the ones responding the most to a credit crunch just because mechanically they will be forced to delever. But there are relatively so few of these constrained borrowers that the aggregate response will be driven instead by the unconstrained borrowers, i.e., the households borrowing, but not at the limit.

To summarize, the two models have similar predictions for the aggregates in the economy, but the soft constraint produces a better fit in terms of the wealth and debt distributions in the baseline framework. In Appendices A.2 and A.3, I will show that alternative specifications of the borrowing conditions still deliver better fits in the soft constraint economy, but
the difference becomes smaller. The better match to the empirical distributions by the soft constraint model should then be interpreted as a strength of the baseline framework, but not as a general result.

1.5 Credit Crunch

A credit crunch is a tightening of the financial conditions faced by the households. In this section, the credit crunch exercise in Guerrieri and Lorenzoni (2015) is replicated, but within a partial equilibrium framework to focus on the response of aggregate consumption. These results can be thought as an upper bound on the general equilibrium effects because if the interest rate was allowed to adjust after the crunch, it would decrease, lessening the initial drop in consumption.\footnote{In fact, if the economy was closed and there was not an exogenous supply of bonds, the net wealth in the economy would have to always be zero, and aggregate consumption would always be equal to aggregate income. Aggregate income is the sum of compensation of employees and the interest income from net wealth. I do not count the borrowing spread in the soft constraint economy as part of income. Instead, I assume that borrowing is conducted by a competitive financial industry using only labor, whose compensation is already counted in GDP. I think of a credit crunch in the soft constraint economy as a negative shock to labor productivity in the sector. The shock would then displace some workers from the financial industry, but they would immediately obtain equivalent jobs in the rest of the economy. Then, aggregate income would not react to a credit crunch and neither would aggregate consumption. In this case, the interest rate would drop inducing savers to consume more to make up for the reduced consumption of borrowers. Debt and gross wealth will decrease by the same amount, so that net wealth will remain constant at zero. Thus, the consumption response to a credit crunch in general equilibrium for a closed economy with zero aggregate net wealth would be zero.}

I follow Guerrieri and Lorenzoni (2015) and I define a credit crunch as a change in borrowing parameters that leads to a new steady state with a lower amount of debt. In their section focusing on unsecured debt, Guerrieri and Lorenzoni (2015) assume an initial debt to GDP ratio of 18% and model the tightening of financial conditions as the decrease in the exogenous borrowing limit necessary for the debt to GDP ratio to drop by 10 percentage points in the new steady state. Because I calibrate the models to match the evidence in the micro data on debt to income averages by age, rather than national accounts figures, debt to GDP in the initial steady state is set to 5.56% and so it cannot decrease by 10 percentage points. Instead, I re-calibrate the borrowing parameters to match a decrease of
55.56% (1-0.08/0.18) in the debt to income ratio in the new steady state as in Guerrieri and Lorenzoni (2015). Thus, I find the borrowing limit in the hard constraint and the borrowing spread in the soft constraint to match a debt to income of 2.47% in the new steady state. In the next section, I show that the results hold when the economies are calibrated to match the moments in Guerrieri and Lorenzoni (2015).

I consider two alternatives for the timing of the credit crunch. First, an unexpected worsening of the conditions that hits the economy at time 1 and forces households to adjust either immediately or over a period of time. Second, I allow for an expected worsening in which households learn about the future credit crunch a few quarters before it actually occurs. Since in the former the households are surprised by the shock, the drop in consumption there can be understood as an upper bound; whereas in the latter, I try to capture the fact that households can anticipate trouble and start adjusting before the shock actually hits, so that the decrease is smaller.

Finally, I consider an alternative definition of a credit crunch, one in which the shock to the amount of debt is the same not in the long run, but in the very short run. In the previous exercises, debt to GDP would converge to the same, lower level in the long run, but implying different paths immediately after the shock. An alternative definition could require debt to GDP (and consumption) to fall by the same amount in both economies in the first period and then evaluate the long run consequences of the credit crunch. I calibrate the financial parameters to produce the same initial drop in consumption after the shock hits, so that the initial decrease in the supply of loanable funds is the same in both economies. And I study the implications of this calibration for the level of debt in the long run.

1.5.1 Unexpected Credit Crunch

In the unexpected credit crunch, households learn at time 1 that financial conditions will start to deteriorate immediately. For the hard constraint, the calibration of tightening of financial conditions yields a new borrowing limit of $12,209, a decrease of 8,720 dollars or
41.7%, similar to the drop obtained in Guerrieri and Lorenzoni (2015), 44.2%. For the soft constraint, the credit crunch will be modeled as an increase in the borrowing interest rate spread to 0.0134, an increase of almost 70% and equivalent to an annual borrowing rate of 9.6%. The new borrowing limit of $12,209 and the new borrowing interest rate spread of 0.0134 are such that in the final steady state the debt to income ratio will be 2.47% in both economies.

I consider two alternative dynamics for the credit shock. First, I assume households are forced to adjust immediately after the shock hits. Because of the size of the shock, around a sixth of average annual income, the deleverage does not appear implausible. In addition, the existence of transfers guarantees that no household will be lead into negative consumption. Second, I follow Guerrieri and Lorenzoni (2015) and allow the adjustment of financial conditions to take place over six quarters. Comparing the differential dynamics will be instructive as the six-quarter adjustment period decreases the importance of forced-deleverage in the aggregate response.

When the credit crunch shock requires immediate adjustment, the initial drop in consumption in the soft constraint economy is only a third of the observed in the hard constraint. As illustrated in Figure 1.7, aggregate consumption drops by 4.8% when the credit crunch hits the hard constraint economy, but only by 1.6% in the soft constraint one. The decrease in the hard constraint is lessened by the presence of transfers which benefit 2.6% of the households when the shock hits, compared with only 0.05% of the households in the soft constraint. Once the new borrowing limit settles in, the drop in consumption decreases in magnitude until it eventually turns positive after 42 quarters. In the soft constraint, the change in consumption also becomes positive after 42 quarters.

The right hand side panel of Figure 1.7 shows how the deleverage takes place almost immediately in the hard constraint version, with the debt to income ratio dropping by 34% within the first year after the shock. On the other hand, the speed of adjustment is much slower in the soft constraint as it takes more than 12 quarters to produce the deleverage that
Consumption and debt decrease in both economies after the credit crunch, but in the hard constraint economy the drop is much more severe.


Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy.

SC. Initial Borrowing Spread: 0.0079. Final Borrowing Spread: 0.0134.

The decrease in the borrowing limit achieved in a year. The mechanism behind these different responses is not surprising. In the hard constraint economy, a quick deleverage is fabricated by forcing households borrowing at the limit or close, to delever immediately, while also inducing greater precautionary savings among households not mechanically affected by the decrease in the limit. In the soft constraint version, the incentives to delever are provided through an increase in the borrowing rate, but highly-indebted households are still optimizing at an interior point of their budget constraint according to their Euler equation and so, it is optimal for them to follow a smoother adjustment path.

Figure 1.8 presents the differential responses to the shocks of groups of households defined in terms of their assets position when the shock hits. With a drop of 21% in their consumption, borrowers drive the adjustment in the hard constraint economy, while savers...
virtually do not react. Households borrowing at the limit when the shock hits reduce their consumption by more than 50%, but since there is relatively few of them, most of the change in borrowers’ consumption is explained by the behavior of the unconstrained borrowers. In a similar fashion, the adjustment in the soft constraint is driven by the borrowers’ response, although their consumption goes down by only 7% when the shock hits. Savers are again almost completely unaffected.

Thus, the drop in aggregate consumption is three times more severe in the hard constraint economy than in the soft constraint when new financial conditions take place immediately. In both cases the adjustment is led by borrowers, but it is more rapid in the hard constraint as these households need to delever faster to avoid the risk of hitting the borrowing limit.

Next, I use the time path in Guerrieri and Lorenzoni (2015) and I split the shock to financial conditions linearly along six quarters. Then, in the hard constraint economy at time 1, when the shock hits, households learn that borrowing conditions will worsen over the following quarters: that quarter they will not be able to borrow more than 19,476, the next one the limit will be 18,022, and so on. Finally, by the sixth quarter, the credit limit will settle into the new steady level, 12,209. I assume the same linear path also applies to the borrowing spread parameter in the soft constraint economy.

The consumption response is again much milder in the soft constraint (-1.2%) than in the hard constraint economy (-2.1%). As shown in Figure 1.10, borrowers lead the contraction in both economies, although in the soft constraint the decrease is significantly milder. Unlike the previous specification where constrained borrowers’ consumption dropped by 40%, here their response is similar to that of the unconstrained borrowers as the adjustment path allows for a more gradual deleverage.

1.5.2 Expected Credit Crunch

An alternative experiment to account for the fact that agents could anticipate the arrival of the shock is to allow households to find out about the credit crunch before it actually takes
In both economies, the aggregate response is driven by the borrowers’ reaction. But in the soft constraint, that response is significantly milder. Borrowers (Savers) refers to the response of households that had a negative (positive) level of assets when the shock hit. Constrained (Unconstrained) refers to the response of borrowers that were (were not) at their borrowing limit. Aggregate refers to the response of the economy as a whole. Refer to Figure 1.7 for further details.
When the credit crunch is gradual, the consumption response is again milder in the soft constraint economy.

Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions decreases the debt to income ratio in the new steady state by 55.56%. Borrowing parameters are assumed to adjust linearly over six quarters. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy.
SC. Initial Borrowing Spread: 0.0079. Final Borrowing Spread: 0.0134.

place. Such a setting will permit the evaluation of the adjustment path chosen by households reducing the concern of the result being driven mechanically by a forced deleverage of those households at the borrowing limit. In this case, at time 1, households learn that within a year borrowing conditions will worsen and new financial conditions will apply. I assume that the magnitude of the shock (i.e., a new borrowing limit of $12,209 and a new borrowing interest rate spread of 0.0134 such that in the final steady state the debt to income ratio will be 2.47% in both economies) is exactly as before so the only difference between the credit crunch with immediate adjustment studied in the previous subsection and this one is that here households find out about the forthcoming tightening one year before it actually happens.
In both economies, the aggregate response is driven by the borrowers’ reaction. But in the soft constraint, that response is significantly milder. Borrowers (Savers) refers to the response of households that had a negative (positive) level of assets when the shock hit. Constrained (Unconstrained) refers to the response of borrowers that were (were not) at their borrowing limit. Aggregate refers to the response of the economy as a whole. Refer to Figure 1.9 for further details.
The consumption response to an expected credit crunch is milder in the soft constraint economy.


Aggregate consumption and debt to income responses in each economy after the arrival of news of a tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. The news arrive four quarters before the actual tightening takes place. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy.

SC. Initial Borrowing Spread: 0.0079. Final Borrowing Spread: 0.0134.

The arrival of news about a forthcoming credit crunch reduces the speed of the adjustment but does not alter the dynamics significantly. As soon as households learn about the shock, they reduce their consumption and start to delever. Since the incentives to delever in this case are weaker, so is the consumption response. Aggregate consumption decreases by 2.4% in the hard constraint economy and by 1.2% in the soft constraint. Thus, anticipating the arrival of a credit crunch reduces significantly the magnitude of the aggregate response to the shock in both economies. The aggregate response is still greater in the hard constraint model.
1.5.3 Short-Run Credit Crunch

The previous exercises defined a credit crunch as a change in borrowing parameters that reduces the amount of debt in the economy in the long run and examine the aggregate implications in the short run. However, a credit crunch could also be defined in terms of a sudden decrease in the amount available to be borrowed in the very short run. In this subsection, I try to capture this idea. I pick the new financial parameters, the borrowing limit in the hard constraint and the borrowing spread in the soft constraint, such that they produce the same drop in consumption (implying the same decrease in loanable funds) in the period when the shock hits. I assume the shock requires immediate adjustment. From there, the long-run implications will be compared. A more severe tightening of borrowing conditions will show up as a greater drop in the amount of debt in the final steady state.

As a target for calibration, I look at the consumption response at the beginning of the Great Recession. Obviously not all of that drop in consumption is attributable to the credit crunch. Many other explanations are also possible: increasing unemployment risk, the collapse of the housing bubble, a change in expectations, and so on. The question here is how large would the credit crunch have needed to be if all those other factors had been muted. Following Blinder (2013) I define the beginning of the credit crunch to be the bankruptcy of Lehman Brothers on September 15, 2008. I target the average drop in consumption per quarter in the following year, which was 2%.

To produce an immediate drop in consumption of 2%, the new borrowing limit in the hard constraint is 16,178, a 22.7% reduction from the initial borrowing limit. In the soft constraint model, the interest rate needs to increase from 7.3% to 10.3%, a 87.0% increment in the borrowing spread. Figure 1.12 shows the aggregate dynamics that follow the shock. The right panel shows that the shock in the soft constraint economy adversely affects the long run twice as much as it does in the hard constraint economy. The credit crunch reduces equilibrium debt in the economy by 62% in the soft constraint economy, but only by 32%
To produce the same initial drop in consumption, a much more severe reduction of the level of debt must take place in the soft constraint economy. HC: Hard Constraint Model. SC: Soft Constraint Model.

Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that produces an immediate drop in aggregate consumption of 2%. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy. HC. Initial Borrowing Limit: -20,952. Final Borrowing Limit: -16,178. SC. Initial Borrowing Spread: 0.0079. Final Borrowing Spread: 0.0149.

in the hard constraint economy. The tightening of financial conditions is significantly more severe in the hard constraint economy.

1.6 Robustness

1.6.1 Heterogeneity in Borrowing Conditions

In the data, there is a great deal of heterogeneity in the financial conditions that households face (Table 1.2). In this subsection, I take this heterogeneity as given and study its implications for the consumption change induced by a credit crunch. Since the model does not include default, I assume agents are born with a credit type which they will carry out
for life. Considering the lack of life-cycle features of the interest rates on unsecured debt, this assumption does not seem completely implausible. This credit type will determine the agent’s borrowing limit in the hard constraint economy or her borrowing interest rate in the soft constraint version.

I define five financial types. Each household draws her type at the beginning of her working life from a uniform distribution independent from any of her other characteristics. This assumption is motivated by the lack of predictive power displayed by observables in the SCF 2007.\textsuperscript{15}

I use the empirical distribution of borrowing conditions in the SCF 2007 to calibrate the financial types in each model. In the hard constraint model, I define the borrowing limit of the $n^{th}$ type to be the mean of the credit card borrowing limit of the $n^{th}$ quintile in the empirical distribution of the borrowing limit from the SCF 2007. The credit card limit is not the ideal target as households can usually obtain credit from other sources such as consumer and educational loans, secured credit, or informal borrowing from family and friends. But it is the only measure available in the data. On the other hand, the target for the soft constraint model, the borrowing spread, is observable in the data. For consistency, I assume the borrowing rate of the $n^{th}$ type to be the mean of the credit card interest rate of the $n^{th}$ quintile. Table 1.2 presents the levels used for the hard constraint borrowing limit (Column 2) and the soft constraint borrowing interest rate (Column 4).

After having imputed directly from the data the borrowing conditions, there is only one free parameter to pick, $\beta$, which I set to match the aggregate debt to income ratio in the economy, 5.56%. In the hard constraint, this yields a $\beta = 0.9886$ (annual discount factor of 0.9552), whereas in the soft constraint I obtain $\beta = 0.9882$ (annual discount factor of 0.9534). Agents are slightly more impatient in the soft constraint model.

\textsuperscript{15}Results are not shown, but are available upon request. Observables include demographic characteristics, income, and net wealth. The SCF does not include credit scores, which are probably key to explain the cross-sectional variance in borrowing conditions. The lack of this variable prevents me from estimating a function of the borrowing spread on the amount of debt directly in the data as such estimation will suffer from severe omitted variable bias.
Table 1.2: Credit Card Financial Conditions by Quintile. SCF 2007

<table>
<thead>
<tr>
<th></th>
<th>Borrowing Limit</th>
<th>Interest Rate</th>
<th>Credit Crunch</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
</tr>
<tr>
<td>1st Quintile</td>
<td>1,495</td>
<td>1,100</td>
<td>4.16</td>
</tr>
<tr>
<td>2nd Quintile</td>
<td>6,288</td>
<td>6,000</td>
<td>9.22</td>
</tr>
<tr>
<td>3rd Quintile</td>
<td>13,201</td>
<td>13,000</td>
<td>12.75</td>
</tr>
<tr>
<td>4th Quintile</td>
<td>27,628</td>
<td>26,000</td>
<td>16.87</td>
</tr>
<tr>
<td>5th Quintile</td>
<td>72,593</td>
<td>60,000</td>
<td>22.27</td>
</tr>
</tbody>
</table>

Columns 2 to 5 are obtained from the SCF 2007. Borrowing limit refers to the reported total limit on the household’s credit cards. Interest rate refers to the rate paid on credit card debt.

Columns 6 and 7 represent the values that these variables need to take after an unexpected and proportional tightening of the credit conditions decreases the debt to income ratio in the new steady state by 55.56%.

This relative impatience of agents in the soft constraint economy slightly reduces the amount of aggregate wealth in the initial equilibrium relative to the hard constraint case. The ratio of gross wealth to income is 1.74 in the soft constraint model, whereas in the hard constraint model it is 1.87. Both are well above the gross wealth to income ratio in the data: 1.47.

I now repeat the credit crunch exercise assuming a homogeneous shock among financial types that leads to a reduction of 55.56% in the amount of debt in the new steady state. First, I compute the ratio by which the five borrowing limits should decrease simultaneously for the final steady state to have a debt to income ratio of 2.47%. The result is 0.502, i.e., the borrowing limit for the first financial type will go down from 1,495 to 751, for the second financial type it will decrease from 6,288 to 3,159, and so on. The complete list is in Column 6 of Table 1.2. Second, in the soft constraint model, I look for the homogeneous increase in the quarterly borrowing spread which produces the same drop in the level of debt to GDP in the economy. In this calibration, the five spreads must simultaneously increase by 624%.
The credit crunch is less severe in the soft constraint economy

Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Percentages are with respect to the initial steady state levels.
Initial and Final Borrowing Parameters as indicated in Table 1.2. HC: Columns 2 and 6. SC: Columns 4 and 7.

For the first financial type this would mean that the annual borrowing rate increases from 4.16% to 5.16%, whereas for the fifth financial type it will soar from 22.27% to 195.93%.

Only under this unrealistic and massive increment in the borrowing interest rates the severity of the consumption drop in the soft constraint economy becomes comparable to that in the hard constraint. Figure 1.13 shows the effects of this credit crunch in consumption and debt when immediate adjustment is assumed. The response of aggregate consumption in the soft constraint is still milder: 2.9% versus 3.7% in the hard constraint. It is only when the adjustment is allowed to take place over six periods, with a linear, gradual adjustment of the borrowing parameters, shown in Figure 1.14, that the drop in consumption is smaller in the hard constraint economy: 1.6% versus 2.0%. Thus, for the drop in consumption in a soft constraint economy to be severe enough to exceed the one in the hard constraint, borrowing
The credit crunch is more severe in the soft constraint economy when borrowing spreads soar by more than 600%.


Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Borrowing parameters are assumed to adjust linearly over six quarters. Percentages are with respect to the initial steady state levels.

Initial and Final Borrowing Parameters as indicated in Table 1.2. HC: Columns 2 and 6. SC: Columns 4 and 7.

interest rates must increase massively, whereas borrowing limits just need to decrease by half.

1.6.2 Other Robustness Checks with Homogeneous Borrowing Conditions

Finally, I return to the case of homogeneous financial conditions to verify that the main result of the chapter, that a credit crunch in a hard constraint economy is much more severe than in the soft constraint, is robust to alternative specifications.

Table 1.3 summarizes the robustness checks. First, I consider a non-degenerate initial distribution of assets estimated empirically from the SCF among agents younger than 25,
instead of the assumption of no initial assets in the baseline model. Second, I calibrate the model to match the NIPA moments used in Guerrieri and Lorenzoni (2015): 1.78 for gross wealth to GDP and 0.18 for debt to GDP. Finally, I consider two other values for $\gamma$, the preference parameter, 0.5 and 4.

The main result of the chapter is robust to all these exercises. The contraction in consumption when the credit crunch is modeled within a hard constraint framework is much more severe than when it happens through interest rates.

1.7 Conclusion

The Great Recession raised once again the question of whether credit conditions can affect the real economy. The literature has modeled credit conditions in the form of a borrowing limit (hard constraint) or a borrowing spread (soft constraint). In this chapter, I have built on the work by Guerrieri and Lorenzoni (2015) and I have shown that the macroeconomic implications of a worsening in the financial conditions largely depend on the modeling approach. I have argued that the standard approach to modeling financial constraints, the hard constraint, mechanically creates a significant drop in consumption by forcing households to deleverage. Modeling financial frictions with a soft borrowing constraint only yields a minor decrease in consumption in response to a credit crunch. My results highlight the importance of examining alternative explanations for the phenomena observed in the recent crisis, while cast doubt on the use of the hard constraint as an appropriate modeling device.

Further work could attempt to endogeneize the borrowing spread by introducing default in the model as in Chatterjee et al. (2007) and Livshits, MacGee, and Tertilt (2007). In such a model, an aggregate shock would increase the probability of default, which in turn would increase the borrowing spread, amplifying the initial shock. Finally, the inclusion of an illiquid asset, e.g., housing, as in Kaplan and Violante (2014) would provide with a
Table 1.3: Robustness Checks

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Initial Assets</th>
<th>NIPA Target</th>
<th>$\gamma = 0.5$</th>
<th>$\gamma = 4$</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>HC</td>
<td>SC</td>
<td>HC</td>
<td>SC</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.950</td>
<td>0.950</td>
<td>0.957</td>
<td>0.957</td>
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<tr>
<td>Borrowing Limit</td>
<td>(20,539)</td>
<td>(100,546)</td>
<td>(20,095)</td>
<td>(26,764)</td>
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<tr>
<td>Borrowing Interest Rate</td>
<td>7.61</td>
<td>3.99</td>
<td>5.90</td>
<td>9.17</td>
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**Initial Steady State**

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<th>SC</th>
<th>HC</th>
<th>SC</th>
<th>HC</th>
<th>SC</th>
<th>HC</th>
<th>SC</th>
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</thead>
<tbody>
<tr>
<td>Debt to Income</td>
<td>0.056</td>
<td>0.056</td>
<td>0.180</td>
<td>0.180</td>
<td>0.056</td>
<td>0.056</td>
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**Initial Drop in Consumption ($\Delta\%$) - Immediate Adjustment**

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<tr>
<td>Savers</td>
<td>0.436</td>
<td>0.369</td>
<td>0.126</td>
<td>0.174</td>
<td>0.480</td>
<td>0.377</td>
<td>0.363</td>
<td>0.285</td>
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**Initial Drop in Consumption ($\Delta\%$) - Adjustment in 6 quarters**

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<tr>
<td>Aggregate</td>
<td>2.650</td>
<td>1.634</td>
<td>4.792</td>
<td>2.411</td>
<td>2.635</td>
<td>1.501</td>
<td>2.657</td>
<td>1.733</td>
<td></td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Borrowers</td>
<td>8.739</td>
<td>5.489</td>
<td>12.486</td>
<td>6.120</td>
<td>8.310</td>
<td>4.708</td>
<td>10.442</td>
<td>6.775</td>
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<tr>
<td>Savers</td>
<td>0.410</td>
<td>0.333</td>
<td>0.120</td>
<td>0.162</td>
<td>0.447</td>
<td>0.338</td>
<td>0.353</td>
<td>0.267</td>
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**Final Steady State**

<table>
<thead>
<tr>
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<th>HC</th>
<th>SC</th>
<th>HC</th>
<th>SC</th>
<th>HC</th>
<th>SC</th>
<th>HC</th>
<th>SC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wealth to Income</td>
<td>1.524</td>
<td>1.520</td>
<td>1.933</td>
<td>1.941</td>
<td>1.523</td>
<td>1.517</td>
<td>1.528</td>
<td>1.524</td>
</tr>
<tr>
<td>Debt to Income</td>
<td>0.025</td>
<td>0.025</td>
<td>0.080</td>
<td>0.080</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
</tr>
</tbody>
</table>

NIPA Target: Guerrieri and Lorenzoni (2015)’s moments for debt and wealth to income (0.18 and 1.78) from the national accounts.
The interest rates and discount factors are reported in annual levels.
complete framework to test the alternative explanations to the recent crisis and compare the results with the empirical evidence.
Chapter 2

Beyond Labor Market Outcomes: The Impact of the Minimum Wage on Nondurable Consumption

2.1 Introduction

The minimum wage is a controversial policy in the United States. A large literature has studied the effects of the minimum wage on labor market outcomes such as employment and wages. However, if the goal of this policy is to raise welfare, its evaluation should be primarily based on its effects on consumption, rather than on labor market outcomes. Examining an individual household’s consumption response to a change in the minimum wage is challenging due to data limitations. But aggregate data allows to measure the response of aggregate consumption, at least among nondurables, where adjustment costs are low and households’ response is likely to be immediate. So, my research question is: does a minimum wage hike increase nondurable consumption?

I use a novel dataset on retail sales of groceries to produce a measure of nondurable consumption at the county level. While the evolution of retail sales is similar to the national
accounts’ measure of nondurable consumption at the state level, retail sales data has several advantages for this project. Retail sales data is available at any frequency. I set the frequency to be a quarter, which allows me to study the dynamics of the consumption response in detail. Also, retail sales are available at a very disaggregated geographic level, allowing me to effectively control for local economic conditions. Third, I am able to exploit the heterogeneity in how binding the minimum wage is in U.S. counties to assess the differential effect of the policy, strengthening the identification strategy.

The minimum wage could increase consumption by redistributing income from rich, low marginal propensity to consume capital owners, towards poor, high marginal propensity to consume workers. The characterization of the minimum wage as a redistributive policy is consistent with recent empirical evidence failing to find sizable disemployment effects even for vulnerable groups such as teenagers and restaurant workers (Dube, Lester, and Reich, 2016). If the increased minimum wage has negligible effects on the level of employment, there will also be negligible effects on output. The minimum wage will thus lead to an increase in labor income for employees at the expense of employers’ profits. If those employees benefiting from the raise have a higher marginal propensity to consume than their employers, aggregate consumption will rise. The minimum wage potentially also has a positive multiplier effect through the aggregate demand channel and a negative effect on hours worked if employers choose to hire less labor along the intensive margin. But as long as all those effects take place within the local economy, they will be captured by my estimate of the net effect of the minimum wage on aggregate nondurable consumption. On the other hand, if the minimum wage has effects beyond the local economy, my estimates will not include them. For instance, if capital owners live in a different county and they reduce their consumption as a response to the policy, I will not be able to measure it. If the minimum wage increases the demand for goods produced in a different county raising employment and consumption there, this effect will not be included in my estimates either. Finally, because I am using aggregate

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1In my baseline specification, I define the local economy to be the county. For robustness, I also explore the response at the state level.
data I cannot decompose the estimated response into the different groups of agents who are affected by the policy.

I find that hikes in the minimum wage raise aggregate expenditure. An increase of 10% in the minimum wage rate increases nominal sales by 1.1% and real sales by 0.7%. The magnitude of the estimated consumption response appears large. For comparison, the mean consumption growth in the post-war period was 1%. Furthermore, the elasticity is greater in counties where the minimum wage is more binding. Higher prices account for part of the increased expenditure, as nominal sales respond more than real sales. Evidence at the store level however, shows that real sales appear to grow slightly more than nominal sales, which suggests that consumers could be switching towards more expensive stores.

The magnitude of the estimated consumption response is consistent with the minimum wage having effects beyond the very bottom of the earnings distribution, benefiting households who are credit-constrained and spend most of their extra resources in nondurables. Using CPS data I show that the minimum wage induces modest but significant increases in labor income for households up to the 25th percentile of the distribution. A 10% minimum wage hike would increase sales by 2 billion dollars, a quarter of the predicted extra labor income. Using the Bureau of Economic Analysis’ prototype estimates on Personal Consumer Expenditures at the state level, I find that the additional nondurable expenditure would be 19 billion, about twice the size of the change in labor income, although the difference is not statistically significant. The strong response of nondurables is consistent with Aaronson, Agarwal, and French (2012)’s finding of an increase in debt in response to the minimum wage and with a lack of response by aggregate durables and services which I document in Section 2.5 and that could be explained by the presence of adjustment costs.

A panel data research design with two-way fixed effects is a suitable framework for this project. By complementing time and county fixed effects with local area variables to proxy for economic conditions, my identification strategy rests on the assumption that counties where the minimum wage rate went up would have experienced the same increase in sales that
was observed in counties where the rate was unchanged, conditional on observable economic conditions. In this setting, county fixed effects capture any static heterogeneity at the local level, whereas time fixed effects absorb the common time trend. In addition, variables such as employment and house prices at the county level enable me to control for local economic conditions, which is particularly important in the context of the Great Recession since not all counties experienced the crisis at the same severity and that severity could be correlated with policy changes. As such, my preferred specification controls for gross state product and for employment, population, and house prices at the county level, in addition to county and time fixed effects.

To identify the nondurable expenditure response, I exploit the wide dispersion of state minimum wage rates across the country and over time during the period 2006-2014. At any point in time during the sample period at least a quarter of the states had set minimum wage rates above the federal level; and in some periods half of the states had done so. I use all the increments in the state legislated minimum wage rate. In addition, the federal rate had a three-step increase starting in July 2007. Since the prevailing minimum wage rates in each state were different, the federal raise was not uniform across the country and therefore allows for the identification of the effect by comparing areas where the new federal rate was binding with those where the new federal legislation did not have an impact because the local minimum wage rate was already higher than the new federal level.

A number of additional checks confirm the robustness of my results. First, I show that there are no significant pretrends in sales that could jeopardize my identification strategy. Second, I perform a difference-in-difference-in-difference exercise and I find that counties where the minimum wage binds more experience a greater expenditure response when compared to other counties in the same state. Third, I obtain similar elasticities when looking at sales at the store and the state level, as well as for nondurable consumption in NIPA, which suggests the baseline Nielsen dataset is reasonably representative. Finally, in the appendix I also show that my results are not driven by the housing bubble, by a subset of states who
annually index their minimum wage rates to the federal inflation rate, or by a small but heavily populated subset of counties.

This chapter offers a new take to the empirical literature studying the effects of the minimum wage, by focusing on the implications for consumption rather than labor market outcomes, which is a better proxy for welfare. The measurement of the effects of the minimum wage has interested labor economists for decades with significant contributions made by Neumark and Wascher (1992), Card and Krueger (1994), Lee (1999), and Autor, Manning, and Smith (2016), among others. In this line, my chapter draws on the methodology from recent work on the identification of the effects on labor market outcomes, most notably from the ongoing discussion between Dube, Lester, and Reich (2010) and Neumark, Salas, and Wascher (2014b) about the need to control for unobservable spatial employment growth heterogeneity. I argue that this concern does not emerge during my sample period and so, my baseline specification is a two-way fixed effects panel design. Nevertheless, I show that my results are robust to the presence of unobservable spatial time trends. To the best of my knowledge, only one other paper explores the effect of the minimum wage on consumption. Using CEX data, Aaronson, Agarwal, and French (2012) measure the expenditure response to minimum wage hikes and find a positive effect mainly on vehicle purchases. This effect is very unequally distributed among low-income households, which they interpret as evidence of borrowing constraints and adjustment costs. Aaronson, Agarwal, and French (2012) also report an insignificant effect of the minimum wage on consumption of a combined category of nondurables and services. However, the measurement of grocery purchases in the CEX-Interview is noisy and its combination with services may further confound the effect. In this chapter, I complement the analysis in Aaronson, Agarwal, and French (2012) by focusing on nondurables rather than durables and by employing a better measure of nondurable expenditures at the county level.

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2Households are asked the usual amount of weekly expense for grocery shopping and not the actual amount spent in a given and recent week, where recall could be higher.
The rest of the chapter is organized as follows. In Section 2.2, I describe the data and show that store sales appear to be a reasonable approximation to consumption aggregates from the national accounts. In Section 2.3, I discuss the identification strategy used to measure the expenditure response to a minimum wage hike. I present the main results in Section 2.4 and I show robustness checks in Section 2.5. In Section 2.6, I explore the quantitative link between the estimated expenditure response and the impact of the minimum wage on the labor income distribution. Finally, Section 2.7 concludes.

2.2 Data Description

My empirical analysis exploits the significant policy heterogeneity across the country and a new measure of consumption by county. In this section, I first describe the dispersion in the prevailing minimum wage rates at the state level in the period 2006-2014. Then, I argue that retail sales data are a good proxy for consumption at the county level, which allows me to specify models that control for the evolution of local area observable variables.

2.2.1 Minimum Wage

In this subsection, I discuss the two sources of variation in the minimum wage that I exploit: federal and state level changes.

The rich variation observed in minimum wage rates (Figure 2.1) emerges from the institutional setting determining the policy. Federal, state, and local governments in the U.S. can set their own minimum wage. The effective minimum wage rate is the maximum of the three. Since only a few counties have recently enacted their own legislation, I abstract from this variation and focus instead on the federal and state minimum wage rates. This data was retrieved from the federal and state Departments of Labor.

The Fair Minimum Wage Act of 2007 increased the federal rate in three steps during my sample period. The federal minimum wage rate rose from $5.15 to $5.85 on July 24, 2007, to
$6.55 on July 24, 2008, and to $7.25 on July 24, 2009. The law induced different changes in the effective rate across states because some states had already legislated rates higher than the federal one. I exploit this variation in my identification strategy.

A number of states enacted changes in the state minimum wage rates during my sample period. Eleven states\(^3\) adopted an annual automatic adjustment of their minimum wage rate to compensate for inflation. In ten of these states,\(^4\) the adjustment follows the federal rate of inflation and it is then arguably exogenous to local economic conditions. Seventeen other states have legislated higher rates as well, usually with increments taking place sequentially over a few years.

The interaction of these state and federal increments produces valuable dispersion in the effective minimum wage rate across the country (Figure 2.2). For half of the county, mostly the South and the Center, the change in the minimum wage between 2006 and 2014 was given by the federal increment, i.e., 41%. For sixteen states, the effective minimum wage rose by less than 40% in these nine years. Maine had the smallest increment in the period, only 15%. Finally, eight states, mainly in the Mountain division, experienced increases above the federal change. Nevada had the largest increment in the period, 60%.

### 2.2.2 Nielsen Sales

In this subsection, I argue that grocery sales as computed from a Nielsen dataset provide a reasonable measure of nondurable consumption at the county level.

To approximate nondurable consumption, I obtain sales by county from a Nielsen dataset mainly covering groceries and drugs. The Nielsen Retail Scanner Data contains weekly information on pricing, volume, and merchandising conditions generated by participating retail store point-of-sale systems in all 48 contiguous states and D.C., from 2006 to 2014. It

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\(^4\)The exception is Colorado where the minimum wage is adjusted using the Consumer Price Index for the Denver-Boulder-Greeley combined metropolitan statistical area.
Significant dispersion in state level minimum wages and over time

The quarterly rate is computed as the average of the minimum wage rates prevalent in each month of the quarter. The effective minimum wage is defined as the maximum of the state and federal minimum wage rates.

The sample includes the 48 contiguous states and D.C. covers approximately 40,000 stores of very diverse size (Figure 2.3). The dataset contains all the products in Nielsen-tracked categories (mainly food, non-food grocery items, health and beauty aids, and select general merchandise) that are labeled with a UPC. According to Nielsen’s own estimates, the information included represented in 2011: 53% of the total sales in food, 55% in drugs, 32% in mass, 1% in liquor, and 2% in C-store (Kilts Center for Marketing, 2014).

To distinguish real from nominal effects, I compute two measures of sales. Nominal sales aggregate all the transactions by store and quarter using current prices. In contrast, real sales aggregate transactions using the 2012 average price for each product across the country. Real sales are then meant to abstract from price changes and price differences across stores and give a sense of the change in quantities sold.
Large geographic variation in the change in the minimum wage
Percentage change in the effective minimum wage between January 2006 and December 2014. The effective minimum wage is defined as the maximum of the state and federal minimum wage rates.

I collapse sales to the county level, my preferred unit of analysis. For consistency, I drop all the stores that are not present during the 36 quarters of my sample period. I show in Section 2.5 that this restriction does not affect my results, so the potential bias introduced by the lack of entry and exit of stores is not a concern. Finally, I drop the county of Ringgold in Iowa because it lacks employment data in the fourth quarter of 2013. My sample then includes 2,226 counties across the 48 contiguous states and D.C.

Counties are my preferred unit of analysis because data availability allows me to control for shocks to local economic activity affecting sales via employment, population, or house prices. Nevertheless, I show in Section 2.5 that my estimate of the elasticity of sales to the minimum wage is very similar when the model is specified either at the state or at the store level.

Retail sales appear to be a good proxy for nondurable consumption at the local level. First, the data provides good geographic coverage as evidenced by Figure 2.4, which shows the number of stores in each county. Second, the evolution of retail sales in the period 2006-
The dataset contains both small and large stores
Annual sales for stores that are present during the 36 quarters of the sample. Sales are in millions of nominal dollars.

2014 is fairly consistent with the changes measured by the national accounts at the state level (Figure 2.5).

### 2.2.3 Other Sources of Data

Additional variables are used to characterize counties and local economic dynamics. I complement the Nielsen and minimum wage data with public sources of data at the county level: annual population from the Census Bureau’s Population Estimates Program, quarterly data on employment and average wages from the Quarterly Census of Employment and Wages (QCEW), house prices from the Federal Housing Finance Agency, and statistics on income distribution from the American Community Survey. I also use data at the state level: Employment from the Bureau of Labor Statistics and Regional Accounts from the Bureau of Economic Analysis, in particular, nominal gross state product and personal
Nielsen data offers a good geographic coverage
Number of stores that are present during the 36 quarters of the sample in each county.

consumer expenditure. Table 2.1 displays summary statistics for the resulting county-level dataset.

Finally, to reconcile my expenditure results with previous work regarding employment and wages, I use the Outgoing Rotation Group from the Current Population Survey as discussed in Section 2.6.

2.3 Identification Strategy

In this section, I argue that a panel data framework is the appropriate choice to study the consumption response to minimum wage changes. County fixed effects absorb static unobservable local characteristics, whereas time fixed effects capture global time trends. In addition, variables such as employment, population, and house prices allow me to control for potentially heterogeneous observable time trends on local economic conditions.

Let $Sales_{c,t}$ be the amount of sales (nominal or real) in quarter $t$ in county $c$, located in state $s$. Then, my baseline model is:
Nielsen sales data seems to be a reasonable approximation to consumption Log growth rates between 2006 and 2014.
Nielsen Sales refers to the nominal sales data aggregated to the state and year level.
NIPA corresponds to different items of the Personal Consumer Expenditures by state as the reported by the Bureau of Economic Analysis.
Table 2.1: Summary Statistics in 2012

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum Wage</td>
<td>7.41</td>
<td>0.36</td>
<td>7.25</td>
<td>7.25</td>
<td>7.40</td>
</tr>
<tr>
<td>Sales</td>
<td>82.06</td>
<td>266.87</td>
<td>2.61</td>
<td>15.79</td>
<td>54.21</td>
</tr>
<tr>
<td>Employment</td>
<td>56.04</td>
<td>169.69</td>
<td>6.09</td>
<td>13.80</td>
<td>38.11</td>
</tr>
<tr>
<td>Population</td>
<td>135.48</td>
<td>373.64</td>
<td>20.85</td>
<td>41.40</td>
<td>104.24</td>
</tr>
<tr>
<td>House Price Index</td>
<td>171.26</td>
<td>20.23</td>
<td>158.28</td>
<td>169.75</td>
<td>180.73</td>
</tr>
<tr>
<td>Average Weekly Earnings</td>
<td>708.74</td>
<td>155.68</td>
<td>608.75</td>
<td>673.23</td>
<td>762.28</td>
</tr>
<tr>
<td>Number of Stores</td>
<td>11</td>
<td>27</td>
<td>1</td>
<td>3</td>
<td>9</td>
</tr>
</tbody>
</table>

**Significant heterogeneity across counties**

Mean, Standard Deviation, 25th percentile, median, and 75th percentile of each variable by county in 2012.

Minimum wage and average weekly earnings are in nominal dollars. Sales are in millions of nominal dollars. Employment and population are in thousands.

\[
\log(Sales_{c,t}) = \kappa_c + \tau_t + \beta \log(\text{Minimum Wage}_{s,t}) + \gamma X_{c,t} + \epsilon_{c,t}
\]

where \(\beta\) is the coefficient of interest, the elasticity of sales (nominal or real) to the minimum wage. \(\text{Minimum Wage}_{s,t}\) is the effective minimum wage rate in state \(s\) in quarter \(t\), \(\kappa_c\) is the county fixed effect, \(\tau_t\) is the time fixed effect, and \(X_{c,t}\) is a set of observables at the county or state level (in my preferred specification: employment, population, gross state product, and house prices).

My identification strategy rests on the assumption of conditional parallel trends across counties. I assume that conditional differences between those counties where the minimum wage increased and those where it did not would have remained constant in the absence of a minimum wage hike. The assumption does not require that every county would have grown at the same pace during the sample period. Instead, it requires that the mean growth in sales that cannot be explained by growth in employment, population, nominal gross state
product, and house prices would have been the same across counties if the minimum wage increments had not taken place. The identifying assumption is untestable, but I will show in Section 2.5 that trends in consumption and observable controls before policy changes were not significantly different between the treatment and control groups, suggesting that the assumption is plausible.

The use of panel data is important to control for fixed unobservable heterogeneity. Counties where the minimum wage is high could be counties where the average wage is also high and so, a cross sectional estimate would not yield the impact of the policy but rather it would just reflect the fact that richer counties consume more. County fixed effects solve this problem by capturing all the static county characteristics and using the change rather than the level of the minimum wage to identify the elasticity.

My econometric model allows for a fairly flexible specification of time trends. Time fixed effects capture any shocks that affect all the counties in the same way, including seasonality. In addition, in my preferred specification I control for local observable economic conditions, allowing different groups of counties to experience different unconditional trends. The inclusion of such controls is important in the context of the Great Recession, which hit different regions with different severity and where the magnitude of those effects could potentially be correlated with the changes in the minimum wage. Failing to control then would bias my estimates. But the inclusion of these controls comes at the cost of some endogeneity concerns because sales, employment, and house prices could be jointly determined. For this reason, I present my results both with and without these local controls and find that the estimates for the elasticity of sales to the minimum wage are fairly stable across specifications, attenuating concerns on misspecification.

My results are robust to the presence of spatially heterogeneous unobservable time trends, a source of ongoing debate in the empirical literature on the minimum wage (Dube, Lester, and Reich, 2010). I discuss this concern in detail in Section 2.5, where I perform a difference-

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5I use nominal gross state product to account for both state level inflation and economic growth.
in-difference-in-difference exercise and find that even after allowing for state-specific time trends, counties where the minimum wage binds relatively more experience larger increments in sales. In addition, I show that heterogeneous time trends do not seem to be a concern during my sample period and the case for lack of pretrends is particularly strong after controlling for local economic conditions.

Since my goal is to obtain a measure of the aggregate response of sales to the minimum wage, I weight counties using their population level in the 2010 Census. Given that Nielsen tracks more stores in more heavily populated areas, this approach also gives more weight to the counties where sales are measured better. Nevertheless, I show in the appendix that the estimated elasticity is not significantly different when weights are not used.

Finally, following Dube, Lester, and Reich (2010), I cluster standard errors at the state level to account for any possible serial correlation and for the bias introduced by the minimum wage policy being the same within the state (Bertrand, Duflo, and Mullainathan, 2004).

2.4 Results

In this section, I present the main results of the chapter. In my baseline specification, retail sales increase by more than 1% after a 10% increment in the minimum wage. The response is stronger in counties where the minimum wage binds more. In terms of composition, the expenditure response is quite homogeneous across product groups.

2.4.1 Baseline Results

I present my baseline results in this subsection. Given the concern about heterogeneous shocks at the county level, my preferred specification includes county and time fixed effects and controls for employment, population, and house prices at the county level, and state level output. I include alternative specifications as well.
Nominal sales increase by more than 1% after a 10% minimum wage hike, a response that is both economically and statistically highly significant. My preferred specification, Model (3), yields the most conservative estimate of the elasticity of nominal sales to the minimum wage: 0.109. But the point estimate is fairly stable across specifications, oscillating between 0.109 and 0.181 (Table 2.2). While the addition of controls does not change the points estimates significantly, it does improve their precision.

The coefficients on the controls have the expected sign. The coefficient on employment is positive, and the one on population is negative. The similar absolute value of these estimates suggests that the employment to population ratio could be a sufficient control. The coefficient on current Gross State Product is positive but not significant from zero, suggesting that house prices and employment are better measures of local economic conditions. House prices have a positive and highly significant coefficient as expected from recent evidence on the Great Recession.⁶

Real sales rise significantly after a minimum wage increment too. The point estimate for the elasticity ranges from 0.070 in my preferred specification to 0.134. In each of the three specifications, the real sales elasticity is around 0.04 points lower than the nominal sales elasticity.⁷ Even if the difference between the nominal and real sales elasticities is not statistically significant, it suggests that some of the increase in sales emerges from consumers paying higher prices. It could be that stores raise prices in response to higher demand and higher costs (their own labor costs or the cost of the products they sell) or that consumers change their shopping behavior after an increase in the minimum wage, replacing cheap stores with expensive ones, and so, increasing nominal expenditures more than real quantities. The

⁶Mian and Sufi (2014) have found that the crisis was more severe in counties with larger drops in net worth, of which housing is the main component.

⁷For comparison, Reich et al. (2016) calculate that labor costs represent 12.2% of operating costs for grocery stores. Using the CPS in 2014 I estimate that 13.4% of the retail workers would be directly affected by a 10% increment in the minimum wage. If the amount of labor hired did not change (consistent with what the literature has found, Dube, Lester, and Reich, 2010) and there were not spillovers beyond the new minimum wage level, the wage bill would rise by 0.4%. Then, if the price paid by retailers for the goods sold were to stay constant (plausible assumption given that industries like manufacturing and transportation are not significant employers of minimum-wage workers) and they did not change their markups, then prices would rise by only 0.05%, only a tenth of the difference between the nominal and real responses.
Table 2.2: Baseline Results

<table>
<thead>
<tr>
<th></th>
<th>Nominal Sales</th>
<th></th>
<th>Real Sales</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(1)</td>
</tr>
<tr>
<td>Minimum Wage</td>
<td>0.163** (0.070)</td>
<td>0.181*** (0.044)</td>
<td>0.109*** (0.037)</td>
<td>0.120* (0.063)</td>
</tr>
<tr>
<td>Employment</td>
<td>0.532*** (0.068)</td>
<td>0.394*** (0.082)</td>
<td></td>
<td>0.519*** (0.074)</td>
</tr>
<tr>
<td>Population</td>
<td>-0.490*** (0.110)</td>
<td>-0.404*** (0.125)</td>
<td></td>
<td>-0.436*** (0.107)</td>
</tr>
<tr>
<td>GSP</td>
<td>0.002 (0.085)</td>
<td></td>
<td></td>
<td>0.016 (0.097)</td>
</tr>
<tr>
<td>House Prices</td>
<td>0.141*** (0.038)</td>
<td></td>
<td></td>
<td>0.124*** (0.040)</td>
</tr>
</tbody>
</table>

Observations: 80,136
Counties: 2,226

A 10% increase in the minimum wage increases nominal sales by 1.1%
* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors (in parenthesis) clustered at state level.
Time and county fixed effects are included in every specification.
latter appears to receive support from the data as discussed in Section 2.5, where I find that nominal and real sales experience the same change when measured at the store level and, if anything, the point estimate is slightly higher for real than for nominal sales.

### 2.4.2 Sales Elasticity by Minimum Wage Bindingness

Counties where the minimum wage binds more should exhibit a stronger expenditure response following a minimum wage hike. In this subsection, I show that there is indeed a stronger response in counties where the average wage is relatively low with respect to the minimum.

To assess the differential impact of an increase in the minimum wage depending on how binding the rate is in a given county, I use the ratio of average to minimum wage, a metric referred in the literature as the Kaitz index (Kaitz, 1970). Previous work\(^8\) has alternatively employed the ratio of median to minimum wage to measure the bindingness of the policy. Unfortunately, median wages are not available at the county level and so, I use average wages (from the QCEW) instead. With the ratio of average to minimum wage in 2005, i.e., the year before the beginning of my sample, I sort counties into four different groups and I run the baseline regression for each group separately. Results are summarized in Figure 2.6.

Counties where the average wage relative to the prevailing minimum rate is lower, and so where the policy binds more, show a stronger expenditure response. In my baseline specification (Panel B of Figure 2.6), following a minimum wage hike of 10%, nominal sales increase by 2.2% for the quarter of the counties where the policy binds the most, but only by 0.7% for the group of counties where it binds the least. Results are very similar for real sales, with an estimated response of 2.5% for the lowest and 0.2% for the highest quartile. While we can reject the elasticity of both nominal and real sales being equal to zero for the half of counties where average wages are low relative to the minimum, the estimates are not statistically different from zero for the other half.

---

\(^8\)Lee (1999), Autor, Manning, and Smith (2016).
The precision of the estimates across these four groups varies significantly and the confidence intervals become narrower for higher-wage counties. The standard error of the estimated elasticity is more than twice as large in the lowest quartile as it is in the highest one. The difference is associated with the use of weights in the estimation. Since high average wage counties tend to be more populated and better measured by Nielsen, the elasticity is estimated with more precision in the highest quartiles. In the appendix, I replicate Figure 2.6 without weighting by population and I find that the estimated expenditure response is again decreasing in the level of average wages, whereas standard errors are more stable across groups of counties.

2.4.3 Sales Elasticity by Fraction of Workers Affected by the Minimum Wage

Counties where a larger fraction of the population are likely to receive the minimum wage should exhibit a stronger expenditure response following a minimum wage hike. In this subsection, I use a measure of income distribution at the county level and show that the increase in consumption is indeed significantly larger when most workers make low wages.

The American Community Survey (ACS) reports the fraction of households with total income lower than certain thresholds by county, providing a rough measure of income distribution at the local level. In 2014, a full-time worker making the minimum wage earned between $15,080 ($7.25, federal rate) and $19,760 ($9.50, rate in D.C.). Then, I use the fraction of households income below $25,000, the smallest bracket that contains these amounts.

I exploit the cross-county heterogeneity by interacting the (log) minimum wage with the fraction of households making less than $25,000 a year. More precisely, I run the regression:

\[
\log(Sales_{c,t}) = \kappa_c + \tau_t + \beta_1 \log(MW_{s,t}) + \beta_2 \text{Fraction}_c \log(MW_{s,t}) + \gamma X_{c,t} + \epsilon_{c,t}
\]
The expenditure response is stronger in counties where the minimum wage binds more.

95% Confidence Intervals shown. Standard errors clustered at state level.

$\beta_n$ is the elasticity of sales to the minimum wage when the sample is limited to those counties that in 2005 belonged to the $n^{th}$ quartile of the Average Wage to Minimum Wage distribution. The minimum wage binds more in counties in the lowest quartiles. Both specifications include county and time fixed effects. Specification (3) also controls for employment, population, gross state product, and house prices.
where $Fraction_c$ is the fraction of households making less than $25,000$ a year and $X_{c,t}$ is a set of local controls as before. In this context, the elasticity of sales to the minimum wage in county $c$ is given by: $\beta_1 + \beta_2 \, Fraction_c$.

In Table 2.3, I report the sales elasticities evaluated at four different levels of the fraction of households making less than $25,000$ a year. Two of those are out-of-sample estimates: when everyone in the county has a low income (Fraction = 1) and when no one does (Fraction = 0). The remaining two are in-sample estimates: when 53.1% and 10.2% of the households make the minimum wage, which are respectively the 99th and 1st percentiles of the distribution of the fraction.

Counties with more people in the lowest brackets exhibit a greater elasticity of sales to the minimum wage, as expected. In counties where more than half of the households report a low income, nominal sales rise by more than 3.2% in response to a 10% minimum wage hike, and the elasticity is highly significant. On the other hand, when only a tenth of the households report low income, the estimated elasticity is basically zero and insignificant. The out-of-sample estimates provide further illustration of the positive connection between the fraction of workers likely to benefit from the minimum wage increment and the local expenditure response.

### 2.4.4 Sales Elasticities by Product Group

In this subsection, I show that the expenditure response is quite homogeneous across product groups.

Decomposing the sales response by product category may be interesting for at least two reasons. First, it provides evidence on how consumers allocate their additional income, which is instructive to infer the nature of different goods. Second, the decomposition may be of relevance to a paternalistic planner who worries that poor workers could increase their consumption of goods with negative externalities or other detrimental effects within the household (e.g., alcohol and tobacco). Results are shown in Table 2.4.
Table 2.3: Sales Elasticity by Fraction of Workers Affected by the Minimum Wage

<table>
<thead>
<tr>
<th>Fraction</th>
<th>Nominal Sales (1)</th>
<th>Nominal Sales (2)</th>
<th>Nominal Sales (3)</th>
<th>Real Sales (1)</th>
<th>Real Sales (2)</th>
<th>Real Sales (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>= 1</td>
<td>0.923***</td>
<td>0.943***</td>
<td>0.670***</td>
<td>0.788***</td>
<td>0.827***</td>
<td>0.583***</td>
</tr>
<tr>
<td></td>
<td>(0.203)</td>
<td>(0.233)</td>
<td>(0.241)</td>
<td>(0.191)</td>
<td>(0.201)</td>
<td>(0.195)</td>
</tr>
<tr>
<td>= p(99)</td>
<td>0.444***</td>
<td>0.461***</td>
<td>0.317***</td>
<td>0.367***</td>
<td>0.384***</td>
<td>0.260***</td>
</tr>
<tr>
<td></td>
<td>(0.103)</td>
<td>(0.093)</td>
<td>(0.099)</td>
<td>(0.088)</td>
<td>(0.080)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>= p(1)</td>
<td>0.005</td>
<td>0.010</td>
<td>-0.006</td>
<td>-0.019</td>
<td>-0.021</td>
<td>-0.035</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.067)</td>
<td>(0.076)</td>
<td>(0.057)</td>
<td>(0.050)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>= 0</td>
<td>-0.099</td>
<td>-0.096</td>
<td>-0.096</td>
<td>-0.083</td>
<td>-0.111</td>
<td>-0.106</td>
</tr>
<tr>
<td></td>
<td>(0.102)</td>
<td>(0.094)</td>
<td>(0.092)</td>
<td>(0.082)</td>
<td>(0.081)</td>
<td>(0.072)</td>
</tr>
</tbody>
</table>

Controls: Employment N Y Y N Y Y; Population N Y Y N Y Y; GSP N N Y N N Y; House Prices N N Y N N Y

Observations: 80,136 80,136 80,136 80,136 80,136 80,136

The expenditure response is stronger in counties where more workers earn the minimum wage using ACS data. Each coefficient is the elasticity, $\beta_1 + \beta_2 \cdot Fraction$, evaluated at four different levels of $Fraction$: 100%, 53.1%, 10.2%, and 0%. Standard errors (in parenthesis) clustered at state level. Time and county fixed effects are included in every specification.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parenthesis) clustered at state level.
The sales response is not statistically different across products. In my preferred specification, Model (3), an increase of the minimum wage induces a greater nominal expenditure in most product groups, the exception being Alcohol for which the point estimate is negative. The strongest nominal responses are in the categories Food (0.119) and General Merchandise (0.131). Interestingly, the real response is less than a fourth of the nominal one for General Merchandise suggesting that higher prices may play a more important role in this category. On the other hand, the point estimates for the nominal and real elasticities are very similar for Health and Beauty Aids and Non-Food Grocery.

There is no evidence that the minimum wage increases alcohol consumption disproportionately. The coefficient of alcohol in not stable across specifications and, in my preferred model, is negative but estimated with very poor precision. Since Nielsen tracks only a small fraction of liquor sales at participating stores (Kilts Center for Marketing, 2014), the poor precision of the estimates is not surprising and prevents further inference.

2.5 Robustness

In this section, I show that my results are robust to a number of alternative specifications and provide evidence favoring my identification strategy. First, I show the absence of significant pretrends in sales by exploring the dynamic response to the policy. Second, I check that my results are robust to unobservable time-changing spatial heterogeneity by running a difference-in-difference-in-difference analysis. Third, I find a positive effect on nondurable expenditure as measured in the preliminary Personal Consumption Expenditure data by state, providing further evidence on the quality of the Nielsen data. Finally, I argue that limiting the sample to stores always present in the Nielsen dataset does not introduce a significant bias for lack of entry and exit by running the regressions at the store level. I also find that nominal and real sales experience a very similar change at the store level, suggesting
<table>
<thead>
<tr>
<th></th>
<th>Nominal Sales</th>
<th></th>
<th></th>
<th></th>
<th>Real Sales</th>
<th></th>
<th></th>
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<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
</tr>
<tr>
<td>Health and Beauty Aids</td>
<td>0.130*</td>
<td>0.132***</td>
<td>0.052*</td>
<td>0.121*</td>
<td>0.121***</td>
<td>0.051*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.041)</td>
<td>(0.030)</td>
<td>(0.065)</td>
<td>(0.037)</td>
<td>(0.029)</td>
<td></td>
</tr>
<tr>
<td>Food</td>
<td>0.169</td>
<td>0.206**</td>
<td>0.119*</td>
<td>0.124</td>
<td>0.149**</td>
<td>0.080</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.106)</td>
<td>(0.080)</td>
<td>(0.070)</td>
<td>(0.079)</td>
<td>(0.056)</td>
<td>(0.051)</td>
<td></td>
</tr>
<tr>
<td>Non-Food Grocery</td>
<td>0.100</td>
<td>0.117</td>
<td>0.040</td>
<td>0.108</td>
<td>0.131*</td>
<td>0.061</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.072)</td>
<td>(0.056)</td>
<td>(0.088)</td>
<td>(0.067)</td>
<td>(0.054)</td>
<td></td>
</tr>
<tr>
<td>Alcohol</td>
<td>−0.021</td>
<td>0.087</td>
<td>−0.102</td>
<td>−0.019</td>
<td>0.062</td>
<td>−0.087</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.243)</td>
<td>(0.203)</td>
<td>(0.242)</td>
<td>(0.244)</td>
<td>(0.218)</td>
<td>(0.265)</td>
<td></td>
</tr>
<tr>
<td>General Merchandise</td>
<td>0.225**</td>
<td>0.256***</td>
<td>0.131***</td>
<td>0.116</td>
<td>0.124***</td>
<td>0.031</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.088)</td>
<td>(0.055)</td>
<td>(0.037)</td>
<td>(0.070)</td>
<td>(0.043)</td>
<td>(0.035)</td>
<td></td>
</tr>
</tbody>
</table>

**Controls**

<table>
<thead>
<tr>
<th></th>
<th>Nominal Sales</th>
<th></th>
<th></th>
<th></th>
<th>Real Sales</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>GSP</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>House Prices</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td></td>
</tr>
</tbody>
</table>

The expenditure response is fairly homogeneous across most product groups

* * p < 0.1, ** * p < 0.05, *** * p < 0.01. Standard errors (in parenthesis) clustered at state level.

The product group Food includes Nielsen’s departments of Dry Grocery, Frozen Foods, Dairy, Deli, Packaged Meat, and Fresh Produce.

Time and county fixed effects are included in every specification.
that consumers shifting towards more expensive stores, rather than stores increasing prices, could explain the greater response of nominal sales found at the county level.

2.5.1 Absence of Pretrends

Significantly different pretrends in sales between treatment and control could raise concerns on the validity of my identification strategy, which rests on the assumption of conditional parallel trends. In this subsection, I explore the dynamic response to the minimum wage and I find that there are no statistically significant pretrends.

To explore the dynamic response to the minimum wage I follow Dube, Lester, and Reich (2010) and estimate my preferred specification with distributed lags spanning 10 quarters, 6 leads\(^9\) and 4 lags:

\[
\log(Sales_{c,t}) = \kappa_c + \tau_t + \sum_{j=-3}^{6} \beta_j \Delta \log(MW_{s,t+j}) + \beta_4 \log(MW_{s,t-4}) + \gamma X_{c,t} + \epsilon_{c,t}
\]

The use of changes rather than values produces coefficients that can be interpreted as the cumulative response to the minimum wage. Figure 2.7 summarizes the results.

Pretrends are not significantly different from zero prior to the change in the minimum wage and the evidence is particularly strong for the baseline specification. The point estimates of the coefficients leading to the minimum wage after controlling for observable trends (Panel B of Figure 2.7) are basically zero both for nominal and real sales. After the minimum wage increment is enacted, the point estimates rise and become significant at the 10% level for nominal sales. The increment is more sluggish for real sales. For both specifications, the standard errors are fairly large since my sample period is short.

From a theoretical point of view, consumption could rise even before the minimum wage hike is enacted if agents were allowed to borrow against future higher incomes, since these

\(^9\)At the time of this draft, information on minimum wage rates is available until the end of 2015, so in this exercise the use of 6 leads effectively ends the sample period in the second quarter of 2014.
changes are usually announced several quarters in advance. But positive coefficients for the leads to the change would also induce concerns of reverse causality. In that sense, the evidence suggests that minimum wage households are financially constrained and react to changes in their current income, supporting my empirical design.

### 2.5.2 Robustness to Unobservable Spatial Heterogeneity in Time Trends

In this subsection, I show that my results are robust to the presence of unobservable spatial heterogeneity in time trends through a difference-in-difference-in-difference exercise. I also argue that the contiguous counties approach does not appear appropriate for my research design because of potential spillovers across state borders.

The desirability of local area controls to account for unobservable and heterogeneous time trends is at the center of an ongoing debate in the literature measuring the impact of the minimum wage on labor market outcomes. Dube, Lester, and Reich (2010) and Allegretto et al. (2017) argue that the standard two-way fixed-effects panel model fails to account for preexisting decreasing time trends in employment during the 1990s and 2000s. Since these decreasing time trends appear to be spatial in nature, the authors propose to account for them by including region or division-specific time fixed effects, or by comparing contiguous border counties. The assumption is that counties within the same region or division, or neighboring counties are better control groups. On the other end of the debate, Neumark, Salas, and Wascher (2014a) and Neumark, Salas, and Wascher (2014b) argue that such an approach throws away a lot of valid information and mechanically produces insignificant results. In their view, it is not clear that within region or division counties, or neighboring counties are better control groups.

Unobservable spatially heterogeneous trends do not appear to be a concern in my sample period. The previous subsection has shown that there are not significant pretrends in sales after controlling for observable local economic conditions. Nevertheless, I explore the ro-
Pretrends are not significantly different from zero
95% Confidence Intervals included. Standard errors clustered at state level.
$\beta_j$ is the cumulative response to a change in the minimum wage after $j$ quarters.
Both specifications include county and time fixed effects. Specification (3) also controls for employment, population, gross state product, and house prices.
bustness of my results through a difference-in-difference-in-difference exercise. I interact the (log) minimum wage by a measure of its bindingness at the county level and I incorporate state-specific time fixed effects, \( \tau_{t,s} \). Formally, I run the following regression:

\[
\log(Sales_{c,t}) = \kappa_c + \tau_{t,s} + \beta \log(\text{Minimum Wage}_{s,t}) \times \text{Bindingness}_c + \gamma X_{c,t} + \epsilon_{c,t}
\]

In this new specification, \( \beta \) measures the differential impact of the minimum wage in counties where the policy binds more tightly by comparing them with other counties within the same state but where the policy binds less tightly. Table 2.5 presents the results for three alternative measures of bindingness: the log of the ratio of the average wage to the minimum wage in 2005, the log of the ratio of median income to the annual income of a full-time minimum wage worker, and the fraction of households with income lower than $25,000.

I find that the expenditure response is indeed stronger in counties where the minimum wage binds more tightly even after allowing for state-specific unobservable and heterogeneous time trends, despite the strong requirements on the data imposed by this identification strategy. In Panel A, counties where the average wage is high compared to the minimum and so, where the policy binds less tightly, show a lower spending response to increments in the minimum wage rate. The estimate is not statistically significant at the 10% level in Specification (3), but it is fairly stable across models.\(^{10}\) For instance, Okanogan County in the state of Washington had the lowest Kaitz ratio in my sample: the average hourly wage in 2005 was 1.47 times the minimum wage. On the other hand, in 2005 King County had the highest Kaitz ratio in the state of Washington: the average hourly wage was 3.27 times the minimum wage. If the state decides to increase the minimum wage rate by 10%, both counties will experience an increase in nominal sales, but the growth rate in Okanogan

\(^{10}\)The p-value is 0.205 for nominal sales and 0.137 for real sales.
County will be 0.4 percent points higher than that in King County because the policy binds more in the former.

The positive link between expenditure response and bindingness of the minimum wage rate also emerges for alternative ways of measuring such bite. Spending in counties with lower median income are more responsive to the minimum wage, as shown in Panel B. In this case, real sales coefficients are statistically significant, but the coefficient for my preferred specification is not significant for nominal sales. Finally, in Panel C, counties where more households have low incomes experience a larger expenditure response to increments in the minimum wage. Again, the results are statistically significant for real sales, but not for nominal sales at a 10% confidence level. Thus, despite the strong requirements of the approach, I still find evidence that my results are robust to heterogeneous time trends.

An alternative approach to deal with the concern on heterogeneous time trends, the use of contiguous counties, does not appear appropriate for my research design. Dube, Lester, and Reich (2010) recommend the identification of the effect of the minimum wage on labor market outcomes using county-pairs across state borders with different policy rates. In their preferred specification, they include county-pair-specific time fixed effects and find that the minimum wage does not affect employment, but it increases workers’ earnings in the restaurant industry. I do not employ this identification strategy for two reasons. First, my data is more limited. I have only nine years of data, while Dube, Lester, and Reich (2010) have 16.5, and my sample period presents less variation. Even when the number of county-pairs with minimum wage differentials was high in the first three years of my sample, the average differential decreased steadily as the federal increments took place. Second, and more important, while Dube, Lester, and Reich (2010) show that in terms of employment and earnings the estimates are not affected by spillovers, it is more difficult to argue that households will limit their extra expenditure to the county where they work. Indeed, in Table 2.6 I show the results of running my specifications separately for border and interior counties. Although the difference is not statistically significant, the response of nominal and
Table 2.5: State-Specific Time Fixed Effects

<table>
<thead>
<tr>
<th></th>
<th>Nominal Sales</th>
<th></th>
<th></th>
<th>Real Sales</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Average Wage Ratio</td>
<td>−0.168**</td>
<td>−0.125</td>
<td>−0.109</td>
<td>−0.160*</td>
<td>−0.133</td>
<td>−0.117</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.093)</td>
<td>(0.085)</td>
<td>(0.089)</td>
<td>(0.086)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>Median Income Ratio</td>
<td>−0.225***</td>
<td>−0.208*</td>
<td>−0.166</td>
<td>−0.215***</td>
<td>−0.224**</td>
<td>−0.182**</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.114)</td>
<td>(0.109)</td>
<td>(0.067)</td>
<td>(0.088)</td>
<td>(0.080)</td>
</tr>
<tr>
<td>% Income ≤ $25,000</td>
<td>0.652***</td>
<td>0.567</td>
<td>0.422</td>
<td>0.636***</td>
<td>0.631**</td>
<td>0.486*</td>
</tr>
<tr>
<td></td>
<td>(0.229)</td>
<td>(0.371)</td>
<td>(0.352)</td>
<td>(0.189)</td>
<td>(0.267)</td>
<td>(0.242)</td>
</tr>
</tbody>
</table>

*Controls*

Employment          | N     | Y    | Y     | N    | Y    | Y     |
Population          | N     | Y    | Y    | N    | Y    | Y     |
House Prices        | N     | N    | Y    | N    | N    | Y     |
Observations        | 80,136| 80,136| 80,136| 80,136| 80,136| 80,136|
Counties            | 2,226 | 2,226 | 2,226 | 2,226 | 2,226 | 2,226 |

The expenditure response is stronger in counties where the minimum wage binds more tightly. Coefficient is the elasticity of sales to the interaction between the minimum wage and a measure of the bindingness of the policy.

“Average wage ratio” refers to the log of the ratio of the average wage in the county from the QCEW to the minimum wage in 2005 times the number of working hours in a year.

“Median income ratio” refers to the log of the ratio of the median household income in the county from the ACS to the minimum wage in 2005 times the number of working hours in a year.

“% Income ≤ $25,000” refers to the fraction of households in the county with annual income below $25,000 according to the ACS.

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors (in parenthesis) clustered at state level.

County and state-specific time fixed effects are included in every specification.
real sales to the minimum wage is almost twice as strong in interior counties than in border counties.

2.5.3 Expenditure Response at the State Level: Nielsen vs. NIPA

In this subsection, I show that the positive effect of the minimum wage on nondurable consumption is also evident using NIPA data.

The Bureau of Economic Analysis has released prototype estimates of Personal Consumption Expenditures (PCE) by state for the period 1997-2014. The methodology is still under revision, but I use these preliminary statistics to estimate the expenditure response and compare it with the one found in the Nielsen dataset. PCE data is available only at the annual level, so I aggregate Nielsen sales by state and year as well. In the first three columns of Table 2.7 I use all the data available for the PCE. And in the last three columns, I restrict the data to the Nielsen sample period (2006-2014).

In my preferred specification, Model (3), the response of nondurable consumption estimated in NIPA is not statistically different from that in Nielsen sales. Using data from the period 2006-2014, I find that a 10% increase in the minimum wage leads to a 1.1% growth in nominal sales and a 0.7% growth in nondurable consumption. Extending the sample period to 1997-2014, the growth in nondurable consumption after a 10% minimum wage hike is 0.9%, again highly significant. The increment appears fairly homogeneous across the four categories (food, clothing, gasoline, and other nondurables). Although the coefficient for gasoline is unstable across specifications, specially for the extended sample period, and it is not statistically different from zero. Model (1) appears particularly noisy for the full sample. Overall, Table 2.7 indicates that the expenditure response found using Nielsen data is not pathological, but that is consistent with alternative measures of nondurable consumption. Nevertheless, my preferred specification is at the county level where local area controls offer a more credible identification strategy.
Table 2.6: Interior vs. Border Counties

<table>
<thead>
<tr>
<th></th>
<th>(1) Border</th>
<th>(1) Interior</th>
<th>(2) Border</th>
<th>(2) Interior</th>
<th>(3) Border</th>
<th>(3) Interior</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal Sales</td>
<td>0.066</td>
<td>0.222***</td>
<td>0.137***</td>
<td>0.211***</td>
<td>0.080</td>
<td>0.137**</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.070)</td>
<td>(0.048)</td>
<td>(0.057)</td>
<td>(0.053)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>Real Sales</td>
<td>0.034</td>
<td>0.168**</td>
<td>0.102**</td>
<td>0.151***</td>
<td>0.053</td>
<td>0.084*</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.066)</td>
<td>(0.046)</td>
<td>(0.050)</td>
<td>(0.050)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Population</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>GSP</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>House Prices</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>30,780</td>
<td>49,356</td>
<td>30,780</td>
<td>49,356</td>
<td>30,780</td>
<td>49,356</td>
</tr>
<tr>
<td>Counties</td>
<td>855</td>
<td>1,371</td>
<td>855</td>
<td>1,371</td>
<td>855</td>
<td>1,371</td>
</tr>
</tbody>
</table>

The expenditure response is stronger in interior counties, suggesting that spillovers may affect border counties.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parenthesis) clustered at state level. County and time fixed effects are included in every specification.
The absence of expenditure responses in durables and services could be attributed to data quality, research design quality, or a non-homogeneous change in households’ consumption. First, the PCE estimates at the state level are prototypes and some of its components are harder to measure than others (e.g., food is probably better measured than housing thanks to rich data on grocery stores sales). The lack of response in durables and services could then reflect a more severe measurement error. Second, the identification strategy used to assess the impact of the minimum wage on nondurable consumption may not be well suited for the other two categories. Services\textsuperscript{11} and durables are probably subject to adjustment costs preventing households from reacting immediately to the extra income. This lack of coordination, together with the fact documented by Aaronson, Agarwal, and French (2012) that only a small number of households adjust their stock of durables after a minimum wage hike, would make it difficult to measure the expenditure response only with data aggregated at the state level and with an econometric model that only uses current levels of the policy rate. Third, it could be that households truly choose to spend all their extra income on nondurables, rather than services and durables. At the end of 2014 a full-time minimum wage worker in D.C. made $9.50, the highest policy rate in the country. For this worker, a minimum wage increment of 3.5\% (i.e., the average increment in the district during my sample period) would mean $682 extra per year ($57 extra per month). If the purchase of services and durables involves the payment of a fixed cost, a lack of response in those categories could be reasonable given the relatively small increment in income.

\textbf{2.5.4 Expenditure Response at the Store Level}

In this subsection, I show that my results are robust to running the regressions at the store level and that the sample restriction to stores that were not present during the entire sample period is not important for my results. I also find very similar elasticities for nominal and

\textsuperscript{11}Housing and utilities represent 30\% of household consumption expenditures for services.
Table 2.7: Nielsen and NIPA Consumption Aggregates

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. NIPA</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PCE</td>
<td>−0.002</td>
<td>0.032*</td>
<td>0.001</td>
<td>0.118**</td>
<td>0.048*</td>
<td>0.038*</td>
</tr>
<tr>
<td>Durable</td>
<td>0.041</td>
<td>0.081</td>
<td>0.003</td>
<td>0.037</td>
<td>0.020</td>
<td>−0.022</td>
</tr>
<tr>
<td>Nondurable</td>
<td>0.020</td>
<td>0.062***</td>
<td>0.087***</td>
<td>0.162***</td>
<td>0.090***</td>
<td>0.070***</td>
</tr>
<tr>
<td>Food</td>
<td>0.079</td>
<td>0.117***</td>
<td>0.073***</td>
<td>0.154**</td>
<td>0.080*</td>
<td>0.041</td>
</tr>
<tr>
<td>Clothing</td>
<td>0.040</td>
<td>0.096**</td>
<td>0.084*</td>
<td>0.091</td>
<td>−0.013</td>
<td>0.037</td>
</tr>
<tr>
<td>Gasoline</td>
<td>−0.016</td>
<td>0.007</td>
<td>0.061</td>
<td>0.195**</td>
<td>0.139**</td>
<td>0.110</td>
</tr>
<tr>
<td>Other Nondurable</td>
<td>0.031</td>
<td>0.076**</td>
<td>0.103***</td>
<td>0.173***</td>
<td>0.102***</td>
<td>0.081**</td>
</tr>
<tr>
<td>Services</td>
<td>−0.023</td>
<td>0.009</td>
<td>−0.029</td>
<td>0.126***</td>
<td>0.046*</td>
<td>0.044</td>
</tr>
<tr>
<td><strong>Panel B. Nielsen</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal Sales</td>
<td></td>
<td></td>
<td></td>
<td>0.172**</td>
<td>0.158***</td>
<td>0.108**</td>
</tr>
<tr>
<td>Real Sales</td>
<td></td>
<td></td>
<td></td>
<td>0.119*</td>
<td>0.105**</td>
<td>0.077*</td>
</tr>
<tr>
<td><strong>Controls</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Population</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>GSP</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>House Prices</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>882</td>
<td>882</td>
<td>882</td>
<td>441</td>
<td>441</td>
<td>441</td>
</tr>
<tr>
<td>States</td>
<td>49</td>
<td>49</td>
<td>49</td>
<td>49</td>
<td>49</td>
<td>49</td>
</tr>
</tbody>
</table>

The expenditure response measured in Nielsen data is consistent with that of nondurable components of consumption in NIPA

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors (in parenthesis) clustered at state level.
Dependent variable is Nielsen sales or NIPA components of consumption by state and year.
Time and state fixed effects are included in every specification.
Sample period for first three columns is 1997-2014. Sample period for last three columns is 2006-2014.
real sales at the store level, evidence against the hypothesis of stores increasing prices after a minimum wage hike.

In my baseline specification I replace county fixed effects with store fixed effects and I define the dependent variable to be sales by store. In Table 2.8, the first three columns use all the stores in the Nielsen dataset, regardless of the number of quarters in which they are active, whereas the last three columns restrict the sample only to those stores always present. The latter is the sample restriction used in all the previous sections.

Table 2.8 offers three takeaways. First, the sample restriction is irrelevant for my results. Both in terms of nominal and real sales, the estimated elasticity to the minimum wage is similar for all stores and for those always present. Thus, lack of entry and exit of stores to my baseline sample is not a concern. Second, nominal and real sales exhibit remarkably similar responses when estimated at the store level. There does not seem to be a change in prices at the store level as a consequence of a minimum wage hike. Instead, consumers appear to be shifting towards more expensive stores and paying higher prices, which is an alternative explanation for the point estimate of nominal sales being higher than that of real sales at the county level.\footnote{My definition of real sales uses average price of each product in 2012 across the country. Let X and Y denote two stores located in the same county. Then, shifting a purchase of one apple from store X to store Y will not affect real sales in the county, but it will increase nominal sales if store X has a lower price than store Y.} Third, the expenditure response of sales at the store level is not statistically different from the response estimated at the county level (Table 2.2), indicating that my selection of the county as the unit of analysis is not critical.

### 2.6 The Link between the Expenditure and Labor Income Responses

In this section, I draw a link between my results on expenditure and the existing literature on the effect of the minimum wage on employment and earnings. First, I discuss how the
Table 2.8: Entry and Exit

<table>
<thead>
<tr>
<th></th>
<th>All Stores</th>
<th></th>
<th>Stores Always Present</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(1)</td>
</tr>
<tr>
<td>Nominal Sales</td>
<td>0.173**</td>
<td>0.187***</td>
<td>0.119***</td>
<td>0.168*</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.057)</td>
<td>(0.044)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>Real Sales</td>
<td>0.175***</td>
<td>0.187***</td>
<td>0.127***</td>
<td>0.170**</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.048)</td>
<td>(0.044)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Population</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>GSP</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>House Prices</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Observations</td>
<td>1,231,642</td>
<td>1,231,640</td>
<td>1,231,640</td>
<td>898,956</td>
</tr>
<tr>
<td>Stores</td>
<td>41,201</td>
<td>41,201</td>
<td>41,201</td>
<td>24,971</td>
</tr>
</tbody>
</table>

No evidence of bias induced by lack of entry and exit of stores to the baseline sample

In the first three columns, the sample includes all the stores with data for at least one quarter. In the last three columns, the sample includes only the stores with data for the 36 quarters.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parenthesis) clustered at state level.

Time and store fixed effects are included in every specification.
empirical literature has not found significant effects on employment, but it has found a modest positive impact on wages at the bottom of the distribution. Next, I argue that household labor income is the appropriate measure to understand the expenditure response and I estimate the impact of the minimum wage across the labor income distribution. I show that a 10% minimum wage hike could increase sales by 2 billion dollars, a quarter of the additional labor income generated by the policy, which benefits particularly the bottom quarter of the distribution.

The minimum wage does not appear to reduce employment significantly. The study of the employment effects of the minimum wage has a very rich tradition in empirical labor. Since the influential work by Card and Krueger (1994), small or insignificant employment elasticities have usually been found for restaurant workers (Dube, Lester, and Reich, 2010; Allegretto et al., 2017; Neumark, Salas, and Wascher, 2014b; Addison, Blackburn, and Cotti, 2015). Disagreement persists on the disemployment effects of the minimum wage for teens. Neumark, Salas, and Wascher (2014a) find an elasticity close to -0.15, whereas Allegretto, Dube, and Reich (2011) argue that negative elasticities are only the result of heterogeneous unobservable time trends unrelated to the minimum wage. Although most of the literature has focused on employment stocks, recent work by Dube, Lester, and Reich (2016) studies employment flows and finds that the minimum wage reduces separations, hires, and turnover for restaurant workers and teenagers. My reading of the literature is that the minimum wage does not affect aggregate employment and that there is only weak evidence of disemployment effects for low-skilled groups.

Even if the minimum wage does not cause employment to decrease, it does raise wages for workers at the bottom of the distribution. Dube, Lester, and Reich (2010) and Allegretto, Dube, and Reich (2011) find that average weekly earnings increase for restaurant workers and teens following a minimum wage hike. More generally, DiNardo, Fortin, and Lemieux (1996) and Lee (1999) explore the effect of the minimum wage on the wage distribution and argue that the policy is an important factor to understand the increasing inequality in the
American labor market in the last decades. Autor, Manning, and Smith (2016) revisit the work by Lee (1999) and propose an instrumental variables approach to deal with endogeneity concerns. They find that the minimum wage has a modest but significant effect on wages at the bottom of the distribution.

To make sense of the expenditure responses in this chapter, it is necessary to understand the impact of the minimum wage on household labor income, rather than on individual wages. Household labor income is a more appropriate measure to connect with the expenditure response because of, at least, three reasons. First, consumption decisions are more likely to be made at the household level, rather than by individual. Second, as discussed earlier, the disemployment effects for some low-skilled groups of workers are still controversial and measuring the impact of the minimum wage on household income would capture changes induced by unemployment of some of its members. Third, the minimum wage could have effects on the intensive margin of employment. Because of data limitations, the vast majority of the literature has focused on the extensive margin, e.g., on the number of employees or the employment to population ratios. But the number of hours worked could also be affected by the policy. Individuals may choose to work more or less at the higher rate depending on income and substitution effects. Or firms could choose to hire workers for fewer hours, rather than to fire workers as a response to the minimum wage hike. Thus, the labor income at the household level accounts for any potential changes in labor supply and it is more likely to influence the household’s expenditure choice.

I apply the methodology in Autor, Manning, and Smith (2016) to measure the impact of the minimum wage on the distribution of household labor income. From the Current Population Survey’s Outgoing Rotation Group I obtain the fraction of households with no labor income and the distribution of household labor income conditional on being positive by state and year. Then, for each percentile $p$ in the labor income distribution I estimate the following model:
\[ y_{s,t}(p) - y_{s,t}(50) = \beta_1(p) [y_{s,t}^m - y_{s,t}(50)] + \beta_2(p) [y_{s,t}^m - y_{s,t}(50)]^2 + \]
\[ + \kappa_s(p) + \gamma_s(p) I_s t + \tau_t(p) + \epsilon_{s,t}(p) \]

where \( y_{s,t}(p) \) is the log real labor income at percentile \( p \) in state \( s \) and year \( t \), \( y_{s,t}^m \) is the log minimum wage in state \( s \) and year \( t \), \( \kappa_s(p) \) are state fixed effects, \( I_s \) is a dummy for state \( s \) so that \( \gamma_s(p) \) is a state-specific linear trend, and \( \tau_t(p) \) is the time fixed effects. The model closely follows Lee (1999) and Autor, Manning, and Smith (2016) in defining the bindingness of the minimum wage as the difference between the log minimum wage and the log median labor income and in assuming the policy to have a quadratic effect on the income distribution. Then, the elasticity of labor income at percentile \( p \) to the minimum wage is given by \( \beta_1(p) + 2\beta_2(p) [y_{s,t}^m - y_{s,t}(50)] \).

The estimation of the model requires the use of instrumental variables. Since the median is employed to construct both the dependent and independent variables, Autor, Manning, and Smith (2016) argue that estimating the previous model yields biased estimates if transitory shocks to the median do not translate one-to-one to other percentiles. Indeed, they find that estimating the model by OLS yields an implausibly large effect of the minimum wage at the top of the wage distribution. They propose to address the problem by instrumenting \( y_{s,t}^m - y_{s,t}(50) \) and its square using the log real minimum wage, the square of the log real minimum wage, and the interaction between the log minimum wage and the average over time of the log median real wage for each state. I follow their approach and I estimate the model for all the percentiles simultaneously using the Generalized Method of Moments to recover the variance-covariance matrix for the entire labor income distribution. Figure 2.8 summarizes my results.

I find that the minimum wage has a significant and positive impact at the bottom of the labor income distribution. Assuming that the median labor income does not react to the
minimum wage, an increase of 10% in the policy rate would increase labor income by 0.8% at the 10th percentile and by 0.6% at the 25th. From there on, the elasticity decreases and becomes indistinguishable from zero. The estimates are basically zero for all the percentiles above the median and up to the 88th, which lends confidence to the identification strategy. The point estimates for the percentiles 89th to 92th are unexpectedly large and three of them are statistically significant from zero at the 95% confidence level. The time changing top-coding of high incomes and the noisy behavior of extreme percentiles may explain these results.

The minimum wage does not have an impact on the fraction of households with zero labor income. I run the model described above for the fraction of households with no labor income as the dependent variable. The marginal effect of the minimum wage rate is zero and we can accept the null hypothesis with a high level of confidence.\textsuperscript{13}

Finally, I employ the estimates of the labor income elasticity to the minimum wage across the distribution to compute the extra labor income generated by a minimum wage hike. I use the federal distribution of labor income in 2014 to predict the extra income in dollars that would have been received by households at each percentile of the distribution up to the median\textsuperscript{14} if the minimum wage had increased everywhere by 10%. I find that aggregate labor income would have increased by 8 billion dollars. Full details on these calculations are provided in the appendix.

The 8 billion dollars of extra labor income generated by a minimum wage hike represents four times the predicted response of Nielsen sales. I use the elasticity of annual nominal sales from Table 2.7 to predict the additional expenditure induced by the policy. I find that nominal sales at Nielsen tracked stores would have risen by 2 billion dollars if the minimum wage had increased everywhere by 10%. My estimates are then plausible if poor workers exhibit high marginal propensities to consume.

\textsuperscript{13}The p-value is 0.996.
\textsuperscript{14}Without muting the response beyond the median, I find that aggregate labor income would have risen by 10 billion dollars, with the lower and upper bounds of the 95% confidence interval being -21 and 41 billions.
The minimum wage has a significant and positive impact at the bottom of the labor income distribution. The variable in the vertical axis, $\epsilon(p)$, is the marginal effect at percentile $p$ of the log minimum wage to median labor income ratio evaluated at the weighted average across states and years. 95% Confidence Intervals included. Standard errors clustered at state level. Household sample weights are employed. Estimation by Generalized Method of Moments. Specification also includes time fixed effects, state fixed effects, and state-specific linear trends. Sample period is 1979-2014.
Table 2.9: Predicted Expenditure and Labor Income Response to a 10% Minimum Wage Hike

<table>
<thead>
<tr>
<th>$ bn</th>
<th>Nominal Sales Nielsen</th>
<th>Nondurables NIPA</th>
<th>Labor Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>2</td>
<td>19</td>
<td>8</td>
</tr>
<tr>
<td>95% Confidence Intervals</td>
<td>(0,4)</td>
<td>(5,32)</td>
<td>(0,17)</td>
</tr>
</tbody>
</table>

A minimum wage hike of 10% would increase sales by $2bn, a quarter of the predicted increment in labor income

95% Confidence Intervals included. Standard errors for change in labor income are computed using delta method.

Labor income in CPS is scaled up to match Compensation of Employees in NIPA.

Elasticities for Nominal Sales and Nondurables are taken from Table 2.7, Specification (3).

Elasticity for labor income is computed in the CPS. Please refer to the main text and the appendix for further details on the calculations.

Nondurable consumption would have grow by 17 billion dollars after a 10% minimum wage increment. Although the point estimate appears high with respect to the predicted change in labor income, the difference is not statistically significant. But a consumption response greater than the income response is not inconsistent with previous findings. First, a minimum wage hike is not a transitory shock to income, but rather a persistent one. As such it can loosen credit constraints by expanding the households’ borrowing limit. Aaronson, Agarwal, and French (2012) document that after a $1 minimum wage hike household income raises by $250 a quarter (in 2005 dollars), whereas spending increases by almost three times as much, and debt indeed raises to make up for the difference. The increase in debt is not limited to auto loans and it is significant for a quarter of the households with income below $20,000. And Reich et al. (2016) estimate the aggregate demand effects of the New York proposed minimum wage increments with marginal propensities to consume that exceed 1 for households with less than $75,000 of income. Second, as discussed in Section 2.5, I do not

\[^{15}\]Auto debt represents a third of the increase in total debt measured ($205 vs. $603), but it is the only category with a statistically significant coefficient at a 10% confidence level.
find evidence of increased expenditure in durables or services in the aggregate. Aaronson, Agarwal, and French (2012) find a large increment in expenditure on vehicles for a small group of households. Both facts are consistent with the presence of adjustment costs in those categories, which could induce most households to spend their additional income mainly on nondurables. Third, the minimum wage could have an aggregate demand effect on tradable goods across the country, raising employment and earnings beyond the local economy, which would not be captured by my estimates of the earnings response in this section, where I limit the analysis to the state labor market. If that were the case, the increase in labor income estimated in Table 2.9 would be a lower bound. To summarize, the large response of nondurable spending is consistent with the minimum wage affecting households beyond the very bottom of the earnings distribution, households who are hand-to-mouth, benefit from a loosening of credit conditions, and spend most of their extra income on nondurables rather than services or durables, due to the presence of adjustment costs.

2.7 Conclusion

In this chapter, I have exploited variation in the minimum wage rates within the U.S. and a novel dataset on retail sales by county to show that the minimum wage can raise aggregate consumption through redistribution in favor of low-wage workers. I have found that a 10% increment in the minimum wage, would increase nominal sales by 1.1%, around $2 billion per year. And consistent with economic theory, the expenditure response is larger in counties where the minimum wage binds more.

My results not only confirm that the minimum wage is an effective policy to foster (modestly) aggregate demand and help fight poverty, but also provide evidence on the positive spillovers beyond the very bottom of the earnings distribution. Furthermore, my estimates measure an outcome of the policy that, although essential for welfare analysis, has largely been ignored. As the campaign for higher minimum wage rates keeps gaining momentum
across the country, more research will be necessary to understand the effects of the policy on other outcomes such as inequality, capital accumulation, and economic growth.
Chapter 3

Cutting Back on Labor Intensive Goods? Implications for Fiscal Stimulus

3.1 Introduction

Many countries around the world responded to the Great Recession with fiscal stimulus. For example, in the United States, the American Recovery and Reinvestment Act of 2008, a package of $800 billion, included tax cuts, government purchases, and transfers. Fiscal stimulus packages such as this one succeed at raising output only if they increase aggregate demand for goods and only if this increased demand for goods leads to an increase in aggregate demand for labor. The first of these requirements – whether fiscal stimulus raises demand for goods – has been well-studied. For instance, it has been found that stimulus programs are most effective when targeting households with high marginal propensity to spend.\footnote{Parker et al. (2013), Oh and Reis (2012), Kaplan and Violante (2014).} However, much less is known about the second requirement – whether this increased goods demand actually translates into an increased labor demand. While in a one-good
model there is an immediate mapping from demand for goods to demand for labor, in reality
different goods are produced with very different labor intensities and so, the extent to which
higher demand for goods leads to higher demand for labor is an empirical question.

In this chapter, I study empirically and theoretically whether fiscal stimulus can effec-
tively raise labor demand. First, I document how households change the composition of their
expenditure bundles upon becoming unemployed and relate it to the labor share with which
those goods are produced. Second, I build a model that reproduces such heterogeneity in
consumption and production to assess its implications for fiscal stimulus.

I show that households who become unemployed disproportionately cut back expenditures
on labor-intensive goods. Upon unemployment, households barely change expenditures on
goods with very low labor shares such as communications, utilities, housing, and food at
home. However, they decrease expenditures on goods with high labor shares, such as food
away from home, clothing, and domestic services, by more than 10%.

Quantitatively, the composition of the expenditure response to unemployment matters
because different goods are produced with significantly different labor shares. The average
labor share of Personal Consumer Expenditures is 0.53, indicating that 53 cents of every
dollar spent by a consumer are paid out as compensation to workers. But the labor share
varies widely across the economy. While only 23 cents of every dollar spent on housing
are paid out as labor compensation, 80 cents of every dollar spent on domestic services are
received by workers.

The drop in aggregate labor demand due to the expenditure response to unemployment
is large. When a household becomes unemployed, it decreases demand for other workers’
labor by 6.5%, a seventh of which is explained by the composition of the expenditure bundle
changing. Between 2007 and 2009, the expenditure response to unemployment accounted
for a fifth of the drop in labor compensation.
To account for the varying degrees of labor intensity of the different industries involved in the production of each final good, I use the network-adjusted labor share.\textsuperscript{2} The network-adjusted labor share measures how much of the value of the final good is paid out to workers along the entire supply chain, and not just by the final industry. For instance, when purchasing a muffin at a cafeteria, standard measures of the labor share would only count the compensation to workers involved in the production of the muffin in that cafeteria. Instead, the network-adjusted labor share also takes into account the compensation to workers producing and distributing the flour, sugar, and milk used to produce the muffin. My results are robust to using labor shares of the final industries and to defining labor intensity as labor requirement or output elasticity of labor demand.

I use a difference-in-difference strategy with household fixed effects to estimate responses of household expenditure to unemployment. My strategy exploits that the Consumer Expenditure Survey collects data on both expenditures and employment status twice for each household in the sample. In my estimation framework, household fixed effects capture any static characteristics such as household head’s gender and education and, critically, household’s preferences and socioeconomic status. Time fixed effects account for any long term trends and seasonality patterns affecting all households equally. Additionally, I include demographic controls to account for changes in the age of the household head and in the household composition.

The expenditure responses to employment and unemployment are fairly symmetric. I allow differential effects for households that move from unemployment to employment and for those that move from employment to unemployment. I find that total expenditure drops by 3% when the household head becomes unemployed and rises by 1.4% when he/she becomes employed, but the difference is not statistically significant. Furthermore, the expenditure

\textsuperscript{2}Baqee (2015) computes the network-adjusted labor share by industry and for final aggregate components of the GDP. Valentinyi and Herrendorf (2008) compute the network-adjusted labor share for aggregate consumption and investment goods. I further disaggregate the network-adjusted labor share for fourteen different consumption goods. Horowitz and Planting (2009) refer to the network-adjusted labor share as the (labor) income requirements matrix.
responses on individual goods are also symmetric. Housing and food at home do not significantly vary with changes in employment status. But expenditures on food away from home, domestic services, recreation, and private transportation drop by more than 10% upon unemployment and rise by more than 10% upon employment.

The positive correlation between expenditure response to employment and labor share is driven by households reducing home-production or purchasing work-related goods, rather than reacting to a change in permanent income. I use cross-sectional variation to decompose the expenditure response of individual goods into a response to total expenditure and a response to employment while keeping total expenditure constant. While the elasticity of expenditure on individual goods to total expenditure does not correlate with labor share, the semi-elasticity to employment does. The correlation that I document is then not just explained by households cutting back on luxuries upon unemployment because of the associated drop in permanent income or borrowing constraints binding.

To evaluate the implications of heterogeneity in consumption and production for fiscal stimulus, I build and calibrate a model that matches the empirical evidence. On the production side of the economy, there are three sectors with different labor shares producing two consumption goods and one investment good. On the consumption side, households are heterogeneous on wealth, productivity, and employment status. Furthermore, unemployed households engage in home-production, which induces a disproportionate reduction in their market demand for the labor-intensive good. Nominal rigidities in the price setting of final goods determine the strength of the aggregate demand externality in transitions outside the steady state.

On impact, the GDP multiplier of government purchases of labor-intensive consumption goods is 76 cents larger than the one for purchases of capital-intensive goods when the elasticity of labor supply is 1. While a model without heterogeneity yields a fiscal multiplier of 0.01, in the model with heterogeneity the multiplier is 0.23 and -0.53 for labor-intensive and capital-intensive goods, respectively. To the old Keynesian notion that fiscal stimulus
programs should target labor-intensive sectors, my model offers quantitative results on how different the effects of alternative policy instruments are.

Accounting for heterogeneity helps explain the different estimates for the size of the fiscal multiplier found in the literature. The fiscal multiplier has been estimated empirically using two alternative frameworks: (i) vector auto-regression models that assume government purchases do not affect the economy immediately and (ii) changes in military spending, which are assumed to be exogenous to economic conditions. Estimates of the fiscal multiplier using the latter approach have generally been lower. Consistent with my findings, the gap can be explained by the different labor shares of those government purchases. While military spending is fairly capital-intensive, regular government expenditures are very labor-intensive.

My chapter contributes to several strands of literature. First, I contribute to the literature on the labor share (Baqaee, 2015; Valentinyi and Herrendorf, 2008; Karabarbounis and Neiman, 2014) by computing labor shares by final good (instead of by industry) and by documenting wide heterogeneity in labor shares across consumption goods. Second, I contribute to the literature on the expenditure response to unemployment (Gruber, 1997; Hendren, 2015; Ganong and Noel, 2015) by estimating the responses of expenditure on individual goods and finding significant heterogeneity consistent with explanations based on home-production and reductions on work-related expenses as in Aguiar and Hurst (2013). Third, I find a positive correlation between expenditure responses to employment and labor shares. This result complements recent work by Jaimovich, Rebelo, and Wong (2015) who find that in recessions expenditure on pricier, higher-quality, and relatively more labor-intensive goods falls disproportionately. Fourth, I contribute to the New-Keynesian literature (Christiano, Eichenbaum, and Evans, 2005; Kaplan, Moll, and Violante, 2016; McKay and Reis, 2016) by building a multi-good, multi-sector, heterogeneous agent model with home-production and realistic expenditure responses to changes in employment. Fifth, I contribute to the empirical literature estimating the size of the fiscal multiplier (Blanchard and Perotti, 2002; Perotti, 2005; Barro and Redlick, 2011; Ramey and Shapiro, 1998) by showing that the lower
effectiveness of military spending at stimulating the economy can be explained quantitatively by its relatively lower labor share.

The rest of the chapter is structured as follows. In Section 3.2, I document that households disproportionately cut back expenditures on labor-intensive goods upon unemployment. In Section 3.3, I describe the framework that I use to quantify the effects of the mechanism. In Section 3.4, I discuss my calibration strategy and some steady state results. In Section 3.5, I explore the implications of my model for fiscal policy. Finally, Section 3.6 concludes.

### 3.2 Measuring the Labor Intensity of the Expenditure Response to Employment

Upon employment, households disproportionately increase their expenditures on goods and services that are very labor-intensive. In this section, I document these facts combining data from consumer surveys and national accounts.

#### 3.2.1 Labor Share of Different Consumption Goods

Contrary to what is implied by standard one-sector models, the labor share varies widely across the economy. First, I discuss the computation of my preferred measure of labor intensity, the network-adjusted labor share. Then, I show that the network-adjusted labor share implies significant heterogeneity in the use of labor in the production of different consumption goods, a fact that is robust to alternative definitions of labor intensity.

**Methodology**

I use the network-adjusted labor share\(^3\) to measure labor intensity for different final goods in the economy. Intuitively, the network-adjusted labor share captures the fraction of the value of the final good that is paid out as labor compensation across the good’s entire supply chain.

\(^3\)Baqaee (2015). Horowitz and Planting (2009) refer to it as the (labor) income requirement matrix.
chain, and not just by its final industry. For instance, 50% of the value of a burger bought at a restaurant\(^4\) is created at the restaurant,\(^5\) 8% is created during the manufacturing of the bread and the beef,\(^6\) 4% is added by the management of the company,\(^7\) and so on. The network-adjusted labor share for that burger is then the average labor share of the different industries involved in its production, each weighted by the fraction of the value they add to the burger.

The network-adjusted labor share is computed using the Input-Output tables. Formally, the network-adjusted labor share of final good \(k\), \(s_k\), is given by:

\[
s_k = \omega \Gamma y_k
\]

where \(\omega\) is the vector of labor compensation as a fraction of total output by industry and \(\Gamma\) is the Domestic Requirements Matrix,\(^8\) a matrix indicating the amount of domestically produced output that each industry needs to deliver one dollar of commodity to final users. Vector \(y_k'\) maps the use of each commodity to final goods using the Personal Consumption Expenditures Bridge. I further aggregate consumption categories as indicated in Table C.1. Further details on the approach to Personal Consumer Expenditures data and on the computation of the labor share are presented in Appendices C.1 and C.2.

**Results**

Out of each dollar that a consumer spends on domestically produced goods and services, 53 cents are paid out as labor compensation to American workers. Personal Consumer Expen-

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\(^4\)Commodity: Purchased meals and beverages.

\(^5\)Industry: Food services and drinking places.

\(^6\)Industry: Food and beverage and tobacco products.

\(^7\)Industry: Management of companies and enterprises.

\(^8\)I differ from previous work on the network-adjusted labor share (Baqaee, 2015; Valentinyi and Herrendorf, 2008) by using Domestic Requirements instead of Total Requirements. The Domestic Requirements Matrix is computed after subtracting imports from the use table. My measure of the labor share then captures the fraction of value of each good that is received as compensation by American workers. Given that my focus is on fiscal stimulus of the domestic economy, the use of the domestic network-adjusted labor share is appropriate. The difference is nevertheless not large and not critical for my results.
ditures are less labor-intensive than the economy as a whole, which has an average labor share of 0.58. Exports have a similar labor share, 0.54. On the other hand, investment and government purchases are more labor-intensive, with labor shares of 0.62 and 0.71 respectively. My findings are consistent with Valentinyi and Herrendorf (2008), who also document that consumption goods are relatively less labor-intensive than investment goods.

There is wide heterogeneity in the labor share of different consumption goods (Figure 3.1). Using the Personal Consumer Expenditures Bridge, I compute the network-adjusted labor share for each category of final consumption. While housing has a labor share of only 0.23 and utilities and communications have labor shares slightly above 0.40, education and domestic services have labor shares greater than 0.75.

Goods that are produced with a high labor share also employ more workers per dollar of output. As an alternative measure of labor intensity, I define labor requirement as the number of employees required to produce a million dollars of each final consumption good.9 I find that producing a million dollars of domestic services requires 19 workers, whereas a million dollars of housing, communications, or utilities requires less than 6 (Figure 3.2). On average, a million dollars of the consumption good requires 9 workers to be produced. These two measure of labor intensity, labor share and labor requirement, are strongly correlated (Figure 3.3).

I find similar heterogeneity using other common measures of labor intensity. The network-adjusted labor share is strongly correlated with two measures of the labor share that the literature has previously used and that do not use requirements matrices in their computation: the gross and value-added labor shares (Figure 3.4).10 A more challenging concern relates to the fact that labor shares are averages, rather than marginal variables. The production of cars is relatively capital-intensive, but if the automobile industry responds to drops in demand mainly by firing workers, the labor share would not be a good metric of

9Hugie Barello (2014) uses a similar measure but employing the Total Requirements Matrix instead of the Domestic Requirements Matrix in her calculations.
10To produce labor shares for goods, rather than for industries, I average the labor shares of the different industries producing a final good weighting them by their market share as implied by the make table.
Figure 3.1: Labor Share of Different Consumption Goods

Significant heterogeneity in the labor share of final consumption goods
Network-adjusted labor share of different categories of final consumption in 2007. Refer to the main text and Appendices C.1 and C.2 for details on the calculations.
Significant heterogeneity in the labor requirements of final consumption goods

Labor requirement is defined as the number of employees required to produce a million dollars of each final consumption good in 2007. Refer to the main text and Appendices C.1 and C.2 for details on the calculations.
Labor share and labor requirements are strongly correlated
Labor share is the network-adjusted labor share. Labor intensity is defined as the number of employees required to produce a million dollars of each final consumption good. Each ball represents one of the final consumption goods in Figures 3.1 and 3.2. The size of each ball is proportional to the share of that final good on total consumption in 2007 according to the national accounts. Corr. refers to the weighted correlation between labor share and labor requirement. Refer to the main text and Appendices C.1 and C.2 for details on the calculations.

changes in labor compensation. In Appendix C.3, I address this concern by estimating the output elasticity of labor demand for different industries and comparing it to their labor requirements. I find that industries that hire more workers per million dollars of sales also show a more responsive labor demand to changes in output.
The network-adjusted labor share is strongly correlated with other measures of the labor share.
Labor share is the network-adjusted labor share. Gross labor share is the weighted average gross labor share (i.e., labor compensation divided by total industry output) of the different final industries that add value to each final consumption good. Value-added labor share is the weighted average value-added labor share (i.e., labor compensation divided by total industry value-added) of the different final industries that add value to each final consumption good. Labor Share (No Self Employed) refers to the network-adjusted labor share without adjusting compensation of employees for the share of self-employed workers in each industry. Labor Share (No Imputed Housing) is the network-adjusted labor share computed after excluding the imputed rental value of owner-occupied housing from GDP and from the output of the real estate industry.
Each ball represents one of the final consumption goods in Figure 3.1. The size of each ball is proportional to the share of that final good on total consumption in 2007 according to the national accounts.
Corr. refers to the weighted correlation between the variables in each panel.
Refer to the main text and Appendices C.1 and C.2 for details on the calculations.
3.2.2 Expenditure Response to Employment

In this subsection, I document that households who become employed disproportionately increase expenditures on goods that are very labor intensive. First, I discuss the data and identification strategy used to estimate the response of expenditure on individual goods to employment. Second, I show my baseline results. Third, I argue that the correlation between labor share and expenditure response to employment appears driven by changes in employment status, rather than by changes in permanent income. Fourth, I show that the responses to employment and to unemployment are fairly symmetric.

Data Description

To explore how household’s expenditures respond to employment I use the Interview component of the Consumer Expenditure Survey (CEX henceforth). The CEX collects extensive information on the consumption choices of American households and it has been deployed since 1980 with relatively minor methodological changes. The survey interviews each household every 3 months for 5 quarters and it provides quarterly expenditure data for the last four interviews. Employment and income data are collected in the second and fifth interviews, which allows me to compare the change in a household’s expenditure bundle after changes in employment status. For each household, I keep only the two interviews with employment data. I use all waves between 1980 and 2014.

To connect production and expenditure data, I try to harmonize the categories of consumption goods in the CEX with those in the national accounts. I split household expenditures in the same fourteen categories as the previous subsection: clothing, communications, education, food at home, food away from home, health care, housing, recreation, utilities, domestic services, consumer durables, private transportation, public transportation, and other. Further details on the data construction are provided in Appendix C.4.

11 Appendix C.4 describes minor corrections required to ensure comparability across the sample period.
12 I refer to them as the first and second interview going forward, although they correspond to the second and fifth interviews in the CEX.
summarizes the expenditure shares of the households in my sample. Housing is the largest
category, accounting for 30% of total expenditure on average. Private transportation and
food at home are also major expenditure categories, accounting for 15% and 13% of total
expenditures on average, respectively.

Identification Strategy

I exploit within-household variation to identify the expenditure response to employment from
the panel dimension of the CEX. Formally, I estimate the following regression separately for
each good $j$:

$$y_{i,j,t} = \beta_j \text{Employed}_{i,t} + \kappa_{i,j} + \tau_{j,t} + \gamma_j X_{i,t} + \epsilon_{i,j,t}$$

where $y_{i,j,t}$ is the expenditure share or log real expenditure on consumption good $j$ in house-
hold $i$ in quarter $t$, Employed$_{i,t}$ is a dummy equal to 1 if household $i$ was employed in quarter
$t$. $\kappa_{i,j}$ is a household fixed effect and $\tau_{j,t}$ is a time fixed effect for the month in which the
interview was conducted. $X_{i,t}$ includes demographic controls: head’s age, family size, and
family type as defined by demographics of other members of the household (e.g., married
couple only, married couple with oldest child under 6 years all, etc.).

My parameter of interest is $\beta_j$, the response of expenditure or expenditure share of
good $j$ to employment. The parameter is identified from households who move into and
out of employment between interviews. When the dependent variable is the expenditure
share, a positive value of $\beta_j$ indicates that expenditure on good $j$ grows as a fraction of
total expenditure upon employment and decreases upon unemployment. On the other hand,
when the dependent variable is the logarithm of expenditure on good $j$, $\beta_j$ measures the semi-
elasticity of expenditure on good $j$ to employment, i.e., the log points change in expenditure
of good $j$ when the household moves from unemployed to employed.

My identification assumption is that changes in expenditure for households that became
employed would have been the same than changes experienced by comparable households
Table 3.1: Summary Statistics: 1980-2014

<table>
<thead>
<tr>
<th>Expenditure Shares</th>
<th>Mean</th>
<th>P10</th>
<th>P50</th>
<th>P90</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clothing</td>
<td>0.03</td>
<td>0.00</td>
<td>0.02</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>Communications</td>
<td>0.03</td>
<td>0.01</td>
<td>0.03</td>
<td>0.07</td>
<td>0.03</td>
</tr>
<tr>
<td>Education</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.02</td>
<td>0.05</td>
</tr>
<tr>
<td>Food at Home</td>
<td>0.13</td>
<td>0.04</td>
<td>0.11</td>
<td>0.25</td>
<td>0.09</td>
</tr>
<tr>
<td>Food Away from Home</td>
<td>0.04</td>
<td>0.00</td>
<td>0.03</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>Health Care</td>
<td>0.05</td>
<td>0.00</td>
<td>0.03</td>
<td>0.13</td>
<td>0.07</td>
</tr>
<tr>
<td>Housing</td>
<td>0.30</td>
<td>0.09</td>
<td>0.26</td>
<td>0.58</td>
<td>0.20</td>
</tr>
<tr>
<td>Recreation</td>
<td>0.06</td>
<td>0.00</td>
<td>0.04</td>
<td>0.14</td>
<td>0.07</td>
</tr>
<tr>
<td>Utilities</td>
<td>0.06</td>
<td>0.01</td>
<td>0.05</td>
<td>0.12</td>
<td>0.05</td>
</tr>
<tr>
<td>Domestic Services</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>Durables</td>
<td>0.03</td>
<td>0.00</td>
<td>0.01</td>
<td>0.08</td>
<td>0.05</td>
</tr>
<tr>
<td>Other</td>
<td>0.08</td>
<td>0.01</td>
<td>0.06</td>
<td>0.17</td>
<td>0.08</td>
</tr>
<tr>
<td>Private Transportation</td>
<td>0.15</td>
<td>0.02</td>
<td>0.11</td>
<td>0.29</td>
<td>0.14</td>
</tr>
<tr>
<td>Public Transportation</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Number of households: 84,655
Number of heads of households with employment change: 5,379
Number of male heads of households with employment change: 2,285
Number of heads of households aged 25-50 with employment change: 3,064
Number of households with increase in the number of members employed: 10,396

The CEX offers a reasonable sample size to study the expenditure response to employment.
The top panel shows summary statistics of expenditures shares in different goods across households. Mean refers to the mean expenditure share in each good across households. P10, P50, and P90 refer to the 10th, 50th, and 90th percentile of the distribution of expenditure shares in each good. SD refers to the standard deviation in expenditure shares in each good. All summary statistics are computed using probability weights.
The bottom panel shows the number of households in the sample and those who satisfy the different definitions of employment discussed in Subsection 3.2.2.
For details on the data construction, refer to the main text and Appendix C.4.
that remained unemployed absent the employment shock. A symmetric assumption is needed for households that moved from employment to unemployment. In my specification, household fixed effects control for any time-invariant household characteristics such as household’s head education, preferences, and socioeconomic status. The month of the interview time fixed effect flexibly controls for seasonality, business cycle variation, and long-term trends affecting expenditures patterns of all households equally. Finally, demographic controls isolate changes in expenditures resulting from predictable variations in household composition.

In my baseline specification, I define a household to be employed if the head of the household reports working a positive number of hours regularly. Because household heads tend to have a stable participation in the labor force, focus on their employment status alleviates concerns about an endogenous response of labor supply to shocks that are themselves affecting the expenditure patterns of the household. For instance, a high-school student graduating and joining the labor force simultaneously increases the household labor supply and decreases the share of education on the household expenditure bundle. But the negative correlation between employment status and expenditure share of education is not causal as it is driven by an omitted variable. Using the household head’s employment status mitigates this endogeneity concern.

My results are robust to two alternative definitions for the employment status of the household. First, I restrict my sample to households with male heads, for whom the attachment to the labor force tends to be the most stable. Second, I base household employment status on the change in the number of earners between interviews. When the number of earners in the household drops, I say that the household has become unemployed. And when it rises, I identify the household as having become employed.

Finally, the estimated expenditure responses to employment are explained by unemployment, rather that by retirement. While I cannot differentiate unemployment from out of the labor force status from occupational questions in the CEX, I show that restricting the sample to households with heads younger than 50 does not affect my results.
Results

Total expenditure increases by 2.5% upon employment. Consistent with prior findings in the literature, I find that households increase total expenditure when they become employed and cut back when they become unemployed. My estimates of the drop in expenditure upon unemployment are slightly lower than what previous research has found. For instance, Saporta-Eksten (2014) finds a drop of 8% in total expenditure upon unemployment using the Panel Study of Income Dynamics, whereas Christelis, Georgarakos, and Jappelli (2014) estimate a decrease of 10% in the Internet Survey of the Health and Retirement Study. My lower point estimate of the expenditure response with respect to previous work likely follows from differential severity of the unemployment/employment spells studied and from different definitions of expenditure. Because I am only able to capture relatively mild unemployment/employment spells in my research design by comparing households’ employment status less than a year apart, my results are likely to be a lower bound on the effect of unemployment on expenditure. Additionally, expenditure measures used in previous work tend to exclude housing, which I find to be very unresponsive and thus, its inclusion reduces the average response.

However, there exists significant heterogeneity in the expenditure responses to employment of different goods (Figure 3.5). While expenditures on food at home, housing, communications, and utilities barely change upon employment; expenditures on food away from home, recreation, domestic services, private transportation, and other goods rise by more than 10%. As a consequence, housing decreases by a percentage point as a fraction of total expenditure when a household becomes employed. The results are consistent with households disproportionally raising their expenditures on work-related expenses (e.g., clothing, food away from home, transportation) and substitutes of home-produced goods (e.g., domestic services, recreation) upon joining the labor force.

The heterogeneity in the estimated expenditure response to employment is consistent with what has been documented in other settings before. Also using CEX data, Aguiar...
Upon employment, households spend disproportionately more on labor-intensive goods.

Panel A (B) shows the response of the expenditure share (the semi-elasticity of expenditure) of each good to a change in the employment status of the household head. 95% confidence intervals are shown with dotted lines. Standard errors are clustered at household level. Goods are sorted by their network-adjusted labor share. The size of each ball is proportional to the share of that good according to the CEX.
and Bils (2015) document that retired households reduce their expenditure on work-related goods and on goods that can be home-produced. Ganong and Noel (2015) use checking accounts data of unemployment insurance recipients and document a large drop on work-related expenses particularly at the onset of unemployment spells.

The expenditure response to employment across different goods is positively correlated with the labor share with which they are produced. The categories of expenditure in Figure 3.5 are sorted in ascending order by the network-adjusted labor share as documented in Figure 3.1. Goods whose expenditure barely change upon employment are produced with very low labor intensity (e.g., housing, utilities, communications, and food at home). On the other extreme, households increase their expenditure disproportionately on goods that are very labor intensity when they become employed (e.g., food away from home, clothing, domestic services).

My results are robust to a number of alternative specifications. I find that defining employment by the occupational status of the male household head (Figure 3.6) or by the change in the number of earners (Figure 3.7), and limiting the sample to young households as defined by the head’s age (Figure 3.8) do not affect the heterogeneity in the expenditure response to unemployment. Housing, utilities, and food at home still fall as a fraction of total expenditure upon employment, whereas food away from home, domestic services, private transportation, and durables rise.

**Decomposition Exercise**

When a household becomes employed, it will adjust its expenditures for two reasons. First, upon employment, the household’s permanent income will rise and its borrowing constraint will be relaxed. As a result, expenditure on normal goods will increase and expenditures on inferior goods will drop. Second, the household will have less time available for home-production and will have to purchase some goods to go to work. In this subsection, I decom-
Upon employment, households spend disproportionately more on labor-intensive goods.

Panel A (B) shows the response of the expenditure share (the semi-elasticity of expenditure) of each good to a change in the employment status of the household head. 95% confidence intervals are shown with dotted lines. Standard errors are clustered at household level. Goods are sorted by their network-adjusted labor share. The size of each ball is proportional to the share of that good according to the CEX.
Upon employment, households spend disproportionately more on labor-intensive goods.

Panel A (B) shows the response of the expenditure share (the semi-elasticity of expenditure) of each good to an increase in the number of household members employed. 95% confidence intervals are shown with dotted lines. Standard errors are clustered at household level. Goods are sorted by their network-adjusted labor share. The size of each ball is proportional to the share of that good according to the CEX.
The heterogeneous expenditure response is driven by unemployment, rather than by retirement.

Panel A (B) shows the response of the expenditure share (the semi-elasticity of expenditure) of each good to a change in the employment status of the head aged 25-50. 95% confidence intervals are shown with dotted lines. Standard errors are clustered at household level. Goods are sorted by their network-adjusted labor share. The size of each ball is proportional to the share of that good according to the CEX.
pose the expenditure response to employment into these two major components. Formally, I estimate the following specification separately for each good $j$:

$$y_{i,j,t} = \beta_j \text{Employed}_{i,t} + \eta_j \text{Total Expenditure}_{i,t} + \tau_{j,s} + \gamma_j X_{i,t} + \epsilon_{i,j,t}$$

where $y_{i,j,t}$ is the log real expenditure on consumption good $j$ in household $i$ in quarter $t$, Employed$_{i,t}$ is a dummy equal to 1 if household $i$ was employed in quarter $t$, Total Expenditure$_{i,t}$ is the household log total expenditure in period $t$, $\tau_{j,t}$ is a time fixed effect for the month in which the interview was conducted, $X_{i,t}$ includes household controls (family size and family type) and controls for the head of the household (age, marital status, race, gender, and education).

The parameters of interest are $\eta_j$, the response of individual goods to total expenditure, and $\beta_j$, the response of individual goods to employment that is orthogonal to changes in total expenditure. The specification corresponds to a log-linear approximation of the Engel curves. Previous work has mainly focused on the estimation of $\eta_j$, but I exploit the framework to also identify $\beta_j$. Together, $\eta_j$ and $\beta_j$ permit the decomposition of the expenditure response to employment into a permanent income or relaxed borrowing constraints component ($\eta_j$) and a home-production or work-related expenses component ($\beta_j$).

I estimate the coefficients $\eta_j$ and $\beta_j$ from the cross-section. Identifying $\eta_j$ and $\beta_j$ from within household variation is challenging given the strong correlation between employment and total expenditure documented previously. As such, I do not include household fixed effects for this decomposition exercise. Then, identification of $\beta_j$ comes from comparing two households with similar demographics and level of total expenditure, but different employment status: one is employed and the other is unemployed. Identification of $\eta_j$ comes from comparing two households with the same employment status and demographics, but different levels of total expenditure.

I address endogeneity concerns raised by measurement error by instrumenting total expenditure in the second interview with total expenditure in the first interview. Measurement
error in the household expenditure of good $j$ is captured by the residual but it is also ac-
cumulated in the household’s total expenditure, biasing estimates of $\eta_j$. To deal with this
concern, I follow Aguiar and Bils (2015) and I instrument total expenditure in the second
interview with total expenditure in the first interview. The relevance of the instrument
comes from the strong correlation of total expenditure over time as expenditure follows a
relatively stable permanent income. For this exercise, I only keep the final interview of each
household.

The positive correlation between expenditure on individual goods and their labor shares
is driven by the response to employment, rather than by the response to total expenditure.
The responses of expenditure on individual goods to employment and total expenditure are
shown in Figure 3.9. The estimated elasticities to total expenditures are in line with previous
work (Aguiar and Bils, 2015). Housing presents a coefficient slightly greater than one, while
utilities, communications, food at home, and public transportation all have a coefficient
lower than one. Food away from home, domestic services, recreation, and clothing exhibit
a more than proportional response to total expenditure, with a coefficient greater than one.
The correlation between these responses to total expenditure and the labor share with which
the goods are produced is 0.07. The estimated responses to employment are qualitative
in line with my previous estimates using within-household variation. And the correlation
between expenditure responses to employment and labor shares is 0.38, as households dis-
proportionately respond to employment by increasing expenditure on very labor-intensive
goods.

Symmetry of the Expenditure Response to Employment and Unemployment

In this subsection, I show that the expenditure response to employment changes is fairly
symmetric. I separately estimate the change in expenditure for households who switch from
employment to unemployment and for those who switch from unemployment to employ-

\footnote{I have also instrumented total expenditure with total income and the results are very similar.}
Figure 3.9: Total Expenditure and Employment Elasticities

The positive correlation between labor share and expenditure is explained by the response to employment rather than to total expenditure.

Panel A (B) shows the response of the expenditure of each good to a 1% change in total expenditure (to a change in the employment status of the household head). 95% confidence intervals are shown with dotted lines. Standard errors are clustered at household level. Goods are sorted by their network-adjusted labor share. The size of each ball is proportional to the share of that good according to the CEX.
ment. The implicit assumption in my previous subsections that the drop in expenditure upon unemployment is the same than the increase in expenditure upon employment is not restrictive.

Formally, I restrict the sample to households that initially report being unemployed and estimate the following regression for each good $j$

$$y_{i,j,t} = \beta_j^{UE} \text{SwitchUE}_{i,t} + \kappa_{i,j} + \tau_{j,t} + \gamma_j X_{i,t} + \epsilon_{i,j,t}$$

And I estimate an analogous specification for households that initially report being employed

$$y_{i,j,t} = \beta_j^{EU} \text{SwitchEU}_{i,t} + \kappa_{i,j} + \tau_{j,t} + \gamma_j X_{i,t} + \epsilon_{i,j,t}$$

where $y_{i,j,t}$ is the expenditure share or log real expenditure on consumption good $j$ in household $i$ in quarter $t$, SwitchUE$_{i,t}$ is a dummy that takes the value of 1 if the head of household $i$ was previously unemployed and has become employed in the second interview. Similarly, SwitchEU$_{i,t}$ is equal to 1 in the second interview if the household has become unemployed after reporting being employed in the first interview. Additionally, $\kappa_{i,j}$ is a household fixed effect, $\tau_{j,t}$ is a time fixed effect for the month in which the interview was conducted, and $X_{i,t}$ includes demographic controls: head’s age, family size, and family type as described above. My parameters of interest in these specifications are $\beta_j^{UE}$ and $\beta_j^{EU}$, which measure the response of expenditure on good $j$ to the head becoming employed and becoming unemployed, respectively.

The expenditure response to employment and unemployment is fairly symmetric. Total expenditure drops by 3% when the head becomes unemployed and rises by 1.5% when he/she becomes employed (Figure 3.10). The difference is not statistically significant. Expenditures on housing and food at home decrease slightly upon unemployment and increase upon employment, but they are not significant from zero. On the other hand, expenditures on food
away from home, recreation, domestic services, other, and private transportation drop by around 10% upon unemployment, and rise by a similar magnitude upon employment.

### 3.2.3 The Labor Intensity of the Expenditure Response to Employment

In this section, I combine my findings on the expenditure response to employment and the labor share of different goods to quantify the magnitude of the mechanism and assess its robustness.

Upon employment, households disproportionately increase their expenditures on goods whose production is very labor intensive. The correlation between the change in the expenditure share upon employment and the network-adjusted labor share is 0.76 (Figure 3.11). The correlation between the labor share and the expenditure response to employment is 0.61.

My results suggest a 6.5% drop in the household’s demand for labor upon unemployment. In 2014, the average American household spent $56 thousand, of which $28 thousand were received by American workers as labor compensation. Upon unemployment, the household reduces its expenditures on different goods at different rates, which decreases compensation to workers by 6.5% to $26 thousand. Furthermore, 15% of the drop is explained by the change in the composition of the expenditure bundle, rather than by the drop in total expenditure.

The decrease in the household’s demand for other workers’ labor upon unemployment explains a fifth of the drop in compensation to labor during the Great Recession. The average unemployment rate in 2007 was 4.6%, but it rose to 9.3% in 2009. The increase of unemployment (4.7 percentage points) multiplied by the estimated decrease in households’

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14 I compute this figure by multiplying the amount spent on each good after excluding imports (using the expenditure weights of employed households) by its network-adjusted labor share.

15 I compute this figure by applying the unemployment elasticities of expenditures estimated from Subsection 3.2.2 to the expenditure bundle of employed households and multiplying them by their network-adjusted labor share.

16 The NBER dates the beginning of the Great Recession in December 2007 and its end in June 2009.
The response to employment and unemployment is fairly symmetric
Panel A (B) shows the response of the expenditure share (the semi-elasticity of expenditure) of each good when the household head becomes employed in red/blue balls and when the head becomes unemployed in grey/white balls. 95% confidence intervals are shown with dotted lines. Standard errors are clustered at household level. Goods are sorted by their network-adjusted labor share. The size of each ball is proportional to the share of that good according to the CEX.
Strong correlation between labor share and expenditure response to employment
Each ball represents one of the fourteen final consumption goods. Expenditure responses to employment are as shown in Figure 3.5. Labor shares are as shown in Figure 3.1. The size of each ball is proportional to the share of that good on total consumption according to the CEX.
Corr. refers to the weighted correlation between the variables in each panel.
demand for other workers’ labor upon unemployment (6.5%) implies a drop in the flow of expenditure towards workers of 0.3%. Between 2007 and 2009, labor compensation increased by 1.4%. Thus, the decrease in expenditure of unemployed workers explains 22% of the drop in labor compensation during the Great Recession.

The positive correlation between expenditure response to employment and labor share is a robust result. Using the network-adjusted labor shares from Subsection 3.2.1 and the expenditure responses to employment estimated in Subsection 3.2.2, I estimate the following regression:

\[ \beta_j = \alpha_0 + \alpha_1 \text{Labor Share}_j + \epsilon_j \]

where \( \beta_j \) is the expenditure (or expenditure share) response to employment for good \( j \) and \( \text{Labor Share}_j \) is the network-adjusted labor share with which the good is produced. Table 3.2 presents the estimates for \( \alpha_1 \) for alternative definitions of the labor share and the expenditure response. In my baseline specification, expenditure on goods with a 0.1 greater labor share increases by almost two percentage points upon employment. Across alternative specifications, the slope fluctuates between 0.14 and 0.33. In a similar way, the expenditure share of goods with a 0.1 greater labor share rises by a quarter of a percentage point upon employment. The result is stable across specifications.

3.3 A Model with Heterogeneous Goods in Consumption and Production

In this section, I propose a model to quantify the implications for fiscal stimulus of the heterogeneity in consumption and production documented in the previous section. The model

\footnote{As discussed in Appendix C.2, I compute labor compensation adjusting the compensation of employees by the ratio of total workers to employees to account for the labor component of entrepreneurial income.}
Table 3.2: Expenditure Response to Employment and Labor Share

Panel A. Expenditure Share

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.024***</td>
<td>0.021***</td>
<td>0.024***</td>
<td>0.031***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.005)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>1998</td>
<td>0.024***</td>
<td>0.022***</td>
<td>0.025***</td>
<td>0.032***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>2014</td>
<td>0.024***</td>
<td>0.022***</td>
<td>0.025***</td>
<td>0.032***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.005)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Excl. Imputed Housing</td>
<td>0.019</td>
<td>0.016</td>
<td>0.019</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.018)</td>
<td>(0.017)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Total Requirements</td>
<td>0.024***</td>
<td>0.021***</td>
<td>0.024***</td>
<td>0.032***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.009)</td>
</tr>
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</table>

Panel B. Expenditure

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.177***</td>
<td>0.152*</td>
<td>0.239***</td>
<td>0.249***</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.078)</td>
<td>(0.052)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>1998</td>
<td>0.167***</td>
<td>0.139*</td>
<td>0.237***</td>
<td>0.235***</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.064)</td>
<td>(0.055)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>2014</td>
<td>0.183***</td>
<td>0.158*</td>
<td>0.251***</td>
<td>0.253***</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.075)</td>
<td>(0.053)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Excl. Imputed Housing</td>
<td>0.257*</td>
<td>0.217</td>
<td>0.327</td>
<td>0.292</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.186)</td>
<td>(0.184)</td>
<td>(0.168)</td>
</tr>
<tr>
<td>Total Requirements</td>
<td>0.180***</td>
<td>0.154*</td>
<td>0.245***</td>
<td>0.253***</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.077)</td>
<td>(0.052)</td>
<td>(0.052)</td>
</tr>
</tbody>
</table>

The positive correlation is a robust result
Each coefficient represents the slope of a linear regression of the expenditure response to employment on the labor share for the different consumption goods.
Columns present alternative specifications of the expenditure response to employment. (1) is the baseline as defined in Figure 3.5. (2) restricts the sample to male heads as in Figure 3.6. (3) restricts the sample to heads aged 25-50 as in Figure 3.8. (4) defines a household becoming employed when the number of earners in the household increases as in Figure 3.7. Rows present alternative specifications of the labor share. Baseline refers to the network-adjusted labor share in 2007 as in Figure 3.1. 1998 and 2014 refer to the labor share computed for years 1998 and 2014 as in Figure C.1. Excl. Imputed Housing refers to the labor share computed after excluding the imputed rental value of owner-occupied housing from GDP and from the output of the real estate industry as in Figure 3.4. Total Requirements refers to the labor share computed without excluding imports as in Figure C.1.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis.
features goods that are produced with different labor shares and whose demand depends on the employment status of consumers.

### 3.3.1 Main Components

The model has no aggregate uncertainty, but individual agents are exposed to idiosyncratic shocks. Time is discrete. In the tradition of the Aiyagari-Bewley-Huggett models,\(^\text{18}\) infinitely-lived households receive every period idiosyncratic productivity and employment shocks that cannot be insured away. Households are allowed to save only in risk-free savings accounts held with a competitive financial sector. The financial sector invests those savings in government bonds and productive capital. Households also own the firms and receive their profits.

The model features heterogeneity in both consumption and production. Heterogeneity in production is modeled with different industries having different labor shares. Heterogeneity in consumption responses upon unemployment is attained through the presence of home-production. Heterogeneity in consumption could have been introduced in the model via non-homothetic preferences or adjustment costs. But based on the evidence on Subsection 3.2.2, a story of home-production appears more plausible.

Following the New-Keynesian literature,\(^\text{19}\) I introduce nominal rigidities on prices to strengthen the aggregate demand channel. Firms are monopolistically competitive and pay an adjustment cost to change prices as in Rotemberg (1982). In this chapter, I assume that the cost of changing the price is infinite and so, prices are fixed. Every period, firms hire labor and capital, and pay back dividends to households.

The model is completed by a government, a monetary authority, and a labor union. The government enacts fiscal policy via direct purchases, taxes on labor income, and unemploy-

\(^{18}\) Aiyagari (1994), Bewley (1986), and Huggett (1996) are the foundational references in this literature. Brinca et al. (2016) offer a recent and related application by studying the impact of wealth inequality on the effectiveness of fiscal stimulus in the context of a life-cycle heterogeneous agent model.

ment insurance. The monetary authority sets the nominal interest rate using a Taylor rule. The labor union prevents the labor market from clearing, introducing unemployment, and producing a positively-sloped labor supply. The labor union in the model does not attempt to match the behavior of labor unions in the U.S. Instead, it is merely an abstraction to aggregate the discrete employment status of workers into a labor supply with a positive wage elasticity and no wealth effect.

3.3.2 Households

In the model, households are both consumers and workers. There is a continuum of households of measure one. An individual household starts period \( t \) with wealth level \( a_t \), permanent productivity shock \( z_t^P \), transitory productivity shock \( z_t^T \), and employment status \( e_t \), a 0 or 1 variable indicating whether the household is unemployed or employed, respectively. Households may differ in their degree of patience, \( \beta_h \). Denote \( \mu_t(\beta_h, a_t, z_t^P, z_t^T, e_t) \) the joint distribution of individual states at time \( t \).

Households have preferences over consumption goods that are represented by the utility function

\[
E_0 \sum_{t=1}^{\infty} \beta_h^t u(c_{1,t}, c_{2,t})
\]

with

\[
u(c_{1,t}, c_{2,t}) = \begin{cases} 
\frac{[c_{1,t}^{1-\nu} c_{2,t}^{\nu}]^{1-\gamma}}{1-\gamma} & \text{if } \gamma \neq 1 \\
(1-\nu) \ln c_{1,t} + \nu \ln c_{2,t} & \text{if } \gamma = 1
\end{cases}
\]

\[c_{1,t} = x_{1,t}\]

\[c_{2,t} = \left[\psi x_{2,t}^p + (1-\psi)(1-e_t)\rho\right]^{\frac{1}{\rho}}\]
where consumption of good 1 \((c_1)\) is equal to market purchases of good 1 \((x_1)\), but good 2 can be home-produced if the household is not employed. The parameters \(\psi\) and \(\rho\) govern how the expenditure bundle of a household changes upon unemployment. In particular, if \(\psi = 1\), there is no home-production and the household always spends a share \(\nu\) of total expenditure on good 2, regardless of its employment status. If \(\psi < 1\), upon unemployment the household home-produces some of good 2 and so, its expenditure on the good drops disproportionately, biasing the expenditure bundle towards good 1.

Households are subject to permanent and transitory productivity shocks that determine their earnings. The permanent shock follows a discrete first-order Markov process given by matrix \(P\). The transitory shock is independent and identically distributed over time. If employed in period \(t\), earnings before tax are given by

\[
z_t = e^{z_t^P + z_t^T}
\]

Households do not choose their employment status. Instead they experience an exogenous employment shock every period. When \(e_t = 0\), the household is unemployed and receives unemployment insurance. When \(e_t = 1\), the household is employed and receives labor compensation. All unemployed households find jobs with probability \(\delta_{ue,t}\) at the end of period \(t\). Employed households lose their jobs in period \(t\) with probability \(\delta_{eu,t}(z_t^P)\), which depends negatively on the level of their permanent productivity shock. These features of the model map to the evidence showing that low productivity workers have higher job destruction rates, but that job finding rates do not vary across productivity groups.\(^{20}\)

I allow the discount factor \(\beta_h\) to be heterogeneous across households. In particular, I assume that households are either patient or impatient and I calibrate the discount factor of each group to simultaneously match the aggregate wealth in the economy and the average expenditure response to unemployment. This heterogeneity in the discount factor yields a

\(^{20}\)Cairo and Cajner (2014) document that workers have very similar job finding rates regardless of their education level, but highly-educated workers have lower separation rates and so, lower unemployment rates.
better match to the wealth distribution and prevents some households from saving enough to perfectly self-insure against the drop in income associated to unemployment. I choose to match the average expenditure response upon unemployment so that by comparing my baseline model with one without heterogeneity in consumption and production I can isolate the effect of the labor composition of the expenditure response to unemployment. Otherwise, such comparison would also capture a differential response on average expenditure.

Finally, households maximize utility subject to the budget constraint

$$P_{1,t} x_{1,t} + P_{2,t} x_{2,t} + a_{t+1} = W_t e_t (1 - \tau_{w,t}) z_t + u_t W_t z_t (1 - e_t) + \Pi_t - T_t + (1 + i_t) a_t$$

where $P_{1,t}$ and $P_{2,t}$ are the prices of the consumption goods, $W_t$ is the nominal wage rate per effective unit of labor, $\tau_{w,t}$ is a proportional tax on labor income, $u_t$ is the unemployment insurance replacement rate, $T_t$ is a nominal lump-sum tax, and $\Pi_t$ are firm profits. Households can save on a risk-free asset that pays a nominal interest $i_t$, but are not allowed to borrow (i.e., $a_{t+1} \geq 0$).

### 3.3.3 Firms

There are three productive sectors in the economy. Two sectors produce consumption goods and a third sector produces investment goods. Each sector has its own labor share and it is composed of a continuum (of measure one) of final and intermediate producers.

#### Final Goods Producers

Let $i$ denote the productive sector with $i = 1, 2, I$. The first two sectors ($i = 1, 2$) produce consumption goods and the third sector ($i = I$) produces investment goods.

---

21Heterogeneity in the discount factor has been used before to improve the match of the wealth distribution (e.g., Krusell and Smith, 1998; McKay and Reis, 2016).
Each sector has a continuum of perfectly competitive final producers who purchase intermediate goods indexed by $j$ and assemble final goods using the production function

$$Y_{i,t} = \left( \int (y^j_{i,t})^{\frac{1}{\epsilon}} \, dj \right)^{\frac{1}{\epsilon}}$$

where $\epsilon$ is the elasticity of substitution across intermediate goods.

Let $p^j_{i,t}$ be the nominal price of intermediate good $j$ in sector $i$ at time $t$. Then, cost minimization yields a standard demand for intermediate good $j$

$$y^j_{i,t}(p^j_{i,t}) = \left( \frac{p^j_{i,t}}{P_{i,t}} \right)^{-\epsilon} Y_{i,t}$$

where

$$P_{i,t} = \left( \int (p^j_{i,t})^{1-\epsilon} \, dj \right)^{\frac{1}{1-\epsilon}}$$

**Intermediate Goods Producers**

Monopolistically competitive firms in each sector hire labor ($\ell$) and capital ($k$) to produce intermediate goods using a Cobb-Douglas technology

$$y^j_{i,t} = A \left( k^j_{i,t} \right)^{\alpha_i} \left( \ell^j_{i,t} \right)^{1-\alpha_i}$$

where $\alpha_i$ varies by sector.

Intermediate producers rent capital at a nominal rate $R_t$ from a competitive financial sector and hire effective units of labor at a nominal rate $W_t$ from a labor union. There are no adjustment costs to capital nor labor at the firm level. Factors can move freely across sectors. The nominal average and marginal cost implied by cost minimization coincide because of constant returns to scale and are given by

$$AC_{i,t} = MC_{i,t} = \frac{1}{A} \left( \frac{R_t}{\alpha_i} \right)^{\alpha_i} \left( \frac{W_t}{1 - \alpha_i} \right)^{1-\alpha_i}$$
Intermediate producers choose their prices to maximize profits

\[ E_0 \sum_{t=1}^{\infty} \prod_{i=1}^{t} \left( 1 + \delta_{t} \right) \left[ y_{i,t}^{j} (p_{i,t}^{j} - AC_{i,t}) - \Theta_{i,t}(p_{i+1,t}^{j}, p_{i,t}^{j}) \right] \]

with menu costs à la Rotemberg (1982)

\[ \Theta_{i,t}(p_{i+1,t}^{j}, p_{i,t}^{j}) = \frac{\theta}{2} \left( \frac{p_{i+1,t}^{j} - p_{i,t}^{j}}{p_{i,t}^{j}} \right)^2 P_{i,t} Y_{i,t} \]

I assume that adjustment costs are paid as transfers to households and so, they do not take up real resources.

I focus only on symmetric equilibria. Then, individual demand for labor and capital equals the sectoral aggregate demand for labor and capital

\[ \ell_{i,t}^{j} = L_{i,t} \]

\[ k_{i,t}^{j} = K_{i,t} \]

### 3.3.4 Labor Union

A labor union intermediates households’ supply of labor to firms. The labor union cares about the real wages and employment rates of its members, aggregating their employment statuses into a positively-sloped labor supply:

\[ L_t = \overline{L} - \left( \alpha_u \frac{W_t}{\omega P_{1,t} + (1 - \omega) P_{2,t}} \right)^{-\frac{1}{\gamma_u}} \]

where \( \overline{L} \) is the total amount of effective labor in the economy

\[ \overline{L} = \int z_t \, d\mu_t(\beta_h, \alpha, z^P_t, z^T_t, e_t) \]
Notice that $\overline{L}$ is not indexed by $t$ because I assume productivities are drawn from their stationary distributions and so, aggregates are constant. I will calibrate the two parameters of this labor supply to match the unemployment rate and the elasticity in the steady state.

The use of a labor union in the model is purely for computational simplicity. In my model, the union does not experience nominal rigidities.\footnote{Some papers have used labor unions to introduce nominal rigidities in wages (e.g., Zubairy, 2014).} Instead, the union aggregates households’ discrete employment status into a labor supply with positive elasticity. In general, New-Keynesian models obtain a positively-sloped labor supply by allowing households to choose the intensive margin of employment (how many hours to work) or by having a continuum of households with different disutility of labor choosing along the extensive margin (whether to work or not). For my analysis, the former choice is undesirable because I want to target expenditure responses to changes in the employment status of the household along the extensive margin as documented in Section 3.2, whereas the latter complicates the solution of the model significantly because the wealth level would factor into the labor supply decision of the household as labor would affect both disutility of working and home-production. A labor union provides with a simple solution to deliver a positively-sloped labor supply.

### 3.3.5 Government

The government implements fiscal policy through taxes, transfers, and direct purchases of final goods. The government collects a tax on labor income and a lump sum tax. And it pays unemployment insurance to unemployed households.

Let $B_t$ be the government debt at period $t$. Then, the government budget constraint is

$$P_{1,t}G_{1,t} + P_{2,t}G_{2,t} + P_{t,t}G_{t,t} + (1 + i_t)B_t = B_{t+1} + W_t L_t \tau_{w,t} - u_t W_t (\overline{L} - L_t) + T_t$$
where \((\bar{L} - L_t)\) is the amount of effective labor unemployed because \(L_t\) is the amount of effective labor employed.

### 3.3.6 Monetary Authority

A monetary authority sets the nominal interest rate every period following a Taylor rule:

\[
i_t = i^* + \psi \pi_t
\]

where \(i^*\) is the noninflationary steady-state nominal interest rate. The inflation rate \(\pi_t\) is computed using a Consumer Price Index

\[
1 + \pi_t = \frac{\omega P_{1,t} + (1 - \omega) P_{2,t}}{\omega P_{1,t-1} + (1 - \omega) P_{2,t-1}}
\]

Because I consider only fixed prices, the Taylor rule becomes an interest rate peg.

### 3.3.7 Financial Sector

There is a perfectly competitive financial sector that takes savings from households and invests on government bonds and productive capital.

Investment on productive capital is given by

\[
I_t = K_{t+1} - (1 - \delta) K_t
\]

Because there is no aggregate uncertainty, profit maximization of the financial sector yields a no arbitrage condition. Government bonds and productive capital pay the same return at every point in time

\[
(1 + i_{t+1}) \frac{P_{I,t}}{P_{I,t+1}} = 1 + \frac{R_{t+1}}{P_{I,t+1}} - \delta
\]
Finally, perfect competition in the financial sector yields a zero-profit condition and so, at time $t$, households receive a nominal interest rate on their savings equal to $i_t$.

### 3.3.8 Market Clearing

A competitive equilibrium for this economy is defined as paths for prices $\{P_{1,t}, P_{2,t}, P_{I,t}, W_t, R_t, i_t\}_{t \geq 0}$, household policy functions $\{x_{1,t}(\cdot), x_{2,t}(\cdot), a_{t+1}(\cdot)\}_{t \geq 0}$, government policies $\{G_{1,t}, G_{2,t}, G_{I,t}, \tau_{w,t}, T_t, u_t\}_{t \geq 0}$, quantities $\{Y_{1,t}, Y_{2,t}, Y_{I,t}, L_t, L_{1,t}, L_{2,t}, L_{I,t}, K_t, K_{1,t}, K_{2,t}, K_{I,t}\}_{t \geq 0}$, and a distribution of individual states over households given by $\{\mu_t(\beta_h, a_t, z^P_t, z^T_t, e_t)\}_{t \geq 0}$ such that in every period $t$:

1. Households maximize their utility given their budget constraint and borrowing limit taking as given equilibrium prices and government policies.

2. Firms maximize profits taking as given equilibrium prices and government policies.

3. The labor union provides labor to firms according to its labor supply schedule.

4. The financial sector maximizes profits taking as given equilibrium prices and government policies.

5. The government budget constraint holds.

6. The distribution of individual states for the following period is consistent with households optimal choices and transition probabilities of exogenous shocks.

7. All markets clear.

There are six markets in the economy: the two consumption goods markets, the investment good market, the asset market, the labor market, and the productive capital market.

The consumption goods markets clear when the amount produced of each good equals what consumers and the government want to buy.
\[ Y_{1,t} = \int x_{1,t}(\beta_h, a_t, z^P_t, z^T_t, e_t) d\mu_t(\beta_h, a_t, z^P_t, z^T_t, e_t) + G_{1,t} \]

\[ Y_{2,t} = \int x_{2,t}(\beta_h, a_t, z^P_t, z^T_t, e_t) d\mu_t(\beta_h, a_t, z^P_t, z^T_t, e_t) + G_{2,t} \]

The investment good market clears when the amount produced equals investment and government purchases

\[ Y_{I,t} = K_{t+1} - (1 - \delta)K_t + G_{I,t} \]

The asset market clears when savings equal productive capital and government bonds

\[ \int a_{t+1}(\beta_h, a_t, z^P_t, z^T_t, e_t) d\mu_t(\beta_h, a_t, z^P_t, z^T_t, e_t) = P_{I,t+1}K_{t+1} + B_{t+1} \]

The labor market clears when labor demand from the three sectors equals labor supply from the final labor union

\[ L_{1,t} + L_{2,t} + L_{I,t} = L_t \]

Finally, the productive capital market clears when capital demand from the three sectors equals the amount of effective capital available that period

\[ K_{1,t} + K_{2,t} + K_{I,t} = K_t \]

### 3.4 Calibration and Steady State Results

In this section, I discuss my calibration strategy for the model to reproduce the expenditure responses to employment and the heterogeneity in production documented previously.

I set a period in the model to be a quarter.
Preferences. I set the intertemporal elasticity of substitution equal to 1 ($\gamma = 1$). I set $\rho$ equal to 0.53 to obtain an elasticity of substitution between time and goods in home-production of 2.13 as estimated by Aguiar and Hurst (2007) for all housework. The calibration of the remaining preference parameters ($\nu$, $\psi$, and the two discount factors $\beta_P$ and $\beta_I$) is discussed below.

Productivity and Employment Shocks. I calibrate the Markov process governing the permanent productivity shock to be a discrete approximation$^{23}$ to an autoregressive process of first order. I follow Guerrieri and Lorenzoni (2015) and set the persistence of the permanent productivity shock to 0.967 and its variance to 0.017 to match the evidence on the persistence and variance of the wage process as documented by Flodén and Lindé (2001). I also follow Guerrieri and Lorenzoni (2015) in setting the quarterly average transition probabilities from unemployment to employment and from employment to unemployment to 0.057 and 0.882, respectively to match aggregate labor market flows as estimated by Shimer (2005). The average unemployment rate in steady state is then 6%. I assume the job destruction rate by permanent productivity level adopts the following functional form

$$\delta_{ue} (z^P) = \delta_{ue} e^{\phi_{ue} (z^P - \tau^P)} C_k$$

where $C_k$ is a constant of integration for the weighted sum of the job destruction rate by productivity level to add up to the average job destruction rate. I set $\phi_{ue} = -0.395$, so that the ratio between the unemployment rates of the highest and lowest productivity types in steady state reproduces the ratio of unemployment rates between high-skilled workers (i.e., with bachelor’s degree or more) and low-skilled workers (i.e., less than a high school diploma) in the data. Figure 3.12 presents the fit of the calibrated function to unemployment rates by education level. Finally, I assume that the distribution of the transitory shock is a

---

$^{23}$I use the discretization method proposed by Rouwenhorst (1995) with eleven gridpoints.
discrete approximation\textsuperscript{24} to a normal variable with zero mean and quarterly variance of 0.19 to reproduce an annual variance of 0.05 as in Kaplan and Violante (2014).

**Technology.** I map the different goods in the economy into the three productive sectors in the model as follows. First, I drop exports and focus only on goods produced and consumed locally. Second, I divide government expenditure into military spending and non-military spending because their labor shares are significantly different (0.60 and 0.74, respectively). Third, I map investment and military spending into the investment good in the model because they have similar labor shares (0.60 and 0.62 respectively). Fourth, I compute the average labor share for the remaining goods (i.e., the fourteen categories of consumption studied in Section 3.2 and non-military government spending) and I allocate them to the labor-intensive or capital-intensive consumption goods in the model depending on whether their labor share is above or below the average. The resulting labor-intensive consumption good has a labor share of 0.70 and represents 48\% of GDP, whereas the capital-intensive consumption good has a labor share of 0.38 and represents 29\% of GDP. The investment good has a labor share of 0.61 and represents the remaining 23\% of GDP. The mapping is summarized in Table 3.3. I set the elasticity of substitution across intermediate goods, $\epsilon$, to 10 which in steady state yields a profit share on GDP of 10\% and a markup of 11\% as in Kaplan, Moll, and Violante (2016). The capital share for each of the production functions is then $\alpha_i = 1 - s_i \epsilon/(\epsilon - 1)$ where $s_i$ is the fraction of output that flows to workers. For the capital-intensive consumption good $\alpha_1 = 0.58$, for the labor-intensive consumption good $\alpha_2 = 0.23$, and for the investment good $\alpha_I = 0.32$. I normalize $A$ to 1. In the next section, I explore results for fixed prices, when the menu cost parameter $\theta \to \infty$.

**Labor Union.** I explore different values of the elasticity of labor supply, namely 0.1, 1, and 7. I pick $\epsilon_u$ to match the elasticity in the steady state. I calibrate $\alpha_u$ to be such that the average unemployment rate in steady state is 6\%, consistent with my calibration of the unemployment shock.

\textsuperscript{24}I use five gridpoints.
The model matches unemployment rates by skill level well
Data corresponds to the average of the monthly seasonally adjusted unemployment rates of workers aged 25 and older for different education levels between January 1992 and September 2016 as reported by the Bureau of Labor Statistics.
Less than HS refers to workers with less than a high school diploma. HS refers to high school graduates with no college. Some college refers to workers with some college or associate degree. College refers to workers with a bachelor’s degree and higher.
Model refers to the unemployment rate in steady state for each level of permanent productivity. Refer to the main text for the functional form of the job destruction probabilities by permanent productivity level and details on its calibration.
Table 3.3: Mapping Goods in the Data to Goods in the Model

<table>
<thead>
<tr>
<th>Good</th>
<th>Labor Share</th>
<th>Fraction of GDP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Capital-Intensive Consumption Good</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Housing</td>
<td>0.23</td>
<td>0.12</td>
</tr>
<tr>
<td>Communications</td>
<td>0.41</td>
<td>0.02</td>
</tr>
<tr>
<td>Utilities</td>
<td>0.42</td>
<td>0.02</td>
</tr>
<tr>
<td>Private Transportation</td>
<td>0.47</td>
<td>0.04</td>
</tr>
<tr>
<td>Food at Home</td>
<td>0.50</td>
<td>0.03</td>
</tr>
<tr>
<td>Recreation</td>
<td>0.54</td>
<td>0.05</td>
</tr>
<tr>
<td>Durables</td>
<td>0.56</td>
<td>0.01</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>0.38</td>
<td>0.29</td>
</tr>
<tr>
<td><strong>Labor-Intensive Consumption Good</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public Transportation</td>
<td>0.60</td>
<td>0.00</td>
</tr>
<tr>
<td>Other</td>
<td>0.61</td>
<td>0.11</td>
</tr>
<tr>
<td>Food Away from Home</td>
<td>0.64</td>
<td>0.04</td>
</tr>
<tr>
<td>Clothing</td>
<td>0.68</td>
<td>0.00</td>
</tr>
<tr>
<td>Health Care</td>
<td>0.72</td>
<td>0.12</td>
</tr>
<tr>
<td>Nondefense Government Spending</td>
<td>0.74</td>
<td>0.17</td>
</tr>
<tr>
<td>Domestic Services</td>
<td>0.75</td>
<td>0.02</td>
</tr>
<tr>
<td>Education</td>
<td>0.78</td>
<td>0.01</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>0.70</td>
<td>0.48</td>
</tr>
<tr>
<td><strong>Investment Good</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Defense Government Spending</td>
<td>0.60</td>
<td>0.05</td>
</tr>
<tr>
<td>Investment</td>
<td>0.62</td>
<td>0.18</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>0.61</td>
<td>0.23</td>
</tr>
</tbody>
</table>

The aggregation of goods in the data to feed into the model preserves heterogeneity.

The table shows the mapping from categories of goods in the data to the three goods in the model (i.e., capital-intensive consumption good, labor-intensive consumption good, and investment good). Refer to the main text for further details.

Labor share refers to the network-adjusted labor share as computed in Subsection 3.2.1.

Fraction of GDP refers to the expenditure on each good divided by GDP (excluding exports) in 2007.
**Government.** Consistent with the mapping in Table 3.3, I assume that the government does not purchase any of the capital-intensive consumption good in steady state \((G_1 = 0)\) and I set \(G_2\) and \(G_I\) so that they represent 5\% and 17\% of output, respectively. I follow Zubairy (2014) by setting the labor tax rate to 0.23 and calibrating the level of debt as a fraction of (annual) GDP to be 0.33. Following Shimer (2005) I set the unemployment insurance replacement rate to be 40\%. Finally, the lump sum tax adjusts to guarantee that the government’s budget constraint holds.

**Monetary Authority.** I follow Kaplan, Moll, and Violante (2016) and I set \(\psi_\pi = 1.25\).

**Financial Sector.** I set the depreciation rate of capital to 10\% annually in steady state as in Kaplan, Moll, and Violante (2016).

**Remaining Parameters.** I calibrate the remaining parameters of the model using the Method of Simulated Moments so that the model in steady state\(^{25}\) reproduces important moments of the data. I simultaneously search for the four parameters that minimize the distance between theoretical and empirical moments, but each parameter can be associated to one particular moment for ease of interpretation. I choose the discount factor of the patient households \(\beta_P\) to reproduce a ratio of capital to annual GDP of 2.31 as in Ríos-Rull and Santaèulàlia-Llopis (2010) which, added to the ratio of government debt to GDP of 0.33, yields a level of wealth to GDP of 2.64. I find \(\beta_P = 0.990\). The average share of household expenditure on the capital-intensive good, 0.48, identifies \(1 - \nu\), the share of the capital-intensive good in the utility function. I find \(1 - \nu = 0.479\), which is slightly lower than 0.48 to compensate for the greater share of the capital-intensive good on the bundle of unemployed households. Finally, the discount factor of the impatient households \(\beta_I\) and the share of the market good on home-production \(\psi\) are identified from the expenditure responses to employment of the different goods. I find that \(\beta_I = 0.976\) and \(\psi = 0.958\) match increases in expenditure upon employment of 4.7\% and 10.6\% for the capital and labor-intensive goods, respectively, as documented in Subsection 3.2.2.

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\(^{25}\)I simulate an economy with 50,000 households for 10,000 periods. The economy reaches steady state much earlier than that.
**Models without Heterogeneity.** To evaluate the effects of heterogeneity in consumption and production, I calibrate two alternative versions of the model where one or both channels are shut down. In Model B, I preserve heterogeneity in labor shares, but I shut down home-production by assuming that time does not factor into home-production, i.e., $\psi = 1$. In Model C, I also shut down heterogeneity in production by assuming that all three goods are produced with the same labor share, the average in the economy, 0.59. Both in Model B and C, I then calibrate the two discount factors and the share of the capital-intensive good in the utility function to match the ratio of capital to annual GDP (2.31), the average share of household expenditure on the capital-intensive good (0.48), and the average expenditure response to employment (0.06). The latter moment is twice as large as the average expenditure increase I documented in Subsection 3.2.2, because it is the weighted average of the expenditure changes in the labor and capital-intensive goods. I choose this target so that the comparison between the models is only about how households change the composition of their expenditure bundle upon employment, and not by how much they change total expenditure.

The model yields a wealth distribution with a significant share of hand-to-mouth households, consistent with empirical evidence\(^\text{26}\) (Figure 3.13). Both with and without heterogeneity, about 20% of the households have assets for less than their current quarterly earnings. The median household has savings for 1.6 years of earnings in the model with heterogeneity, and 1.4 in the model without. The model also delivers very rich households, with the household at the 95th percentile of the wealth to earnings distribution having savings for 35 years of earnings.

The model successfully reproduces the disproportionate increase in expenditure on labor-intensive goods upon employment. In the model without heterogeneity (Model C), the

\(^{26}\)Kaplan and Violante (2014) identify households as hand-to-mouth in the Survey of Consumer Finances if their level of liquid wealth is less than half of their earnings. Kaplan, Moll, and Violante (2016) document that 25% of the households are poor hand-to-mouth and an additional 20% are wealthy hand-to-mouth because they have positive illiquid assets, but very low liquid assets. My model abstracts from differences in the liquidity of assets.
The asset distribution is very similar in the models with and without heterogeneity.

Stationary distribution of assets as a fraction of household (annual) income in the models with and without heterogeneity. Model with heterogeneity refers to the model described in Section 3.3 and calibrated in Section 3.4. Model without heterogeneity (Model C) refers to the model without home-production (i.e., $\psi = 1$) and with the same labor share in the production of the three goods.

The y-axes has been truncated to facilitate visualization.

The stationary distribution is found after simulating the economy described in Section 3.3 for 50,000 households and 10,000 periods.
The model with heterogeneity reproduces the disproportionate increase in expenditure on labor-intensive goods upon employment.

The expenditure response is expressed as a percentage with respect to the expenditure level of the household when unemployed (i.e., 0.2 means that upon employment a previously unemployed household increases expenditure by 20%).

Expenditure responses computed from the household policy functions evaluated at the average level of permanent and transitory shock for an impatient type (i.e., household with relatively low discount factor).

Asset level expressed as fraction of annual GDP in each model to facilitate comparison.

Expenditure response upon employment is the same for both goods (Figure 3.14). But in the model with heterogeneity, the increase in expenditure is much larger for the labor-intensive good than for the capital-intensive good. Even for rich households, expenditure on the labor-intensive good rises significantly upon employment.

### 3.5 Implications for Fiscal Stimulus Programs

In this section, I present the implications for fiscal stimulus of the heterogeneity in consumption and production. First, I compute the fiscal multipliers associated to different fiscal policies and discuss the quantitative importance of targeting. Second, I argue that my re-
results can explain the difference in effectiveness of military and total expenditure found by the literature.

### 3.5.1 The Size of the Fiscal Multiplier and Implications for Fiscal Targeting

In this subsection, I explore how GDP responds on impact to a one-time fiscal stimulus program equivalent to 1% of annual GDP financed by lump sum taxes.

I consider four types of fiscal stimulus programs: government purchases of the three goods in the model and increments in unemployment insurance benefits. I focus on the fiscal multiplier on impact. For government purchases of good $i$, I define the fiscal multiplier as

$$\text{Fiscal Multiplier of } G_i = \frac{\Delta GDP}{P_i^* \Delta G_i}$$

where $P_i^*$ is the initial steady state price level of good $i$. For unemployment insurance, I define the multiplier as

$$\text{Fiscal Multiplier of UI} = \frac{\Delta GDP}{\Delta UI}$$

where $UI$ is the total amount of unemployment insurance payments.

In a model with no heterogeneity in production and consumption (Model C in Table 3.4), an increase in government purchases does not raise output significantly. Households cut back on expenditures to pay for the lump sum taxes that finance the fiscal stimulus program and so, employment and GDP barely change. When the labor supply is relatively inelastic (elasticity = 0.1), the GDP multiplier of any type of government purchases is 0.002. The multiplier rises to 0.003 when the labor supply is elastic, but drops to 0.000 when it is relatively elastic (elasticity=7).

In a model with heterogeneity in production and consumption (Model A in Table 3.4), the fiscal multiplier is significantly larger for government purchases of the labor-intensive
consumption good as compared to purchases of the capital-intensive consumption good. Government purchases of the labor-intensive good raise GDP by 20 cents on a dollar when the labor supply is relatively inelastic (elasticity = 0.1). Government purchases of the capital-intensive good reduce GDP by 46 cents as they bias the production bundle of the economy towards the capital-intensive sector, decreasing the demand for labor. As a consequence, employment and output drop in this case. Thus, a model without heterogeneity overestimates the fiscal multiplier on purchases of capital-intensive goods by 46 cents, but underestimates the multiplier of purchases on labor-intensive goods by 20 cents when the labor supply is inelastic.

The difference between the fiscal multiplier of capital and labor-intensive government purchases is 66 cents when the labor supply is relatively inelastic, it grows to 76 cents when the labor supply is unit-elastic, and drops to 0.30 when the elasticity of labor supply is 7. The latter is explained by a reduction in the size of fiscal multipliers as they exhibit a non-monotone relationship with the elasticity of labor supply. When the elasticity of labor supply is low, a greater elasticity means relatively more unemployed households get jobs and, because they tend to have relatively high marginal propensities to spend and their bundle gets redirected towards labor-intensive goods, the increase in labor demand is larger. But when the elasticity of labor demand is already large, a greater elasticity induces larger losses for the firms, which negatively affects all households equally because firm shares are equally distributed across households in the model.

Although the size of the fiscal multiplier is not monotone with respect to the elasticity of labor supply, the amplification mechanism induced by the positive correlation between expenditure responses to employment and labor shares is. The more elastic the labor supply, the greater the initial response of employment to the fiscal stimulus shock to labor demand (as opposed to higher wages), the more households will shift from unemployment to employment, and the greater will be the additional expansion of labor demand as more households redirect their expenditure bundles towards labor-intensive goods. I quantify this
amplification mechanism by comparing the fiscal multiplier in a model with heterogeneity in consumption and production (Model A in Table 3.4) with the fiscal multiplier in a model that only has heterogeneity in production (Model B in Table 3.4) and where home-production is shut down. The amplification mechanism increases the multiplier of government purchases of the labor-intensive good by 1% when the elasticity of labor supply is 0.1, by 5% when the labor supply is unit-elastic, and by 14% when the elasticity of labor supply is 7.

Unemployment insurance does not have large effects in my model. Despite the fact that unemployed households tend to be poor and so, are more likely to be hand-to-mouth, an increase in unemployment insurance benefits does not have large effects because there is relatively few of them and, as a fraction of total expenditures, they represent an even smaller share. Additionally, in the model with heterogeneity in both consumption and production (Model A in Table 3.4), their expenditure bundle is biased towards capital-intensive goods.

That fiscal stimulus should target labor-intensive sectors has long been conventional wisdom among policymakers, but my exercise offers a quantitative evaluation of the effectiveness of different policies. In their review of the state of the literature on fiscal multipliers, Batini et al. (2014) report that government investment and government consumption in the U.S. have multipliers of 0.6 and 0.35, respectively. But the different size of those multipliers emerges from investment having positive supply side effects, rather than by acknowledging their different labor intensities.

### 3.5.2 Implications for the Empirical Assessment of Fiscal Multipliers

My results in the previous subsection suggest that it matters what the government is purchasing and not just how much it is purchasing. In this subsection, I document that indeed

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27 For instance, Goolsbee and Krueger (2015) discuss how the high capital intensity of the auto industry was taken into account by the Obama administration when considering bailouts for General Motors and Chrysler in 2009.

28 Those multipliers are restated from Coenen et al. (2012).
**Table 3.4: Fiscal Multipliers in the Model: Tax-Financed Fiscal Stimulus**

<table>
<thead>
<tr>
<th>Policy</th>
<th>(A)</th>
<th>(B)</th>
<th>(C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inelastic Labor Supply (Elasticity = 0.1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor-Intensive Consumption Good</td>
<td>0.202</td>
<td>0.200</td>
<td>0.002</td>
</tr>
<tr>
<td>Investment Good</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>Capital-Intensive Consumption Good</td>
<td>-0.459</td>
<td>-0.456</td>
<td>0.002</td>
</tr>
<tr>
<td>Unemployment Insurance</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Unit-elastic Labor Supply (Elasticity = 1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor-Intensive Consumption Good</td>
<td>0.230</td>
<td>0.219</td>
<td>0.003</td>
</tr>
<tr>
<td>Investment Good</td>
<td>0.012</td>
<td>0.011</td>
<td>0.003</td>
</tr>
<tr>
<td>Capital-Intensive Consumption Good</td>
<td>-0.530</td>
<td>0.525</td>
<td>0.003</td>
</tr>
<tr>
<td>Unemployment Insurance</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Elastic Labor Supply (Elasticity = 7)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor-Intensive Consumption Good</td>
<td>0.091</td>
<td>0.080</td>
<td>0.000</td>
</tr>
<tr>
<td>Investment Good</td>
<td>-0.069</td>
<td>-0.062</td>
<td>0.000</td>
</tr>
<tr>
<td>Capital-Intensive Consumption Good</td>
<td>-0.206</td>
<td>-0.187</td>
<td>0.000</td>
</tr>
<tr>
<td>Unemployment Insurance</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

**Heterogeneity in consumption and production has a large impact on the size of the fiscal multiplier**

Figures in the table correspond to the GDP multiplier on impact of a one-time fiscal stimulus policy financed with a lump sum tax. For government purchases of good $i$, the multiplier is $\frac{\Delta GDP}{P_1^* \Delta G_i}$ where $P_1^*$ is the initial steady state price level of good $i$. For unemployment insurance, the multiplier is $\frac{\Delta GDP}{\Delta UI}$ where $UI$ is the total unemployment insurance benefits. Column (A) refers to the model with heterogeneity in consumption and production described in Section 3.3 and calibrated in Section 3.4. Column (B) refers to a model with heterogeneity in labor shares, but no home-production (i.e., $\psi = 1$). Column (C) refers to a version of the model with the same labor shares in production of the three goods and no home-production.
The fiscal multiplier estimated for defense spending is lower than the multiplier for total spending. The histograms show the frequency with which different values of fiscal multipliers have been estimated in the last twenty years depending on whether the identification strategy exploited variation in defense spending (left-hand side histogram) or in total spending (right-hand side figure). Further details on the methodology for reviewing the literature and collecting these multipliers are presented in Appendix C.5.

The empirical literature has found smaller multipliers for military spending, which is more capital-intensive.

The literature has empirically estimated the size of the fiscal multiplier using two alternative approaches on aggregate data. On the one hand, some work has measured the fiscal multiplier using structural vector autoregression (VAR) techniques on total government expenditure. In this strand of literature, identification is usually attained by assuming that government spending cannot respond to output shocks immediately, but that it lags for a quarter or a year (Blanchard and Perotti, 2002; Perotti, 2005). On the other hand, military spending has been used instead of total government spending because it is less likely to respond to output (Hall, 2009; Barro and Redlick, 2011) or by exploiting unanticipated war news in an event study approach (Ramey and Shapiro, 1998; Ramey, 2011).
The labor share of defense spending is and has been significantly lower than the share of nondefense spending. Network-adjusted compensation share is equal to the network-adjusted labor share without the adjustment for self-employment described in Appendix C.2 because of data limitations. Also because of data limitations, the total requirements matrix is used instead of the domestic requirements matrix, and the use and make matrices are before-redefinitions, but still at producer prices. The vertical lines represent the dates of two major changes in methodology: 1987 and 1997.
The fiscal multiplier estimated for military spending is lower than the multiplier estimated for total spending. In Figure 3.15, I compile all the estimates of fiscal multipliers published in the top 30 economic journals in the last 20 years. Appendix C.5 provides details on the construction of the histogram. The average fiscal multiplier for military spending is 0.55, whereas it is 0.67 for total spending.

Military spending is more capital-intensive than nondefense spending. In 2007, while the network-adjusted labor share for military spending was 0.60, it was 0.74 for nondefense spending. Figure 3.16 confirms that military spending has been significantly more capital-intensive over the last four decades.29

The difference in effectiveness between military and nondefense spending can be explained in the context of my model.30 The fiscal multiplier associated to government purchases of goods with labor-intensity similar to defense spending is 0.01 when the labor supply is unit-elastic. The remaining government purchases are very labor-intensive and so, have a fiscal multiplier of around 0.22. As a back-of-the-envelope calculation,31 since military expenditures represent a fifth of government expenditures, the average multiplier of a dollar spent keeping that proportion is 0.18, seventeen cents higher than the multiplier for defense and roughly in line with the difference found in the empirical literature.

3.6 Conclusion

In this chapter, I have documented significant heterogeneity in consumption and production. I have shown that the labor share of final consumption aggregates such as Personal Consumer Expenditures hides a great deal of heterogeneity. The production of some goods is very capital-intensive (e.g., housing, communications, utilities), while for others is very labor-

29The figure shows the network-adjusted labor share but without the adjustments for imports and self-employment because of data limitations for the period before 1997.
30This point is also made by Baqee (2015), but without quantification and excluding heterogeneity in consumption.
31It is only a rough approximation because changes in defense and nondefense expenditure exploited in empirical work do not need to be correlated.
intensive (e.g., education, domestic services, health care). Using the Consumer Expenditure Survey, I have also shown that upon unemployment household disproportionately cut back expenditures on labor-intensive goods.

In the context of a heterogeneous agent New-Keynesian model that matches this heterogeneity in consumption and production, I find that it matters a great deal for fiscal stimulus. From the point of view of fiscal targeting, I find that government purchases of the labor-intensive consumption good are more than 70 cents more effective at raising GDP than purchases of the capital-intensive good when the elasticity of labor supply is 1. From the point of view of empirical assessment, I find that the difference in multipliers of defense and total government spending found by the literature can be explained quantitatively by my model.
Appendix A

Appendix to Chapter 1

A.1 Annual Transitory Shock

In this appendix, I explore the implications of an annual transitory shock, instead of the quarterly shock employed in the main body of Chapter 1. I show that the credit crunch still leads to a more severe drop in consumption in the hard constraint economy than in the soft constraint one.

The model I have used in Chapter 1 is at a quarterly frequency, however data on earnings is available only at the annual level. Estimations of the earnings process have typically used individual longitudinal data on annual labor income or wages as found in the Panel Study of Income Dynamics (Flodén and Lindé, 2001; Guvenen, 2009) or, more recently, using U.S. administrative records (Guvenen et al., 2015). And so, no information is available regarding the nature of the transitory shock at higher frequencies than a year. Guerrieri and Lorenzoni (2015) opt to introduce transitory risk at the quarterly level through an unemployment shock. In the main body of Chapter 1, I assumed households draw a new transitory shock every quarter with the variance of this quarterly shock chosen to match, when aggregated, the variance of the annual transitory shock as in Kaplan and Violante (2010). Telyukova (2013) follows a similar approach when calibrating the income process at the monthly level. In this
Consumption decisions are very similar regardless of the frequency of the transitory shock. Quarterly consumption level as a function of the assets held by an agent of age 29 and 62 (15 and 150 in the model) with average earnings history, average permanent shock, average individual fixed effect, and average transitory shock. Consumption and assets are expressed in thousands of U.S. dollars. Annual corresponds to the annual specification for the transitory shock as described in this appendix. Quarterly refers to the quarterly transitory shock employed in the main body of Chapter 1.

appendix, I explore an annual specification for the transitory shock, which delivers the same variance at the annual frequency, but has very different implications for risk insurance.

I modify the baseline model described in Section 1.2 only in what respects to the transitory shock, $\epsilon_{i,t}$. I assume households now find out about the new realization of the transitory shock at the beginning of the calendar year and that realization lasts for four quarters.\(^1\) I set the variance of this annual transitory shock to 0.05 as in Kaplan and Violante (2010). And I recalibrate the discount factor and the borrowing parameters to match debt and wealth to GDP ratios.

\(^1\)I achieved this with a time-varying transition matrix for the Markov process, which implies an i.i.d. shock in quarters 1, 5, 9, ... and full persistence otherwise.
Figure A.2: Assets and Debt Distribution during Working Life

Assets and debt distributions are very similar regardless of the frequency of the transitory shock.
Assets and debt are in thousands of U.S. dollars. The axis have been truncated to facilitate visualization.
Annual corresponds to the annual specification for the transitory shock as described in this appendix. Quarterly refers to the quarterly transitory shock employed in the main body of Chapter 1.
Figures A.1 and A.2 show that, after recalibrating the models, the frequency of the transitory shock does not produce major differences in the consumption policy functions, nor in the distribution of assets. The only noticeable difference in Figure A.1 is that in the soft constraint economy the Natural Borrowing Limit is greater in the case of annual shocks because the smallest value is not as small as the smallest value in the quarterly specification, which allows young workers to borrow more. In Figure A.2, the main difference between transitory shock specifications is in the debt distribution for the hard constraint economy where a lower calibrated borrowing limit produces a greater spike. However, the debt distributions even for that model look very similar below $15,000. The life-cycle patterns for mean consumption and insurance coefficients\(^2\) are also very similar across specifications (not shown).

Finally, I recalibrate the borrowing parameters in each economy to reproduce the credit crunch exercise. I find that the consumption response to a credit crunch (Figure A.3) is stronger in the hard constraint economy, but milder in the soft constraint when the transitory shock is annual rather than quarterly. So, the difference between the hard constraint and soft constraint is even magnified with respect to the results reported in the main body of Chapter 1.

### A.2 Hard Constraint as a Fraction of the Natural Borrowing Limit

In this appendix, I show that my results are robust to modeling the hard constraint as a fraction of the natural borrowing limit, rather than a constant amount over the life-cycle.

\(^2\)The insurance coefficient for the transitory shock exhibits a bumpier evolution in the quarterly specification, being lower in the quarters where the new realization arrives but jumping up to 1 in the following quarters as the household smooths consumption. Nevertheless, this bumpier behavior oscillates around the insurance coefficient in the quarterly specification.
Figure A.3: Unexpected Credit Crunch for Annual and Quarterly Transitory Shocks

Panel A. Hard Constraint

The credit crunch is much less severe in the soft constraint economy
Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Percentages are with respect to the initial steady state levels.
Annual corresponds to the annual specification for the transitory shock as described in this appendix. Quarterly refers to the quarterly transitory shock employed in the main body of Chapter 1.
In the main body of Chapter 1, I modeled the hard constraint as a limit on the amount households could borrow that was given exogenously and did not depend on household characteristics, i.e., $\bar{\phi}$. In that setting, households were able to borrow up to the minimum between the exogenous limit $\bar{\phi}$ and their natural borrowing limit $NBL_t$:

$$\bar{A}_t = \min \{ \bar{\phi}, NBL_t \}$$

In this appendix, I instead model the maximum amount that households can borrow as a fraction of their natural borrowing limits.

$$\bar{A}_t = \bar{\phi}_{NBL} NBL_t$$

where $\bar{\phi}_{NBL}$ is a number between 0 and 1. The smaller $\bar{\phi}_{NBL}$, the tighter the borrowing constraint because households can borrow up to a lower fraction of their natural borrowing limit.

As before, I recalibrate the discount factor and borrowing limit to match the wealth and debt to GDP ratios. I find that, under this new parametrization of the hard constraint, $\beta = 0.9874$ (equivalent to an annual discount factor of 0.9506) and $\bar{\phi}_{NBL} = 0.2215$.

Both in terms of life-cycle averages and distributions, the resulting model does not differ substantially from the baseline specification of the hard constraint discussed in the main body of the Chapter 1. Figure A.4 shows that the hard constraint does a slightly better job at matching the debt to income ratio early in life, but it overestimates the amount of debt later. On the other hand, the debt distribution is matched better by this new version of the hard constraint (Figure A.5) as there is not a single borrowing limit inducing a mass point. However, the soft constraint model still yields a better match to the distribution of both assets and debt. The Jensen-Shannon divergence between the model-derived debt distribution and its empirical counterpart is 0.1500 in the hard constraint economy.
Both models predict a similar pattern for the ratios of wealth and debt to income, overstating the amount of debt early in life and understating it in middle age. Debt to income is the ratio of the absolute value of aggregate negative assets to aggregate annual income. Gross wealth to income is the ratio of aggregate positive assets to aggregate annual income.


than the 0.1556 in the baseline model, but still much greater than the 0.0718 in the soft constraint economy.

The two versions of the hard constraint produce very similar results in the initial steady state because in this model the main driver for borrowing is consumption smoothing early in life, when income is very low and is expected to grow significantly. As most of the debt is contracted in that period of life, rather than being distributed more smoothly over the lifetime, there is not much difference on effective borrowing limits in the cross-section for agents willing to borrow heavily, because most young agents will have fairly similar natural borrowing limits. Then, a hard constraint expressed as a constant amount is not too different from one expressed as a fraction of the natural borrowing limit.

Finally, the milder response of consumption to a credit crunch in the soft constraint with respect to the hard constraint still holds for the new specification of the hard constraint. As
The soft constraint model produces assets and debt distributions closer to the data.

Assets and debt are in thousands of U.S. dollars. The axis have been truncated to facilitate visualization.


before, I calibrate the tighter borrowing limit to obtain of drop of 55.56% in debt to income in the new steady state. The new value of the borrowing parameter is $\bar{\phi}_{NBL} = 0.1308$, a contraction of 41.0%, very close to the 41.7% found for the baseline specification of the hard constraint. Figure A.6 shows that when adjustment to the credit crunch is required to be immediate, the consumption drop is three times greater in the hard constraint. And when the adjustment is allowed to extend for six periods (Figure A.7), the consumption drop in the hard constraint is twice the response in the soft constraint model.
Consumption and debt decrease in both economies after the credit crunch, but in the hard constraint economy the drop is much more severe.


Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy.

A.3 Soft Constraint with an Interest Rate Increasing in Debt

In this appendix, I show that my results are robust to modeling the soft constraint as a strictly increasing function on the level of debt, rather than a constant spread.

In particular, I assume that the interest rate is given by:

\[ R(A) = \begin{cases} 
R_f & \text{if } A \geq 0 \\
R_f + \phi(A) & \text{if } A < 0 
\end{cases} \]

where:

\[ \phi(A) = \phi_1 + \left( -\frac{A}{A_{max}} \right)^{\phi_2} \]
Consumption and debt decrease in both economies after the credit crunch, but in the hard constraint economy the drop is much more severe.
Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Borrowing parameters are assumed to adjust linearly over six quarters. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy.

I use $A_{max}$ to normalize the amount of debt. By setting it equal to $300,000$, the ratio $\frac{A}{A_{max}}$ will be positive but lower than 1 for the relevant debt levels.$^3$ $\phi_1$ allows for the existence of a discontinuity in the interest rate when the household becomes a debtor. If $\phi_2$ is greater than 1, the borrowing cost will be increasing and convex on the amount of debt. Figure A.8 shows the borrowing interest rate for different values of the parameters used in the credit crunch exercises in this appendix.

To keep the calibration approach as close as possible to the one in the main text, I start by assuming that in the initial steady state $\phi_1 = 0$. The borrowing cost function is then parametrized only by $\phi_2$. As before, I use the Method of Simulated Moments to match the ratios of debt and wealth to GDP with the discount factor, $\beta$, and the borrowing parameter,

---

$^3$The maximum natural borrowing limit is around 150,000.
The functional form chosen to model a convex borrowing cost allows alternative definitions of a credit crunch. Debt is in thousands of U.S. dollars. Interest rate is reported in annual levels. Initial SS corresponds to borrowing parameters $\phi_1 = 0$ and $\phi_2 = 1.9978$. Credit Crunch via $\phi_1$ corresponds to borrowing parameters $\phi_1 = 0.0083$ and $\phi_2 = 1.9978$. Credit Crunch via $\phi_2$ corresponds to borrowing parameters $\phi_1 = 0$ and $\phi_2 = 1.4967$. In this case $\phi_2$, I obtain $\beta = 0.9874$ (equivalent to an annual discount factor of 0.9507) and a borrowing parameter of $\phi_2 = 1.9978$, which implies an annual borrowing interest rate of 5.9% for a debt of $20,000 and a rate of 16.0% for a debt of $50,000.

The use of a strictly convex borrowing cost makes the soft constraint economy more similar to the hard constraint one. Figure A.9 shows that both models have now almost identical predictions in terms of average debt and wealth accumulation during the life-cycle. The cross-sectional distribution of debt and assets (Figure A.10) is also now very similar between the two models, although the soft constraint does not exhibit a mass point. The Jensen-Shannon divergence between the model-derived debt distribution and its empirical
The soft constraint economy with a convex borrowing cost predicts very similar life-cycle patterns of asset accumulation to the hard constraint economy. Debt to income is the ratio of the absolute value of aggregate negative assets to aggregate annual income. Gross wealth to income is the ratio of aggregate positive assets to aggregate annual income.


counterpart in the soft constraint economy is now 0.1087, greater than the baseline model, but still better than the 0.1556 divergence in the hard constraint economy.

Next, I consider two versions of a credit crunch in this soft constraint environment. A credit crunch can take place either through an increase in $\phi_1$, a shock that hits every borrower by the same magnitude, or through a decrease in $\phi_2$, a shock that hits more severely highly indebted borrowers. I separately recalibrate each of these borrowing parameters to obtain a reduction of 55.56% in the debt to income ratio in the new steady state. I find that such deleverage in the long run can be attained by an increase in $\phi_1$ from 0 to 0.0083, while keeping constant the convexity of the borrowing cost function. In this setting, the annual borrowing rate of a $20,000 debt would be 9.4%, whereas it would be 19.8% for a debt of $50,000. Alternatively, the deleverage can be induced by a decrease in $\phi_2$ to 1.4967 while keeping $\phi_1$ equal to zero. Here, the annual borrowing rate of a $20,000 debt would be 15.0%,
The soft constraint economy with a convex borrowing cost predicts very similar assets and debt distributions to the hard constraint economy. Assets and debt are in thousands of U.S. dollars. The axis have been truncated to facilitate visualization.


whereas it would be 39.4% for a debt of $50,000. As before, I study both the consequences of an immediate adjustment shock and of a gradual shock where the new borrowing parameters adjust linearly over six quarters.

Figures A.11 to A.12 show that the response to a credit crunch is still significantly milder in the soft constraint economy regardless if the credit crunch affected all the borrowers in a similar fashion (via $\phi_1$) or hit disproportionately the heavily indebted (via $\phi_2$). The aggregate consumption response appears only slightly lower for the former case. The mild response of consumption to a credit crunch operating through interest rates is then robust to the specification of the borrowing spread.
Consumption decreases more severely in the hard constraint economy.

Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy.
Consumption decreases more severely in the hard constraint economy.
Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Borrowing parameters are assumed to adjust linearly over six quarters. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy.
Consumption decreases more severely in the hard constraint economy.


Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy.
Consumption decreases more severely in the hard constraint economy.


Aggregate consumption and debt to income responses in each economy after an unexpected tightening of the credit conditions that decreases the debt to income ratio in the new steady state by 55.56%. Borrowing parameters are assumed to adjust linearly over six quarters. Percentages are with respect to the initial steady state levels. The x-axis measures the number of quarters after the credit crunch hits the economy.
Appendix B

Appendix to Chapter 2

B.1 Pretrends in Observables

My identification strategy rests on the assumption of conditional parallel trends, an assumption that is untestable by definition. In Section 2.5 I showed that the lack of pretrends assumption seems to hold. To further the case, in this appendix, I show that treatment and control groups do not exhibit different trends in observable variables measuring economic conditions before minimum wage changes.

To assess the existence of pretrends on observables, I regress them on twelve leads of the minimum wage:

$$
\log(Y_{c,t}) = \kappa_c + \tau_t + \gamma + \sum_{j=-12}^{0} \beta_j \log(Minimum \text{ Wage}_{s,t+j}) + \epsilon_{c,t}
$$

where $Y_{c,t}$ is employment, house prices, current gross state product, and regional price deflator,\(^1\) $\gamma$ is a constant, $\kappa_c$ is a county fixed effect, $\tau_t$ is a time fixed effect, and

\(^1\)The regional price deflator is a recent measure of local inflation produced by the Bureau of Economic Analysis. It has been released only for the period 2008-2012. I have not included it in my baseline model because of its limited sample period and because GDP at the state level is measured in nominal terms and so, it already includes inflation. But I include it in this exercise to show that the lack of differential pretrends between treatment and control applies both to inflation and economic activity.
Minimum Wage_{s,t+j} is the minimum wage in state \( s \) and period \( t + j \). In this case, I choose to regress on levels and not on changes of the minimum wage because the interpretation of cumulative response does not make sense for these variables.

Figure B.1 shows that economic conditions were not changing in a systematically different fashion prior to the minimum wage hike for treatment and control counties.

### B.2 Use of Weights

In this appendix, I show that the strong expenditure response to the minimum wage is not limited to a small set of highly-populated counties, which receive more weight in my baseline estimation strategy. On the contrary, in this appendix I find that when counties are not weighted by their population, the estimates of the expenditure response are even higher, consistent with the fact that less populated counties tend to be less productive and so, more affected by the minimum wage.

Table B.1 shows that without weighting counties by their population yields expenditure elasticities that are greater to those shown in Table 2.2. In my preferred specification, Model (3), a 10% increment in the minimum wage induces a 1.8% growth in nominal sales and a 1.4% growth in real sales, versus the 1.1% and 0.7% growth rates predicted when the estimation uses weights. The difference is sizable from the economic point of view, but not statistically significant. However, since the goal of the chapter is to obtain an estimate of the aggregate consumption response, I choose to weight counties by population.

To complete the analysis, in Figure B.2 I show the expenditure response by bindingness of the minimum wage without using weights. As before, I find that the minimum wage has a larger impact on counties with relatively low average wages, where the policy binds more. In comparison with Figure 2.6, the point estimates are not very different but the size of the confidence intervals is now almost constant across county groups.
Observables do not exhibit pretrends
95% Confidence Intervals included. Standard errors clustered at state level.
\( \beta_j \) is the elasticity of the observable variable to the level of the minimum wage within \( j \) quarters.
County and time fixed effects are included.
Effective sample period for employment, gross state product, and house prices is 2006-2012.
Effective sample period for regional deflator is 2008-2012.
Table B.1: Use of Weights

<table>
<thead>
<tr>
<th></th>
<th>Nominal Sales (1)</th>
<th>Nominal Sales (2)</th>
<th>Nominal Sales (3)</th>
<th>Real Sales (1)</th>
<th>Real Sales (2)</th>
<th>Real Sales (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Minimum Wage</td>
<td>0.259***</td>
<td>0.268***</td>
<td>0.184***</td>
<td>0.215**</td>
<td>0.223***</td>
<td>0.140**</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.065)</td>
<td>(0.055)</td>
<td>(0.080)</td>
<td>(0.069)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Employment</td>
<td>0.447***</td>
<td>0.374***</td>
<td>0.446***</td>
<td>0.373***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>(0.070)</td>
<td>(0.082)</td>
<td>(0.073)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>−0.507***</td>
<td>−0.433***</td>
<td>−0.490***</td>
<td>−0.417***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.096)</td>
<td>(0.100)</td>
<td>(0.105)</td>
<td>(0.107)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GSP</td>
<td>0.043</td>
<td>0.043</td>
<td>0.052</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.213)</td>
<td>(0.185)</td>
<td>(0.185)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>House Prices</td>
<td>0.233***</td>
<td>0.228***</td>
<td>0.228***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.065)</td>
<td>(0.065)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>80,136</td>
<td>80,136</td>
<td>80,136</td>
<td>80,136</td>
<td>80,136</td>
<td>80,136</td>
</tr>
<tr>
<td>Counties</td>
<td>2,226</td>
<td>2,226</td>
<td>2,226</td>
<td>2,226</td>
<td>2,226</td>
<td>2,226</td>
</tr>
</tbody>
</table>

The estimated expenditure response is larger when the observations are not weighted by population.

*\( p < 0.1 \), **\( p < 0.05 \), ***\( p < 0.01 \). Standard errors (in parenthesis) clustered at state level. Counties are not weighted by population.

Time and county fixed effects are included in every specification.
The expenditure response is stronger in counties where the minimum wage binds more. 95% Confidence Intervals shown. Standard errors clustered at state level. Counties are not weighted by population. \( \beta_n \) is the elasticity of sales to the minimum wage when the sample is limited to those counties that in 2005 belonged to the \( n^{th} \) quartile of the Average Wage to Minimum Wage distribution. The minimum wage binds more in counties in the lowest quartiles. Both specifications include county and time fixed effects. Specification (3) also controls for employment, population, gross state product, and house prices.
B.3 Indexing States

In this appendix, I show that my results are not driven by states indexing their minimum wage rates.

As discussed in Section 2.2, eleven states were indexing the minimum wage to the cost of living at some point during my sample period. For ten out of these eleven states the adjustment follows the federal level of inflation and so, it is more likely to be exogenous to local economic conditions. However, if this automatic adjustment of the minimum wage rate induces structural changes in the state economy that make it more responsive to the policy (for instance it could be that, as a consequence of the indexing, the federal rate of inflation becomes more widely used for wage negotiation in the state, and so federal inflation leads to a higher minimum wage rate in the state, but also to higher wages in general), my estimate would overstate the effect of a minimum wage increment. In addition, the changes in the minimum wage in these states are very likely to be anticipated by workers and firms. To explore this concern, I repeat my regressions separately for indexing and non-indexing states. The exercise is similar to the one performed in Table 5 in Allegretto, Dube, and Reich (2011).

The expenditure response is fairly similar for indexing and non-indexing states as shown in Table B.2. A 10% minimum wage hike increases nominal sales by 1.2% in the indexing states and by 0.9% in the rest of the country in my preferred specification. Real sales also have a point estimate slightly greater for indexing states. The differences are not statistically significant.

B.4 Housing Bubble

In this appendix, I show that excluding the counties that were most severely affected by the bust of the housing bubble does not affect my results.
Table B.2: Indexing vs. Non-Indexing States

<table>
<thead>
<tr>
<th></th>
<th>Indexing States</th>
<th></th>
<th></th>
<th>Non-Indexing States</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Nominal Sales</td>
<td>0.081</td>
<td>0.124**</td>
<td>0.118**</td>
<td>0.174*</td>
<td>0.200***</td>
<td>0.090*</td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td>(0.050)</td>
<td>(0.037)</td>
<td>(0.092)</td>
<td>(0.065)</td>
<td>(0.050)</td>
</tr>
<tr>
<td>Real Sales</td>
<td>0.038</td>
<td>0.078</td>
<td>0.072*</td>
<td>0.130</td>
<td>0.150***</td>
<td>0.055</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.048)</td>
<td>(0.038)</td>
<td>(0.079)</td>
<td>(0.055)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Population</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>GSP</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>House Prices</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>13,968</td>
<td>13,968</td>
<td>13,968</td>
<td>66,168</td>
<td>66,168</td>
<td>66,168</td>
</tr>
<tr>
<td>Counties</td>
<td>388</td>
<td>388</td>
<td>388</td>
<td>1,838</td>
<td>1,838</td>
<td>1,838</td>
</tr>
</tbody>
</table>

Results are not driven by states indexing their minimum wage rates

"Indexing States" refers to Arizona, Colorado, Florida, Missouri, Montana, Nevada, New Jersey, Ohio, Oregon, Vermont, and Washington because at some point during the sample period, they have indexed their minimum wage rates. All remaining states are referred to as "Non-Indexing States".

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors (in parenthesis) clustered at state level.

Time and county fixed effects are included in every specification.
If the severity of the recession that followed the bust of the housing bubble was correlated
with changes to the minimum wage beyond what is captured by the control of house prices,
my identification strategy could yield biased estimates. To explore this possibility I drop the
quarter of counties that experienced the most severe drops in house prices between the first
quarter of 2006 and the first quarter of 2008. Table B.3 presents the results for this smaller
sample.

I find that my results are not driven by the housing bubble or its consequences. The
expenditure responses in Table B.3 are not statistically different from those in my baseline
model, Table 2.2. If anything, the point estimates are higher in my preferred specification,
Model (3), when the sample is restricted to counties relatively less affected by the bust of
the bubble.

B.5 Estimating the Additional Labor Income after a
Minimum Wage Hike

In this appendix I discuss in detail the methodology I employ to obtain my estimates of
additional labor income after a minimum wage hike as shown in Table 2.9.

First, I estimate the effects of the minimum wage across the distribution of household
labor income following Autor, Manning, and Smith (2016). As discussed in the main text, us-
ing CPS data aggregated at the state level, I estimate the following model for each percentile
p in the labor income distribution:

\[ y_{s,t}(p) - y_{s,t}(50) = \beta_1(p) \left[ y_{s,t}^m - y_{s,t}(50) \right] + \beta_2(p) \left[ y_{s,t}^m - y_{s,t}(50) \right]^2 + \]
\[ + \kappa_s(p) + \gamma_s(p) I_s + \tau_t(p) + \epsilon_{s,t}(p) \]
Table B.3: Results excluding Counties most exposed to the Housing Bubble

<table>
<thead>
<tr>
<th></th>
<th>Nominal Sales</th>
<th></th>
<th>Real Sales</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)   (2)     (3)</td>
<td>(1)    (2)     (3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum Wage</td>
<td>0.142** (0.065)</td>
<td>0.174*** (0.056)</td>
<td>0.146*** (0.047)</td>
<td>0.142** (0.069)</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Population</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>GSP</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>House Prices</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Observations</td>
<td>60,444</td>
<td>60,444</td>
<td>60,444</td>
<td>60,444</td>
</tr>
<tr>
<td>Counties</td>
<td>1,679</td>
<td>1,679</td>
<td>1,679</td>
<td>1,679</td>
</tr>
</tbody>
</table>

Results are not driven by the housing bubble
The 25% of counties that experienced the most severe drops in house prices between 1Q2006 and 1Q2008 are excluded from the sample.

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors (in parenthesis) clustered at state level. Time and county fixed effects are included in every specification.
The estimation by the Generalized Method of Moments yields a vector of coefficients 
\( \hat{\beta}' = (\hat{\beta}_1(1), \hat{\beta}_2(1), ..., \hat{\beta}_1(p), \hat{\beta}_2(p), ..., \hat{\beta}_1(99), \hat{\beta}_2(99)) \). Let the associated variance-covariance matrix be denoted by \( \hat{V}_\beta \).

Evaluating the log difference of the minimum wage and the median income at its weighted average across states and years, \( \bar{y}^m - \bar{y}(50) \), the elasticity of household labor income in percentile \( p \) to the minimum wage is given by:

\[
\hat{\eta}(p) = \hat{\beta}_1(p) + 2\hat{\beta}_2(p) [\bar{y}^m - \bar{y}(50)]
\]

And, using the Delta method, the variance-covariance matrix of the elasticity estimates is:

\[
\hat{V}_\eta = H' \hat{V}_\beta H
\]

where \( H \) is the Jacobian matrix of the linear transformation used to compute elasticities, a matrix of dimension 198x99\(^2 \) given by:

\[
H = \begin{pmatrix}
1 & 0 & ... & 0 \\
2 [\bar{y}^m - \bar{y}(50)] & 0 & ... & 0 \\
0 & 1 & ... & 0 \\
0 & 2 [\bar{y}^m - \bar{y}(50)] & ... & 0 \\
: & : & : & : \\
0 & 0 & ... & 1 \\
0 & 0 & ... & 2 [\bar{y}^m - \bar{y}(50)]
\end{pmatrix}
\]

Combining the elasticity of labor income for each percentile with the income distribution of working households in 2014 in the country, \( y' = (y(1), ..., y(p), ..., y(99)) \), the additional

\(^2\)There are two estimates, \( \hat{\beta}_1 \) and \( \hat{\beta}_2 \), for each of the 99 percentiles.
labor income for CPS households (measured in dollars) induced by a $\Delta$ percent change in
the minimum wage is:

$$\hat{S} = \hat{y}' \hat{\eta} \Delta$$

Again, the Delta method allows the computation of the variance of this statistic:

$$\hat{V}_S = \hat{y}' \hat{V}_\eta \hat{y} \Delta^2$$

Finally, I scale up the estimates by a factor $\kappa$, the ratio of Compensation of Employees\(^3\)
in the national accounts to the total amount of labor income as measured in the CPS, to
match the aggregate labor income in the country. The additional labor income generated by
a $\Delta$ percent change in the minimum wage is:

$$\hat{S}^F = \hat{y}' \hat{\eta} \Delta \kappa$$

and its variance is:

$$\hat{V}_{S^F} = \hat{y}' \hat{V}_\eta \hat{y} \Delta^2 \kappa^2$$

\(^3\)Table 6.2D. Compensation of Employees by Industry from NIPA.
Appendix C

Appendix to Chapter 3

C.1 Methodological Approach to PCE Data

In this appendix, I discuss my approach to the data in the national accounts for Personal Consumer Expenditures.

I connect data on the production of commodities to its different uses by final consumers using the Personal Consumer Expenditures (henceforth PCE) Bridge. Table C.1 summarizes the mapping from categories of expenditure in the PCE to the ones defined for this project. I include Final consumption expenditures of nonprofit institutions serving households (NPISHs) as part of government expenses, rather than PCE.

As part of the robustness checks, I exclude “imputed rental of owner-occupied housing” and “rental value of farm dwellings” from PCE, from GDP, and from the output of the real estate industry. The exercise introduces an asymmetry in the production of housing services as houses then add value to the economy if they are rented, but not if they are occupied by their owners. Furthermore, if upon employment, a household were to buy a house and stop renting, excluding rental equivalence of the house owned would suggest that the household is now spending less on housing, whereas the actual change depends on how the rent paid on the previous house compares to the opportunity cost of the new one. As shown in Figure
<table>
<thead>
<tr>
<th>Good</th>
<th>PCE Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clothing</td>
<td>Children’s and infants’ clothing; Jewelry and watches; Men’s and boys’ clothing; Other clothing materials and footwear; Women’s and girls’ clothing</td>
</tr>
<tr>
<td>Communications</td>
<td>Internet access; Postal and delivery services; Telecommunication services</td>
</tr>
<tr>
<td>Domestic Services</td>
<td>Nursing homes; Social services and religious activities</td>
</tr>
<tr>
<td>Durables</td>
<td>Furniture and furnishings; Glassware, tableware, and household utensils; Household appliances; Household supplies; Telephone and facsimile equipment; Tools and equipment for house and garden</td>
</tr>
<tr>
<td>Education</td>
<td>Commercial and vocational schools; Educational books; Higher education; Nursery, elementary, and secondary schools</td>
</tr>
<tr>
<td>Food at Home</td>
<td>Food and nonalcoholic beverages purchased for off-premises consumption; Food produced and consumed on farms</td>
</tr>
<tr>
<td>Food Away from Home</td>
<td>Food furnished to employees (including military); Purchased meals and beverages</td>
</tr>
<tr>
<td>Health Care</td>
<td>Dental services; Hospitals; Net health insurance; Paramedical services; Pharmaceutical and other medical products; Physician services; Therapeutic appliances and equipment</td>
</tr>
<tr>
<td>Housing</td>
<td>Imputed rental of owner-occupied nonfarm housing; Rental value of farm dwellings; Group housing; Net household insurance; Rental of tenant-occupied nonfarm housing; Household maintenance</td>
</tr>
<tr>
<td>Other</td>
<td>Alcoholic beverages purchased for off-premises consumption; Financial services furnished without payment; Financial service charges, fees, and commissions; Life insurance; Luggage and similar personal items; Personal care and clothing services; Personal care products; Professional and other services; Tobacco</td>
</tr>
<tr>
<td>Private Transportation</td>
<td>Motor vehicle fuels, lubricants, and fluids; Motor vehicle maintenance and repair; Motor vehicle parts and accessories; Net motor vehicle and other transportation insurance; Net purchases of used motor vehicles; New motor vehicles; Other motor vehicle services</td>
</tr>
<tr>
<td>Public Transportation</td>
<td>Ground transportation</td>
</tr>
<tr>
<td>Recreation</td>
<td>Accommodations; Air transportation; Audio-video, photographic, and information processing equipment services; Net foreign travel (Other services); Gambling; Magazines, newspapers, and stationery; Membership clubs, sports centers, parks, theaters, and museums; Musical instruments; Net expenditures abroad by U.S. residents (Other nondurable goods); Other recreational services; Recreational items; Recreational books; Sporting equipment, supplies, guns, and ammunition; Sports and recreational vehicles; Video, audio, photographic, and information processing equipment and media; Water transportation</td>
</tr>
<tr>
<td>Utilities</td>
<td>Electricity; Fuel oil and other fuels; Natural gas; Water supply and sanitation</td>
</tr>
</tbody>
</table>
C.3 and Table 3.2, the positive correlation between labor share and changes in expenditure upon employment is robust to excluding rental equivalence.

C.2 Computation of the Labor Share

The computation of the network-adjusted labor share relies mainly on national accounts data. In this appendix, I discuss methodological choices to compute the labor share shown in this chapter.

I compute the network-adjusted labor share using the Industry-by-Commodity Domestic Requirements Matrix.\(^1\) The matrix has industries in the rows and commodities in the columns. The entry in row \(i\) and column \(j\) indicates the amount of domestically produced output of industry \(i\) that is required to deliver one dollar of commodity \(j\) to final users. The Domestic Requirements Matrix is computed using the Domestic Input table, instead of the Use table. The Domestic Input table is obtained by subtracting the imports matrix from the use matrix, thus finding the use of domestically produced commodities by industry and final users. Previous work (Baqaee, 2015; Valentinyi and Herrendorf, 2008) has used instead the Total Requirements Matrix in the computation of the network-adjusted labor share. I show in Figure C.1 that the two definitions are strongly correlated.

In terms of disaggregation, I choose to work with the Input-Output tables at the summary level, which divides the economy into 71 industry groups. I choose the summary level because the detail level (389 industries) is only available for benchmark years and because the PCE Bridge maps to the commodities produced at the summary level. Following Valentinyi and Herrendorf (2008), I use the Producer Value tables After Redefinitions. The Producer Value tables treat transportation and trade margins as final goods rather than inputs in the production process of other industries.

\(^1\) Refer to Horowitz and Planting (2009) for a very rich description of the methodology employed in the production of the Input-Output Tables.
For my analysis, I take 2007 as baseline because the most recent benchmark Input-Output tables were produced that year following the 2007 Economic Census. The labor share has declined significantly over the last 20 years, but the decline has been larger for capital-intensive goods and so, the labor share is still strongly correlated over time (Figure C.1). The choice of baseline year is then not critical for my results.

The computation of the labor share also requires disaggregating entrepreneurial income into labor and capital income. National accounts divide national income into compensation of employees, corporate profits, and proprietor’s income. The literature has long understood that proprietor’s income mixes both labor and capital income as entrepreneurs invest both their own work and physical resources on their projects (Johnson, 1954).

I account for the labor component in entrepreneurial income by multiplying the ratio of compensation of employees to output\(^2\) by the ratio of number of workers (both employees and self-employed workers) to employees. The assumption behind this adjustment is that the annual compensation of employees is the same than the annual labor compensation of self-employed workers. This approach follows Valentinyi and Herrendorf (2008) and is similar to the one employed by the Bureau of Labor Statistics in its headline measure of the labor share.\(^3\) Because of data limitations, I compute the adjustment factor at the sector level (15 industry groups), rather than at the summary level. My results are robust to using compensation share (i.e., compensation of employees as fraction of industry output) to measure labor share (Figure 3.4).

The adjustment is far from perfect. As Elsby, Hobijn, and Sahin (2013) point out, the correction implied a labor income to entrepreneurs larger than the sum of all proprietor’s income during the 1980s and, as a consequence, a negative return on capital for a decade, indicating a likely overstatement of the labor share. However, given that self-employment

\(^2\)Elsby, Hobijn, and Sahin (2013) refer to the ratio of compensation of employees as fraction of gross value added as “payroll share”. Gollin (2002) refer to it as “employee compensation share”. In the context of my analysis, the compensation share is defined as fraction of total output.

\(^3\)The Bureau of Labor Statistics uses as adjustment factor the ratio of total hours worked (by both employed and self-employed workers) to the number of hours worked by employees. The assumption for that adjustment is that the average hourly compensation for employed and self-employed workers is the same.
The labor share is strongly correlated over time and the adjustment for imports is not quantitatively very large

The top two panels present the network-adjusted labor share in 1998, 2007, and 2014. 1998 and 2014 are the first and last year for which employment and Input-Output tables are available under the NAICS framework, respectively. Labor share (Total Req.) refers to the network-adjusted labor share computed using the Total Requirements Matrix, instead of the Domestic Requirements Matrix.

Each ball represents one of the final consumption goods in Figure 3.1. The size of each ball is proportional to the share of that final good on total consumption in 2007 according to the national accounts.

Corr. refers to the weighted correlation between the variables in each figure.

Refer to the main text and Appendix C.2 for details on the calculations.
varies significantly across sectors in the economy and it is particularly relevant in the production of services, it is important to account for it.

Other strategies have been used in the literature to deal with the allocation problem, but they appear unsuitable for my project. As noted by Krueger (1999) a common response after Johnson (1954) was to allocate two-thirds of the proprietor’s income to labor and one-third to capital. But the recent decline in the labor share makes the use of a constant fraction, across industries and over time, unappealing. Alternatively, Karabarbounis and Neiman (2014) argue for the use of the corporate labor share that gets around the problem. But corporations only produce 60% of the American GDP and different sectors have different levels of incorporation, particularly in the service industry.

C.3 Output Elasticity of Labor Demand

In this appendix, I provide evidence that industries hiring relatively more workers exhibit a labor demand more responsive to changes in output.

The labor demand of capital-intensive sectors may be very responsive to output in the presence of adjustment costs. For instance, the automobile industry could respond to drops in demand by firing workers, rather than by reducing capital stock or other inputs in the short run. In that case, my measure of the labor share would not capture how labor compensation reacts to demand shocks.

The ideal approach to address this concern would be to estimate the output elasticity of labor demand for each industry. Formally, I would like to estimate this regression for each industry $j$:

$$L_{i,j,t} = \beta_j Y_{i,j,t} + \gamma_j K_{i,j,t} + \delta_j A_{i,j,t} + \kappa_{i,j} + \tau_{i,j} + \epsilon_{i,j,t}$$

where $L_{i,j,t}$, $Y_{i,j,t}$, $K_{i,j,t}$, and $A_{i,j,t}$ are the log employment, log output, log capital, and productivity level of firm $i$ in industry $j$ at time $t$, respectively. Firm fixed effects and
industry-specific time fixed effects are represented by $\kappa_{i,j}$ and $\tau_{t,j}$, respectively. The specification could also include other inputs and higher order terms as in the trans-log functional form.

However, such specification is unfeasible because productivity shocks are unobservable and so, ignoring them, introduces severe omitted variable bias. The industrial organization literature (De Loecker, 2011, De Loecker and Warzynski, 2012) has responded to this challenge with a proxy for productivity inverted from the firm’s demand for materials or other inputs not subject to adjustment costs. This approach requires rich levels of data and so, estimations have usually been performed at the plant level for the manufacturing sector. But, as shown in the main text, services compose the most interesting part of my story.

I deal with this endogeneity concern by instrumenting output by the levels and growth rates of the markets where the firm sells its products. I use Worldscope data on American public firms in the period 1980 to 2014. I sort firms into 17 different industries, mainly following the SIC divisions. The dataset includes annual (fiscal year) information on sales, employment, capital, and sales exposure to different geographic markets (i.e., fraction of sales in the domestic and international markets).\footnote{The dataset also includes compensation of employees for a small subset of firms because reporting it is not required in the United States. Because of data limitations, I use output and sales interchangeably in this appendix.} I use the sales exposure to different markets to construct instruments for firm sales:

$$Y_{i,j,t}^D = \omega_{i,j} GDP_{US}^t + (1 - \omega_{i,j}) GDP_{ROW}^t$$

$$Y_{i,j,t}^G = \omega_{i,j} g_{US}^t + (1 - \omega_{i,j}) g_{ROW}^t$$

where $\omega_{i,j}$ is the average fraction of firm sales to the domestic market over time, $GDP_{US}^t$ and $GDP_{ROW}^t$ are the levels of GDP in year $t$ in the U.S. and the rest of the world, respectively,
as obtained from the World Economic Outlook dataset. The growth rates of GDP in the U.S. and in the rest of the world are given by $g_t^{US}$ and $g_t^{ROW}$.

For each industry $j$, I estimate the regression

$$L_{i,j,t} = \beta_j Y_{i,j,t} + \gamma_j K_{i,j,t} + \kappa_{i,j} + \tau_{t,j} + \epsilon_{i,j,t}$$

where $L_{i,j,t}$, $Y_{i,j,t}$, and $K_{i,j,t}$ are the log employment, log sales, and log capital of firm $i$ in industry $j$ and year $t$, respectively. I include firm fixed effects ($\kappa_{i,j}$) and industry-specific time fixed effects ($\tau_{t,j}$). And I instrument log sales with the weighted average of the level and growth of the markets where the firm is active, $Y^D_{i,j,t}$ and $Y^G_{i,j,t}$.

The output elasticity of labor demand is positively correlated with labor requirements across industries (Figure C.2). In the context of this exercise, I define labor requirements as the number of employees required to produce a million dollars of sales in each industry. Thus, industries employing relatively more workers respond to changes in output with larger changes in labor demand.

### C.4 Methodological Approach to CEX Data

In this appendix, I discuss my approach to the data in the Consumer Expenditure Survey.


Since the purpose of this chapter is to combine expenditure and production data, I define expenditure categories that match goods in the CEX and in the Personal Consumer Ex-
Industries employing relatively more workers respond to changes in output with larger changes in labor demand

Labor requirement is the average number of employees per million dollars of sales in the industry in 2014. Output elasticity of labor demand is estimated using an instrumental variable approach as described in Appendix C.3.

The size of each ball is proportional to the amount of employment in the industry in 2014 according to Worldscope.

Corr. refers to the weighted correlation between labor requirement and output elasticity of labor demand.
penditures of the national accounts as closely as possible. This requires a number of minor adjustments. First, I include “phone services” as part of communications, which also includes internet access, rather than as utilities. Second, I include “lodging away from home” as recreation, not as shelter. Third, I include “nursing homes” as domestic services, instead of medical services, because the main purpose of those facilities tends to be residential accommodations rather than health care. Fourth, I include clothing services such as repairs and rental in the category other, with personal care services, rather than in clothing. Fifth, I count all parking expenses as private transportation. Sixth, I count motorcycles as recreational items, not as private transportation. Seventh, I include “air transportation” and “water transportation” as recreation, rather than as public transportation, when purchased by households.

My main divergence with respect to the methodology in the CEX is in the treatment of shelter for homeowners. The CEX defines shelter for homeowners as the sum of out-of-pocket expenditures: maintenance expenditures, interest on mortgages, and property taxes; whereas the national accounts impute the rental equivalence of the home owned to account for the opportunity cost. For consistency with the national accounts, I define housing for homeowners as the sum of the rental equivalence, maintenance expenditures, property taxes, and net household insurance. I exclude interest on mortgages because it is associated to a saving decision, rather than to an expenditure choice. For vacation houses, the CEX started collecting data on rental equivalence only after 1999, so I follow Aguiar and Bils (2015) and use out-of-pocket expenditures for them. The CEX did not start collecting rental equivalence until the 1982-1983 wave. Following Aguiar and Bils (2015), I impute rental equivalence in the 1980-1981 wave by estimating a regression of rental equivalence on household income; marital status, age, race, education, and gender of the household head; family size; and number of earners using the 1982-1983 wave. For renters, I define housing as the sum of rent, net household insurance, and household maintenance. My results on the positive
correlation between labor share and changes in expenditure upon employment are robust to using out-of-pockets expenditures as a measure of housing (Figure C.3).

Consistent with the CEX methodology, I only consider expenditures associated to consumption, not to saving or investment decisions. Thus, I exclude capital improvements, house purchases, and payments of principal on mortgages or home equity loans.

To ensure that the household head remains the same across interviews, I drop all household heads whose gender changed or whose age increased by more than two years. I also drop households with negative income and with negative expenditures in at least one category. Afterwards, I add 1 to every category of expenditure before taking logs when estimating a log-log specification. I do not implement that adjustment when estimating the effect on the expenditure share.

Following Aguiar and Bils (2015), I increase by 11% the value of food at home in the surveys between 1982 and 1987, as the wording of the question in those waves appears to have yielded abnormally low values. A similar correction is implemented by Krueger and Perri (2006).

I use the CEX-derived measure of after-tax income in the previous twelve months and I add the rental equivalence for homeowners. I deflate all nominal expenditures and total income using the aggregate Consumer Price Index for the three and twelve months before each interview, respectively. However, this adjustment is only relevant for interpretation purposes, because all regressions include time fixed effects.

For my baseline specification, I keep only households whose heads are aged 25-65. For robustness exercises, I further restrict the sample to only those with male heads or with heads aged 25-50. The number of households used to identify the expenditure response to employment is shown in Table 3.1, which also includes summary statistics of the distribution of expenditure shares for each good.

In every regression, I use probability weights and I cluster standard errors at the household level.
The positive correlation between labor shares and expenditure responses to employment is robust to excluding imputed housing for homeowners. Panel A (B) shows the response of the expenditure share (the semi-elasticity of expenditure) of each good to a change in the employment status of the household head. 95% confidence intervals are shown with dotted lines. Standard errors are clustered at household level. Goods are sorted by their network-adjusted labor share. The size of each ball is proportional to the share of that good according to the CEX.
C.5 Methological Approach to the Assessment of Fiscal Multipliers Estimated in the Literature

In this appendix, I describe my methodology for reviewing the empirical literature on the size of the fiscal multiplier and producing the histogram in Figure 3.15.

I search for empirical estimates of the fiscal multiplier published recently in top-tier journals. Concretely, I search for the words fiscal multiplier in the field “full text” using the search engines on the websites of the top 30 journals in economics as listed by IDEAS/RePEc. If the journal engine does not allow to search by full text, I use the engine provided by the Princeton University Library. I limit attention to estimates for the U.S. that used aggregate data and were published between January 1996 and the present. I include papers with cross-country data only if they offered separate estimates for the U.S.

For comparability, I use only estimates for the fiscal multiplier on impact. When the results are displayed as impulse-responses functions, I use the response of GDP in the first period. If standard errors are shown, I include the estimates for all the specifications that are statistically significant from zero. If standard errors are not shown, I keep all the estimates. I restate elasticities into fiscal multipliers dividing them by 0.22 or 0.05 when they use total spending or only military spending, consistent with Table 3.3.

I categorize estimates into defense and total spending based on the variation exploited in the research design. Papers using structural vector autoregression (VAR) techniques on total government expenditure belong to the latter. Papers using military spending or war-related news are included in the former.

A small number of papers reports results for both defense and nondefense spending. Blanchard and Perotti (2002) find a multiplier of 2.67 for nondefense spending and 2.50 for defense spending under deterministic trend, but they do not report standard errors, nor the multipliers for their specification under stochastic trend. Auerbach and Gorodnichenko

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7 IDEAS/RePEc Aggregate Rankings for Journals, All years.
8 http://library.princeton.edu
(2012) find that nondefense is more effective than defense in expansions, but the opposite result holds for recessions. Finally, Perotti (2007) concludes “Thus, the evidence from the SVAR approach is that civilian government spending shocks appear to be associated with stronger responses of GDP and its components.”

These results are not included in my sample because they are not published in a journal, but in a working paper.

Gali, Lopez-Salido, and Valles (2007) do not report defense versus nondefense multipliers, but nondefense and total. They find that nondefense multiplier is greater than total spending multiplier in their larger VAR specification for the samples 1954-2003 and 1960-2003, but smaller in their small VAR. They do not report standard errors.


Baqee, David Rezza. 2015. “Labor Intensity in an Interconnected Economy”.


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Ganong, Peter, and Pascal Noel. 2015. “How Does Unemployment Affect Consumer Spending?”


Guerrieri, Veronica, and Guido Lorenzoni. 2015. “Credit Crises, Precautionary Savings, and the Liquidity Trap”.


Hendren, Nathaniel. 2015. “Knowledge of Future Job Loss and Implications for Unemployment Insurance”.


Saporta-Eksten, Itay. 2014. “Job Loss, Consumption and Unemployment Insurance”.