Essential Business Cycles

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Abstract

In response to an increase in interest rates, households cut non-essential spending more than essentials. This causes a larger fall of labour demand in the non-essential sector, which employs a higher share of workers with lower earnings and with higher marginal propensity to consume out of disposable income. We use micro data for the United States and a structural model with nominal rigidities, non-homothetic preferences and skill heterogeneity to quantify this novel channel of monetary transmission. Our findings suggest that the interaction of spending heterogeneity and worker heterogeneity results in greater inequality during recessions and amplifies the effects of monetary policy on consumption and employment by about 20% and 40% respectively.

Keywords: non-essentials, inequality, recessions, monetary policy, amplification.
JEL Classification Codes: E52, D31, E21.

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1 Introduction

Does the composition of household expenditure matters for aggregate fluctuations? What categories of consumer spending are easier to postpone in the face of economic adversities? And which type of workers are employed in the sectors most sensitive to cyclical fluctuations? Despite recent advances on household and firm heterogeneity, little is know about the contribution of *spending* heterogeneity and its interaction with *worker* heterogeneity to business cycle fluctuations.

In this paper, we use detailed micro data on consumer prices, employment, and input/output tables for the United States, a series of identified monetary policy shocks and a structural model with non-homothetic preferences on consumption, skill heterogeneity and nominal rigidities to answer these important questions. In so doing, we uncover and an evaluate a novel theoretical channel of the transmission mechanism and find that it is empirically significant.

The key insight hinges upon two observations: (i) non-essential spending is easier to postpone; (ii) the non-essential sector employs a larger share of low-income workers. These two facts imply that any contractionary shock that shifts spending away from non-essentials also triggers a fall in labour demand for low-earning workers, who are more likely to exhibit a higher marginal propensity to consume. This sets in motion a wave of second round effects that have the potential to amplify business cycle fluctuations on both consumption and employment.

This paper explores this novel channel of transmission, which we refer to as essential business cycles, along two dimensions, empirical and theoretical. On the empirical side, we show that non-essential consumption falls around 70% more than essential consumption over four years after a 100bp contractionary monetary policy shock. Prices of non-essentials fall more than prices of essential goods, though this effect is relatively small in magnitude. The non-essential labour market responds even more dramatically compared with the goods market response. Employment in non-essential sectors accounts for the overwhelming majority of the aggregate fall in employment; employment in essentials does not fall significantly whereas there is a peak decline in non-essential employment of 1.5% around two years after the shock. Median earnings in non-essential sectors falls over 4% four years after the shock, while essential earnings do not fall significantly. The non-essential workers earn less than those in essential sectors and the decline in earnings after a shock is particularly sharp for the lowest paid in the non-essential sector. This suggests that accounting for the difference between essentials and non-essentials is crucial to understanding the transmission and rami-

fications of business cycle shocks. The cyclicality of earnings in the non-essential sector also provides a novel microfoundation for the countercyclicality of income inequality. We identify monetary policy shocks with the high-frequency approach developed by Gertler and Karadi (2015) and refined by Jarociński and Karadi (2020). We estimate IRFs using the smooth local projections method proposed by Barnichon and Brownlees (2019).

On the theoretical side, we develop a heterogeneous agent New Keynesian model featuring both essential and non-essential spending as well as low-skilled and high-skilled workers. Households have non-homothetic preferences on two types of goods with different income elasticities to identify essential and non-essential spending. This utility specification has been proposed by Deaton (1974) and Deaton (1978) and used by Browning and Crossley (2000) to show that luxury goods are easier to postpone (e.g. delaying a vacation or eating out) in the face of a negative shock compared with necessity goods (e.g. heating or food at home). Households are of two types: low productivity constrained households and higher productivity unconstrained households. Low productivity households are a relatively larger share of the non-essential sector labour force compared to the essential sector.

These additions to a standard New Keynesian model allow us to match key implications of the empirical analysis. First, low-income families have a larger budget share allocated to essential goods and services. Second, we microfound the higher cyclicality of non-essentials goods consumption. As a result, the income of the set of households with highest marginal propensities to consume, who are more likely to work in the non-essential sector, varies the most, which amplifies the effect of the business cycle shock to a similar degree to the data.

Amplification Our empirical approach and structural model allow us to provide a decomposition of how spending heterogeneity and worker heterogeneity interact to exacerbate shocks. The presence of non-essentials amplifies the fall in consumption by 20% following a contractionary monetary policy shock relative to a representative agent/ representative goods model, according to our empirical approach. This feeds into effects on the labour market that are even more heterogeneous between essential and non-essential industries. Employment in non-essential sectors accounts for the overwhelming majority of the aggregate fall in employment; non-essentials amplifies the overall decline in employment by over 40%.

Direct and indirect effects We use our empirical results and our structural model, calibrated on the micro data, to understand the relative importance of the direct effect on prices and indirect effects via the labour market of consumption heterogeneity. A relative decline in non-essential prices affects low-income families most, as their budget is dominated by essen-

tials, which become relatively more expensive. This could directly amplify the effect of the shock, as they are forced to reduce consumption more. However, we find in both the empirical results and the model that the direct price effect is relatively minor. In contrast, the indirect effect via the labour market amplification mechanism is the more important channel through which consumption heterogeneity amplifies the business cycle. The magnitude of both the absolute fall in non-essential employment and the relative response compared to essentials is much higher. The labour market amplifies the consumption response via the effect on low income non-essential workers, who are forced to cut consumption even further.

Data contibution A key contribution of our paper is that we construct novel time series for essentials and non-essentials consumption, price indices, employment, and earnings. We closely follow the approach of Aguiar and Bils (2015) to classify consumption categories into essentials and non-essentials (with income elasticities below and above one, respectively), using micro-data on consumption within the CEX. Armed with this classification, we then construct consumption and price series using PCE sub-indices. We then link the consumption categories to industries, by classifying final goods produced by industries as essential and non-essential, and using an input-output approach to classify intermediate industries by the final goods production they contribute primarily to. Using this industry classification, we then construct employment and earnings time-series for essentials and non-essentials using data from the CPS.

Related literature This paper relates to the literature on how household heterogeneity affects the transmission of monetary policy, to which contributions include Bilbiie (2008), Bilbiie (2020), Debortoli and Galí (2017), McKay, Nakamura and Steinsson (2016), Werning (2015), Auclert (2019), Kaplan, Moll and Violante (2018) and Cloyne, Ferreira and Surico (2020). This primarily focuses heterogeneity of aggregate consumption responses due to differing degrees of financial constraints across households. Here we explore the implications of heterogeneity of consumption bundles and non-homotheticities of utility functions, whereas much of this literature assumes homogeneous consumption bundles for different households[1]. Other papers have developed models where with different types of goods within the consumption bundle which affect the transmission of monetary policy; durables versus non-durables (in Barsky, House and Kimball (2007), Monacelli (2009), Sterk (2010), and McKay and Wieland

[1]Recently, Cantore et al. (2021) highlight the role of IES heterogeneity in a TANK model, which could be microfounded with non-homothetic preferences, to highlight heterogeneous labour supply choices but focus on a representative employment sector.

(2019)) and flexible price goods (food) versus sticky price goods (Anand, Prasad and Zhang (2015)). This paper focuses on differences in consumption bundles due to non-homothetic preferences rather than traits of the goods being consumed.

More directly focused on the implications of non-homothetic demand for different consumption goods is Orchard (2022). He shows empirically that during recessions prices rise more for products purchased relatively more by low-income households (necessities) and that the aggregate share of spending devoted to necessities is counter-cyclical. He then builds a representative agent New-Keynesian model with an AIDS[2] demand to account for this fact. Sonnervig (2022) also explores how consumption heterogeneity between poor and rich households affects the business cycle. The most significant difference of our contribution is that we focus on the amplification of non-homothetic preferences though the labour market.

Our empirical approach builds on a detailed literature developing approaches to identify causal responses to monetary policy changes. This paper uses the local projection approach to estimating impulse responses to shocks due to Jordà (2005) and the high-frequency approach to identifying monetary policy shocks (Gurkaynak, Sack and Swanson (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018), Jarociński and Karadi (2020)). We also use disaggregated consumption and price data and labour market survey data to show the heterogeneous impact of macroeconomic shocks following the spirit of Cloyne and Surico (2017), Cloyne et al. (2018), Coibion et al. (2017) and Cloyne, Ferreira and Surico (2020).

Our theoretical contribution relates to the long literature on Engle curves and non-homothetic preferences, initiated by Engel (1857) and developed by (Deaton and Muellbauer (1980), Stone (1954), Geary (1950); Boppart (2014) and Comin, Lashkari and Mestieri (2021) more recently), with influential applications within economics including in trade (Linder (1961)), consumer demand (Deaton and Muellbauer (1980)), social welfare and tax policy (Banks, Blundell and Lewbel (1997)), structural change and long-run growth (Foellmi and Zweimüller (2008)) and the measurement of the cost-of-living (Hamilton (2001)).We build on the preferences proposed by Browning and Crossley (2000) and integrate them in a general equilibrium framework, in order to explore the implications of non-homothetic preferences in the responses to macroeconomic shocks. De Nardi (2004) and De Nardi and Fella (2017) cleverly employ non-homothetic preferences on wealth/bequest to study wealth inequality and saving decisions at retirement whereas Andreolli and Surico (2021) demonstrate analytically a tight link between income elasticity and the Elasticity of Intertemporal Substitution (EIS), a key parameter for the transmission of macroeconomic shocks in RBC and New-Keynesian

[2]Almost ideal demand system

models: luxury goods and services exhibit a much higher EIS. Relative to this literature, we focus on non-homotheticities over different types of goods, rather than non-homothetic preferences for overall consumption, and link non-homothetic demand for different goods to a labour market amplification channel. Cavallari and Etro (2020) and Cavallari (2020) also explore the implications of non-homothetic preferences for the business cycle and the transmission of monetary policy, but do so for a representative household and using a different preference specification.

Structure of the paper Section 2 describes our data construction, descriptive evidence and empirical approach. Section 3 shows the responses of the series to monetary policy shocks and presents back of the envelope calculations to show the contribution of the essentials versus essentials to aggregate changes in consumption, employment and earnings. Section 5 outlines the model and Section 6 discusses the results from the model. Finally, Section 7 concludes.

2 Data and classification approach

In this section, we outline how we construct non-essential and essential series for consumption, prices, employment. We discuss first how we classify consumption categories into essentials and non-essentials, and the data sources used to construct the series, then turn to the labour market data.

2.1 Consumption classification

The first step to construct our data is to classify consumption categories into essentials and non-essentials. To do this, we closely follow the approach used by Aguiar and Bils (2015), who infer changes in consumption inequality by estimating Engel curves using data from the Consumer Expenditure Survey (CEX), in order to correct for mismeasurement of total consumption in the CEX. We use data from the CEX for the years 1995-1997 and group household expenditure into 24 categories. We then use the same empirical approach as Aguiar and Bils (2015) to estimate income elasticities of demand for the different goods categories. In brief, we regress the expenditure share at the household level on total expenditure, instrumented by net household income. We classify any consumption category with an elasticity to total expenditure greater than (less than) 1 as a non-essential (essential). See Appendix Section A for a detailed explanation and the estimated elasticities. This classification categorises the 24 consumption categories as outlined in Table A.2. We use the same consumption categori-

sation for the entire sample period, following evidence from Aguiar and Bils (2015) that the Engel curve slopes are stable over time.

2.2 Consumption and Price series using PCE data

Armed with the classification of consumption categories, outlined in the previous section, we map these consumption categories to the PCE by Type of Product tables produced by the BEA. These provide nominal expenditure, real consumption and price indices for categories of consumption, at varying levels of aggregation. Using the aggregated PCE data, rather than for instance microdata from the CEX, has a number of advantages for our purposes. The PCE data provides us with consistent categories reported monthly since January 1959. The accompanying price indices means we are able to distinguish between consumption and price movements, rather than rely on expenditure series. In addition, the BEA reports housing consumption rather than expenditure on housing, which is more consistent with our theoretical framework and allows us to distinguish more between the cyclicality of durable expenditure and cyclicality of non-essential consumption (a distinction we discuss in more detail in Appendix H).

We omit or adjust some categories of consumption from our classified essential and non-essential series, where we either are unable to reasonably estimate Engel curves using the CEX microdata, or where we see the expenditures as inconsistent with our theoretical framework, following the approach of Aguiar and Bils (2015) for the CEX. Major examples of these are that we exclude most professional and financial service fees and adjust down the share of health expenditure by the proportion of healthcare spending made out of pocket. These omissions and adjustments are detailed in Appendix Section A.1, and result in our essential and non-essential indices covering on average 80% of total expenditure over the sample.

We construct Fisher indices for consumption and prices following the approach outlined in the BEA's NIPA handbook, Chapter 4[3]. Details of this are discussed in Appendix A.1.

2.3 Mapping consumption to employment data

We next map from the consumption categorisation to an industry classification, in order to construct employment and earnings series for essentials and non-essentials. This is an important step when matching final consumption data to employment data as a large fraction of workers are employed in intermediate goods sectors.

[3] NIPA (2021)

We first manually classify each industry code included in the CPS to the most closely linked consumption category, leaving unclassified any industries that either don't have a direct counterpart or don't supply final goods at all. See Appendix Section B for further details. For industries that primarily produce intermediate goods, we are primarily interested in how the cyclicality of demand of the downstream good affects their labour demand. To focus on this, we use an input-output approach, where we use the BEA Input-Output Accounts Data to construct a Leontief inverse, as outlined in more detail in Appendix B.1 to uncover the proportion of output produced by intermediate industries to each final consumption category. If an intermediate industry's downstream final consumption contributed to is primarily essential, we classify the industry as essential.[4]

2.4 Employment and earnings series using CPS data

Using the industry classification discussed above, we construct employment and earnings series for workers in essential and non-essential industries using the microdata from the Current Population Survey (CPS). The CPS provides us with a representative monthly sample of around 60,000 US households, including details of the industry of their employment. We use the IPUMS harmonized CPS data[5], which includes harmonized industry codes, reducing the inconsistency in NAIC codes over time. We construct a monthly series of employment for essentials and non-essentials by summing (using the survey weights) the total count of workers in industries we have classified as essential or non-essential, using the basic sample from the CPS. This series begins in 1976.

We then use the earnings data from the Outgoing Rotation Group (ORG), which is a subsample of roughly a quarter of the main CPS sample. We construct monthly series of median earnings and the percentiles of the earnings distribution reported each month, using the usual weekly earnings reported in the CPS, again using the weights provided by the CPS[6]. The median and percentiles refer to within category medians and percentiles. As discussed below, the distribution of earnings within non-essentials is lower the distribution, compared with essentials. This series begins in 1982 and is deflated using the overall PCE price index

[4] An alternative approach is to construct employment series using the *shares* of downstream production that is essential or non-essential, rather than a binary classification approach. We prefer the binary approach's simplicity, but test that our results are robust to either approach, results are available upon request.

[5] Flood et al. (2020)

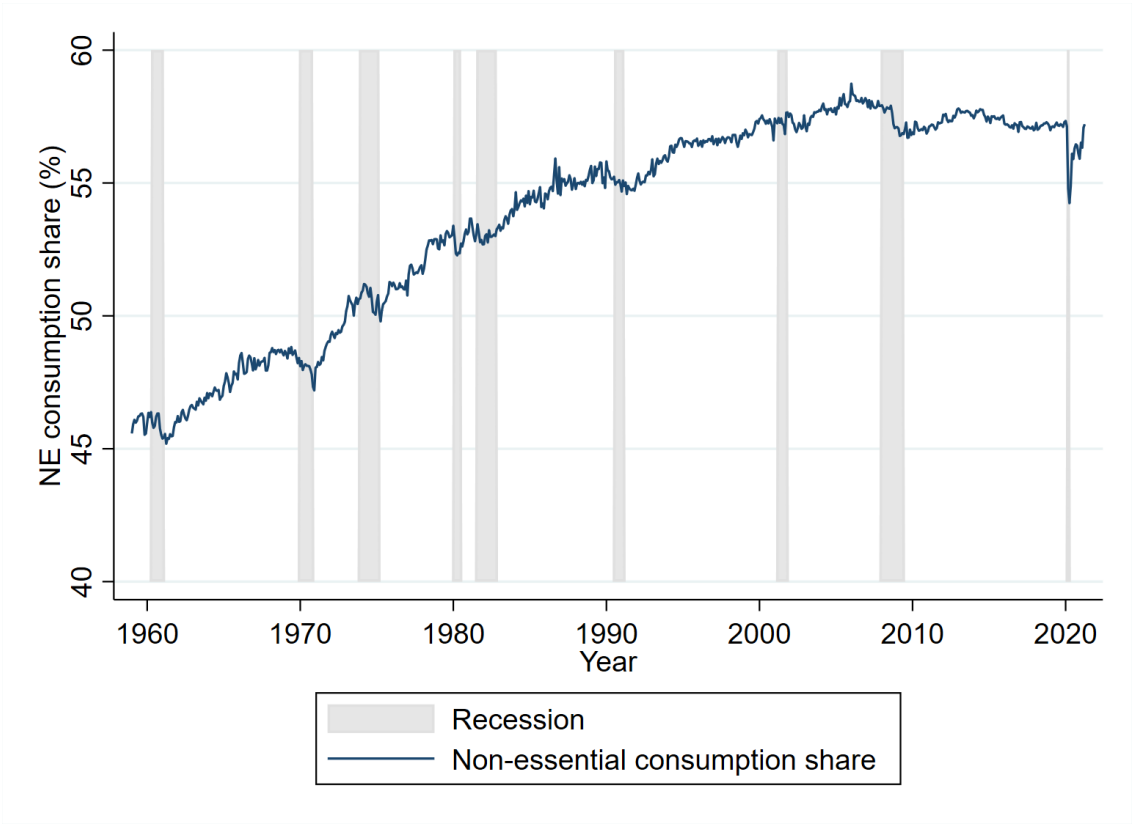
[6] The ORG is sampled and weights provided such that it is representative at a quarterly frequency, but not necessarily a monthly frequency. We construct monthly series in order to maximise the time-series variation in our earnings series, but this results in noisy and - potentially - unrepresentative series. In acknowledgement of this, we also report in Appendix I.8 corresponding quarterly time-series and IRFs, which corroborate the qualitative results from our monthly series.

to 2012$.

We seasonally adjust all series from the CPS using the Census Bureau's X-12-ARIMA Seasonal Adjustment procedure.

2.5 Essential vs non-essentials series - descriptive evidence

Figure 1: Non-essential consumption share over time



Notes: Consumption shares of non-essentials, constructed from chained (2000$) consumption series. Non-essential consumption as a proportion of only classified consumption is shown. Underlying data sources are the PCE by Type of Product tables from the BEA, described in detail in the text. NBER recession dates shaded.

Our newly constructed series show that the non-essential share of consumption has become a markedly more important component of consumption in the US economy (Figure 1). The implications of the higher cyclicality of non-essential consumption which we will demonstrate, are therefore getting increasingly more important for the dynamics of business cycles. Non-essential consumption, employment and earnings are markedly more cyclical than essentials. Figure 2 shows the typical behaviour of consumption, inflation, employment

and total earnings in the essential and non-essential sectors after a recession begins[7][8].

Non-essential consumption falls much more sharply than essential consumption. A year after the onset of the recession, non-essential consumption has fallen over 3% below trend, over twice the amount of essential consumption and increasing the cyclicality of overall consumption. Inflation in the non-essential decelerates more rapidly than in the essential sector, though this heterogeneity is more mild. Here, we focus on core inflation, to remove the more supply-driven dynamics of energy and food inflation[9].

The heterogeneity in labour market outcomes is even more extreme. Employment in the non-essential sector sharply contracts, to a peak of nearly 4% below trend in the second year of the recession, while essential earnings decline by only 1%. Total earnings in the essential sector barely decline after the recession begins, while non-essential earnings drive the majority of the decline of overall earnings.

In Appendix Table D.1 we further present descriptive statistics for the series (standard deviations relative to industrial production and correlations with industrial production), which confirm quantitatively some of the patterns just described. Consumption, employment and median earnings of non-essentials are more volatile than that of essentials, and more positively covary with industrial production (used as a proxy for overall output). Table D.2 provides average amounts and shares of non-essential and essential in the series; over the full sample, the non-essential consumption and employment shares are 53% and 67% [10]. Median earnings in the non-essential sector are 11% lower than the essential sector, an important factor for our mechanism which is discussed in more detail in Section 3.3.

3 Empirical results

In this section, we present the main empirical findings of the paper. Following contractionary monetary policy shocks, consumption of non-essentials falls more than the consumption of essentials. This is associated with an increase in the relative price of essentials and a stronger fall in employment and earnings of workers in the essential sector, especially for the low income non-essential workers.

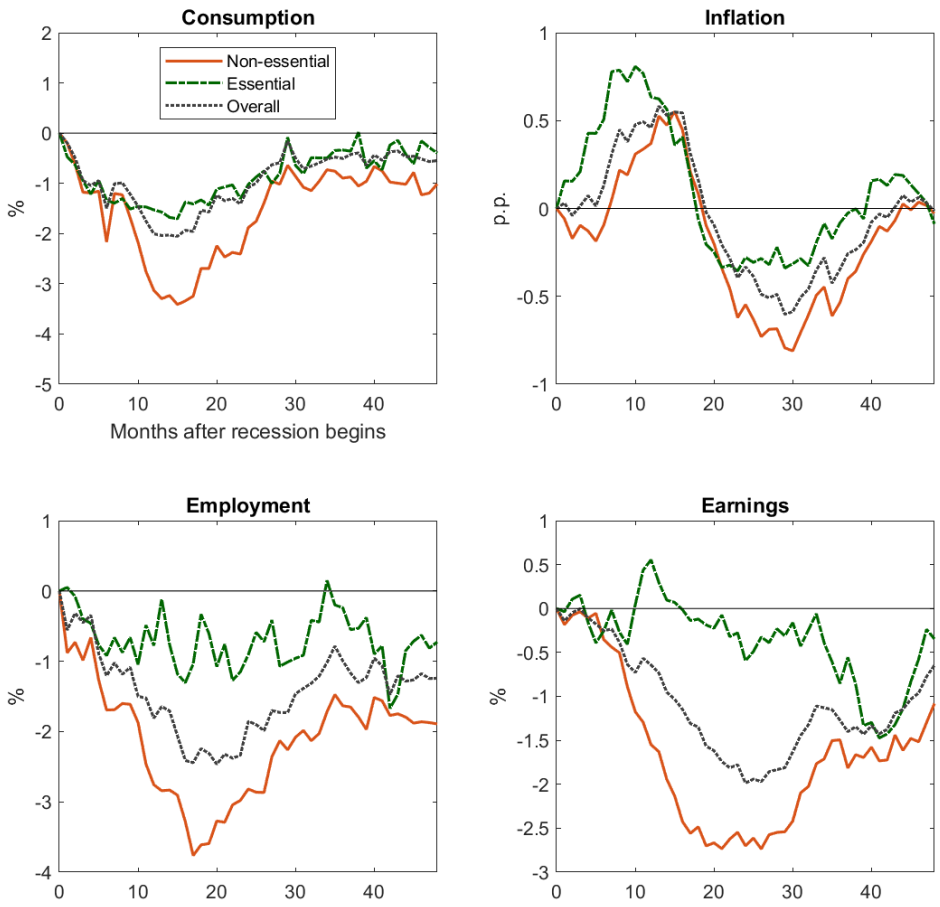
[7] In Appendix D we show additional charts of the full timeseries.

[8] We also find similarly large declines in non-essential consumption and employment when estimating Generalised IRFs, results available upon request.

[9] For the rest of the paper where we analyse identified responses to exogenous monetary policy shocks, this is no longer necessary and we instead address the response of the complete price index.

[10] These exclude the unclassified portions of consumption and employment, which are approximately 20% and 10% respectively.

Figure 2: Response of Essentials and Non-essentials over the business cycle



Response of essential and non-essential series, starting from the peak of the previous expansion, as defined by NBER. Includes all recession peaks since 1973 where non-essential and essential series for each variable are available for a full 48 months after the peak (peaks in 1973m11, 1981m7, 1990m7, 2001m3, 2007m12 and see sample definitions in text). For consumption, employment and earnings, this shows the cyclical component of the logged variable detrended using the HP filter ($\lambda = 14,440$). For earnings, the inital log series is centred 6-month rolling average, to reduce noise. Inflation is y/y core inflation, also detrended using the HP filter. Earnings here refers to total earnings, average weekly usual earnings multiplied by employment. All series are normalised to 0 at the inital period by taking the peak observation from all periods.

3.1 Empirical specification and identification strategy

Monetary policy shocks. To understand the dynamics of non-essentials and essentials over the business cycle, we require plausibly exogenous shocks which affect the entire economy. In our case, in addition to avoiding the typical reverse causality problem when understand the relationships between macroeconomic variables - consumption dynamics affecting monetary

policy, rather than the reverse, for instance - we also need to avoid focusing on shocks which originate from either essential or non-essential sectors, and so cause heterogeneous effects that are not due to the resulting response of households' demand for the two types of goods. We focus here on the responses to monetary policy surprises which also fulfil this second requirement. As our mechanism relates more broadly to the responses to demand shocks, we aim to extend this to other shocks, such as fiscal policy shocks, in the future.

We use the high-frequency identified (HFI) monetary policy shocks developed by Gertler and Karadi (2015), building on Gurkaynak, Sack and Swanson (2005). These shocks measure changes in Fed Funds futures over a short window around monetary policy announcements. These provide exogenous variation in interest rates under the identifying assumption that information about the macroeconomic situation that would affect monetary policy has already been anticipated and so the only variation during this period is due to differences in monetary policy decisions from expectations. A more recent literature has discussed the 'information effect' also contained in meeting announcements, if the central bank has private information about the state of the economy beyond that of the Federal Reserve (Jarociński and Karadi (2020), Miranda-Agrippino and Ricco (2021), Nakamura and Steinsson (2018)) so to account for this, we also check the robustness of our results to using the Jarociński and Karadi (2020)'s alternative monetary policy surprise series.

Econometric methodology. The HFI monetary policy instruments are available for 1990-2016. However, as outlined by Cloyne et al. (2018), by estimating a proxy-SVAR as developed and outlined by Mertens and Ravn (2013) and Stock and Watson (2018) and used by Gertler and Karadi (2015) and Gerko and Rey (2017), an extended monetary policy series can be produced by estimating a VAR over an extended period and identifying the monetary policy surprise series using the HFI monetary policy instrument. We extract the shocks from a VAR similar to that of Gertler and Karadi (2015), on the sample January 1973 to December 2020. In the Proxy-VAR, we include the 1y government bond yield, excess bond premium, first difference of log industrial production, and first difference of log PCE price index as endogenous variables. We include the monetary policy instruments as internal instruments, as outlined in Ramey (2011) and Plagborg-Møller and Wolf (2021), which is robust to non-invertibility of the VAR. We use 12 lags for the endogenous variables and 4 for the external instrument. The extracted monetary policy surprises are shown in Appendix Figure E.1.

To check for weak instruments in our specification, we run the weak instruments test proposed by Olea and Pflueger (2013). The critical value for the test is 12.039, assuming a 5% confidence and worst-case bias of 30%. Using the Gertler and Karadi shocks, the correspond-

ing robust F-statistic is 13.89, passing the weak instrument test. When using Jarocinski and Karadi shocks, the F-stat is 10.29, suggesting some weak instrument issues, so we use the Gertler and Karadi shocks in our baseline and report the results using Jarocinski and Karadi in the appendix as a robustness check against the information effect, but acknowledging that weak instruments may present an issue for these results.

We proceed to estimate IRFs using a instrumental variable local projections, developed originally by Jordà (2005):

$$y_{i,t+h} = \alpha^i_{h,0} + \beta^i_h 1\text{y yield}_t + \sum_{l=1}^{L} Y^i_{t-l}\gamma^i_{h,l} + \epsilon_{i,t,h} \tag{1}$$

We estimate the local projections using the smooth local projection instrumental variable (SLP-IV) first suggested by Barnichon and Brownlees (2019)[11]. The dependent variables y_i are the logs of our essential, non-essential and aggregate series for consumption, prices, employment and earnings. β^i_h is our coefficient of interest, the response to a 100bp increase in 1y yields at time t, which we instrument using the monetary policy surprise series extracted from the VAR. We include as controls (Y_{t-l}) 12 lags of the variables included in the VAR (1y yields, the excess bond premium, log industrial production and the log PCE price index) in addition to PCE consumption, employment, earnings and the LHS variable (where not already included), all in logs. We estimate the LPIVs for the maximum samples possible given data availability for the LHS variables and the controls. All samples end in December 2020 but the start of the samples varies: for consumption, 1973, for prices 1978, for employment 1976 and for earnings 1982. All IRFs are estimated up to four years after the shock.

We vary the specific controls for the type of LHS variable, primarily to maximise the sample periods. For consumption, we use total employment and average earnings from the Current Employment Statistics (CES), as there is a longer time-series available than corresponding series from the CPS. For prices, we use the same but also add 12 lags of Michigan price expectations to reduce the price puzzle and an interaction of a dummy for 1978-82 with the instrument. For employment, we use total employment from the CPS and average earnings from the CES for the employment and earnings controls. For earnings, we use employment and median earnings from the CPS for the employment and earnings controls.

Standard errors given are Newey-West, details of our implementation of these using the smoothed local projection IV approach are included in Appendix Section F. We also test robustness to using the lag-augmentation approach suggested by Montiel Olea and Plagborg-

[11] We follow them in using afive-fold cross-validation approach to selecting the smoothing parameter and smooth towards a line.

Møller (2021) (results omitted for brevity), which produce similar results.

3.2 Results

Figures 3 and 4 show impulse response functions for consumption, prices, employment and earnings estimated using the SLP-IV approach outlined in the previous section. We also present in Appendix Figure I.1 the IRFs of other macro aggregate series included in the proxy-SVAR and as controls in the SLP-IV specifications. These are estimated using SLP-IV and we discuss how they are comparable to other results in the literature (for instance, those presented by Gertler and Karadi (2015)).

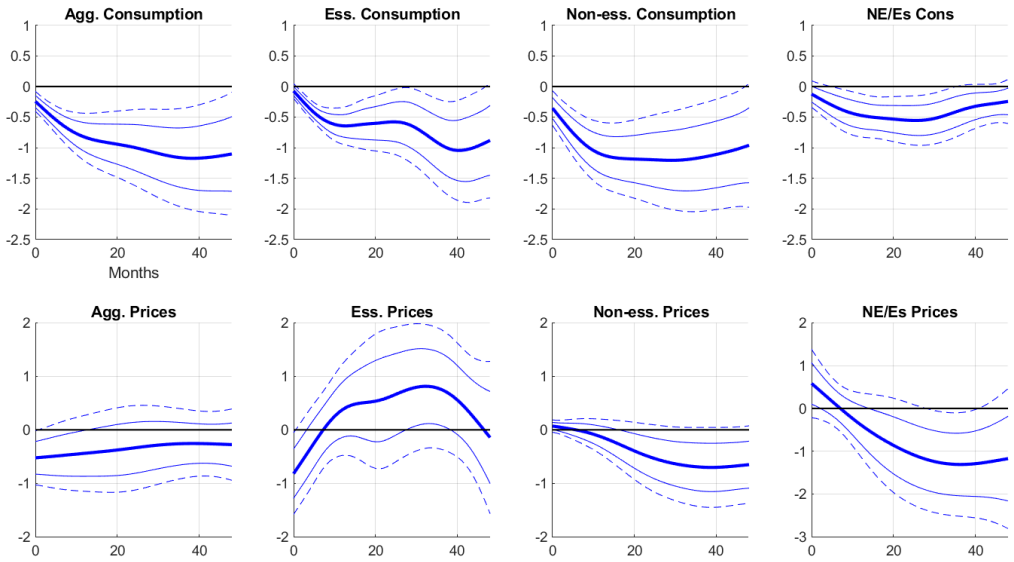
Following a 100bp exogenous increase in interest rates, consumption of non-essentials falls 1.5-2 times the amount of essentials, by 1-2 years after the shock, before becoming more similar four years after the shock (shown in the first row of Figure 3). This is consistent with our expectation that household would be more willing to postpone non-essential consumption during a contraction. In addition, in the second row of Figure 3, we find some evidence of prices responding to these relative demand shifts; while overall prices fall slightly, the essential price series rises while non-essential prices fall. All of these price responses are insignificant at the 90% level, though. This suggests that the general equilibrium channel through prices is somewhat weak, but the relative fall in non-essentials prices compared to essentials is statistically significant as shown in the final column of Figure 3.

The heterogeneity between essentials and non-essentials is even more stark for the labour market outcomes, with industries facing more cyclical demand reducing employment and earnings significantly more. While the fall in overall employment peaks at just over 100bp, non-essentials employment falls more sharply, peaking at 150bp, while essentials employment does not significant fall over the entire horizon, as shown in the first row of Figure 4. In the second row of the same figure we can see that median earnings fall more slowly, with overall median earnings falling by 3pp by the end of the horizon. Again, there is significant heterogeneity between earnings responses by category. Non-essentials earnings which fall over 4pp by the end of the horizon, whereas essentials earnings only fall slightly and insignificantly.

Table 1 summarises the average impact on consumption, employment and earnings over the four years after the shock. We find that non-essential consumption declines account for $120 of the approximately $200 decline in per capita consumption following a 100bp monetary policy shock, over the four years after the shock. We quantify the amplification of the business cycle due to goods heterogeneity with a back-of-the-envelope (partial equilibrium) calculation in the last two columns of Table 1. We ask how much larger the business cycle is due to

the higher cyclicality of non-essentials, by calculating how disproportionate the contribution of non-essentials is to the fluctuation compared to its share of the aggregate variable. If non-essentials respond similarly to essentials the amplification would be zero. Non-essentials amplify the impact on consumption by 20%. For employment and earnings, the amplification is even larger; employment declines are 44% larger due to non-essentials, while the decline in earnings is amplified by 31%. All of these responses are significant at the 90% level, using bootstrapped standard errors, other than for earnings, due to the large noise in the earnings series. We reproduce the same amplification calculations with the model IRFs in the last column of Table 1, and we can match the amplification relative magnitudes and all estimates are within the empirical confidence bands.

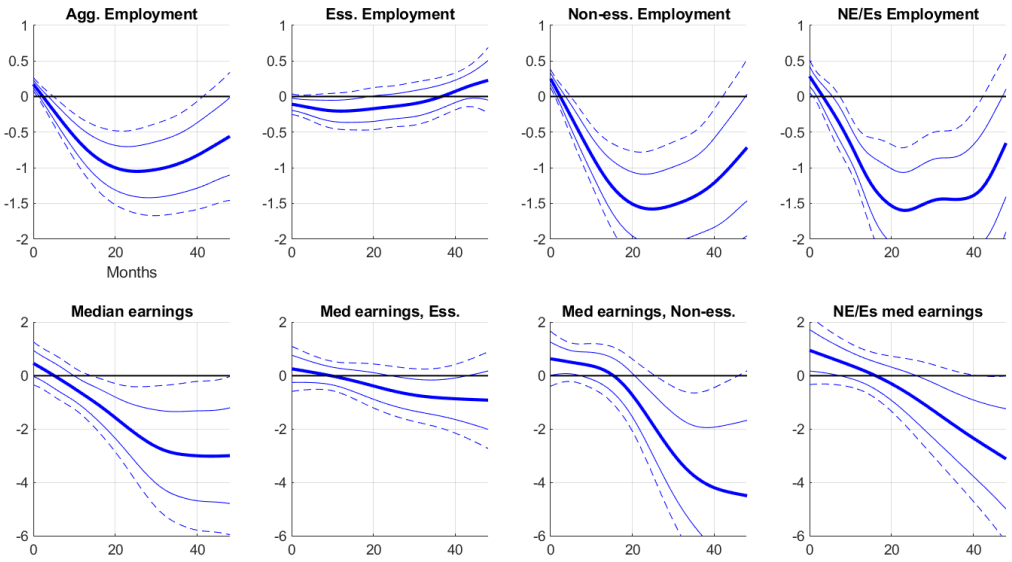
Figure 3: IRFs to contractionary monetary policy shock - Consumption and Prices



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. 90 and 68% confidence intervals. Consumption IRFs estimated on data January 1973-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Price IRFs estimated on data January 1978-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations, and a dummy for before 1983 interacted with the instrument and the LHS variable as controls.

Taken together, the smaller heterogeneity in consumption responses, the larger heterogeneity in labour market outcomes, and the higher cyclicality of earnings at the lower end of the non-essential earnings distribution suggest that the general equilibrium effects in the labour market may be dampening the heterogeneity in consumption responses. If the earn-

Figure 4: IRFs to contractionary monetary policy shock - Employment and Earnings



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Employment IRFs estimated on data January 1976-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Median wage IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, and the LHS variable as controls.

ings of low income households are particularly negatively affected by the cyclicality of non-essential demand, and these households are more financial constrained and more likely to reduce consumption in the face of a negative income shock, then they would have to reduce essential spending, as that makes up a larger proportion of their consumption bundle. As a result, the essentials consumption fall that we observe may be partly amplified by the fall in non-essential earnings, whereas the direct effect on essentials consumption would otherwise, without this indirect effect, be much smaller.

Table 1: Back-of-the-envelope calculations

	Average annual impact			Amplification by non-essentials	
	Overall	Essential	Non-essential	Data	Model
Consumption	-$202	-$70	-$120	20%	30%
	[-349, -90]	*[-138,-15]*	*[-210,-59]*	*[4%,62%]*	
Employment	-682k	-24k	-676k	44%	37%
	[-1227, -347]	*[-92, 71]*	*[-1158, -333]*	*[29%,66%]*	
Earnings	-$545	-$148	-$523	31%	30%
	[-979, 95]	*[-457, 226]*	*[-992, 188]*	*[-47%,115%]*	

Notes: The table shows the average annual change in consumption per capita, employment years and median annual earnings, averaged over a four year period after a temporary 100bp cut in interest rates. These are calculated by averaging the IRFs and multiplying by the average value of each variable over the sample periods. Amplification reflects how much larger the business cycle is due to the higher cyclicality of non-essentials, by calculating how disproportionate the contribution of non-essentials is to the fluctuation compared to its share of the aggregate variable. Details of the calculations and data sources are included in Appendix Section I.1. 90% CI using bootstrapped SEs displayed. Only the value of consumption and employment categorised into essentials and non-essentials is included in 'Overall', excluding uncategorised. The non-essential and essential values does not perfectly sum to the overall for consumption and employment because of statistical error (for earnings there is no direct mapping between the essential and non-essential response and the overall response as these are median earnings). Consumption is per capita chained PCE in 2012$, earnings are median earnings deflated to 2012$. The model based amplification numbers are computed with the same methodology but with the model IRFs.

3.3 Earnings distribution

The heterogeneity of non-essential and essential responses is important in its own right, but also may result in an amplification via the labour market not yet explored in the literature. This is because the workers in non-essentials, who suffer the largest income declines, are lower paid than those in the more stable, essential sectors.

Figure 5 shows the earnings distributions within essentials and non-essentials. Median earnings are 12% lower in non-essential industries than in essential. This is not only true on average; earnings within non-essential industries are lower than in essential industries across the entire distribution[12]. The figure shows the pooled earnings over the entire sample period; we omit for brevity distributions over time, but this fact has remained consistent across the sample period.[13]

Furthermore, when we split the response of earnings across the non-essential and essential

[12]They are first order stochastically dominated as shown by the CDF in Appendix Figure I.2.

[13]We don't seek to explain why non-essentials earnings are lower in this paper but take it as given. Possible explanations could be that workers are anticipating the additional cyclicality of wages in these sectors, and higher productivity workers choose to avoid these sectors to avoid this, or that the cyclicality of employment prevents as much match-specific productivity from building up within these industries, but we leave this for future work.

earnings distributions, we find that the largest declines in earnings are at the bottom of the non-essential distribution. Figure 6 shows the responses of deciles of the earnings distribution, over the four years after the shock (first row) and focusing only on the point two years after the shock. These results suggest that the highest cyclicality of earnings is found at the bottom end of the non-essential earnings distribution. There is much less of a systematic difference in earnings cyclicality across the essential distribution, while earnings of those at the top of the non-essential earnings distribution barely decline. The cyclicality of earnings is disproportionately accounted for by the bottom half of the non-essential earnings distribution. Further empirical results on the earnings distribution are included in I.3.

This suggests a possible explanation for countercyclical income inequality found in the literature (for instance, Heathcote, Perri and Violante (2010) and Heathcote, Perri and Violante (2020)). The higher cyclicality of non-essentials earnings (particularly at the bottom of the distribution) and the fact that non-essentials earnings are lower on average over time suggests that the cyclicality of demand for non-essentials and the resulting labour market responses may explain some of the rise in earnings inequality during recessions found in the literature.

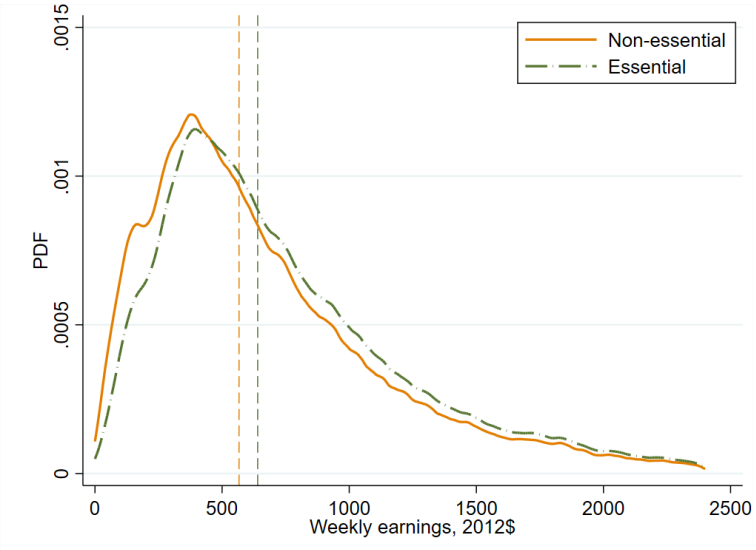
Lower income non-essential workers are therefore doubly disadvantaged; they typically earn less than essential workers and during a recession, their earnings fall most. This suggests to the prospect of a labour market amplification channel not yet explored by the literature. As non-essential consumption (primarily consumed by the rich) falls during a recession, this results in negative effects on workers in the non-essential sector. These lower income workers are likely to reduce consumption disproportionately, given the correlation between income and marginal propensities to consume. This would result in a further reduction in consumption, amplifying the effects of the initial shock.

3.4 Additional results and robustness checks

3.4.1 Alternative categorisations

One challenge for our identification is that the income elasticity of demand for goods could be correlated with other characteristics which could also explain the increased cyclicality. We discuss extensively in Appendix Section H why we view two possible alternative categorisations - durables versus non-durables, and tradeables versus non-tradeables - as unable to explain or counfound our results. Durability is correlated with how non-essential a good is, with more durable goods identified as non-essentials in the data. However, durable goods are a relatively small proportion of overall consumption compared to non-essentials, our re-

Figure 5: Non-essential and essential - Earnings distribution



Notes: Earnings distributions within essential and non-essential industries. Underlying data is pooled over the full sample, from the CPS, as described in the text. Kernel density plot along the median of each distribution.

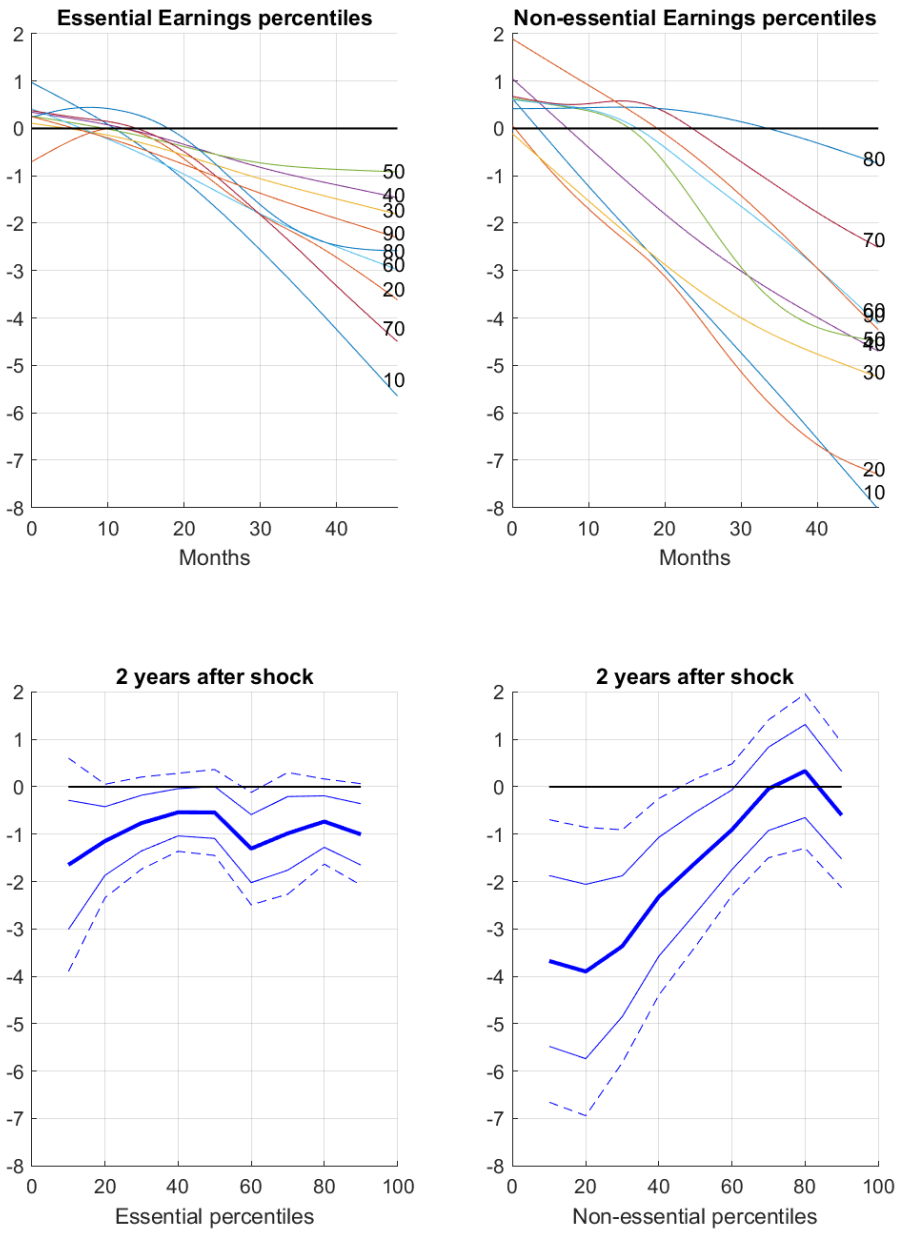
sults continue to hold when analysing only within non-durable and services. Moreover, the correlation with income that is crucial for our labour market amplification mechanism is not present for durables; non-essential workers are paid less than essential workers, but the same is not true for workers producing durable goods. Similarly, we do not find that the distinction between tradeables and non-tradeables accounts for our results; tradability is has a close to zero correlation with how non-essential a good is.

3.5 Robustness to alternative estimation specifications

In the main analysis, we use (updated) shocks from Gertler and Karadi (2015). As outlined in Jarociński and Karadi (2020), Miranda-Agrippino and Ricco (2021) and Nakamura and Steinsson (2018), these shocks may be contaminated by the 'information effect', if monetary policy announcements also included information about the state of the economy that was privately held by the central bank. Given this, in Appendix I.4, we also estimate IRFs using monetary policy surprises robust to the information effect, from Jarociński and Karadi (2020). We find that the results remain similar, although the difference between the essential and non-essential price and median earnings series is no longer significantly different from zero at the 90% level.

Appendix I also shows how our results are robust to ending the sample periods in De-

Figure 6: IRFs to contractionary monetary policy shock - Earnings distribution



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Earnings IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, and the LHS variable as controls. Earnings percentiles are from the CPS, and percentiles are calculated separately for the non-essential and essential earnings distributions. 90% confidence intervals displayed.

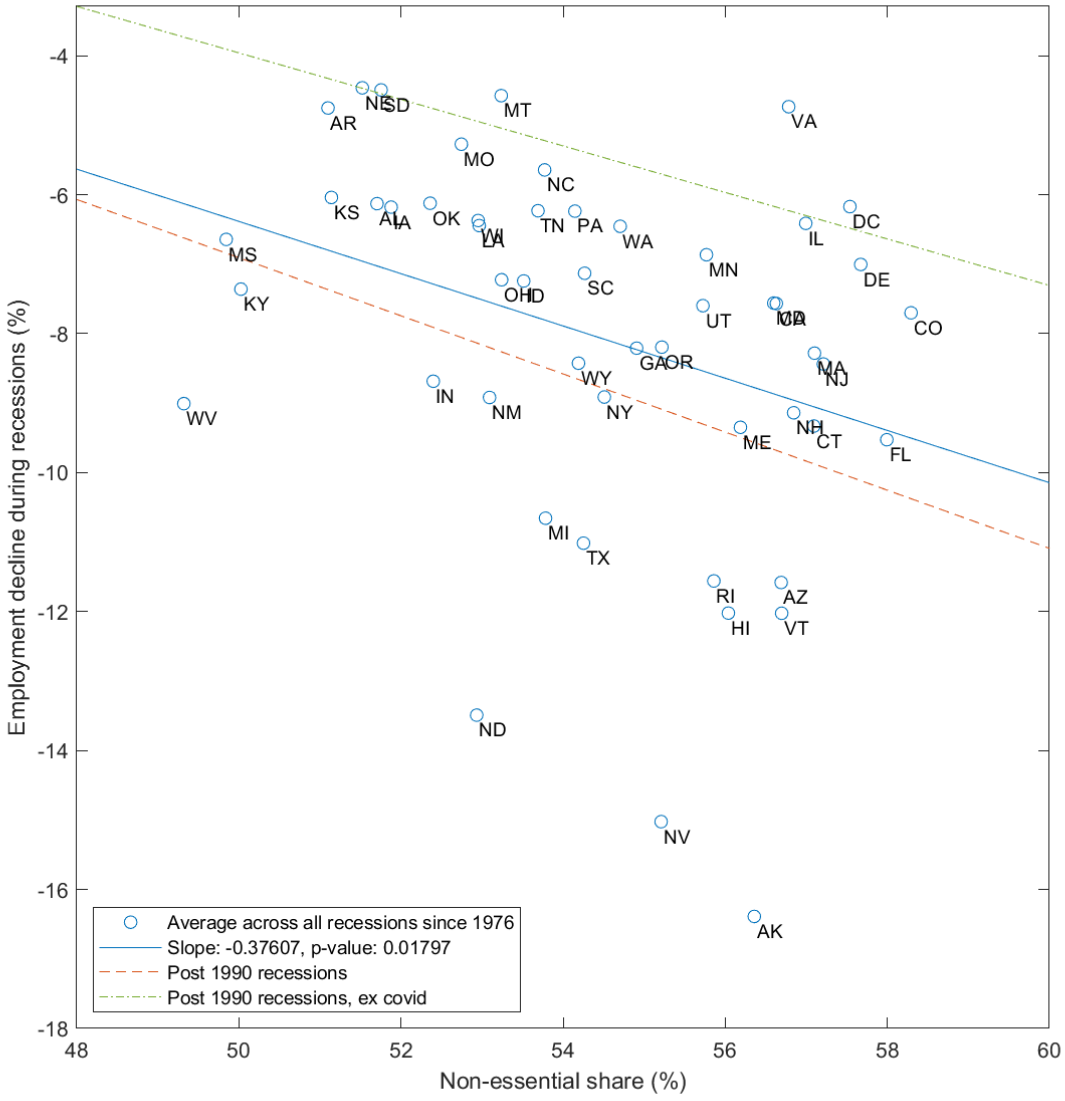
cember 2019, to entirely remove the effects of the Covid-19 Pandemic and to using standard (non-smoothed) local projections. Section I.8 shows the earnings IRF results for quarterly frequency, the recommended aggregation of the earnings data from the CPS. The quarterly results are similar qualitatively, but no longer significant. We also find that beginning all the estimation samples in January 1982, rather than different samples for variables with longer availability gives similar results (results available upon request).

4 State-level analysis

To complement our main results, we use state–level data to show that states with higher non-essential consumption shares have seen deeper employment declines during recent recessions. We use annual PCE data to construct average non-essential consumption shares for each state, since 1997. We then calculate the decline in employment during recent recession at the state level, using state-specific timing of the on-set and end of nationally defined recessions. Appendix J gives details on the data construction for the state-level analysis.

Figure 7 shows the resulting correlation between employment declines during recessions and non-essential consumption shares. Employment declines both statistically and economically significantly more during recessions in states with higher non-essential consumption shares, relative to ones with lower consumption shares. Our subsample analysis of more recent recessions (post 1990) and excluding the covid recession suggests that this is a typical feature of state-level recessions. This suggests that as non-essential consumption shares continue to rise (Figure 1), recessions could be amplified.

Figure 7: State-level employment during recessions vs non-essential consumption shares



Notes: Employment uses the BLS's monthly state level employment series, seasonally adjusted. Employment declines reflect log-differences. Employment declines are calculated state-specific timing of national recessions (see text). Non-essential shares are consumption shares constructed from the BEA's state-level annual PCE expenditure (by type of product) series, deflated using the corresponding national PCE price indices shares from the BEA's state-level annual PCE series, averaged 1997-2021. All recessions since 1976 included in average.

5 Outline of model

We next develop a model that is able to rationalise the differences in the business cycle behaviour between non-essentials and essentials we have shown empirically in consumption, prices, employment, and earnings.

The model is a heterogeneous agent New Keynesian model with three key ingredients to generate the essential business cycles mechanism. First, households are either rich and unconstrained or poor and constrained (with the distinction determined by their productivity). Second, they consume two types of goods: essential and non-essentials. The third key ingredient is that the non-essential sectors employ more low productivity workers, consistent with the data. When a contractionary monetary policy shock hits, household cut their non-essential consumption. This hits especially poor constrained households as they work mainly in the non-essential sector. As poor households have a higher MPC, this amplifies the business cycle with a general equilibrium feedback loop.

In addition to the key ingredients, we model a standard goods production function for wholesalers, retailers with sticky good prices, unions with sticky wages, good type and labour skill aggregators, a government which set taxes, and a central bank following a Taylor rule.

5.1 Non-homothetic preferences

To allow for differences in consumption bundles, we use a non-homothetic utility function which is an infinite horizon version of that proposed by Browning and Crossley (2000), which has been used in Andreolli and Surico (2021) to understand the heterogeneity in MPCs across households. Within each period, the household with skill level i ($i = H, L$) receives additively separable utility of power utility form consuming two types of goods, essentials (C^E) and non-essentials (C^N), and disutility from supplying labour for each member of the household (N_k):

$$U(C^E_{i,t}, C^N_{i,t}, \{N_{i,k,t}\}^1_{k=0}) = \frac{(C^E_{i,t})^{1-\frac{1}{\gamma^E}}}{1-\frac{1}{\gamma^E}} + \varphi \frac{(C^N_{i,t})^{1-\frac{1}{\gamma^N}}}{1-\frac{1}{\gamma^N}} - \xi \int_0^1 \frac{N^{1+\chi}_{i,k,t}}{1+\chi} dk \tag{2}$$

γ^E is the good's specific intertemporal elasticity of substitution for the essential good and γ^N for the non-essential good. There is a one-to-one mapping between the good specific IES and the income elasticity of demand of the same good, which is shown in Browning and Crossley (2000) for a two-period model and in Andreolli and Surico (2021) for a infinite horizon model. The good with the higher IES also has the higher income elasticity of

substitution, so is by definition a luxury, or non-essential, good:

$$\gamma^E < \gamma^N \tag{3}$$

This is shown in Andreolli and Surico (2021). Intuitively, households are very unwilling to delay consumption of necessities like groceries - they strongly prefer to smooth consumption over these types of goods - but are more willing to delay consumption of non-essentials like going out to a restaurant or bar: non-essentials are easier to anticipate and postpone than essentials. Note that the mapping between income elasticity and IES is not an artefact of these specific preferences: Browning and Crossley (2000) prove that this mapping holds for any utility function which is additive separable in good varieties.

These preferences have a few other useful related properties. They imply that households with lower incomes will spend a proportionately larger fraction of their budget on essentials, which results from the lower income elasticity of demand of essentials. They also imply time-varying intertemporal elasticities of substitution which are higher for wealthier households, which has been documented by Crossley and Low (2011).

To conclude the discussion of preferences, χ is the inverse of the macro Frisch elasticity, φ and ξ are scaling constants which help calibrate the steady state solution.

5.2 Household problem

Households i have preferences for essential goods $C^E_{i,t}$ and non-essential goods $C^N_{i,t}$. In addition, they are comprised of a continuum of members $k \in [0,1]$ with different dis-utility of working who are insured within the household and each works $N_{i,k,t}$ hours. The utility is as specified in equation 2 above.

We have two type of agents in this economy: high H and low L skilled. These agents differ along two dimensions: steady state income levels and whether they can access financial markets or not. We assume that H agents have higher income and are Ricardian, whereas L agents have lower income and are hand to mouth[14].

Rich agents earn average wage $W_{H,t}$ and member specific wage $W_{H,k,t}$ and poor agents earn $W_{L,t}$ ($W_{L,k,t}$). Agents also obtain profits from firms $\Pi_{i,t}$ and transfers from the government $T_{i,t}$.

[14]This simplification would arise endogenously in a heterogeneous agent model with uninsurable income risk and borrowing constraint. The framework can be amended to include wealthy hand to mouth easily, but we abstract from them for tractability and to highlight the new channel we are proposing.

5.2.1 Ricardian agent problem

Unconstrained agents can invest in bonds $B_{H,t}$ that earn risk free nominal rate R_t. Their problem is:

$$\max_{C^E_{H,t+j},C^N_{H,t+j},B_{H,t+j}} \mathbb{E}_t \sum_{j=0}^{\infty} \beta^j \left\{ \frac{\left(C^E_{H,t+j}\right)^{1-\frac{1}{\gamma^E}}}{1-\frac{1}{\gamma^E}} + \varphi \frac{\left(C^N_{H,t+j}\right)^{1-\frac{1}{\gamma^N}}}{1-\frac{1}{\gamma^N}} - \xi \int_0^1 \frac{N^{1+\chi}_{H,k,t}}{1+\chi} dk \right\}$$

s.t.

$$P^E_{t+j} C^E_{H,t+j} + P^N_{t+j} C^N_{H,t+j} + B_{H,t+j} \leq \int_0^1 W_{H,k,t+j} N_{H,k,t+j} dk + \Pi_{H,t+j} + T_{H,t+j} + R_{t+j-1} B_{H,t+j-1}$$

Where the budget constraint is expressed in nominal dollar terms. Households lets the union make the decision for labour supply. The solution to the problem is:

$$\frac{\left(C^E_{H,t}\right)^{-\frac{1}{\gamma^E}}}{\left(C^N_{H,t}\right)^{-\frac{1}{\gamma^N}}} = \frac{1}{p^N_t} \varphi$$

$$1 = \mathbb{E}_t \left(\beta \left(\frac{C^E_{H,t+1}}{C^E_{H,t}} \right)^{-\frac{1}{\gamma^E}} \frac{1}{\pi^E_{t+1}} R_t \right)$$

Where $\pi^E_{t+1} \equiv \frac{P^E_{t+1}}{P^E_t}$ is the inflation of essential goods, and similarly for non-essentials, and $p^N_t \equiv \frac{P^N_t}{P^E_t}$ is the relative price of non-essential in terms of essentials.

We obtain an intra-temporal choice between consumption of essentials and non-essentials and the inter-temporal Euler equation. Notice that we can use the SDF for essential or non-essentials to price bonds and similarly the marginal utility from essential or non-essential consumption to chose how much labour to supply.

5.2.2 Hand-to-mouth agent problem

Constrained agents do not have access to bond markets. Their problem is purely intra-temporal:

$$\max_{C^E_{L,t+j},C^N_{L,t+j}} \mathbb{E}_t \sum_{j=0}^{\infty} \beta^j \left\{ \frac{\left(C^E_{L,t+j}\right)^{1-\frac{1}{\gamma^E}}}{1-\frac{1}{\gamma^E}} + \varphi \frac{\left(C^N_{L,t+j}\right)^{1-\frac{1}{\gamma^N}}}{1-\frac{1}{\gamma^N}} - \xi \int_0^1 \frac{N^{1+\chi}_{L,k,t+j}}{1+\chi} dk \right\}$$

s.t.

$$P^E_{t+j} C^E_{L,t+j} + P^N_{t+j} C^N_{L,t+j} \leq W_{L,t+j} N_{L,t+j} + \Pi_{L,t+j} + T_{L,t+j}$$

The solution is as above without the Euler equation so that we have 2 equilibrium conditions for the constrained agent:

$$\frac{(C^E_{L,t})^{-\frac{1}{\gamma^E}}}{(C^N_{L,t})^{-\frac{1}{\gamma^N}}} = \frac{1}{p^N_t}\varphi$$
$$P^E_t C^E_{L,t} + P^N_t C^N_{L,t} = W_{L,t}N_{L,t} + \Pi_{L,t} + T_{L,t}$$

5.3 Labour packers

For each type of labour skill H and L there is a perfectly competitive labour packer which combines the different, imperfectly substitutable, varieties with a CES aggregator. For the high skilled households:

$$N_{H,t} = \left(\int_0^1 (N_{H,k,t})^{\frac{\varepsilon_H - 1}{\varepsilon_H}} dk\right)^{\frac{\varepsilon_H}{\varepsilon_H - 1}}$$

This creates a demand schedule by the labour packer for each variety of high skilled labour:

$$N_{H,k,t} = N_{H,t}\left(\frac{W_{H,k,t}}{W_{H,t}}\right)^{-\varepsilon_H}$$

Similarly, for the low skilled labour:

$$N_{L,k,t} = N_{L,t}\left(\frac{W_{L,k,t}}{W_{L,t}}\right)^{-\varepsilon_L}$$

5.4 Unions

Monopolistically competitive unions represent households of a given variety k and skill level i and set wages $W_{i,k,t}$ for their members, as in the model by Erceg, Henderson and Levin (2000). Their per-period objective is to maximize the marginal utility from labour income $\lambda_{i,t}N_{i,k,t}W_{i,k,t}(1+\tau^{W_i})$ less disutility from labour $\xi\frac{N^{1+\chi}_{i,k,t+j}}{1+\chi}$ and less lump sum taxes $T^{W_i}_t$. There is a fixed subsidy τ^{W_i} that eliminates the steady state unemployment distortion and a lump sum taxation that finances the subsidy exactly. The unions cannot freely change wages and are subject to a Calvo friction: with probability θ_i they cannot reset their prices. Their objective function when they cannot reset the wage (with the demand for the variety of

labour already substituted in):

$$\max_{W^*_{i,k,t}} \mathbb{E}_t \sum_{j=0}^{\infty} (\beta\theta^i)^j \left[\lambda_{i,t+j} N_{i,t+j} \left(\frac{W^*_{i,k,t}}{W_{i,t+j}} \right)^{-\varepsilon_i} W^*_{i,k,t}(1+\tau^{W_i}) - \xi \frac{\left(N_{i,t+j} \left(\frac{W^*_{i,k,t}}{W_{i,t+j}} \right)^{-\varepsilon_i} \right)^{1+\chi}}{1+\chi} - T^{W_i}_{t+j} \right]$$

The subsidy τ^{W_i} equals $\frac{1}{1-\varepsilon_i}$ to remove any distortion in steady state in the labour market and the lump sum tax is $T^{W_i}_t = \tau^{W_i} W_{i,t} N_{i,t}$, to pay for the subsidy. Notice that the marginal utility of consumption and the disutility of labour do not impact the subsidy as these are utility costs rather than real resources that enter in market clearing conditions. Taking the first order condition:

$$\mathbb{E}_t \sum_{j=0}^{\infty} (\beta\theta_i)^j \left(N_{i,t+j} \left(\frac{W^*_{i,k,t}}{W_{i,t+j}} \right)^{-\varepsilon_i} \right) \left[\lambda_{i,t+j} - \frac{1}{1+\tau^{W_i}} \frac{\varepsilon_i}{\varepsilon_i - 1} \xi \left((W^*_{i,k,t})^{-(1+\varepsilon_i\chi)} N^{\chi}_{i,t+j} W^{\varepsilon_i\chi}_{i,t+j} \right) \right] = 0$$

We rearrange recursively the above expression, use the wage index expression, use the marginal utility for essentials for a household with skill type i, define the real wage in terms of the essential good price ($w_{i,t} \equiv \frac{W_{i,t}}{P^E_t}$), and define wage inflation ($\pi_{W_i,t} \equiv \frac{W_{i,t}}{W_{i,t-1}}$). With these steps, we arrive to three equations that represent a non-linear New-Keynesian wage Phillips curve.

$$\begin{aligned}
X^w_{1,i,t} &= (N_{i,t})^{1+\chi} + \beta\theta_i \mathbb{E}_t \left(\pi_{W_i,t+1} \right)^{\varepsilon_i(1+\chi)} X^w_{1,i,t+1} \\
X^w_{2,i,t} &= (C^E_{i,t})^{-\frac{1}{\gamma^E}} N_{i,t} + \beta\theta_i \mathbb{E}_t \frac{1}{\pi^E_{t+1}} (\pi_{W_i,t+1})^{\varepsilon_i} X^w_{2,i,t+1} \\
(1+\tau^{W_i}) \frac{\varepsilon_i - 1}{\varepsilon_i} \frac{X^w_{1,i,t}}{X^w_{2,i,t}} \frac{1}{w_{i,t}} &= \left(\frac{1 - \theta_i \pi^{\varepsilon_i - 1}_{W_i,t}}{1 - \theta_i} \right)^{\frac{1}{1-\varepsilon_i}}
\end{aligned}$$

When linearised, these three equations simplify to a standard New-Keynesian wage Phillips curve in one equation.

5.5 Firms

We have two sets of firms, the first that produces essential goods and the second that produces non-essential goods. The two sets differ on how many high and low skilled workers they employ, with the essential sector employing more high skilled workers.

5.5.1 Final good producers

In this economy there are two perfectly competitive sectors with final good producers who combine different retail varieties of the essential and of the non-essential goods according to a CES aggregator. For the essential good:

$$Y_t^E = \left(\int_0^1 (y_{k,t}^E)^{\frac{\varepsilon-1}{\varepsilon}} dk \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

This leads to the demand that the final good producers have for different varieties:

$$y_{k,t}^E = Y_t^E \left(\frac{P_{k,t}^E}{P_t^E} \right)^{-\varepsilon}$$

Similarly, we obtain a demand function for the non-essential good:

$$y_{k,t}^N = Y_t^N \left(\frac{P_{k,t}^N}{P_t^N} \right)^{-\varepsilon}$$

5.5.2 Calvo retailers

Retailers of a given type of good, say essential[15], buy a wholesale good of the same type at a wholesale price $P_t^{E,w}$ and use it to produce the retail variety $y_{k,t}^E$ with a linear technology that maps one-to-one the wholesale good to the retail variety. As each variety is differentiated they have market power and face a Calvo friction to change prices. Their real marginal cost $\mathcal{S}_t^E = \frac{P_t^{E,w}}{P_t^E}$ is the wholesale price relative to its retail average value. They receive a subsidy τ^E for each unit of good they produce and pay lump sum taxes T_t^E; these taxes allow to have zero profit in steady state but do not affect the profit allocation off-steady state. The probability of not being able to reset prices is equal to θ^E in each period. This leads to a standard non-linear New-Keynesian Phillips Curve. The objective function, the discounted present value of profits in the non-reset states:

$$\mathbb{E}_t \sum_{j=0}^{\infty} SDF_{t,t+j} (\theta^E)^j \left(\tilde{P}_t^E Y_{k,t+j}^E - P_{t+j}^E (1-\tau^E) \mathcal{S}_{t+j}^E Y_{k,t+j}^E - T_t^E \right)$$

[15] We solve the essential retailers problem, the non-essential retailers one is fully symmetric.

We substitute the demand equation, take the first order condition, substitute-in the SDF for the H household[16], and rearrange to arrive to three equations representing the non-linear New Keynesian Phillips Curve.

$$K_t^{E,f} = \left(C_{H,t}^E\right)^{-\frac{1}{\gamma^E}} Y_t^E \mathcal{S}_t^E \frac{\varepsilon^E}{\varepsilon^E - 1}(1-\tau^E) + \theta^E \beta \mathbb{E}_t (\pi_{t+1}^E)^{\varepsilon^E} K_{t+1}^{E,f}$$
$$F_t^{E,f} = \left(C_{H,t}^E\right)^{-\frac{1}{\gamma^E}} Y_t^E + \theta^E \beta \mathbb{E}_t (\pi_{t+1}^E)^{\varepsilon^E - 1} F_{t+1}^{E,f}$$
$$\frac{K_t^{E,f}}{F_t^{E,f}} = \left(\frac{1-\theta^E(\pi_t^E)^{\varepsilon^E-1}}{1-\theta^E}\right)^{\frac{1}{1-\varepsilon^E}}$$

For the non-essential goods we can solve the same problem and arrive to the same equations:

$$K_t^{N,f} = \left(C_{H,t}^N\right)^{-\frac{1}{\gamma^N}} Y_t^N \mathcal{S}_t^N \frac{\varepsilon^N}{\varepsilon^N - 1}(1-\tau^N) + \theta^N \beta \mathbb{E}_t (\pi_{t+1}^N)^{\varepsilon^N} K_{t+1}^{N,f}$$
$$F_t^{N,f} = \left(C_{H,t}^N\right)^{-\frac{1}{\gamma^N}} Y_t^N + \theta^N \beta \mathbb{E}_t (\pi_{t+1}^N)^{\varepsilon^N - 1} F_{t+1}^{N,f}$$
$$\frac{K_t^{N,f}}{F_t^{N,f}} = \left(\frac{1-\theta^N(\pi_t^N)^{\varepsilon^N-1}}{1-\theta^N}\right)^{\frac{1}{1-\varepsilon^N}}$$

5.5.3 Wholesalers

Wholesalers produce one type of good, say essentials, are perfectly competitive and they combine high-skill labour $N_{H,t}^E$ and low-skill labour $N_{L,t}^E$ with technology:

$$Y_t^E = A_t^E (N_{L,t}^E)^{\alpha^E} (N_{H,t}^E)^{1-\alpha^E}$$

They sell these goods at nominal price $P_t^{E,w}$ to retailers. They pay nominal wage $W_{H,t}$ for each unit of high-skilled household labour and nominal $W_{L,t}$ for each unit of low-skilled household labour. The low-skilled share in production is α^E. Crucially we have $\alpha^E < \alpha^N$ from the data: there are relatively more low-skilled workers in non-essential goods production than in essential goods production. Technology is stochastic and its process is follows an AR(1) in

[16] As we take a first order Taylor approximation to solve the model, the choice of whose SDF we take drops out. However, we need to specify to whom the off-steady state profits are allocated as this affects the propagation mechanism in a heterogeneous agents model: we specify a profit allocation rule directly. Notice that one could use indifferently the SDF for essential and non-essential goods as they are equal in each state of nature for a given agent, we use the SDF for essentials for the essential good producers and the one for non-essentials for the non-essential retailer.

logs:

$$\frac{A_t^E}{A^E} = \left(\frac{A_{t-1}^E}{A^E}\right)^{\rho_A^E} \exp(\varepsilon_t^{E,A})$$

The solution to their optimization problem is:

$$\mathcal{S}_t^E \alpha^E \frac{Y_t^E}{N_{L,t}^E} = \frac{W_{L,t}}{P_t^E}$$
$$\mathcal{S}_t^E (1-\alpha^E) \frac{Y_t^E}{N_{H,t}^E} = \frac{W_{H,t}}{P_t^E}$$

We can get a similar set of equilibrium conditions for the non-essential wholesalers:

$$Y_t^N = A_t^N (N_{L,t}^N)^{\alpha^N} (N_{H,t}^N)^{1-\alpha^N}$$
$$\frac{A_t^N}{A^N} = \left(\frac{A_{t-1}^N}{A^N}\right)^{\rho_A^N} \exp(\varepsilon_t^{N,A})$$
$$\mathcal{S}_t^N \alpha^N \frac{Y_t^N}{N_{L,t}^N} = \frac{W_{L,t}}{P_t^N}$$
$$\mathcal{S}_t^N (1-\alpha^N) \frac{Y_t^N}{N_{H,t}^N} = \frac{W_{H,t}}{P_t^N}$$

5.6 Market clearing

In this economy the population is divided in the two types of households with total mass equal to one:

$$1 = \mu_H + \mu_L$$

The market clearing conditions for the two goods markets:

$$Y_t^E = \frac{\Pi_{f,t}^E}{P_t^E} + C_t^E = \frac{\Pi_{f,t}^E}{P_t^E} + \sum_{i=\{H,L\}} \mu_i C_{i,t}^E$$
$$Y_t^N = \frac{\Pi_{f,t}^N}{P_t^N} + C_t^N = \frac{\Pi_{f,t}^N}{P_t^N} + \sum_{i=\{H,L\}} \mu_i C_{i,t}^N$$

Where $\frac{\Pi_{f,t}^E}{P_t^E}$ and $\frac{\Pi_{f,t}^N}{P_t^N}$ are the real profits paid back to foreigners according to a transfer

rule. The labour market clearing conditions for the two types of labour:

$$N^E_{H,t} + N^N_{H,t} = \mu_H N_{H,t}$$
$$N^E_{L,t} + N^N_{L,t} = \mu_L N_{L,t}$$

The government bonds market clearing:

$$B_t = \mu_H B_{H,t}$$

We can define CPI Inflation with Laspeyres, Paasche, or Fisher price indices. With this model we do not have a clear-cut ideal price index, therefore we could compute them in a similar way as statistical agencies. However, notice that when log-linearised, all these indices simplify to inflation being a weighted average of essential inflation and non-essential inflation, weighted by the economy wide consumption shares.

$$\pi_{t,Lasp} = \frac{P^E_t C^E_{t-1} + P^N_t C^N_{t-1}}{P^E_{t-1} C^E_{t-1} + P^N_{t-1} C^N_{t-1}}$$
$$\pi_{t,Paasche} = \frac{P^E_t C^E_t + P^N_t C^N_t}{P^E_{t-1} C^E_t + P^N_{t-1} C^N_t}$$
$$\pi_{t,Fisher} = \left(\pi_{t,Lasp} \pi_{t,Paasche}\right)^{1/2}$$

We can compute real GDP with production in the two sectors weighted by prices in steady state:

$$Y_t = P^E Y^E_t + P^N Y^N_t$$

5.7 Government

The government consists of a central bank that sets interest rates according to a Taylor rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left(\left(\mathbb{E}_t(\pi_{t+1,Fisher})\right)^{\phi_\pi} \left(\frac{Y_t}{Y}\right)^{\phi_Y} \right)^{1-\rho_R} \exp(\varepsilon^{mp}_t)$$

And of a treasury that sets aggregate transfers according to a transfer policy rule, subject to the government budget constraints that determines bond issuance. Notice that we write the aggregate transfer policy rule linearly as, with zero steady state transfers/bonds, we cannot

log-linearise them, but we linearise them instead.

$$T_t = \phi^T B_{t-1}$$
$$B_t = T_t + R_{t-1} B_{t-1}$$

And a transfer policy and profit policy rule[17]:

$$T_{i,t} = \phi_{T,i} T_t \quad i = \{H, L\}$$
$$\Pi_{i,t} = \phi^E_{\Pi,i} \Pi^E_t + \phi^N_{\Pi,i} \Pi^N_t \quad i = \{H, L\}$$

With $\Pi^E_{f,t} = \left[1 - \sum_{i=\{H,L\}} \phi^E_{\Pi,i}\right] \Pi^E_t$ and $\Pi^N_{f,t} = \left[1 - \sum_{i=\{H,L\}} \phi^N_{\Pi,i}\right] \Pi^N_t$ being the profits paid to foreign equity holders. The profit rule can accommodate profits from either sector being redistributed to H, L households, or to foreigners. Moreover, the government sets a lump sum tax on each Calvo retailer (union) such that it pays in a non-distortive way for the subsidy to the same retailer (union). With this tax, retailers profits are zero in steady state.

$$T^E_t = \tau^E P^E_{t+j} \mathcal{S}^E_{t+j} Y^E_{t+j}$$
$$T^N_t = \tau^N P^N_{t+j} \mathcal{S}^N_{t+j} Y^N_{t+j}$$
$$T^{W_H}_t = \tau^{W_H} W_{H,t} N_{H,t}$$
$$T^{W_L}_t = \tau^{W_L} W_{L,t} N_{L,t}$$

5.8 Equilibrium, steady state, and log-linearisation

We present in Appendix K the equilibrium definition, the steady state computation, and the log-linearisation around a zero inflation steady state.

6 Model calibration and results

6.1 Calibration

We take a standard calibration for most parameters. This is presented in Table 2. For the IES for Essential goods we pick $\gamma^E = 2/3$ and for the IES for Non-essential goods we pick $\gamma^N = 3/2$. This choice leads to an average economy wide income elasticity for Essential goods

[17] Capital letter Π are profits, small letter π are inflation rates.

of 0.5894 and for Non-essential goods of 1.3064 which are both in the middle of the range for the empirically estimated income elasticity shown in Appendix Table A.3. The implied economy wide IES is 1.1439, close to an aggregate IES of 1.

Table 2: Model Calibration

Parameter	Value	Description
γ^E	0.6667	IES for essential goods
γ^N	1.5	IES for non-essential goods
β	0.99	Time preference
η	0.1	Inverse of the macro Frisch elasticity
ξ	1	Dis-utility of working scaling parameter
α^E	0.1	Low skilled workers share in production of essential goods
α^N	0.2	Low skilled workers share in production of non-essential goods
θ^E	0.75	Calvo degree of stickiness in essential goods prices
θ^E	0.75	Calvo degree of stickiness in non-essential goods prices
θ^H	0.75	Calvo degree of stickiness for high skilled wages
θ^L	0.75	Calvo degree of stickiness for low skilled wages
ε^E	2	Elasticity of substitution across essential goods varieties
ε^N	2	Elasticity of substitution across non-essential goods varieties
ε^H	2	Elasticity of substitution across high skilled labour varieties
ε^L	2	Elasticity of substitution across low skilled labour varieties
ϕ_π	1.5	Coefficient of the Taylor rule on expected inflation
ϕ_Y	0.125	Coefficient of the Taylor rule on output
τ^T	0	Tax policy: response to debt
$\tau_{T,H}$	0	Tax policy: share of transfers to high skilled households
$\tau_{T,L}$	0	Tax policy: share of transfers to low skilled households
ρ_R	0.8	Smoothing of the monetary policy process
s_{mp}	0.25	Standard deviation of the monetary policy process
$\phi_H^{\Pi,E}$	0	Share of profits by essential retailers going to high skilled households
$\phi_L^{\Pi,E}$	0	Share of profits by essential retailers going to low skilled households
$\phi_H^{\Pi,N}$	0	Share of profits by non-essential retailers going to high skilled households
$\phi_L^{\Pi,N}$	0	Share of profits by non-essential retailers going to low skilled households
μ^L	1/3	Fraction of low skilled hand-to-mouth households
$\bar{C}_H^E$	0.43	Steady state share of essential good consumption by high skilled households
$\bar{C}_L^E$	0.56	Steady state share of non-essential good consumption by high skilled households
π^E	1	Steady state inflation in essential goods
π^N	1	Steady state inflation in non-essential goods
B	0	Steady state public debt level over GDP

Notes: The first column shows the parameter or steady state value calibrated. The scaling parameter for the relative utility of non-essential goods (φ) and the relative productivity between essential good production and non-essential good production ($a^E = A^E/A^N$) are computed to with the aid of other parameters to match the steady state share of essential good consumption by high skilled households ($\bar{C}_H^E$) and low skilled households ($\bar{C}_L^E$).

The share of low skilled households, who are hand-to-mouth, (μ^L) is calibrated to 1/3, a standard parameter for the share of hand-to-mouth households in the economy.

We calibrate the low skilled workers share in production of essential goods (α^E) and non-essential goods (α^N) to match the fraction of the overall wage bill in the production of each good category that goes to the lowest tercile of earners in that sector. We use the

employment data.

Other parameters are in line with estimated DSGE as Christiano, Eichenbaum and Evans (2005), Smets and Wouters (2007), Christiano, Trabandt and Walentin (2010), or Herbst and Schorfheide (2016). To highlight our new channel we pick the same price stickiness and wage stickiness across goods and skill levels, as well as the same elasticity of substitution across good type varieties and labour skill varieties. Taylor rule parameters are standard. The inverse of the macro Frisch elasticity is 0.1, in line with the posterior reported by Christiano, Trabandt and Walentin (2010).

To highlight our labour market channel we give all profits to foreigners ($\phi_i^{\Pi,j} = 0$ for $i = \{H, L\}$ and $j = \{N, E\}$). Counter-cyclical profits would have relatively increased incomes of high skilled households, who are more likely to own shares, separately to the labour demand channel of where they work. We are tying our hands by doing this, ensuring that our results are driven by the labour market channel we focus on. If we profits went to high skilled households this would result in even stronger amplification results.

We force the government to maintain a balanced budget in every period with no public debt. Moreover, we shut down transfers across households of different skill levels to highlight the labour market channel.

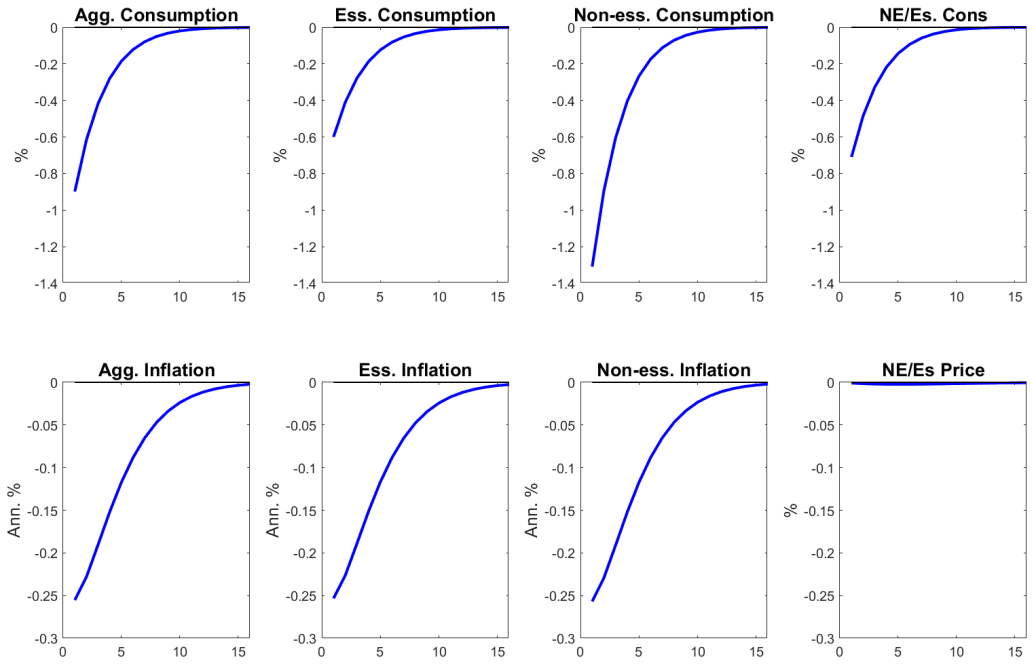
We calibrate the steady state consumption shares of essential goods for high skilled households ($\bar{C}_H^E$) and low skilled households ($\bar{C}_L^E$) to 0.43 and 0.56 respectively from the expenditure share data as shown in Appendix Table A.4. We match these moments by varying the scaling parameter for the relative utility of non-essential goods (φ) and the relative productivity between essential good production and non-essential good production ($a^E = A^E/A^N$). With non-homothetic preferences, consumption shares depend on the wages of the two households and we can affect them differentially by varying the relative productivity in the two sectors, as households are differentially employed in the two sectors. We detail the moment matching algorithm and the steady state computation in Appendix K. The values for the two parameters are: $\varphi = 1.3465$ and $a^E = 2.1933$.

6.2 Model IRFs

In this subsection, we present the model Impulse Response Functions to an annualised 100 basis points monetary policy shock. Figure 8 presents the responses of consumption and inflation and matches Figure 3 of the empirical estimation. Figure 9 presents the responses of employment and earnings and matches Figure 4 of the empirical estimation.

The IRFs of this simple model can match well the overall peak magnitude of the empirical

Figure 8: Model IRFs to contractionary monetary policy shock - Consumption and Inflation



Notes: The IRFs present the response to an annualised 100 basis points monetary policy shock. The consumption responses weight the percent reaction of each consumption subcategory by its steady state consumption share. The aggregate inflation response weights essential and non-essential inflation by their steady state consumption response. The relative price response is the response of non-essentials over essentials prices.

effects[18]. All the presented IRFs have a peak response which is in the confidence bands of the corresponding peak empirical response.

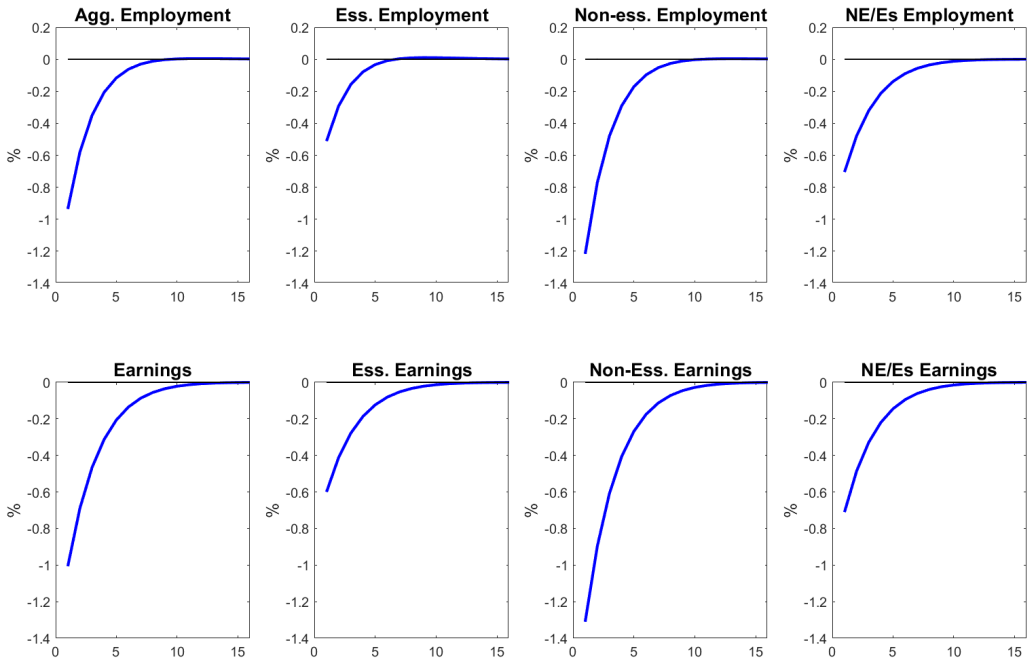
In Figure 8, we can see that aggregate consumption declines by about 0.9%, but this aggregate effect marks substantial heterogeneity. Consumption in Essentials falls only by 0.6% and consumption of non-essentials by more than double that, at -1.3%. We can see the heterogeneity by plotting the behaviour of the ratio of non-essential consumption to essential consumption which falls by 0.7%. When a recession arrives, households cut first their non-essential spending as it is this easier to postpone to better times.

We also see that non-essential inflation declines marginally more than essential inflation, but only marginally so. The overall inflation response is quite low, in line with empirical results that point to only slightly significant inflation responses.

As households cut non-essential consumption, employment and earnings in the non-

[18]They cannot match the hump shape, as to keep the model parsimonious we abstract from the mechanisms as capital, habit, or sticky information that could match the hump share but would obscure the key mechanism.

Figure 9: Model IRFs to contractionary monetary policy shock - Employment and Earnings



Notes: The IRFs present the response to an annualised 100 basis points monetary policy shock. The employment (earnings) responses weight the percent reaction of each employment subcategory by its steady state employment hours (earnings) share. Earnings off steady state are computed by multiplying hours by the appropriate wage.

essential sector decline relatively more than in the essential sector. From Figure 9 we can see that the relative decline is about 0.7% both for relative employment and for relative earnings.

Quantifying the amplification It is mainly low skilled hand-to-mouth households who work in the non-essential sector. Therefore, it is mainly their employment and labour earnings which decline the most following the monetary policy shock. As these households are hand-to-mouth and have a high MPC, they amplify the effect of business cycles in this model. The differential employment in the two sectors is a potential micro-foundation of why low income households are more likely to become unemployed during recessions.

Low income household are disproportionally hit on their labour market outcomes and this makes them cutting their consumption even more, thereby affecting everyone in the economy. As low income households are consuming relatively more essentials than non-essentials, the relative decline in non-essential masks a general equilibrium response. If low-income household were not hit as much, we would see even a higher differential decline

in Non-essential consumption, but overall a lower magnitude of reaction.

We can see this by looking the model based amplification numbers in the last column of Table 1. The amplification by non-essentials is higher in employment than in consumption because low skilled households cut their predominantly essential consumption and lower the observed heterogeneity. Amplification by non-essentials is 30% for consumption, but 37% for employment.

7 Conclusion

This paper has demonstrated that understanding how different consumption patterns by the rich and the poor of essentials and non-essentials is crucial to understand the transmission and amplification of business cycle shocks. As the purchase of non-essentials is easier to postpone than the purchase of necessities, high income households cut their spending on non-essentials during recessions and following contractionary monetary policy actions. This impacts poorer households as they more likely to work in sectors producing non-essential goods and services. Taken together, the families with less resources in society lose twice because of the spending behaviour of affluent households, via: (i) a small direct effect that makes their necessity-dominated consumption bundle more expensive, (ii) an large indirect effect that lowers their labour income and thus the resources that they have available for spending.

Our empirical evidence suggests that the presence of non-essentials amplifies contractions of consumption by 20% and employment by 44%. We find weaker evidence that price responses are also increasing the impact of consumption heterogeneity on poorer households; essential prices do not decline as much as non-essential prices, but only mildly so.

We outline a heterogeneous agent New Keynesian model which features three key ingredients. First, households have non-homothetic utility over non-essentials and essentials. Second households differ in skill levels and low skilled households are hand-to-mouth. Finally, low skilled workers are more likely to work in producing non-essential goods. The model matches key moments of the data: the amplification due to non-essentials and the the magnitude of the responses of key variables to a monetary policy shock.

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Appendix

A Classification procedure for consumption and prices in PCE data

Table A.1: Consumption categorisation

Essentials	Non-Essentials
Rent	Other car spending
Used car purchases	(leasing, financing, insurance)
Communication, telephone contracts	Entertainment equipment
Food at home	and subscription television
Utilities	Alcoholic beverages
Children's clothing	Men's and women's clothing
Gas and vehicle maintenance	Food away from home
Health expenditures including insurance	Household appliances
Personal care	Owner occupied housing consumption
	Furniture and fixtures
	Education
	Domestic services and childcare
	New car purchases
	Public transport
	Entertainment fees, admissions, reading
	Cash contributions

Notes: Classification of consumption categories into essential and non-essential, as described in text and Appendix A. Categories listed in order of estimated income elasticity of demand, lowest to highest within each classification.

The consumption and price series for non-essential and essentials are constructed using the BEA's Personal Consumption Expenditure by Type of Product tables. We classify the products within the tables into essentials and non-essentials by estimating Engel Curves closely following the approach used by Aguiar and Bils (2015), and categorising (non-)essentials as products with an income/total expenditure elasticity of demand less than (greater than) one.

Aguiar and Bils (2015)'s approach is to use household microdata from three waves of the Consumer Expenditure Survey and estimate the expenditure elasticities as β_j from:

$$\ln x_{hjt} - \ln \bar{x}_{hjt} = \alpha_{jt} + \beta_j \ln X_{ht} + \Gamma_j \mathbf{Z}_h + u_{hjt} \tag{4}$$

Where x_{hjt} is the expenditure by household h on goods of type j in year t, $\bar{x}_{hjt}$ is the equivalent average across households, X_{ht} is total household expenditure, instrumented by

Table A.2: Consumption categorisation

Essentials	Non-Essentials
Rent	Other car spending
Used car purchases	(leasing, financing, insurance)
Communication, telephone contracts	Entertainment equipment
Food at home	and subscription television
Utilities	Alcoholic beverages
Children's clothing	Men's and women's clothing
Gas and vehicle maintenance	Food away from home
Health expenditures including insurance	Household appliances
Personal care	Owner occupied housing consumption
	Furniture and fixtures
	Education
	Domestic services and childcare
	New car purchases
	Public transport
	Entertainment fees, admissions, reading
	Cash contributions

Notes: Classification of consumption categories into essential and non-essential, as described in text and Appendix A. Categories listed in order of estimated income elasticity of depand, lowest to highest within each classification.

household income (dummies for category and log real after-tax income), α_{jt} are good fixed effects and $\mathbf{Z}_h$ are household characteristics (age range, earners and household size). For full details see the original paper, which we replicate the identical empirical specification.

We make two minor alterations to Aguiar and Bils (2015)'s approach. Firstly, we alter slightly the set of product categories, introducing some narrower categories where the broader categories included goods that varied considerably in their elasticities. Specifically, we split "Applicances, phones, computers with associated services" into "Communications" and "Household appliances", "All other transportation" into "Gas and vehicle maintenance" and "Public transport", "Housing" into "Rents" and "Owner-occupied housing consumption" and "Vehicle purchasing, leasing and insurace" into "New car purchases", "Used car purchases" and "Other car spending (leasing, financing and insurance". We also omit tobacco from the product categories, as the intertemporal substitutability of tobacco is likely more related to the addictive nature of the good than the income elasticity, so less related to our theoretical framework. Secondly, we estimate the Engel curves for 1995-1997 rather than 1994-1996, in order to use the more consistent goods categories reported in the CEX Interview FMLI files during these years. As Aguiar and Bils (2015) note, the expenditure

elasticities do not vary considerably over time, and consistent with this using the slightly different sample period makes minimal difference to their original estimated elasticities.

Table A.3 reports the estimated expenditure elasticities and expenditure shares for the revised goods categories, which is a replication of Table II of Aguiar and Bils (2015), omitting the final two columns[19]:

[19] Aguiar and Bils (2015) use two specifications, either using income to instrument total expenditure, or lagged total expenditure to instrument current total expenditure. We prefer to use the former here. This is particularly a concern for new cars, because of the lumpiness of car investment. We were concerned that the second specification would bias down the estimated elasticity, if households save in earlier quarters and have lower total lagged expenditure, in order to spend more in the later quarters to buy a car (or visa versa). When a household buys a car they have higher total expenditure in that quarter, but the predicted expenditure from the instrument of the last quarter would be lower, therefore associating a higher car expenditure with a lower total predicted expenditure, biasing the IED estimate towards a necessity. This attenuation in the elasticity estimate isn't present with the income instrument, and in practice makes a substantial difference to the estimated IED for new cars.

Table A.3: Engel curves used for Essential/Non-essential classification

Good category	CE share 1995-1997	Elasticity	SE
Rent	5.5	-1.1	0.09
Used car purchases	5.53	0.23	0.16
Communication, telephone contracts	2.59	0.31	0.04
Food at home	11.63	0.4	0.02
Utilities	5.21	0.47	0.02
Children's clothing	0.96	0.65	0.07
Gas and vehicle maintenance	6.14	0.72	0.03
Health expenditures including insurance	4.9	0.81	0.05
Personal care	0.97	0.96	0.05
Shoes and other apparel	1.47	1.07	0.09
Other car spending (leasing, financing, insurance)	5.45	1.14	0.06
Entertainment equipment and subscription television	4.01	1.22	0.07
Alcoholic beverages	0.96	1.22	0.09
Men's and women's clothing	2.47	1.36	0.05
Food away from home	4.53	1.37	0.05
Household appliances	2.3	1.42	0.07
Owner occupied housing consumption	22.25	1.45	0.04
Furniture and fixtures	1.51	1.5	0.11
Education	1.31	1.58	0.18
Domestic services and childcare	1.48	1.61	0.14
New car purchases	3.91	1.74	0.2
Public transport	1.25	1.78	0.13
Entertainment fees, admissions, reading	2.17	1.78	0.07
Cash contributions	2.18	1.78	0.17

Notes: Replication of Table II of Aguiar and Bils (2015), for 1995-1997 and for revised categories. The elasticity is the estimated β_j from (4). (Non-)Essential goods are those with an elasticity less than (greater than) one, above (below) the dashed line. The CE share is the share of expenditure of each category reported in the Consumer Expenditure Survey over the sample period.

Using these estimated elasticities and classification into essential and non-essentials, we then match these consumption categories in the CEX to their counterparts in the PCE by type of product tables. The consumption categories included in the above do not cover the entire consumption bundle of households, but our approach is to maximise the coverage as much as possible. Following Aguiar and Bils (2015), we omit some expenditure categories where the expenditure is either not fully reported in the CEX or where the expenditure isn't consumption, such as financial service fees or life insurance purchases.

We also calculate the expenditure shares of non-essentials vs essentials by housing tenure type using the elasticities above, on the same CEX sample. For mortgagors the non-essential share is 63.9%, for owner-occupiers without a mortgage this is 60.6% and for renters it is 33.6% (see Table A.4). Note that the expenditure shares here differ from consumption shares reported from PCE data because of the different underlying data and because expenditure shares here reflect nominal expenditure shares, rather than real consumption shares constructed from chained consumption series.

Table A.4: Non-essential expenditure shares: by tenure type and across income distribution

	Non-essential share	
By housing tenure type		
Mortgagor	63.9%	
Owner occupier (without mortgage)	60.6%	
Renter	33.6%	
	Non-essential share	
By income tercile		
First	44.3%	
Second	56.1%	Top 2/3: 60.3%
Third	63.3%	
	Non-essential share	
By income quintile		
First	43.1%	
Second	48.7%	
Third	55.8%	
Fourth	59.8%	
Fifth	64.9%	

Notes: Non-essential expenditure shares from CEX data (see text). Income terciles and quintiles are based on after tax income.

A.1 Construction of Consumption and Price Indices

We first map the consumption categories we estimate Engel curves for to the Type of Product tables produced by the BEA. This mapping closely follows a similar exercise in Aguiar and Bils (2015). As noted above, there are a small proportion of consumption categories which we alter or leave unclassified. These omissions and adjustments largely follow Aguiar and Bils (2015) and include cases where either:

1. Expenditures not made entirely by private, US households for their own personal con-

sumption; if they are made on behalf of households by non-profits, employers or insurers.

2. The expenditure might reasonably not be considered consumption which generates personal utility, and is instead a form of saving or cost of saving or other expense.

3. We don't trust or unable to estimate reasonable Engel curve estimates using the CEX microdata, due to incomplete or inaccurate consumption reporting.

These omitted categories are (sorted approximately by rationale):

1. Food on farms, Food supplied to military, Net expenditures abroad, expenditures relating to net foreign travel, final consumption expenditures of nonprofit institutions serving households, some categories of insurance.

2. Financial services (bank/pension fund fees, investment service commissions), some categories of insurance.

3. Professional and other services (legal, accounting, union, professional associations, funerals), Foundations and grantmaking and giving services to households .

In addition to this, we follow Aguiar and Bils (2015) in adjusting clothing and health expenditure categories. In the former, as we classify children's clothing as essential and adults clothing as non-essential, using CEX data. In the PCE, there are three clothing categories; 'Women's and girls' clothing', 'Men and boys; clothing', and 'Children's and inflant's clothing'. We follow Aguiar and Bils (2015) in splitting the former two categories, attributing 22% to children's, essential clothing, and 78% to adults, non-essential clothing. For health expenditures, we also follow Aguiar and Bils (2015) in only including the proportion of health expenditure made out of pocket by households, by adjusting down the health expenditure and net health insurance expenditures using National Health Expenditure Data from Centers for Medicare and Medicaid Services. This helps reduce the proportion of health expenditure which is contributed to by (for instance) government programmes and so not discretionary spending by households directly, but still included in PCE.

Following this process, we classify on average over the sample period 36% of expenditure reported in the PCE as essential, 44% as non-essential and the remaining 20% is left unclassified.

We then construct Fisher price and consumption quantity indices for essentials and non-essentials by aggregating the (nominal) expenditure and price subindices following the

approach outlined NIPA (2021), Chapter 4. The quantity index aggregated from all the subindices i categorised as essentials (E) is given by:

$$Q^F_{t,E} = \sqrt{\frac{\sum_{i\in E} p_{i,t-1}q_{i,t}}{\sum_{i\in E} p_{i,t-1}q_{i,t-1}} \times \frac{\sum_{i\in E} p_{i,t}q_{i,t}}{\sum_{i\in E} p_{i,t}q_{i,t-1}}} \tag{5}$$

Where the (deflated) values within the summations are calculated using the nominal expenditure $e_{i,t}$ and price indices $p_{i,t}$ as appropriate, for instance:

$$p_{i,t-1}q_{i,t} = p_{i,t-1} * \frac{p_{i,t}q_{i,t}}{p_{i,t}} = p_{i,t-1} * \frac{e_{i,t}}{p_{i,t}} \tag{6}$$

And similarly for different combinations of lagged quantities and prices.

We construct the Fisher price indices for essentials as:

$$P^F_{t,E} = \sqrt{\frac{\sum_{i\in E} p_{i,t}q_{i,t-1}}{\sum_{i\in E} p_{i,t-1}q_{i,t-1}} \times \frac{\sum_{i\in E} p_{i,t}q_{i,t}}{\sum_{i\in E} p_{i,t-1}q_{i,t}}} \tag{7}$$

And the equivalent formulas for non-essentials. When we refer to consumption shares with the PCE data, we use chained consumption series also following the NIPA guidelines.

B Mapping of final goods classification to industries for labour market variables

The first stage of our process to map consumption categories to industries is to classify all industries included in the CPS. We use the harmonized 1990 census codes provided by IPUMS, and manually classify all 245 industry codes as either essential, non-essential or unclassified, based on whether the industry produces final consumption goods which fit into our classified consumption categories. We take an unconservative approach to this, in order to maximise the amount of employment we are able to categorise. If there is an industry which is primarily producing intermediate goods, but related to one consumption category, we still classify it. This is because the input output approach we use will reassign an industry's sales of input goods to different sectors according to their eventual downstream use. For example, hardware, plumbing and heating supplies (census code 521) would be an essential if purchased by households, but supplies a lot of intermediate inputs which are used in non-essential industries, so this is eventually classified as a non-essential industry. Sometimes we classify industries that produce a range of goods to the consumption category which they are

most rather than entirely associated with. For instance, employees working for department stores may supply both essential and non-essential consumption goods, but we assume that the majority of goods supplied are within the non-essential consumption categories, and so classify these as non-essential.

B.1 Input-Output approach to classify intermediate industries

In order to match final good & services consumption categories into employment categories we use the input-output tables. We take the *Use of commodities by industry* table from the BEA Input-Output Accounts Data for 2007 at the most detailed disaggregation of 405 industries. From there we exclude government, private households, secondary smelting and alloying of aluminum, scrap, used and secondhand goods, noncomparable imports, and rest of the world adjustment. This allows to have a square matrix of input-output linkages with 391 industries both as suppliers and buyers of intermediate inputs. We link each intermediate industry to the final products with the Leontief inverse, in order to assign each industry the essential or non-essential final products. A simple production network model in the spirit of Acemoglu et al. (2012) can help to explain all the steps. For categories that we do not have downstream sales data, we use the final product classification from the CEX.

We take an economy with N industries comprising intermediate and final products. Each industry i has total sales $X_i = p_i x_i$ which can be made to intermediate producers $p_i x_{i,j}$, consumers for personal consumption expenditures $C_i = p_i c_i$ or other agents for final good expenditures $Z_i = p_i z_i$ (these can be government, investment, inventories, or exports). Total quantity sold is:

$$x_i = \sum_{j=1}^{N} x_{i,j} + c_i + z_i$$

The production function of industry j uses intermediate inputs $x_{i,j}$ and other inputs l_j in order to produce x_j with a Cobb-Douglas production function:

$$x_j = A_j l_j^{\alpha_j} \prod_{i=1}^{N} x_{i,j}^{(1-\alpha_j)\omega_{i,j}}$$

The first order condition under perfect competition for each intermediate input is: $p_i x_{i,j} = p_j x_j (1-\alpha_j)\omega_{i,j}$. This allows a recursive structure on the industry sales by substituting it in:

$$X_i = \sum_{j=1}^{N}(1-\alpha_j)\omega_{i,j}X_j + C_i + Z_i$$

Which we can write in matrix form and invert it to find the Leontief inverse L. Notice that we use $\circ$ for the Hadamard product (the element-wise product).

$$\begin{aligned} X &= (((1-\alpha)\mathbf{1}'_N) \circ \Omega)X + C + Z \\ X &= (I_N - ((1-\alpha)\mathbf{1}'_N) \circ \Omega)^{-1}(C+Z) \\ X &= L(C+Z) \end{aligned}$$

We have a classification of final products as essential E, non-essential N, or unclassified U we can build three $N \times 1$ indicator vectors taking value one if the final product is of that category and zero otherwise: $\mathbb{1}_k$ for $k = \{E, N, U\}$. We can assign an industry to essential if this industry sells more to essential final goods than non-essential final goods and if the sum of these sales is higher than the sales to unclassified sectors. Mathematically, we assign industry i to essentials if:

$$\begin{aligned} \{L(C \circ \mathbb{1}_E)\}_i &> \{L(C \circ \mathbb{1}_N)\}_i \\ \{L(C \circ \mathbb{1}_E)\}_i + \{L(C \circ \mathbb{1}_N)\}_i &> \{L(C \circ \mathbb{1}_U)\}_i \end{aligned}$$

And similarly for non-essentials. We leave as unclassified each remaining industry. Intuitively this method allows to match intermediate industries to their most important final goods. As an example, we match *Grain farming* to essentials, and *Iron, gold, silver, and other metal ore mining* to non-essential, despite not being classified within final goods (as they are intermediates).

Mapping from Model to Data. Given the intermediate input-output matrix cleaned with the steps above, $((1-\alpha)\mathbf{1}'_N)$ is the IO matrix with each intermediate input sales $p_i x_{i,j}$ divided by the *Total industry output (basic value)* line: $p_j x_j$. The C vector we use to weight each sales to assign to the three categories is *Personal consumption expenditures*.

B.2 Mapping between 1990 census industry codes and NAIC 2007 codes

We have census 1990 codes for the CPS data and NAIC 2007 codes for input-output matrices so we map between these using the cross-walk supplied by the Census Bureau. This mapping is not one-to-one, so we use some discretion and make some assumptions to do this. Some census codes are more disaggregated than NAIC codes used in the input-output tables, and visa versa, and some don't have a direct mapping.

Census and NAIC code mapping Our initial classification is based on 1990 census codes, so we first map these to NAIC codes to categorise industries in the input-output tables and then map back to census codes with the adjusted classification. This requires some approximations:

1. A portion of NAIC codes have multiple NAIC codes in the industry data for one census code. An example of this is dairy product manufacturing (census code 101) which in the input output tables maps to four NAIC industry categories (Cheese manufacturing; Dry, condensed, and evaporated dairy product manufacturing; Fluid milk and butter manufacturing; Ice cream and frozen dessert manufacturing). For these cases, we apply the same classification for all NAIC codes that related to a particular census code, treat them as separate industries in the input-output table processing, and then average the final sales shares to different categories of industries (essential, non-essential and unclassified) across a census industry using the total sales of each NAIC industry as weights.

2. For retail industry codes (census codes 580-691) many of the census codes are more disaggregated than the available NAIC codes. For those, we use the initial classification of the industry rather than the input-output tables, as these industries primarily supply final goods which are more straightforward to classify directly than intermediate industries.

3. Some census codes are more detailed than the NAIC codes in the input-output tables. For example, there is a census code (402) for taxicab services, which corresponds to NAIC code 485300 but only the more aggregated NAIC code 485000 is available in the input-output tables. In these cases, we assign the sales shares of the more aggregated NAIC industry to the more disaggregated census industry. This assumes that the disaggregated industry does not vary substantially in what it supplies goods to compared to the more aggregated industry.

4. Some census codes are only mapped to large NAIC categories in the crosswalk, often because they are non-specificed or miscellaneous industries. For example, the census code 472 (non-specified utilities) is part of NAIC code 22, although there are more direct mappings between the codes in NAIC 22 and the census codes. For those industries, we also take an weighted average of all sales shares of all relevant industries (here, for example, 221100, 221200 and 221300), again assuming that the average of the larger group will be representative of the industries in the census code.

5. Finally, there a few remaining cases where the mapping is less straightforward, because industries are divided differently in the two industry classifications. For example, knitting mills (census code 132) corresponds to NAIC codes 31324 and 3151, but in the input-output tables only the larger categories 3132 and 315 are available. In the same spirit as the previous approaches, we select all NAIC codes at the more aggregated level that include relevant industries, and take a total sales-weighted average of the sales shares to essentials, non-essentials and apply this to the census industry. Again this assumes that the census industry's sales shares are represented reasonably by the more aggregated industry.

Full mappings between NAIC 2007 industries in the input-output tables and the 1990 census industry codes used are given in the replication files.

B.3 Classification of durable/non-durable consumption and industries

For PCE, we classify goods as durable following the categorisation in the PCE. We only include consumption categories that we also have an essential or non-essential classification. This latter cover the majority (approximately 80%) of overall expenditure, but omits some durables/ nondurables which are categorised in the PCE data. We categorise according the nature of the final good, not the intermediate goods. If a good is not a final good, it is not classified.

For intermediate industries, we classify industry production according to the nature of the final downsteam goods it supplies rather than the intermediate industry, following the same approach as for the IO aproach to classifying intermediate industries. In addition, we classify construction industries as durable, but in the consumption data this is non-durable because we use the consumption flow of housing, which is a service in the national accounts/ PCE data.

B.4 Final classification of industries into essentials and non-essentials

Using the combination of final goods classifications (for final goods producing firms) and the downstream goods classification from the Input-Output approach for intermediate industries, we classify all industries as either essential, non-essential or unclassified. We omit all workers working in agriculture or for the government. The final industry classification is presented in Table B.1. Using this classification, over the sample period 62% of employment is classified as non-essential, 30% as essential and the remaining 8% is unclassified.

Essential
coal mining; oil and gas extraction; meat products; dairy products; canned, frozen, and preserved fruits and vegetables; grain mill products; bakery products; sugar and confectionery products; misc. food preparations and kindred products; food industries, n.s; miscellaneous paper and pulp products; drugs; soaps and cosmetics; agricultural chemicals; industrial and miscellaneous chemicals; petroleum refining; miscellaneous petroleum and coal products; tires and inner tubes; farm machinery and equipment; construction and material handling machines; office and accounting machines; guided missiles, space vehicles, and parts; medical, dental, and optical instruments and supplies; photographic equipment and supplies; u.s. postal service; pipe lines, except natural gas; wired communications; telegraph and miscellaneous communications services; electric light and power; gas and steam supply systems; electric and gas, and other combinations; water supply and irrigation; sanitary services; utilities, n.s; professional and commercial equipment and supplies; drugs, chemicals, and allied products; groceries and related products; petroleum products; wholesale trade, n.s; grocery stores; dairy products stores; food stores, n.e.c; auto and home supply stores; gasoline service stations; drug stores; fuel dealers; retail florists; insurance; personnel supply services; automobile parking and carwashes; automotive repair and related services; beauty shops; barber shops; funeral service and crematories; miscellaneous personal services; offices and clinics of physicians; offices and clinics of dentists; offices and clinics of chiropractors; offices and clinics of optometrists; offices and clinics of health practitioners, n.e.c; hospitals; nursing and personal care facilities; health services, n.e.c; residential care facilities, without nursing; accounting, auditing, and bookkeeping services; management and public relations services;
Non-essential
metal mining; nonmetallic mining and quarrying, except fuels; all construction; beverage industries; knitting mills; dyeing and finishing textiles, except wool and knit goods; carpets and rugs; yarn, thread, and fabric mills; miscellaneous textile mill products; apparel and accessories, except knit; miscellaneous fabricated textile products; pulp, paper, and paperboard mills; paperboard containers and boxes; newspaper publishing and printing; printing, publishing, and allied industries, except newspapers; plastics, synthetics, and resins; paints, varnishes, and related products; other rubber products, and plastics footwear and belting; miscellaneous plastics products; leather tanning and finishing; footwear, except rubber and plastic; leather products, except footwear; logging; sawmills, planing mills, and millwork; wood buildings and mobile homes; miscellaneous wood products; furniture and fixtures; glass and glass products; cement, concrete, gypsum, and plaster products; structural clay products; pottery and related products; misc. nonmetallic mineral and stone products; blast furnaces, steelworks, rolling and finishing mills; iron and steel foundries; primary aluminum industries;

other primary metal industries; cutlery, handtools, and general hardware; fabricated structural metal products; screw machine products; metal forgings and stampings; ordnance; miscellaneous fabricated metal products; metal industries, n.s; engines and turbines; metalworking machinery; computers and related equipment; machinery, except electrical, n.e.c; machinery, n.s; household appliances; radio, tv, and communication equipment; electrical machinery, equipment, and supplies, n.e.c; electrical machinery, equipment, and supplies, n.s; motor vehicles and motor vehicle equipment; aircraft and parts; ship and boat building and repairing; railroad locomotives and equipment; cycles and miscellaneous transportation equipment; toys, amusement, and sporting goods; manufacturing industries, n.s; railroads; bus service and urban transit; taxicab service; warehousing and storage; water transportation; air transportation; services incidental to transportation; radio and television broadcasting and cable; motor vehicles and equipment; furniture and home furnishings; lumber and construction materials; metals and minerals, except petroleum; electrical goods; hardware, plumbing and heating supplies; machinery, equipment, and supplies; scrap and waste materials; miscellaneous wholesale, durable goods; paper and paper products; apparel, fabrics, and notions; farm-product raw materials; alcoholic beverages; farm supplies; miscellaneous wholesale, nondurable goods; lumber and building material retailing; hardware stores; retail nurseries and garden stores; mobile home dealers; department stores; variety stores; miscellaneous general merchandise stores; retail bakeries; motor vehicle dealers; miscellaneous vehicle dealers; apparel and accessory stores, except shoe; shoe stores; furniture and home furnishings stores; household appliance stores; radio, tv, and computer stores; music stores; eating and drinking places; liquor stores; sporting goods, bicycles, and hobby stores; book and stationery stores; jewelry stores; gift, novelty, and souvenir shops; sewing, needlework, and piece goods stores; catalog and mail order houses; vending machine operators; direct selling establishments; miscellaneous retail stores; retail trade, n.s; savings institutions, including credit unions; credit agencies, n.e.c; real estate, including real estate-insurance offices; advertising; services to dwellings and other buildings; computer and data processing services; detective and protective services; business services, n.e.c; automotive rental and leasing, without drivers; electrical repair shops; miscellaneous repair services; private households; hotels and motels; lodging places, except hotels and motels; laundry, cleaning, and garment services; shoe repair shops; dressmaking shops; theaters and motion pictures; bowling centers; miscellaneous entertainment and recreation services; elementary and secondary schools; colleges and universities; vocational schools; educational services, n.e.c; child day care services; family child care homes; museums, art galleries, and zoos; labor unions; religious organizations; membership organizations, n.e.c; engineering, architectural, and surveying services; miscellaneous professional and related services;
Unclassified
tobacco manufactures; manufacturing, non-durable - allocated; scientific and controlling instruments; watches, clocks, and clockwork operated devices; miscellaneous manufacturing industries; trucking service; banking; security, commodity brokerage, and investment companies; legal services; libraries; job training and vocational rehabilitation services; social services, n.e.c; research, development, and testing services;

Table B.1: Industry classification

Classification of 1990 Census industry codes into essential, non-essential and unclassified.

As an alternative, we have also constructed employment and earnings series where we attribute shares employment and earnings in intermediate industries to non-essential and

essential series according to the shares of final downstream goods produced. For instance if a worker is employed in an industry where 60% of downstream consumption is essential 30% is non-essential and the remainder unclassified, in our baseline series we classify this employee as one essential worker. In our shares series, the employee would be counted as 0.6 of a person in the essential total employment series and 0.3 of a person in the non-essential employment series.

C Other macroeconomic data sources

In addition to the constructed non-essential and essential series for consumption, prices, employment and earnings, we also use additional aggregate macroeconomic time-series in our Proxy-SVAR and local projection estimation, the sources for which are detailed below.

In the Proxy SVAR:

- Industrial production (INDPRO), PCE price index (PCEPI) and end of month 1y Treasury yields (DGS1) - downloaded from St Louis Fed's FRED, specific variable names in brackets.
- Excess bond premium, from the Federal Reserve Board[20]
- Monetary policy surprise series - both taken from the replication files of Jarociński and Karadi (2020):
  - The Gertler and Karadi shocks we use are the FF4 surprises updated and provided by Jarocinski and Karadi, which go from 1990m2 to 2016m12. There is a missing value on 2001m9 which we fill as zero.
  - The Jarconski and Karadi shocks we use, mitigating the information effect, are the FF4 surprise if there is a negative correlation between the FF4 surprise and the SP500 surprise. These go from 1990m2 to 2016m12..There is a missing value on 2001m9 which we fill as zero.

In the smooth local projection estimations, in addition to the Proxy SVAR, we add:

- Total employment - depending on the sample, this is aggregated from the CPS data described previously for employment and earnings IRFs, otherwise we use total private

[20] https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html

employment recorded by the Current Employment Statistics (Establishment Survey, CES), taken from FRED (variable name USPRIV).

- Earnings - median earnings series constructed using CPS data described previously, for SLP-IV IRFs for earnings. Otherwise, to give a longer time-series, we use Average Weekly Earnings of Production and Nonsupervisory Employees, for Private employees from the CES, also taken from FRED (CES0500000030).

- For the price IRFs, we also use inflation expectations as an additional control. For these, we use University of Michigan Inflation expectations, also taken from FRED (MICH)

D Descriptive statistics and additional charts

Table D.1: Descriptive statistics

	Consumption	Prices	Employment	Median Earnings
Correlation with Industrial Production				
Aggregate	0.51	-0.32	0.37	0.07
Essentials	0.46	-0.34	0.003	-0.08
Non-essentials	0.53	-0.30	0.42	0.09
St. dev relative to Industrial Production				
Aggregate	0.40	0.28	0.44	0.59
Essentials	0.37	0.51	0.35	0.66
Non-essentials	0.57	0.24	0.57	0.69

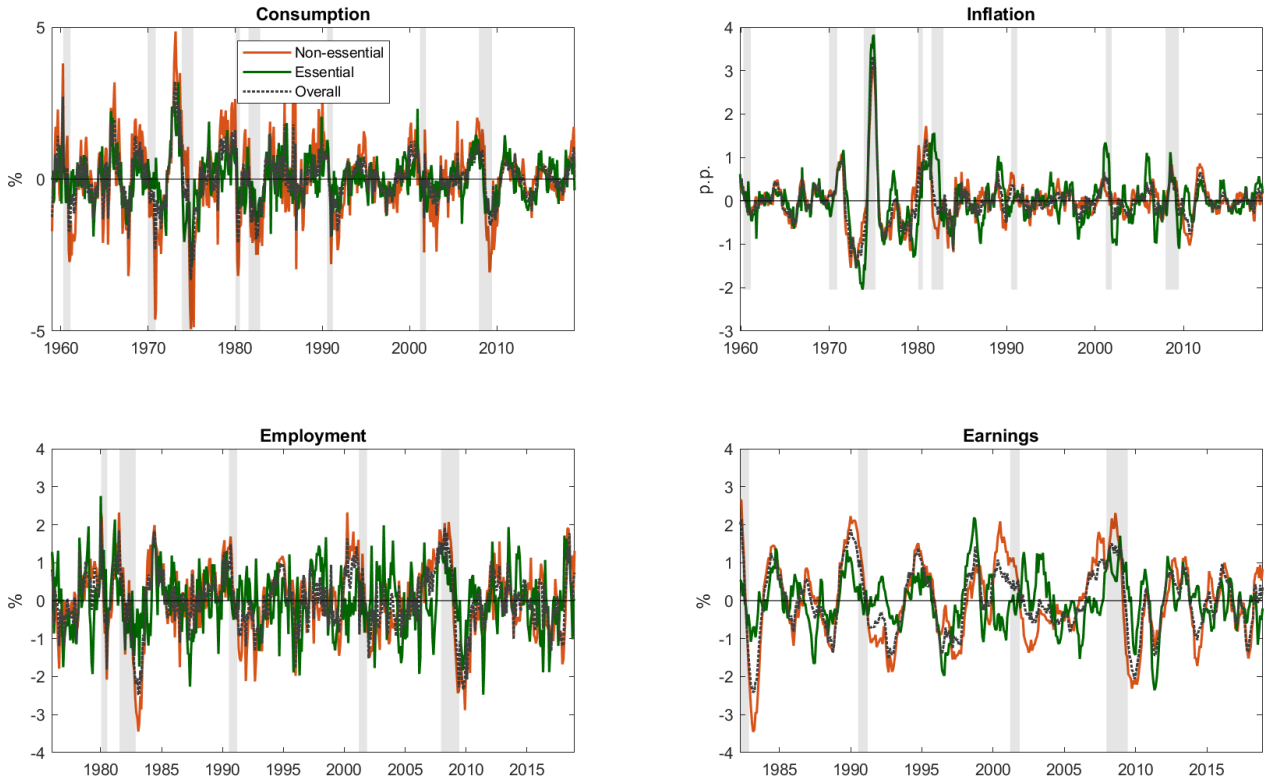
Notes: Descriptive statistics for essentials and non-essentials series. All variables are year-on-year log differences. Panel 1 shows the standard deviation of the series, divided by the standard deviation for industrial production. Panel 2 shows the correlation between the series and industrial production. Monthly data used, the sample period ends in March 2020, and begins at the earliest available point for each series; January 1960 for consumption and prices, January 1977 for employment and January 1983 for median earnings. Price and consumption are based on PCE data and employment and earnings are from CPS data, constructed as described in the text. Earnings refers to median usual weekly earnings.

Table D.2: Average amount and share, Essentials vs Non-essentials

	Average annual amount			Non-essential % of overall
	Overall	Essential	Non-essential	
Consumption per cap. ($)	21,710	10,267	11,443	53%
Employment (mn)	93.4	30.6	62.9	67%
Median earnings	31,127	33,025	29,333	94%

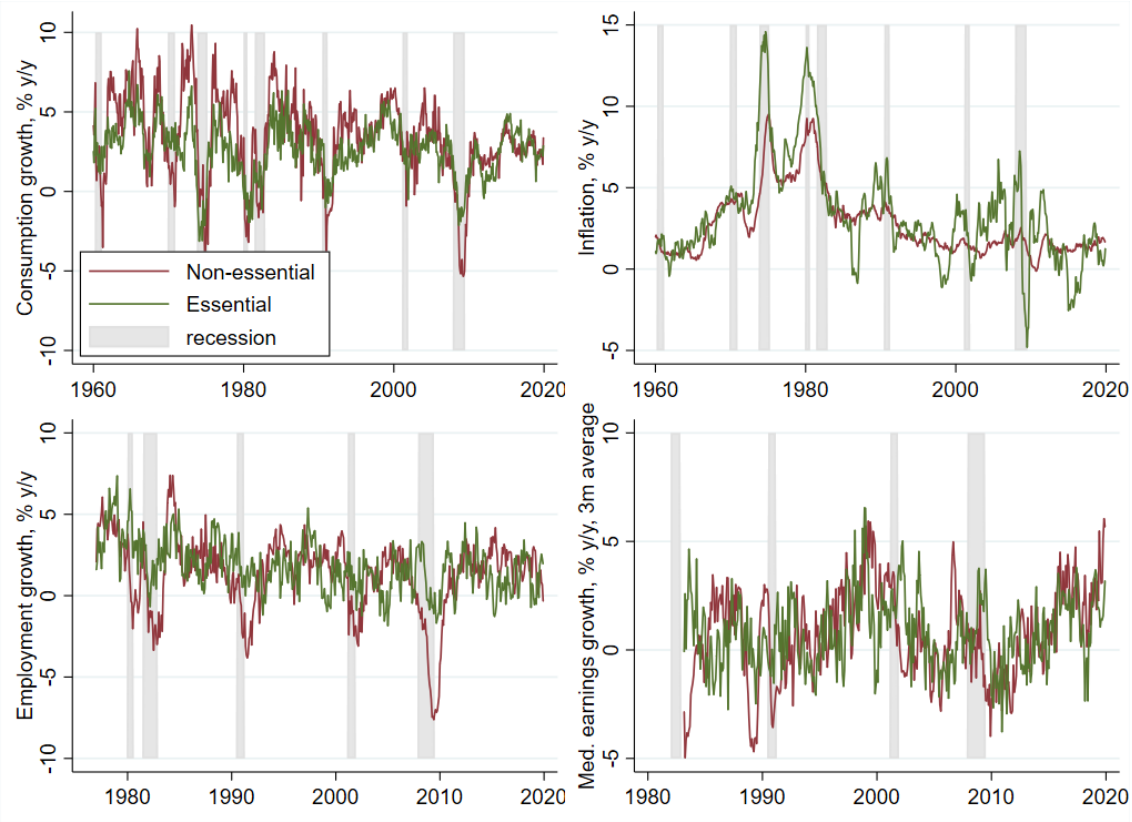
Notes: The table shows the average annual amount of consumption, employment and median annual wages, in essentials and non-essentials, over the sample period. The final column shows the non-essential consumptiona and employment shares and the non-essential median wage as a % of overall median wages. Only the value of consumption and employment categorised into essentials and non-essentials is included in 'Overall', excluding uncategorised. Consumption is per capita chained PCE in 2012$, median wages are deflated to 2012$. Details of the calculations and data sources are included in text.

Figure D.1: Essentials and Non-essentials over time



Underlying series of Figure 2. For consumption, employment and earnings, this shows the cyclical component of the logged variable detrended using the HP filter ($\lambda = 14,440$). For earnings, this refers to total earnings and the inital log series is centred 6-month rolling average, to reduce noise. Inflation is y/y core inflation, also detrended using the HP filter.

Figure D.2: Non-essential and essentials over time



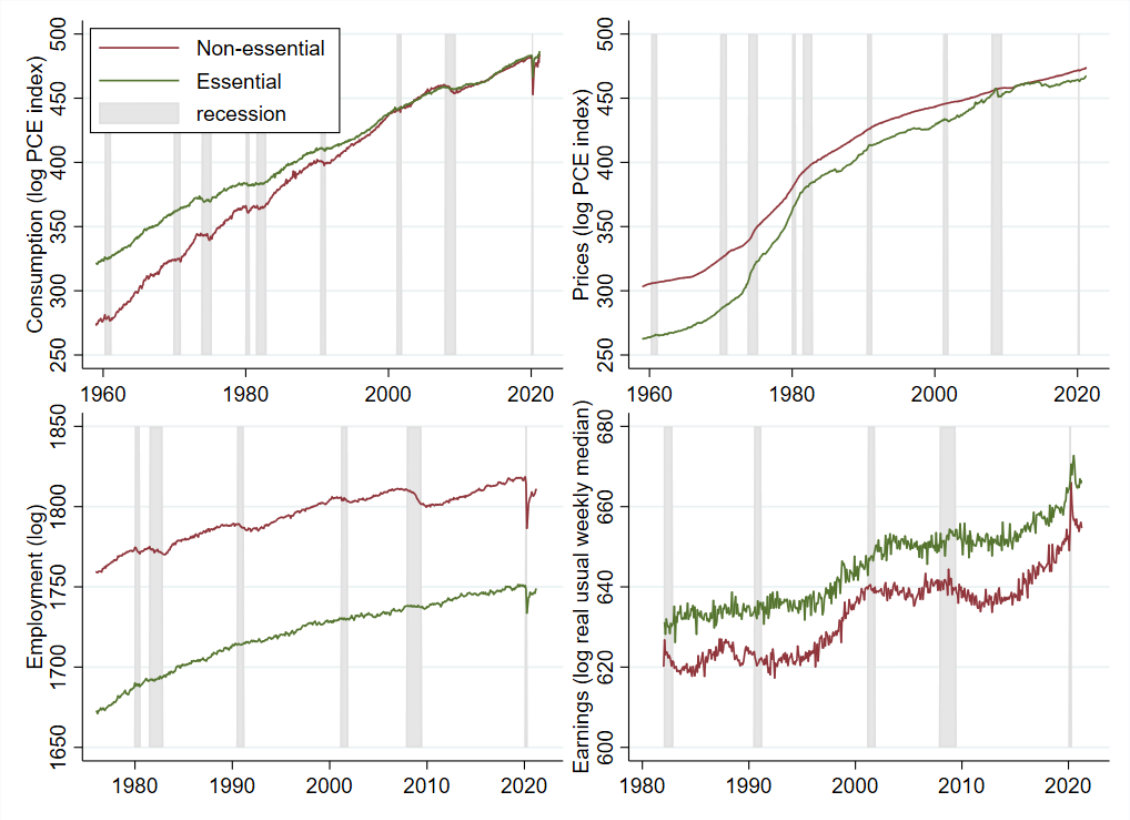
Notes: Non-essential and essential time-series for consumption, price, employment and median earnings growth. All y/y %, except median earnings growth, where the rolling 3-month average of y/y % growth rates is shown, to reduce noise. Underlying data sources are the PCE by Type of Product tables from the BEA, for consumption and prices, and CPS for employment and earnings, described in detail in the text. NBER recession dates shaded.

Table D.1 gives descriptive statistics of the constructed essential and non-essential series described above and in the main text. Consumption, employment and median earnings of non-essentials are more volatile than that of essentials, and more positively covary with industrial production (used as a proxy for overall output). In contrast, prices of non-essentials are less volatile and more negatively correlated with output, a fact we ascribe to the volatility of food and energy prices and that their variation may primarily not be caused by demand shocks.

Figure D.2 shows the growth rates of the essentials and non-essential series, Figure D.3 shows the corresponding levels of the consumption and price indices, employment and median wages. These show that there have been substantial structural shifts in these series, in addition to the business cycle frequencies focussed on in this paper. Figures D.4, D.5 and D.6 shows some other relevant series; the relative cyclicality of different percentiles of the

earnings distribtion, and shares of expenditure, employment and relative earnings within essentials and non-essentials.

Figure D.3: Non-essential and essentials over time - levels

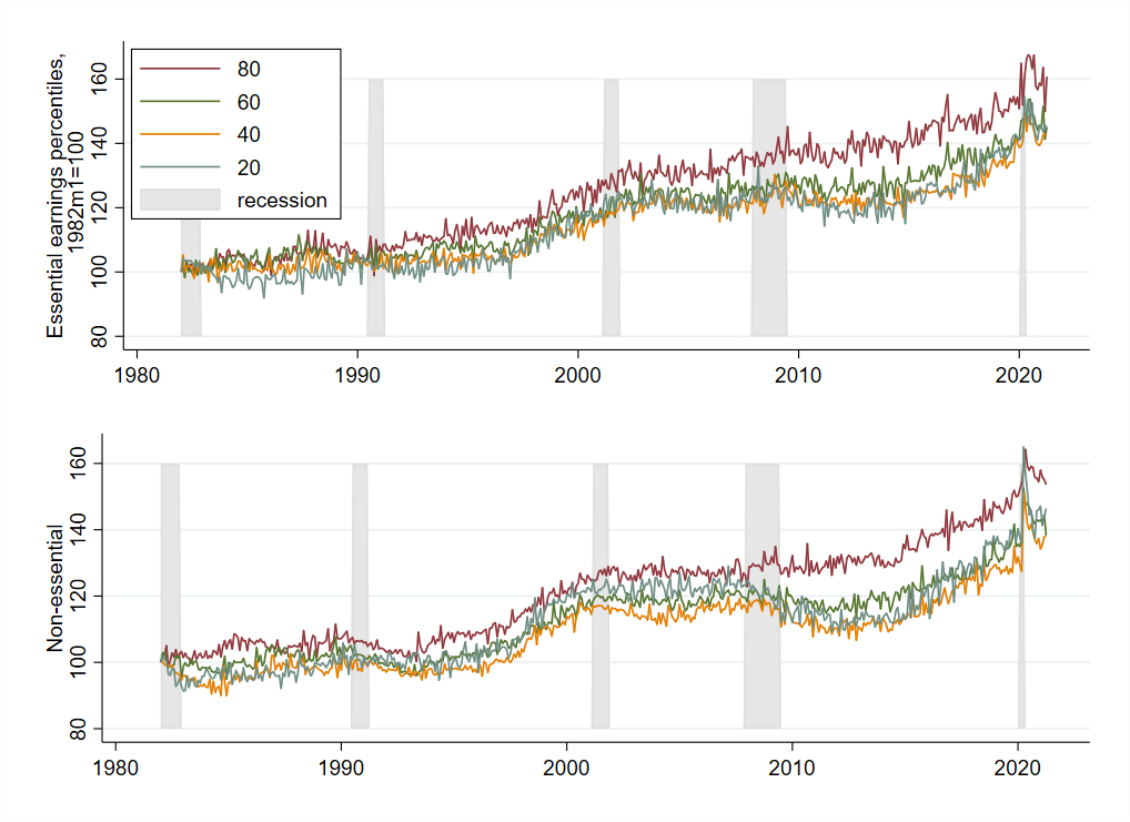


Notes: Non-essential and essential time-series for consumption, price, employment and median earnings growth. All logs, of consumption and price indices and levels of total employment and earnings. Underlying data sources are the PCE by Type of Product tables from the BEA, for consumption and prices, and CPS for employment and earnings, described in detail in the text. NBER recession dates shaded.

D.1 Core timeseries

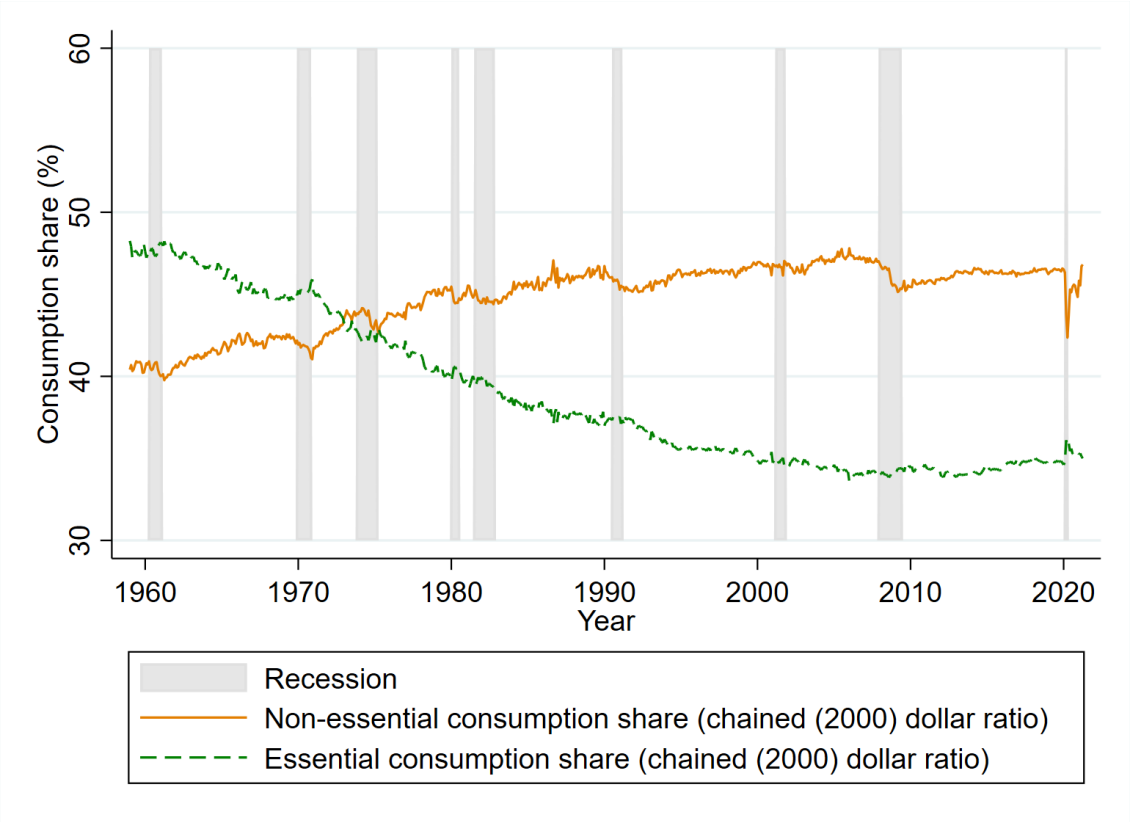
Food and energy are essential categories, and may account for much of the variability in the essential price series, where the essential prices are (perhaps unexpectedly) more volatile than the non-essentials. We construct core essential and non-essential series, excluding the same categories as in the aggregate core series from the BEA. Comparison of the timeseries are in Figure D.7.

Figure D.4: Non-essential and essential - earnings distribution over time



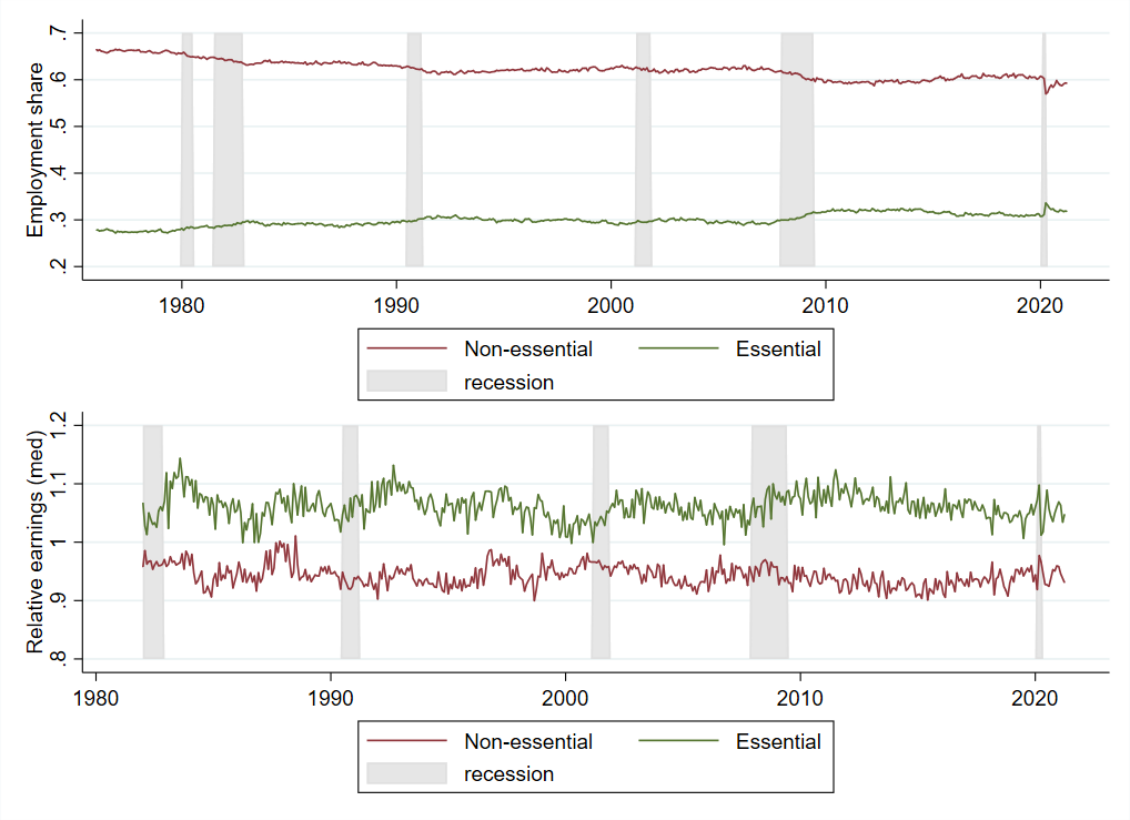
Notes: This figure shows the earnings of percentiles of the non-essential and essential industries over time. These are indexed to 100 in 1982 to compare cyclicality. Data is from the CPS, categorised into essentials and non-essentials as described in the text.

Figure D.5: Non-essential and essential - Consumption shares



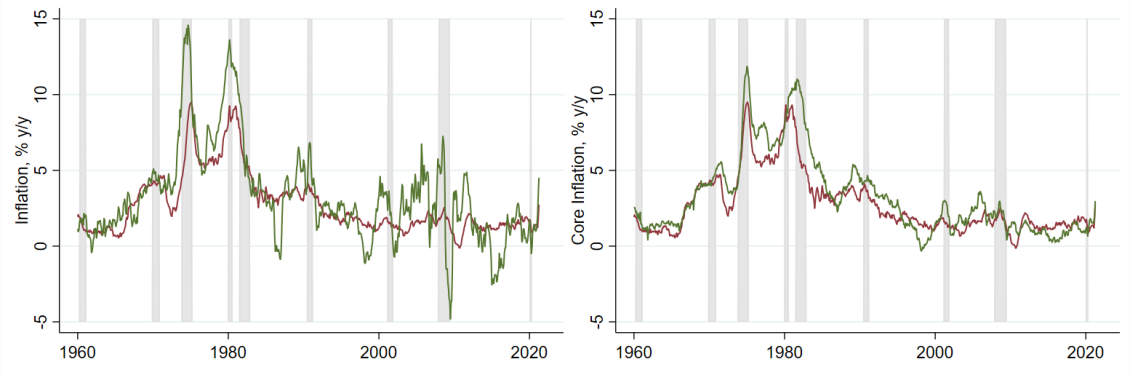
Notes: Consumption shares for essential and non-essential series, out of total consumption, based on chained 200 dollar consumption series. Underlying data sources are the PCE by Type of Product tables from the BEA, described in detail in the text. NBER recession dates shaded.

Figure D.6: Non-essential and essential - Labour market shares



Notes: Employment shares (top) and earnings relative to median earnings (bottom) in essentials and non-essentials. Data from the CPS, as descibed in the text. NBER recession dates shaded.

Figure D.7: Non-essential and essentials inflation - Headline vs Core



Notes: Non-essential and essential time-series inflation, LHS is headline, RHS is core (excluding food and energy). Underlying data sources are the PCE by Type of Product tables from the BEA, described in detail in the text. NBER recession dates shaded.

E Monetary policy surprises

Figure E.1: Monetary policy surprise series



Notes: Monetary policy surprises, extracted from a proxy SVAR as described in . The Gertler-Karadi surprises are extracted from a proxy SVAR estimated using the (updated) monetary policy instrument proposed by Gertler and Karadi (2015), while the Jarocinski-Karadi surprises are from using the monetary policy instrument robust to the information effect proposed by Jarocinski and Karadi (2020).

F SLP-IV implementation details

The point estimates for the IRFs for the SLP-IV approach have been estimated using the procedure suggested in Barnichon and Brownlees (2019):

1. We estimate a (standard) first stage by regressing the 1-year yield on the instrument and controls, and extract the predicted values of the endogenous variables $\hat{x}$

2. Use the predicted values in the SLP approach (following the notation in Barnichon and Brownlees (2019)):

- $\hat{\mathcal{X}}_{\beta,t}$ is a d_t x K matrix where the (h,k)th element is $B_k(h)\hat{x}_t$, and this is stacked with the control matrices in the same way to produce the matrix $\hat{\chi}$.

3. Estimate the second stage SLP by generalised ridge regression: $\hat{\theta} = (\hat{\mathcal{X}}'\hat{\mathcal{X}} + \lambda\mathbf{P})^{-1}\hat{\mathcal{X}}'Y$

λ is selected using a five-fold cross-validation procedure, as suggested by Barnichon and Brownlees. We shrink towards a B-spline of order 2, which shrinks towards a line.

The SLP Newey-West standard errors Barnichon and Brownlees (2019) suggest are:

$$\begin{aligned}\widehat{V}(\hat{\theta}) =& T\left[\sum_{t=1}^{T-H_{\min}} \mathcal{X}_t'\mathcal{X}_t + \lambda\mathbf{P}\right]^{-1}\left[\hat{\Gamma}_0 + \sum_{l=1}^{L} w_l\left(\hat{\Gamma}_l + \hat{\Gamma}_l'\right)\right] \\ &\times\left[\sum_{t=1}^{T-H_{\min}} \mathcal{X}_t'\mathcal{X}_t + \lambda\mathbf{P}\right]^{-1}\end{aligned}$$

where $w_l = 1 - l/(1+L)$ and $\hat{\Gamma}_l = \frac{1}{T}\sum_{l+1}^{T-H_{\min}} \mathcal{X}_t'\hat{\mathcal{U}}_t\hat{\mathcal{U}}_{t-l}'\,\mathcal{X}_{t-l}$ where $\hat{\mathcal{U}}_t$ are the residuals from the second stage.

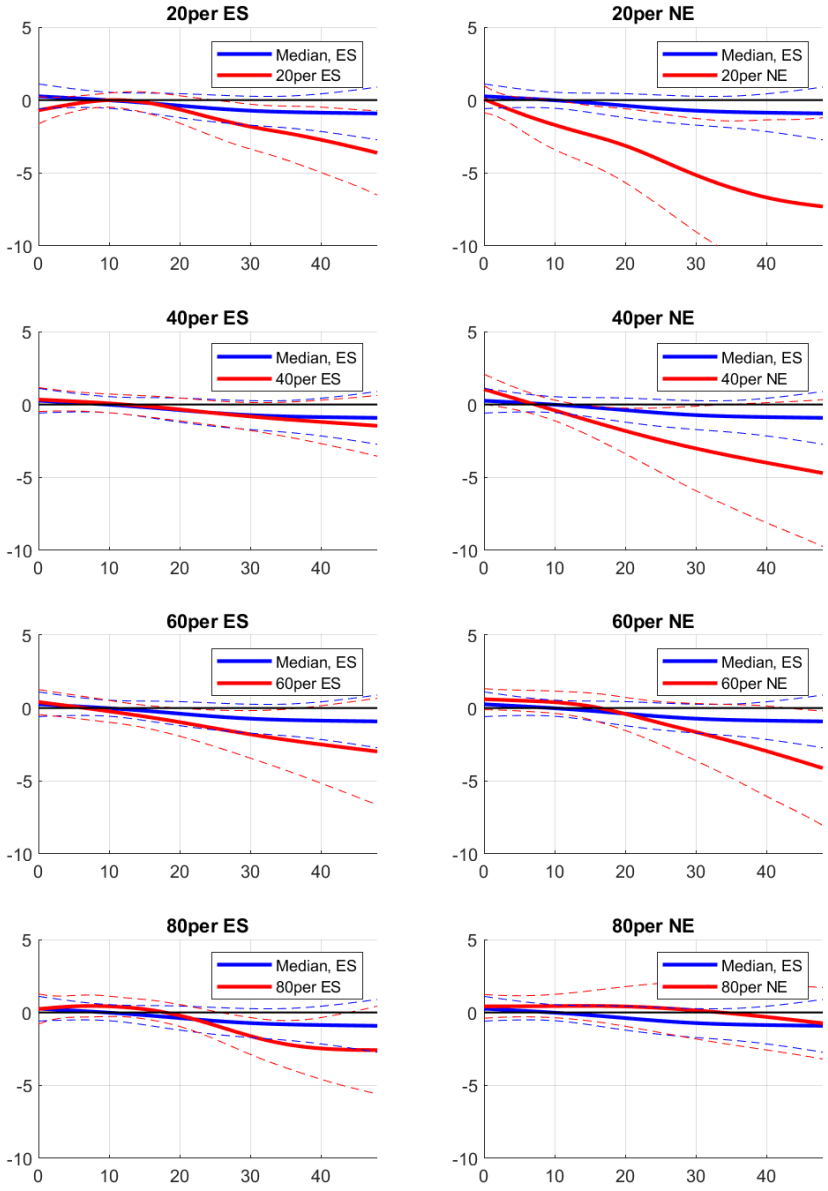
To contruct SLP-IV SEs, we use the generated regressor equivalent of this:

$$\begin{aligned}\widehat{V}(\hat{\theta}) =& T\left[\sum_{t=1}^{T-H_{\min}} \hat{\mathcal{X}}_t'\hat{\mathcal{X}}_t + \lambda\mathbf{P}\right]^{-1}\left[\hat{\Gamma}_0 + \sum_{l=1}^{L} w_l\left(\hat{\Gamma}_l + \hat{\Gamma}_l'\right)\right] \\ &\times\left[\sum_{t=1}^{T-H_{\min}} \hat{\mathcal{X}}_t'\hat{\mathcal{X}}_t + \lambda\mathbf{P}\right]^{-1}\end{aligned}$$

where $w_l = 1 - l/(1+L)$ and $\hat{\Gamma}_l = \frac{1}{T}\sum_{l+1}^{T-H_{\min}} \hat{\mathcal{X}}_t'\hat{\mathcal{U}}_t\hat{\mathcal{U}}_{t-l}'\,\hat{\mathcal{X}}_{t-l}$. Following Hansen (2021) $\hat{\mathcal{U}}_t = Y - \mathcal{X}\hat{\theta}$ are the residuals used, ie using the controls $\mathcal{X}$ constructed using the actual values of x rather than the first stage predicted values $\hat{x}$. If we set $\lambda = 0$, so no smoothing and penalising the results, this is the same as standard Newey-West standard errors for LP-IV. The autocorrelation lag used is the minimum between the Newey-West (1994) suggestion ($T^{1/4}$) and a linear increase with the estimation horizon. In an omitted robustness check, we also use lag-augmentation, with an extra lag of the controls and White standard errors, which set L=0, so no correction for auto-correlation.

G Additional empirical results

Figure G.1: IRFs to contractionary monetary policy shock - Earnings distribution



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Earnings IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, and the LHS variable as controls. Earnings percentiles are from the CPS, and percentiles are calculated separately for the non-essential and essential earnings distributions. 90% confidence intervals displayed.

H Durables versus Non-essentials and other alternative characteristics

One major alternative characteristic that has been extensively discussed in the literature is the durablity of goods (Barsky, House and Kimball (2007), McKay and Wieland (2019)). For instance, in our classification furniture and new cars are non-essentials and durable. To explore this, we further break down our essential and non-essential series into durables and non-durables. We discuss how these are constructed in Appendix B.3, but we follow the same broad approach and use the same data sources as for the overall non-essential and essential series.

Indeed, within essentials, there are almost no durables, whereas durables make up a substantial minority of non-essential expenditure and almost half of non-essentials employment. Table H.1 shows the shares of consumption accounted for by durables and non-durables vs essentials and non-essentials.

Figure H.1 is the equivalent of Figure 2 for durables and non-durables. It shows that durables are more cyclical than non-durables, as expected, but the fact that durables account for a much smaller proportion of overall consumption and employment means that the response of the aggregate series is extremely close to the non-durable and services series; in constrast, non-essential cyclicality appears to be contributing relatively more to overall cyclicality.

Figure H.2 shows the earnings distributions for this four-way split. Non-essential non-durables are the subsection of industries which generate the lower earnings, so the labour market channel we discuss is distinct from any general equilibrium effects on labour markets of the cyclicality of durables.

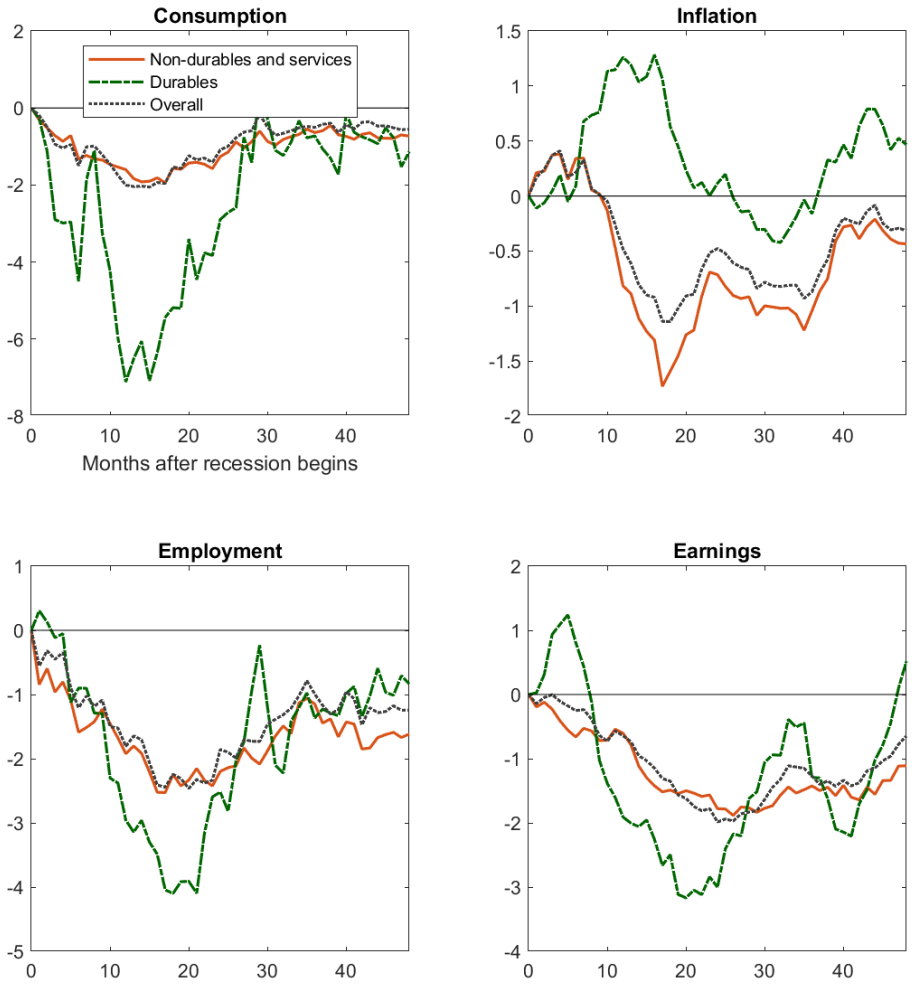
We estimate the IRFs for these subcategories of consumption, employment and earnings. The results are shown in Appendix Figures H.3, H.4 and H.5. Focussing on the heterogeneity between non-durable essentials and non-durable non-essentials, we find our results remain. For consumption, non-essential non-durables falls by less than the overall non-essentials series, but still falls significantly more than essentials non-durables. For employment and earnings, the results for non-durables are similar to consumption.

Durables consumption and employment does fall substantially more than non-durables, consistent with previous findings in the literature, and durables are more cyclical than non-essentials. However, given that durables account for a minority of expenditure and employment, whereas non-essentials account for a much larger share, the overall contribution of

non-essentials to the cyclicality of these variables is comparable.

Therefore, we view our non-essential channel as separate and distinct from the durables channel discussed previously in the literature.

Figure H.1: Response of Durables and Non-durables over the business cycle



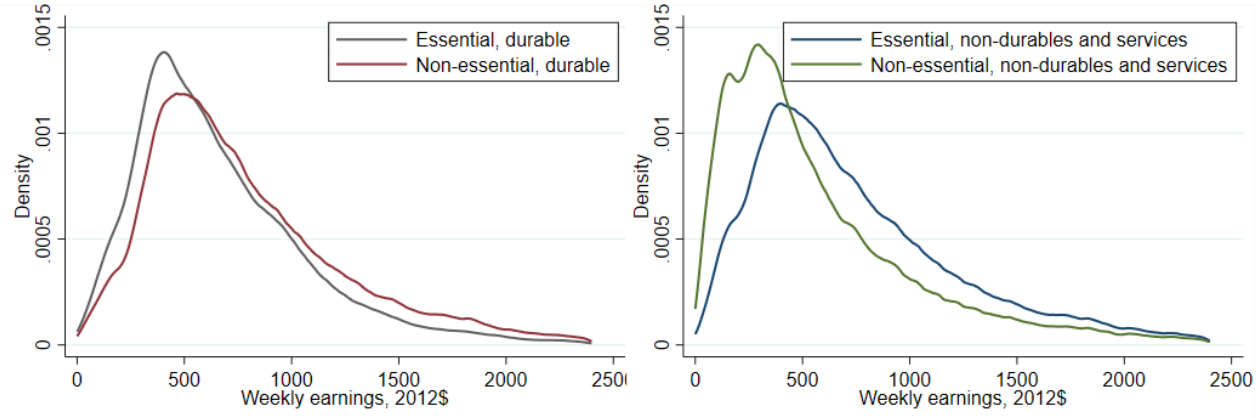
Equivalent of Figure 2 for of durables and non-durables. Series starting from the peak of the previous expansion, as defined by NBER. Includes all recession peaks since 1973 where non-essential and essential series for each variable are available for a full 48 months after the peak (peaks in 1973m11, 1981m7, 1990m7, 2001m3, 2007m12 and see sample definitions in text). For consumption, employment median wages, this shows the cyclical component of the logged variable detrended using the HP filter ($\lambda = 14,440$). For median wages, the inital log series is centred 6-month rolling average, to reduce noise. For inflation, the y/y inflation rate is also detrended using the HP filter. All series are normalised to 0 at the inital period by taking the peak observation from all periods.

Table H.1: Durables vs Non-essentials

	All	Durable goods	Non-durable goods and services
Essential	45.00	2.57	42.43
Non-essential	55.00	10.86	44.14
Both	100.00	13.43	86.57

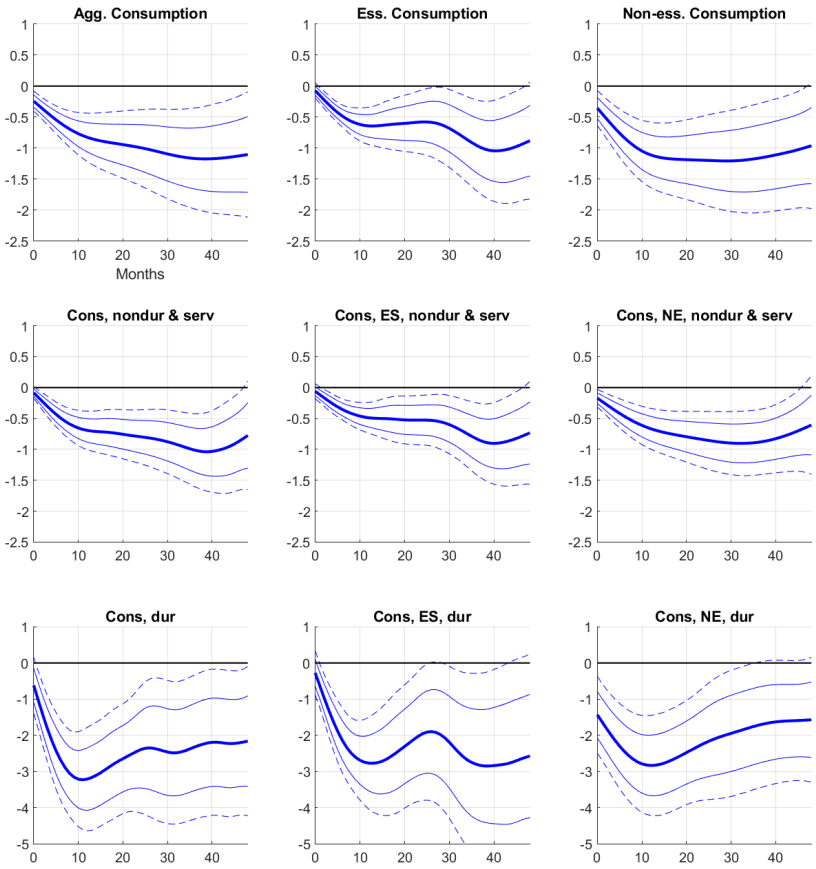
Percentages of total consumption. Calculated using PCE expenditure data, consumption shares based on chained 2000 dollar consumption series; only consumption categories in the essentials/ non-essentials classification are included. Averaged over 1973-2020.

Figure H.2: Earnings distribution - non-essentials and essentials, split into durables vs non-durables and services



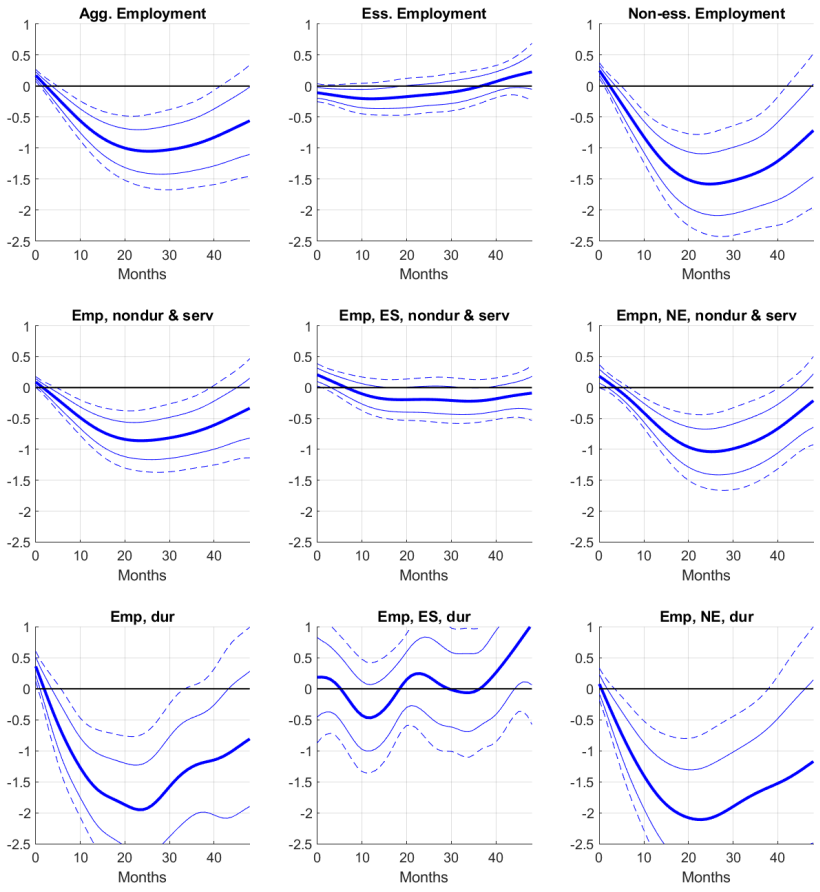
Notes: Kernel density of earnings 1982-2020, pooled, for non-essentials and essentials, split by durables vs non-durables and services.

Figure H.3: IRFs of consumption - non-essentials and essentials, split into durables and non-durables



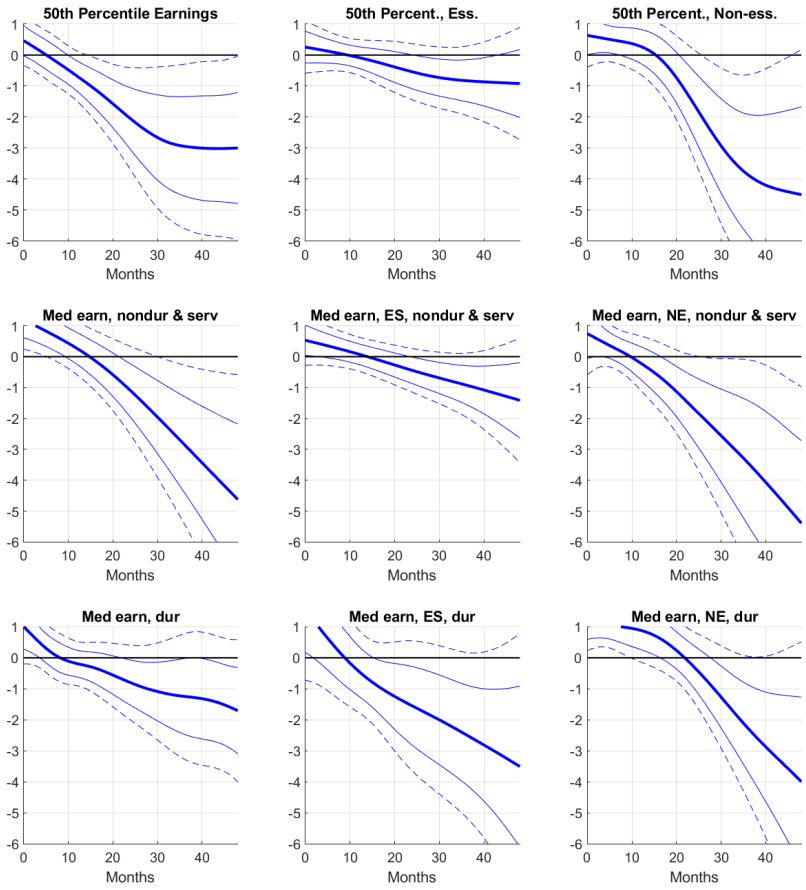
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. The sample periods and controls are as described in the main text. 68% and 90% confidence intervals.

Figure H.4: IRFs of employment - non-essentials and essentials, split into durables and non-durables



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. The sample periods and controls are as described in the main text. 68% and 90% confidence intervals.

Figure H.5: IRFs of medians earnings - non-essentials and essentials, split into durables and non-durables



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. The sample periods and controls are as described in the main text. 68% and 90% confidence intervals.

H.1 Other categorisations

There are other, alternative categorisations in addition to durables vs non-durables which could potentially confound our results. Two prominent examples include tradeables versus non-tradeables and good versus services. If our non-essential/essential classification strongly correlates with these alternative classifications, then then our empirical results could be caused by the correlated trait of the consumption goods, rather than by the mechanism we suggest.

Table H.2 shows the proportion of essentials and non-essentials that are made of up these different categories. The definitions of durables and services are from the PCE by type of product tables, while we define tradeables using the classification of consumption categories provided by Johnson (2017). Unlike durables, which is correlated with our non-essential classification, the proportions of services and tradables are quite similar between non-essentials and essentials. This suggests that it would be hard for a correlation with either of these characteristics to be driving our results.

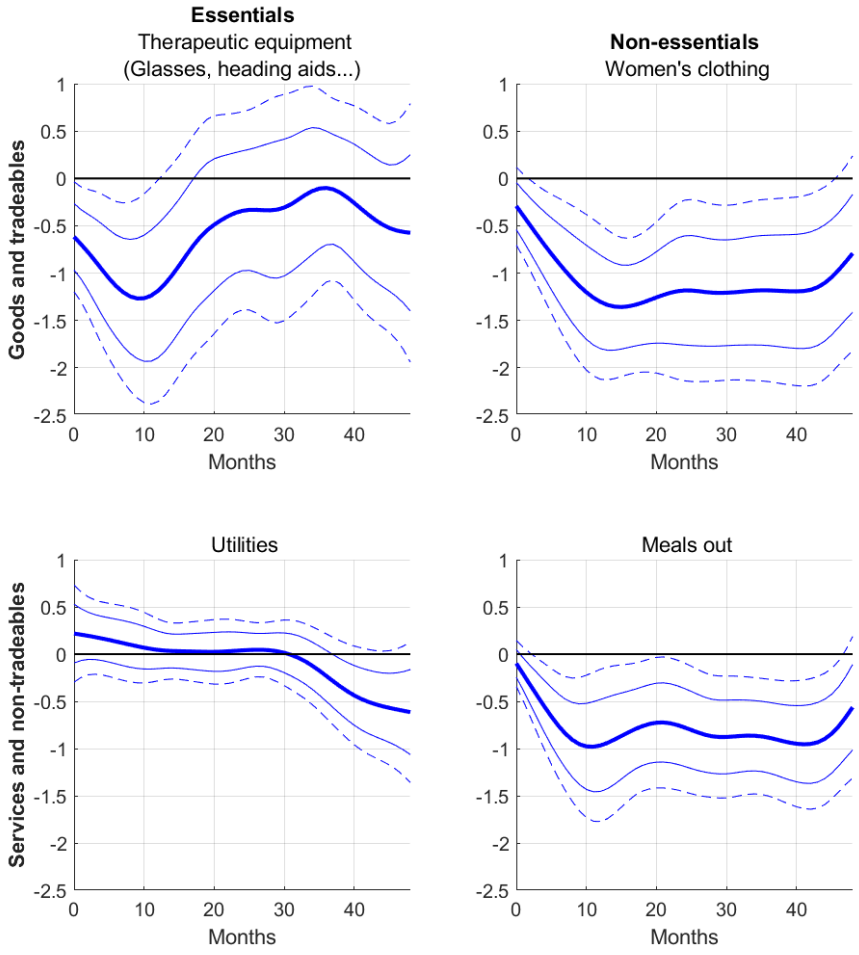
Table H.2: Alternative categorisations

	Durable	Services	Tradeable
Essential	8.3%	53.9%	25.3%
Non-essential	20.0%	63.3%	31.3%

Notes: Proportion of essentials and non-essentials which are durable, services (rather than goods), and tradeable. Calculated using PCE expenditure data; only consumption categories in the essentials/ non-essentials classification are included. Proportions are weighted by average expenditure of the catgeories 1973-2019. Durable and services definitions from the PCE by type of product tables, tradeables defined using the classification of consumption categories provided by Johnson (2017).

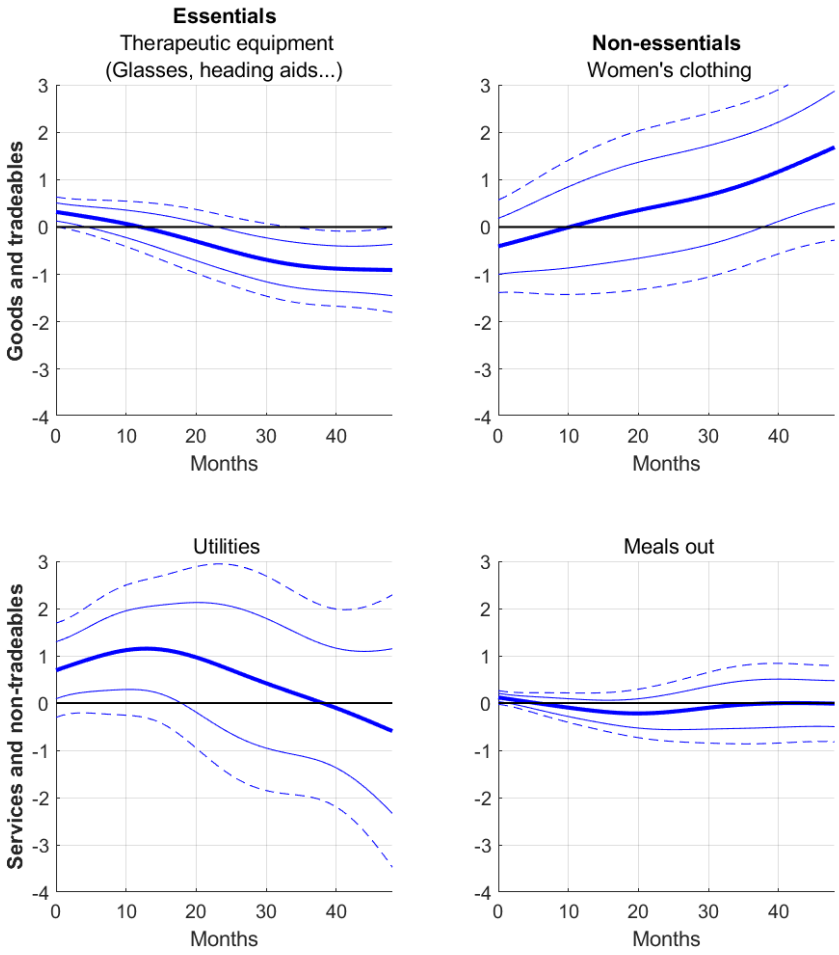
To make this more concrete, Figure H.6 and H.7 show IRFs for consumption and prices of example subcategories of consumption from the PCE, used to construct our essential and non-essential series. The charts show examples of essential and non-essential series in both tradeables/goods (which are strongly correlated categorisations, here examples stand for both categorisations) and non-tradeables/services.

Figure H.6: Consumption IRFs of example consumption categories, services and non-tradeables versus goods and tradeables



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. The sample period and controls are as described in the main text. 68% and 90% confidence intervals.

Figure H.7: Price IRFs of example consumption categories, services and non-tradeables versus goods and tradeables



Notes: IRFs of selected PCE (by type of Product) subcategories of consumption, classified as either essential or nonessential and as services (or non-tradeables) or goods (or tradeables). IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. The sample period and controls are as described in the main text. 68% and 90% confidence intervals.

I Additional results and robustness checks

I.1 Calculations for back-of-the-envelope calculations

The figures in Table 1 are calculated as follows:

For the average change value of a variable:

$$\text{Average change} = (\text{Average annual value over estimation sample}) * \frac{1}{49} \sum_{m=\ 0\ \text{months}}^{48\ \text{months}} \text{Estimated \% change, months after shock}_m \quad (8)$$

For consumption and employment, the amplification is calculated by comparing how disportiortionate the size of the non-essential fluctuation is comapred to its share of the overall variable.

$$\text{Amplification} = \frac{\text{Average change, NE}/(\text{Average change, ES} + \text{Average change, NE})}{\text{Non-essential share}} - 1 \quad (9)$$

For example, non-essential employment accounts for 97% ($= \frac{-676}{(-676)+(-24)}$) , see Table 1) of the total fluctuation, despite non-essentials employment only accounting for 67% (Table D.2) of total employment. We then calculate amplification as the percent larger contribtion of non-essentials, compared to a uniform contribution, ie 44% $= \frac{97\%-67\%}{67\%}$. This intuition simplifies to a comparison of cumulated IRFs. We use the essential and non-essential IRFs here for consistency with the earnings calculation, below.

For median earnings, we treat this "as if" all workers' earnings respond with the median earning of their category, and weight the IRFs by both the earning amount and the employment amount:

$$\text{Amplification} = \frac{\frac{\text{Employment, NE}*\text{Average change earnings, NE}}{\text{Employment, ES}*\text{Averafe change, ES}+\text{Employment, NE}*\text{Average change, NE}}}{\frac{\text{Employment, NE}*\text{Median earnings, NE}}{\text{Employment, ES}*\text{Median earnings, ES}+\text{Employment, NE}*\text{Median earnings, NE}}} - 1 \quad (10)$$

Average values are calculated over the estimation sample period of the corresponding IRF. Consumption per capita is calculated using averaged chained (2012$) PCE (calculated for each consumption type, and summed to give the overall categorised PCE value), divided

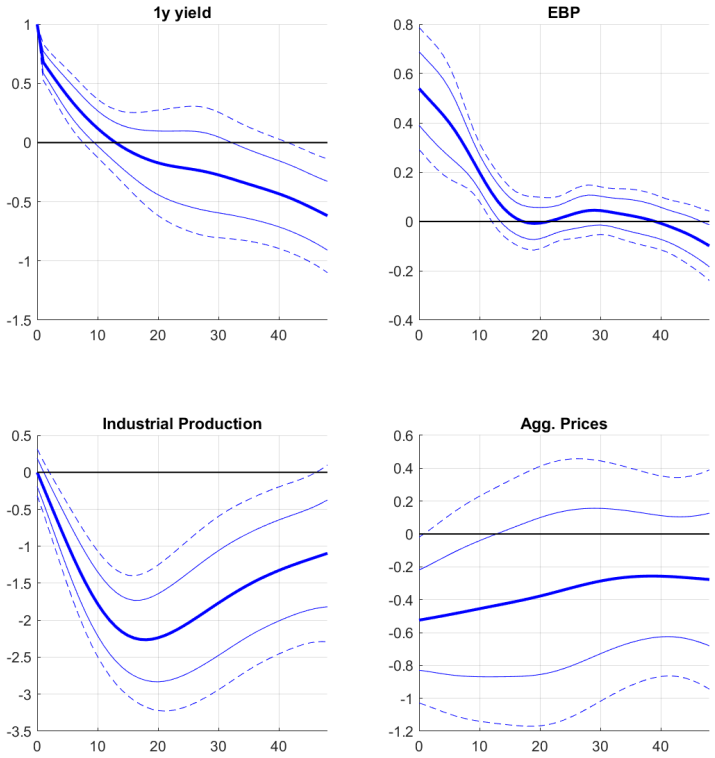
by total NSA population from the BEA. Total employment and median wages are calculated using CPS data, processed as in the above description.

The model based amplification numbers are computed with the same methodology, where we use steady state values instead of average annual values over estimation sample and where we average model IRFs rather than empirical IRFs.

I.2 IRFs for other macro aggregates

Figure I.1 shows the IRFs estimated using our SLP-IV specification for the other macroeconomic aggregate series used as controls and in the Proxy-SVAR. These are 1y yields, the excess bond premium, industrial production and the PCE price index. The results are broadly consistent with standard responses, for instance those given in Gertler and Karadi (2015) using their HFI instrument and SVAR. The shock is a 100bp exogenous rise in 1y yields, after which 1y yields fall and here fall significantly below their prior level by four years after the shock, rather than reverting back to their prior level. The excess bond premium rises about half the amount of 1y yields, but reverts to zero by 18 months after the shock. Industrial production falls by 2% by 15 months after the shock before recoving and becoming insignificantly different from zero by three years after the shock. Aggregate prices fall insignificantly.

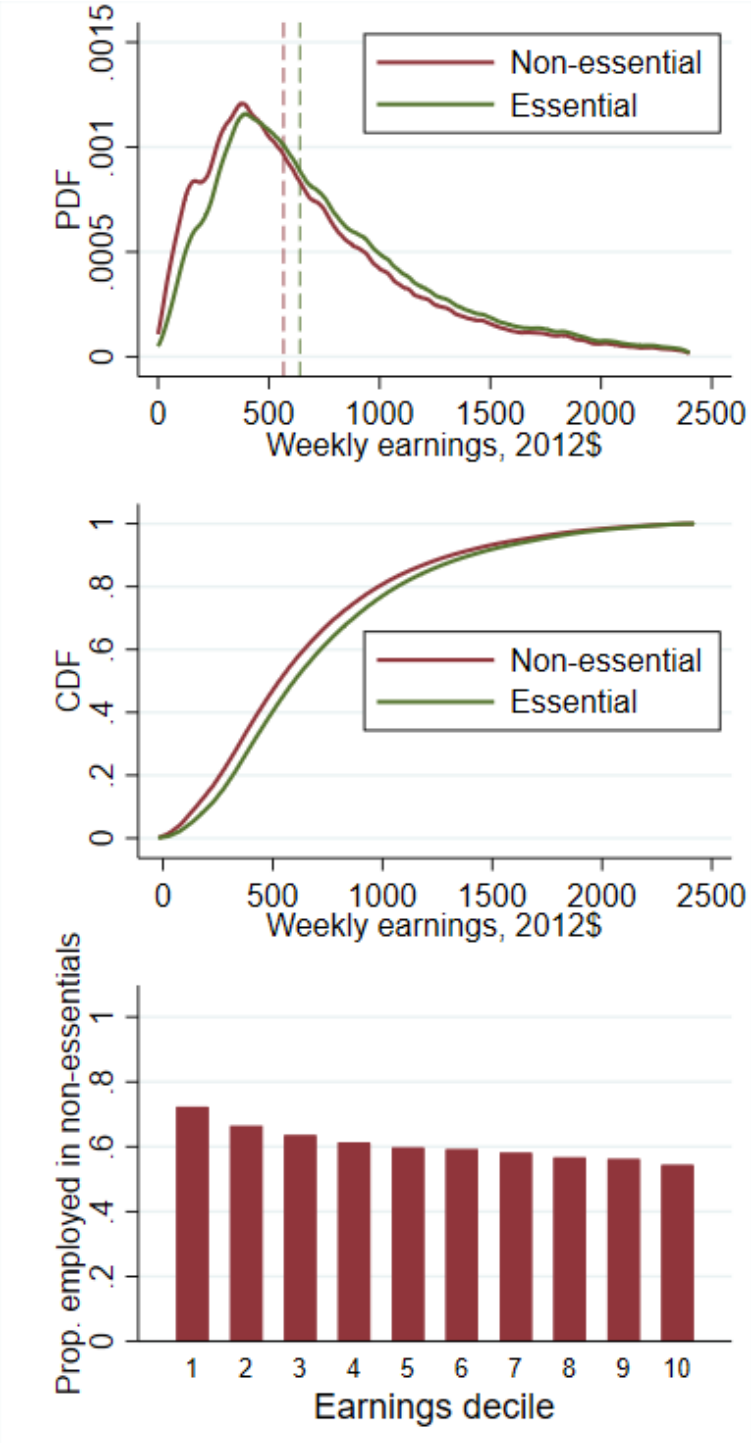
Figure I.1: IRFs to contractionary monetary policy shock - Macro aggregates



Notes: IRFs estimated by smooth local projections, response to 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Responses of 1y yield, excess bond premium and industrial production estimated using data January 1973-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings and employment as controls. Price IRFs estimated on data January 1978-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations and a dummy for before 1983 interacted with the instrument as controls

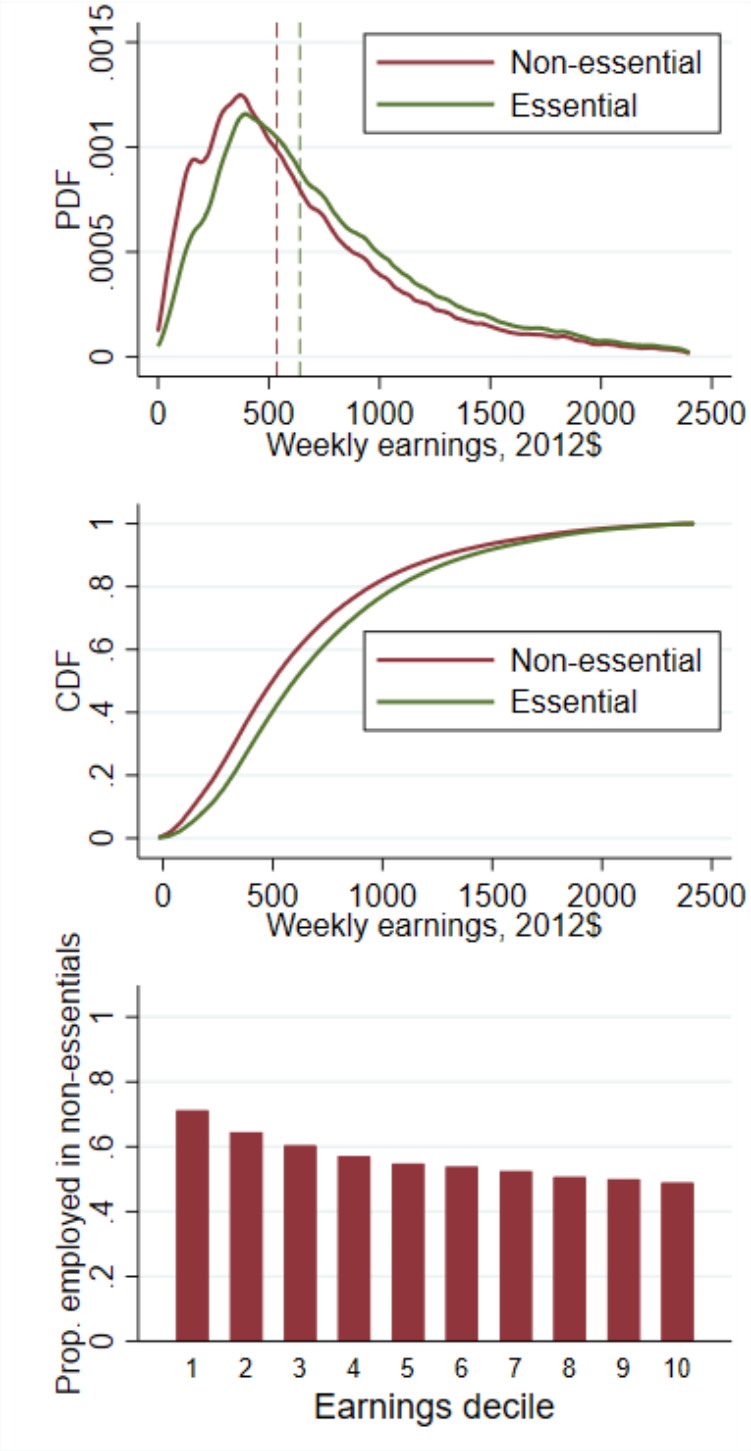
I.3 Additional earnings distribution results

Figure I.2: Non-essential and essential - Earnings distribution



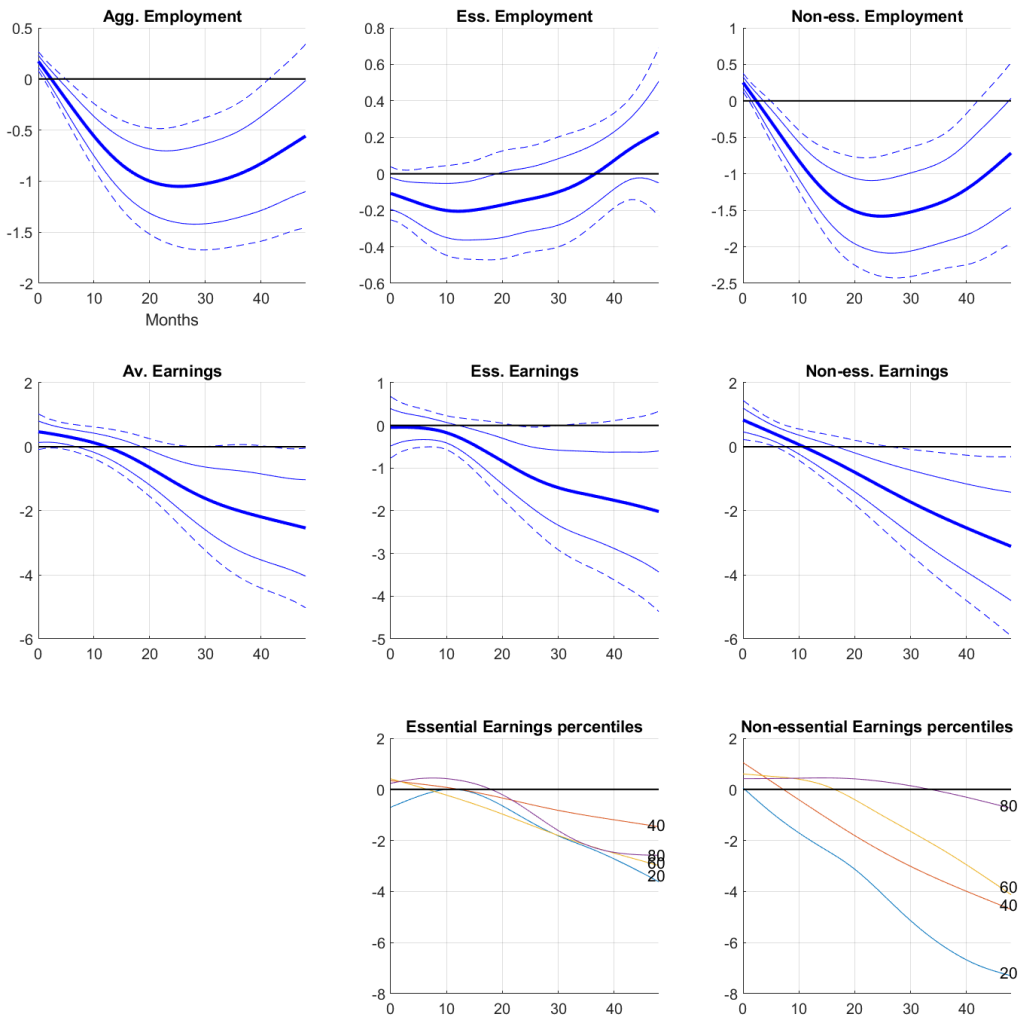
Notes: Earnings distributions within essential and non-essential industries. Underlying data is pooled Jan 1982 - December 2020, from the CPS, as described in the text. Panel 1 shows the kernel density plot along the median of each distribution, panel 2 shows the corresponding CDF, and panel 3 shows the percent of employees working in essential industries for each decile of the income distribution (deciles computed annually).

Figure I.3: Non-essential and essential - Earnings distribution - Excluding construction and related industries



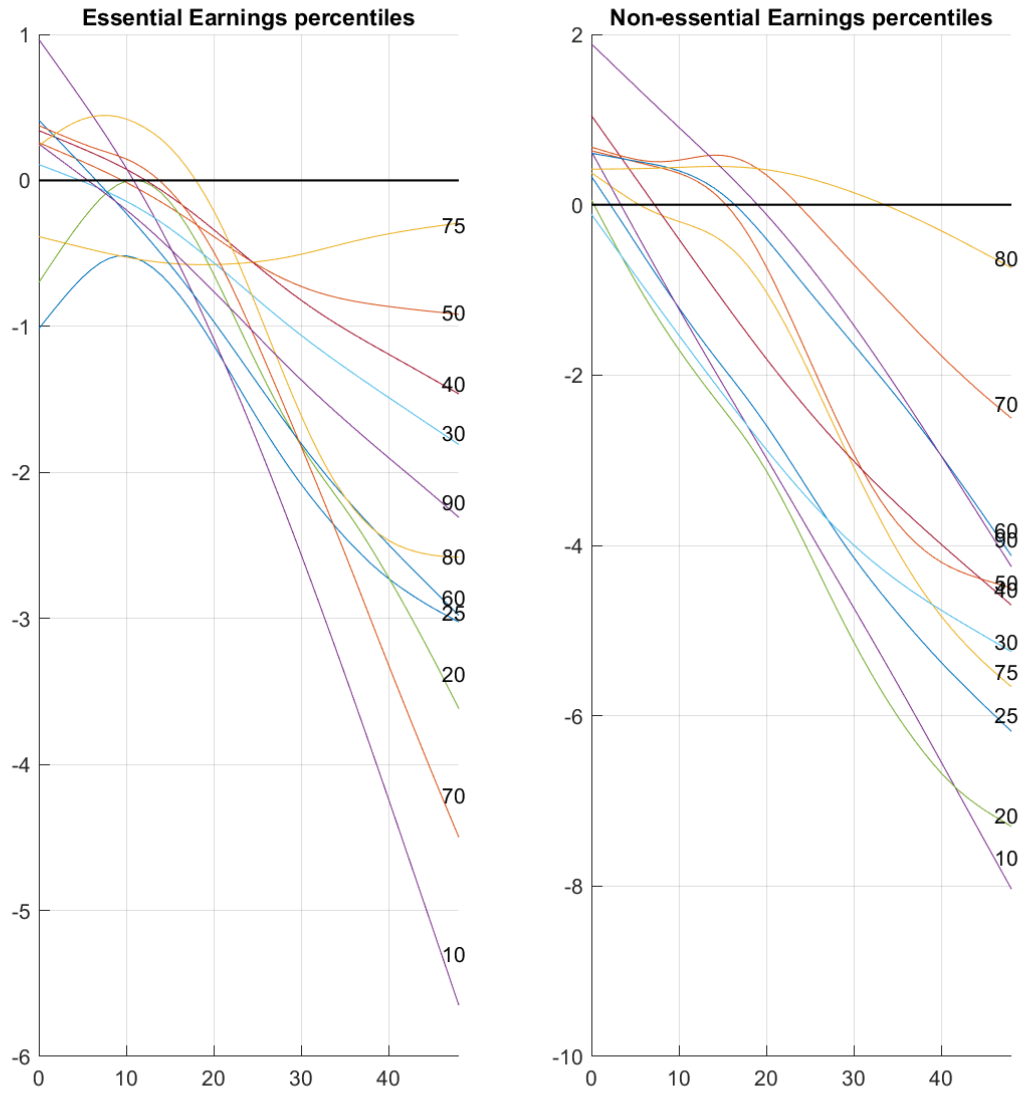
Notes: Earnings distributions within essential and non-essential industries. Underlying data is pooled Jan 1982 - December 2020, from the CPS, as described in the text. Panel 1 shows the kernel density plot along the median of each distribution, panel 2 shows the corresponding CDF, and panel 3 shows the percent of employees working in essential industries for each decile of the income distribution (deciles computed annually).

Figure I.4: IRFs to contractionary monetary policy shock - Employment and Earnings



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Employment IRFs estimated on data January 1976-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Median wage IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations, a dummy for before 1983 interacted with the instrument and the LHS variable as controls.

Figure I.5: IRFs to contractionary monetary policy shock - Earnings distribution



Notes: Point estimate IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Earnings IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, and the LHS variable as controls. Earnings percentiles are from the CPS, and percentiles are calculated separately for the non-essential and essential earnings distributions.

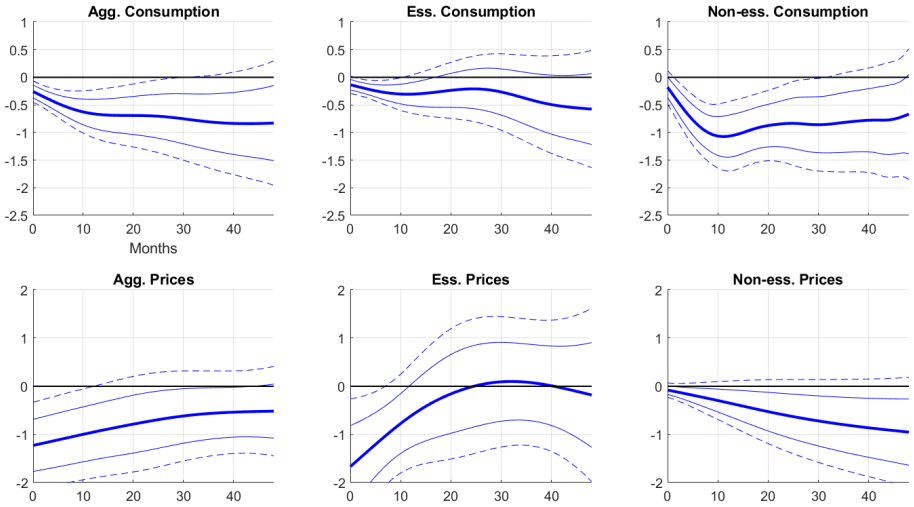
I.4 Robustness to information effect

In the main body, we use monetary policy shocks derived from Gertler and Karadi's high-frequency identified monetary policy instrument. Later literature, particularly Nakamura and Steinsson (2018), Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2021) have explored how these shocks may be confounded by an 'information effect', if the monetary policy announcement also conveys information about the state of the economy that was privately held by the central bank.

To ensure our results are robust to this, we also estimate IRFs using monetary policy shocks derived from the instrument from Jarociński and Karadi (2020) - specifically, the shock to the Fed Funds futures (FF4) if there is a negative correlation between the FF4 surprise and the SP500 surprise. The rationale behind this instrument is that if there is privately held positive news about the economy that is part of the reason for a more contractionary monetary policy decision, then this may also result in a positive response of the stock market. Removing these instances leaves monetary policy surprises that are less likely to be contaminated by the information effect.

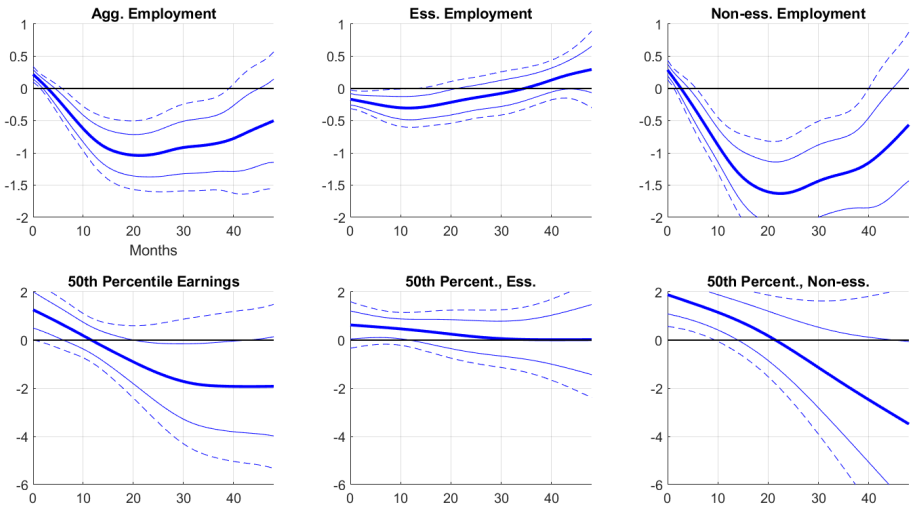
Figures I.6, I.7, I.8 and I.9 are the counterparts to the IRFs in the main text, using these alternative monetary policy surprise series. The results are substantively similar; consumption, prices, employment and earnings (particularly at the lower end of the distribution) in non-essentials fall more than in essentials. However, the difference between essentials and non-essentials responses of prices and median earnings is no longer significant at the 90% level.

Figure I.6: IRFs to contractionary monetary policy shock - Consumption and Prices



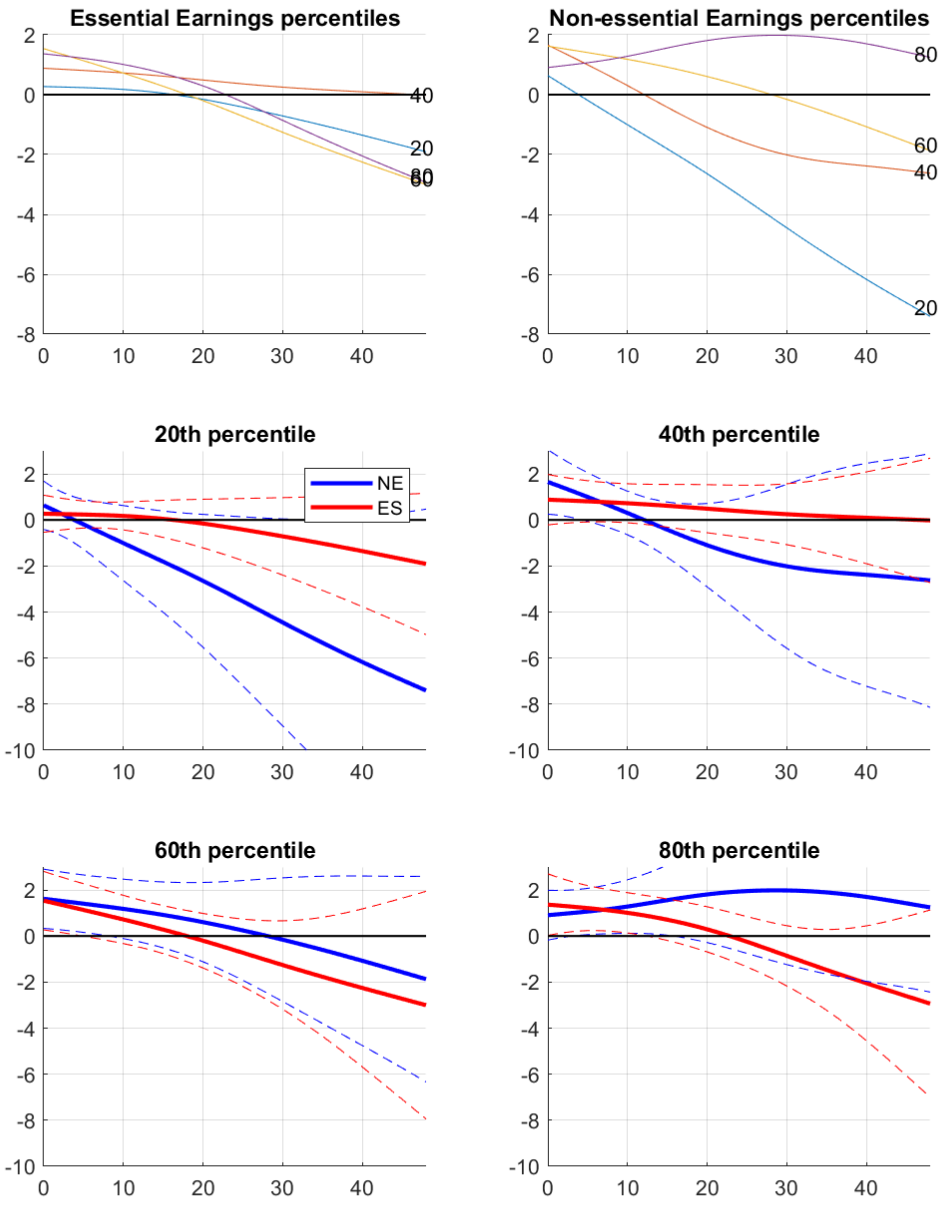
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Jarocinski and Karadi (2020) high-frequency identified monetary policy instrument, robust to the information effect. Consumption IRFs estimated on data January 1973-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Price IRFs estimated on data January 1978-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations, a dummy for before 1983 interacted with the instrument and the LHS variable as controls.

Figure I.7: IRFs to contractionary monetary policy shock - Employment and Earnings



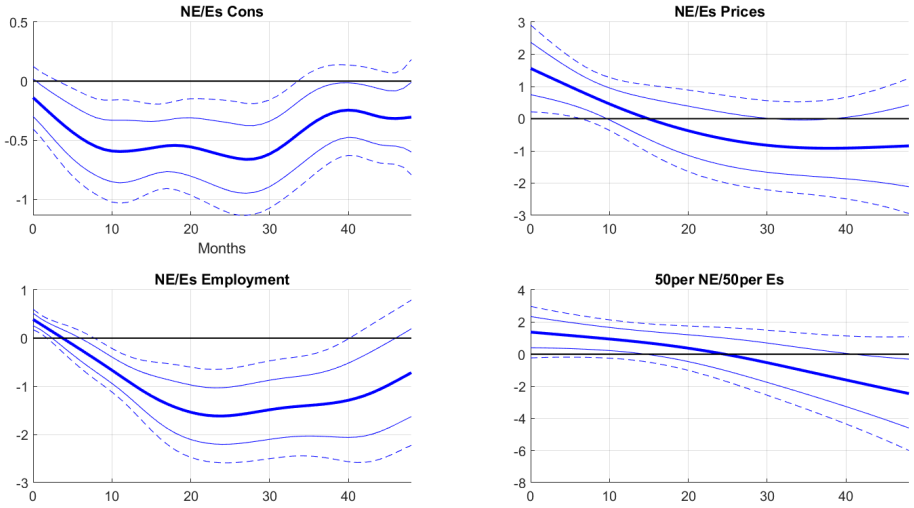
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, i instrumented using monetary policy shocks derived from Jarocinski and Karadi (2020) high-frequency identified monetary policy instrument, robust to the information effect. Employment IRFs estimated on data January 1976-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Median wage IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations and the LHS variable as controls.

Figure I.8: IRFs to contractionary monetary policy shock - Earnings distribution



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Jarocinski and Karadi (2020) high-frequency identified monetary policy instrument, robust to the information effect. Earnings IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, and the LHS variable as controls. Earnings percentiles are from the CPS, and percentiles are calculated separately for the non-essential and essential earnings distributions. 90% confidence intervals displayed.

Figure I.9: IRFs - ratios of essential and non-essential series



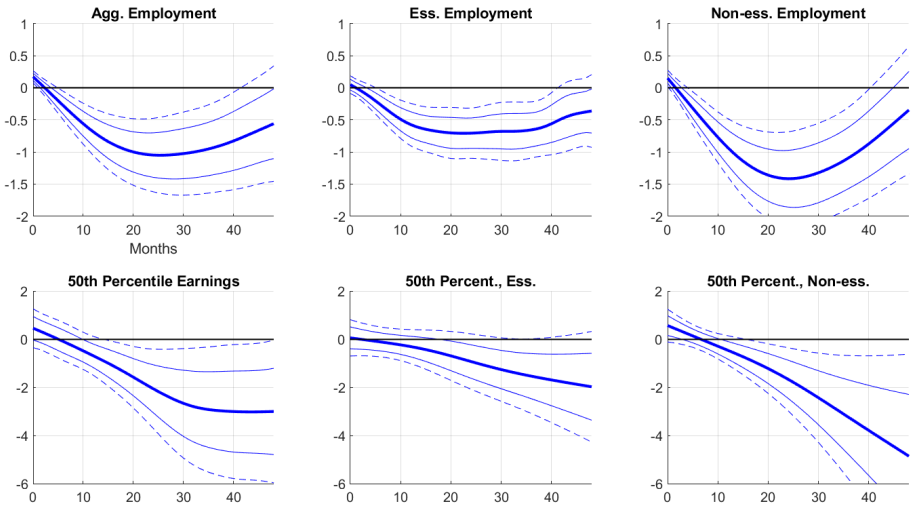
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Jarocinski and Karadi (2020) high-frequency identified monetary policy instrument, robust to the information effect. These show the SLP-IVs for relative effects between the non-essentials and essentials: the LHS variable is log(non-essentials series) $-$ log(essentials series). The sample periods and controls are as described in the main text. 68% and 90% confidence intervals.

I.5 Alternative 'shares' labour market classification approach

The main approach used to map between consumption categories and industry categories, outlined in detail in Appendix Section B is to classify industries into either essentials, non-essenital or unclassified, based on the type of consumption that is the main downstream consumption type supplied by the industry. An alternative approach is to construct series based on the shares of downstream consumption supplied to essentials and non-essentials. For instance, the industry 'paper and paper products' is classified as non-essential, in our main classification, as 47% of its downstream consumption contributed to is non-essential, 28% is essential and 25% is unclassified. As an alternative, we directly use the sales shares, so for instance, an employee working in paper and paper products counts as '0.47' of an employee in the total employment of non-essential. This may, to some extent, more accurately reflect the employment accounted for by non-essential consumption, but is less intuitive in our view than the main approach used.

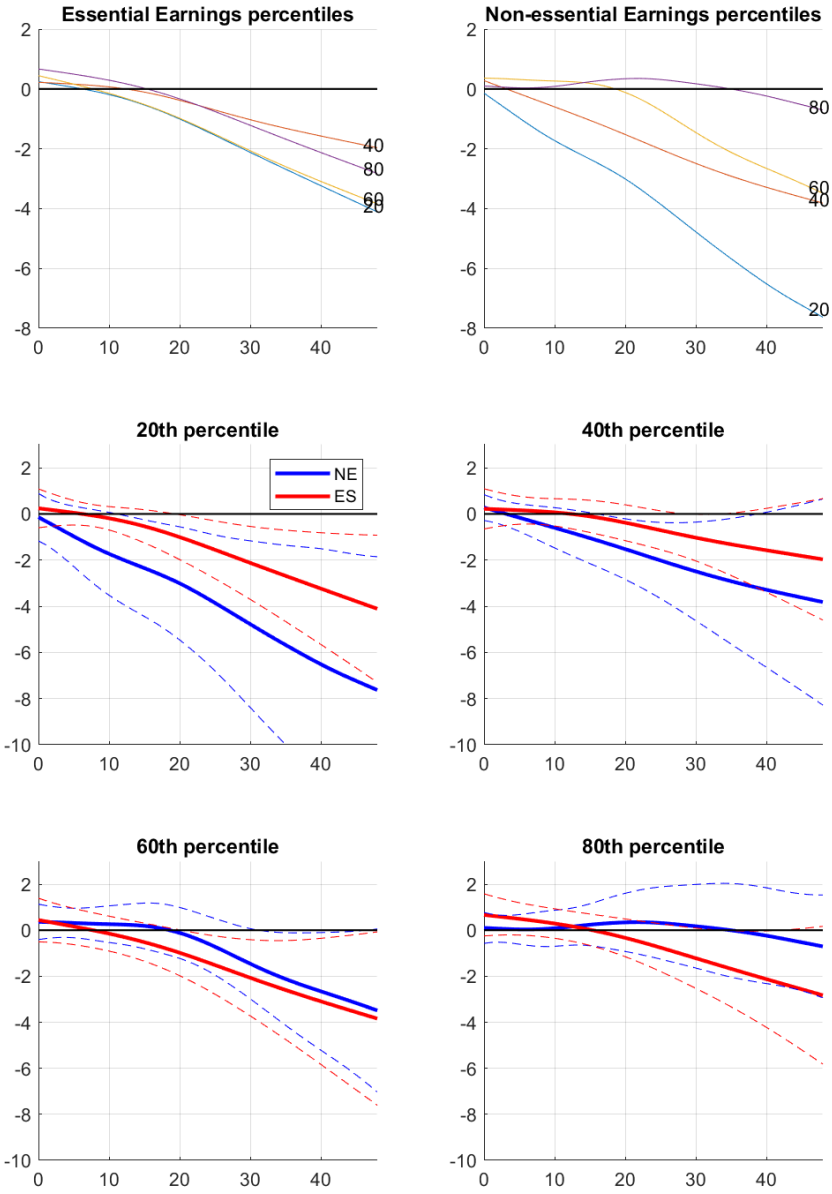
In this section, we show that the main labour market results of our analysis also hold using this alternative approach.

Figure I.10: IRFs to contractionary monetary policy shock - Employment and Earnings



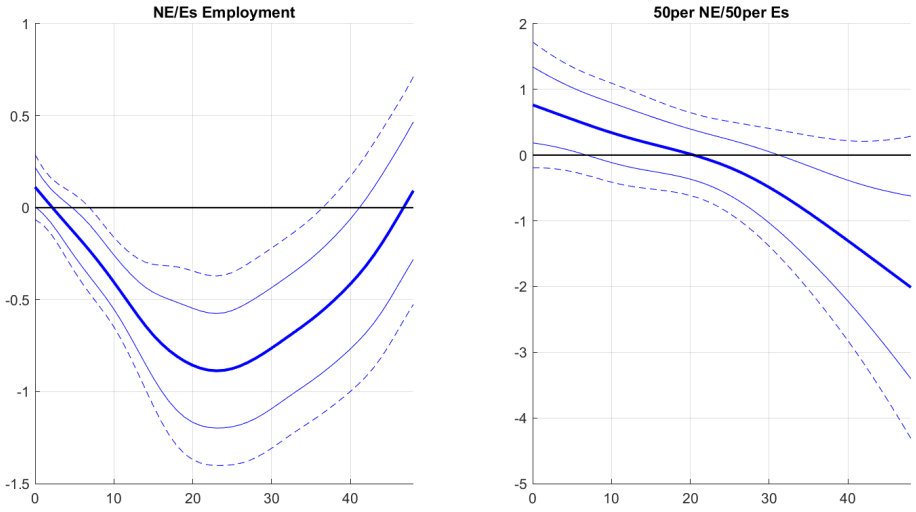
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from an updated version of Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Industry classification used is the 'shares' approach rather than a binary classification approach, as described in the text. Employment IRFs estimated on data January 1976-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Median wage IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations and the LHS variable as controls.

Figure I.11: IRFs to contractionary monetary policy shock - Earnings distribution



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from an updated version of Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Industry classification used is the 'shares' approach rather than a binary classification approach, as described in the text. Earnings IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, and the LHS variable as controls. Earnings percentiles are from the CPS, and percentiles are calculated separately for the non-essential and essential earnings distributions. 90% confidence intervals displayed.

Figure I.12: IRFs - ratios of essential and non-essential series

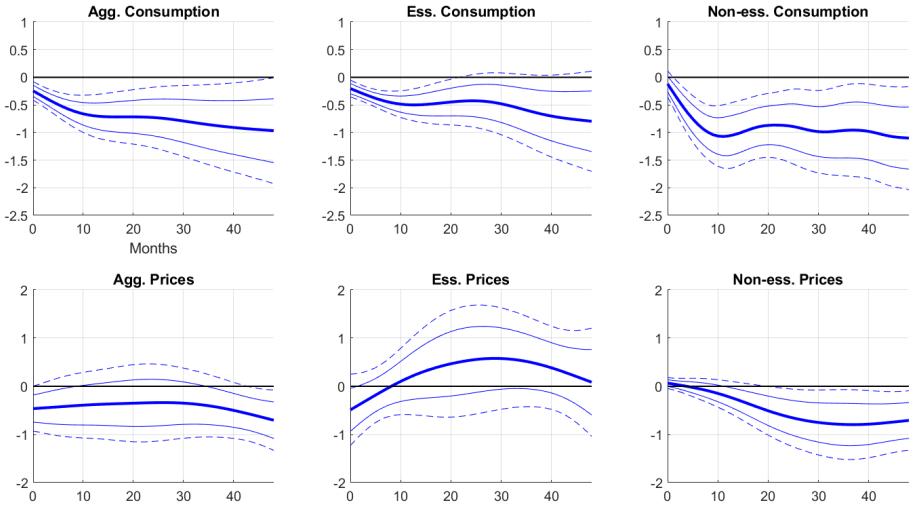


Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from an updated version of Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Industry classification used is the 'shares' approach rather than a binary classification approach, as described in the text. These show the SLP-IVs for relative effects between the non-essentials and essentials: the LHS variable is log(non-essentials series) $-$ log(essentials series). The sample periods and controls are as described in the main text. 68% and 90% confidence intervals.

I.6 Removing COVID from sample period

In our main sample, we end the estimation period in December 2020. This includes the start of the effects of Covid-19, where non-essentials and essentials responded diffferently to the shock partly due to sector-specific reductions in activity not directly driven by the mechanism we propose here[21]. To check that our results are robust to removing the effects of the Covid-19 period, we estimate the IRFs for samples ending in December 2019 in Figures I.13, I.14, I.15 and I.16. The results are similar, perhaps unsurprisingly as only a small part of the sample is removed.

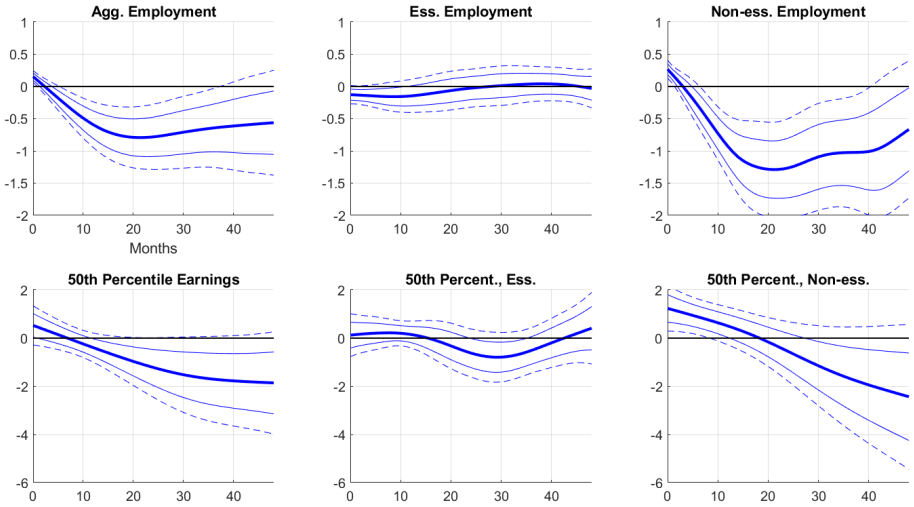
Figure I.13: IRFs to contractionary monetary policy shock - Consumption and Prices



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument, robust to the information effect. Consumption IRFs estimated on data January 1973-December 2019, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Price IRFs estimated on data January 1978-December 2019, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations, a dummy for before 1983 interacted with the instrument and the LHS variable as controls.

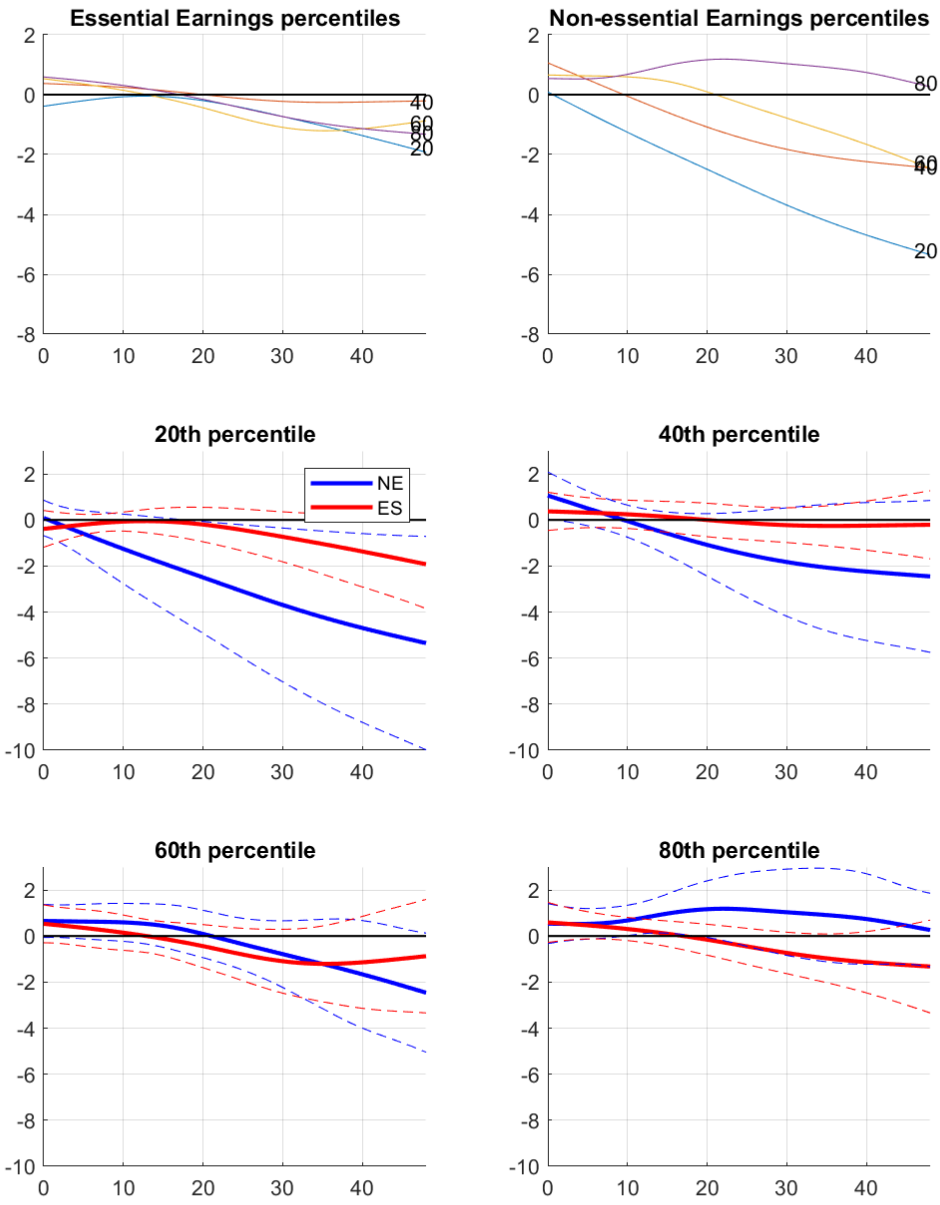
[21] Although we envisage that a large reason for the differential shutdowns of different sectors were precisely because certain types of consumption are not intertemporally substitutable, consistent with our mechanism, and that our identification strategy of estimating the response to monetary policy shocks should aleviate this issue

Figure I.14: IRFs to contractionary monetary policy shock - Employment and Earnings



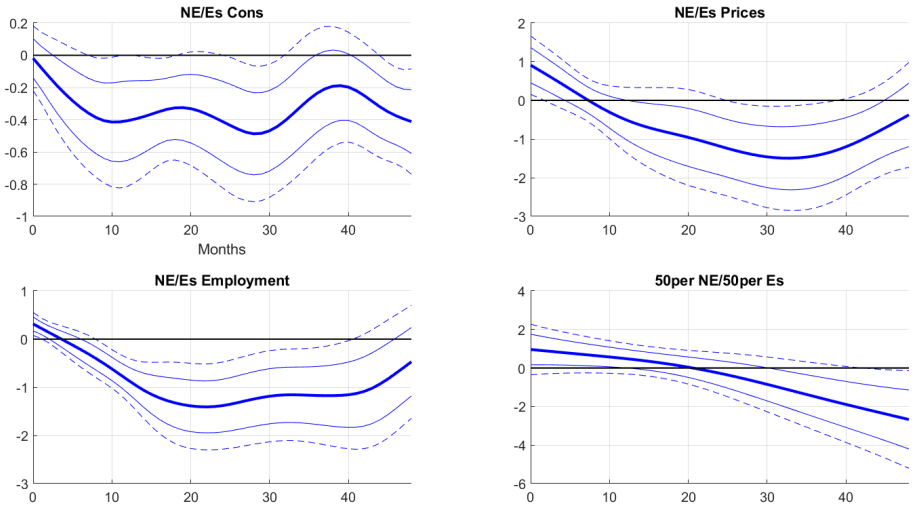
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, i instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument, robust to the information effect. Employment IRFs estimated on data January 1976-December 2019, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Median wage IRFs estimated on data January 1982-December 2019, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations, a dummy for before 1983 interacted with the instrument and the LHS variable as controls.

Figure I.15: IRFs to contractionary monetary policy shock - Earnings distribution



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument, robust to the information effect.. Earnings IRFs estimated on data January 1982-December 2019, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, and the LHS variable as controls. Earnings percentiles are from the CPS, and percentiles are calculated separately for the non-essential and essential earnings distributions. 90% confidence intervals displayed.

Figure I.16: IRFs - ratios of essential and non-essential series

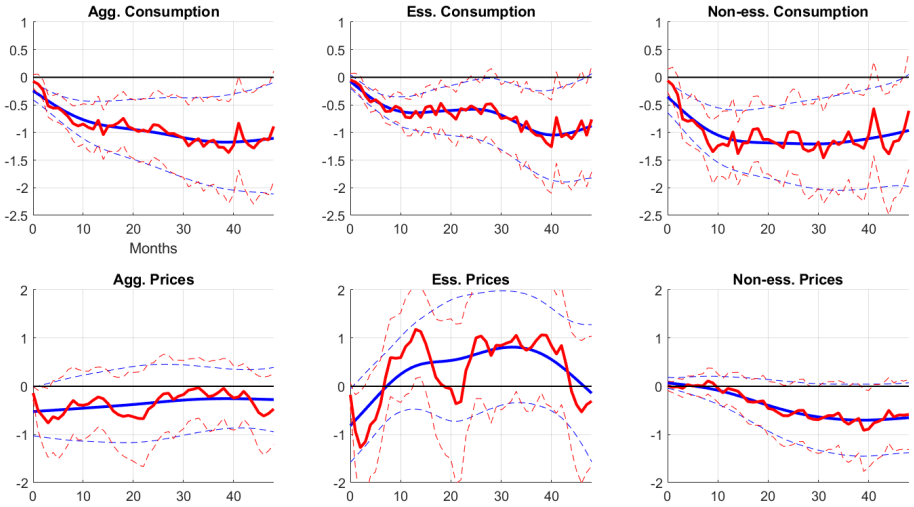


Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument, robust to the information effect. These show the SLP-IVs for relative effects between the non-essentials and essentials: the LHS variable is log(non-essentials series) $-$ log(essentials series). The sample periods and controls are as described in the main text, but ending in December 2019 rather than December 2020. 68% and 90% confidence intervals.

I.7 IRFs with (unsmoothed) local projections

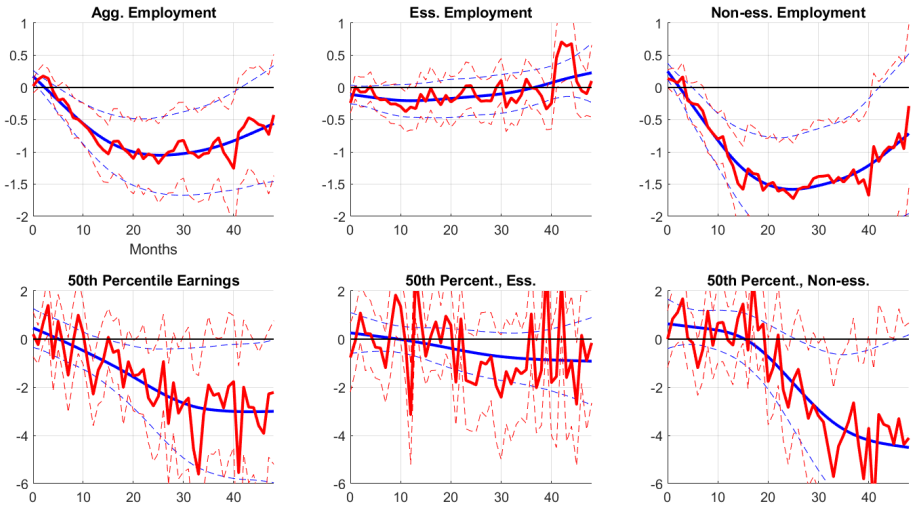
To show that our results are robust to using standard local projections, rather than smoothed local projections, Figures I.17, I.18 and I.19 show our consumption, price, employment and earnings IRFs with both our SLP IRFs and standard local projections. The IRFs are similar, but particularly for the more noisy time-series, the standard approach gives more noisy IRFs.

Figure I.17: IRFs to contractionary monetary policy shock - Consumption and Prices



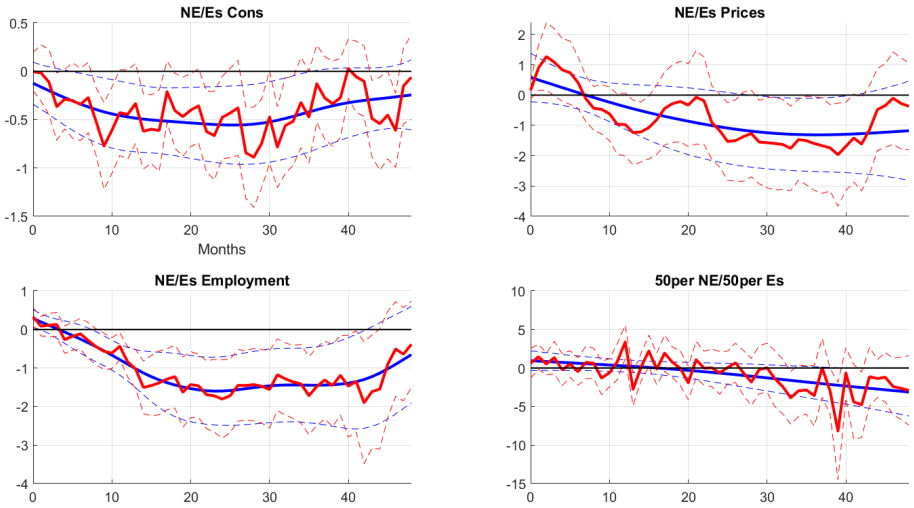
Notes: IRFs estimated by smooth local projections (blue) and standard local projections (red), response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument, robust to the information effect. Consumption IRFs estimated on data January 1973-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Price IRFs estimated on data January 1978-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations, a dummy for before 1983 interacted with the instrument and the LHS variable as controls. 90% confidence intervals.

Figure I.18: IRFs to contractionary monetary policy shock - Employment and Earnings



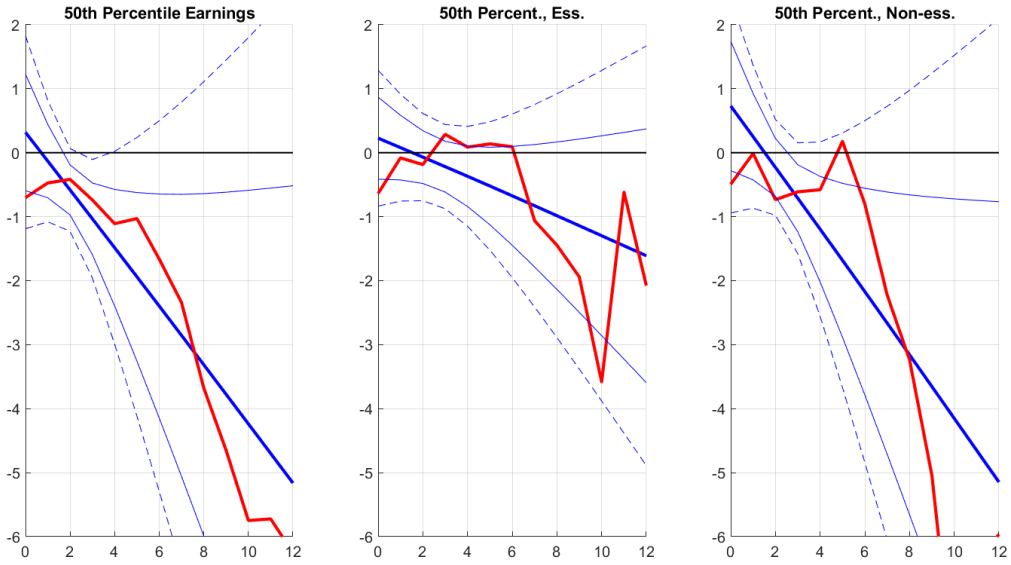
Notes: IRFs estimated by smooth local projections (blue) and standard local projections (red), response to a 100bp increase in 1y yields, i instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument, robust to the information effect.. Employment IRFs estimated on data January 1976-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment and the LHS variable as controls. Median wage IRFs estimated on data January 1982-December 2020, with 12 lags of 1 year yields, the excess bond premium, industrial production, consumption, prices, earnings, employment, Michigan inflation expectations, a dummy for before 1983 interacted with the instrument and the LHS variable as controls. 90% confidence intervals.

Figure I.19: IRFs - ratios of essential and non-essential series



Notes: IRFs estimated by smooth local projections (blue) and standard local projections (red), response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument, robust to the information effect. These show the SLP-IVs for relative effects between the non-essentials and essentials: the LHS variable is log(non-essentials series) $-$ log(essentials series). The sample periods and controls are as described in the main text. 90% confidence intervals.

Figure I.20: IRFs to contractionary monetary policy shock - Median earnings, quarterly frequency



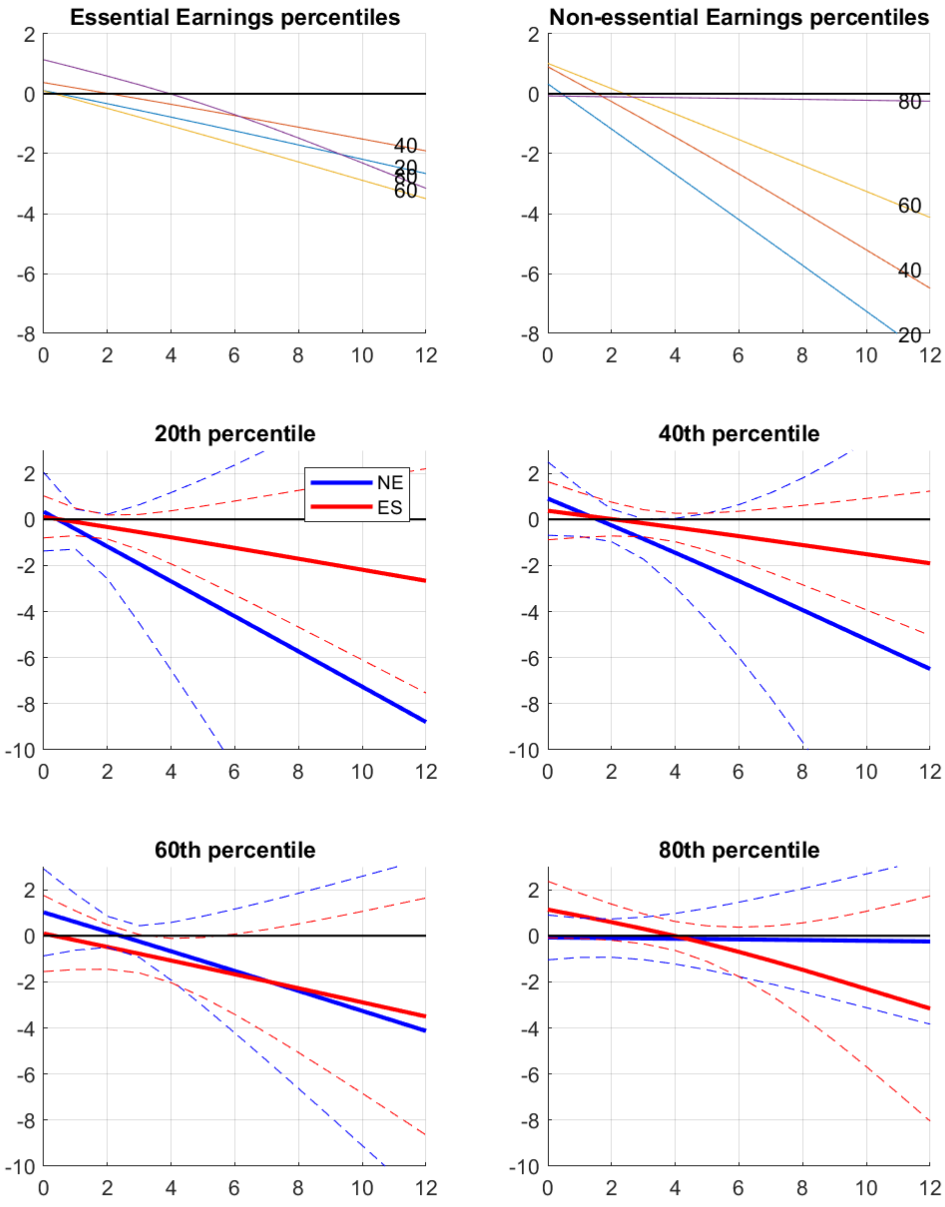
Notes: IRFs estimated by smooth local projections (blue) and standard local projections (red), response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Earnings IRFs estimated on data Q1 1982-Q1 2020, with 4 lags of 1 year yields, consumption, prices, earnings, employment, and the LHS variable as controls. Earnings percentiles are from the CPS, and percentiles are calculated separately for the non-essential and essential earnings distributions. 68% and 90% confidence intervals displayed.

I.8 Earnings IRFs using quarterly data

The Outgoing Rotation Group of the CPS, which we use for our earnings data, is designed to be representative at the quarterly level, rather than the monthly level. We use a monthly series to maximise the variation in monetary policy surprises, but to verify that the results we find are robust to using the recommended quarterly aggregation of the CPS data, we also run the same analysis at a quarterly frequency. The empirical specification we use here is identitical, other than summing the monthly monetary policy surprises extracted from the VAR over quarters. We use four lags of controls in SLP-IV estimation and estimate the impulse responses over 12 quarters after the shock.

The results are shown for median earnings in Figure I.20 and for the earnings distribution in Figure I.21. The qualitative results are similar; non-essential earnings fall more and this is driven by the bottom of the earnings distribution. However, most of the results are no longer significant. We see this as tentative support for the main results, but prefer to use the monthly frequency earnings series.

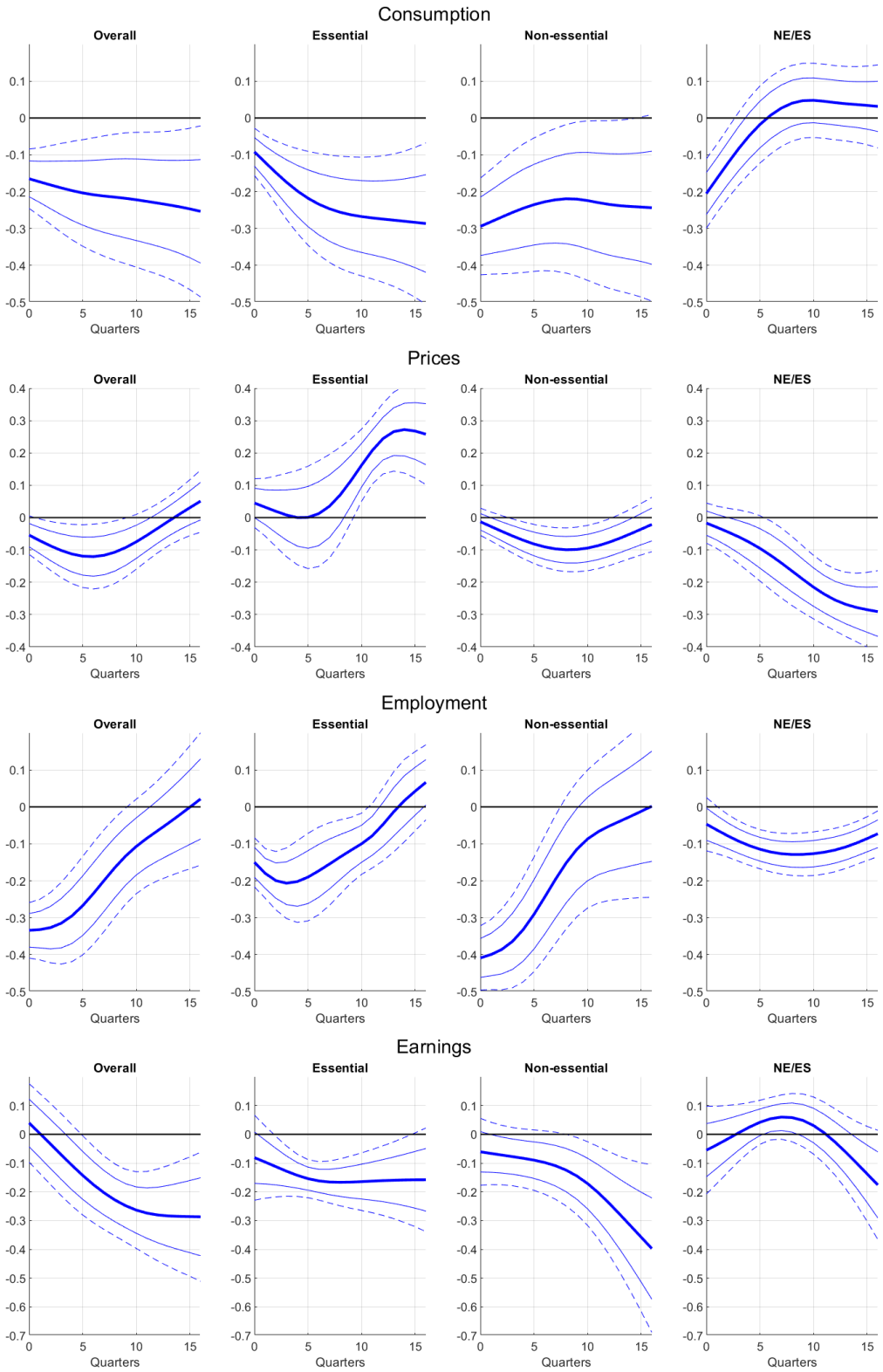
Figure I.21: IRFs to contractionary monetary policy shock - Earnings distribution, quarterly frequency



Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Earnings IRFs estimated on data Q1 1982-Q1 2020, with 4 lags of 1 year yields, consumption, prices, earnings, employment, and the LHS variable as controls. Earnings percentiles are from the CPS, and percentiles are calculated separately for the non-essential and essential earnings distributions. 90% confidence intervals displayed.

I.9 Shocks from Business Cycle Anatomy (Angeletos et al.)

Figure I.22: Response to business cycle shock from Angeletos et al



Notes: Specifically, the shock here is the one that maximises the variation in unemployment, which is the main shock used by Angeletos. Shocks which maximise other variables are strongly correlated with this shock, and give similar results here. Results estimated using SLP, same sample and specification as the main results, other than no instrument used and quarterly frequency. Earnings refers to median earnings

J State-level analysis methodology

Figure 7 in the main text shows the the correlation between state-level employment changes during recessions and state-level non-essential consumption shares.

To construct this we used:

- Monthly BLS state-level employment data, derived from the CES.
  - We used the raw (non-seasonally adjusted) series, which starts in 1939, and seasonally adjusted it using the X-13ARIMA-SEATS approach. This gives seasonally adjusted state level employment series. These only start in 1973, due to limits on how long the series you can seasonally adjust can be using this procedure (but covers most of our sample period).
  - To identify state-specific recession dates by identifying the state-specific peak and trough of employment within 12 months before/after the NBER recession dates, excluding states where employment did not decline.
- State-level PCE series. The BEA provides these annually for 1997-present. The consumption categories available are somewhat more aggregated than those we are using for our main analysis, so the average non-essential shares do not exactly correspond. Non-essential shares are consumption shares from the BEA's state-level annual PCE series. We average these over the entire sample available for the series show on the x axis.

K Model Derivation

TO BE ADDED