Non-Essential Business-Cycles

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Abstract

Using newly constructed time series of consumption, prices and earnings for essentials and non-essentials, we document three main empirical regularities on post-WWII U.S. data: (i) spending on non-essentials is more sensitive to the business-cycle than spending on essentials; (ii) earnings in non-essential sectors are more cyclical than earnings in essential sectors; (iii) low-earners are more likely to work in non-essential industries. We develop and estimate a structural model with non-homothetic preferences over two expenditure goods, hand-to-mouth consumers and heterogeneity in labour productivity that is consistent with these findings. We use the model to quantify the contribution of each channel to the transmission of monetary policy and find that the *interaction* of the unequal spending composition across goods and the unequal workers composition across sectors greatly amplifies business-cycle fluctuations relative not only to a representative agent/representative good benchmark but also to models that feature heterogeneity only in the cyclical composition of either product or labour demand.

Keywords: income elasticity, recessions, monetary policy, amplification, inequality.
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 earnings.

This paper explores this novel channel of transmission, which we refer to as non-essential business cycles, along two dimensions, empirical and theoretical. On the empirical side, we show that non-essential consumption falls twice as much as 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. Labour earnings in the non-essential sector decline by 4.8% at peak, while earnings in the essential sector do not decline significantly. This labour heterogeneity is explained by both a significant decline in employment in the non-essential sector and a relative decline in median weekly earnings in non-essentials compared to essentials.

This suggests that accounting for the difference between essentials and non-essentials is crucial to understanding the transmission and ramifications 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), who show the general property 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). This intuitive property that non-essentials are easier to postpone implies that they have a higher intertemporal elasticity of substitution (IES) than essentials. Given the central role of intertemporal elasticities of substitution within macroeconomic models, we highlight how heterogeneity in the IES can interact with the labour market and amplify business cycle fluctuations.

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 with a structural estimation. 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 estimated structural model allow us to provide a decomposition of how spending heterogeneity and worker heterogeneity interact to exacerbate shocks. We find that our three key features of our model: i) Non-homothetic preferences, ii) Hand-to-mouth households, and iii) Earning inequality among workers due to the non-essential sector employing disproportionately more lower productivity workers. As a counterfactual exercise to understand the role of each of these features, we switch all features off and add them back incrementally. The conclusion is that the interaction between spending heterogeneity and earning inequality is key to account for our main findings. Without all three features, we can explain no more than half of the variation in consumption in our full model. We also prove that non-homothetic preferences in a representative agent model have no impact on aggregate fluctuations, provided they do not interact with other sectoral heterogeneities.

Direct and indirect effects We use our empirical results and our structural model 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 essentials, 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, earnings, and employment. 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 earnings and employment time-series for essentials and non-essentials using data from the CPS.

Related literature Our paper contributes to several strands of work in macroeconomics. Growing research efforts have been successfully devoted to quantify the contribution of income inequality and income risk to the amplification of business-cycle fluctuations. Bilbiie (2020) and Patterson (2023) identify the crucial role played by the covariance between the marginal propensity to consume and earning cyclicality across workers, while McKay, Nakamura and Steinsson (2016), Ravn and Sterk (2017, 2021) and Bilbiie, Primiceri and Tambalotti (2023) highlight the contribution of counter-cyclical income risk. Cloyne, Ferreira and Surico (2020) show that the indirect effects of monetary policy on income across households are key to account for the aggregate consumption response, while Holm, Paul and Tischbirek (2021), Amberg et al. (2022), Andersen et al. (2023) document significant heterogeneity in the earning responses to monetary policy along the income distribution.[1] Relative to these studies, we emphasize an overlooked dimension of income (and spending) heterogeneity: essentials versus non-essentials. By documenting and modelling the unequal incidence of recessions *both* in goods markets *and* in the labour market, we show that the skill composition of the labour force across industries provides yet another powerful amplification mechanism, which so far has been overlooked.

A prominent literature has investigated the role of demand composition in shaping business-cycle dynamics. Barsky, House and Kimball (2007) focus on the transmission of monetary policy when durable goods are characterized by different degrees of price stickiness, while Sterk (2010) and Monacelli (2009) extend their analysis to the presence of credit frictions; McKay and Wieland (2019), and Beraja and Wolf (2021) show that the lumpy nature of durable spending can significantly alter the transmission of monetary policy and the strength of recoveries after a recession; Mian and Sufi (2014) emphasize the role of the non-tradeable sector in explaining the drop in employment during the Great Recession. The distinction between essentials and non-essentials differs from the type of demand composition studied in the papers cited above along two important dimensions. First, we document a strong co-variance between the cyclicality of non-essential spending and the cyclicality of non-essential earnings, but find much lower comovements between consumption and income in either the durable or the non-tradeable sector. Second, non-essential industries witness a much higher concentration of low-income workers than durable goods producers. We show that these two features of the data are crucial to generate significant amplification in our estimated structural model.

Finally, earlier contributions have used non-homothetic preferences to analyse salient features of consumption and saving behaviour, including heterogeneity in the intertemporal elasticity of substitution (Browning and Crossley, 2000), wealth accumulation (De Nardi and Fella, 2017), price rigidities (Clayton, Jaravel and Schaab, 2018), cost of living (Orchard, 2022), marginal propensity to consume (Andreolli and Surico, 2021) and demand cyclicality across educational levels (Sonnervig, 2022).[2] We departure from these works along two

[1] Another important literature emphasizes the role of heterogeneity in the marginal propensity to consume. For instance, Kaplan, Moll and Violante (2018), Auclert (2019) and Debortoli and Galí (2017) separate the direct effects from the indirect effects of monetary policy on consumption, while Auclert, Rognlie and Straub (2020) and Bilbiie, Känzig and Surico (2022) highlight the role of capital investment.

[2] Non-standard preferences (and non-homotheticity in particular) have been used extensively outside the

main dimensions. First, we provide novel evidence on the labour market responses across essential and non-essential industries (as well as along their income distribution). Second, we develop and estimate a structural model in which the cyclicality of non-essential spending and the cyclicality of non-essential earnings interact in general equilibrium to generate a novel complementarity that greatly amplifies the effects of monetary policy.

Structure of the paper In Section 2, we present our measurement strategy spanning across multiple granular datasets, and provide descriptive evidence about the newly constructed time series for essentials and non-essentials. In Section 3, we describe the identification of monetary policy shocks, lay out the empirical approach based on local projections and report the responses of consumption and earnings, both across essential and non-essential sectors as well as along the labour earning distributions. In Section 4, we develop a structural business-cycle model that features three main ingredients: (i) hand-to-mouth consumers, (ii) non-homothetic preferences over two consumption goods characterized by different IESs, and (iii) heterogeneity in the skill composition of the labour force across industries. In Section 5, we estimate the structural model by minimizing the distance of its theoretical responses to a monetary policy shock from the IRFs estimated via local projections. Finally, in Section 6, we use the estimated structural model to perform counterfactual analyses that allow us to identify and quantify the contribution of each channel, (i) to (iii), to altering the transmission of monetary policy and amplifying business-cycle fluctuations.

2 Data and Descriptive Evidence

In this section, we outline the construction of novel time series for essentials and non-essentials in consumption, prices, earnings, and employment. We proceed in four steps which involves using multiple (micro) datasets from several sources over different samples. First, we classify spending categories into essentials and non-essentials estimating Engel curves on CEX data. Second, we apply the categorization above to PCE data and obtain indexes of quantities and prices for essential and non-essential spending. Third, we rely on the input-output accounts data and the Leontief inverse to group all industries (including those producing intermediate goods) into essentials and non-essential sectors. Fourth, we exploit CPS data to compute monthly time series for employment and for several percentiles of the earning

business-cycle literature. Notable examples include inequality (Comin, Mestieri and Danieli, 2020), the equity premium puzzle (Ait-Sahalia, Parker and Yogo, 2004), portfolio allocation (Wachter and Yogo, 2010), and structural change (Foellmi and Zweimüller, 2008, Boppart, 2014, Comin, Lashkari and Mestieri, 2021).

distributions in essential and non-essential industries. At the end of this section, we present descriptive statistics that summarize the cyclical properties of our newly constructed time-series, unconditionally. In the next section, we will explore the responses of consumption and earnings in essentials and non-essentials conditional to an identified monetary policy shock.

2.1 Measurement

The starting point of our data construction exercise is to pin down a precise definition for essentials and non-essentials. It is important to emphasize, however, that nothing of what we describe below hinges upon any specific definition: our method is general enough to accommodate different user's choices, including the possibility of allowing some spending categories to move between essentials and non-essentials over time.

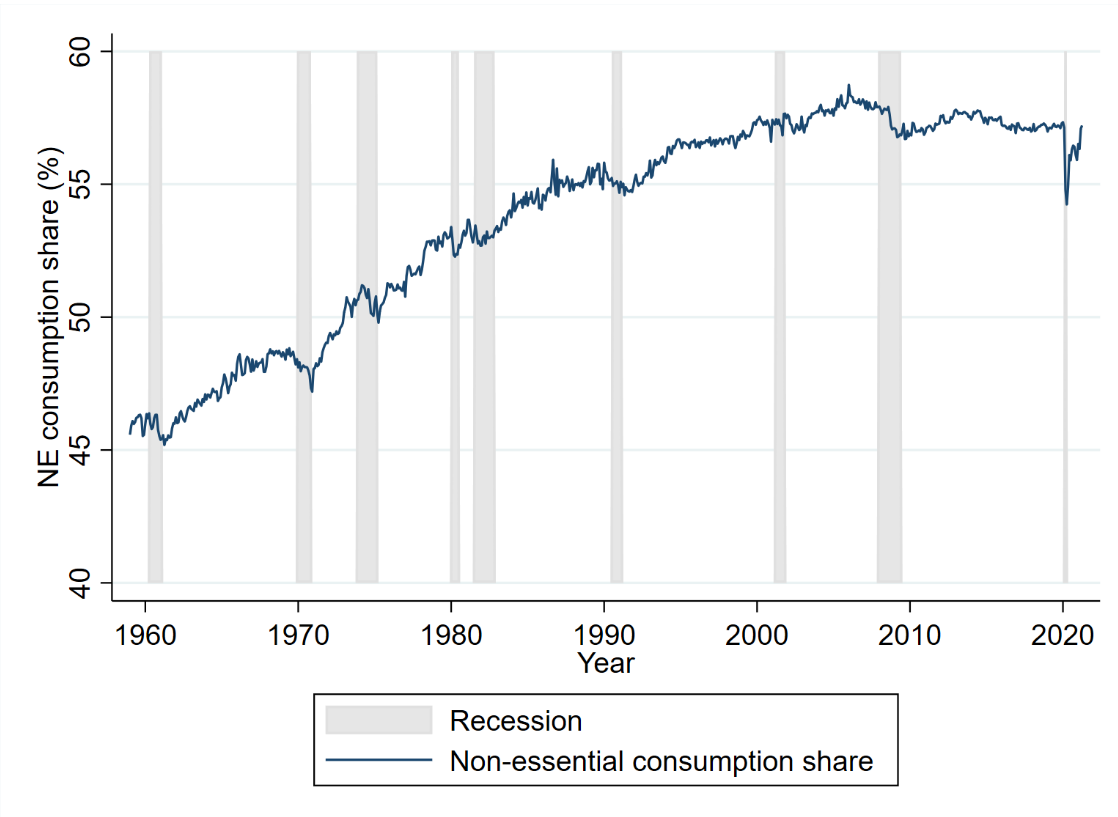
I) Consumption classification. For the consumption categorization into essentials and non-essentials, we follow Aguiar and Bils (2015), and use data from the Consumer Expenditure Survey (CEX) over the period 1995-1997 to estimate income elasticities of demand for 24 spending groups. More specifically, we regress expenditure shares at the household level for each of these 24 categories on total expenditure, using net household income as an instrument for total spending. Consumption categories with an elasticity to total expenditure greater than (less than) one are regarded as non-essentials (essentials). The resulting categorization is displayed in Appendix A.1.[3]

II) Building consumption and price series using PCE data. In this step, we map essential and non-essential spending from the CEX to the Personal Consumption Expenditure (PCE) classification by Type of Product from the U.S. Bureau of Economic Analysis (BEA), following Aguiar and Bils (2015). A main advantage of using PCE data is that the BEA produces nominal expenditure, real consumption, and price indices at a very detailed level of disaggregation and at monthly frequency, consistently since 1959. This allow us to distinguish between movements in quantities and movements in prices for both essentials and non-essentials. In addition, and unlike the CEX, the BEA reports the flow consumption of

[3] In Appendix A.1, we report the estimated elasticities of demand for each spending category and provide details of the method in Aguiar and Bils (2015). We use the same consumption classification into essentials and non-essentials over the entire sample, consistent with the evidence in Aguiar and Bils (2015) that the slope of the Engel curve has been relatively stable over time. As discussed in the main text, however, our method can be easily extended to accommodate time-varying Engel curve slopes, and thus allow spending categories to move between essentials and non-essentials over time. Likewise, users may choose to set the elasticity cutoff that separates essentials from non-essentials to a value different from one.

housing services (e.g. imputed rents for owner occupiers) rather than the actual spending on housing (e.g. mortgage payments), and the former is consistent with the concept used in theoretical models like the one we develop in Section 4.[4] Finally, we construct Fisher indices for consumption and prices following the approach outlined in the BEA NIPA (2021) handbook, Chapter 4.

Figure 1: Non-essential consumption share over time



Notes: Personal consumption expenditure shares of non-essentials, constructed from chained (2000$) spending series, and as a proportion of total classified expenditure. Underlying data are from the BEA PCE by Type of Product tables. Shaded areas in grey represent NBER recession dates.

In Figure 1, we report the outcome of these two initial steps in the form of non-essential consumption as a share of total expenditure. This newly constructed series displays two main regularities. First, the non-essential expenditure share has trended upward, moving from about 45% in the early 1960 to 57% in the late 2010s. Second, the share of spending

[4] As in Aguiar and Bils (2015), we either adjust or omit from our essential/non-essential classification, spending categories that are likely to be poorly measured, such as 'health expenditure' (which we scale down by the proportion of healthcare spending made out of pocket) or such as 'professional and financial services fees' (which we exclude). These adjustments and omissions are detailed in Appendix A.1, and result in our essential and non-essential indices covering an average of about 80% of total expenditure over the sample.

that goes into non-essentials appears to drop significantly and systematically during (NBER) recessions, which are highlighted as grey areas in Figure 1. We will come back to the cyclical properties of our newly constructed series in the descriptive evidence of next section.

III) Mapping consumption to employment data. In our third step, we construct time series for earnings and employment in essential and non-essential sectors. A main challenge we face is that a large fraction of workers are employed in intermediate industries, and therefore we need a strategy to link industry classifications to downstream consumption categories so as to identify the extent to which the cyclicality of final demand affects labour demand in essential and non-essential sectors. We begin by manually classify each industry code included in the Current Population Survey (CPS) to the most closely linked final consumption category. As for industries that primarily produce intermediate goods, we use the BEA Input-Output Accounts Data to construct a Leontief inverse that uncovers the contribution of output produced by intermediate industries to each final consumption category.[5] We classify an intermediate industry as essential (non-essential) if the downstream final consumption it mostly contributes to is essential (non-essential).[6]

IV) Employment and earnings series using CPS data. Given the industry classification outlined above, we take the final step of our data construction and compute employment and earnings series for workers in essential and non-essential industries using the microdata from the CPS. This covers a representative sample of around 60,000 households who are surveyed monthly, and includes information on the industry in which each worker is employed. We use the IPUMS harmonized CPS industry codes from Flood et al. (2020), which reduce the inconsistency in the NAIC codes over time. Finally, monthly time series for employment are calculated by summing up the total count of workers in each industry that we have classified as either essential or non-essential in the previous step, using the survey weights and the basic sample from the CPS. The two series for essential and non-essential employment begin in 1976.

As for earnings, we use data from the Outgoing Rotation Group (ORG), which is a subsample of roughly a quarter of the main CPS sample, to construct monthly series for average earnings per worker and for median earnings. In each month, we also compute the percentiles

[5] Details on the industry classification and the mapping of intermediate goods industry into final expenditure essential and non-essential sectors are outlined in Appendix A.2.

[6] 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.

of the earnings distribution for the essential and the non-essential sector, respectively, based on the weigths and the weekly earnings reported by the CPS.[7] The earnings series for the essential and the non-essential sectors begin in 1982, are deflated using the overall PCE price index in 2012$, and are seasonally adjusted by the Census Bureau's X-12-ARIMA Seasonal Adjustment procedure.

It is worth emphasizing that our proposed classification into essentials and non-essentials is conceptually and quantitatively different from the more traditional divide between durables and non-durables. First, on average over our sample, non-essentials account for more than 50% of household expenditure whereas the share of durable purchases is typically around 15% only. Furthermore, not only the vast majority of non-essential spending consists of non-durable consumption but also about half of non-durable consumption is spent on non-essential goods and services. In Appendix A.6, we present extensive evidence in support of the notion that the essentials/non-essentials classification is very different (and far more pervasive) from the distinctions between durable/non-durable, goods/services and tradeables/non-tradables.

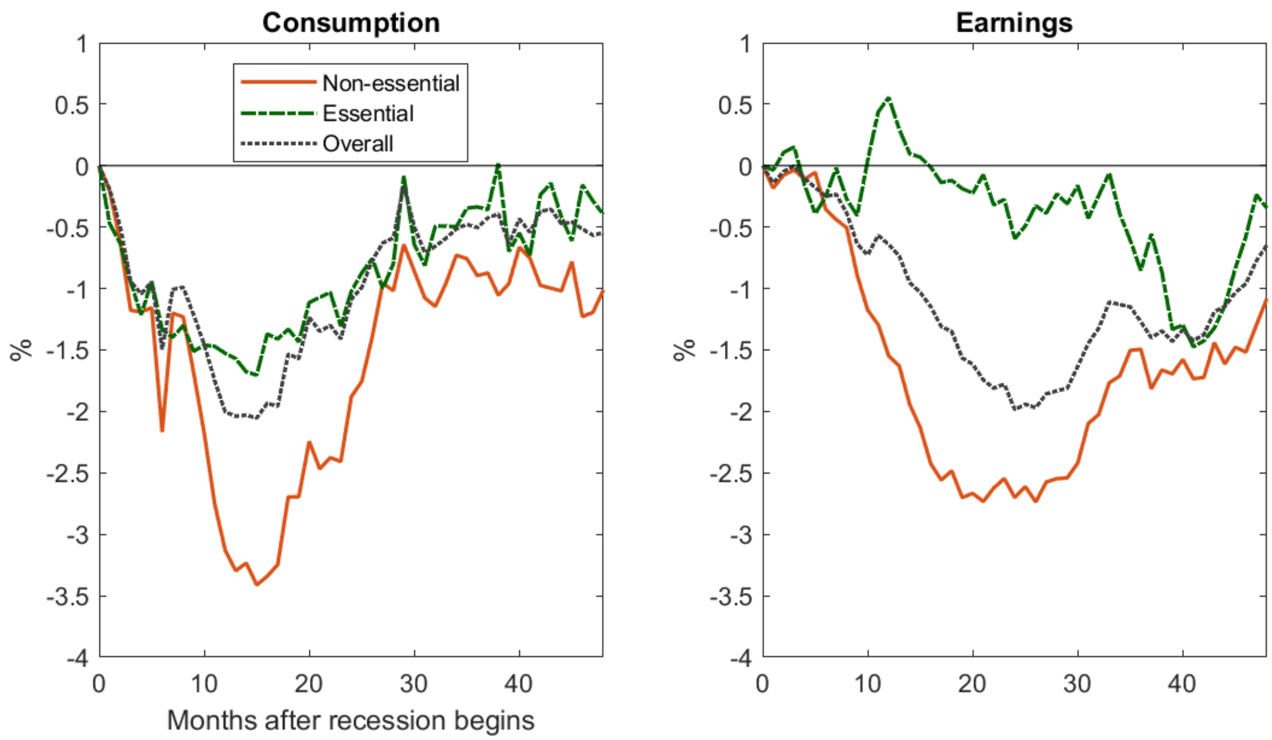
2.2 Unconditional correlations

In the previous section, we have noted that the share of non-essential consumption seems to drop systematically during recessions (Figure 1). In this section, we present descriptive statistics that speaks more directly to the cyclical properties of consumption and earnings in essentials and non-essentials. More specifically, for each newly constructed series and for each recession, we compute the percentage change from the local peak to the log-level during each of the subsequent 48 months. This yields a set of 48 observations after each peak, which we average across all recessions in our sample. The findings of this exercise are reported in Figure 2. The left panel refers to consumption while the right panel to earnings. Solid lines in orange represent non-essentials, broken lines in green stand for essentials while dotted lines in black summarize the behaviour of the whole economy.

Three main take-away emerge from Figure 2. First, the consumption of non-essentials

[7] In our data construction, we combine the mean earnings per worker from the ORG subsample of the CPS with total employment from the full sample of the CPS to calculate monthly earnings for: (i) the whole U.S. economy, (ii) non-essential sectors, and (iii) essential industries. The ORG sample and weights, however, are designed to be representative of the U.S. population at quarterly frequency, and not necessarily at monthly frequency. To ameliorate any possible representativeness concern, we provide two piece of evidence. First, in Appendix Figure C.4, we show that the response of our newly constructed aggregate earning series from the CPS to an identified monetary policy shock is very similar to the response of total compensation of employees from the BEA. Second, we have verified that our results are not overturned if we aggregate overall earnings in the CPS at quarterly frequency, instead. Results are available upon request.

Figure 2: Sensitivity of Essentials and Non-essentials to Recessions



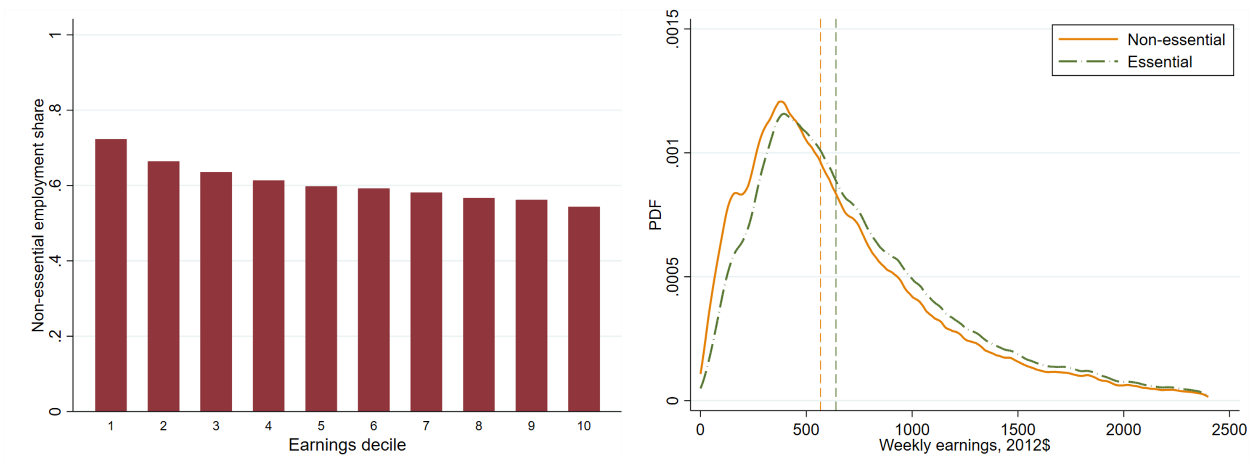
Notes: Response of essential and non-essential series after the start of a recession. To construct these responses, we first log the series and detrend using the HP filter ($\lambda = 14,440$). For the earnings series, we report a 6-month moving average to reduce noise. We then calculate the average decline in the series after all recessions. Recession dates are as defined by the NBER, and we include recessions between 1973-2007 which the data are available for.

is far more sensitive to the business-cycle than its essential counterpart (left panel). Non-essential spending drops by almost 3.5% after one year from the inception of the average U.S. recession whereas essential spending only falls by 1.5%. The gap is still significant four years after the peak, with non-essential spending, at -1%, more than doubling the shortfall in essentials. Second, the heterogeneity in earnings is even more pronounced than in consumption: two years into a typical recession, and earnings in the non-essential sectors still witnesses a dramatic 2.5% fall against the backdrop of a more gentle -0.3% in essentials (right panel). Third, looking at the aggregate series in dotted black masks the pervasive heterogeneity across essentials and non-essentials, with the latter being a main driver of the aggregate results, especially for earnings.

Motivated by Figure 2, we zoom into the distribution of earnings within sectors. In the left panel of Figure 3, we report the share of employment in non-essential sectors across the deciles of the earning distribution. This decays monotonically, moving from a value shy of

75% in the bottom decile to a number below 55% in the top decile. The right panel of Figure 2 plots the kernel density of wages across the two sectors. The distribution of earnings in non-essential industries is always to the left of the distribution in non-essential industries, with median earnings recording a 12% gap relative to their essential counterparts.[8] Putting these pieces of evidence together suggests that: (i) low-income workers are more likely to work in non-essential sectors (Panel (a) of Figure 3), and (ii) non-essential workers tend to be paid less than their essential counterparts (Panel (b)).

Figure 3: Non-essential and essentials across the earnings distribution



(a) Non-essential shares

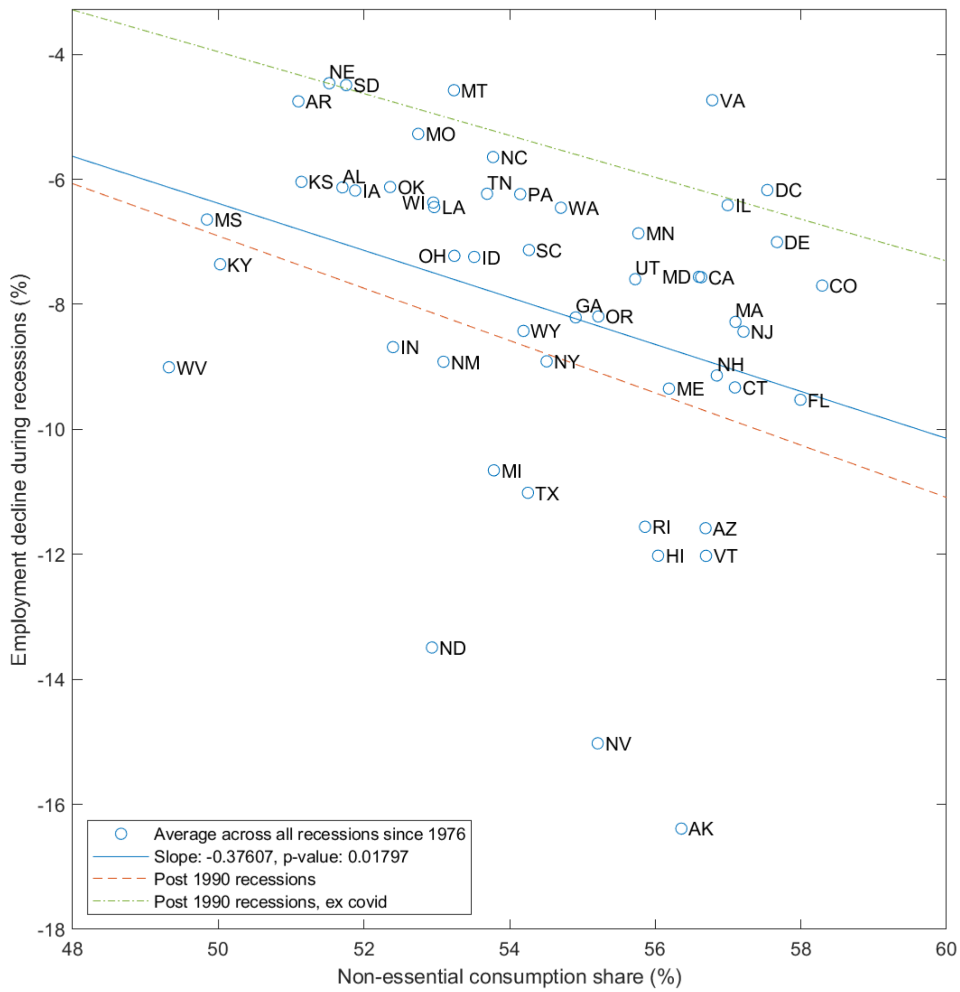
(b) Kernel

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 (a) shows the percent of employees working in non-essential industries for each decile of the income distribution (deciles computed annually). Panel (b) shows the kernel density plot along the median of each distribution

State-level analysis. To complement the results above, which are based on variation over time, in this section we use state-level data that exploits variation over both time and space to estimate the reduced-form relationship between non-essential spending and employment during recessions. More specifically, we use annual PCE data to construct average non-essential consumption shares for each state of the United States, since 1997. We then calculate the average decline in employment during all recessions since 1976, using the timing of changes in state-level employment around nationally defined recessions to identify

[8] In Appendix Figure C.5, we show that the CDF of essential earnings first order stochastically dominates the CDF of non-essential earnings. While Figure 3 pools earnings in each sector over the entire sample period, we have verified that the findings in both charts apply also to each individual year over time.

Figure 4: State-level employment during recessions vs non-essential consumption shares



Notes: Seasonally adjusted monthly state level employment series is from the BLS. Employment declines are calculated around state-specific timing of national recessions (see main text), and averaged across all recessions since 1976. 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 over the period 1997-2021.

state-level downturns.[9] The analysis in Figure 4 reveals that, on average across all recessions in our sample, U.S. states with a higher share of non-essential consumption have experienced a larger decline in employment. This finding holds true not only over the full-sample but also during the most recent post-1990 downturns (independently of Covid), suggesting that the correlation between non-essential spending and employment is relatively stable over time.

[9]Appendix A.8 provides details on the data construction for the state-level analysis.

3 Empirical Framework

In the previous section, we have used reduced-form correlations to document a number of novel empirical regularities: non-essential spending and non-essential earnings fall far more than their essential counterparts during recessions; non-essential wages tend to be lower than essential salaries; low-income workers are more likely to be employed in non-essential sectors. In this section, we corroborate these findings by using an identified monetary policy shock and tracing out the responses of consumption, earnings and prices to an unanticipated increase in the interest rate. While focusing on a specific shock has the advantage of allowing us to distinguish correlation from causation, the evidence of the previous section suggests that the findings in this part of the paper may extend also to other identified business-cycle shocks. In the next section, we will develop and estimate a structural model that can account for the effects of monetary policy on essentials and non-essentials documented in this section.

3.1 Identification and Estimation

Before presenting our empirical results, we briefly discuss our identification strategy and our empirical framework. Both are borrowed from the state-of-the-art and therefore, for full details and motivations, we refer the interested readers to the original contributions by Gurkaynak, Sack and Swanson (2005), Gertler and Karadi (2015) and Jordà (2005).

Monetary policy shocks. To further investigate the dynamic effects of business-cycle fluctuations on essentials and non-essentials, we need to identify plausibly exogenous variation in a macro variable that can affect the entire economy. In our case, over and above any reverse causality concern, the challenge is complicated by the fact that we also need to make sure that the identified shocks do not originate from either the essential or the non-essential sector, otherwise it would be hard to attribute any possible heterogeneous response to differences in demand elasticities across the two types of goods as opposed to asymmetry in the shocks themselves. Monetary policy surprises appear to fulfil both requirements. More specifically, we follow the High-Frequency Identification (HFI) of monetary policy shocks of Gertler and Karadi (2015), who in turn build on Gurkaynak, Sack and Swanson (2005). This measures changes in Fed Funds futures over a short window of time, typically 30 minutes, around monetary policy announcements. These provide plausibly exogenous variation in interest rates under the identifying assumption that any information about macroeconomic conditions that could have potentially affected the endogenous response of monetary policy has actually been already anticipated by financial markets. This implies that the only variation in Fed

Funds future prices during the short-time window around policy announcements could only be due to differences in monetary policy decisions from financial market expectations.[10]

Econometric method. The high-frequency identified monetary policy instrument is available for period 1990 to 2016. However, as pointed out by Cloyne et al. (2018), an extended monetary shock series can be produced by estimating a proxy-VAR in the tradition Mertens and Ravn (2013) and Stock and Watson (2018) over a longer sample, and then identifying the monetary policy surprise series using the HFI monetary policy instrument over the shorter period over which is available (as in Gertler and Karadi, 2015). In practice, we extract the monetary shocks estimating a proxy-VAR similar to that of Gertler and Karadi (2015) on the sample January 1973 to December 2020, using the 1y government bond yield, the excess bond premium, the first difference of log industrial production, and the first difference of log PCE price index. We include the monetary policy instruments as as internal instrument, in the language of Ramey (2011) and Plagborg-Møller and Wolf (2021). This specification is robust to the non-invertibility of the VAR. We use 12 lags for the endogenous variables and 4 lags of the external instrument. The extracted monetary policy surprises are reported in Appendix Figure A.7.

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 shocks identified à la Gertler and Karadi (2015), the corresponding robust F-statistic is 13.89, passing the weak instrument test. When using the shocks identified à la Jarociński and Karadi (2020), however, the F-stat lowers to 10.29, which is below the critical value and thus suggests a possible weak instrument issue. Accordingly, we use the Gertler-Karadi shocks as our baseline case and report the results using Jarocinski-Karadi's refinement in the Appendix as a robustness check against the information effect.

The impulse response functions to a monetary policy shock are computed using the smooth local projection instrumental variable (SLP-IV) estimator of Barnichon and Brownlees (2019) on the following sequence of local projections, as developed by Jordà (2005):

[10] A more recent empirical literature has further refined this high-frequency identification by isolating also the 'information effect' that may also be contained in meeting announcements if the central bank has private information about the state of the economy relative to financial market participants (see for instance Jarociński and Karadi, 2020, Miranda-Agrippino and Ricco, 2021, Nakamura and Steinsson, 2018). In one of the robustness exercises at this section end, we will show that we obtain very similar results if the analysis was based instead on the refined monetary policy surprises constructed by Jarociński and Karadi (2020).

$$y_{t+h} = \alpha_{h,0} + \beta_h 1\text{y yield}_t + \sum_{l=1}^{L} Y_{t-l}\gamma_{h,l} + \epsilon_{t,h} \tag{1}$$

The dependent variables y are, in turn, the logs of our newly constructed series for essential, non-essential, and aggregate measures of consumption, prices, employment and earnings. The coefficients β_hs are the object of our interest, as they summarize the impulse responses of the ys at each horizon h to an unanticipated 100bp increase in the one year government bold yield (1y yield). This is instrumented with the series of monetary policy surprises extracted from the proxy-SVAR.

The local projections in (1) are estimated with SLP-IVs over a forecast horizon h of up to four years, using the five-fold cross-validation selection of the smoothing parameter recommended by Barnichon and Brownlees (2019). Standard errors are computed applying the Newey and West (1987) correction. To maximize the number of observations, all samples end in December 2019 (so as to avoid any contamination from Covid) but the starting point varies slightly with the availability of the dependent variable: this is 1973 for consumption; 1978 for prices; 1976 for employment; and 1982 for earnings. In all specifications, we include as controls the first 12 lags of all variables in the VAR (1y yields, the excess bond premium, log industrial production, and the log PCE price index) as well as 12 lags of aggregate or sectoral consumption and labour market variables, all in logs. Each model features additional model-specific controls, such as 12 lags of the dependent variable, in an effort to balance the trade-off between the benefits of lag-augmentation discussed in Montiel Olea and Plagborg-Møller (2021) and the cost of over-fitting. Details of the smoothed local projection IV estimation as well as the full list of controls for each specification are reported in Appendix B.

3.2 Results across spending categories

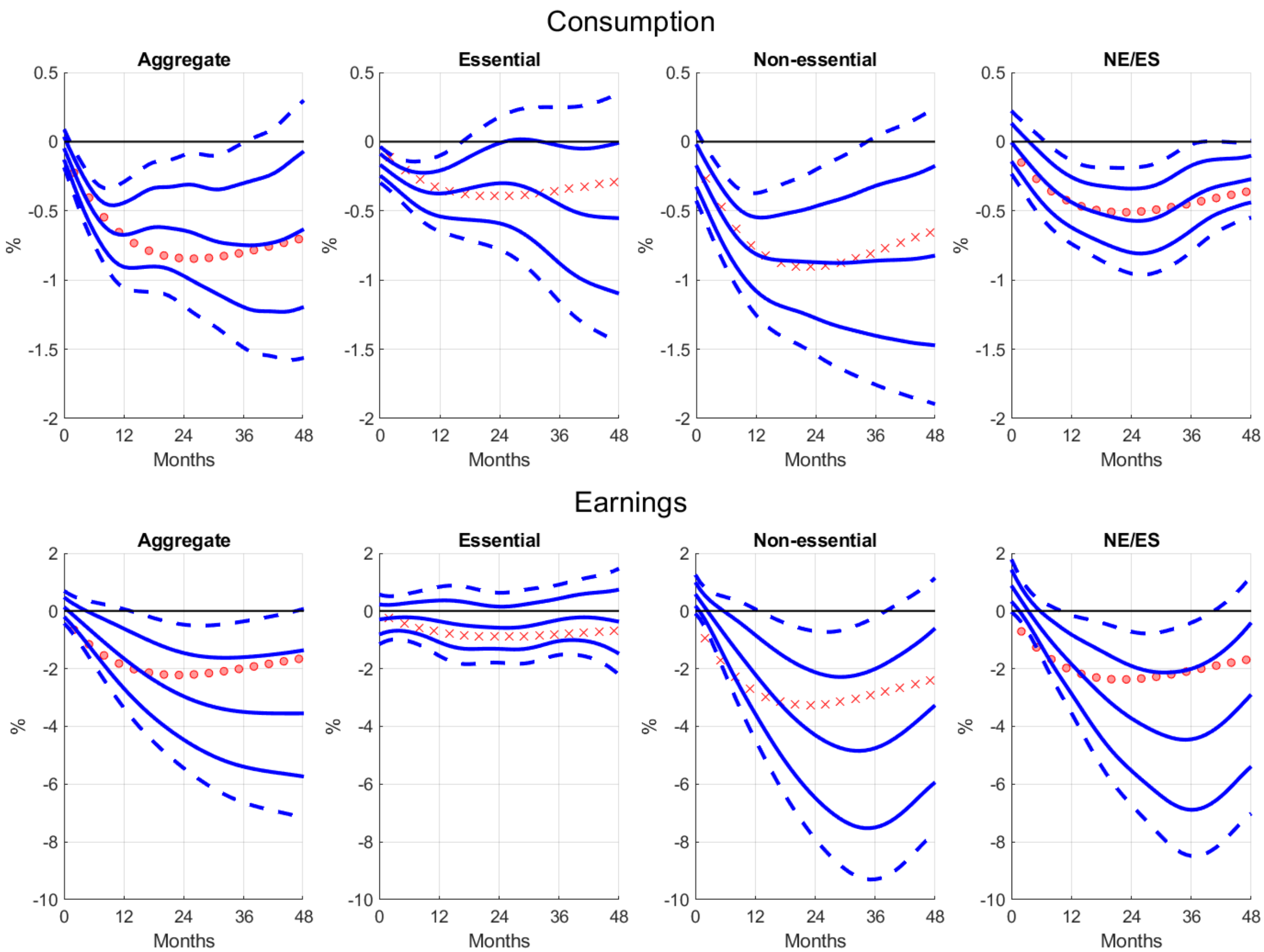
In this section, we employ the empirical framework of Section 3.1 to estimate the effects of monetary policy on the newly constructed data of Section 2. The main results are presented in Figure 5. This shows the Impulse Response Functions (IRFs) for consumption (top row) and total earnings (bottom row). The first column refers to the response of the aggregate variable for the whole U.S. economy, and this is what has been typically featured in earlier empirical studies. The second and third columns record the IRFs of essential and non-essential, which is a main contribution of our paper. The fourth column reports the IRFs of the (log-)ratio between non-essentials and essentials in each row, and therefore any significant effect in that column can be interpreted as a rejection of the null hypothesis that the responses of essentials and non-essentials for consumption (in the top row) and for earnings (in the bottom row) are the same. Solid (dashed) blue lines refer to 68% (90%) confidence intervals. Red dots and crosses refer to the IRFs of the estimated structural model of Section 4, which will be discussed in Section 5.

Three main results emerge from Figure 5. First, the aggregate effects displayed in the first column resemble the findings in earlier empirical work. After a 100bp interest rate hike, consumption expenditure falls significantly, up to -0.8%, before the changes become insignificant three years after the shock. The response of income is delayed but larger, peaking shy of -4%, and reverting to values not statistically different from zero by the end of the forecast horizon. Second, the aggregate effects in the first column average (and therefore mask) sizable heterogeneity in the middle two columns, both across sectors and variables. More specifically, the decline in non-essential spending in the top row is about two times as large and persistent as the decline in essential spending. But the sharpest heterogeneity emerges in the bottom row: earnings in the non-essential sectors decline significantly, up to about -4%, whereas the drop in the earnings of the essential sectors is insignificant, never exceeding -1%. Third, the responses of essential and non-essential, for both consumption and earnings, are statistically different one from another, as exemplified by the significant IRFs in the last column.

In summary, during a (monetary-policy induced) recession, households are more likely to cut back on non-essential spending. As non-essential industries face a more cyclical demand, these sectors also tend to reduce wage payments significantly, whereas essential industries do not, possibly reflecting the lower sensitivity of their demand to the business-cycle: the responses of non-essentials drive the aggregate results, both for consumption and earnings. In Appendix C, we document significant heterogeneity in the responses of both (median) earnings per worker and employment, with a possibly more pronounced contribution of the latter (i.e. the extensive margin) to the effects on total earnings in Figure 5. Finally, we find mild evidence of essential and non-essential prices responding to these relative demand shifts: overall prices fall slightly, as a result of a larger (negative) movement in non-essential prices and a smaller (positive) change in essential prices.[11] The sectoral responses, however, are insignificant at the 90% confidence level, thereby suggesting that the general equilibrium channel through prices is unlikely to be very strong in post-WWII U.S. data.

[11] The heterogeneity in the price responses across essentials and non-essentials is consistent with the evidence in Stock and Watson (2020) that the slope of the Phillips curve is steeper in sectors with more cyclical demand. In Appendix C, we also report the IRFs of the other macro aggregate series included in the proxy-SVAR. These are estimated using SLP-IV and are similar to those in the literature (e.g. Gertler and Karadi, 2015).

Figure 5: IRFs to contractionary 100bp monetary policy shock - Consumption and Earnings



Notes: Blue lines are empirical impulse response functions (IRFs) to a 100bp increase in the 1y year government bond yields estimated by smooth local projections instrumental variable, where the instrument is the monetary policy shocks derived from the Gertler and Karadi (2015) high-frequency monetary policy surprises. Confidence intervals are reported at the 90% (dashed line) and 68% (solid line) level. Sample periods and controls for each column are specified in the main text and Appendix B.1. Red markers refer to quarterly IRFs from the estimated structural model of Section 4. Red "X"s correspond to variables that have been targeted in the structural estimation whereas red "O"s stand for variables that have not been targeted.

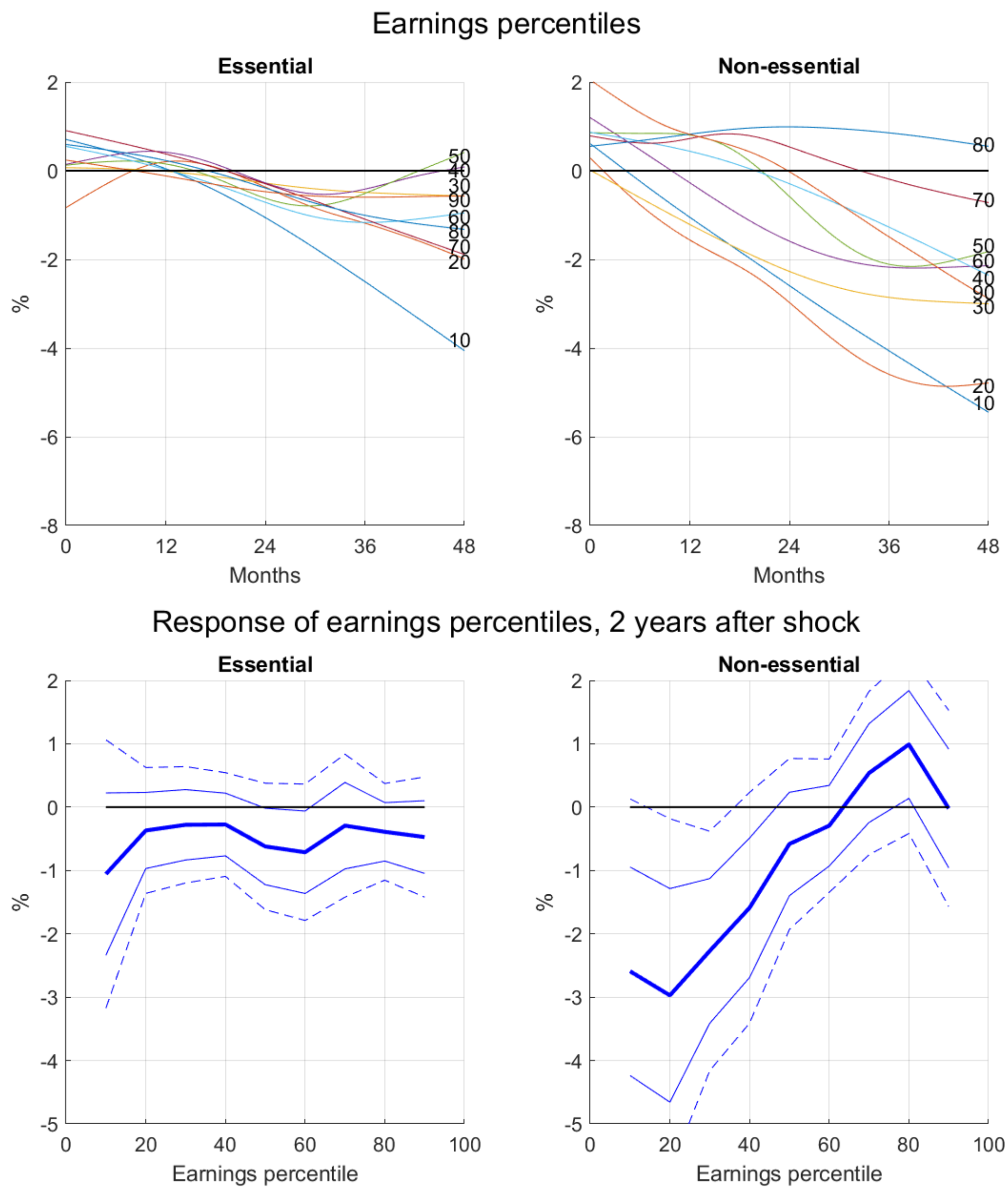
3.3 Results across the earnings distribution

In the previous sections, we have shown that a (monetary policy-induced) recession causes: (i) households to reduce their non-essential spending more than their essentials, and (ii) firms in non-essential industries to cut their labour demand more than in essentials. In Section 2, we have further shown that (iii) low-income workers are more likely to be employed in non-essential sectors. Finally, a long-standing empirical literature on survey and administrative data find that low-income households exhibit a high Marginal Propensity to Consume (MPC), (see for instance Johnson, Parker and Souleles, 2006, Patterson, 2023, among many others). In this section, we want to go at the heart of the triple interaction emphasized in the introduction and ask: do the labour earnings of low-income (and thus high-MPC) workers in non-essential (i.e. more cyclical) industries fall more than the wages of (low-income) employees in essential sectors, after a contractionary monetary policy shock. We find that they do, very significantly. In the next section, we show that the triple interaction of high-MPC workers with more cyclical salaries, and employed in more business-cycle sensitive industries provides a powerful, yet overlooked, amplification mechanism in an estimated model for the analysis of business-cycles.

To build an answer to the question above, in the top row of Figure 6, we display the labour earnings response along the earnings distribution in each sector, along the forecast horizon of up to four years after the monetary policy shock. The bottom row zooms on the two-year forecast horizon and report point estimates as well as confidence intervals for the earnings response across the earnings distribution at that particular horizon. Three main results can be inferred from this exercise. First, the heterogeneity in the earnings responses across the income distribution within essential industries is modest, both economically (top row) and statistically (bottom row). Second, the earnings responses at the bottom deciles of the earning distribution of non-essentials is significantly larger than the responses at the top deciles. Third, the salaries of low-income workers in non-essentials fall about three times more than the salaries of low-income workers in essentials. In other words, the estimates of Figure 6 reveals that earnings cyclicality is highr for the low-income workers in more cyclical industries.

The results in this section may also contribute to explain the counter-cyclicality of income inequality reported by Heathcote, Perri and Violante (2010). The higher responsiveness of salaries in non-essential sectors (especially, at the bottom of the earning distribution) and the finding that non-essential wages tend to be lower than in essential industries suggests that earnings inequality should increase during recessions as a results of the labour market

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



Notes: Empirical impulse response functions (IRFs) to a 100bp increase in the 1y year government bond yields estimated by smooth local projections instrumental variable, where the instrument is the monetary policy shocks derived from the Gertler and Karadi (2015) high-frequency monetary policy surprises. Sample periods and controls for each column are specified in the main text and Appendix B.1. Earnings percentiles are from the CPS, and percentiles are calculated separately for the non-essential and essential earnings distributions. Solid (dashed) blue lines refer to 68% (90%) confidence intervals.

responses to the higher cyclicality of non-essential demand. The reason is that low-income workers in non-essentials lose out twice in bad times: not only they are worse paid than essential employees over the business-cycle but also, during recessions, their earnings decline by more. This bodes well for the prospect of a novel amplification channel. During recessions, households cut back non-essential spending more than essentials. This results into a larger fall in labour demand for non-essential workers, which in turn translates into a larger drop of their earnings. As low-income workers are more likely to exhibit high-MPC, this logic suggests that low-earning employees in non-essentials reduce consumption disproportionately, feeding into the second-round effects on aggregate demand that further amplify the initial impact of the shock.

It is interesting to note that: (i) the sectoral heterogeneity in labour market outcomes, (ii) the higher wage cyclicality at the lower end of the non-essential earnings distribution, and (iii) the higher incidence of essential spending among low-income households, together, suggest that the general equilibrium effects of the heterogeneity in the labour market responses may be dampening the heterogeneity in the consumption responses. The reason is that the higher cyclicality of non-essential spending has a particularly negative effect on the pay of low-earners in that sector. But those are also the households who not only have a larger MPC but also who spend a higher share of their budget on essentials. Accordingly, in the face of a negative income shock, low-income workers in non-essentials are forced to reduce significantly also their essential spending, which makes up a larger proportion of their consumption bundle. As a result, the fall in essential spending that we estimate in Section 3.2 may have been indirectly amplified by the decline in non-essential earnings. This chimes with the evidence in Coibion et al. (2017), who document that a contractionary U.S. monetary policy shock causes a larger increase in earning inequality than in consumption inequality.

3.4 Additional results

In this section, we show that our results are unlikely to be driven by confounding factors, such as the cyclicality of durables, tradeables or other types of goods, and that are robust to several sensitivity checks, including a different identification of either monetary policy or business-cycle shocks, different (rectangularized) samples, quarterly frequency of the data and an alternative estimation method. Further details are provided in Appendices D and A.6.

Alternative expenditure classifications. A possible challenge for our interpretation of non-essentials as highly cyclical industries is that the heterogeneity in income elasticities of demand could be correlated with other product characteristics which may also account for the cyclicality across essentials and non-essentials that we have documented above. In Appendix A.6, we discuss extensively two popular alternative spending classifications, such as durables versus non-durables and tradeables versus non-tradeables, and show that these are unable to account for the sensitivity of non-essential spending to business-cycle fluctuations. In short, while about 78% of durable goods are non-essentials, there are about 50% of non-durables goods and services that are also non-essentials (and indeed display a far higher cyclicality than the other half of non-durables). Furthermore, durable goods are a relatively small proportion of overall consumption (less than 15%) compared to non-essentials (more than 50%) and they barely contribute to move aggregate income. Finally, the positive correlation between income level and elasticity of demand that is crucial for the labour market amplification discussed in this paper is weak for durables: non-essential workers are typically paid less than essential workers whereas wages in durable industries are not necessarily lower than in non-durable sectors. Finally, we find that also the distinction between tradeables and non-tradeables bears little correlation with the distinction between essentials and non-essential, and therefore it also seems an unlikely confounding factor behind the evidence in this paper.

Information effect. Our baseline specification employs an (updated) series of shocks from Gertler and Karadi (2015). As outlined by Nakamura and Steinsson (2018), Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2021), however, these shocks could be contaminated by the 'information effect', namely the notion that monetary policy announcements may also reflect private information held by the central bank about the state of the economy. Earlier in this section, we have reported that while the standard HFI monetary policy surprise series of Gertler and Karadi (2015) passes the weak instrument test, the refined series that also clean for the information effect does not. Still, in Appendix D.1, we report the impulse responses of all the main aggregate variables and our newly constructed sectoral series on consumption, prices and earnings to monetary policy shocks that remove the information effect, following the strategy proposed by Jarociński and Karadi (2020). We find that the results remain similar to those in Figure 5, suggesting that the information effect does not have any significant influence on our findings.

Business-cycle shocks. To separate correlation from causation, our main results are based on a well-understood and widely used source of business-cycle variation, namely monetary policy shocks. The findings in Section 2.2, however, suggest that our mechanism may apply more broadly to other types of business-cycle shocks, as the heterogeneity across essentials and non-essentials, both within and across spending and earnings, emerges also when we look at the 'unconditional' impulse responses of Figure 2, which shows the percentage change in consumption and wage bills from the incept of a typical recession in the post-WWII period for the United States.

To further investigate the breadth of our mechanism beyond the transmission of monetary policy, in Appendix D.2, we report the impulse responses of consumption, prices and earnings (both in the aggregate and across essential and non-essential sectors) to the business-cycle shocks identified by Angeletos, Collard and Dellas (2020). The idea is to isolate the shock that explains the maximum share of variation in unemployment at business-cycle frequencies between 6 and 32 quarters, in a multi-equation system like a VAR. The estimates of this exercise in Appendix D.2 are qualitatively very similar to the findings in Figure 5, despite the two sets of IRFs are based on very different identification strategies.[12]

Further sensitivity. In Appendix D.3, we also show that our results are robust, if not stronger, when ending the sample in December 2020, and therefore including the effects of the Covid-19 Pandemic. Part of the effects estimated over this sample, however, may simply reflect a mechanical correlation between spending and earnings, simply because low-income workers and non-essential sectors were more likely to be in lockdown (Blundell et al., 2020). Accordingly, we exclude 2020 from our baseline estimates and keep the inclusion of Covid as a robustness check.

In Appendix D.4, we show that using unsmoothed local projection instrumental variables produce qualitatively similar results, though the point estimates are more jaggered and less precise. In a recent contribution, however, Montiel Olea and Plagborg-Møller (2021) recommend using smoothed local projection as an efficient way to shrink a potentially overparameterized model with many variables and lags, and therefore we kep the latter as our baseline specification.

Finally, in Appendix D.5, we display the impulse responses of earnings based on quarterly data. This is an important cross-check for our monthly estimates because the Current Population Survey makes clear that representativeness of their sample is ensured only at quarterly frequency. The estimates of this exercise, which are reported in Appendix D.5, are qualitatively similar to the estimates in Figure 5, though far less accurate, possibly reflecting

[12]We also find similarly large declines in non-essential consumption and employment when estimating Generalised IRFs. Results are available upon request.

the smaller variability and the lower number of observations associated with the quarterly sample. We also find that using a rectangularized sample period across all variables and specifications, which corresponds to beginning all estimation samples in January 1982 (as opposed to maximizing information by using different samples for variables with longer data availability), produces very similar results, which we make available upon request.

4 A Model of Consumer Spending Heterogeneity

In the previous sections, we have shown that —during recessions— spending and earnings in non-essentials fall significantly more than their essential counterparts. In this section, we develop a stuctural model with non-homothetic preferences in consumption and heterogeneity in labour productivity that is capable to account for this evidence. We add three dimensions to an otherwise standard business-cycle model with nominal rigidities and heterogeneous agents. First, households consume two types of goods, which differ for their demand elasticities: essentials and non-essentials. Second, workers are characterized by either high productivity (and hence enjoy high-income and face no financial constraint) or low productivity (and thus have low-income and face a financial constraint). Third, non-essential industries employ a higher share of low productivity workers, consistent with the evidence in Section 2.2. In the next section, we estimate this structural model and show that contractionary monetary policy encourages households to cut their non-essential consumption. This particularly affects low-income families, whose workers are disproportionately employed in non-essential industries. As low-income households have a higher MPC, this non-essential channel amplifies business-cycle fluctuations through a general equilibrium effect. In Section 6, we use the estimated model to run counterfactual simulations that quantify the extent of amplification relative to a benchmark with either no heterogeneity in spending or no heterogeneity in earnings or no heterogeneity in the composition of the labour force across sectors.

4.1 Non-homothetic preferences

Our starting point are consumers' preferences that allows us to think about spending categories which may be characterized by potetially different elasticites of demand. For this purpose, we introduce a non-homothetic utility function that builds on the partial equilibrium, finite horizon analysis of Browning and Crossley (2000). In Andreolli and Surico (2021), we study the implication of non-homothetic preferences for heterogeneity in MPCs across households.

Within each period, households with skill/productivity level i ($i = H, L$) receive additively separable flows utility from spending on two categories of consumption, essentials (C^E) and non-essentials (C^N). They also receive disutility from supplying labour (N):

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

where χ is the inverse of the macro Frisch elasticity, φ and ξ are scaling constants that will help calibrate the steady state solution, while γ^E and γ^N are the category-specific Intertemporal Elasticity of Substitution (IES) for essentials and for non-essentials, respectively. Browning and Crossley (2000) show that there is a one-to-one mapping between the spending category-specific IES and the Income Elasticity of Demand (IED) for that type of goods and services in a two-period model; in Andreolli and Surico (2021), we extend that result to an infinite horizon setting. In that paper, we also show that the consumption category with the highest IES also exhibits the highest IED, implying that —by definition— the ranking of γs distinguishes essentials from non-essentials:

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

Intuitively, households are very unwilling to delay consumption of necessities such as groceries, and prefer instead to smooth their consumption. In contrast, households are more willing to delay spending on large durables or on hospitality and food away from home: non-essentials are easier to postpone (or move forward) than essentials. Note that the mapping between income elasticity and intertemporal substitution is not an artefact of these preferences. Browning and Crossley (2000) prove that this holds for any additively separable utility function in good varieties.

The specification in (2) display a few other useful properties. For instance, households with a lower income will spend a proportionately larger fraction of their budget on essentials, due to the lower income elasticity of demand for essentials. Furthermore, the intertemporal elasticity of substitution varies over time and is higher for wealthier households, as documented by Crossley and Low (2011).[13] Finally, while these preferences are not aggregable, we do not regard this as a major limitation for our purposes. The reason is that we are primarily interested in modelling spending heterogeneity and in eliciting a mapping from IEDs

[13] Stiglitz (1969) show how non-homothetic preferences are linked to risk aversion while Ait-Sahalia, Parker and Yogo (2004) use a version of (2) to rationalise the equity premium puzzle, in a combination of the volatility in the luxury spending of the rich an their consumption-specific risk aversion.

to IESs, which in turn allows us to quantify the contribution of non-essentials to business-cycle fluctuations. In our view, this benefit exceeds any potential cost of being unable to derive an aggregate Euler equation for the phantomatic representative agent.[14]

4.2 Households problem

Households i have an instantaneous utility for essentials, $C^E_{i,t}$, and for non-essentials, $C^N_{i,t}$, and instantaneous dis-utility for working $N_{i,t}$ hours. They are also inattentive, as in Mankiw and Reis (2007). Households update their expectations sporadically, with probability λ. Anyone who updates their expectations today has a probability λ of updating them tomorrow, $\lambda(1-\lambda)$ of updating them in two periods, $\lambda(1-\lambda)^2$ in three periods, $\lambda(1-\lambda)^j$ in $j+1$ periods, and so on. As in Beraja and Wolf (2021), household inattentiveness is introduced to match the hump-shape response of consumption (while preserving the differential spending category-specific IES).

As households realise that they might not be able to update, they make plans for future choices in the current period. They choose consumption of a variety, say essentials, for today, $C^E_{i,t,0}$, and for the future if they do not update for j periods ahead, $C^E_{i,t+j,j}$. The same applies to non-essentials. A perfectly competitive union frictionlessly sets wages for households, implying that the choice of hours is not affected by household inattention, as in Mankiw and Reis (2007). Unlike these authors, however, households make plans for two separate consumption goods.

The economy is populated by two types of agents: high-skilled, H, and low-skilled, L. They differ along two dimensions: steady state income levels and whether they can access financial markets. A large empirical literature on survey and administrative data has made the case that low-income households exhibit high marginal propensity to consume (e.g Johnson, Parker and Souleles, 2006). Accordingly, we assume that H agents have higher income and are Ricardian, whereas L agents have lower income and are hand to mouth.[15] High-earning agents are paid an average wage $W_{H,t}$, while low-earning agents face a salary $W_{L,t}$. Households also obtain profits from firms, $\Pi_{i,t}$, and transfers from the government, $T_{i,t}$. We present the derivation of the household and the union problem in Appendices E.1 and E.2.

[14]Other stands of the literature, especially on structural transformation, use aggregable preferences (e.g. the PIGL preferences in Boppart, 2014), as these are helpful for modelling a balanced growth path.

[15]This simplification would arise endogenously in a heterogeneous agent model with uninsurable income risk and borrowing constraint. The framework can be easily extended to include wealthy hand-to-mouth agents, but we abstract from this here, both for tractability and to highlight the new channel that we propose.

4.3 Firms

There are two sets of firms or industries: those that produce essentials and those that produce non-essentials. The two sectors differ in the skill composition of their labour force, with non-essential industries employing a relatively higher share of low-skilled workers. As these shares turn out to be an important dimension of heterogeneity, both in the model and in the data, in Section 5 we will estimate these parameters. Each set of firms consists of three separate entities: a final good producer, a Calvo retailer, and a wholesaler.

Final good producers. Final good producers combine different retail varieties of essentials and non-essentials according to a CES aggregator. This leads to a standard demand facing final good producers for different varieties of either essentials or non-essentials:

$$y^i_{k,t} = Y^i_t \left(\frac{P^i_{k,t}}{P^i_t}\right)^{-\varepsilon} \quad i = \{E, N\}$$

Calvo retailers. Retailers of essentials buy a wholesale essential good at a wholesale price $P^{E,w}_t$ and use it to produce the retail variety $y^E_{k,t}$ with a linear technology that maps one-to-one the wholesale good to the retail variety. As each variety is differentiated, producers have market power and face a Calvo friction to change prices. Their real marginal cost $\mathcal{S}^E_t = \frac{P^{E,w}_t}{P^E_t}$ is the wholesale price relative to its retail average value. Firms receive a subsidy τ^E for each unit of good produced and pay lump sum taxes T^E_t; these taxes allow them 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 in each period. This leads to a standard non-linear New-Keynesian Phillips Curve. The non-essential retailers problem is fully symmetric.

Wholesalers. These produce one type of good, either essential or non-essential, under perfect competition and combine high-skill, $N^i_{H,t}$, and low-skill labour, $N^i_{L,t}$, with technology:

$$Y^E_t = A^E_t (N^E_{L,t})^{\alpha^E} (N^E_{H,t})^{1-\alpha^E}$$
$$Y^N_t = A^N_t (N^N_{L,t})^{\alpha^N} (N^N_{H,t})^{1-\alpha^N}$$

Wholesalers sell goods to retailers at nominal price $P^{i,w}_t$, and pay nominal wage $W_{H,t}$ ($W_{L,t}$) for each unit of high-skilled (low-skilled) household labour. The low-skilled share in production is α^i. Consistent with the evidence in Section 2.2, we assume that there are relatively more low-skilled workers in the production of non-essentials than in the essentials production:

$$\alpha^E < \alpha^N$$

As shown in Section 6, this heterogeneity is a main source of amplification in our estimates.

4.4 Rest of the model

The model is closed by two goods market clearing conditions (for essentials and non-essentials), two labour market clearing conditions (for high and low skilled labour), and a bond market clearing condition by which bonds are in zero net supply. Equations are detailed in Appendix E.4. The central bank sets interest rates according to a Taylor rule:

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

Fiscal policy ensures that Calvo retailers' profits are zero in steady state. Off-steady state, we specify an allocation rule that assigns profits to Ricardian households, as in Bilbiie (2008) and Debortoli and Galí (2017). In Section 6, we explore alternative profit allocation mechanisms. In Appendix E, we present the equilibrium definition, steady state computation, and the log-linearisation of the model around a zero inflation steady state (i.e. π^E=π^N=1).

5 Structural Estimation

In the previous section, we have developed a novel model of the business-cycle featuring non-homothetic preferences on two consumption goods, heterogeneity in productivity across workers, and uneven skill-composition of the labour force across sectors. In the next section, we will use this structural model to perform counterfactual analyses to elicit the contribution of both non-essential spending and non-essential labour market dynamics to business-cycle fluctuations, and the transmission of monetary policy in particular. For this exercise to provide a realistic quantification of our amplification channel, however, we require our structural model to replicate, as close as possible, the results from the IRFs analysis of Section 3 based on local projections.

In this section, we evaluate the ability of the structural model to produce evidence consistent with the findings of Section 3, by estimating its key parameters via impulse response matching. As customary in the literature, we split the parameters space into two groups.

The first set consists of standard coefficients that we calibrate following earlier studies. The second group refers to key parameters that are specific to our novel mechanism, which therefore we estimate. These are coefficients that govern the heterogeneity across essential and non-essential sectors, and that will be switched off in Section 6 to identify their relative contribution to the effects of monetary policy on aggregate consumption and income.

Calibration. In Panel A of Table 1, we collect the parameters that are calibrated, using standard values in the literature. Low-skilled households are hand-to-mouth and their share, (μ^L), is set to 1/3, consistent with the average MPC reported in micro empirical studies such as Johnson, Parker and Souleles (2006). The inverse of the macro Frisch elasticity is 0.1, consistent with the evidence reported by Christiano, Trabandt and Walentin (2010). The interest rate rule parameters are borrowed from Taylor (1993). We calibrate the standard deviation of the monetary policy shock so as to have an effect of 1% on annualised interest rates, on impact.

We calibrate the steady state consumption shares of essential goods for high-skilled households, ($\bar{C}_H^E$), and low-skilled families, ($\bar{C}_L^E$), to 0.43 and 0.56 respectively, using the expenditure share data in Appendix Table A.2. We match these moments by varying the scaling parameter for the relative utility of non-essential goods (φ) and the relative steady-state 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 workers in the two households. These can be affected differentially by varying the relative productivity in the two sectors, given the uneven skill composition of the labour force across industries. We detail the moment matching algorithm and the steady state computation in Appendix E.7. The resulting values are: $\varphi = 1.3507$ and $a^E = 1.3807$. Finally, we follow Bilbiie (2008) and Debortoli and Galí (2017) by allocating firms' profits to Ricardian agents.[16]

Estimation procedure and prior distributions. We estimate the model parameters by minimizing the distance of the theoretical IRFs from the end-of-quarter impulse responses estimated with SLPs (for essential and non-essential consumption, prices and earnings), and with the proxy-SVAR (for the 1y yields) in Section 3. We use a maximum a-posteriori approach, with a diagonal weighting matrix that exploits the standard errors of each estimated impulse to construct the likelihood function, following Guerron-Quintana, Inoue and Kilian (2017). Key moments of the prior distributions are summarized in Panel B of Table 1. The means for essentials and non-essentials IESs are chosen so as to imply an aggregate IES of

[16] More specifically, we assume that $\phi_H^{\Pi,E} = \phi_H^{\Pi,N} = 1$ and that $\phi_L^{\Pi,E} = \phi_L^{\Pi,N} = 0$.

Table 1: Model Parameters

Panel A - Calibrated parameters

Description	Parameter	Value
Time preference	β	0.99
Inverse of the macro Frisch elasticity	η	0.1
Dis-utility of working scaling parameter	ξ	1
Interest rate rule coefficient on inflation	ϕ_π	1.5
Interest rate rule coefficient on output gap	ϕ_Y	0.125
Standard deviation of the monetary policy process	s_{mp}	0.255
Fraction of hand-to-mouth/low-skilled households	μ^L	1/3
Steady state share of essential good consumption by high skilled households	$\bar{C}^E_H$	0.43
Steady state share of essential good consumption by low skilled households	$\bar{C}^E_L$	0.57

Panel B - Estimated parameters

Description	Parameter	Distribution	Prior		Posterior	
			Mean	SD	Mean	SE
IES for essentials	γ^E	Normal	0.250	0.050	0.197	0.110
IES difference for non-essentials	$\gamma^N - \gamma^E$	Normal	1.000	1.000	0.679	0.182
Low skilled share in essentials	α^E	Beta	0.100	0.004	0.019	0.077
Low skilled share difference in non-essentials	$\alpha^N - \alpha^E$	Beta	0.100	0.004	0.311	0.083
Inattentiveness	λ	Normal	0.050	1.000	0.013	0.028
Interest rate smoothing	ρ_R	Beta	0.900	0.040	0.952	0.007
Price stickiness	θ	Beta	0.900	1.000	0.958	0.010

Notes: Panel A shows the calibrated parameters and steady-state values. 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 ($\bar{C}^E_H$) and low skilled households ($\bar{C}^E_L$). Panel B shows the estimated parameters. The first column describes the parameter or convolution of parameters being estimated. The second column shows the corresponding symbol. The third column shows the distribution over which we draw the priors, whose mean and Standard Deviation (SD) are reported in columns 4 and 5. The sixth and seventh columns show the posterior mean and posterior standard error.

0.86, which represents the middle point between the point estimate of Smets and Wouters (2007) and the log-utility case. The priors on the shares of low-skilled workers are diffuse and centered around 10% for essential industries and 20% for non-essentials, consistent with the evidence from the CPS. The prior on the inattentiveness parameter is relatively uninformative and its mean corresponds to the point estimate in Beraja and Wolf (2021). Interest rate smoothing and price stickness coefficients display prior distributions in line with the available evidence (see for instance Smets and Wouters, 2007, Justiniano and Primiceri, 2008).

Estimation results. In Table 1 Panel B, we report the estimated parameters of the structural model. The IES for Essential goods is $\gamma^E = 0.20$ and the IES for Non-essential goods is $\gamma^N = 0.88$: the difference between the two IESs is economically and statistically very significant, implying an economy-wide IES of 0.58. These estimates correspond to an average income elasticity around 0.35 for essentials and about 1.50 for non-essentials. The average

IEDs fall well within the range of income elasticities estimated in Appendix Table A.1 on the basis of CEX spending categories data, though those moments have not been targeted in the model estimation.

Our estimates of significant heterogeneity in IESs across spending categories draw on macro data and on a classification strategy that covers most of household expenditure and employment in the economy. Still, our evidence is well aligned, and indeed complement, the estimates in Attanasio, Banks and Tanner (2002) and Calvet et al. (2021) which, based on fewer categories, suggest that low-income families have a smaller intertemporal elasticity of substitution relative to high-income households. This latter finding is consistent with both non-homothetic preferences and the IES heterogeneity across essentials and non-essentials that we uncover.

As for the shares of low-skilled workers in each sector, our posterior distributions move towards an even more unequal labour force skill composition than the priors, with the vast majority of low-skilled/hand-to-mouth workers employed in non-essential industries. Finally, the posteriors on the coefficients that govern inattentiveness, interest rate smoothing and price stickiness imply a larger inertia than the priors. While this may partially reflect the absence of an internal propagation mechanism in our parsimonious model, we note that the estimates of ρ_R, θ and λ are consistent with the evidence in earlier contributions (e.g. Smets and Wouters, 2007, Justiniano and Primiceri, 2008, Beraja and Wolf, 2021).

Model impulse response functions. Figure 5 reveals that the IRFs of consumption and earning implied by the estimates of our structural model track well the corresponding IRFs estimated with SLP-IVs, both for essentials and non-essentials. In Appendix Figure F.1, we report the full set of results, including also the effects on essential prices, non-essential prices, and on the interest rate. Spending and earnings on non-essentials decline by more than for essentials. The estimated structural model is also able to reproduce the dampening of consumption relative to earnings discussed in Section 3.3: the gap between the decline in essential and non-essential earnings is larger than the gap for spending. More generally, the estimated model appears able to match not only the qualitative patters of the empirical IRFs for spending and earnings but also the magnitude and the timing of their responses, with all peaks of the model IRFs within the 68% confidence intervals of the IRFs estimated with local projections. Finally, high price stickiness results in small changes in prices: non-essential prices fall more than for essentials, but both series are associated with only a small decline, which remains within the 90% empirical confidence bands of the SLPs. Unlike in the local projections IRFs, the estimated structural model suggests that essential prices decline (rather than rise), though neither IRFs appear of any statistical significance.

6 Inspecting the mechanism

The estimated structural model highlights three ingredients that can potentially alter the propagation of business-cycle shocks relative to a representative agent/representative good benchmark. First, non-homothetic preferences imply that non-necessities are easier to anticipate or postpone, and therefore their demand responds relatively more to income changes. The second ingredient is labour market heterogeneity: low-income workers are more likely to be employed in non-essential sectors and thus they face a labour demand that is relatively more sensitive to the business-cycle. Finally, low-income households have a high MPC (i.e. hand-to-mouth) and hence the relatively stronger decline in their labour earnings during recessions strongly feed back into lower aggregate demand, setting in motion a second round of spending and earnings effects, across sectors and along the income distribution, that further exacerbate the contraction.

In this section, we isolate the contribution of these channels to the transmission of monetary policy. In the first exercise, we take our estimated full model as benchmark and compute the share of the cumulated consumption response that one can explain using restricted versions that progressively strip down one or more of these dimensions. In the second exercise, we use the representative agent/representative good model as benchmark and quantify how much amplification one can obtain by adding each channel in isolation, and then jointly. The main take away is that the triple interaction between unequal MPC distribution (between hand-to-mouth and savers), unequal spending composition (between essentials and non-essentials) and unequal labour market sectoral composition (between low-skilled and high-skilled workers) greatly amplify business-cycle fluctuations. In contrast, the contribution of each channel in isolation is much smaller; in fact, we show analytically that non-homothetic preferences lead to no amplification at all in an otherwise standard representative agent model.

6.1 Accounting for the aggregate effects of monetary policy

In Table 2, we seek to decompose the cumulative effects of monetary policy on consumption estimated by our structural model into the contribution of three sources of heterogeneity in: (i) spending composition, (ii) marginal propensity to consume, and (iii) labour sectoral composition. The first row focuses on the case of two identical goods under homothetic preferences whereas the second row represents the non-homothetic case in which the two goods exhibit different income elasticities of demand. The first column refers to the model with a representative agent, the second column reports the results of versions that feature also hand-to-mouth consumers, while the third column further adds an uneven share of low-skilled workers across sectors.

At the two extremes of the models spectrum, there are the case with a representative agent and a representative good in the top-left corner of Table 2 and the estimated full structural model with hand-to-mouth consumers, unequal spending composition (i.e. non-homothetic preferences) and unequal labour composition (i.e. a higher share of low-skill workers in the non-essential sector) in the bottom-right corner. In all intermediate cases featured in the table, we either consider only one dimension of heterogeneity (i.e. only non-homotheticity in the bottom-left corner or only hand-to-mouth consumers in the top-middle entry) or at most two channels (i.e. non-homothetic preferences and hand-to-mouth households in the bottom-middle entry or hand-to-mouth consumers and unequal labour sectoral composition in the top-right corner).[17]

For sake of exposition, we normalize all results in Table 2 by the cumulative response of consumption to a monetary policy shock in the estimated structural model (at the bottom right of the table), so that all other entries can be interpreted as the percentage contribution of each channel, either in isolation or in conjuction with another source of heterogeneity, to explaining the estimated overall effects on consumption. For instance, moving from the top-middle entry to the top-right corner (bottom-middle entry), we learn about the marginal contribution of unequal labour (spending) composition. On the other hand, by going diagonally from the top-middle cell to the bottom-right corner, we can evaluate the contribution of the interaction between unequal spending and unequal labour composition to explain the consumption response.

A few findings emerge from this exercise. First, both representative agent models account for only 22% of the cumulative effects of monetary policy on consumption estimated using the full structural model.[18] Second, adding hand-to-mouth consumers in the second column brings the shares of the explained consumption response to 35% and 38%, respectively with

[17]To implement the homothetic preference cases in the first row, we set the IES equal to the average IES, γ, implied by the full model and its estimated parameters in Table 1 (i.e. $\gamma = \gamma_E = \gamma_N$). In the representative agent models of the first column, we set the share of constrained agents μ_L to zero and fix the share of low-skilled workers in production to zero: $\alpha_E = \alpha_N = 0$. In the heterogeneous agent models, we set $\mu_L > 0$ and distinguish between two cases: (i) in the second column, we study a model where the share of low-skilled workers is the same in the two sectors (i.e. $\alpha_E = \alpha_N > 0$), with the common α chosen so as to match the relative steady state labour earnings across workers; (ii) in the third column, we use instead the values of α_E and α_N estimated in Table 1 using the full structural model.

[18]In the next section, we show analytically that non-homothetic preferences do not lead to any amplification at all in a representative agent model, thereby generalizing the result in the rows of Table 2 first column.

and without equal spending composition. Interestingly, the increase recorded when moving from the first to the second column is consistent with the estimates in Patterson (2023) who, as in Bilbiie (2020), emphasizes the 'unequal incidence' of recessions on the earnings of high-MPC and low-MPC workers.[19] In the top-right corner, we set the labour share of low-skilled workers in the non-essential sector to the value estimated in Table 2, while counterfactually imposing equal spending composition. This raises the share of the explained consumption response to 48%.

The main take away from Table 2, however, is that the interaction between unequal spending composition (i.e. $\gamma^N \neq \gamma^E$) and unequal labour composition (i.e. $\alpha^N \neq \alpha^E$) accounts for the bulk of the estimated cumulative consumption response in the full structural model. We conclude this by noticing that the jumps from, respectively, 0.38 and 0.48 to 1 (when our two novel channels are *jointly* considered) are much larger than the increases from 0.35 to, respectively, 0.38 and 0.48 (when each channel is assessed *individually*). In other words, the interaction of these two sources of heterogeneity provides a far more powerful amplification than each of them in isolation, suggesting a quantitatively important complementarity between unequal spending composition across goods and unequal labour composition across sectors in accounting for business-cycle fluctuations.

Table 2: Counterfactual exercise: amplification

	Representative Agent	Heterogeneous Agents	
		Equal Labour Composition	Unequal Labour Composition
Equal spending composition	0.22	0.35	0.48
Unequal spending composition	0.22	0.38	1.00

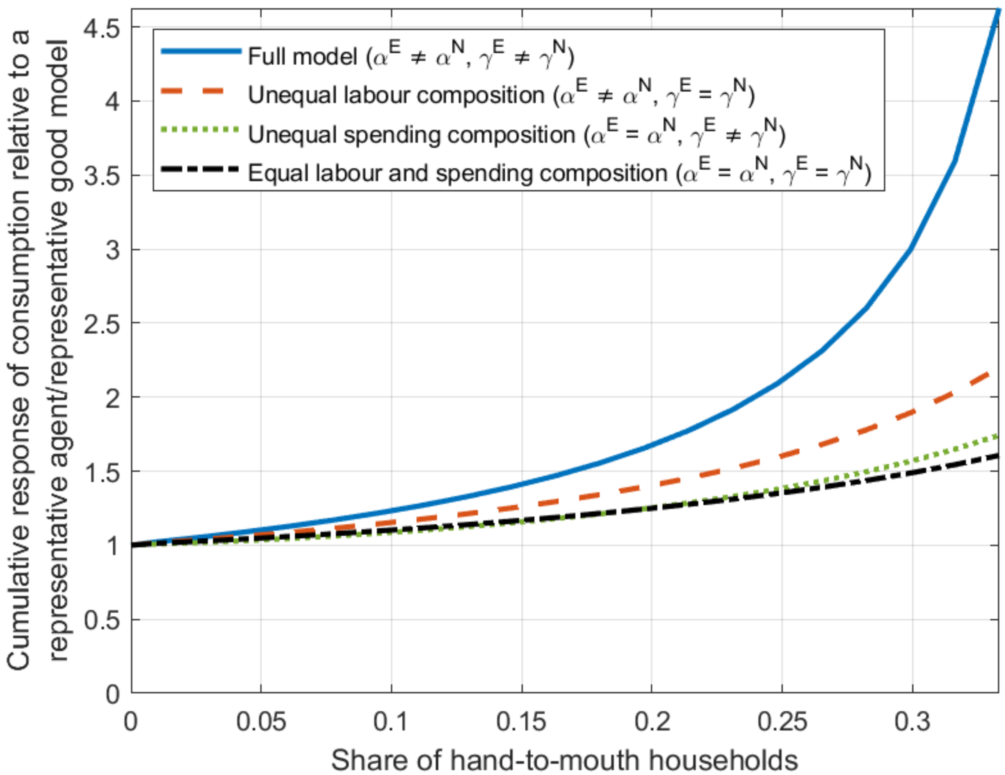
Notes: Each cell display the ratio of the cumulative IRF of the counterfactual model in that cell over the cumulative IRF of estimated model int he bottom-right corner. In the homothetic case, which we refer to as 'equal spending composition' (i.e. $\gamma^N = \gamma^E$), we set the IES equal to the estimated average IES in the economy. In the representative agent column, we set $\mu^L = 0$ and $\alpha^E = \alpha^N = 0$. Under 'equal labour composition', we fix $\alpha^E = \alpha^N > 0$ so as to match the relative steady state labour earnings across the two agents.

A key difference between the representative agent cases and the heterogeneous agents models is the presence of hand-to-mouth consumers only in the latter. This feature interacts with both cyclical product demand composition and cyclical labour demand composition to further amplify the effects of monetary policy. To illustrate this triple interaction, in Figure 7, we report the aggregate consumption response in the four heterogeneous agents cases of

[19] We have verified that even in the special case of equal spending (i.e. $\gamma^N = \gamma^E$) and equal labour composition (i.e. $\alpha^N = \alpha^E$) in the top-middle entry of Table 2, the estimates of Table 1 imply that the income elasticity of hand-to-mouth agents with respect to aggregate income, χ, is larger than one, which is a necessary and sufficient condition for amplification in this class of models (Bilbiie, 2020).

Table 2 as we vary the share of hand-to-mouth households, μ^L, from 0 to 0.33, a value consistent with the empirical MPC literature (e.g. Johnson, Parker and Souleles, 2006).[20]

Figure 7: On the Sources of Amplification



Notes: Amplification is measured by the cumulative IRF of consumption of each model, divided by the cumulative response of consumption in the restricted model with no hand-to-mouth agents. The figure depicts four scenarios: (i) the unrestricted full model as blue solid line, (ii) unequal labour sectoral composition (i.e. $\gamma^E = \gamma^N$) as orange dashed line, (iii) unequal spending composition (i.e. $\alpha^E = \alpha^N$) as green dotted line, and (iv) equal labour and equal spending composition (i.e. $\alpha^E = \alpha^N$ and $\gamma^E = \gamma^N$) as black broken line. The latter is often referred to in the literature as Two-Agents New-Keynesian (TANK) model. As in Table 2, whenever $\alpha^E = \alpha^N = \tilde{\alpha}$, we set $\tilde{\alpha}$ so as to match the relative steady state labour earnings across the two agents. Whenever $\gamma^E = \gamma^N$, we set the IES to equal the average IES in the estimated full structural model.

In each simulation, the cumulated consumption response is normalized by the cumulated effect in the representative agent/good case. This implies that each point of Figure 7 can be interpreted as the extent of amplification of that model (and for that value of μ^L) relative to the representative benchmark. The blue line refers to the full structural model that features both cyclical product demand composition and cyclical labour demand composition, whereas the black broken line summarizes the results of the restricted model with neither of the two. The dashed orange line and the dotted green line stand for the two intermediate cases of only unequal labour composition or only unequal spending composition, respectively.

[20]To ensure that the economic significance of hand-to-mouth agents reflects their relative size, for any value of μ^L, we adjust the labour income shares accrued to hand-to-mouth households in Figure 7 such that $\alpha^J = \bar{\alpha}^J \frac{\mu^L}{\bar{\mu}^L}$, where $\bar{\mu}^L, \bar{\alpha}^J$ are the values taken by these parameters in the estimated full structural model.

Four main results emerge from this exercise. First, in all models, a higher share of hand-to-mouth consumers leads to a monotonic increase in the extent of amplification, though the nonlinearity of this relationship is very heterogeneous across models. Second, the case with both equal labour composition and equal spending composition, often referred to as Two-Agents New-Keynesian (TANK) model, exhibits a degree of amplification relative to the representative agent/representative that is between 15% and 50%, over the empirically plausible range of [0.15, 0.33] for the average MPC, consistent with the evidence in earlier studies on U.S. data such as Patterson (2023) and Bilbiie, Primiceri and Tambalotti (2023). Third, non-homothetic preferences seem to add little amplification over TANK, whereas the marginal contribution of the unequal labour sectoral composition appears relatively larger. Fourth, the extent of amplification in the full model (depicted as blue line) is consistently larger than the sum of the dashed orange line and the green dotted line over the whole range of values for μ^L. This reveals that the triple interaction between cyclical product demand composition, cyclical labour demand composition and hand-to-mouth households generates a strong complementarity that greatly amplifies business-cycle fluctuations relative not only to the representative agent/representative good case but also to heterogeneous agents model that only feature the double interaction between constrained agents and heterogeneity in either consumers' spending or workers' sectoral composition.

6.2 Non-homotheticity alone does not lead to amplification

In this paper, we highlight how non-homotheticities matter for aggregate fluctuations. In this section, we present the conditions under which non-homotheticity does not matter; while heterogeneities might be interesting in their own right for understanding the heterogeneous impacts of business cycles on sectoral outcomes, they do not always matter for aggregates. Our key finding is that in representative agent settings where there are no interactions between sectoral heterogeneities and non-homothetic preferences, we can summarise aggregate fluctuations with the average IES of the economy. The split between essentials and non-essentials has no further impact on aggregate fluctuations. In Appendix G, we present Proposition 1 where we prove analytically this result in a simplified model. We take an attentive representative agent version with non-homothetic utility and a simplified Taylor rule of the form $R_t = \phi_\pi \mathbb{E}_t(\pi_{t+1}) + \varepsilon_t^{mp}$. We show that the impact of the monetary policy shock on total consumption is characterised by the average intertemporal elasticity of substitution. Next, we take a homothetic version of the same model where the IES is equal to the average IES in the economy of the non-homothetic model. In Corollary 1, we show what the responses of consumption and inflation to a monetary policy shock is identical to the non-homothetic version.

$$\text{Non-Homothetic} \rightarrow \frac{\partial \hat{C}_t}{\partial \varepsilon_t^{mp}} = -(\underbrace{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N)}_{Average\ IES})$$

$$\text{Homothetic} \rightarrow \frac{\partial \hat{C}_t}{\partial \varepsilon_t^{mp}} = -IES$$

The simplification allows for clean analytical expressions, but this result is more general than the simple statements outlined above. As demonstrated in the previous section, the cumulated responses of aggregate earnings and consumption in the representative agent model, not simplified, are also identical. This does not mean that the disaggregated responses of sectors within the model are the same with non-homothetic preferences. In Appendix Table F.1, we show the disaggregated responses in the representative agent models of essential and non-essential consumption and earnings, relative to aggregates. Essential consumption and earnings fall less than those of non-essentials. However, in the representative agent setting with non-homothetic preferences, the heterogeneity in responses between essentials and non-essentials perfectly offset and result in the same aggregate response as in the homothetic case, with the same average IES. This demonstrates the irrelevance of non-homotheticity for aggregates in the representative agent setting. Papers that would like to explore the importance of non-homotheticities for aggregegates should explore the interaction of consumption heterogeneity with other heterogeneities within the producing sectors. Our labour market heterogeneity is one such interaction, other examples could include heterogeneity in price or wage stickiness across sectors.

7 Conclusions

What drives business-cycle fluctuations? Demand or supply? Consumer spending or workers' earnings? The top or the bottom of the income distribution? And what are the mechanisms through which shocks propagate to the rest of the economy? These questions have fascinated macroeconomists for centuries; yet, they are still hotly debated. In this paper, we take a fresh look at these important topics by uncovering a novel transmission mechanism that cut through demand and supply, household expenditure and wage payments, high-income and low-income families.

The main idea is based on the observation that households and workers differ greatly in their exposure to the business-cycle along the income distribution, and that the composition of goods and labour demand, in particular the divide between essentials and non-essentials, is crucial to identify and quantify their cyclical exposure to shocks. The key intuition is that the consumption of the rich becomes the income of the poor. In the face of economic adversities, non-essential purchases are easier to postpone and their contraction is dominated by the spending behaviour of high-income households. The latter has a particularly large effect on low-income households, whose workers are more likely to be employed in non-essential industries, and therefore their labour demand suffers more from the drop in product demand: the higher cyclicality of non-essential spending leads to a higher cyclicality of non-essential earnings. Taken together, the families with less resources in society lose twice because of the spending behaviour of affluent households, via: (i) a direct (price) effect that makes their necessity-dominated consumption bundle relatively more expensive, (ii) an indirect (income) effect that lowers their labour earnings and thus the resources that they have available for both types of spending.

Using newly constructed, nationally representative time series, we show that: (i) high-income consumers mostly spend on non-essentials while the budget of low-income households is tilted towards essentials; (ii) low-earning workers are more likely to be employed in non-essential industries; (iii) during recessions, non-essential spending and non-essential earnings fall far more than their essential counterparts. Furthermore, we find that the indirect effects of demand composition on income largely dominates the direct effect on relative prices. We develop and estimate a structural model with nominal rigidities, non-homothetic preferences on essentials and non-essentials, two types of workers: low-productivity/financially-constrained and high-productivity/financially-unconstrained, and heterogeneity in the skill composition of the labour force across essential and non-essential industries to revisit the transmission of monetary policy. We first show that the estimated model replicates well both the higher cyclicality of non-essential spending and the even higher-cyclicality of non-essential earnings after an interest rate change. Then, we use the estimated model to decompose the aggregate effects of monetary policy into the contribution of each of the heterogeneity that we document. We find that the triple interaction between the unequal incidence of recessions in the goods markets (i.e. non-essential spending contracts by more), the unequal incidence of recessions in the labour markets (i.e. non-essential earnings fall by more), and the uneven skill distribution of the labour force (i.e. low-income workers are concentrated in non-essential industries) accounts for about 50% of the effects of monetary policy on aggregate consumption and aggregate income.

Our findings have potentially significant ramifications for normative and policy analyses. Central banks may find it desirable to consider separately the dynamics of inflation and the dynamics of output in the essential and non-essential sectors. These are likely to vary extensively across a number of dimensions that are crucial for the design of optimal policies, including for instance consumption smoothing, price elasticity of demand, and potentially price stickiness. In addition, the sectoral heterogeneity between essentials and non-essentials may also be relevant for the design of fiscal interventions: industrial policies and labour market policies targeted to non-essential sectors are more likely to short-circuit the amplification mechanism documented in this paper, as low-income workers are disproportionally employed in those sectors. We leave these fascinating topics for future research. But, we hope that our analysis could stimulate, and possibly help, national statistical offices and central banks to lever on the available granular data sets on households, workers and sectors to construct nationally representative series for the prices, consumption and earnings of essential and non-essential industries, building on the methods developed in this paper.

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Appendix

A Measurement

A.1 Classification procedure for consumption and prices in PCE data

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 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.1 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[21]:

[21] 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.1: 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.2). 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.2: 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.1.1 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 consumption; 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.

A.2 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.

A.2.1 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*.

A.2.2 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.

A.2.3 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.

A.2.4 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 A.3. 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 A.3: 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.

A.3 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[22]
- 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 employment recorded by the Current Employment Statistics (Establishment Survey, CES), taken from FRED (variable name USPRIV).

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

- Overall earnings - to compare with our constructed earnings series, we use the BEA NIPA series Total Compensation of Employees (Received: Wage and Salary Disbursements)

- Per worker 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)

A.4 Descriptive statistics and additional charts

Table A.4: Descriptive statistics

	Consumption	Prices	Employment	Earnings
Correlation with Industrial Production				
Aggregate	0.68	-0.11	0.74	0.47
Essential	0.52	-0.02	0.36	0.17
Non-essential	0.73	-0.22	0.75	0.51
St. dev relative to Industrial Production				
Aggregate	0.15	0.10	0.16	0.24
Essential	0.14	0.19	0.13	0.22
Non-essential	0.21	0.09	0.21	0.32

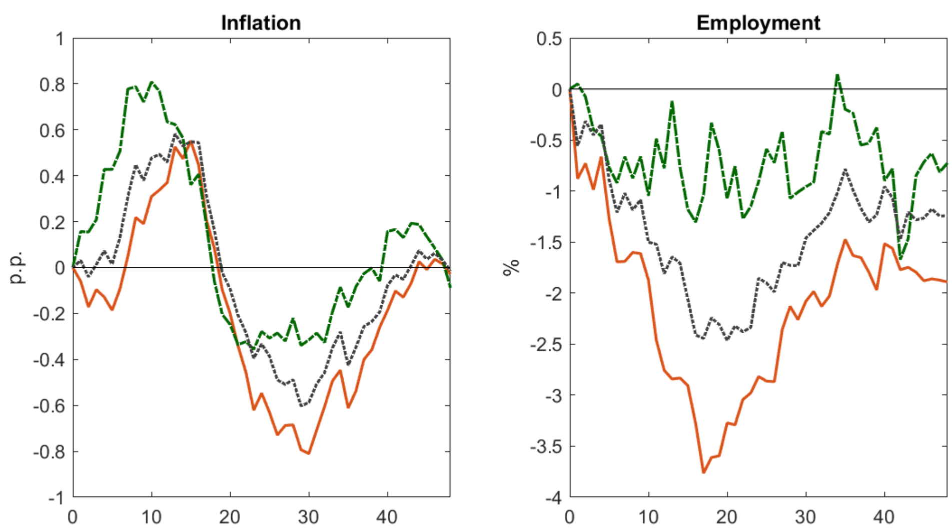
Notes: Descriptive statistics for essentials and non-essentials series. All variables are year-on-year log differences. Panel 1 shows the standard deviation of the series, divided by the standard deviation for industrial production. Panel 2 shows the correlation between the series and industrial production. 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 earnings. Price and consumption are based on PCE data and employment and earnings are from CPS data, constructed as described in the text.

Table A.5: 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 A.1: Response of Essentials and Non-essentials over the business cycle - Prices and Employment



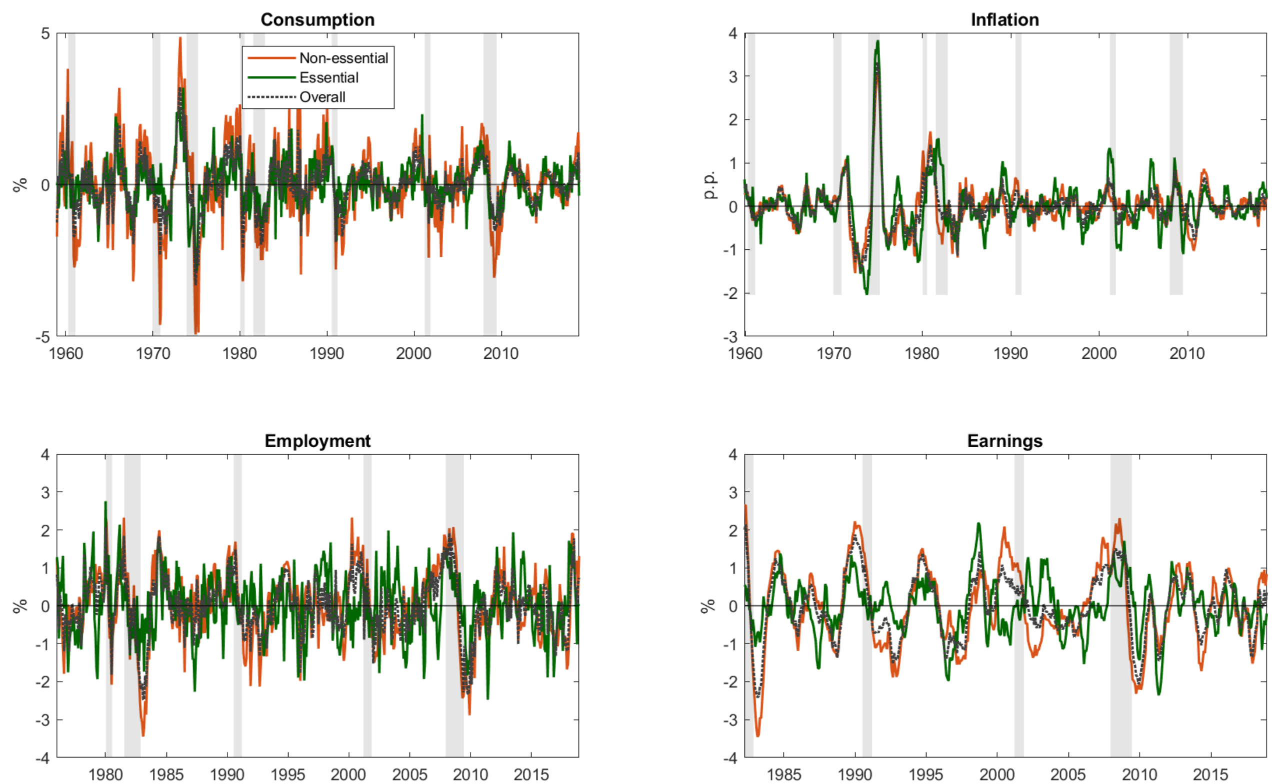
Response of essential and non-essential series, starting from the peak of the previous expansion, as defined by NBER. Includes all recession peaks since 1973 where non-essential and essential serie s for each variable are available for a full 48 months after the peak (peaks in 1973m11, 1981m7, 1990m7,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

As shown in Figure A.1, 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[23]. Employment in

[23]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.

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%.

Figure A.2: Essentials and Non-essentials over time

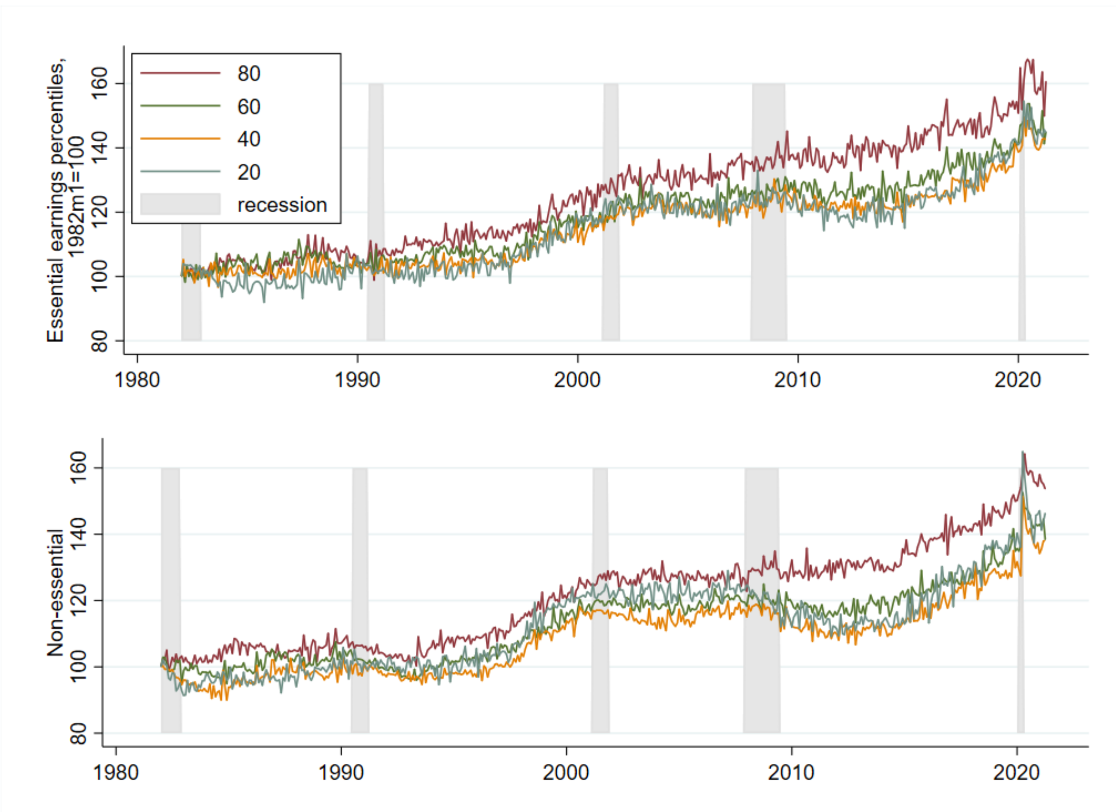


Underlying series of Figure 2. For consumption, employment and earnings, this shows the cyclical component of the logged variable detrended using the HP filter ($\lambda = 14,440$). For earnings, this refers to total earnings and the inital log series is centred 6-month rolling average, to reduce noise.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

Table A.4 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.

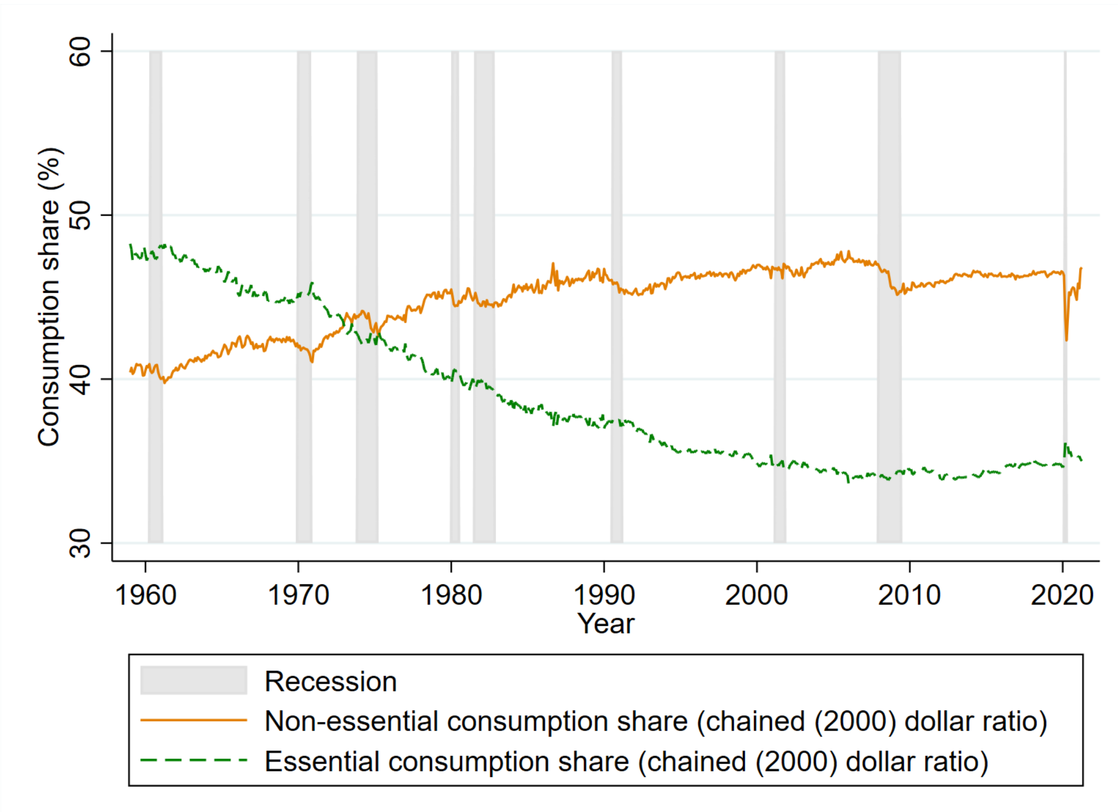
Figure A.2 shows the underlying timeseries of Figure 2. Figures A.3 and A.5 shows some other relevant series; the relative cyclicality of different percentiles of the earnings distribution, shares of employment and relative earnings within essentials and non-essentials.

Figure A.3: Non-essential and essential - earnings distribution over time



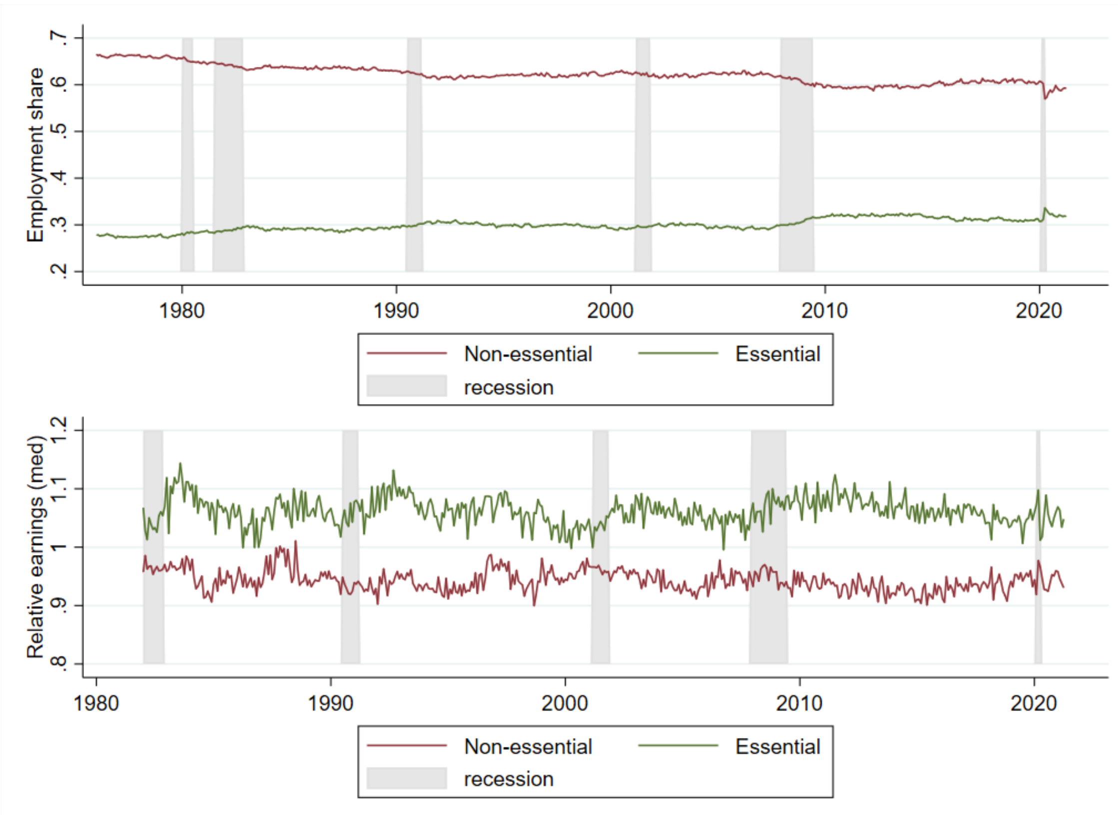
Notes: This figure shows the earnings of percentiles of the non-essential and essential industries over time. These are indexed to 100 in 1982 to compare cyclicality. Data is from the CPS, categorised into essentials and non-essentials as described in the text.

Figure A.4: 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.

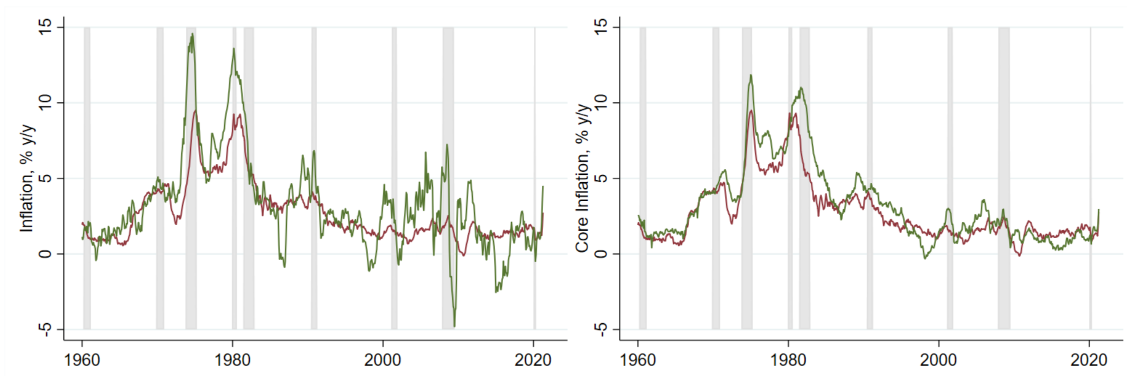
Figure A.5: Non-essential and essential - Labour market shares



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.

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 A.6.

Figure A.6: 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.

A.5 Monetary policy surprises

Figure A.7: Monetary policy surprise series

Notes: Monetary policy surprises, extracted from a proxy SVAR as described in Section 3.1. 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).

A.6 Durables versus non-durables

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 A.2.3, 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 A.6 shows the shares of consumption accounted for by durables and non-durables vs essentials and non-essentials.

Figure A.8 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.

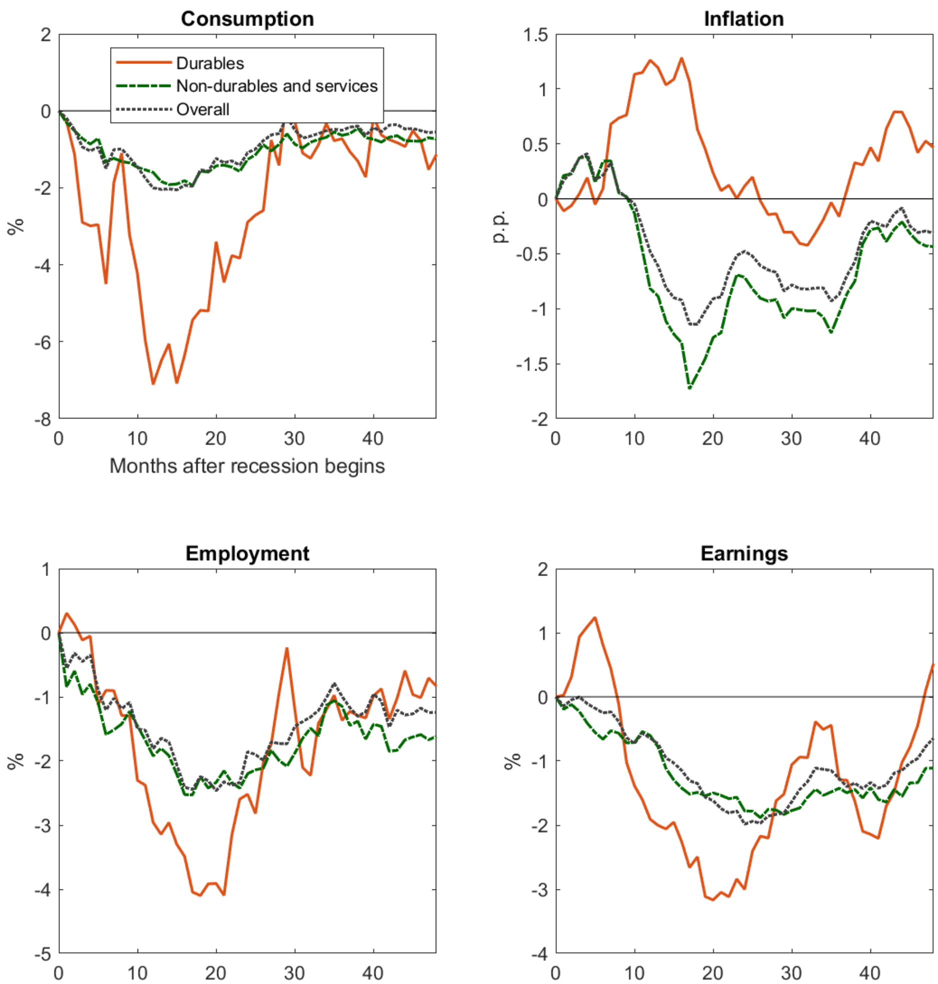
Figure A.9 shows the earnings distributions for this four-way split. Non-essential non-durables are the subsection of industries which generate the lower earnings, so the labour market channel we discuss is distinct from any general equilibrium effects on labour markets of the cyclicality of durables.

We estimate the IRFs for these subcategories of consumption and earnings. The results are shown in Appendix Figures A.10 and A.11. Focusing 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 substantially more than essentials non-durables. For 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 consumption 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. We also still find substantial heterogeneity in labour market outcomes within durables.

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

Figure A.8: Response of Durables and Non-durables over the business cycle



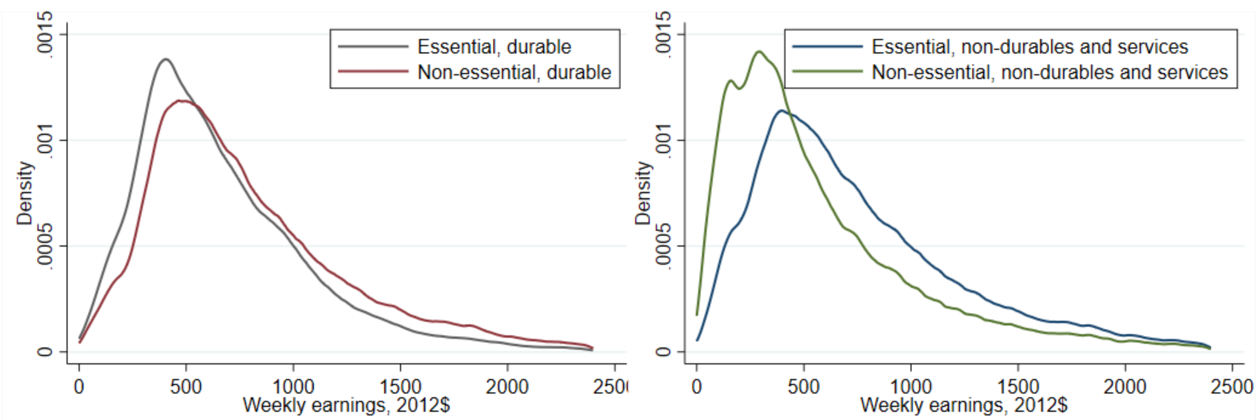
Equivalent of Figure 2 for of durables and non-durables. Series starting from the peak of the previous expansion, as defined by NBER. Includes all recession peaks since 1973 where non-essential and essential series for each variable are available for a full 48 months after the peak (peaks in 1973m11, 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 A.6: 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

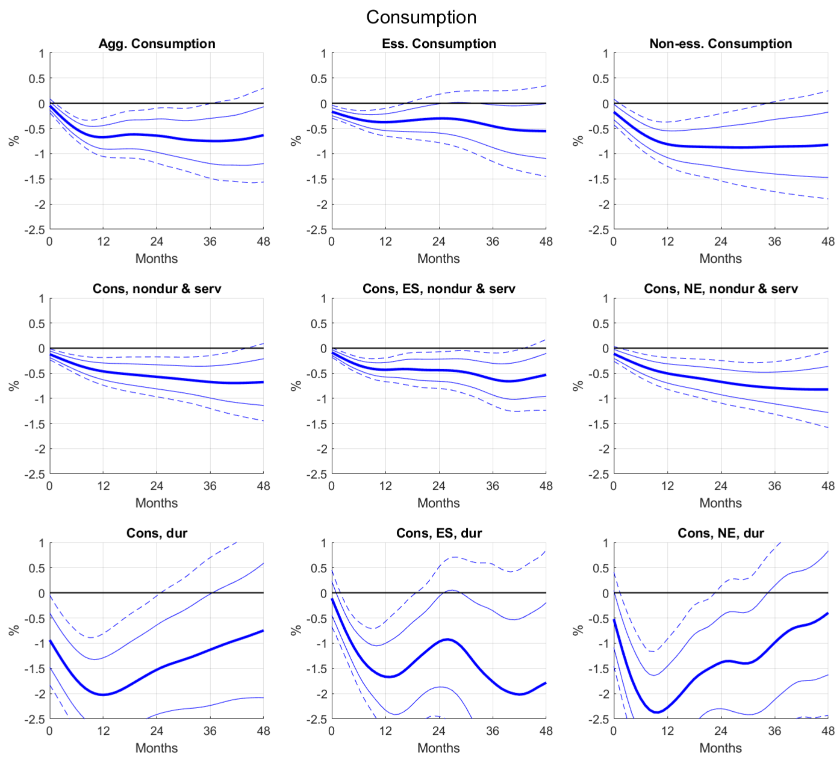
Percentages of total consumption. Calculated using PCE expenditure data, consumption shares based on chained 2000 dollar consumption series; only consumption categories in the essentials/ non-essentials classification are included. Averaged over 1973-2020.

Figure A.9: Earnings distribution - non-essentials and essentials, split into durables vs non-durables and services



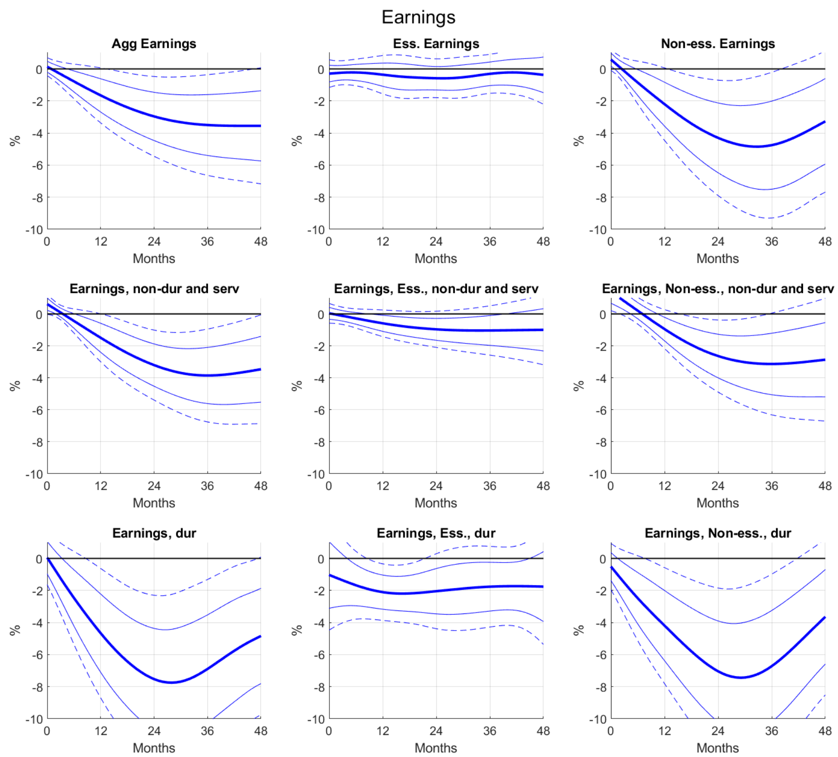
Notes: Kernel density of earnings 1982-2020, pooled, for non-essentials and essentials, split by durables vs non-durables and services.

Figure A.10: 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 A.11: IRFs of 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.

A.7 Other consumption 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 A.7 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 A.7: Alternative categorisations

	Durables	Non-durables	Goods	Services	Tradeables	Non-tradables
Share essential	19.1	49.0	49.2	41.2	36.9	48.2
Share non-essential	80.9	51.0	50.8	58.8	63.1	51.8
Share overall	13.4	86.6	44.6	55.4	29.8	70.2

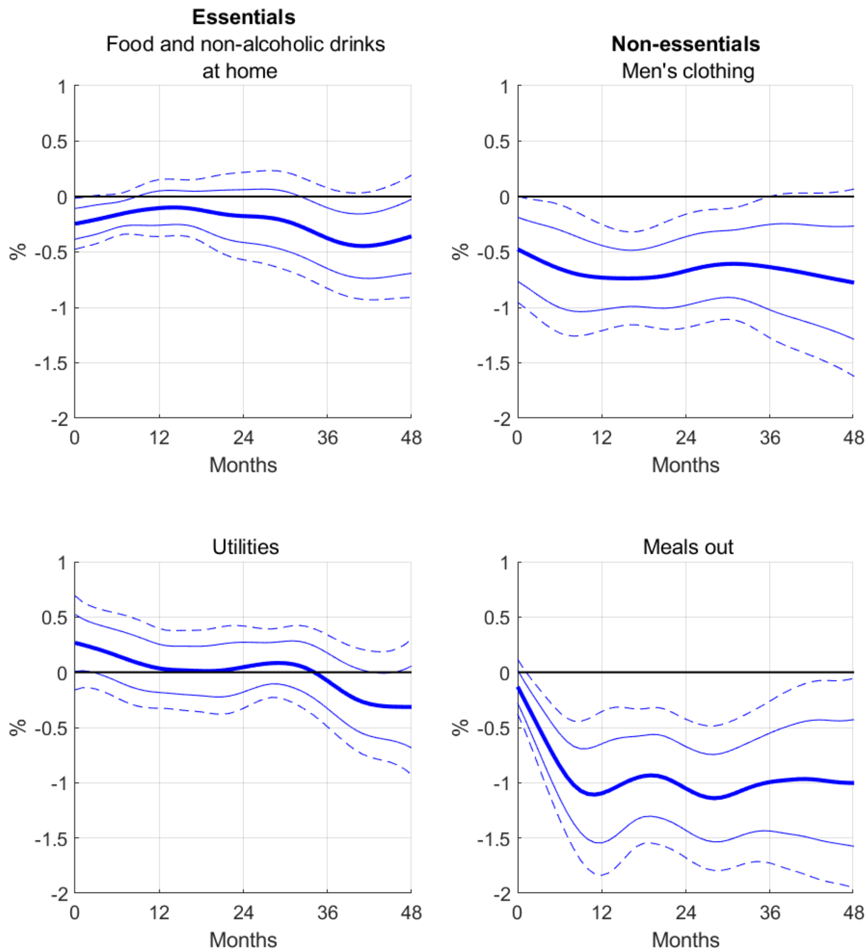
Notes: Proportion durables/non-durables, services/goods and tradaeables/non-tradeables which are non-essential or essential. Calculated using PCE expenditure data; only consumption categories in the essentials/ non-essentials classification are included. For durables and non-durables, we show the shares of consumption, based on chained 2000 dollar consumption series. For other categories we show expenditure shares. Proportions are weighted by average expenditure of the catgeories 1973-2019. Durable/nondurable and services/goods 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 A.12 shows IRFs for consumption of example sub-categories 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 goods versus services. In both cases, the example non-essential consumption type falls more than the essential example.

A.8 State-level analysis methodology

Figure 4 in the main text shows the the correlation between state-level employment changes during recessions and state-level non-essential consumption shares.

Figure A.12: Consumption IRFs of example consumption categories, goods versus services



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.

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.

B 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.

B.1 SLP-IV Controls

In our baseline specifications, we control for one year worth of data, with 12 lags of the 1y yields, IP, excess bond premium, log PCE price index, plus aggregate and disaggregated series for consumption and earnings depending on LHS variable. We add model-specific controls, such as 12 lags of the dependent variable, in an effort to balance the trade-off between the benefits of lag-augmentation discussed in Montiel Olea and Plagborg-Møller (2021) and the cost of over-fitting.

The key idea is to include for every aggregate variable, its lags and the non-essential counterpart lags, and for every disaggregated variable both the non-essential or the essential counterpart lags. As an example, for aggregate consumption, we add aggregate and non-essential consumption. For the spending on essentials, non-essentials, and their ratio, we use both non-essential and essential consumption as controls.

We use aggregate variables as controls in other variables regressions (i.e. when the left hand side is any earning variable, we use aggregate consumption as a control). Moreover, when we control for aggregate earnings in the consumption regressions, we use the BEA NIPA series of total compensation of employees because of its longer time-series availability relative to CPS data we constructed.

In subsection C, we show also results for prices, employment, and median earnings; here, we detail the controls of these regressions. For prices and employment, we use our aggregate and disaggregated series in the same way we have done for other dependent variables above, in addition to aggregate consumption and the BEA NIPA compensation of employees series. For prices, we 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 earnings per-worker earnings series in a given sector at different percentiles, we control also for consumption, employment, and median earnings in that sector series plus the LHS variable if not already included.

C Additional empirical results

C.1 Prices, employment and median earnings responses

We can deconstruct the overall earnings response in each sector, shown in the main text, separately into employment and per worker earnings responses. This is shown in Figure C.1. The fall in overall employment peaks at just over 75bp, non-essentials employment falls more sharply, peaking at 120bp, while essentials employment does not significant fall over the entire horizon. In the second row of the same figure we can see that median per worker earnings fall more slowly, with peak responses around 3 years after the shock. Again, there is significant heterogeneity between earnings responses by category. Non-essentials earningshave a peak decline of over 2% , whereas essentials earnings only fall slightly and insignificantly. Due to the noise in the earnings data in the CPS - as it draws on the smaller ORG sample described in the main text - the overall and non-essential earnings declines responses are only significant at the 68% confidence level. Nonnetheless, at the end of the horizon, the heterogeneity between non-essential and essential median earnings is significant.

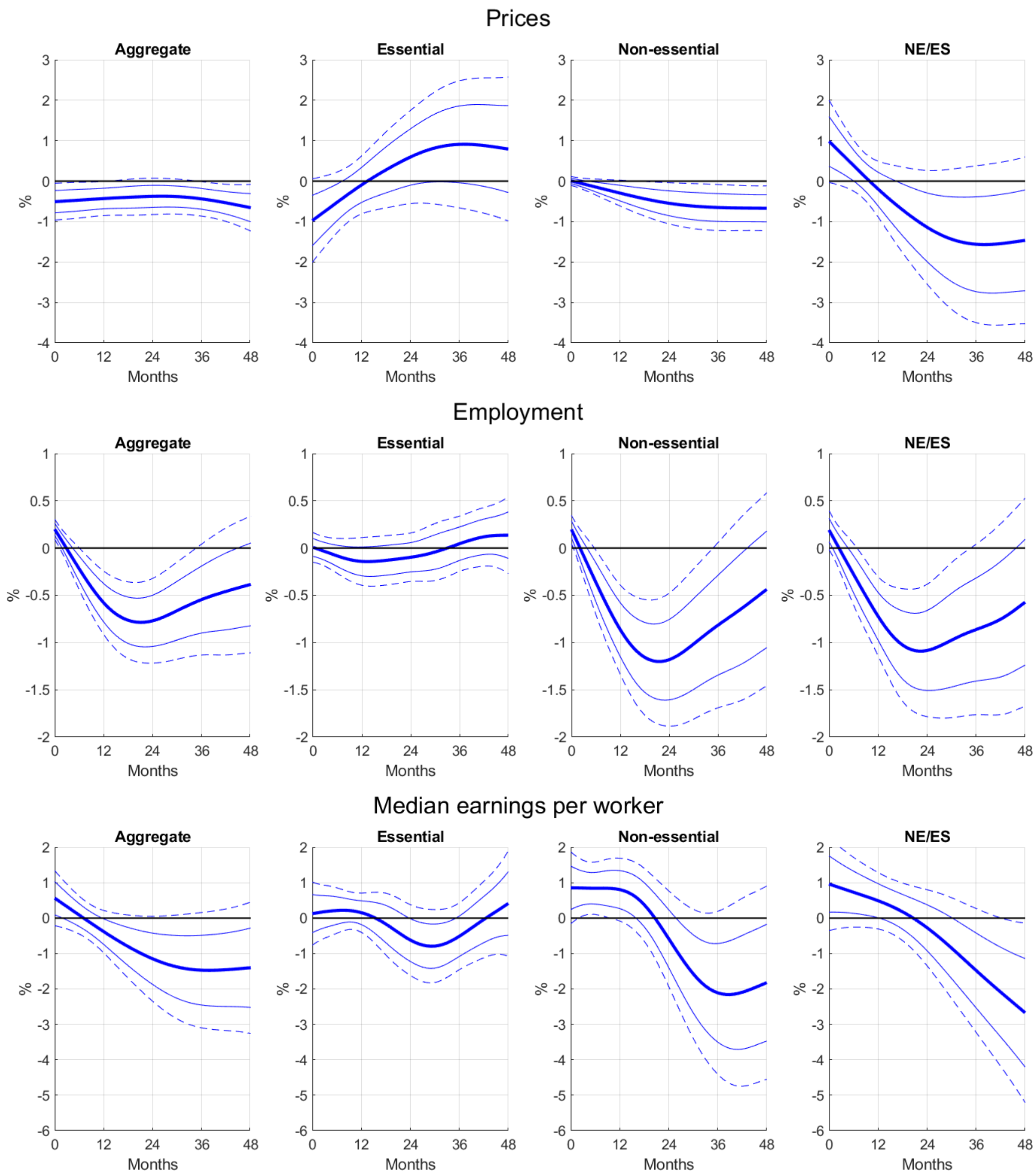
C.2 Earnings distribution IRFs

Figure C.2 shows the IRFs of earnings percentiles show in the main text, Figure 6, with their confidence intervals.

C.3 IRFs for other macro aggregates

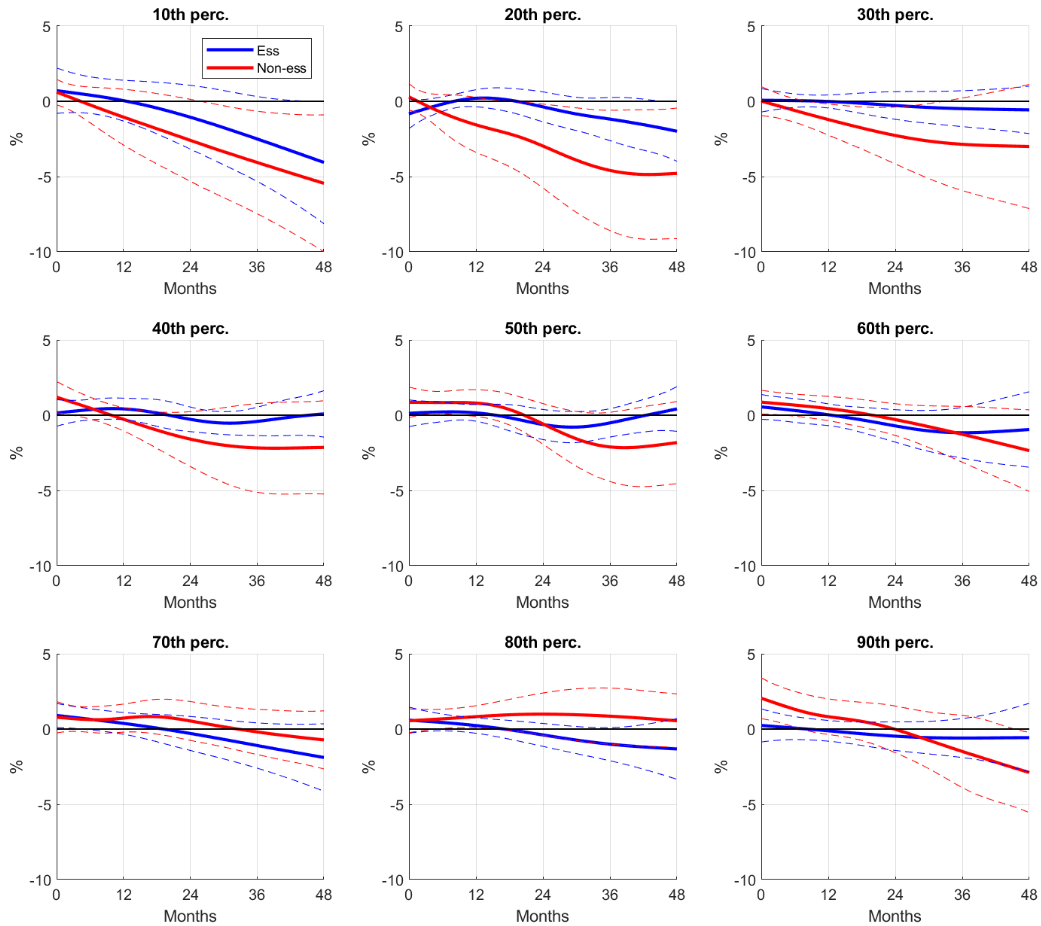
Figure C.3 shows the IRFs estimated using our SLP-IV specification for the other macroeconomic aggregate series used as controls and in the Proxy-SVAR. These are 1y yields, the excess bond premium, industrial production and the PCE price index. The results are broadly consistent with standard responses, 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 C.1: IRFs to contractionary monetary policy shock - Earnings and Employment



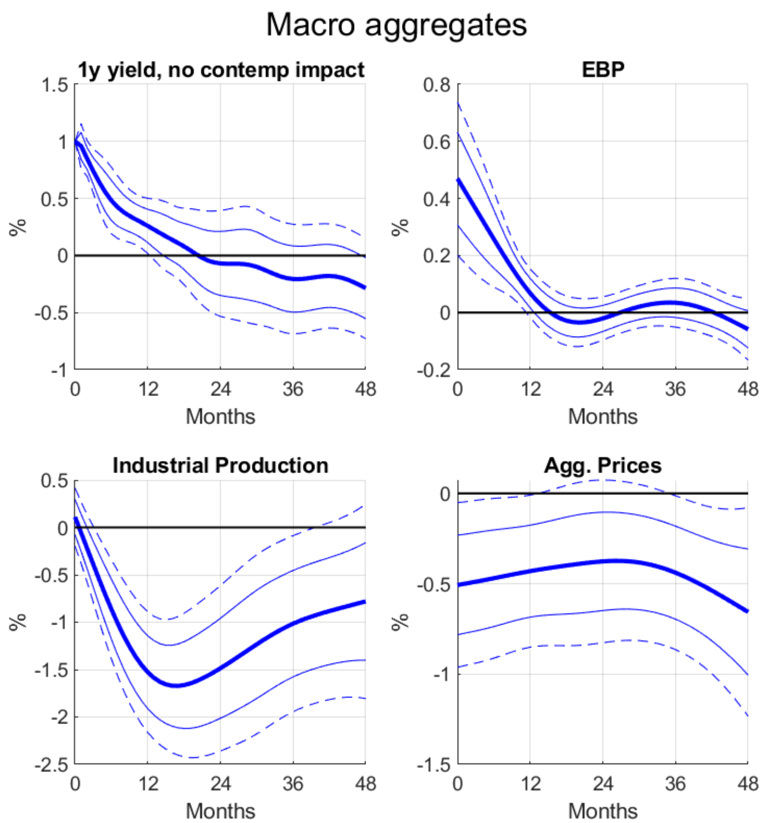
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. Sample periods and controls are specified in the main text and Appendix B.1.

Figure C.2: IRFs to contractionary monetary policy shock - Earnings distribution



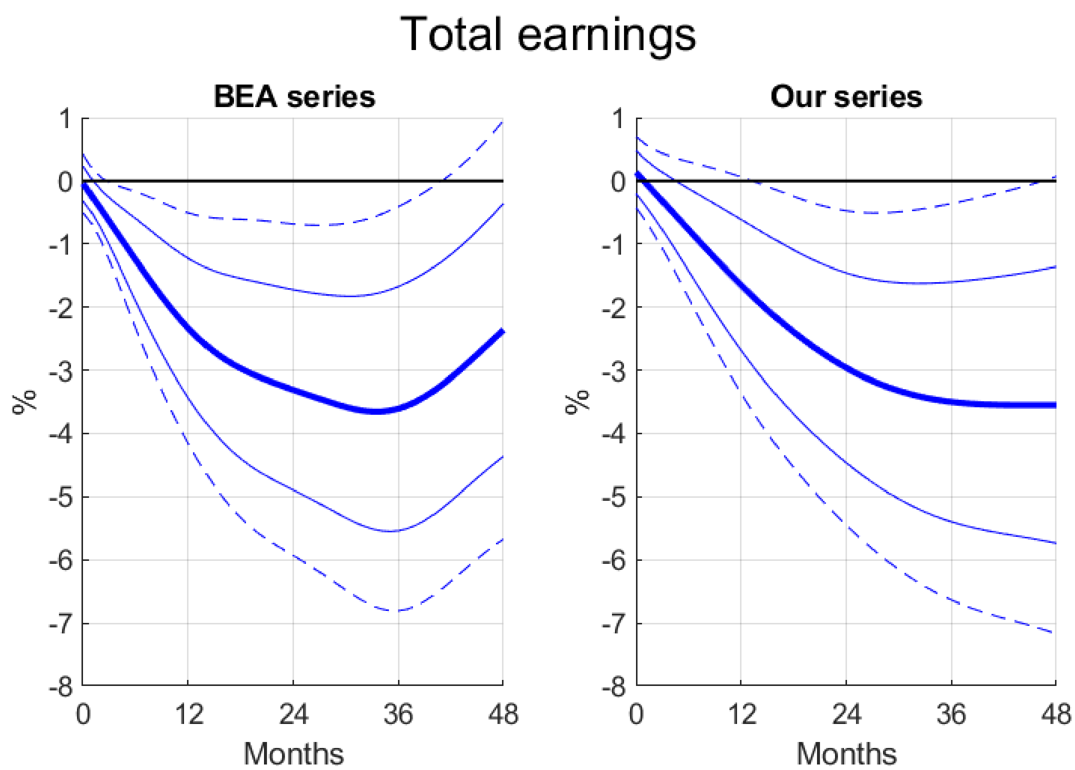
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument. 90% confidence intervals displayed. Sample periods and controls are specified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

Figure C.3: 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.

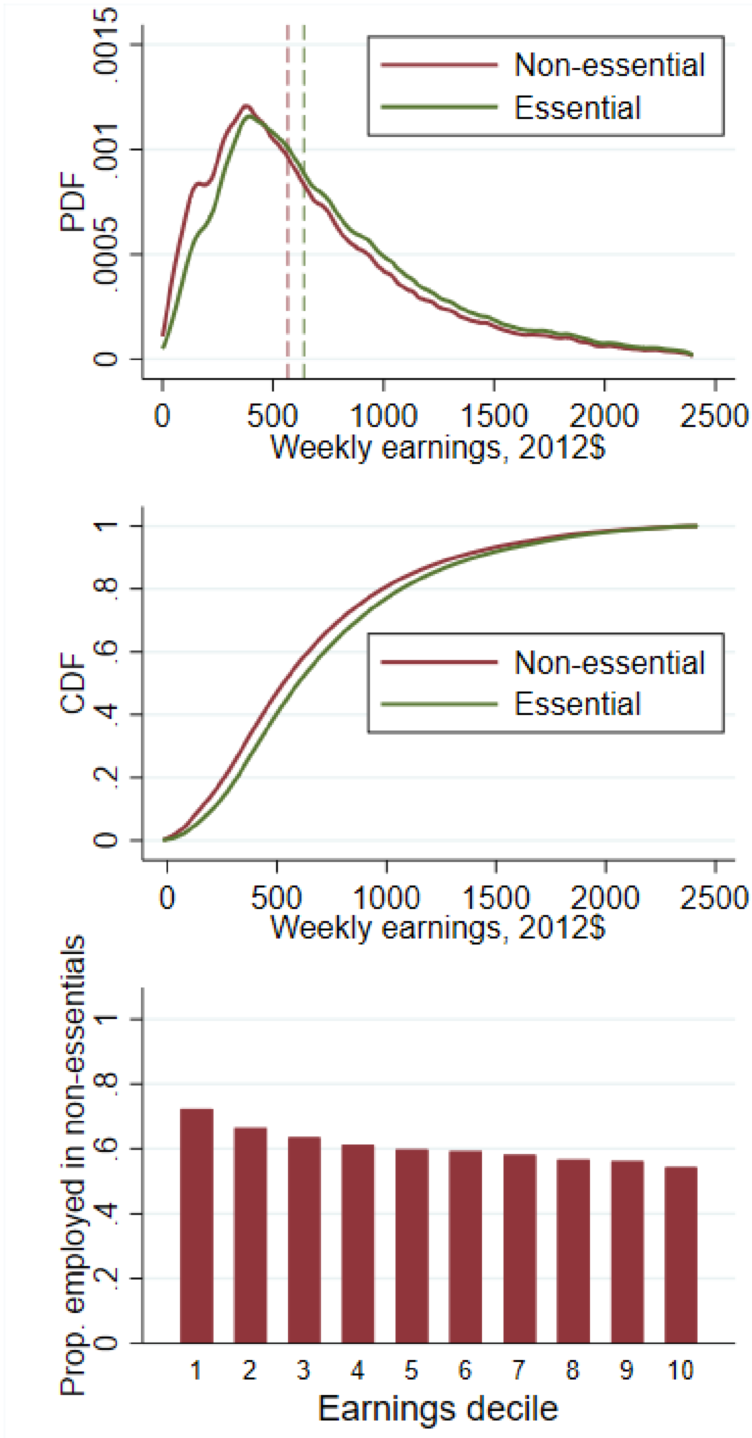
Figure C.4: IRFs to contractionary monetary policy shock - Comparison of total earnings series



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. The LHS series is the IRF of total compensation of employees (Received: Wage and Salary Disbursements) from the BEA NIPA data. The RHS series is the IRF our constructed equivalent series using CPS data.

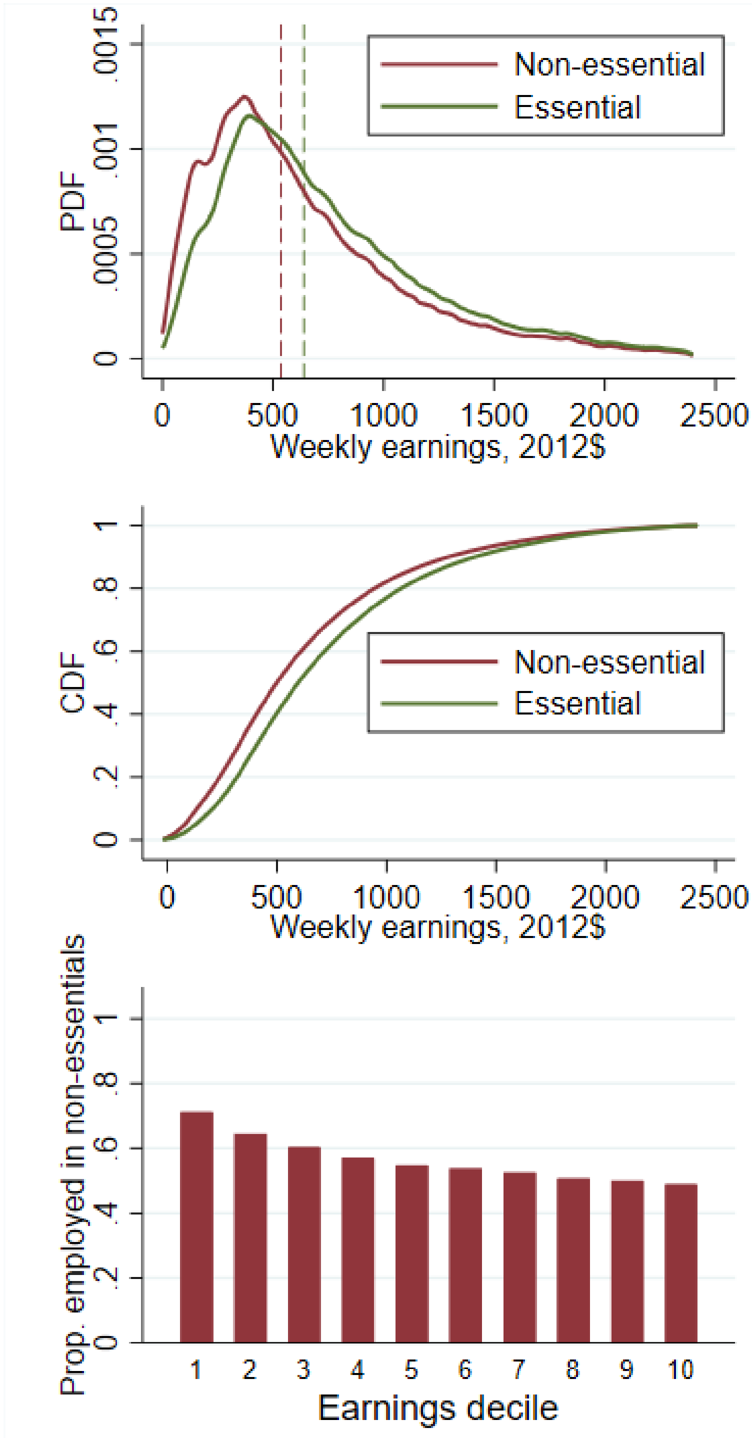
C.4 Additional earnings distribution results

Figure C.5: 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 non-essential industries for each decile of the income distribution (deciles computed annually).

Figure C.6: 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).

D Robustness

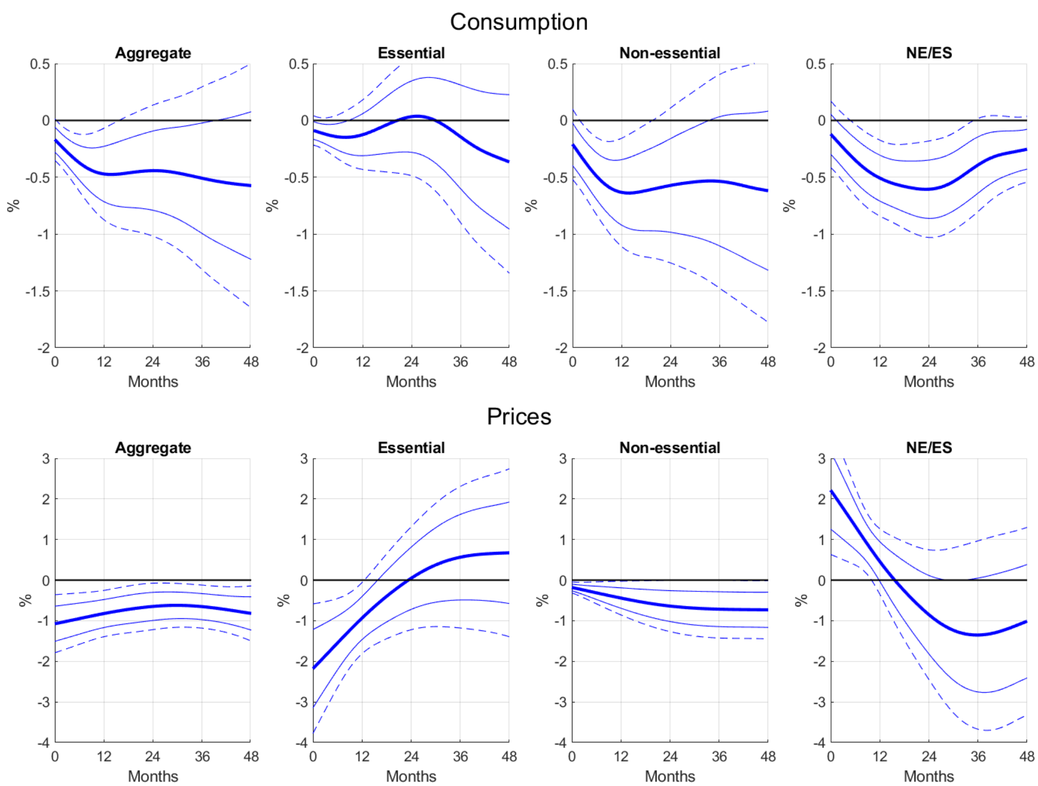
D.1 Robustness to information effect

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.

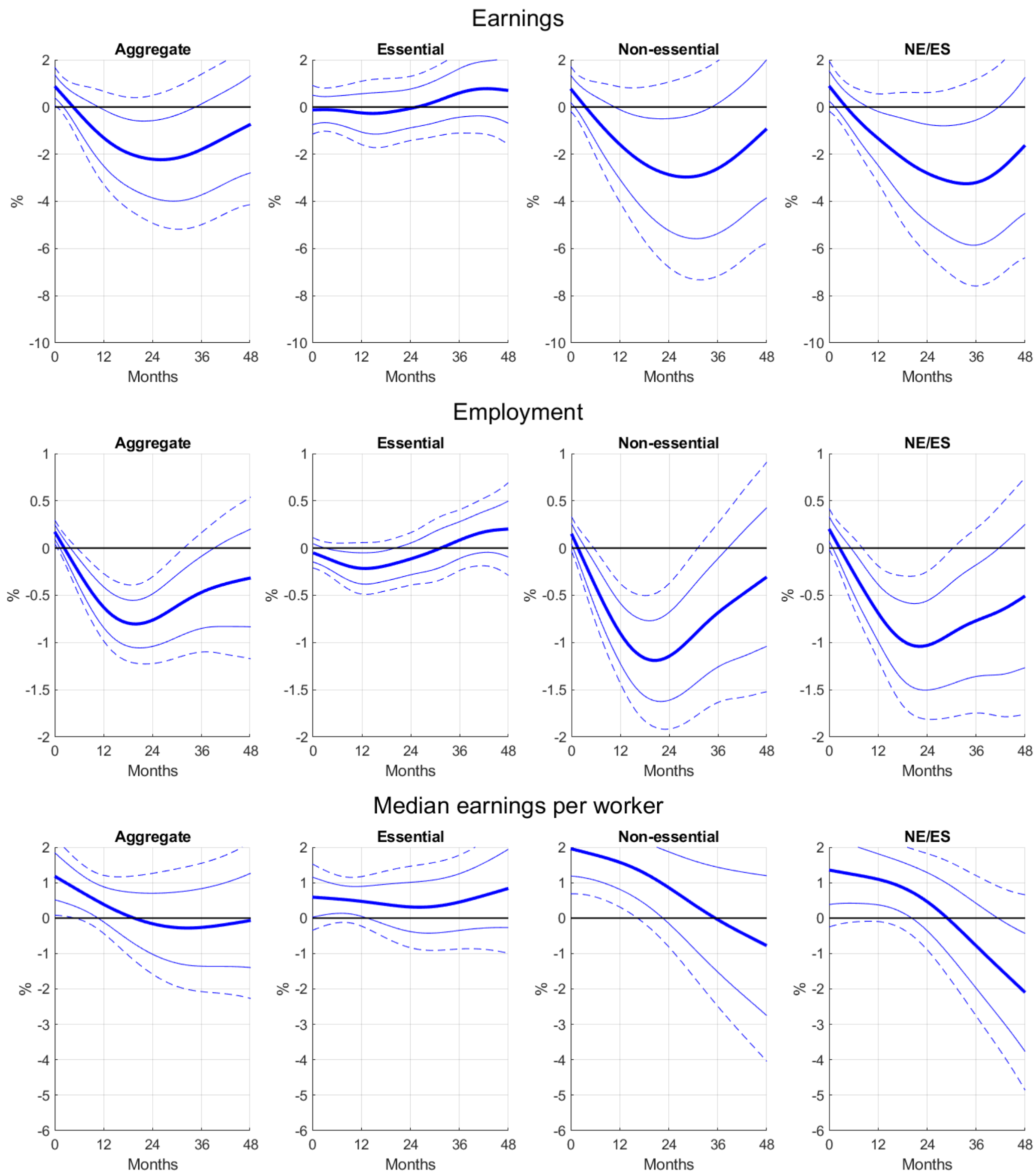
Figures D.1, D.2 and D.3 are the counterparts to the IRFs in the main text, using these alternative monetary policy surprise series. Sample and controls are as in the baseline regressions. The results are substantively similar; consumption, prices, employment and earnings (particularly at the lower end 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 D.1: IRFs to contractionary monetary policy shock - Consumption and Prices



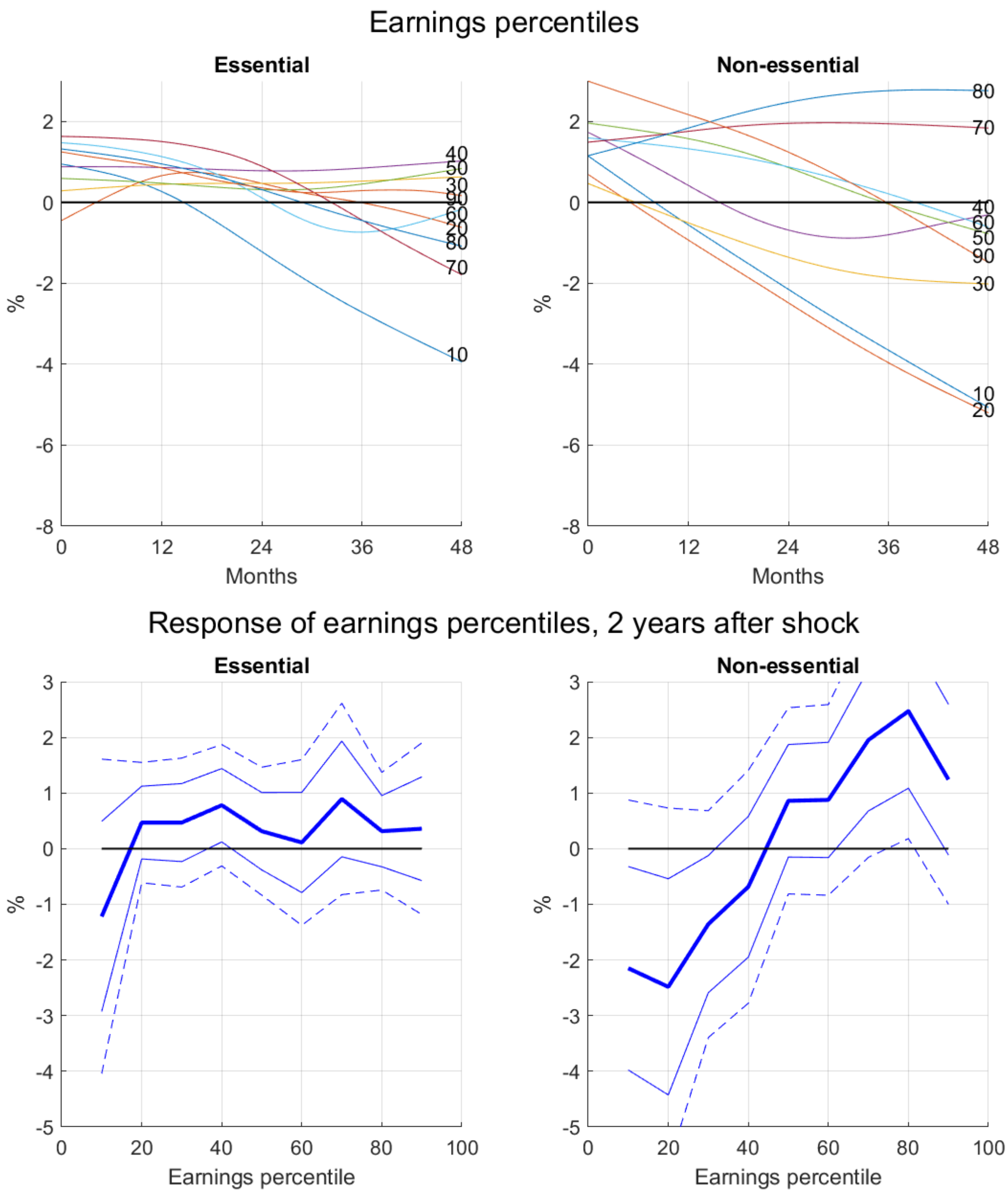
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Jarocinski and Karadi (2020) high-frequency identified monetary policy instrument, robust to the information effect.

Figure D.2: 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.

Figure D.3: IRFs to contractionary monetary policy shock - Earnings distribution



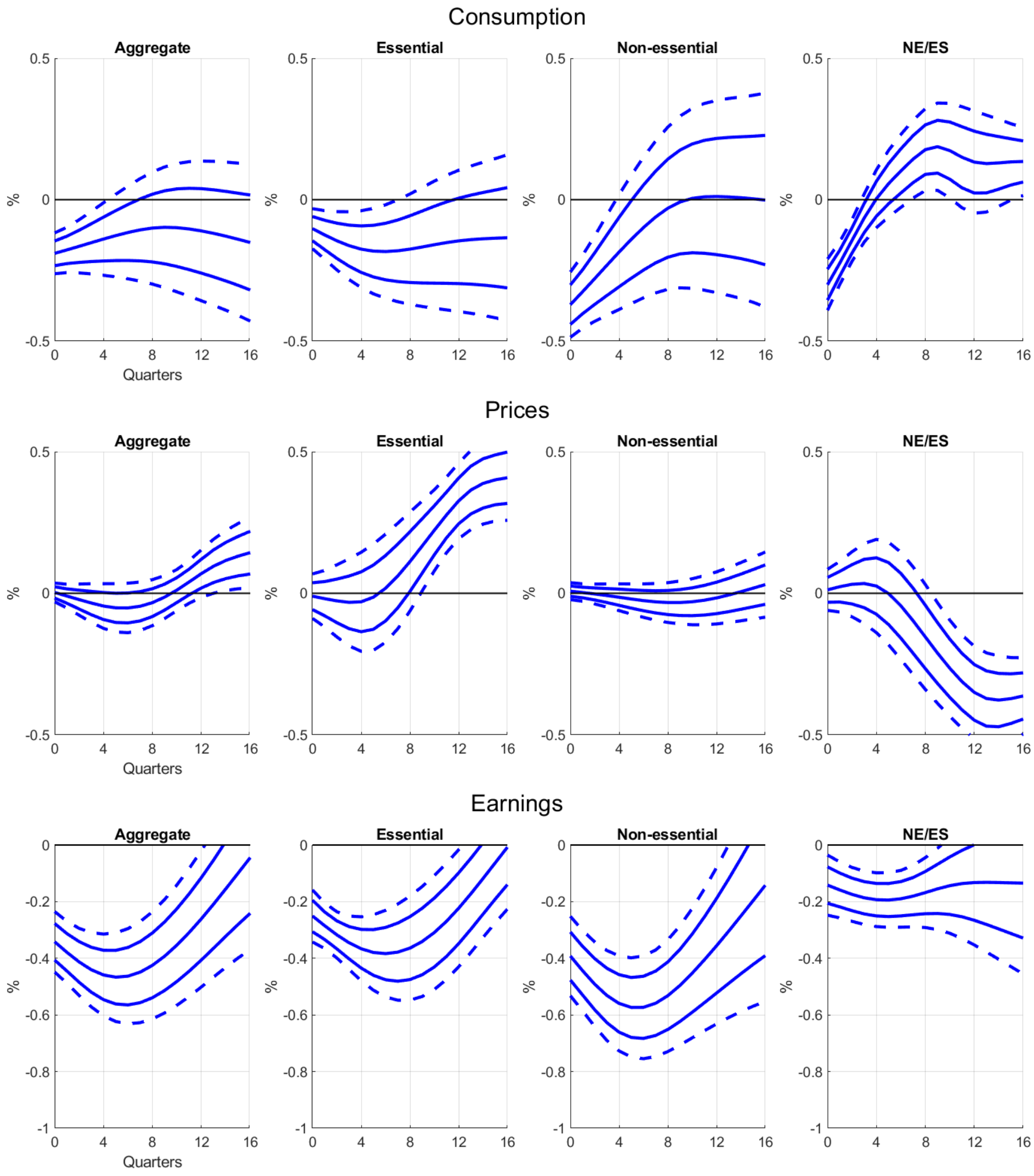
Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Jarocinski and Karadi (2020) high-frequency identified monetary policy instrument, robust to the information effect. Earnings IRFs estimated on data January 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.

D.2 Shocks from Business Cycle Anatomy (Angeletos, Collard and Dellas (2020))

We view our main mechanism as a general property of business cycles, not exclusive to the response to monetary policy shocks. In our main identified empirical results, we focus on responses to monetary policy shocks, both because they are an important and well-identified source of business cycle shocks and because we can draw policy implications for the conduct of monetary policy. However, as a complement to this and our unidentified IRFs in Figure 2, we also estimate the responses to more general business cycle shocks, provided by Angeletos, Collard and Dellas (2020). We use shock directly rather than as an instrument and using a quarterly frequency, similarly to that paper. We specifically use the shock from Angeletos, Collard and Dellas (2020) which maximises the variation in unemployment. Shocks which maximise other key macro-variables are strongly correlated with this shock, and give similar results in our setting. We use the same controls and the same starting sample as in the monetary policy regressions. We end the sample in 2017q4 due to data availability.

Figure D.4 shows the results. As in our main results, we find that the decline in non-essential consumption and earnings is larger than that of essentials, particularly in the first two years after the shock. We corroborate the message that Non-Essential Business Cycles are a broad phenomenon of business cycle amplification, and it is not only specific to monetary policy.

Figure D.4: Response to business cycle shock from Angeletos, Collard and Dellas (2020)



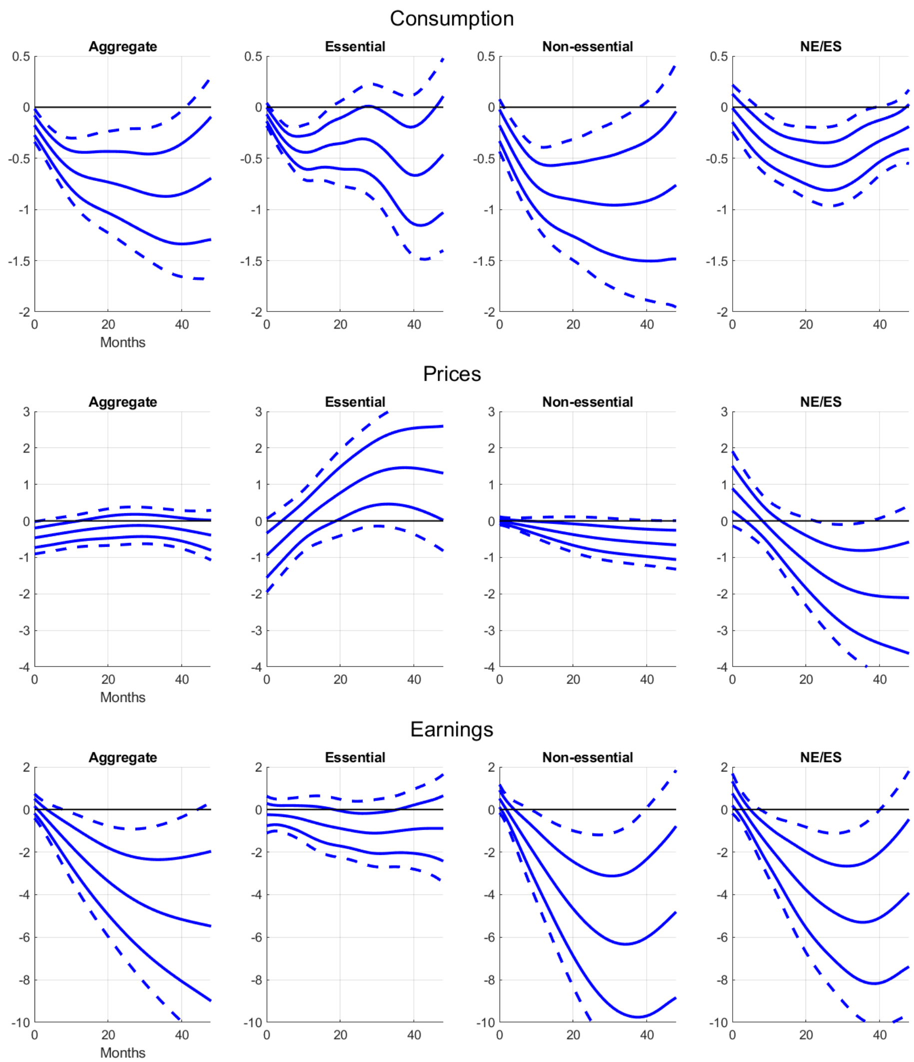
Notes: We use the shock that maximises the variation in unemployment, which is the main shock used by Angeletos, Collard and Dellas (2020). Results estimated using SLP, same specification as the main results, other than no instrument used and quarterly frequency and sample ending in 2017q4.

D.3 Adding COVID to the sample period

In our main sample, we end the estimation period in December 2019. This omits the effects of Covid-19, where non-essentials and essentials responded differently to the shock partly due to sector-specific reductions in activity not directly driven by the mechanism we propose here[24]. To check that our results are robust to adding the effects of the Covid-19 period, we estimate the IRFs for samples ending in December 2020 in Figures D.5 and D.6. The magnitude and degree of heterogeneity in responses is increased with this sample, but in our main results we prefer to focus on the more conservative set of results, excluding Covid, to ensure that only entirely voluntary deferral of non-essential consumption is considered.

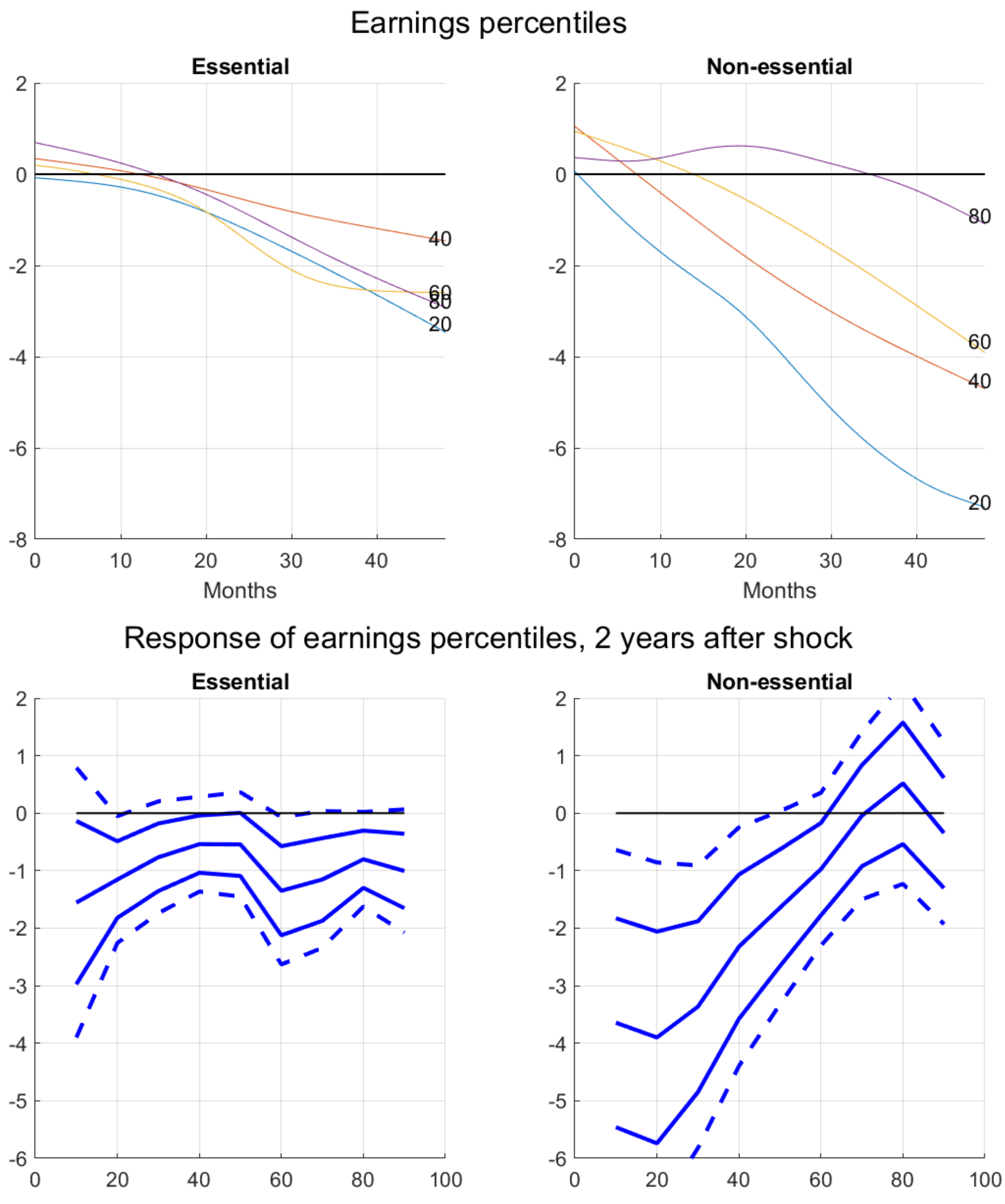
[24] Although we envisage that a large reason for the differential shutdowns of different sectors were precisely because certain types of consumption are not intertemporally substitutable, consistent with our mechanism, and that our identification strategy of estimating the response to monetary policy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

Figure D.5: 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. Sample period ends in December 2020, otherwise specification is as in the main text.

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

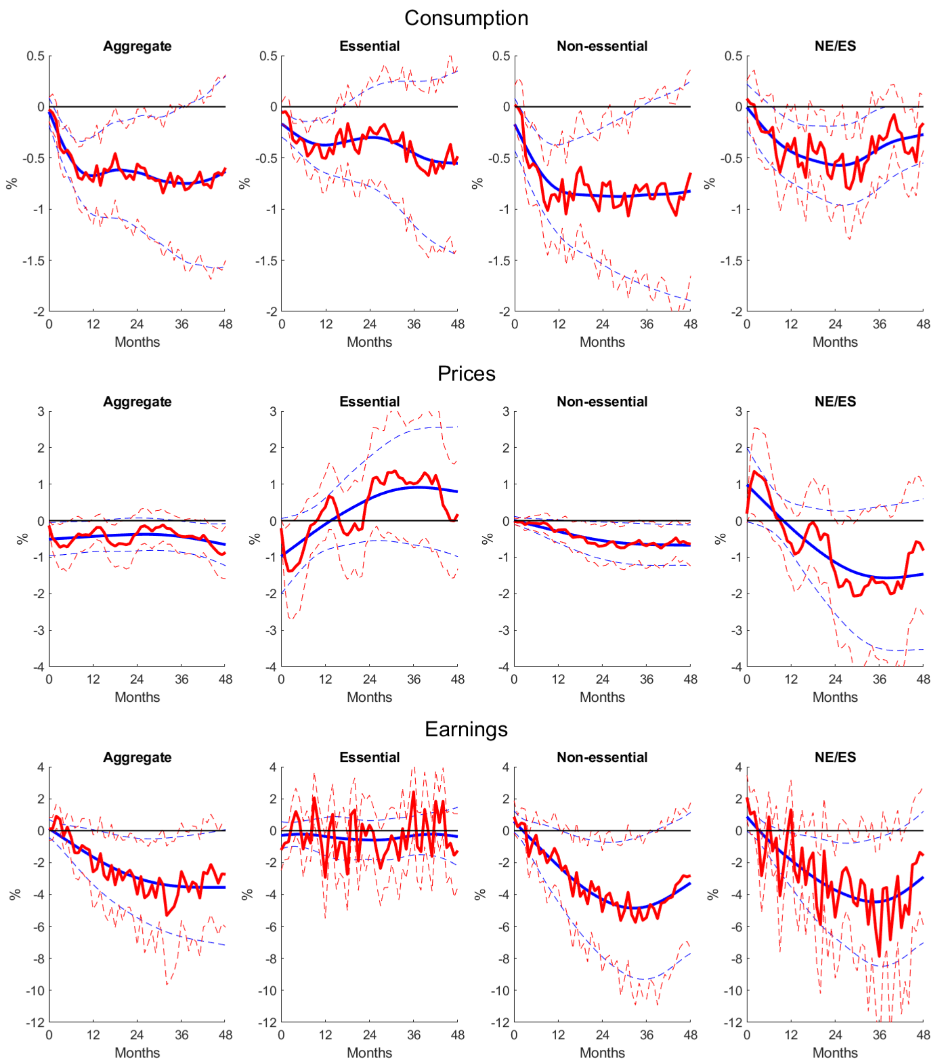


Notes: IRFs estimated by smooth local projections, response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument, robust to the information effect. Sample ends December 2020, otherwise the specification remains in the main body of the text. 68 and 90% confidence intervals displayed.

D.4 IRFs with (unsmoothed) local projections

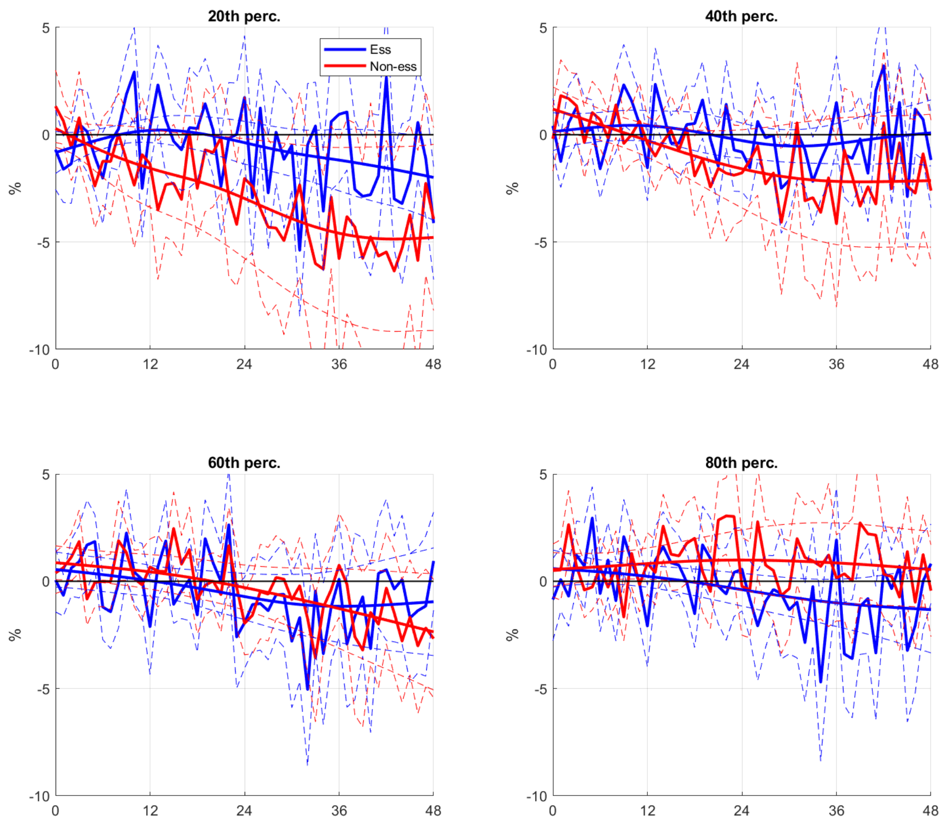
To show that our results are robust to using standard local projections, rather than smoothed local projections, Figures D.7 shows our main results for consumption, prices and earnings are similar for standard LP, but the introduction of smoothing allows us to more clearly see the key results. D.8 shows the IRFs for selected percentiles of the earnings distribution; due to the noise in the earnings series, it is harder to see clear patterns from the LP results.

Figure D.7: IRFs to contractionary monetary policy shock - Consumption, Prices and Earnings



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. Samples and specifications as described in the main text.

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

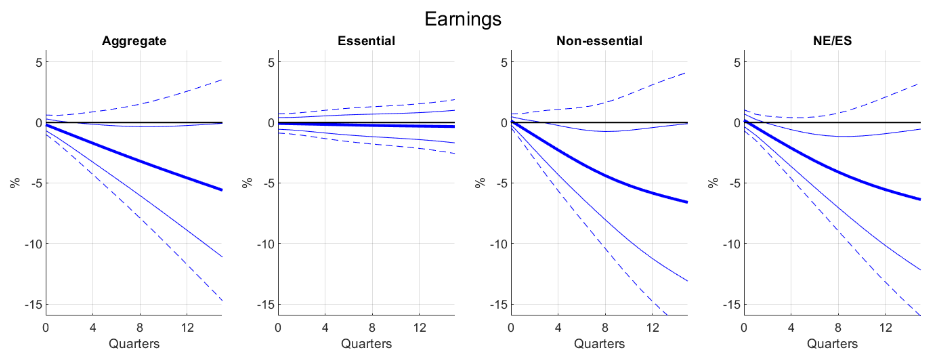


Notes: IRFs estimated by smooth local projections (smooth IRFs) and standard local projections (non-smooth IRFs), response to a 100bp increase in 1y yields, instrumented using monetary policy shocks derived from Gertler and Karadi (2015) high-frequency identified monetary policy instrument, robust to the information effect. Sample and specification as in main text. 90% confidence intervals.

D.5 Quarterly earnings IRFs

The CPS ORG sample is formally designed to be representative only at the quarterly frequency, but in our main results we use monthly frequency. To verify our results still hold at the lower frequency, Figure D.9 shows our main results for earnings using quarterly frequency data. As the quarterly frequency removes some of the higher frequency variation useful for identifying responses, the results are less significant but qualitatively similar to the baseline results.

Figure D.9: IRFs to contractionary monetary policy shock - Earnings at quarterly frequency



Notes: IRFs estimated by smooth local projections (smooth IRFs) and standard local projections (non-smooth IRFs), 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. Sample and specification as in main text, quarterly frequency data used. 90% and 68% confidence intervals.

E Model derivations

In this appendix, we provide more detailed derivations for the theoretical model.

E.1 Households

We solve separately the Ricardian agent problem and the hand-to-mouth one.

E.1.1 Ricardian agent problem

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

$$P_t^E C_{H,t}^E + P_t^N C_{H,t}^N + B_{H,t} \leq W_{H,t} N_{H,t} + \Pi_{H,t} + T_{H,t} + R_{t-1} B_{H,t-1}$$

We can rewrite the budget constraint defining wealth in terms of the essential price $a_{H,t}$:

$$\begin{aligned}
a_{H,t} &= b_{H,t-1}\frac{R_{t-1}}{\pi_t^E} + w_{H,t}N_{H,t} + \Pi^r_{H,t} + t_{H,t} \\
a_{H,t+1} &= \tilde{R}_{t+1}(a_{H,t} - (C^E_{H,t} + p_t^N C^N_{H,t})) + w_{t+1}N_{H,t+1} + \Pi^r_{H,t+1} + t_{H,t+1} \\
a_{H,t+m+1} &= \prod_{k=0}^{m} \tilde{R}_{t+k+1} a_{H,t} - \sum_{j=0}^{m}\prod_{k=j}^{m} \tilde{R}_{t+k+1}(C^E_{H,t+j} + p^N_{t+j}C^N_{H,t+j}) \\
&\quad + \sum_{j=0}^{m}\prod_{k=j+1}^{m} \tilde{R}_{t+k+1}(w_{t+j+1}N_{H,t+j+1} + \Pi^r_{H,t+j+1} + t_{H,t+j+1})
\end{aligned}$$

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, $\tilde{R}_{t+1} \equiv R_t/\pi^E_{t+1}$ is real ex-post rate in terms of the essential price inflation, and all lower case variables are the corresponding uppercase variable in terms of the essential price: $p_t^N \equiv \frac{P_t^N}{P_t^E}$, $w_{H,t} \equiv \frac{W_{H,t}}{P_t^E}$, $t_{H,t} \equiv \frac{T_{H,t}}{P_t^E}$, and $b_{H,t} \equiv \frac{B_{H,t}}{P_t^E}$. We define $\Pi^r_{H,t} \equiv \frac{\Pi_{H,t}}{P_t^E}$ as real profits to avoid confusion with inflation.

We can now turn to the Bellman equation. Households update their expectations only sporadically, specifically update with probability λ. Somebody who updates today has probabilities λ of updating tomorrow, $\lambda(1-\lambda)$ of updating in 2 periods, $\lambda(1-\lambda)^2$ in 3 periods, $\lambda(1-\lambda)^j$ in $j+1$ periods, and so on. When they update, the problem is as in year zero, so we use the recursive structure to solve their choice. As they realise that they might not be able to update, households make plans for future choices in the current period. They choose consumption of a variety, say essentials, for today: $C^E_{i,t,0}$ and for the future if they don't update $C^E_{i,t+j,j}$ for j periods ahead, and similarly for non-essential consumption and savings. As households delegate the labour choice to unions, we ignore the disutility of labour without loss of generality.

$$
\begin{aligned}
V(a_{H,t}) = &\max_{\{C^E_{H,t+m,m}, C^N_{H,t+m,m}\}_{m=0}^{\infty}} \left(\sum_{m=0}^{\infty} \beta^m (1-\lambda)^m \left(\frac{\left(C^E_{H,t+m,m}\right)^{1-\frac{1}{\gamma^E}}}{1-\frac{1}{\gamma^E}} + \varphi \frac{\left(C^N_{H,t+m,m}\right)^{1-\frac{1}{\gamma^N}}}{1-\frac{1}{\gamma^N}} \right) \right. \\
&\left. + \beta\lambda \sum_{m=0}^{\infty} \beta^m (1-\lambda)^m \mathbb{E}_t V(a_{H,t+m+1}) \right) \\
&s.t. \\
a_{H,t+m+1} = &\prod_{k=0}^{m} \tilde{R}_{t+k+1} a_{H,t} - \sum_{j=0}^{m} \prod_{k=j}^{m} \tilde{R}_{t+k+1} (C^E_{H,t+j} + p^N_{t+j} C^N_{H,t+j})
\end{aligned}
$$

Where the household makes plans for when they cannot update (first terms) and for when they can update the problem becomes the same (second terms). Start by taking the FOC for the essential good:

$$
\begin{aligned}
\frac{\partial V(a_{H,t})}{\partial C^E_{H,t+j,j}} &= \beta^j (1-\lambda)^j (C^E_{H,t+j,j})^{-\frac{1}{\gamma^E}} - \beta\lambda \sum_{m=j}^{\infty} \beta^m (1-\lambda)^m \mathbb{E}_t V'(a_{H,t+m+1}) \frac{\partial V(a_{H,t+m+1})}{\partial C^E_{H,t+j,j}} = 0 \\
\frac{\partial V(a_{H,t})}{\partial C^E_{H,t+j,j}} &= \beta^j (1-\lambda)^j (C^E_{H,t+j,j})^{-\frac{1}{\gamma^E}} - \beta\lambda \sum_{m=j}^{\infty} \beta^m (1-\lambda)^m \mathbb{E}_t V'(a_{H,t+m+1}) \prod_{k=j}^{m} \tilde{R}_{t+k+1} = 0
\end{aligned}
$$

Rewrite the FOC for the current period and use the expression to express compactly the envelope condition:

$$
\begin{aligned}
\frac{\partial V(a_{H,t})}{\partial C^E_{H,t,0}} &= (C^E_{H,t,0})^{-\frac{1}{\gamma^E}} - \beta\lambda \sum_{m=0}^{\infty} \beta^m (1-\lambda)^m \mathbb{E}_t V'(a_{H,t+m+1}) \prod_{k=0}^{m} \tilde{R}_{t+k+1} = 0 \\
V'(a_{H,t}) &= \beta\lambda \sum_{m=0}^{\infty} \beta^m (1-\lambda)^m \mathbb{E}_t V'(a_{H,t+m+1}) \frac{\partial V(a_{H,t+m+1})}{\partial a_{H,t}} \\
&= (C^E_{H,t,0})^{-\frac{1}{\gamma^E}}
\end{aligned}
$$

This means we can rewrite the FOC with the envelope condition plugged in, so that the choice of the attentive consumer in this period is a function of the choices of the attentive consumer in the future:

$$\frac{\partial V(a_{H,t})}{\partial C^E_{H,t+j,j}} = \beta^j(1-\lambda)^j(C^E_{H,t+j,j})^{-\frac{1}{\gamma^E}} - \beta\lambda\sum_{m=j}^{\infty}\beta^m(1-\lambda)^m\mathbb{E}_t(C^E_{H,t+m+1,0})^{-\frac{1}{\gamma^E}}\prod_{k=j}^{m}\tilde{R}_{t+k+1} = 0$$

$$\frac{\partial V(a_{H,t})}{\partial C^E_{H,t,0}} = (C^E_{H,t,0})^{-\frac{1}{\gamma^E}} - \beta\lambda\sum_{m=0}^{\infty}\beta^m(1-\lambda)^m\mathbb{E}_t(C^E_{H,t+m+1,0})^{-\frac{1}{\gamma^E}}\prod_{k=0}^{m}\tilde{R}_{t+k+1} = 0$$

Use the recursive structure to write the FOC as a traditional Euler equation:

$$(C^E_{H,t,0})^{-\frac{1}{\gamma^E}} = \beta\mathbb{E}_t(C^E_{H,t+1,0})^{-\frac{1}{\gamma^E}}\tilde{R}_{t+1}$$

Use a similar method to massage the FOC for j periods ahead:

$$(C^E_{H,t+j,j})^{-\frac{1}{\gamma^E}} = \mathbb{E}_t(C^E_{H,t+j,0})^{-\frac{1}{\gamma^E}}$$

Having solve the essential good choice, we now turn to the non-essential good choice. The FOC:

$$\frac{\partial V(a_{H,t})}{\partial C^N_{H,t+j,j}} = \beta^j(1-\lambda)^j(C^N_{H,t+j,j})^{-\frac{1}{\gamma^N}}\varphi - \beta\lambda\sum_{m=j}^{\infty}\beta^m(1-\lambda)^m\mathbb{E}_tV'(a_{H,t+m+1})\frac{\partial V(a_{H,t+m+1})}{\partial C^N_{H,t+j,j}} = 0$$

$$\frac{\partial V(a_{H,t})}{\partial C^N_{H,t+j,j}} = \beta^j(1-\lambda)^j(C^N_{H,+j,j})^{-\frac{1}{\gamma^N}}\varphi - \beta\lambda\sum_{m=j}^{\infty}\beta^m(1-\lambda)^m\mathbb{E}_tV'(a_{H,t+m+1})\prod_{k=j}^{m}\tilde{R}_{t+k+1}p^N_{t+j} = 0$$

For the N good we need to keep track of the relative price. However, the solution is easier as we can use directly the essential good solutions. Start with the time zero problem:

$$(C^N_{H,t,0})^{-\frac{1}{\gamma^N}}\varphi = p^N_t\beta\lambda\sum_{m=0}^{\infty}\beta^m(1-\lambda)^m\mathbb{E}_tV'(a_{H,t+m+1})\prod_{k=0}^{m}\tilde{R}_{t+k+1}$$

$$(C^N_{H,t,0})^{-\frac{1}{\gamma^N}}\varphi = p^N_t(C^E_{H,t,0})^{-\frac{1}{\gamma^E}}$$

The FOC for j periods ahead:

$$\beta^j(1-\lambda)^j(C^N_{H,t+j,j})^{-\frac{1}{\gamma^N}}\varphi = \beta\lambda\sum_{m=j}^{\infty}\beta^m(1-\lambda)^m\mathbb{E}_tV'(a_{H,t+m+1})\prod_{k=j}^{m}\tilde{R}_{t+k+1}p^N_{t+j}$$

$$(C^N_{H,t+j,j})^{-\frac{1}{\gamma^N}} = \mathbb{E}_t(C^N_{H,t+j,0})^{-\frac{1}{\gamma^N}}$$

We can summarise the problems of the Ricardian agents with four equilibrium conditions, a budget constraint, and two aggregation equations. The equilibrium conditions consist of: an Euler equation for the attentive consumer in terms of the essential good, an intra-temporal condition linking consumption of essential goods to non-essential goods for an attentive consumer, and two conditions, one for essential goods and one for non-essential goods, linking the consumption plans for consumers who do not update to the expectation of what an attentive consumer would do.

$$\begin{aligned}
(C^E_{H,t,0})^{-\frac{1}{\gamma^E}} &= \beta \mathbb{E}_t \left((C^E_{H,t+1,0})^{-\frac{1}{\gamma^E}} \frac{R_t}{\pi^E_{t+1}} \right) \\
\varphi (C^N_{H,t,0})^{-\frac{1}{\gamma^N}} &= p^N_t (C^E_{H,t,0})^{-\frac{1}{\gamma^E}} \\
(C^E_{H,t+j,j})^{-\frac{1}{\gamma^E}} &= \mathbb{E}_t \left((C^E_{H,t+j,0})^{-\frac{1}{\gamma^E}} \right) \\
(C^N_{H,t+j,j})^{-\frac{1}{\gamma^N}} &= \mathbb{E}_t \left((C^N_{H,t+j,0})^{-\frac{1}{\gamma^N}} \right)
\end{aligned}$$

The Ricardian agents budget constraint, which drops out in the equilibrium definition due to Walras law:

$$C^E_{H,t} + p^N_t C^N_{H,t} + b_{H,t} = w_{H,t} N_{H,t} + \Pi^r_{H,t} + t_{H,t} + R_{t-1} b_{H,t-1} \frac{R_{t-1}}{\pi^E_t}$$

Consumption aggregation across attentive and non-attentive consumers:

$$\begin{aligned}
C^E_{H,t} &= \lambda \sum_{j=0}^{\infty} (1-\lambda)^j C^E_{H,t-j,j} \\
C^N_{H,t} &= \lambda \sum_{j=0}^{\infty} (1-\lambda)^j C^N_{H,t-j,j}
\end{aligned}$$

We plug-in the last FOC to express overall consumption as a function of the expected actions of attentive consumers:

$$\begin{aligned}
C^E_{H,t} &= \lambda \sum_{j=0}^{\infty} (1-\lambda)^j \left[\mathbb{E}_{t-j} \left((C^E_{H,t,0})^{-\frac{1}{\gamma^E}} \right) \right]^{-\gamma^E} \\
C^N_{H,t} &= \lambda \sum_{j=0}^{\infty} (1-\lambda)^j \left[\mathbb{E}_{t-j} \left((C^N_{H,t,0})^{-\frac{1}{\gamma^N}} \right) \right]^{-\gamma^N}
\end{aligned}$$

E.1.2 Hand-to-mouth agent problem

Constrained agents face the same problem, with the same information friction, but do not have access to bond markets. They make plans for consumption choices in the future, as they can also be inattentive, but do not have saving choices to smooth out inconsistent plans as the Ricardian agents. Therefore, we posit a risk sharing agreement across hand-to-mouth households, to ensure that each household follows ex-post their consumption plans and the overall hand-to-mouth agents budget constraint is satisfied[25].

First, we show the budget constraint in terms of wealth:

$$\begin{aligned} P_t^E C_{L,t}^E + P_t^N C_{L,t}^N &\leq W_{L,t} N_{L,t} + \Pi_{L,t} + T_{L,t} \\ C_{L,t}^E + p_t^N C_{L,t}^N &\leq a_{L,t} = w_{L,t} N_{L,t} + \Pi_{L,t}^r + t_{L,t} \end{aligned}$$

Their maximisation problem, for the periods in which they cannot update:

$$\begin{aligned} V(a_{L,t}) = \max_{\{C_{L,t+m,m}^E, C_{L,t+m,m}^N\}_{m=0}^\infty} \sum_{m=0}^{\infty} \beta^m (1-\lambda)^m \Bigg(\frac{\left(C_{L,t+m,m}^E\right)^{1-\frac{1}{\gamma^E}}}{1-\frac{1}{\gamma^E}} + \varphi \frac{\left(C_{L,t+m,m}^N\right)^{1-\frac{1}{\gamma^N}}}{1-\frac{1}{\gamma^N}} \\ + \eta_{t+j} \mathbb{E}_t \left(a_{L,t+m} - C_{L,t+m,m}^E - C_{L,t+m,m}^N p_{t+m}^N \right) \Bigg) \end{aligned}$$

To find the solution, take the FOC for the two goods and equate the marginal utilities:

$$\beta^j (1-\lambda)^j \left(C_{L,t+j,j}^E\right)^{-\frac{1}{\gamma^E}} = \beta^j (1-\lambda)^j \left(C_{L,t+j,j}^N\right)^{-\frac{1}{\gamma^N}} \varphi \frac{1}{\mathbb{E}_t(p_{t+j}^N)}$$

Use this condition to arrive to the three equilibrium conditions as for the Ricaridan agents, minus the Euler equation:

$$\begin{aligned} \varphi \left(C_{L,t,0}^E\right)^{-\frac{1}{\gamma^E}} &= \left(C_{L,t,0}^N\right)^{-\frac{1}{\gamma^N}} \frac{1}{p_t^N} \\ \left(C_{L,t+j,j}^E\right)^{-\frac{1}{\gamma^N}} &= \mathbb{E}_t \left(C_{L,t+j,0}^E\right)^{-\frac{1}{\gamma^N}} \\ \left(C_{L,t+j,j}^N\right)^{-\frac{1}{\gamma^N}} &= \mathbb{E}_t \left(C_{L,t+j,0}^N\right)^{-\frac{1}{\gamma^N}} \end{aligned}$$

We can still aggregate goods consumption across attentive and non-attentive consumers. By assuming risk sharing across consumers, agents can follow through with their plans ex-post.

$$C_{L,t}^E = \lambda \sum_{j=0}^{\infty} (1-\lambda)^j \left[\mathbb{E}_{t-j} \left(\left(C_{L,t,0}^E\right)^{-\frac{1}{\gamma^E}} \right) \right]^{-\gamma^E}$$

[25] This is a shortcut for the idea that there is a government in the background that provides insurance across hand-to-mouth agents. With this assumption, we avoid transfers across agent types, which would affect the transmission mechanism.

$$C_{L,t}^{N}=\lambda\sum_{j=0}^{\infty}(1-\lambda)^{j}\left[\mathbb{E}_{t-j}\left((C_{L,t,0}^{N})^{-\frac{1}{\gamma^{N}}}\right)\right]^{-\gamma^{N}}$$

E.2 Unions

Unions are perfectly competitive and fully attentive. There are two unions, one to represent each type of consumer, Ricardian and hand-to-mouth. We follow Mankiw and Reis (2007) in separating the consumption choice from the labour supply choice, by employing unions. As each union represents the totality of the family, they take overall consumption to compute the labour supply choice. We end up with two standard intra-temporal equilibrium conditions:

$$\xi\frac{N_{L,t}^{\chi}}{(C_{L,t}^{E})^{-\frac{1}{\gamma^{E}}}}=w_{L,t}$$
$$\xi\frac{N_{H,t}^{\chi}}{(C_{L,t}^{H})^{-\frac{1}{\gamma^{E}}}}=w_{H,t}$$

E.3 Firms

Final good producers. The final good producers combine different retail varieties of the essential and of the non-essential goods according to a CES aggregator.

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

This leads to a standard demand that the final good producers have for different varieties of a given good category (essential and non-essentials):

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

Calvo retailers. Retailers of a given type of good, say essential[26], 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

[26] The non-essential retailers one is fully symmetric.

off-steady state. The probability of not being able to reset prices is equal to θ in each period. This leads to a standard non-linear New-Keynesian Phillips Curve. The objective function, the discounted present value of profits is:

$$\mathbb{E}_t \sum_{j=0}^{\infty} SDF_{t,t+j} \left(P^E_{k,t+j} Y^E_{k,t+j} - P^E_{t+j} \mathcal{S}^E_{t+j} Y^E_{k,t+j} \right)$$

All firms that in period t can reset their price face the same problem (this happens with probability $1-\theta$), therefore will choose the same price $\tilde{P}^E_t$, that maximises profits as long as it remains in place:

$$\mathbb{E}_t \sum_{j=0}^{\infty} SDF_{t,t+j} (\theta)^j \left(\tilde{P}^E_t Y^E_{k,t+j} - P^E_{t+j}(1-\tau^E)\mathcal{S}^E_{t+j} Y^E_{k,t+j} - T^E_{t+j} \right)$$

We substitute the demand equation, take the first order condition, substitute-in the SDF for the H household[27], and rearrange to arrive to three equations representing the non-linear New Keynesian Phillips Curve.

$$\begin{aligned}
K^{E,f}_t &= \left(C^E_{H,t}\right)^{-\frac{1}{\gamma^E}} Y^E_t \mathcal{S}^E_t \frac{\varepsilon^E}{\varepsilon^E - 1}(1-\tau^E) + \theta\beta\mathbb{E}_t(\pi^E_{t+1})^{\varepsilon^E} K^{E,f}_{t+1} \\
F^{E,f}_t &= \left(C^E_{H,t}\right)^{-\frac{1}{\gamma^E}} Y^E_t + \theta\beta\mathbb{E}_t(\pi^E_{t+1})^{\varepsilon^E - 1} F^{E,f}_{t+1} \\
\frac{K^{E,f}_t}{F^{E,f}_t} &= \left(\frac{1-\theta(\pi^E_t)^{\varepsilon^E - 1}}{1-\theta} \right)^{\frac{1}{1-\varepsilon^E}}
\end{aligned}$$

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

$$\begin{aligned}
K^{N,f}_t &= \left(C^N_{H,t}\right)^{-\frac{1}{\gamma^N}} Y^N_t \mathcal{S}^N_t \frac{\varepsilon^N}{\varepsilon^N - 1}(1-\tau^N) + \theta\beta\mathbb{E}_t(\pi^N_{t+1})^{\varepsilon^N} K^{N,f}_{t+1} \\
F^{N,f}_t &= \left(C^N_{H,t}\right)^{-\frac{1}{\gamma^N}} Y^N_t + \theta\beta\mathbb{E}_t(\pi^N_{t+1})^{\varepsilon^N - 1} F^{N,f}_{t+1} \\
\frac{K^{N,f}_t}{F^{N,f}_t} &= \left(\frac{1-\theta(\pi^N_t)^{\varepsilon^N - 1}}{1-\theta} \right)^{\frac{1}{1-\varepsilon^N}}
\end{aligned}$$

[27]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.

E.3.1 Wholesalers

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

$$
\begin{aligned}
Y^E_t &= A^E_t (N^E_{L,t})^{\alpha^E} (N^E_{H,t})^{1-\alpha^E} \\
Y^N_t &= A^N_t (N^N_{L,t})^{\alpha^N} (N^N_{H,t})^{1-\alpha^N}
\end{aligned}
$$

They sell these goods at nominal price $P^{i,w}_t$ 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^i. The crucial innovation we present is that $\alpha^E < \alpha^N$: there are relatively more low-skilled workers in non-essential goods production than in essential goods production. As discussed in the main text, this is the source of labour marker heterogeneity and the resulting amplification.

The solution to the optimisation problem of the essential wholesalers is:

$$
\begin{aligned}
\mathcal{S}^E_t \alpha^E \frac{Y^E_t}{N^E_{L,t}} &= w_{L,t} \\
\mathcal{S}^E_t (1-\alpha^E) \frac{Y^E_t}{N^E_{H,t}} &= w_{H,t}
\end{aligned}
$$

For the non-essential wholesalers:

$$
\begin{aligned}
\mathcal{S}^N_t \alpha^N \frac{Y^N_t}{N^N_{L,t}} &= \frac{w_{L,t}}{p^N_t} \\
\mathcal{S}^N_t (1-\alpha^N) \frac{Y^N_t}{N^N_{H,t}} &= \frac{w_{H,t}}{p^N_t}
\end{aligned}
$$

E.4 Market clearing

We close the model with two goods market clearing condition, for essential and non-essential goods, two labour market clearing conditions, for high and low skilled labour, and bond marker clearing condition by which bonds are in zero net supply.

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:

$$Y_t^E = C_t^E = \sum_{i=\{H,L\}} \mu_i C_{i,t}^E$$
$$Y_t^N = C_t^N = \sum_{i=\{H,L\}} \mu_i C_{i,t}^N$$

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

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

The bonds market clearing specifies that bonds are in zero net supply:

$$\mu_H B_{H,t} = 0$$

In this model with non-homothetic preferences, we cannot construct an ideal price index, so we model CPI inflation as statistical agencies do, with Laspeyres, Paasche, or Fisher price indices. We define CPI inflation to be inflation computed with the Fisher index. It is imporant to note 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.

$$\pi_{t,Lasp} = \frac{P_t^E C_{t-1}^E + P_t^N C_{t-1}^N}{P_{t-1}^E C_{t-1}^E + P_{t-1}^N C_{t-1}^N}$$
$$\pi_{t,Paasche} = \frac{P_t^E C_t^E + P_t^N C_t^N}{P_{t-1}^E C_t^E + P_{t-1}^N C_t^N}$$
$$\pi_{t,Fisher} = \left(\pi_{t,Lasp}\pi_{t,Paasche}\right)^{1/2}$$
$$\pi_t \equiv \pi_{t,Fisher}$$

We compute real GDP with production in the two sectors weighted by prices in steady state, with P^E being normalised to one:

$$Y_t = Y_t^E + p^N Y_t^N$$

E.5 Government

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

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

The only role of fiscal policy is to ensure that Calvo retailers profits are zero in steady state. The government sets a lump sum tax on each Calvo retailer such that it pays in a non-distortive way for the subsidy to the same retailer. With this tax, retailers profits are zero in steady state.

$$T_t^E = \tau^E P_t^E \mathcal{S}_t^E Y_t^E$$
$$T_t^N = \tau^N P_t^N \mathcal{S}_t^N Y_t^N$$

With $\tau^E = 1/\varepsilon^E$ and $\tau^N = 1/\varepsilon^N$. Taxes to households are zero and there is no government spending. Therefore, the government runs a balanced budget.

We specify a profit allocation rule off steady state, where we give profits to Ricardian households in our baseline model in the spirit of Bilbiie (2008) or Debortoli and Galí (2017). We explore alternative profit allocation mechanism in the counterfactual exercise. The generic transfer policy[28]:

$$\Pi_{k,t} = \phi_{\Pi,k}^E \Pi_t^E + \phi_{\Pi,k}^N \Pi_t^N \quad k = \{H, L\}$$

E.6 Equilibrium

The competitive equilibrium consists of 29 endogenous allocations $\{C_t,\ C_t^E,\ C_t^N,\ C_{H,t}^E,\ C_{H,t}^N,\ C_{L,t}^E,\ C_{L,t}^N,\ C_{H,t,0}^E,\ C_{H,t,0}^N,\ C_{L,t,0}^E,\ C_{L,t,0}^N,\ N_{H,t},\ N_{L,t},\ N_{H,t}^E,\ N_{H,t}^N,\ N_{L,t}^E,\ N_{L,t}^N,\ b_{H,t},\ \Pi_{H,t}^r,\ \Pi_{L,t}^r,\ \Pi_t^{r,N},\ \Pi_t^{r,E},\ Y_t,\ Y_t^E,\ Y_t^N,\ K_{E,t}^f,\ F_{E,t}^f,\ K_{N,t}^f,\ F_{N,t}^f\}$, 13 prices $\{w_{H,t},\ w_{L,t},\ \pi_t,\ \pi_t^E,\ \pi_t^N,\ \pi_{t,Lasp},\ \pi_{t,Paasche},\ p_t^N,\ P_t^E,\ P_t^N,\ R_t,\ \mathcal{S}_t^E,\ \mathcal{S}_t^N\}$, and 3 exogenous processes $\{A_t^E,\ A_t^N,\ \varepsilon_t^{mp}\}$, with P_0^E normalised to one; such that households, final good producers, retailers, and wholesalers optimise, the central bank follows a Taylor rule, the treasury follows the tax rule, profits are disbursed according to the profit rule, and markets clear. To avoid repetition, we re-write the full set of equations only in the linearised equilibrium.

[28] Recall capital letter Π are profits, small letter π are inflation rates.

E.7 Steady state computation

We define a steady state variable simply without the time subscript. We solve for a zero-inflation steady state ($\pi^E = \pi^N = 1$). We set the transfers to the Calvo retailers at $\tau^E = 1/\varepsilon^E$ and $\tau^N = 1/\varepsilon^N$ to ensure no steady state markups ($\mathcal{S}^E = \mathcal{S}^N = 1$) and zero steady state profits. We normalise the steady state price level for the essential good at 1 ($P^E = 1$) and solve for the steady state relative price p^N.

Wages. We solve for wages from the wholesalers problem. As long as $\alpha^E \neq \alpha^N$, the formula is:

$$w_L = (p^N)^{\frac{1-\alpha^E}{\alpha^N-\alpha^E}} \left[\left(A^E (1-\alpha^E)^{1-\alpha^E} (\alpha^E)^{\alpha^E} \right)^{-(1-\alpha^N)} \left(A^N (1-\alpha^N)^{1-\alpha^N} (\alpha^N)^{\alpha^N} \right)^{(1-\alpha^E)} \right]^{\frac{1}{\alpha^N-\alpha^E}} \tag{8}$$

$$w_H = (p^N)^{\frac{-\alpha^E}{\alpha^N-\alpha^E}} \left[\left(A^E (1-\alpha^E)^{1-\alpha^E} (\alpha^E)^{\alpha^E} \right)^{\alpha^N} \left(A^N (1-\alpha^N)^{1-\alpha^N} (\alpha^N)^{\alpha^N} \right)^{-\alpha^E} \right]^{\frac{1}{\alpha^N-\alpha^E}} \tag{9}$$

Consumption. To solve for consumption, first note that in steady state attentive and inattentive consumers all have the same consumption level. Next plug the labour supply choice, the intra-temporal choice between essential and non-essential goods in the budget constraint and use the zero profit and zero transfer in steady state. This leads for each household $k = \{H, L\}$ to a one non-linear equation in the consumption of essentials:

$$C_k^E + \varphi^{\gamma^N} \left(p^N\right)^{1-\gamma^N} (C_k^E)^{\frac{\gamma^N}{\gamma^E}} = w_k^{1+\frac{1}{\chi}} \xi^{-\frac{1}{\chi}} (C_k^E)^{-\frac{1}{\chi\gamma^E}} \quad k = \{H, L\} \tag{10}$$

With non-homotheticity, this equation cannot be solved analytically, but can be solved easily numerically.

Algorithm to find the steady state. For a given set of structural parameters, we compute the steady state with the following algorithm. Vary p^N such that we compute:

1. w_H, and w_L analytically with (8) and (9).
2. C_H^E and C_L^E numerically with (10).
3. C_H^N, C_L^N, N_H, N_L from the household/union problem.
4. Y^E and Y^N from the goods market clearing conditions.

5. N_H^E and N_L^N from firms' labour demand functions.

6. The difference between $N_H^E + N_H^N$ and $\mu_H N_H$.

Iterate on p^N until the difference it is zero. Alternatively, the last step can be substituted with the difference between $N_L^E + N_L^N$ and $\mu_L N_L$ by Walras law (one market clearing condition can be ignored).

In each estimation draw, we target the steady state consumption shares of Ricardian and hand-to-mouth agents of non-essentials: $\bar{C}_H^N \equiv \frac{p^N C_H^N}{p^N C_H^N C_H^E}$ and $\bar{C}_L^N \equiv \frac{p^N C_L^N}{p^N C_L^N C_L^E}$. To do so, we vary the relative preference parameter for non-essentials φ and the relative productivity of the two sectors $a^E \equiv A^E/A^N$. φ affects the average consumption share. a^E affects the relative wage, and, therefore, the relative consumption shares, thanks to non-homotheticity in the utility function.

E.8 Log-linear equilibrium

We solve the log-linearised model. Steps are standard, we log-linearise each variable, except for profits, which we linearise as they are zero in steady state. Log-linearised and linearised variables are hatted. The only feature to note is that all CPI inflation indices simplify to the same steady states weighted average of inflation:

$$\hat{\pi}_t = \hat{\pi}_{t,Lasp} = \hat{\pi}_{t,Paasche} = \frac{C^E}{C^E + p^N C^N}\hat{\pi}_t^E + \frac{p^N C^N}{C^E + p^N C^N}\hat{\pi}_t^N$$

Equilibrium. The competitive equilibrium consists of 25 endogenous allocations $\{\hat{C}_t$, $\hat{C}_t^E$, $\hat{C}_t^N$, $\hat{C}_{H,t}^E$, $\hat{C}_{H,t}^N$, $\hat{C}_{L,t}^E$, $\hat{C}_{L,t}^N$, $\hat{C}_{H,t,0}^E$, $\hat{C}_{H,t,0}^N$, $\hat{C}_{L,t,0}^E$, $\hat{C}_{L,t,0}^N$, $\hat{N}_{H,t}$, $\hat{N}_{L,t}$, $\hat{N}_{H,t}^E$, $\hat{N}_{H,t}^N$, $\hat{N}_{L,t}^E$, $\hat{N}_{L,t}^N$, $\hat{\Pi}_{L,t}^r$, $\hat{\Pi}_t^{r,N}$, $\hat{\Pi}_t^{r,E}$, $\hat{Y}_t$, $\hat{Y}_t^E$, $\hat{Y}_t^N$, $E\hat{arn}_t^E$ $E\hat{arn}_t^N\}$, 9 prices $\{\hat{w}_{H,t}$, $\hat{w}_{L,t}$, $\hat{\pi}_t$, $\hat{\pi}_t^E$, $\hat{\pi}_t^N$, $\hat{p}_t^N$, $\hat{R}_t$, $\hat{\mathcal{S}}_t^E$, $\hat{\mathcal{S}}_t^N\}$, and 3 exogenous processes $\{\hat{A}_t^E$, $\hat{A}_t^N$, $\varepsilon_t^{mp}\}$; such that households, final good producers, retailers, and wholesalers optimise, the central bank follows a Taylor rule, the treasury follows the tax rule, profits are disbursed according to the profit rule, and markets clear. The equilibrium is characterised by the following equations:

$$-\frac{1}{\gamma^E}\hat{C}_{H,t,0}^E + \frac{1}{\gamma^N}\hat{C}_{H,t,0}^N = -\hat{p}_t^N$$

$$\frac{1}{\gamma^E}\mathbb{E}_t\left(\hat{C}_{H,t+1,0}^E\right) = \frac{1}{\gamma^E}\hat{C}_{H,t,0}^E - \mathbb{E}_t(\hat{\pi}_{t+1}^E) + \hat{R}_t$$

$$\hat{C}_{H,t}^E = \lambda\sum_{j=0}^{\infty}(1-\lambda)^j\mathbb{E}_{t-j}\left(\hat{C}_{H,t,0}^E\right)$$

$$
\begin{aligned}
\hat{C}^N_{H,t} &= \lambda \sum_{j=0}^{\infty} (1-\lambda)^j \mathbb{E}_{t-j}\left(\hat{C}^N_{H,t,0}\right) \\
-\frac{1}{\gamma^E}\hat{C}^E_{L,t,0} + \frac{1}{\gamma^N}\hat{C}^N_{L,t,0} &= -\hat{p}^N_t \\
C^E_L \hat{C}^E_{L,t} + p^N C^N_L(\hat{p}^N_t + \hat{C}^N_{L,t}) &= w_L N_L(\hat{w}_{L,t} + \hat{N}_{L,t}) + \frac{\hat{\Pi}^r_{L,t}}{\mu_L} \\
\hat{C}^E_{L,t} &= \lambda \sum_{j=0}^{\infty} (1-\lambda)^j \mathbb{E}_{t-j}\left(\hat{C}^E_{L,t,0}\right) \\
\hat{C}^N_{L,t} &= \lambda \sum_{j=0}^{\infty} (1-\lambda)^j \mathbb{E}_{t-j}\left(\hat{C}^N_{L,t,0}\right) \\
\chi \hat{N}_{H,t} + \frac{1}{\gamma^E}\hat{C}^E_{H,t} &= \hat{w}_{H,t} \\
\chi \hat{N}_{L,t} + \frac{1}{\gamma^E}\hat{C}^E_{L,t} &= \hat{w}_{L,t} \\
\hat{\pi}^N_t &= \beta \mathbb{E}_t(\hat{\pi}^N_{t+1}) + \kappa^N \hat{\mathcal{S}}^N_t \\
\hat{\pi}^E_t &= \beta \mathbb{E}_t(\hat{\pi}^E_{t+1}) + \kappa^E \hat{\mathcal{S}}^E_t \\
\pi^N_t &= \pi^E_t + p^N_t - p^N_{t-1} \\
\hat{Y}^N_t &= \hat{A}^N_t + \alpha^N \hat{N}^N_{L,t} + (1-\alpha^N)\hat{N}^N_{H,t} \\
\hat{\mathcal{S}}^N_t + \hat{Y}^N_t - \hat{N}^N_{H,t} &= \hat{w}_{H,t} - \hat{p}^N_t \\
\hat{\mathcal{S}}^N_t + \hat{Y}^N_t - \hat{N}^N_{L,t} &= \hat{w}_{L,t} - \hat{p}^N_t \\
\hat{Y}^E_t &= \hat{A}^E_t + \alpha^E \hat{N}^E_{L,t} + (1-\alpha^E)\hat{N}^E_{H,t} \\
\hat{\mathcal{S}}^E_t + \hat{Y}^E_t - \hat{N}^E_{H,t} &= \hat{w}_{H,t} \\
\hat{\mathcal{S}}^E_t + \hat{Y}^E_t - \hat{N}^E_{L,t} &= \hat{w}_{L,t} \\
N^E_H \hat{N}^E_{H,t} + N^N_H \hat{N}^N_{H,t} &= \mu_H N_H \hat{N}_{H,t} \\
N^E_L \hat{N}^E_{L,t} + N^N_L \hat{N}^N_{L,t} &= \mu_L N_L \hat{N}_{L,t} \\
\hat{\pi}_t &= \frac{C^E}{C^E + p^N C^N}\hat{\pi}^E_t + \frac{p^N C^N}{C^E + p^N C^N}\hat{\pi}^N_t \\
Y\hat{Y}_t &= Y^E \hat{Y}^E_t + p^N Y^N \hat{Y}^N_t \\
\hat{R}_t &= \rho_R \hat{R}_{t-1} + (1-\rho_R)\left(\phi_\pi\left(\mathbb{E}_t(\hat{\pi}_{t+1})\right) + \phi_Y \hat{Y}_t\right) + \varepsilon^{mp}_t \\
\hat{\Pi}^r_{L,t} &= \phi^E_{\Pi,L}\hat{\Pi}^{r,E}_t + \phi^N_{\Pi,L}\hat{\Pi}^{r,N}_t \\
\hat{\Pi}^{r,E}_t &= -Y^E \hat{\mathcal{S}}^E_t \\
\hat{\Pi}^{r,N}_t &= -Y^N p^N \hat{\mathcal{S}}^N_t \\
C^E \hat{C}^E_t &= \mu_H C^E_H \hat{C}^E_{H,t} + \mu_L C^E_L \hat{C}^E_{L,t}
\end{aligned}
$$

$$
\begin{aligned}
C^N \hat{C}_t^N &= \mu_H C_H^N \hat{C}_{H,t}^N + \mu_L C_L^N \hat{C}_{L,t}^N \\
\hat{Y}_t^E &= \hat{C}_t^E \\
\hat{Y}_t^N &= \hat{C}_t^N \\
E\hat{arn}_t^E &= \frac{w_H N_H^E}{w_H N_H^E + w_L N_L^E}(\hat{w}_{H,t} + \hat{N}_{H,t}^E) + \frac{w_L N_L^E}{w_H N_H^E + w_L N_L^E}(\hat{w}_{L,t} + \hat{N}_{L,t}^E) \\
E\hat{arn}_t^N &= \frac{w_H N_H^N}{w_H N_H^N + w_L N_L^N}(\hat{w}_{H,t} + \hat{N}_{H,t}^N) + \frac{w_L N_L^N}{w_H N_H^N + w_L N_L^N}(\hat{w}_{L,t} + \hat{N}_{L,t}^N)
\end{aligned}
$$

Notice that the equilibrium conditions include four equations with an infinite sum of past expectations (the mapping from each inattentive consumer consumption to the family wide one). To solve the model with a state space representation, we adopt a method proposed by Verona and Wolters (2014) for sticky expectations models. We solve for a truncated set of past expectations. The key insight is that if we care only about IRFs, as we do here where our estimation uses IRF matching, we can truncate the expectations at the horizon of the IRFs and have no loss in precision (say in period 16). $\mathbb{E}_{t-j}(\hat{C}_{H,t,0}^E)$ will be zero for each $j > 16$, that is before the shock happens.

F Model estimation and counterfactual

F.1 Estimation

We estimate the model with a limited-information Bayesian approach, that is, with a impulse response matching with a maximum a posteriori (MAP) estimation procedure. We follow the estimation procedure of Mertens and Ravn (2011), with the weighting matrix choice of Guerron-Quintana, Inoue and Kilian (2017), extended to a MAP setting. Given our model, we estimate a vector of parameters Θ_2 (the parameters in Panel A of Table 1) conditional on a vector of calibrated parameters Θ_1 (the parameters in Panel B of Table 1). The quasi-likelihood:

$$F(\hat{\Lambda}_d|\Theta_2, \Theta_1) = \left(\frac{1}{2\pi}\right)^{\frac{T}{2}} |\Sigma_d| \exp\left[-\frac{1}{2}\left(\hat{\Lambda}_d - \Lambda(\Theta_2|\Theta_1)\right)' \Sigma_d^{-1} \left(\hat{\Lambda}_d - \Lambda(\Theta_2|\Theta_1)\right)\right]$$

Maps the difference in the estimated IRFs with smooth local projections $\hat{\Lambda}_d$ to the model based IRFs $\Lambda(\Theta_2|\Theta_1)$. We stack the IRFs in a vector of dimension T, in the baseline setting equal to 112 (16 quarters times 7 variables). As weighting matrix, we follow Guerron-Quintana, Inoue and Kilian (2017) and use a diagonal matrix with the squared standard errors from the smooth local projection estimates for each IRF element. We denote $p(\Theta_2)$ the prior distribution over the estimated parameters. We follow the common procedure of imposing bounds in the prior draws, but none binds at the estimated value. The quasi-posterior:

$$F(\Theta_2|\hat{\Lambda}_d, \Theta_1) \propto F(\hat{\Lambda}_d|\Theta_2, \Theta_1)p(\Theta_2)$$

Maximum a posterior estimation maximises the posterior over estimated parameters. The practical benefit, over frequentist impulse response matching matching, is that it allows to incorporate priors over parameters.

$$\hat{\Theta}_2 = \arg\max_{\Theta_2} F(\Theta_2|\hat{\Lambda}_d, \Theta_1)$$

We compute the standard errors of $\hat{\Theta}_2$ with the delta method. The formula for the asymptotic covariance matrix, from Mertens and Ravn (2011):

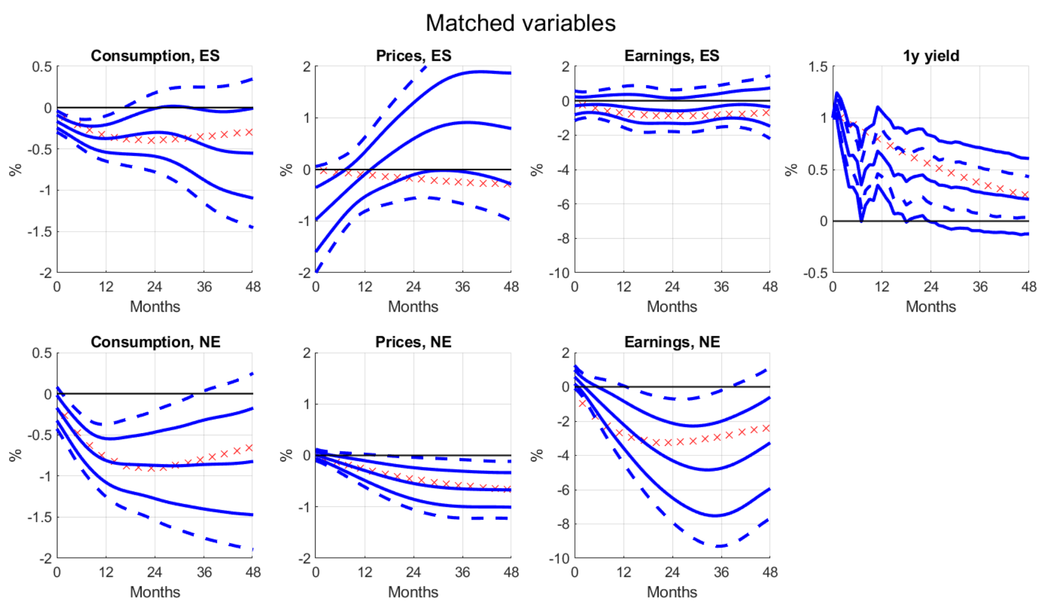
$$\Sigma_{\Theta_2} = \Lambda_{\Theta_2} \frac{\partial \Lambda(\Theta_2|\Theta_1)'}{\partial \Theta_2} \Sigma_d^{-1} \Sigma_S \Sigma_d^{-1} \frac{\partial \Lambda(\Theta_2|\Theta_1)}{\partial \Theta_2} \Lambda_{\Theta_2}$$
$$\Lambda_{\Theta_2} \equiv \left[\frac{\partial \Lambda(\Theta_2|\Theta_1)'}{\partial \Theta_2} \Sigma_d^{-1} \frac{\partial \Lambda(\Theta_2|\Theta_1)}{\partial \Theta_2}\right]$$

$$\Sigma_S \equiv \Sigma_d + \Sigma_m$$

Where we use Σ_d in the last line following Guerron-Quintana, Inoue and Kilian (2017). Notice that we use the model based IRFs, not the IRFs estimated on data simulated from the model as Mertens and Ravn (2013), so that $\Sigma_m = 0$ and the overall expression for the parameters covariance matrix simplifies.

Estimated IRFs. Figure F.1 shows the empirical IRFs in blue and the estimated IRFs in red for the whole set of matched variables. We estimate the end-quarter impulse response for these variables, as described in the main text. For consumption, earnings and prices we match the estimated IRFs for non-essentials and essentials using our SLP empirical approach. For 1y yields we estimate the impulse response from the proxy-SVAR, below we show the corresponding IRFs using the SLP specification are similar.

Figure F.1: IRFs to contractionary monetary policy shock - Matched variables from model



Notes: Consumption, prices, earnings: 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. Sample periods and controls are specified in the main text. Interest rate: Estimated using Proxy-SVAR, as described in text.

F.2 Counterfactual

Table F.1, we compare the cumulative IRFs of non-essential and essential consumption and earnings between the non-homothetic and homothetic representative agent counterfactuals. Unlike for aggregates, non-homotheticity does change sectoral outcomes. However, our irrelevance result of Appendix Section G demonstrates the irrelevance of sectoral heterogeneities for aggregates in the representative setting (albeit for a simpler model than that used in the counterfactuals). This table demonstrates numerically the same result for the representative agent model used in the counterfactuals.

Table F.1: Counterfactuals of Essentials and Non-essentials in the Representative Agent Model

PANEL A - CONSUMPTION

	Representative Agent		
	C	C^E	C^N
Homothetic	1.00	1.00	1.00
Non-Homothetic	1.00	0.34	1.51

PANEL B - EARNINGS

	Representative Agent		
	$Earn$	$Earn^E$	$Earn^N$
Homothetic	1.00	1.00	1.00
Non-Homothetic	1.00	0.77	1.18

Notes: Each cell display the ratio of the cumulative IRF of counterfactual experiment over the cumulative IRF of representative agent with homothetic preferences with the estimated model parameters. In the homothetic case, we set the IES equal to the estimated average IES in the baseline model.

G When non-homotheticity matters for aggregates, a proof

In this appendix, we present the a proof on when non-homotheticity does not amplify business cycles. We show that the non-homothetic RANK has the same response to monetary policy of aggregate variables then a homothetic RANK with the IES equal to the IES of the non-homothetic RANK. This implies that non-homotheticity does not matter per-se for amplification, but it matters only when interacts with other features, as labour market heterogeneity, price stickiness, heterogeneous capital intensities, etc. We formalize this idea with Proposition 1 and Corollary 1.

Proposition 1 *Consider a simplified version of the model of Sections 4 and E. Take an attentive representative agent version with non-homothetic utility* (2) *and a simplified Taylor rule of the form* $R_t = \phi_\pi \mathbb{E}_t(\pi_{t+1}) + \varepsilon_t^{mp}$. *The impact of the monetary policy shock on total consumption is characterised by the average intertemporal elasticity of substitution and on CPI inflation by the average intertemporal elasticity of substitution and the slope of the Phillips curves:*

$$\frac{\partial \hat{C}_t}{\partial \varepsilon_t^{mp}} = -(\underbrace{\gamma^E(1-\bar{C}^N) + \gamma^N \bar{C}^N)}_{Average\ IES})$$

$$\frac{\partial \hat{\pi}_t}{\partial \varepsilon_t^{mp}} = -\underbrace{\kappa}_{Slope\ of\ NKPC}(1 + \underbrace{\gamma^E(1-\bar{C}^N) + \gamma^N \bar{C}^N)}_{Average\ IES})$$

Corollary 1 *Consider a simplified version of the model of Sections 4 and E. Take an attentive representative agent version with homothetic utility*

$$U(C_t^E, C_t^N, N_t) = \frac{(C_t^E)^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}} + \varphi \frac{(C_t^N)^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}} - \xi \frac{N_t^{1+\chi}}{1+\chi}$$

such that the intertemporal elasticity of substitution γ *is equal to* $\gamma^E(1-\bar{C}^N) + \gamma^N \bar{C}^N)$ *of the model presented in Proposition 1, and a simplified Taylor rule of the form* $R_t = \phi_\pi \mathbb{E}_t(\pi_{t+1}) + \varepsilon_t^{mp}$. *The impact of the monetary policy shock on total consumption is characterised by the intertemporal elasticity of substitution and on CPI inflation by the intertemporal elasticity of* *substitution and the slope of the Phillips curves:*

$$\frac{\partial \hat{C}_t}{\partial \varepsilon_t^{mp}} = -\underbrace{\gamma}_{IES}$$
$$\frac{\partial \hat{\pi}_t}{\partial \varepsilon_t^{mp}} = -\underbrace{\kappa}_{Slope\ of\ NKPC}(1+\underbrace{\gamma}_{IES})$$

We now move to prove both statements. The intuition of the result is that relative prices are a state variable but they do not respond to an aggregate shock in the representative agent model. In addition, the two New-Keynesian Phillips curves have the same expressions to map aggregate consumption to overall inflation.

Proof of Proposition 1.

We solve analytically the model which features non-homothetic preferences with a representative agent who is attentive. Operationally, we set $\alpha^N = \alpha^E = 0$ as we have one agent only. We set $\lambda = 1$. We as have only one agent, we have $C_{H,t} = C_t$ and similarly for sector specific variables and employment variables. We can rewrite the first set of equilibrium conditions:

$$\begin{aligned}
\hat{p}_t^N &= \frac{1}{\gamma^E}\hat{C}_t^E - \frac{1}{\gamma^N}\hat{C}_t^N \\
\hat{N}_t + \frac{1}{\gamma^E}\hat{C}_t^E &= \hat{w}_t \\
\hat{Y}_t^N &= \hat{N}_t^N \\
\hat{\mathcal{S}}_t^N &= \hat{w}_t - \hat{p}_t^N \\
\hat{Y}_t^E &= \hat{N}_t^E \\
\hat{\mathcal{S}}_t^E &= \hat{w}_t \\
\hat{Y}_t^N &= \hat{C}_t^N \\
\hat{Y}_t^E &= \hat{C}_t^E \\
\hat{C}_t &= (1-\bar{C}^N)\hat{C}_t^E + \bar{C}^N\hat{C}_t^N \\
\hat{N}_t &= (1-\bar{C}^N)\hat{N}_t^E + \bar{C}^N\hat{N}_t^N
\end{aligned}$$

We can solve this systems to express $\hat{\mathcal{S}}_t^N$ and $\hat{\mathcal{S}}_t^N$ as function of $\hat{C}_t$ and $\hat{p}_t^N$:

$$\begin{bmatrix} \hat{\mathcal{S}}_t^E \\ \hat{\mathcal{S}}_t^N \end{bmatrix} = \begin{bmatrix} \frac{1+\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} & \frac{\gamma^N\bar{C}^N}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} \\ \frac{1+\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} & \frac{\gamma^E(1-\bar{C}^N)}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} \end{bmatrix} \begin{bmatrix} \hat{C}_t \\ \hat{p}_t^N \end{bmatrix}$$

Compactly:

$$\begin{bmatrix} \hat{S}_t^E \\ \hat{S}_t^N \end{bmatrix} = \begin{bmatrix} a_C^{SE} & a_p^{SE} \\ a_C^{SN} & a_p^{SN} \end{bmatrix} \begin{bmatrix} \hat{C}_t \\ \hat{p}_t^N \end{bmatrix}$$

Next, we map goods specific consumption and inflation to their aggregate counterparts. First, express consumption of essentials as a function of overall consumption and relative prices with the overall consumption definition and the intra-termprial consumption good choice.

$$\begin{aligned} \hat{C}_t &= (1-\bar{C}^N)\hat{C}_t^E + \bar{C}^N \hat{C}_t^N \\ \hat{C}_t &= (\gamma^E(1-\bar{C}^N) + \gamma^N \bar{C}^N)\frac{1}{\gamma^E}\hat{C}_t^E - \gamma^N \bar{C}^N \hat{p}_t^N \end{aligned}$$

We can express inflation in essential and non-essential as function of overall inflation and relative prices with the mapping between relative prices and the inflation rates:

$$\begin{aligned} \hat{\pi}_t &= (1-\bar{C}^N)\hat{\pi}_t^E + \bar{C}^N \hat{\pi}_t^N \\ \hat{\pi}_t^N &= \hat{\pi}_t + (1-\bar{C}^N)(\hat{p}_t^N - \hat{p}_{t-1}^N) \end{aligned}$$

and symmetrically:

$$\hat{\pi}_t^E = \hat{\pi}_t - \bar{C}^N(\hat{p}_t^N - \hat{p}_{t-1}^N)$$

We can now turn to the inter-temporal part of the model. The equations are:

$$\begin{aligned} \hat{\pi}_t^E &= \beta \mathbb{E}_t(\hat{\pi}_{t+1}^E) + \kappa^E \hat{\mathcal{S}}_t^E \\ \hat{\pi}_t^N &= \beta \mathbb{E}_t(\hat{\pi}_{t+1}^N) + \kappa^N \hat{\mathcal{S}}_t^N \\ \frac{1}{\gamma^E}\mathbb{E}_t\left(\hat{C}_{t+1}^E\right) &= \frac{1}{\gamma^E}\hat{C}_t^E - \mathbb{E}_t(\hat{\pi}_{t+1}^E) + \hat{R}_t \end{aligned}$$

Substitute-in the mappings from inflation in essential and non-essentials and essential consumption to overall consumption, inflation, and relative prices.

$$\begin{aligned} \hat{\pi}_t - \bar{C}^N(\hat{p}_t^N - \hat{p}_{t-1}^N) &= \beta \mathbb{E}_t(\hat{\pi}_{t+1}) - \beta \bar{C}^N(\mathbb{E}_t(\hat{p}_{t+1}^N) - \hat{p}_t^N) + \kappa^E \hat{\mathcal{S}}_t^E \\ \hat{\pi}_t + (1-\bar{C}^N)(\hat{p}_t^N - \hat{p}_{t-1}^N) &= \beta \mathbb{E}_t(\hat{\pi}_{t+1}) + \beta(1-\bar{C}^N)(\mathbb{E}_t(\hat{p}_{t+1}^N) - \hat{p}_t^N) + \kappa^N \hat{\mathcal{S}}_t^N \\ \frac{1}{\gamma^E(1-\bar{C}^N) + \gamma^N \bar{C}^N}\mathbb{E}_t\left(\hat{C}_{t+1}\right) + \frac{\bar{C}^N(1-\bar{C}^N)(\gamma^N - \gamma^E)}{\gamma^E(1-\bar{C}^N) + \gamma^N \bar{C}^N}\mathbb{E}_t\left(\hat{p}_{t+1}^N\right) &= \end{aligned}$$

$$= \frac{1}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N}\hat{C}_t + \frac{\bar{C}^N(1-\bar{C}^N)(\gamma^N-\gamma^E)}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N}\hat{p}_t^N - \mathbb{E}_t(\hat{\pi}_{t+1}) + \hat{R}_t$$

We can substitute in a simplified Taylor rule: $\hat{R}_t = \phi_\pi \mathbb{E}(\pi_{t+1}) + \varepsilon_t^{mp}$ and the expressions that map responses of consumption and relative prices to marginal costs and write the system in matrix form. In the final system the only parameter or convolutions that matter are: γ^E, γ^N, β, κ, $\bar{C}^N$.

$$\begin{bmatrix} 0 & \beta & -\beta\bar{C}^N \\ 0 & \beta & \beta(1-\bar{C}^N) \\ \frac{1}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} & \phi_\pi - 1 & \frac{\bar{C}^N(1-\bar{C}^N)(\gamma^N-\gamma^E)}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} \end{bmatrix} \begin{bmatrix} \mathbb{E}_t(\hat{C}_{t+1}) \\ \mathbb{E}_t(\hat{\pi}_{t+1}) \\ \mathbb{E}_t(\hat{p}_{t+1}^N) \end{bmatrix} +$$

$$\begin{bmatrix} \kappa\frac{1+\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} & -1 & \bar{C}^N(\beta+1)+\kappa\frac{\bar{C}^N\gamma^N}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} \\ \kappa\frac{1+\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} & -1 & -(1-\bar{C}^N)(\beta+1)-\kappa\frac{(1-\bar{C}^N)\gamma^E}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} \\ -\frac{1}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} & 0 & -\frac{\bar{C}^N(1-\bar{C}^N)(\gamma^N-\gamma^E)}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} \end{bmatrix} \begin{bmatrix} \hat{C}_t \\ \hat{\pi}_t \\ \hat{p}_t^N \end{bmatrix} +$$

$$\begin{bmatrix} 0 & 0 & -\bar{C}^N \\ 0 & 0 & (1-\bar{C}^N) \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \hat{C}_{t-1} \\ \hat{\pi}_{t-1} \\ \hat{p}_{t-1}^N \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \varepsilon_t^{mp} = 0$$

$$A\mathbb{E}(X_{t+1}) + BX_t + CX_{t-1} + H\varepsilon_t^{mp} = 0$$

We solve this system in the case of iid monetary policy shock. We solve it with the undetermined coefficient method. The solution depends on the monetary policy shock and on the state variable, the relative price in the previous period $\hat{p}_{t-1}^N$:

$$\begin{bmatrix} \hat{C}_t \\ \hat{\pi}_t \\ \hat{p}_t^N \end{bmatrix} = \begin{bmatrix} e_1\hat{p}_{t-1}^N + d_1\varepsilon_t^{mp} \\ e_2\hat{p}_{t-1}^N + d_2\varepsilon_t^{mp} \\ e_3\hat{p}_{t-1}^N + d_3\varepsilon_t^{mp} \end{bmatrix} = \begin{bmatrix} e_1 & d_1 \\ e_2 & d_2 \\ e_3 & d_3 \end{bmatrix} \begin{bmatrix} \hat{p}_{t-1}^N \\ \varepsilon_t^{mp} \end{bmatrix}$$

The system with the solution plugged in becomes:

$$A\mathbb{E}(X_{t+1}) + BX_t + CX_{t-1} + H\varepsilon_t^{mp} = 0$$

$$A \begin{bmatrix} e_1(e_3\hat{p}_{t-1}^N + d_3\varepsilon_t^{mp}) \\ e_2(e_3\hat{p}_{t-1}^N + d_3\varepsilon_t^{mp}) \\ e_3(e_3\hat{p}_{t-1}^N + d_3\varepsilon_t^{mp}) \end{bmatrix} + B \begin{bmatrix} e_1\hat{p}_{t-1}^N + d_1\varepsilon_t^{mp} \\ e_2\hat{p}_{t-1}^N + d_2\varepsilon_t^{mp} \\ e_3\hat{p}_{t-1}^N + d_3\varepsilon_t^{mp} \end{bmatrix} + C \begin{bmatrix} 0 \\ 0 \\ \hat{p}_{t-1}^N \end{bmatrix} + H\varepsilon_t^{mp} = 0$$

This creates two sets of systems of equations to solve for, from the coefficients associated with the state variable and with the monetary policy shock:

$$
\begin{aligned}
Ae_3 \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} + B \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} + C \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = 0 \\
Ad_3 \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} + B \begin{bmatrix} d_1 \\ d_2 \\ d_3 \end{bmatrix} + H = 0
\end{aligned}
$$

This would be daunting to solve analytically if monetary policy affected the relative price d_3. However, we show that the solution has $d_3 = 0$ by guessing it and verifying it. The uniqueness of the solution is guaranteed by the Taylor principle $\phi_\pi > 1$. The key idea is that the responses of consumption and inflation to the monetary policy shock depend on the average IES only $\gamma^E(1-\bar{C}^N) + \gamma^N \bar{C}^N$ and not on its element separately. Moreover, the two NKPC display the same terms for inflation and consumption. If this was not the case, say due to labour market heterogeneity or price stickiness heterogeneity, the proof would not go through, showing that non-homotheticity matters only in conjunction with other relevant heterogeneity for aggregate fluctuation.

Guess $d_3 = 0$, then:

$$
\begin{aligned}
A0 \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} + B \begin{bmatrix} d_1 \\ d_2 \\ 0 \end{bmatrix} + H = 0 \\
B \begin{bmatrix} d_1 \\ d_2 \\ 0 \end{bmatrix} + H = 0 \\
\begin{bmatrix} \kappa \frac{1+\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} d_1 - d_2 = 0 \\ \kappa \frac{1+\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} d_1 - d_2 = 0 \\ -\frac{1}{\gamma^E(1-\bar{C}^N)+\gamma^N\bar{C}^N} d_1 - 1 = 0 \end{bmatrix} \\
d_1 = -(\gamma^E(1-\bar{C}^N) + \gamma^N\bar{C}^N) \\
d_2 = -\kappa(1 + \gamma^E(1-\bar{C}^N) + \gamma^N\bar{C}^N)
\end{aligned}
$$

That is consumption responds by the average IES to a monetary policy shock and inflation responds by the Phillips curve slope times by one plus the average IES. This concludes the proof that in a non-homothetic RANK, only the average IES matters for aggregate fluctuations. This concludes the proof. ■

We now move to the corollary: the non-homothetic RANK responses of aggregate variables to monetary policy are the same to a homothetic-RANK with the same average IES.

Proof of Corollary 1. This is immediate, substitute $\gamma = \gamma^E(1-\bar{C}^N) + \gamma^N \bar{C}^N$ for γ^E and γ^N. The system becomes:

$$\begin{bmatrix} 0 & \beta & -\beta\bar{C}^N \\ 0 & \beta & \beta(1-\bar{C}^N) \\ \frac{1}{\gamma} & \phi_\pi - 1 & 0 \end{bmatrix} \begin{bmatrix} \mathbb{E}_t(\hat{C}_{t+1}) \\ \mathbb{E}_t(\hat{\pi}_{t+1}) \\ \mathbb{E}_t(\hat{p}^N_{t+1}) \end{bmatrix} +$$
$$\begin{bmatrix} \kappa\frac{1+\gamma}{\gamma} & -1 & \bar{C}^N(\beta+1+\kappa) \\ \kappa\frac{1+\gamma}{\gamma} & -1 & -(1-\bar{C}^N)(\beta+1+\kappa) \\ -\frac{1}{\gamma} & 0 & 0 \end{bmatrix} \begin{bmatrix} \hat{C}_t \\ \hat{\pi}_t \\ \hat{p}^N_t \end{bmatrix} +$$
$$\begin{bmatrix} 0 & 0 & -\bar{C}^N \\ 0 & 0 & (1-\bar{C}^N) \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \hat{C}_{t-1} \\ \hat{\pi}_{t-1} \\ \hat{p}^N_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \varepsilon^{mp}_t = 0$$

The proof goes through in the same way, with the solution to a monetary policy shock being:

$$\begin{aligned} d_1 &= -\gamma \\ d_2 &= -\kappa(1+\gamma) \\ d_3 &= 0 \end{aligned}$$

This concludes the proof. Notice that the same result would go through also with more complicated models, as long as non-homotheticity does not interact directly with other heterogeneity. It would go through with inattentiveness, sticky wages, or persistent monetary policy. ■