Sectoral Exposure to Aggregate Fluctuations, Employment Risk and Monetary Policy*

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February, 2024

Abstract

This paper studies how differences in employment risk across sectors affect the transmission mechanism of monetary policy. I first show, using micro-level data, that households working in sectors more exposed to business cycles—i.e. experience higher employment risk—accumulate more precautionary savings than those working in less exposed sectors. I then build a two-sector HANK model with sector-specific employment risk and study the monetary policy transmission mechanism in a multi-sector environment. The consumption response following an expansionary monetary policy is larger and more persistent in the sector, which is more exposed to business cycles. The reason is that higher employment risk in more exposed sectors endogenously increases sectoral MPC and generates more procyclical income. I identify two channels through which differences in employment risk affect sectoral and aggregate consumption responses: (i) the market incompleteness channel and (ii) the relative labour demand channel. Moreover, I show how the interaction between the two channels amplifies the aggregate consumption response.

Keywords: Incomplete markets, Multi-sector, Labour markets, Business cycles, Monetary policy

*I am grateful to Efi Adamopoulou, Florin Bilbiie, Antoine Camous, Lena Dräger, Céline Gimet, Eren Gürer, Philipp Harms, Mehdi Hosseinkouchack, Leo Kaas, Tobias Krahnke, Matija Lozej, Ralph Luetticke, Gernot Müller, Victor Gimenez Perales, Xavier Ragot, Morten Ravn, Philip Sauré, Mathias Trabandt, Alain Trannoy for helpful comments and suggestions. I am also thankful to the seminar participants at the T2M 2023, the 2022 Frankfurt–Mannheim Macro Workshop, and the 2022 FFM–MN PhD Conference. I gratefully acknowledge financial support from the French government under the "France 2030" investment plan managed by the French National Research Agency Grant ANR-17-EURE-0020 and ANR-21-CE41-0010, and by the Excellence Initiative of Aix-Marseille University - A*MIDEX. All errors are my own. First version: September 2022.

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1 Introduction

US sectors exhibit very different employment sensitivity to business cycle fluctuations (Petersen and Strongin (1996); Berman and Pfleeger (1997); McLaughlin and Bils (2001); Geremew and Gourio (2018)).[1] Some sectors, like construction or manufacturing, experience large fluctuations in employment as economic conditions change, while others, like utilities or healthcare, are almost unaffected by economic swings. This differential sensitivity of employment to business cycles implies that workers in different sectors face different employment risk.[2]

Employment risk is the most important source of income risk for most households and, as such, plays a crucial role in heterogeneous agent models. With incomplete markets and borrowing constraints, income risk induces a precautionary savings motive, generating wealth inequality and heterogeneous MPCs. Most heterogeneous agent literature assumes that all households work in one sector and face the same employment risk. However, labour literature has found, and I also show in this paper, that the labour market in the US is far from homogeneous, and there are large differences in employment risk across sectors.

This paper studies how differences in employment risk across sectors affect the channels through which monetary policy decisions impact the economy. There are two main contributions. First, I demonstrate that sectoral net worker flows can be informative about sectoral employment risk and, therefore, the strength of the precautionary savings motive. Second, I develop a two-sector Heterogeneous Agent New Keynesian (HANK) model augmented with search and matching market frictions, which I use to quantify how exactly differences in employment risk across sectors affect the transmission mechanism of monetary policy.

To motivate the analysis, I use a simple consumption-savings model to show analytically how employment risk affects the amount of precautionary savings. To do this, I propose an approach in which employment risk is a function of a constant separation rate and a stochastic job-finding rate. In this reduced-form framework, the level of precautionary savings depends on three observables: (i) the separation rate and two parameters describing the job-finding rate process, i.e. (ii) the persistence parameter and (iii) the variance of its innovations. Households tend to accumulate more precautionary savings when they are more likely to be separated from their current jobs and when exposed to larger but more transitory changes in the job-finding rate.

Then, I present some new empirical facts about sectoral employment risk and precautionary savings. My measure of employment risk is based on net worker flows over the

[1] Throughout the paper, I focus on two-digit industries which are classified as "sectors" by the North American Industry Classification System (NAICS).

[2] For example, cyclical sectors tend to experience larger fluctuations in demand as economic conditions change, leading to larger fluctuations in employment and, therefore, more uncertain job prospects.

business cycle. I conjecture that households working in sectors more exposed to business cycles experience more uncertain job prospects and, therefore, experience higher employment risk.[3] To capture cross-sectoral differences in employment risk, I allocate sectors into cyclical and non-cyclical, depending on the sensitivity of sectoral net worker flows to business cycles. Then, I merge information on the sectoral employment risk with household balance sheets. Since I can not directly infer the amount of additional savings due to the precautionary motive from household balance sheets, I propose a novel way and use the difference in net liquid asset holdings of comparable households with similar net wealth in cyclical and non-cyclical sectors as a proxy.[4] I find that households working in sectors more exposed to business cycles, i.e. cyclical sectors, hold larger balances of net liquid assets than otherwise similar households working in sectors less exposed to business cycle fluctuations, i.e. non-cyclical sectors. Moreover, the difference is larger for poor households and decreases with net wealth. These findings are consistent with a stronger precautionary saving motive of households working in more "risky" cyclical sectors.

In the following section, I build a two-sector HANK model to analyse the macroeconomic implications of my empirical findings. My model features two additional elements relative to a standard HANK model augmented with search and matching frictions. The first element is labour market segmentation. Households in my model work in either a cyclical or a non-cyclical sector and are exposed to different employment risk, which, in turn, depends on the state of the business cycle and the characteristics of each labour market segment. The second element is the multi-sector setup. While having more than one sector is standard in the representative agent models, it is less common in heterogeneous agent models. A multi-sector framework with heterogeneous agents allows studying the interaction between changes in relative demands across sectors—i.e. demand spillovers—and features of a standard HANK model, such as MPC heterogeneity and precautionary saving motive.

I calibrate the model to capture some of the labour market characteristics of the two sectors in the US. In particular, differences in employment risk are captured through differences in separation rates, which are calibrated to match average sectoral transition rates from employment to unemployment observed in the data. Households in the cyclical sector face more than three times higher separation rates than households working in non-cyclical sectors.

Following an expansionary monetary policy shock, the consumption response is larger and more persistent in the cyclical sector than in the non-cyclical sector. In my model, there are two channels through which employment risk affects consumption responses.

[3]I use Current Population Survey (CPS) microdata to calculate transition rates from employment to unemployment and confirm that households in cyclical sectors are exposed to higher employment risk.

[4]If one controls for all relevant household observables and partial out other saving motives, the only difference in net liquid asset holdings in the two (groups of) sectors should be due to differences in employment risk.

The first channel is the "market incompleteness channel". A higher separation rate makes employment riskier and increases sectoral MPC. More precisely, a higher separation rate plays two roles in determining the size of the sectoral MPC. First, it makes the consumption function more concave, which mechanically increases MPCs. Second, it also makes households poorer. Taken together, the interaction of these two factors contributes to a higher sectoral MPC.

Moreover, the separation rate also determines the size of flows in and out of unemployment and labour market tightness. The latter is a crucial determinant of wages and hiring costs and, therefore, sectoral marginal costs. Because the labour market in the non-cyclical sector is more rigid, the initial increase in labour market tightness is larger than in the cyclical sector. As a result, wages, hiring costs, and hence real marginal costs increase more than in the cyclical sector, making production in the non-cyclical sector more expensive. This shifts goods and labour demand towards the cyclical sector, increasing employment and income in the cyclical sector. This second channel is the "relative labour demand channel" and is operative even if there is no employment risk.

With incomplete markets, this channel has an additional effect on consumption responses; because households in the cyclical sector have high MPCs, additional income in the cyclical sector pushes sectoral and aggregate consumption response even further via the Keynesian multiplier. However, additional income in the cyclical sector also makes income risk more procyclical, strengthening the precautionary savings motive and restraining the consumption response.

Then, I study how a two-sector HANK model differs from a two-sector Representative Agent New Keynesian model (RANK) with search and matching frictions. In the RANK model, households are perfectly insured against employment risk, and, therefore, the only operative channel is the relative labour demand channel (alongside intertemporal substitution). I show that a two-sector RANK model generates larger differences in sectoral outputs than the HANK model. With incomplete markets, households self-insure via asset accumulation, which dampens the relative labour demand channel and effectively reduces asymmetries in sectoral responses. From a policy perspective, this can have important implications for designing (optimal) sector-specific stabilisation policies, as there might be less need for policy interventions than suggested by the RANK model.

As a sensitivity analysis, I study how results change when I vary (i) the coefficient of elasticity of substitution between the two sectors and (ii) the persistence of the monetary policy shock. When sectoral outputs are more substitutable, or the shock is more persistent, the redistribution of income through the relative labour demand channel intensifies, leading to larger consumption increases in the cyclical sector and a more significant drop in the non-cyclical sector compared to the baseline. However, the difference in sectoral consumption responses is less pronounced than in the representative agent framework. This attenuation occurs because additional income in the cyclical sector amplifies the procyclicality of income risk, which increases savings and reduces consumption in that sector. Conversely, less income in the non-cyclical sector decreases the procyclicality of income risk, resulting in reduced savings and increased consumption relative to the representative agent model.

Related literature. This paper relates to several strands of the literature related to labour market segmentation, market incompleteness and the monetary transmission mechanism.

Empirical labour literature has found that workers face very heterogeneous employment risk over the business cycle (e.g. Hall (2005); Elsby, Hobijn, and Sahin (2010); Davis and Haltiwanger (2014); Elsby, Hobijn, and Şahin (2015); Haltiwanger, Hyatt, and McEntarfer (2018)).[5] In particular, Hobijn, Sahin, and Song (2010) and Hoynes, Miller, and Schaller (2012) document that workers in cyclical industries experience steeper rises in unemployment rates during economic downturns, indicating that they face higher unemployment risk. More recently, Chapuis and Coglianese (2024) use a nonparametric machine learning approach on millions of workers in the US and find that workers in cyclical industries experience higher unemployment risk. They also find that the difference in unemployment risk between the most and least exposed workers is larger in these industries.

In the paper, I relate to the growing literature studying monetary policy transmission in HANK models with search and matching frictions. I build on the previous work by Gornemann, Kuester, and Nakajima (2016); Challe and Ragot (2016); Den Haan, Rendahl, and Riegler (2017); Ravn and Sterk (2017); Challe, Matheron, Ragot, and Rubio-Ramirez (2017); Broer, Harbo Hansen, Krusell, and Öberg (2019); Challe (2020); Ravn and Sterk (2020); McKay and Reis (2021) among others, which incorporated a search and matching framework into an incomplete market model and studied various aspect of monetary policy.[6] Differently from Dolado, Motyovszki, and Pappa (2021), my model generates different labour market outcomes by relying only on sector-specific characteristics without capital-skill complementarity. However, most authors have a single labour market where all workers face the same labour market frictions and hence the same employment risk. I add to this literature by introducing two sectors with different labour market characteristics leading to differences in (sectoral) employment risk.[7]

[5] Previous literature which uncovered differences in employment fluctuations across sectors has mostly focused on explaining underlying factors *leading* to this empirical observation. Among the more prominent explanations for the differential cyclicality of employment across sectors are (i) the durability of goods (Lucas (1977)), (ii) labour hoarding (Bernanke and Parkinson (1991); Burnside, Eichenbaum, and Rebelo (1993)), and (iii) nominal wage rigidities (Bils (1991)).

[6] Some other literature that merges search and matching frictions with incomplete market models but does not study monetary policy includes, for example, Krusell, Mukoyama, and Sahin (2010); Graves (2020); Kekre (2021).

[7] In this sense, my approach is similar to Herman and Lozej (2022). They use a HANK model to study how differences across labour market segments but with only one goods sector—where segments differ in terms of households' labour productivity—affect monetary policy transmission.

I also relate to the literature studying monetary policy transmission in a multi-sector framework. Whereas this is a standard and well-explored feature in the RANK framework (Aoki (2001); Woodford (2010); Petrella and Santoro (2011); Carvalho and Nechio (2016); Cantelmo and Melina (2017)), it remains rather unexplored in HANK models. Interactions between elements of a multiple-sector environment—relative prices and relative demands—and incomplete markets—MPC heterogeneity and precautionary saving motive—can give rise to new channels (or reinforce existing ones) while making others less important. For example, Auclert, Rognlie, Souchier, and Straub (2021) use a small open economy model, where relative prices of domestic vs foreign goods matter, with heterogeneous agents and show that this setup can change predictions about the potency of monetary transmission relative to the standard RANK model. However, to the best of my knowledge, these interactions have not been studied in a closed economy.

An important feature of the paper is also the role of the cyclicality of income risk in the transmission of monetary policy (see, e.g., Werning (2015); Bilbiie (2018); Auclert, Rognlie, and Straub (2018); Bilbiie (2020); Challe (2020); Acharya and Dogra (2020); Ravn and Sterk (2020) among others). The literature generally finds that the effectiveness of monetary policy and the determinacy of equilibrium in HANK models crucially depends on the cyclical properties of income risk. Empirical evidence suggests that the skewness of income growth rates is procyclical—in booms, large positive income shocks are more likely than large negative ones.[8] In my model, income risk is procyclical; the income gap between the high- and the low-income state (employed vs unemployed) is large during an expansion; employed households receive procyclical income comprising wages and dividends, net of taxes, whereas unemployed households receive constant unemployment benefits.

Another strain of literature studying the effectiveness of monetary policy focuses on the differential exposure of individuals to aggregate fluctuations. Here, the amplification or dampening arises due to the interaction between individual MPC and the incidence of aggregate income. For example, Patterson (2023) looks at the covariance between MPC and the elasticity of individual income to aggregate income. She finds that if individuals more exposed to fluctuations in aggregate income have higher MPCs, an amplification follows after an aggregate shock. Similarly, Bilbiie (2018) shows that the amplification mechanism of an aggregate shock depends on the cyclicality of income of constrained individuals, i.e. high MPC individuals. This mechanism is operative in my model; higher employment risk in the cyclical sector increases MPCs in that sector, pushing sectoral and aggregate demand even further via a standard Keynesian multiplier effect.

The paper also discusses the role of sectoral demand spillovers in the amplification of aggregate demand. Caramp, Colino, and Restrepo (2017) find that employment in

[8] See Guvenen, Ozkan, and Song (2014); Busch, Domeij, Guvenen, and Madera (2022); Guvenen, McKay, and Ryan (2022).

durable manufacturing industries is more cyclical than in other industries and that this cyclicality is amplified in general equilibrium at the commuting zone level. They identify a potential source of propagation operating via demand spillovers; lower consumption by laid-off workers working in durable industries may affect demand in non-durable industries, which further reduces employment in durable industries.[9] In my model, sectoral spillovers are driven by demand effects and differences in labour market characteristics across the two sectors. A higher separation rate in the cyclical sector makes production relatively cheaper than in the non-cyclical sector. As a result, there is a labour and goods spillover from the non-cyclical towards the cheaper cyclical sector, increasing households' income and consumption in the cyclical sector.

Broer, Druedahl, Harmenberg, and Öberg (2021) study the role of the "unemployment-risk channel" for the amplification of business cycles. In their model, a contractionary shock is endogenously amplified through workers' accumulation of precautionary savings. The latter reduces aggregate demand and intensifies recession. Their link between unemployment risk and aggregate demand is very similar to the reasoning in my model, yet, there are important differences between models. First, they have a unified labour market, and in my framework labour market is segmented. Second, they have endogenous separations and sluggish vacancy creation, whereas I have a constant exogenous separation rate and free-entry condition for new vacancies. Finally, I do not impose zero liquidity, meaning that employment risk in my model is not mapped one-to-one to consumption risk because households have access to an additional savings vehicle.

Structure of the paper. The remainder of the paper is structured as follows. Section 2 shows how employment risk affects the amount of precautionary savings using a stylised consumption-savings model. Section 3 presents the empirical evidence on employment risk and net liquid asset holdings across sectors. Section 4 describes the quantitative model, Section 5 discusses the results, and Section 6 concludes.

2 Employment Risk and Precautionary Savings

This section shows how employment risk affects consumption in a stylised consumption-saving model, which will be helpful when discussing results from a quantitative model in Section 4. Employment risk is a function of a constant separation rate and a stochastic job finding rate, where the latter is modelled as an AR(1) process.[10]

Time is discrete, denoted as $t = 1, 2, 3, \ldots$. Consider a household that was employed

[9]More recently, Guerrieri, Lorenzoni, Straub, and Werning (2022) shows in a two-sector HANK model with incomplete markets how a shutdown of a sector can lead to insufficient demand in other sectors of the economy and cause a recession.

[10]This specification is consistent with the empirical observation by Shimer (2012), that fluctuations in the job finding rate explain 75% of the fluctuations in the US unemployment rate.

at the end of period $t-1$. At the beginning of each subsequent period t, there is an exogenous probability $\delta \in [0,1]$ that the household will be separated from its current job. If separated, then a household immediately engages in a job search. The probability of finding a new job is given by the job finding rate M_t. If a household fails to secure a new job within the same period, it becomes unemployed with probability $s_t \equiv \delta(1-M_t)$. A household remains employed with probability $(1-s_t) \equiv 1-\delta(1-M_t)$.[11]

Each period, a household solves the following maximization problem

$$\max_{c_t, a_{t+1}} u\left(c_t\right) + \beta\,\mathbb{E}\,u\left(c_{t+1}\right) \tag{1}$$

subject to

$$c_t + a_{t+1} \leq Ra_t + \left(1-s_t\right)\overline{w} + s_t\,\overline{b}. \tag{2}$$

Here, the felicity function $u(c)$ is a standard constant elasticity of substitution (CES) function, with $u' > 0$, $u'' < 0$, and $u''' > 0$, c_t is consumption in period t, and a_t are asset holdings at the beginning of period t. If employed, a household earns a constant wage $\overline{w}$ and, if unemployed, then receives an unemployment benefit $\overline{b}$, where $\overline{b} \leq \overline{w}$.

The solution to the problem yields the standard Euler equation

$$u'(c_t) \leq \beta R \mathbb{E}\left[u'\left(c_{t+1}\right)\right]. \tag{3}$$

To analyse the effect of employment risk on precautionary saving, I derive a second-order Taylor expansion of the right-hand side of (3) around c_t to obtain

$$u'(c_t) \approx \beta R \mathbb{E}\left[u'(c_t) + u''(c_t)\left(c_{t+1}-c_t\right) + \frac{1}{2}u'''(c_t)\left(c_{t+1}-c_t\right)^2\right]. \tag{4}$$

The expression (4) can be rearranged to obtain the following consumption equation

$$c_t \approx \frac{\beta R - 1}{\beta R}\underbrace{\frac{u'(c_t)}{u''(c_t)}}_{-A(c)^{-1}} + \mathbb{E}\left[c_{t+1}\right] + \frac{1}{2}\underbrace{\frac{u'''(c_t)}{u''(c_t)}}_{-\gamma(c)}\mathbb{E}\left[\left(c_{t+1}-c_t\right)^2\right], \tag{5}$$

where *A(c)* is the coefficient of absolute risk aversion, and $\gamma(c)$ is the coefficient of absolute prudence. The term of interest is the third term in (5), which is associated with the precautionary saving motive—households reduce current consumption and increase savings as a hedge against uncertain consumption in the future.

To simplify the analysis, I assume that a household chooses to hold zero assets in period t.[12] In this case, expected consumption is equal to expected income, $\mathbb{E}\left(c_{t+1}\right) =$

[11] This setup follows the labour market structure used in the quantitative model in Section 4.1.

[12] In a more realistic setup, the precautionary savings channel will depend on the amount of net (liquid) assets a household holds. With sufficiently large asset holdings, this channel becomes negligible.

$\mathbb{E}\left[(1-s_{t+1})\,\overline{w}+s_{t+1}\,\overline{b}\right] \equiv \mathbb{E}\left[(1-\delta\,(1-M_{t+1}))\,\overline{w}+\delta\,(1-M_{t+1})\,\overline{b}\right]$. Using this fact in (5) yields

$$c_t \approx -\frac{\beta R-1}{\beta R}A(c)^{-1}+\overline{w}\,\mathbb{E}\left[1-\delta\,(1-M_{t+1})\left(1-\frac{\overline{b}}{\overline{w}}\right)\right]-\frac{1}{2}\gamma(c)\,\mathbb{E}\left[\left((M_{t+1}-M_t)\left(\overline{w}-\overline{b}\right)\,\delta\right)^2\right]. \tag{6}$$

Employment risk is captured through a stochastic job finding rate $\{M_t\}$, with $M_t \in [0,1]$. I assume that the job finding rate follows an AR(1) process

$$M_t = (1-\rho)\,\overline{M}+\rho M_{t-1}+\varepsilon_t\,, \qquad \varepsilon_t \sim \text{iid}\,(0,\sigma_\epsilon^2) \tag{7}$$

where $\overline{M} \geq 0$ is the unconditional mean (the steady-state value) of the job finding rate process, $\rho \in [0,1)$ is the persistence parameter, and ε_t is the innovation term. Using the process in (7) in (6) one obtains

$$c \approx -\frac{\beta R-1}{\beta R}A(c)^{-1}+\underbrace{\overline{w}\left[1-\delta\,(1-\overline{M})\left(1-\frac{\overline{b}}{\overline{w}}\right)\right]}_{\equiv\,\mathcal{PI}}-\underbrace{\gamma(c)\left[\frac{\sigma_\epsilon^2}{1+\rho}\right]\left(\overline{w}-\overline{b}\right)^2\delta^2}_{\equiv\,\mathcal{S}}, \tag{8}$$

where the second term is akin to households's permanent income $\mathcal{PI}$ and the last term determines the amount of precautionary saving $\mathcal{S}$.[13] As seen from (8), the amount of precautionary saving $\mathcal{S}$ depends on the separation rate δ, income difference in the two employment states $(\overline{w}-\overline{b})$, and on two parameters describing the job finding rate process: (i) the variance of innovations σ_ϵ^2 and (ii) the persistence parameter ρ.

Proposition 1 (Precautionary savings with an AR(1) process for the job finding rate)**.** *For a given parameter of absolute prudence $\gamma(c)$, income dispersion $(\overline{w}-\overline{b})$, and an exogenous separation rate δ, the amount of precautionary savings $\mathcal{S}$ is larger when (i) the variance of innovations of the job finding rate process σ_ϵ^2 is high and (ii) the persistence parameter ρ is low.*

PROOF: *See appendix A.1.* □

Proposition 1 shows that in this stylised framework, two parameters of the job finding rate process determine the amount of precautionary savings—households accumulate more precautionary savings when exposed to large but transitory changes in the job finding rate. Intuitively, a higher variance of the innovation term means that the household faces larger shocks to the job finding rate, increasing uncertainty about future income. As a result, the household wants to save more to self-insure against these income fluctuations. Similarly, a lower persistence of the job finding rate makes the current job finding rate less informative about the future job finding rate, which increases uncertainty about

[13]The first term on the right-hand side is associated with the intertemporal substitution motive βR and absolute risk aversion $A(c)$.

future income and strengthens the precautionary saving motive.[14]

In Section 4, I build a quantitative model and analyse how differences in employment risk across sectors, modelled as differences in separation rates, affect the monetary policy transmission mechanism. Using Proposition 1, the following two corollaries will be helpful when discussing the results.

Corollary 1.1 (Separation rate and precautionary savings)**.** *For a given parameter of absolute prudence $\gamma(c)$, income dispersion $(\overline{w} - \overline{b})$, and a job finding rate process $\{M_t\}$, the amount of precautionary saving $\mathcal{S}$ is increasing in the separation rate δ.*

Corollary 1.1 states that an increase in the separation rate δ leads to an increase in the precautionary savings $\mathcal{S}$. A higher separation rate increases job loss probability, which increases income uncertainty. Moreover, frequent unemployment makes it more likely for poor households to hit a borrowing constraint. Both factors strengthen the precautionary saving motive. When $\delta = 0$, there are no job separations and, therefore, no employment risk. A household is a permanent income consumer, with consumption equal to the constant wage $\overline{w}$.

The separation rate also affects permanent income $\mathcal{PI}$ via the second term in (8). The following corollary relates the separation rate with permanent income.

Corollary 1.2 (Separation rate and permanent income)**.** *For a given parameter of absolute prudence $\gamma(c)$, income dispersion $(\overline{w} - \overline{b})$, and a job finding rate process $\{M_t\}$, permanent income $\mathcal{PI}$ is decreasing in the separation rate δ.*

This corollary shows how differences in separation rates across sectors affect sectoral permanent income and, therefore, average wealth levels.[15] Higher separation rates lead to more frequent unemployment spells, reducing household lifetime income by preventing them from climbing the job ladder (see, e.g., Ozkan, Song, and Karahan (2023)).

3 Sector-specific Employment Risk and Net Liquid Asset holdings

In the previous section, I show how employment risk affects precautionary savings using a stylised model with a homogeneous labour market. However, literature has found that

[14]Note that the persistence parameter plays a dual role in the model since it also affects permanent income—more persistent shocks have a larger effect on the permanent part of income. Appendix A.2 explores this in more detail. Constantinides and Duffie (1996); Kaplan and Violante (2022), among others, discuss how more persistent income shocks make self-insurance through precautionary savings less effective and more difficult.

[15]The fact that households maintain a target wealth level that is proportional to permanent income is a standard feature of buffer stock models (Carroll (2004)). See Jappelli and Pistaferri (2020) for empirical evidence.

the labour market is far from homogeneous, and there are significant differences in employment risk across sectors over the business cycle.[16] Yet, it is less clear whether these differences in employment risk also translate into differences in precautionary savings. For example, do households working in sectors with high employment risk accumulate more precautionary savings than those working in sectors with low employment risk? If so, are these differences in precautionary savings smaller for wealthier households, as the theory suggests?

This section provides some answers using micro-data containing information on sectoral employment risk and household balance sheets. To the best of my knowledge, no one has yet merged these two data sources and empirically analysed how cross-sectoral differences in employment risk translate into precautionary savings.

Throughout this section, my main data sources are (i) the Survey of Consumer Finance (SCF) data for household balance sheets and (ii) the Longitudinal Employer-Household Dynamics (LEHD) data for sector-specific employment risk. To complement the analysis, I also use data from the Survey of Income and Program Participation (SIPP) for household balance sheets and the Job Openings and Labor Turnover Survey (JOLTS) data for employment risk.[17]

I proceed as follows. First, I select industries into cyclical and non-cyclical sectors using industry-level data of net worker flows. With this information at hand, I show that there are important differences in employment risk between the two sectors, even after I condition net worker flows on identified monetary policy shocks. Next, I estimate how these differences in sectoral employment risk translate into differential holdings of net liquid assets, which is my proxy for the strength of the precautionary saving motive. Finally, I formally test the prediction of Proposition 1.

3.1 Data description

3.1.1 Survey of Consumer Finances.

In the analysis, I use the survey waves between 1989 and 2016. I focus on households with at least two members, who are either married or live together, who obtain labour

[16]For example, Hall (2005) compares employment reduction across industries during recessions and finds that cyclically-sensitive sectors, such as Construction and Manufacturing, shrink the most.

[17]There are some important differences among data sets. For example, the SIPP survey oversamples households in low-income areas, whereas the SCF oversamples high-income households. (see, e.g., Czajka, Jacobson, and Cody (2003), Eggleston and Klee (2015), and Eggleston and Gideon (2017) for a detailed comparison between the SCF and the SIPP wealth data). Another difference is the data frequency. The SCF is a triennial survey, whereas the SIPP data are available annually, with some gaps. Similarly, there are differences between the LEHD and the JOLTS data sets. The JOLTS is a survey covering approximately 16,000 business establishments each month. The LEHD is administrative data constructed from various administrative sources, such as the Quarterly Census of Employment and Wages, Unemployment Insurance earnings data, and surveys and censuses. The advantage of the JOLTS data relative to the LEHD data is that the JOLTS has information on quits versus layoffs, while the LEHD does not have it.

income from the same sector—where one member could be unemployed or not in the labour force—and the household head is between 25 and 55 years old. These restrictions allow me to focus on households in their prime working age, who pool income risk and are exposed to the same sector-specific employment risk.[18]

Net liquid assets. The definition of net liquid assets is the same as in Bayer, Luetticke, Pham-Dao, and Tjaden (2019). Specifically, net liquid assets comprise the money market, checking, savings, and call accounts, certificates of deposit, private loans, and bond holdings minus credit card debt.[19] The data is measured in real terms, i.e. CPI adjusted to 2016 dollars.

Income. I employ two income measures that vary based on the types of income households receive. The first measure includes all income sources—earned, unearned income, and government transfers. This choice is motivated by the fact that to quantify precautionary savings accurately, it is crucial to take into consideration all alternative income sources that can mitigate earnings losses during unemployment spells. As an alternative, I also consider a more narrow income measure which includes only earned income— wages, salary income, and income from businesses, sole proprietorships, and farms.[20] Both income measures are expressed in real terms, before tax, and annualised. Summary statistics of the SCF sample can be found in the left panel of Table B.2.1 in the appendix.

3.1.2 Survey of Income and Program Participation.

Another source of information on household balance sheets is the Survey of Income and Program Participation (SIPP) by the US Census Bureau. The main advantage of SIPP relative to SCF is that it oversamples low-income households and provides better information on households that are more likely to be affected by job losses. The shortcoming of the SIPP survey is that it misses some asset classes and is not as detailed as the SCF. As in the SCF sample, I focus on households with at least two members who are either married or live together, obtain labour income from the same sector (where one member can be unemployed or not in the labour force), and the household head is between 25 and 55 years old.

[18]Restricting the sample to households where both members work in the same sector is very restrictive and reduces the sample considerably. Therefore, I also allow for instances where one household member is working and the other one is not doing any work for pay.

[19]As an alternative, I also consider a more narrow definition of net liquid assets by Kaplan, Moll, and Violante (2018), which includes money market, checking, savings, and call accounts, government and corporate bonds net of credit card debt.

[20]Note that income from sole proprietorship and business can occasionally be negative, potentially resulting in a negative earned income. However, in my sample, such instances are infrequent, accounting for less than 0.5 percent of the sample. Following Kaplan, Violante, and Weidner (2014), I exclude these from the analysis.

Net liquid assets. Data on the (net) wealth of households are part of topical modules and thus available only at certain waves.[21] Focusing on these waves provides information on households' balance sheets for years between 2001–2005, 2009–2011, and 2013–2016. In total, this yields 12 years of observations. For surveys before 2014 Panel Waves, I calculate net liquid assets as the sum of municipal or corporate bonds and/or US government securities, interest-bearing checking accounts, savings accounts, money market, certificate of deposit, and non-interest checking accounts minus store bills or credit card debt. In 2014, the US Census Bureau redesigned the SIPP and changed some variables I use to calculate net liquid assets. Therefore, for 2014 Panel Waves 1–4, I calculate net liquid assets as the sum of the value of assets held at financial institutions (checking and savings account, CDs, non-interest checking account), the value of other interest-earning assets (municipal or corporate bonds and/or US government securities) minus store bills or credit card debt.

Income. I use the same income measures as in the SCF sample.[22] The data is CPI adjusted to 2016 dollars. Summary statistics of the SIPP sample can be found in the right panel of Table B.2.1 in the appendix.

3.1.3 Longitudinal Employer-Household Dynamics.

My main measure of employment risk is net worker flows, which I obtain from the Longitudinal Employer-Household Dynamics (LEHD) database.[23] I define net worker flows as the difference between hire and separation rates to nonemployment.[24] The advantage of the LEHD data is that it has extensive coverage; it covers approximately 95 percent of private sector employment, state and local government, and in addition, it also includes some individual demographic and firm characteristics.[25] From the LEHD data, I use the information on workers' age, gender, and two-digit industry classification. The data are quarterly and cover the period 2001q2–2017q3. To make it comparable with the SCF data, I focus on workers between 25 and 55 years old.

I calculate two measures of net worker flows, depending on the definition of nonemployment. The first measure of net worker flows uses flows to and from *persistent nonemployment*. The second measure uses flows to and from *full-quarter nonemployment*. The difference between persistent and full-quarter nonemployment is whether nonemployment

[21] In the SIPP data, these are following Panel Waves: 2001 Panel Waves 3, 6, and 9; 2004 Panel Waves 3, and 6; 2008 panels waves 4, 7, and 10; 2014 Panel Waves 1, 2, 3, and 4.

[22] Note that in the SIPP sample, individual annual income is top-coded at $150,000.

[23] The LEHD data is publicly available administrative data from the US Census Bureau. The data is compiled from various administrative sources, such as the Quarterly Census of Employment and Wages, Unemployment Insurance earnings data, surveys and censuses.

[24] I use rates to make worker flows in and out of employment comparable across sectors. I abstract from job-to-job flows because I am interested in employment risk, and voluntary quits for, e.g., better-paying jobs are not part of it.

[25] For more details about the LEHD data see Abowd, Stephens, Vilhuber, Andersson, McKinney, Roemer, and Woodcock (2009).

also includes workers who have single-quarter jobs in the quarters following a separation from the main job. For example, workers with transitory jobs are included in persistent nonemployment but not in full-quarter nonemployment.[26] Both measures of net worker flows are expressed as a share of average employment within the sector. Summary statistics of the LEHD sample are shown in the top panel of Table B.2.2 in appendix.

3.1.4 Job Openings and Labor Turnover Survey.

As an alternative measure of employment risk, I calculate net worker flows from the Job Openings and Labor Turnover Survey (JOLTS) data. JOLTS is a monthly survey that provides information on hires, separations, layoffs and discharges across two-digit industries, but in contrast to the LEHD, there is no information on worker demographics. The advantage of the JOLTS data relative to the LEHD is that it contains information on quits versus layoffs and discharges, which is the relevant margin for employment risk. To ensure comparability with the LEHD data, I average the monthly data to a quarterly frequency and restrict the sample to the period between 2001q2–2017q3. The data is seasonally adjusted. As for the LEHD sample, net worker flows are expressed as a share of average employment within the sector. The bottom panel of Table B.2.2 in appendix presents some summary statistics of the JOLTS sample.

3.2 Employment risk in Cyclical and Non-cyclical sectors

To determine whether households in the SCF sample belong to cyclical or non-cyclical sectors, I first need to classify which industries are cyclical and which are non-cyclical. However, I cannot directly infer industry cyclicality from the SCF data itself because the survey is triennial, and one needs information at a business cycle frequency to capture differences in cyclicality. To address this, I rely on the Longitudinal Employer-Household Dynamics (LEHD) data. However, the LEHD and the SCF data set are not fully comparable in terms of industries; in the publicly available SCF data, the standard four-digit North American Industry Classification System (NAICS) industries are merged into seven distinct SCF-industry groups for confidentiality reasons. To bridge this gap and relate the SCF data with the LEHD data, I establish a correspondence between 20 two-digit NAICS industries from the LEHD dataset and the seven industry groups defined in the SCF. The mapping is relatively straightforward in most cases, as each two-digit NAICS industry

[26] Note that for the LEHD data, nonemployment is defined as the lack of the main job, not the lack of a job. Moreover, the lack of the main job at the end of a quarter does not necessarily mean that a worker has no observed earnings in that quarter or the following quarter. In fact, a worker could have a single quarter job during either of these quarters and still be considered nonemployed in the LEHD data. However, roughly 90 percent of transitions to/from persistent nonemployment have zero earnings the quarter after separating or before starting their new job. For that reason, I find net worker flows a good proxy for the employment risk (see Hyatt, McEntarfer, McKinney, Tibbets, Vilhuber, Walton, Hahn, and Janicki (2017)).

from the LEHD dataset aligns with a single SCF-industry group. However, there are instances where an industry spans two SCF groups. In such cases, I assign the industry to the SCF-industry group, where this industry has the largest employment share. For a more detailed discussion on how I map LEHD industries into SCF groups, see appendix B.1.1.

3.2.1 Identification of cyclical and non-cyclical sectors in the SCF sample

To identify cyclical and non-cyclical sectors, I regress net worker flows on a business cycle measure and controls

$$F_{i,g,t} = \alpha_i + Ind_g + \delta \left(SCF_{ind.group} \times X_t \right) + \tau_t + Ind_g \times \tau_q + \epsilon_{i,g,t} \, , \tag{9}$$

where $F_{i,g,t}$ are net worker flows with characteristics i in industry g at time t, α_i are gender and age fixed effects, and Ind_g captures industry-specific unobservable characteristics, and X_t is a measure of the business cycle.[27] $SCF_{ind.group}$ is the mapping of the LEHD industry into the SCF-industry group, τ_t are year-by-quarter fixed effects controlling for common shocks in the economy, and $Ind_g \times \tau_q$ are industry-by-quarter fixed effects to control for industry-specific seasonality since the LEHD data is not seasonally adjusted. The coefficient of interest is δ, which measures the differential responsiveness of net worker flows to business cycle fluctuations across SCF groups relative to the US average.

Table 1 reports results from estimating (9). In the left panel of Table 1, I use flows from/to persistent nonemployment as the dependent variable, while in the right panel, I use flows to/from full-quarter nonemployment. Columns 1 and 4 show the results using the change in (the negative of) the log of real GDP as a business cycle measure. In columns 2 and 5, I use dummies for NBER recession episodes, while in columns 3 and 6, I use changes in the log of unemployment level. For all specifications, net worker flows in SCF-industry groups 2 and 3 are consistently more sensitive to business cycle fluctuations than the US average. In contrast, net worker flows in SCF-industry groups 6 and 7 are consistently less sensitive. The sensitivity of net worker flows in other SCF-industry groups is not statistically significantly different from the US average.

[27] I consider the change in (the negative of) the log of real GDP, the change in the log of unemployment, and NBER recession episodes

Table 1: Cyclicality of SCF-industry groups

	Net worker flows Persistent nonemployment			Net worker flows Full-quarter nonemployment		
	(1)	(2)	(3)	(4)	(5)	(6)
SCF–ind. group 1	0.024	-0.001	0.002	0.013	-0.001	-0.002
	(0.145)	(0.002)	(0.017)	(0.138)	(0.002)	(0.016)
SCF–ind. group 2	-0.533***	-0.005***	-0.056***	-0.495***	-0.004***	-0.051***
	(0.107)	(0.002)	(0.012)	(0.102)	(0.002)	(0.011)
SCF–ind. group 3	-0.251***	-0.005***	-0.040***	-0.244***	-0.005***	-0.039***
	(0.085)	(0.001)	(0.008)	(0.081)	(0.001)	(0.008)
SCF–ind. group 4	0.018	0.000	0.001	0.002	-0.000	-0.002
	(0.073)	(0.001)	(0.007)	(0.069)	(0.001)	(0.006)
SCF–ind. group 5	0.072	0.002*	0.018**	0.081	0.001	0.016**
	(0.074)	(0.001)	(0.007)	(0.070)	(0.001)	(0.007)
SCF–ind. group 6	0.212***	0.003***	0.027***	0.205***	0.003***	0.024***
	(0.070)	(0.001)	(0.007)	(0.067)	(0.001)	(0.006)
SCF–ind. group 7	0.426***	0.008***	0.068***	0.396***	0.008***	0.063***
	(0.076)	(0.001)	(0.007)	(0.073)	(0.001)	(0.007)
Observations	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.89	0.89	0.89	0.90	0.89	0.90

Notes: This table shows results from OLS regressions with various proxies for the business cycle and different measures of net worker flows. All results are relative to the US average net worker flows. In the left panel of Table 1, I use flows from/to persistent nonemployment as the dependent variable, while in the right panel, I use flows to/from full-quarter nonemployment. Column 1(4) shows the results using $-\Delta$ *log real GDP* as a business cycle measure; in column 2(5), I use dummies indicating *NBER recession episodes*, and in column 3(6), I use Δ *log of unemployment level*. All regressions include controls for worker characteristics (gender and age), two-digit industry classification, year-by-quarter fixed effects, and industry-by-quarter fixed effects. Standard errors are corrected for heteroskedasticity.

Based on the results presented in Table 1, I classify SCF-industry groups 2 and 3 as "cyclical sectors" and SCF-industry groups 6 and 7 as "non-cyclical sectors". Cyclical sectors comprise Mining, Quarrying, Oil and Gas Extraction, Construction, and Manufacturing. Non-cyclical sectors include Utilities, Transportation and Warehousing, Information, majority of Services, Health Care and Social Assistance, and Public Administration.[28]

[28]Geremew and Gourio (2018) study the cyclicality of US employment across industries using the Cur-

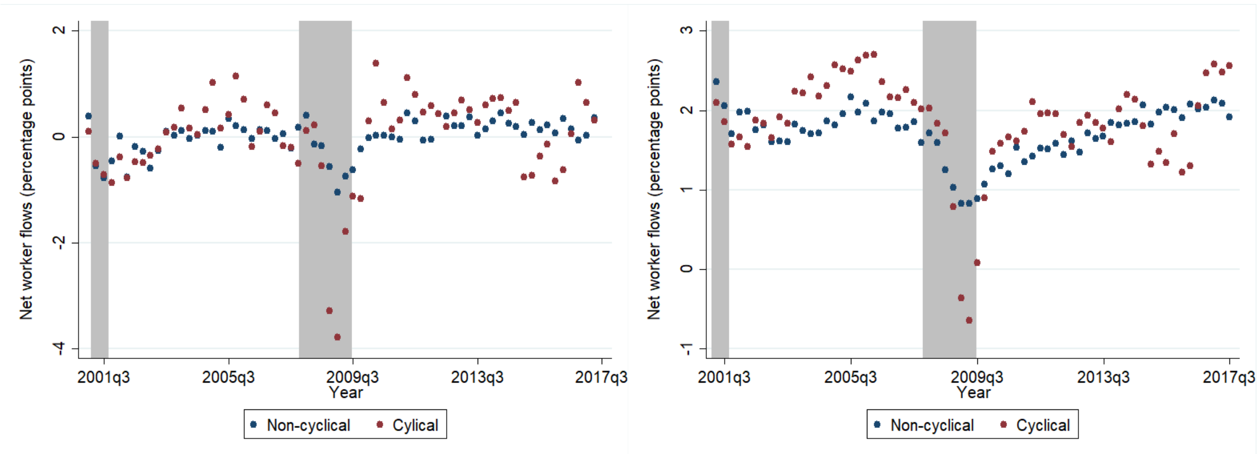
However, due to the specific role of Public Administration and to mitigate any potential concerns that this sector drives my results, I exclude it from the analysis altogether.

3.2.2 Employment risk in cyclical and non-cyclical sectors

Figure 1 shows net worker flows in cyclical and non-cyclical sectors over the business cycle. The selection into cyclical and non-cyclical sectors is based on results in Table 1. There are significant differences in the magnitude and volatility of net worker flows between the two sectors. For example, workers in cyclical sectors are more likely to lose a job during a downturn but also more likely to gain one during an expansion than workers in non-cyclical sectors. Moreover, the standard deviation of net worker flows in cyclical sectors is twice as large as in non-cyclical sectors, implying that workers in cyclical sectors experience higher employment risk than those in non-cyclical sectors.[29]

Figure 1: Net worker flows in cyclical and non-cyclical sectors

(A) LEHD (B) JOLTS



Notes: PANEL (A): Net worker flows are calculated as the difference between hire and separation rates to persistent nonemployment. Hire and separation rates are flows in and out of persistent nonemployment normalised by employment, and multiplied by 100. PANEL (B): Net worker flows are calculated as the difference between hires and layoffs & discharges, expressed as a share of employment and multiplied by 100. Quarterly data are obtained by averaging monthly data of the corresponding quarter. Both panels cover the period 2001q2–2017q3. Data is seasonally adjusted by including quarter-by-sector fixed effects. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1. Shaded areas denote NBER recession episodes.

rent Employment Statistics survey and find that Construction, Mining and Manufacturing have the most cyclical employment. At the same time, Public Administration, Education and Other services are the least cyclical. Similarly, McLaughlin and Bils (2001) analyse 22 industries between 1964 and 1995 using the BLS survey of establishments and finds that employment fluctuations are largest in Construction and all Durable Manufacturing industries. In contrast, Agriculture, Food and Tobacco, Communication and Utilities, Public Administration, and the majority of Services exhibit the lowest cyclical movements.

[29]Section C.2 in the appendix displays gross worker flows (hire and separation rates) over the business cycle, confirming that worker flows are larger and more volatile in cyclical sectors than in non-cyclical sectors. See also Table B.2.2 in the appendix for summary statistics of worker flows.

All in all, the results presented are in line with Guvenen, Schulhofer-Wohl, Song, and Yogo (2017), which shows that the earnings of workers working in cyclical industries are the most exposed to business cycle fluctuations. They find that most exposed workers are working in Construction and Durable Manufacturing, whereas the least exposed are workers in Transportation, Health and Education.

3.2.3 Employment risk conditional on identified monetary policy shocks

All results presented until now are unconditional, i.e. differences in net worker flows are driven by different shocks at different horizons. However, I am interested in how differences in employment risk across sectors affect the transmission mechanism of monetary policy, hence, I condition sectoral net worker flows on identified monetary policy shocks. I use the local projections (LP) method introduced by Jordà (2005) and regress net worker flows on a US monetary policy shocks series, its lagged values, and additional controls.[30] The US monetary policy shocks come from the work by Bu, Rogers, and Wu (2021).[31] The data is quarterly, seasonally adjusted, and covers the period 2001q2–2017q3.

I estimate the following LP model for cyclical and non-cyclical sectors separately

$$F_{t+h} = \alpha_h + \tau_h t + \varphi_h \, \nu_t + \sum_{q=1}^{Q} \omega^F_{h,q} \, F_{t-q} \; + \sum_{k=1}^{K} \omega^C_{h,k} \, C_{t-k} + \, \epsilon_{t+h} \,, \tag{10}$$

where F_t are net worker flows, ν_t is the series of monetary policy shocks, C_t are additional controls (the log of real GDP and the log of unemployment), and τ_h is the coefficient on the linear time trend. The projection horizon is 12 quarters ($h = 0, ..., 12$). Since I have quarterly data, I opt for 4 lags in both the lagged dependent variable and in the controls ($K = Q = 4$).[32] The impulse responses are constructed based on the estimated coefficient φ_h. Standard errors are adjusted for heteroskedasticity and autocorrelation (Newey–West standard errors).

Figure (2) shows the impulse responses of net worker flows to an expansionary monetary policy shock across the two sectors for the LEHD and the JOLTS samples. The shock is defined as an annualised 1 standard deviation decrease in the monetary policy shock series.[33] I find that in both samples, net worker flows in non-cyclical sectors are much less responsive than in cyclical sectors, conditional on a monetary policy shock. While the

[30] See Ramey (2016) for a detailed discussion of the approach.

[31] The advantage of this series relative to other monetary policy shock series found in the literature is that it is purged of the "Fed information effect". The series can be found here: `https://www.federalreserve.gov/econres/feds/a-unified-measure-of-fed-monetary-policy-shocks.html`.

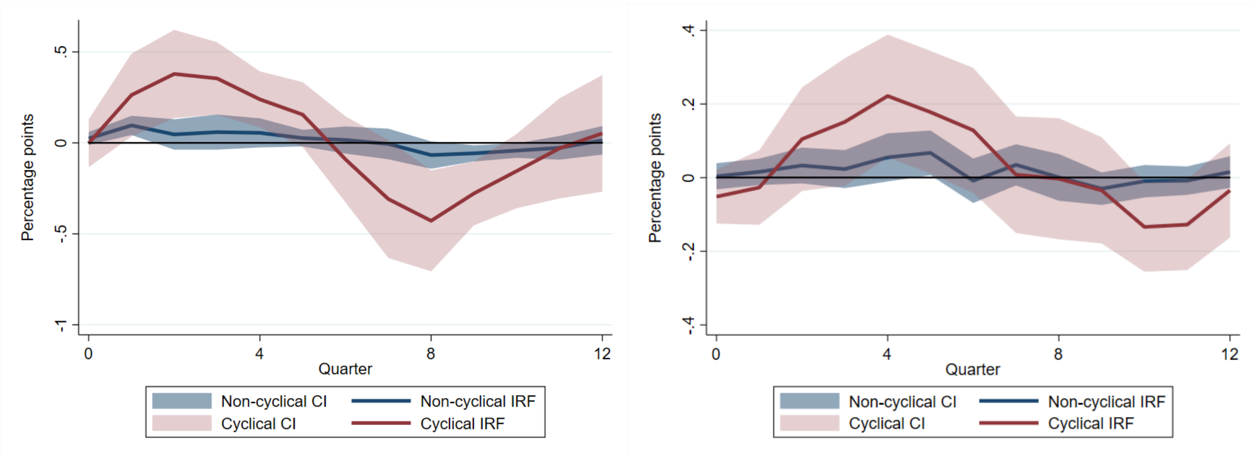
[32] While pre-testing for the number of lags suggests 3 lags in my model, I add an additional lag. As Montiel Olea and Plagborg-Møller (2021) shows, adding an extra lag of the control variables—lag augmentation—significantly simplifies and robustifies LP inference.

[33] Appendix C.4.1 shows the effect of expansionary monetary policy shocks on the real interest rate, aggregate unemployment rate, and sectoral unemployment rates.

timing and the size of peaks in cyclical sectors are somewhat different in the two samples, the dynamic of net worker flows is surprisingly similar.[34]

Figure 2: Responses of net worker flows conditional on a monetary policy shock

(A) LEHD (B) JOLTS



Notes: This figure shows impulse responses following an expansionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors). Selection into the cyclical and non-cyclical sector is based on results in section 3.2.1.

What could explain these results? To get some insight into the underlying dynamics of net worker flows, I plot impulse responses for each margin separately, that is, hiring and separations (see Figures C.4.3 and C.4.4 in appendix). While there are differences in the cyclicality of hiring, it seems that it is indeed the separation rate that contributes somewhat more to differential responses of net worker flows in the two samples. This result is in line with Broer, Druedahl, Harmenberg, and Öberg (2021), who find that the job separation rate contributes almost 60% to fluctuations in the unemployment rate conditional on an identified monetary policy shock. All in all, although results come with a decent amount of uncertainty, it is reassuring that the difference in the cyclicality of net worker flows across sectors persists even after I condition flows on an identified monetary shock.

3.3 Holdings of Net Liquid Assets in Cyclical and Non-cyclical sectors

Do households working in cyclical sectors and experiencing higher employment risk have a stronger precautionary savings motive than otherwise similar households who work in non-cyclical sectors? If so, is this motive stronger for poorer households? Standard incomplete-markets literature suggests that households with greater income risk should hold more liquid assets for a precautionary reason. Moreover, this self-insurance motive

[34] Hubert and Savignac (2023) use French data and find that flows into unemployment, conditional on identified monetary policy shocks, are larger for more cyclical sectors.

should be even more important for poor households because they are more likely to be borrowing-constrained. In this section, I empirically test these predictions: (i) are there differences in net liquid asset holdings between sectors, and (ii) do these differences in net liquid asset holdings between sectors vary across the wealth distribution?

To shed light on these two questions, I sort households into net wealth quintiles and estimate the relationship between net liquid asset holdings and the cyclicality of a sector using the following regression

$$Y_{i,q,c,t} = \gamma + \gamma_c + \gamma_q + \gamma_t + \phi\left(\gamma_c \times \gamma_q\right) + \Theta X_{i,t} + \gamma_s + \tau_{t,s} + \epsilon_{i,q,c,t}\ , \tag{11}$$

where $Y_{i,q,c,t}$ is the amount of net liquid assets held by a household i, who is in quintile q of net wealth distribution, working in sector c, at time t. γ is an intercept, γ_c is a dummy variable for working in a cyclical sector, γ_q is a dummy for being in quintile q, γ_t are year-fixed effects, γ_s are US state-fixed effects, $\tau_{t,s}$ are state-by-year fixed effects, allowing for unobserved state-level heterogeneity to vary over time, and $X_{i,t}$ is a vector of household characteristics.[35]

The coefficient of interest is ϕ, which measures the difference in net liquid asset holdings in quintile q between households working in cyclical and non-cyclical sectors. The idea is that once I control for all relevant households' observables and partial-out all other savings motives (e.g., intertemporal, bequest, life-cycle, smoothing), the only difference in net liquid assets of comparable households with similar wealth across the two sectors can be attributed to the precautionary savings motive due to differences in employment risk.

In Figure 3 are results from estimating (11). The left panel shows results using the SCF data, and the right panel shows results using the SIPP data. Households working in cyclical sectors tend to hold more net liquid assets than households with similar characteristics and similar wealth working in non-cyclical sectors. This difference is statistically significant for poor(er) households, amounting to approximately USD 10,000, and it decreases with net wealth. For the wealthiest households, the difference in net liquid asset holdings is statistically insignificant. These findings remain consistent regardless of the income measure used.

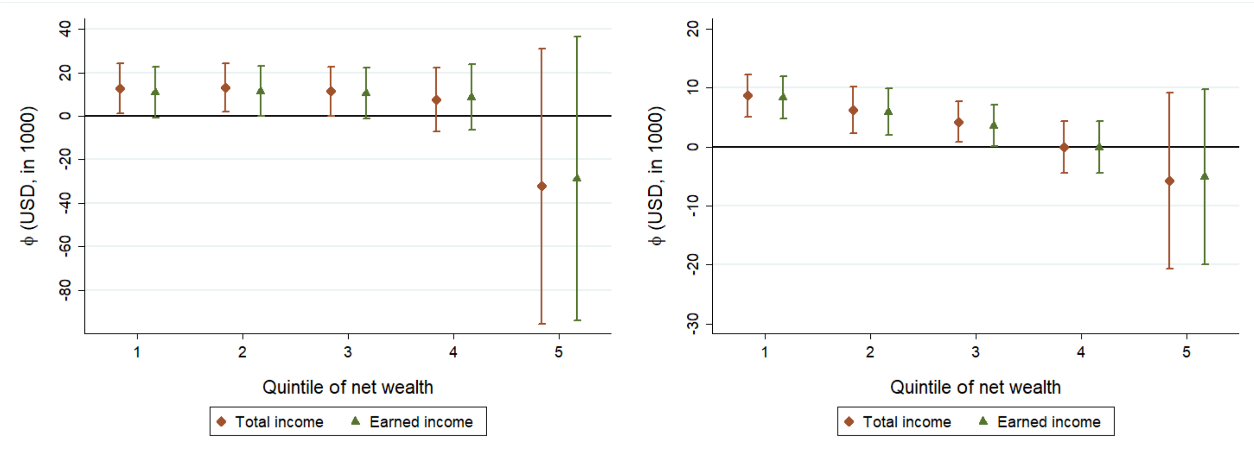
The differences in net liquid assets presented here are in levels. Alternatively, one can also express net liquid assets as a share of household income, making the interpretation somewhat more intuitive.[36] Figure C.5.1 in the appendix presents results where net liquid assets are normalised by annual income. For the SCF sample, the difference in normalised

[35] I include gender, age and age squared, race bins, educational attainment bins, occupation bins, tenure, number of kids, income measure, self-employment dummy, home-ownership dummy, and a dummy indicating whether a household member was unemployed during the past twelve months. These are standard controls used in the literature (see, e.g., Carroll and Samwick (1998); Lugilde, Bande, and Riveiro (2019)). With the SCF sample, I omit state-fixed effects and state-by-year fixed effects because the information about the state is not publicly available.

[36] One of the downsides of this approach is that the ratio is sensitive to the numerator/denominator levels.

Figure 3: Differences in net liquid assets across sectors

(A) SCF (B) SIPP



Notes: In PANEL (A) are point estimates together with 90 percent confidence intervals using the SCF sample. The regression includes year-fixed effects. PANEL (B) shows point estimates and 90 percent confidence intervals using the SIPP sample. The regression includes state-fixed effects and state-by-year fixed effects to capture any state-specific (unobservable) characteristics and time variation that is common to all households within a state and year. In both panels, I use observations between 2001 and 2016. All nominal variables are adjusted to 2016 dollars. All regressions are computed using survey weights. Standard errors are clustered at the household level.

net liquid assets is statistically significant for the second quintile of the net wealth distribution. I find that households working in cyclical sectors hold approximately 10 percentage points more normalised net liquid assets than comparable households working in non-cyclical sectors, with the difference being the largest for the second quintile of the net wealth distribution. For the SIPP sample, the difference in normalized net liquid assets is similar to that of the SCF sample but statistically significant only when net liquid assets are normalized by earned income.

The finding that households working in cyclical sectors and hence facing higher employment risk hold more net liquid assets is consistent with a stronger precautionary saving motive.[37] Households would like to avoid the situation where they have to reduce their consumption if they lose a job. To avoid this, they save for precautionary reasons. Furthermore, I also find that the difference in holdings of net liquid assets is larger for poor(er) households and that it decreases with net wealth. Due to the large net wealth and thus the ability to effectively smooth their consumption path, households become more homogeneous in terms of consumption risk as their wealth increases.[38]

[37] Empirical estimates of the amount of precautionary savings in an economy are inconclusive. Lugilde, Bande, and Riveiro (2019) and Baiardi, Magnani, and Menegatti (2020) survey empirical studies analysing precautionary savings and find that most work finds some evidence of the precautionary saving motive. Nevertheless, there is no consensus on the importance of the precautionary saving motive in terms of additional savings.

[38] This does not mean that they face the same employment risk. On the contrary, households in cyclical sectors (might) still experience a larger employment risk than households in non-cyclical sectors. However,

A problem that typically arises in the literature estimating the strength of the precautionary savings motive is self-selection into jobs or, in my case, sectors; more risk-tolerant individuals choose to work in more risky industries and also save less—since they are less risk-averse—which downward biases the estimates of income risk on precautionary savings (Browning and Lusardi (1996); Lusardi (1997); Fuchs-Schündeln and Schündeln (2005)). However, this means that, if anything, the difference in net liquid asset holdings between the two sectors in Figure 3 should be even larger.

3.4 Testing predictions of Proposition 1

With the information on sectoral employment risk and precautionary savings, I can test the prediction of Proposition 1. The proposition predicts that households facing large and less persistent changes in job finding rates tend to save more for self-insurance. To construct job finding rates f_t, I use matched monthly Current Population Survey (CPS) data and calculate gross worker flows from March 2002 to October 2017. The data is seasonally adjusted and corrected for time aggregation (see Shimer (2012)).[39]

I estimate the following equation at a monthly and a quarterly frequency

$$f_t = \mu + \rho f_{t-1} + \varepsilon_t \,, \tag{12}$$

where μ is the constant, ρ is the persistence parameter, and ε_t is the innovation term.

they have enough liquid wealth to smooth their consumption path.

[39] Further details on the construction of sectoral job finding rates, sample selection, and restrictions can be found in Section B.1.3 in appendix. Figure C.3.1 in appendix plots job finding rates.

Table 2: Estimation of sectoral job finding rates

	Monthly		Quarterly	
	Cyclical	Non–cyclical	Cyclical	Non–cyclical
μ	0.219	0.243	0.552	0.564
	(0.01)	(0.01)	(0.04)	(0.03)
ρ	0.668	0.769	0.873	0.892
	(0.05)	(0.05)	(0.05)	(0.05)
σ_ε	0.041	0.033	0.044	0.036
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	187	187	63	63

Notes: This table shows results from ML estimation of $f_t = \mu + \rho f_{t-1} + \varepsilon_t$, where μ is the constant, ρ is the persistence parameter, and σ_ε is the standard deviation of the innovation ε_t. The data is seasonally adjusted and covers the period 2002q2–2017q3. To obtain quarterly data, I rescale instantaneous transition rates to a quarterly frequency and then average them within a quarter. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1. Standard errors are corrected for heteroskedasticity and autocorrelation.

Table 2 presents estimates of sectoral job finding rates. I find that the job finding rate in cyclical sectors is less persistent, and the standard deviation of its innovation is larger than in non-cyclical sectors. According to Proposition 1, these characteristics of the job finding rate process are associated with a stronger precautionary savings motive. The results are robust to various specifications, i.e., including a linear time trend, a quadratic time trend, and controlling for heteroskedastic and autocorrelated (Newey-West) standard errors.

4 A two-sector Heterogeneous Agent New Keynesian model

I now build a two-sector HANK model with search and matching frictions. The model extends the previous work by McKay, Nakamura, and Steinsson (2016) and McKay and Reis (2021) and is a version of the general equilibrium incomplete markets model. I depart from the existing literature by introducing multiple sectors that differ in terms of endogenous employment risk.

Environment Time is discrete, and the horizon is infinite. The economy is populated by a continuum of households that live and work either in a Cyclical or a Non-Cyclical sector and face uninsurable idiosyncratic income risk. Income risk takes the form of a change in employment status, with exogenous job separation rates and endogenous job finding rates. Households consume a final good produced by a representative competitive firm that aggregates bundles of intermediate goods from the two sectors into a final good. Intermediate goods in each sector are produced by a continuum of monopolistically competitive firms facing Rotemberg (1982) price adjustment costs and search frictions as in Blanchard and Galí (2010). Intermediate goods firms are held by a mutual fund managed by a risk-neutral manager, who collects profits and distributes them as dividends to employed households. Households can save but not borrow by holding and trading risk-free real bonds issued by the government. Bonds are in positive and constant net supply. The government runs a balanced budget, using linear taxes levied on the income of employed households to pay for unemployment benefits and interest on the constant real bond stock.

4.1 Households

There is a continuum measure one of households who work either in a cyclical or a non-cyclical sector.[40] Households are ex-ante identical but differ ex-post through realisations of their sector-specific employment status $e^x_{it} \in \{0, 1\}$, with $x \in \{C, NC\}$ denoting the respective sector. The sector-specific employment process follows a Markov chain with transition matrix $\Pi^x_{ee'}$ over time. All households have the same productivity level normalised to 1. They enjoy the consumption of the final consumption good and, when employed, inelastically supply one unit of labour.[41] A household i working in sector x solves the following problem

$$V_t(a^x_{it-1}, e^x_{it}) = \max_{c^x_{it},\, a^x_{it}} \frac{\left(c^x_{it}\right)^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_t \left[V_{t+1}\left(a^x_{it}, e^x_{it+1}\right) \right] \tag{13}$$

subject to

$$c^x_{it} + a^x_{it} = (1 + r_t) a^x_{it-1} + I^x_{it}\,, \tag{14}$$

$$a^x_{it} \geq 0\ . \tag{15}$$

Here, c^x_{it} is the final good consumption of household i in sector x at time t, a^x_{it} are real bond holdings, r_t is the ex-post real interest rate, and I^x_{it} is household's real income, which depends on the employment status

$$I^x_{it} = \begin{cases} (1 - \tau^x_t)\left(w^x_{it} + D^x_{it}\right) & \text{if employed } (e = 1) \\ b^x\, \overline{w}^x & \text{if unemployed } (e = 0) \end{cases} \tag{16}$$

[40] I assume that households can not migrate between the two sectors to make the model more tractable. However, this assumption can be relaxed at no cost.

[41] With an inelastic labour supply, households can not self-insure via increased labour supply—therefore, this setup generates a stronger precautionary savings motive relative to the setup with endogenous labour supply.

Employed households receive real wage w_{it}^x and real dividends from intermediate goods firms D_{it}^x, net of taxes τ_t^x. Households who do not find jobs become unemployed and receive unemployment benefits, which are equal to the replacement rate b^x of the sectoral steady-state wage $\overline{w}^x$.

Labour market. Labour market structure closely follows the framework introduced by Blanchard and Galí (2010). In this approach, labour market frictions are captured through hiring costs which are increasing in labour market tightness. The idea is that the expected cost of hiring a household increases when the labour market becomes tighter.[42] In what follows, I describe the labour market in more detail.

Timing and sectoral labour market flows. At the beginning of every period, a fraction $\delta^x \in (0,1]$ of employed households lose their job and join the pool of unemployed households from the previous period. The mass of unemployed households looking for a job at the beginning of period t consists of households who were already unemployed in the previous period and newly separated households

$$U_t^x = U_{t-1}^x + \delta^x N_{t-1}^x, \tag{17}$$

where U_{t-1}^x is the mass of unemployed households from the period $t-1$ and N_{t-1}^x is the mass of employed households before separations occur at the beginning of period t.[43] From this pool of unemployed households, firms hire H_t^x of households who become productive in the same period they are matched with a firm.[44] Sectoral hiring in period t evolves according to

$$H_t^x = N_t^x - (1-\delta^x)N_{t-1}^x. \tag{18}$$

Labour market tightness. Defining labour market tightness as the ratio of hires to the number of unemployed $M_t^x \equiv H_t^x / U_t^x$.[45] Substituting (17) and (18) in the labour market tightness definition yields

$$M_t^x \equiv \frac{H_t^x}{U_t^x} = \frac{N_t^x - (1-\delta^x)N_{t-1}^x}{U_{t-1}^x + \delta^x N_{t-1}^x}. \tag{19}$$

[42] Blanchard and Galí (2010) shows that their approach is similar to a canonical Diamond-Mortensen-Pissarides model with respect to the expected hiring cost; in both approaches, expected hiring costs are increasing in labour market tightness.

[43] There is no voluntary unemployment; all households are either employed or willing to work given the prevailing labour market conditions.

[44] With this timing assumption, households who lose their jobs can get rehired in the same quarter without becoming unemployed.

[45] Note that the latter can also be seen as the job finding rate from the perspective of unemployed households. I use the two terms interchangeably.

Hiring costs. Hiring is costly. The cost per hire in a sector x is equal to

$$\psi^x M_t^x, \tag{20}$$

with $\psi^x > 0$, and is expressed in terms of final consumption good. The sectoral hiring costs are equal to the product of a cost per hire (20) and aggregate sectoral hiring (18)

$$\psi^x M_t^x H_t^x. \tag{21}$$

Wage determination. Wages are flexible. I follow McKay and Reis (2021) and use a version of their wage rule, in which real wages are increasing function of labour market tightness

$$w_t^x = \overline{w}^x \left(\frac{M_t^x}{\overline{M}^x} \right)^{\zeta}, \tag{22}$$

where variables with a bar denote its steady-state values, and ζ^x is the elasticity of wages to labour market tightness, which determines sectoral wage rigidity.

4.2 Firms

4.2.1 Final good

There is a representative competitive final good firm that produces final good, Y_t, by combining a bundle of intermediate goods produced in the cyclical sector Y_t^C and another bundle of intermediate goods produced in the non-cyclical sector Y_t^{NC}, according to the CES aggregator

$$Y_t = \left[\alpha^{1-\eta} \left(Y_t^C \right)^{\eta} + (1-\alpha)^{1-\eta} \left(Y_t^{NC} \right)^{\eta} \right]^{\frac{1}{\eta}}. \tag{23}$$

Here, the parameter α is the cyclical sector output share in total output and $(1-\eta)^{-1}$ is the elasticity of substitution between the two input bundles.[46] Both bundles of sectoral intermediate goods are themselves CES aggregates

$$Y_t^C = \left(\int_0^1 y_{jt}^{\frac{1}{\mu_C}} \, dj \right)^{\mu_C} \qquad Y_t^{NC} = \left(\int_0^1 y_{kt}^{\frac{1}{\mu_{NC}}} \, dk \right)^{\mu_{NC}}, \tag{24}$$

where $\mu_x / (\mu_x - 1) > 1$ is the elasticity of substitution of intermediate goods within a sector.

[46] Note that α effectively determines the size of the cyclical sector in a steady-state, i.e. when relative prices are 1.

The demand for intermediate good j produced in the cyclical sector is

$$y_{jt} = \left(\frac{p_{jt}}{P_t^C}\right)^{-\mu_C/(\mu_C-1)} \left(\frac{P_t^C}{P_t}\right)^{-1/(1-\eta)} \times \alpha Y_t \qquad \forall\, j, \text{ and} \tag{25}$$

while the demand for intermediate good k produced in the non-cyclical sector is

$$y_{kt} = \left(\frac{p_{kt}}{P_t^{NC}}\right)^{-\mu_C/(\mu_C-1)} \left(\frac{P_t^{NC}}{P_t}\right)^{-1/(1-\eta)} \times (1-\alpha)\, Y_t \qquad \forall\, k\,. \tag{26}$$

p_{jt} is the price charged by firm j operating in a cyclical sector, and p_{kt} is the price charged by firm k operating in a non-cyclical sector. Sector-specific price indices are given by

$$P_t^C = \left(\int_0^1 p_{jt}^{\frac{1}{1-\mu_C}}\, dj\right)^{1-\mu_C} \qquad P_t^{NC} = \left(\int_0^1 p_{kt}^{\frac{1}{1-\mu_{NC}}}\, dk\right)^{1-\mu_{NC}}, \tag{27}$$

and the price index of the final good is

$$P_t = \left[\alpha \left(P_t^C\right)^{\frac{\eta}{\eta-1}} + (1-\alpha) \left(P_t^{NC}\right)^{\frac{\eta}{\eta-1}}\right]^{\frac{\eta-1}{\eta}}. \tag{28}$$

Benchmark specification. As my benchmark specification, I consider a special case of (23), where the final good is being bundled together using Cobb-Douglas aggregator ($\eta = 0$)

$$Y_t = \kappa \left(Y_t^C\right)^{\alpha} \left(Y_t^{NC}\right)^{1-\alpha}, \tag{29}$$

where $\kappa \equiv \left[\alpha^{\alpha}(1-\alpha)^{(1-\alpha)}\right]^{-1}$ is a normalisation parameter. The relative demands for good j and good k read

$$y_{jt} = \left(\frac{p_{jt}}{P_t^C}\right)^{-\mu_C/(\mu_C-1)} \left(\frac{P_t^C}{P_t}\right)^{-1} \times \alpha Y_t \qquad \forall\, j, \text{ and} \tag{30}$$

$$y_{kt} = \left(\frac{p_{kt}}{P_t^{NC}}\right)^{-\mu_C/(\mu_C-1)} \left(\frac{P_t^{NC}}{P_t}\right)^{-1} \times (1-\alpha) Y_t \qquad \forall\, k. \tag{31}$$

Price indices in the two sectors are the same as in (27), while the price index of the final good simplifies to

$$P_t = \left(P_t^C\right)^{\alpha} \left(P_t^{NC}\right)^{1-\alpha}. \tag{32}$$

Dividing both sides of (32) by P_{t-1} and defining $\pi_t \equiv P_t/P_{t-1}$, one obtains aggregate inflation

$$\pi_t = \left(\pi_t^C\right)^{\alpha} \left(\pi_t^{NC}\right)^{1-\alpha}. \tag{33}$$

4.2.2 Intermediate goods

Intermediate goods in each sector of the two sectors are produced by a continuum of firms indexed by $m \in \{j,k\}$, where index j corresponds to firms operating in a cyclical sector and k to firms operating in a non-cyclical sector. Firms in both sectors use linear production technology

$$y_{mt} = Z_t \, n_{mt} \,, \tag{34}$$

where n_{mt} is the amount of labour employed by the intermediate goods firm m at time t and Z_t is the common level of labour productivity. Employment in firm m evolves according to

$$n_{mt} = (1-\delta^x)\, n_{mt-1} + h_{mt} \,, \tag{35}$$

with $\delta^x \in (0,1]$ being the sector-specific separation rate, and h_{mt} the amount of new labour employed by a firm m in period t.

Prices in both sectors are sticky and set in a Rotemberg fashion. For ease of exposition, I focus only on the problem for firms operating in the cyclical sector. A firm j operating in the cyclical sector chooses a price p_{jt} subject to hiring costs $\psi^C M_t^C$ and quadratic price adjustment costs $\Theta_t^C = \frac{\alpha\vartheta}{2}\left(\frac{p_{jt}}{p_{jt-1}} - 1\right)^2 Y_t$, with $\vartheta > 0$. The latter costs are measured in terms of the final good and proportional to the sector size. The profit maximisation problem of a firm reads

$$\max_{\{p_{js}, n_{js}, y_{js}, h_{js}\}} \mathbb{E}_t \sum_{s \geq t} \left(\frac{1}{1+r}\right)^{s-t} \left\{ \frac{p_{js}}{P_s} y_{js} - w_s^C n_{js} - \psi^C M_s^C h_{js} - \frac{\alpha\vartheta}{2}\left(\frac{p_{js}}{p_{js-1}} - 1\right)^2 Y_s \right\}, \tag{36}$$

subject to (30), (34), and (35). As shown in appendix D.1, the solution to this problem yields the New Keynesian Phillips curve in the cyclical sector

$$\pi_t^C(\pi_t^C - 1) = \frac{1}{\vartheta(\mu_C - 1)} \underbrace{\left[\mu_C \frac{P_t}{P_t^C}\, mc_t^C - 1\right]}_{\widetilde{mc_t}^C} + \frac{1}{1+r} \mathbb{E}_t\, \pi_{t+1}^C\, (\pi_{t+1}^C - 1) \frac{Y_{t+1}}{Y_t} \,, \tag{37}$$

where $\widetilde{mc_t}^C$ is the deviation of real marginal cost from its steady-state value. The New Keynesian Phillips curve in the non-cyclical sector is

$$\pi_t^{NC}(\pi_t^{NC} - 1) = \frac{1}{\vartheta(\mu_{NC} - 1)} \underbrace{\left[\mu_{NC} \frac{P_t}{P_t^{NC}}\, mc_t^{NC} - 1\right]}_{\widetilde{mc_t}^{NC}} + \frac{1}{1+r} \mathbb{E}_t\, \pi_{t+1}^{NC}\, (\pi_{t+1}^{NC} - 1) \frac{Y_{t+1}}{Y_t} \,. \tag{38}$$

4.3 Government

The government runs a balanced budget, using linear taxes τ_t^x levied on the income of employed households to pay unemployment benefits b and interest on a constant level of real bonds B

$$B + \sum_x \tau_t^x \left(w_t^x + D_t^x\right) N_t^x = B(1 + r_t) + \sum_x \left(b^x\, \overline{w}^x\right) U_t^x. \tag{39}$$

The relation between nominal interest rate, real interest rate, and inflation is given by

$$1 + r_t = \frac{1 + i_{t-1}}{\pi_t}\,. \tag{40}$$

4.4 Monetary authority

In my benchmark specification, the monetary authority sets the path of the real interest rate following a simple rule

$$r_t = \bar{r} + \rho_R (r_{t-1} - \bar{r}) + \epsilon_t\,, \tag{41}$$

where $\bar{r}$ is the real interest rate in steady state, ρ_R determines how fast the real interest rate converges back to its steady-state level, and ϵ_t is a monetary policy shock.[47]

4.5 Equilibrium

Definition. *$\Gamma_t^x\left(a^x, e^x\right)$ is the sector-specific distribution of households over idiosyncratic states that satisfies*

$$\Gamma_{t+1}^x\left(\mathcal{A}, e_{t+1}^x\right) = \int_{\{(a^x,\, e^x):g_t(a^x,e^x)\in\mathcal{A}\}} \Pi_{ee'}^x \; d\Gamma_t^x\left(a^x, e^x\right)\,, \qquad x \in \{C, NC\} \tag{42}$$

where $\mathcal{A} \subset \mathbb{R}_{\geq 0}$. Bond market clearing condition is given by

$$B = \sum_x \int g_t\left(a^x, e^x\right)\, d\Gamma_t^x\left(a^x, e^x\right)\,. \tag{43}$$

Using (34) in (30) and (31), integrating both sides, and taking into account that all firms in a sector face the same problem and hence choose the same price, sectoral production functions are

$$Y_t^C \equiv \alpha \left(\frac{P_t^C}{P_t}\right)^{-1} Y_t = Z_t\, N_t^C\,, \tag{44}$$

[47] This specification allows me to analyse the model without endogenous feedback from other variables on monetary policy. See McKay, Nakamura, and Steinsson (2016), Auclert, Rognlie, and Straub (2018), and Auclert (2019), among others, for a similar approach.

and

$$Y_t^{NC} \equiv (1-\alpha)\left(\frac{P_t^{NC}}{P_t}\right)^{-1} Y_t = Z_t\, N_t^{NC}\,. \tag{45}$$

Real dividends by intermediate firms in sector x are paid to employed households and are equal to

$$D_t^x = \frac{1}{N_t^x}\left(Y_t^x - \psi^x M_t^x H_t^x\right) - w_t^x\,. \tag{46}$$

Aggregate labour supply is equal to the total number of employed households in the economy

$$L_t = \sum_x L_t^x = \sum_x \int d\Gamma_t^x\left(a^x, 1\right) = 1 - \left(U_t^C + U_t^{NC}\right) = 1 - U_t\,, \tag{47}$$

aggregate labour demand by intermediate firms is equal to

$$N_t = \sum_x N_t^x = N_t^C + N_t^{NC}, \tag{48}$$

where market clearing for each sectoral input requires $N_t^C \equiv \int n_{jt}\, dj$ and $N_t^{NC} \equiv \int n_{kt}\, dk$. Sectoral labour market clearing condition reads $L_t^x = N_t^x$. The aggregate labour market clears

$$N_t = L_t\,. \tag{49}$$

The goods market clearing condition requires

$$Y_t = C_t + \psi M_t H_t + \Theta_t\,, \tag{50}$$

where Y_t is aggregate output from (29), $C_t \equiv \sum_x \int c_t\left(a^x, e^x\right) d\Gamma_t^x\left(a^x, e^x\right)$ is aggregate consumption, $\psi M_t H_t \equiv \sum_x \psi^x M_t^x H_t^x$ are aggregate hiring costs, and $\Theta_t \equiv \sum_x \Theta_t^x$ are aggregate price adjustment costs, both expressed in terms of a final consumption good. In equilibrium, all decision rules and value functions satisfy all optimality conditions, definitions, and budget constraints.

4.6 Model calibration

I calibrate the model at a quarterly frequency to the US economy. I consider a "quasi" symmetric model, in which most parameters are identical across the two sectors, except that households in the cyclical sector face higher job separation rates than households in the non-cyclical sector, in line with the empirical evidence in the previous section. I intentionally keep the calibration simple because I am primarily interested in how sector-specific employment risk affects the transmission of monetary policy, and I want to circumvent other confounding factors that would make the analysis less tractable.

Table 3 summarises the baseline calibration of the model. For simplicity, I assume that the two sectors are symmetric in terms of size $\alpha = \frac{1}{2}$. The substitution parameter between sectors η is set to 0 to match the unitary elasticity of substitution between the sectoral bundles of intermediate goods. I set discount factor β to target the steady state annual real interest rate of $r = 3\%$. The Rotemberg price adjustment cost is set to 55, matching the average price duration of 4 quarters. Bond supply B is calibrated to match annual household net liquid assets to income ratio of 0.55 in the data.[48] I set household elasticity of intertemporal substitution to $\gamma = 0.5$ and the steady-state markup for intermediate firms to $\mu = 1.2$, as in Christiano, Eichenbaum, and Rebelo (2011).

Table 3: Baseline calibration

Description	Parameter	Value: Cyclical	Value: Non-cyclical	Target
PREFERENCES				
Discount factor	β	0.9892		Annual real interest rate of 3%
EIS	$1/\gamma$	0.5		Standard
PRODUCTION				
Sector size	α	0.5		Symmetric sectors
Substitutability btw. sectors	η	0		Cobb-Douglas
Markup	μ	1.2		See text
Price adj. costs	ϑ	55		Avg. price duration of 4 qtr.
LABOUR MARKET				
Unemployment rate	U	0.063		Unempl. rate: 2001q2–2017q3
Job separation rate	δ	0.266	0.076	See text
Vacancy posting cost	ψ	0.031		McKay and Reis (2021)
Elasticity of wages w.r.t. labour market tightness	ζ	1		See text
GOVERNMENT				
Bond supply	B	1.803		Avg. liq. assets to income = 0.55
Replacement rate	b	0.4		Avg. repl. rate: 2001q2–2017q3
Shock persistence	ρ_R	0.7		

The steady-state unemployment rate in the economy is set to $U = 6.3\%$, which is the average unemployment rate in the US over the period 2001q2–2017q3. Job separation rates are calibrated to match sectoral transition rates from employment to unemployment observed in the CPS data (see Table B.2.3 in the appendix). This delivers a job separation rate of $\delta^{NC} = 0.075$ in the non-cyclical sector and $\delta^{C} = 0.266$ in the cyclical sector. The replacement rate in both sectors equals $b = 40\%$ to match the average replacement rate in the US in that period.[49] In the baseline calibration, wages are flexible, and the elasticity of

[48] This is an average value of the SIPP estimate (0.61) and the SCF estimate (0.48) for the period 2001–2016. The definition of liquid assets and income is the same as in Section 3.1.

[49] Source: https://oui.doleta.gov/unemploy/ui_replacement_rates.asp.

wages with respect to labour market tightness is set to 1. Vacancy posting costs are equal to $\psi = 0.031$, following McKay and Reis (2021).

4.6.1 Calibration results

Table 4 presents baseline calibration results. The model predicts higher job finding $\overline{M}$ and job loss rates $\bar{s}$ in a steady state for the cyclical sector. It also delivers lower before-tax income for households in the cyclical sector, consistent with the household balance sheet data (see Table B.2.1 in the appendix).

Moreover, the model predicts the aggregate $\overline{MPC}$ of 0.054 at a quarterly frequency, corresponding to an annual value of approximately 0.22, with higher values in the cyclical sector than in the non-cyclical sector.[50] This value is comparable with values from other models and empirical estimates. For example, Parker (1999), Jappelli and Pistaferri (2010), and Parker, Souleles, Johnson, and McClelland (2013) find empirical estimates for the annual MPC between 0.1 and 0.4. Kaplan and Violante (2022) finds that a standard one-asset heterogeneous agent model delivers an annual MPC of approximately 0.15. Moreover, a higher average MPC in the cyclical sector relative to the non-cyclical sector is consistent with Patterson (2020). The paper finds that individuals working in industries more exposed to the Great Recession shock, i.e. more cyclically sensitive industries, have higher MPCs.[51]

Table 4: Steady-state results

Description	Parameter	Aggregate	Cyclical	Non-cyclical
Job finding rate	$\overline{M}$	0.714	0.796	0.523
Job loss rate	$\bar{s}$	0.049	0.054	0.036
Pre-tax income (in USD)			15,920	16,006
– Post-tax income (in USD)	$\bar{I}$		15,321	15,405
Unemployment benefits (in USD)			5,299	5,334
Average MPC (quarterly)	$\overline{MPC}$	0.054	0.061	0.047
– Employed			0.054	0.041
– Unemployed			0.158	0.139
Bond holdings (% of total)			39.10	60.90

What explains these differences in MPC across the two sectors? In the model, the separation rate affects both the level of employment and income dispersion. A higher sepa-

[50]The fact that households in the cyclical sector have higher average MPCs holds across the wealth distribution. Figure E.1.1 in the appendix plots average MPCs across sectors for different quintiles of the sectoral wealth distribution.

[51]The most exposed industry was construction, and the least exposed industry was education.

ration rate not only increases the probability of households being unemployed each period but also increases income dispersion and, therefore, income risk.[52] Carroll, Holm, and Kimball (2021) shows that both effects—income risk and the presence of borrowing constraints—make the consumption function more concave, heightening the prudence and strengthening the precautionary saving motive.[53] With a concave function, MPCs are very large in the region where the gradient of the consumption function is large, i.e. where the poor households are. This has important implications for the magnitude of sectoral responses to additional income after an expansionary monetary policy shock.

Figure 4 plots consumption functions and MPCs for employed and unemployed households in the two sectors. A higher separation rate in the cyclical sectors delivers a more concave consumption function and higher MPCs, especially among poor households.[54] When households become wealthier, MPCs in both sectors converge to the MPC, which would prevail under complete markets.[55]

Sectoral and aggregate MPCs also depend on stationary wealth distributions of households in each sector, which are also affected by the separation rate. Figure 5 plots stationary wealth distributions of households across employment statutes in the two sectors. The model predicts that households in the non-cyclical sector are wealthier than those in the cyclical sector, which is consistent with what I observe in the household balance sheet data (see Table B.2.1 in the appendix).[56] As shown in Section 2, a higher separation rate effectively reduces the level of permanent income, making households in the cyclical sector poorer.[57] This is consistent with Ozkan, Song, and Karahan (2023), who argue that frequent unemployment spells reduce household lifetime income by preventing them from climbing the job ladder. Similarly, Low, Meghir, and Pistaferri (2010) suggest that the rate of wealth accumulation decreases with a higher job destruction rate because unemployment spells reduce opportunities to accumulate wealth.

[52]See Carroll and Kimball (1996) how the introduction of uncertainty causes MPCs to increase at any wealth level.

[53]Kaplan and Violante (2022) quantifies how much income risk and borrowing constraints contribute to the increase in an average MPC relative to the certainty MPC. They find that borrowing constraints explain more than two-thirds of the increase, while uninsurable income risk explains one-third.

[54]Figures E.1.2 and E.1.3 in appendix plot consumption functions and MPC for different values of the separation rate. As one can see, the concavity of the consumption function increases with the separation rate, and so do MPCs. When $\delta = 0$, there is no employment risk in the economy, consumption functions are linear, and the MPC is equal to the MPC under certainty.

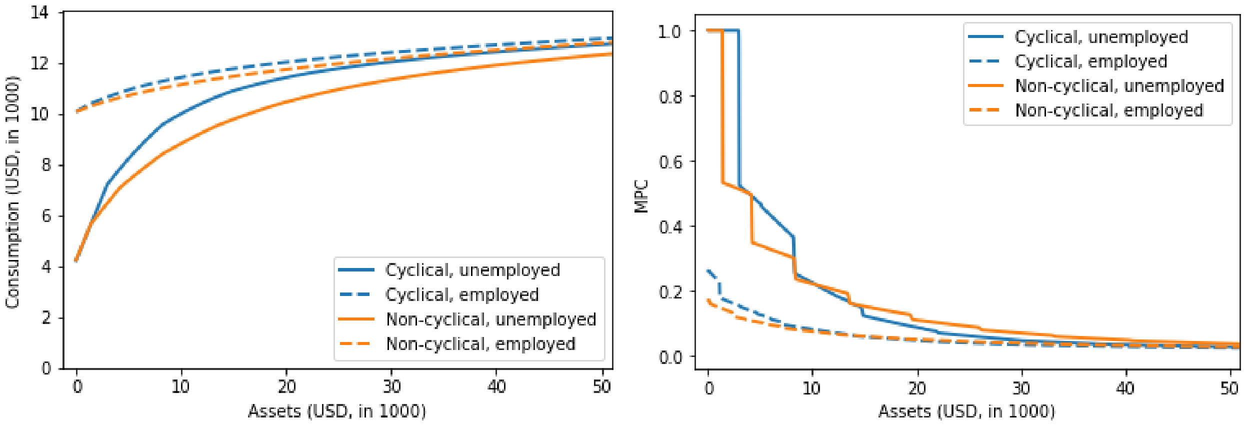
[55]These steps in the MPCs are due to the fact that I have discrete-time and a discrete-state transition process in my model.

[56]The model delivers the mean liquid wealth in the cyclical sector of USD 22,866 and USD 35,621 in the non-cyclical sector. While these levels are below the levels observed in the data, the relative size of mean liquid wealth in the cyclical vs non-cyclical sector is remarkably similar.

[57]There, the job finding rate $\overline{M}$ is exogenous, whereas, in the model, it is a function of the separation rate. Using the steady-state value of the job finding rate (19) in equation (8) delivers the same result, i.e., permanent income is decreasing in the separation rate. See also wealth distributions for different values of the separation rate in Figure E.2.2 in the appendix.

Figure 4: Consumption functions and MPCs

(A) Consumption functions (B) MPCs

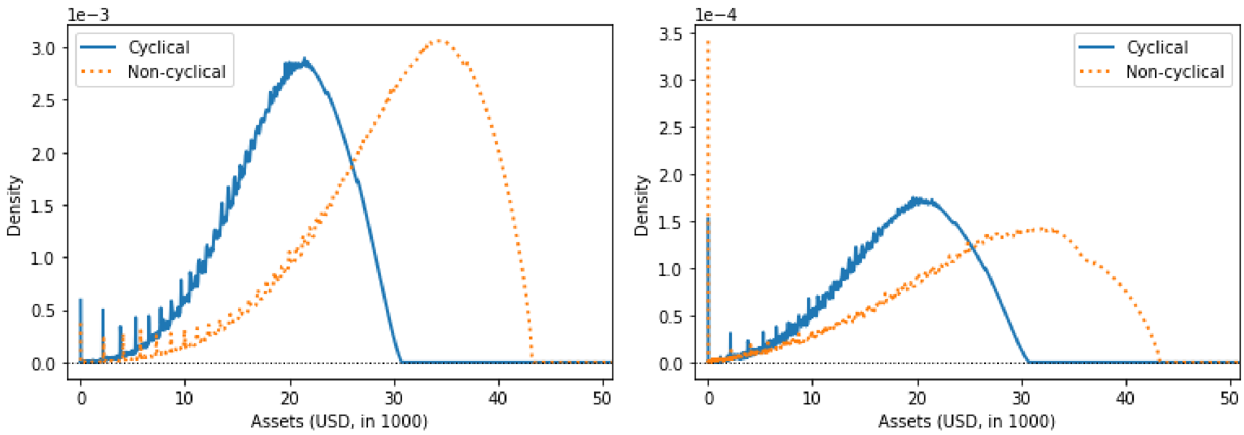


Notes: This figure shows consumption functions and MPCs across sectors and employment statuses, calibrated as shown in Table 3.

There are also more unemployed households at the borrowing constraint in the non-cyclical sector than in the cyclical one. This can be attributed to the fact that the separation rate effectively determines the persistence of the (un)employment state. A lower separation rate in the non-cyclical sector makes the state more persistent, which results in a more prolonged period of unemployment—once a household is unemployed, this state will likely persist for longer than in the cyclical sector.[58] This implies that a household is more likely to be at the borrowing constraint, which is what we observe in panel (B) of Figure 5.

Figure 5: Stationary wealth distributions

(A) Employed (B) Unemployed



Notes: This figure shows stationary wealth distributions in the cyclical and the non-cyclical sector.

[58] In other words, with lower separation rates, it is more likely to stay unemployed (poor) if you start as unemployed (poor), and conversely, you are more likely to stay employed if you start as employed.

5 Sectoral Exposure to Aggregate Shocks and Propagation of Business Cycles

In this section, I study the implications of sectoral employment risk in the transmission mechanism of monetary policy. To do this, I solve a two-sector HANK model augmented with search and matching frictions and analyse impulse responses to monetary policy shock along the perfect-foresight transition path ("MIT shock"). The shock is an annualised 1 percentage point decrease in the real interest rate R_t.

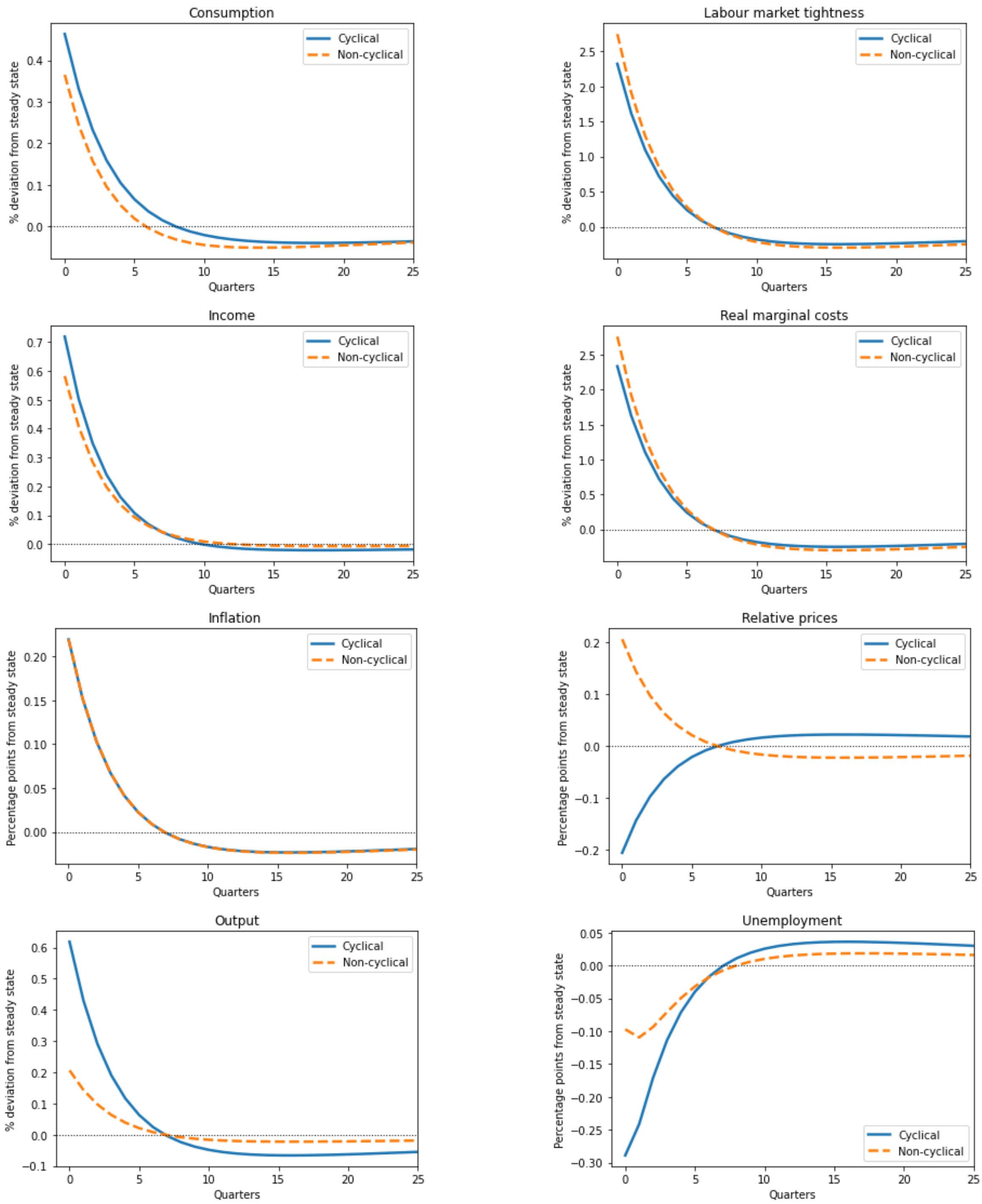
5.1 The effect of a monetary policy shock in a two-sector HANK model

The monetary policy shock is modelled as an annualised 1 percentage point decrease in the real interest rate r_t with the persistence $\rho_R = 0.7$. Results from the simulation are shown in Figure 6.

The top-left figure shows sectoral consumption responses. The consumption increase is larger in the cyclical sector (solid blue line) than in the non-cyclical sector (dashed orange line). The reason for this more pronounced consumption increase in the cyclical sector is that households in the cyclical sector have the most procyclical income coupled with the highest MPCs. We have seen in the previous section that with a higher separation rate, the consumption function is more concave, and households are poorer. Both factors contribute to a higher average sectoral MPC. As a result, the consumption increase in the cyclical sector will be larger for a given income increase than in the non-cyclical sector. Second, a higher separation rate also makes production in the cyclical sector cheaper, increasing employment in the cyclical sector by more than in the non-cyclical sector, which is consistent with the empirical evidence on net worker flows in Section 3.2.3.

The basic mechanism behind impulse responses is the following; after an accommodative monetary policy shock, demand for a final consumption good increases. To satisfy the demand, firms in cyclical and non-cyclical sectors increase production and hire more households, which increases employment (reduces unemployment) and income in both sectors. Since households in the cyclical sector have higher MPCs, this additional income increases consumption in the cyclical sector more than in the non-cyclical sector. This propagation is due to differences in employment risk, and hence, I refer to it as the *market incompleteness channel*.

Figure 6: The effect of a monetary policy shock



Notes: The figure shows impulse responses to a monetary policy shock with persistence $\rho_R = 0.7$. Income comprises wages and dividends, net of taxes. Unemployed households receive unemployment benefits that are equal to the replacement rate of the sectoral steady state wage.

How much employment and income in each sector increases depends crucially on the "fluidity" of the respective labour market. I follow Blanchard and Galí (2010) and Blanchard and Galí (2010) and characterise a labour market with a high separation rate, and large worker flows as *"fluid"*. Conversely, a labour market with a low separation rate and low worker flows is characterised as *"rigid"*. Because the labour market in the non-cyclical sector is more rigid, the initial increase in tightness (expressed as a percentage change) is larger than in the cyclical sector. The reason is that with a lower separation rate, the pool of unemployed households that can be hired at the beginning of the period is smaller, which increases the sensitivity of labour market tightness to additional hiring.[59]

Since wages (22) and hiring costs (20) are increasing in labour market tightness, this increases real marginal costs and makes goods produced in the non-cyclical sector more expensive.[60] This shifts production and labour demand towards the cheaper cyclical sector, further increasing employment, income and consumption of households in the cyclical sector. I refer to this channel as the *relative labour demand channel* and is operative even if there is no employment risk as long as there are differences in real marginal costs across sectors. Finally, because households in the cyclical sector have high MPCs, additional income in the cyclical sector pushes sectoral and aggregate consumption even further via the Keynesian multiplier.[61]

With incomplete markets, the relative labour demand channel has an additional effect on consumption responses because it also affects the cyclicality of income risk and, therefore, the precautionary savings motive. The literature found that countercyclical income risk amplifies aggregate demand responses (dynamic amplification) in HANK models following an accommodative monetary policy shock. In contrast, procyclical income risk dampens them (dynamic discounting).[62] Following Acharya and Dogra (2020), I use the

[59]Observe from (19) that the steady state elasticity of labour market tightness with respect to employment, assuming $N + U = 1$, is equal to $\mathcal{E}_{M,N} = \frac{d \ln M}{d \ln N} = \frac{1}{((1-N)+\delta N)N}$. For a given employment level N, $\mathcal{E}_{M,N}$ will be higher for lower values of δ, that is when the labour market is more rigid.

[60]Real marginal costs include wages, and current and future hiring costs. See equation (D.23) in appendix. In a one-sector RANK model by Blanchard and Galí (2010), marginal costs affect inflation only. However, in my two-sector model with a segmented labour market, production costs affect relative prices and, therefore, sectoral labour demand and income.

[61]Market incompleteness makes income and wealth redistribution crucial for the transmission mechanism of monetary policy (Auclert (2019); Kaplan, Moll, and Violante (2018)). Accommodative monetary policy redistributes wealth along two dimensions in the model. The first redistribution is happening *across* sectors due to the relative labour demand channel. Differences in production costs redistribute income from a more expensive non-cyclical sector to a cheaper cyclical sector. However, there is also a redistribution happening *within* the sectors; with lower real interest rates, wealth is redistributed from unemployed to employed households for two reasons. First, employed households pay taxes to finance interest on the outstanding amount of bond holdings. With an interest rate cut, debt servicing becomes cheaper and only employed households gain from it—employed and unemployed households own bonds and lose interest income due to lower interest rates, but only employed households gain from lower taxes (see Hagedorn, Luo, Manovskii, and Mitman (2019) among others how interest rate changes lead to wealth redistribution across households with different MPCs). Second, the cost of unemployment benefits, which needs to be financed by employed households, is lower with lower unemployment. As a result, the government can reduce the tax rate and keep the budget balanced. Again, this benefits employed households, who are the taxpayers. Because employed households have, on average, lower MPCs, this somewhat restrains the effectiveness of monetary policy interventions.

[62]See Acharya and Dogra (2020) for a detailed discussion about the role of the cyclicality of income risk in HANK models. For countercyclical income risk see Werning (2015); Den Haan, Rendahl, and Riegler (2017); Acharya and Dogra (2020); Ravn and Sterk (2020), among others. For procyclical income risk, see McKay, Nakamura, and Steinsson (2016).

"income gap", i.e. the income difference between high- and low-income states, which in my case corresponds to the income difference when employed and unemployed, as a measure of income risk. Employed households receive procyclical after-tax income, while unemployed households receive constant unemployment benefits.

My model also incorporates endogenous employment risk, which is countercyclical—households are more likely to be employed during a boom than during a downturn. This means that households' expected income, and thus the income gap, also depends on the probability of being employed or unemployed. To take this into account, I adjust households' income for the (sector-specific) job finding and job loss probabilities.[63] Figure F.1.1 in the appendix plots the income gap in the two sectors following an expansionary monetary policy shock. Income risk in both sectors is procyclical because the income gap between employed and unemployed households increases during a boom.[64]

5.2 The Market Incompleteness channel and the Relative Labour Demand channel

In the following section, I perform some experiments to investigate further the two channels and their importance in the monetary policy transmission mechanism.

In the first experiment, I make wages in the cyclical sector more sticky than in the non-cyclical sectors, which would be in line with higher unionisation rates typically observed in cyclical sectors.[65] To do this, I set the parameter governing wage stickiness in the wage equation (22) to $\zeta^C = 0.5$. This is the "Sticky wages" calibration.

Then, in the second experiment, I explore how differences in employment risk propagate the aggregate consumption response via the Keynesian multiplier. Specifically, I increase employment risk in the cyclical sector by doubling the separation rate in that sector($\delta^C \approx 0.53$). I refer to this as the "High-risk" calibration.

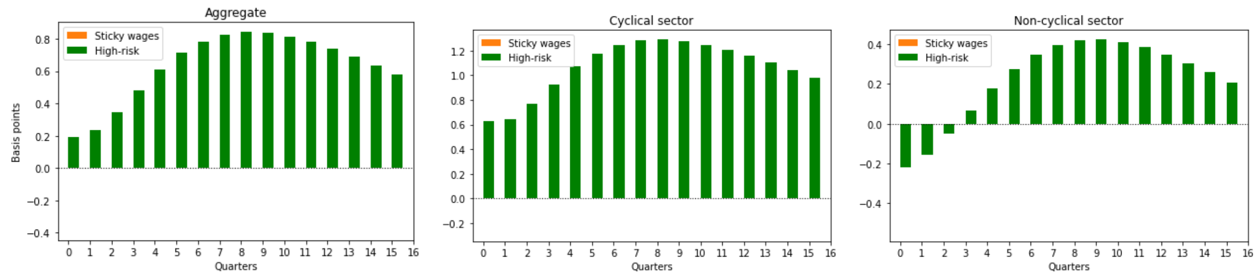
[63] The probability of being in the high-income state is equal to the probability of finding a job if unemployed, M_t^x, and the probability of remaining employed, $1 - \delta^x(1 - M_t^x)$. Similarly, the probability of being in a low-income state equals the probability of losing a job if employed, $\delta^x(1 - M_t^x)$, and the probability of remaining unemployed, $1 - M_t^x$.

[64] Wages are procyclical, whereas dividends are countercyclical because of sticky prices. The overall after-tax income is procyclical due to the countercyclical nature of tax rates τ_t^x in the model (tax rates are larger during recessions to finance a larger pool of unemployed households). The additional income in the cyclical sector—due to the relative labour demand channel—makes income risk even more procyclical.

[65] For more direct evidence on wage stickiness across sectors, see `https://www.frbsf.org/economic-research/indicators-data/nominal-wage-rigidity`. It is well known that wage stickiness plays an important role in HANK models as it determines whether dividends are pro- or counter-cyclical, which then affects the cyclicality of income risk (see, e.g., Broer, Harbo Hansen, Krusell, and Öberg (2019) among many others).

5.2.1 The market incompleteness channel

Figure 7: Market incompleteness channel



Notes: The bars show the effect of the market incompleteness channel, calculated as the difference in consumption responses for different calibrations. In green is the difference between the "High-risk" calibration ($\delta^C \approx 0.53$) and the baseline calibration. In orange is the difference between the "Sticky wages" calibration ($\zeta^C = 0.5$) and the baseline calibration. The relative labour demand channel is "switched off" in all models, i.e. $P^C/P = P^{NC}/P = 1$.

Figure 7 shows the effect of the market incompleteness channel in the model. To avoid any confounding effect from the relative labour demand channel, I fix relative sectoral prices in all models to the steady-state values $P^C/P = P^{NC}/P = 1$. The green bars show the effect of the market incompleteness channel for the "High-risk" calibration, while the orange bars show the effect of market incompleteness for the "Sticky wages" calibration.

In the “High-risk” calibration, a higher separation rate in the cyclical sector increases employment risk and households’ MPCs in that sector. As a result, the consumption in the cyclical increases by more for a given income increase. This initial increase is then amplified via the Keynesian multiplier, leading to higher aggregate consumption and, with a lag, higher consumption in the non-cyclical sector than in the baseline calibration.[66]

The “Sticky wages” calibration does not affect the market incompleteness channel. The reason is that wage stickiness does not have a first-order effect on sectoral MPCs when relative prices are fixed to the steady state.[67] However, as I show next, wage stickiness is important for the relative labour demand channel.

5.2.2 The relative labour demand channel

The relative demand channel is calculated as the difference between the consumption response from the model with “active” relative prices and the response from the model with fixed relative prices.

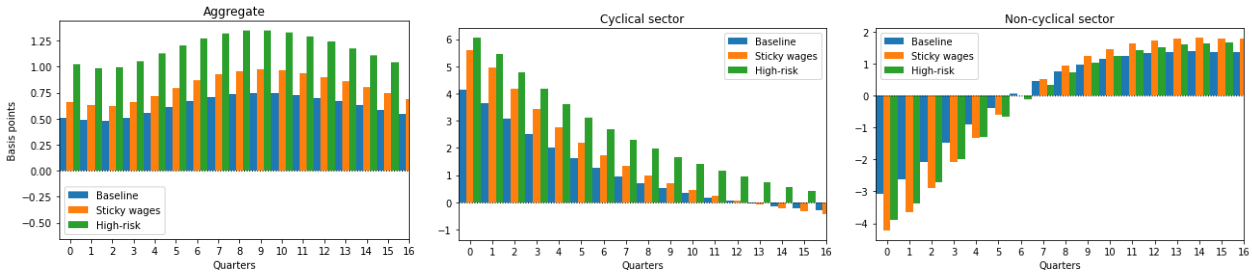
The relative labour demand channel from the baseline calibration is in the blue bars of Figure (8). I find that the relative labour demand channel increases consumption in the

[66]The reduction of consumption in the non-cyclical sector for the “High-risk” calibration is due to a lower steady-state MPCs in that sector, as a result of changes in the stationary distribution of households. Note that the discount factor is the same as in the baseline calibration.

[67]It does not affect the stationary distribution nor households’ MPCs.

cyclical sector and reduces consumption in the non-cyclical sector. As discussed above, a more rigid labour market in the non-cyclical sector makes real marginal costs more sensitive—real marginal costs increase by more—to additional hiring, putting upward pressure on production costs and relative prices. As a result, production and labour demand is shifted towards the cheaper cyclical sector, increasing employment, income, and consumption in the cyclical sector. Moreover, the income redistribution to the high MPC sector boosts (through the Keynesian multiplier) the aggregate consumption response above the aggregate response in which the channel is absent.

Figure 8: The relative labour demand channel



Notes: The bars show the strength of the relative labour demand channel for different calibrations. The relative labour demand channel is calculated as the difference between the baseline response and the response in which the relative price is at its steady-state value.

With more sticky wages in the cyclical sector, the channel is stronger, and the consumption increase in the cyclical sector is even larger (in orange). This is because, with more sticky wages in the cyclical sector, an increase in real marginal costs in the cyclical sector becomes more restrained.[68] This makes production in the cyclical sector even cheaper, which amplifies the relative demand channel and further increases consumption in the cyclical sector. As before, the aggregate consumption response is further amplified by an additional income in the high MPC sector.

The green bars show results from the "High-risk" calibration. In this specification, two forces amplify consumption responses in the cyclical sector relative to the non-cyclical one. First, a higher separation rate in the cyclical sector makes the labour market more fluid, which, via the relative labour demand channel, increases employment and income in the cyclical sector. Second, a higher separation rate increases employment risk and the sectoral MPC. Together, both factors contribute to a much stronger consumption response in the cyclical sector than in the non-cyclical sector.

Moreover, the income redistribution into the high-risk and, hence, high MPC sector further increases aggregate consumption response. Naturally, the amplification is stronger

[68]Real marginal costs comprise wages, and current and future hiring costs. One might argue that with more sticky wages, hiring costs—due to additional hiring—might increase enough to increase real marginal costs. In my model, this can not happen because wages represent by far the biggest component of real marginal costs.

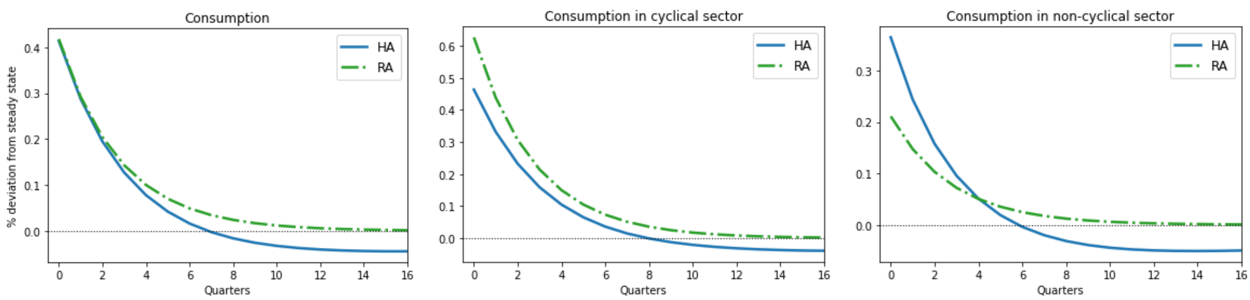
here, given the much higher average MPC in the cyclical sector than in the other two experiments. This shows how the interaction of the relative labour demand channel and high MPCs amplifies the aggregate consumption response via the multiplier.

5.3 A two-sector Representative-Agent New Keynesian (RANK) model

Next, I compare how HANK responses differ from those obtained from a two-sector RANK model. The main difference between the two models is that households in the HANK model are not insured against idiosyncratic employment risk, while households in the RANK are. This means that the only operative channel in the RANK model is the relative labour demand channel. The calibration is identical for both models.

For brevity, I only show consumption responses.[69] Figure 9 plots aggregate and sectoral responses in the two models. In the short run, aggregate consumption responses in the two models are very similar. However, after two quarters, the HANK aggregate response falls below the response in the RANK model and only slowly converges back. This muted aggregate consumption response in the HANK model relative to the RANK model is consistent with the procyclical nature of income risk in the economy.

Figure 9: Monetary policy shock, HANK vs RANK



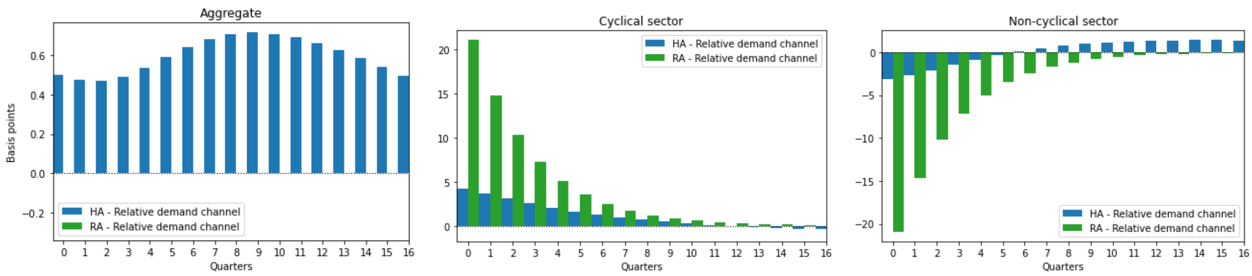
Notes: The solid blue line shows impulse responses from the baseline HANK model, and the dash-dotted green line shows responses from the corresponding RANK model.

The middle and the right panel show consumption responses in the two sectors, respectively. There is a significant difference between HANK and RANK responses in the two sectors; in the cyclical sector, the HANK response is always below the RANK one, which is not the case in the non-cyclical sector. There, the HANK response is initially above the RANK response, and after three quarters, it falls below it. The reason for these differential consumption responses is income smoothing; due to imperfect insurance, households in the cyclical sector save part of this additional income resulting from higher labour demand, and then they slowly de-accumulate these savings over time. In contrast, households in the non-cyclical sector dissave on impact to finance their consumption path, pushing consumption response above the RANK response. Over time, they build up their asset

[69]Figure F.2.1 in the appendix shows impulse responses in the RANK model for other variables.

holdings again, pushing the HANK response below the RANK one. Intuitively, as seen in the middle and the right panel of Figure 10, market incompleteness effectively mutes the relative labour demand channel in the HANK model and hence reduces differences in consumption responses between the two sectors.

Figure 10: The relative labour demand channel, HANK vs RANK



Notes: Bars show the relative labour demand channel in the two models, calculated as the difference between the baseline consumption response and the response where relative prices are fixed to the steady-state values $P^C/P = P^{NC}/P = 1$.

Finally, compared to the HANK model, the redistribution of income via the relative labour demand channel does not affect the aggregate consumption response in the RANK model (see the left panel of Figure 10). The reason is that in the RANK model, households in cyclical and non-cyclical sectors have the same MPCs, and income redistribution does not affect the aggregate consumption response (i.e. there is no amplification via the multiplier).

5.4 Sensitivity analysis

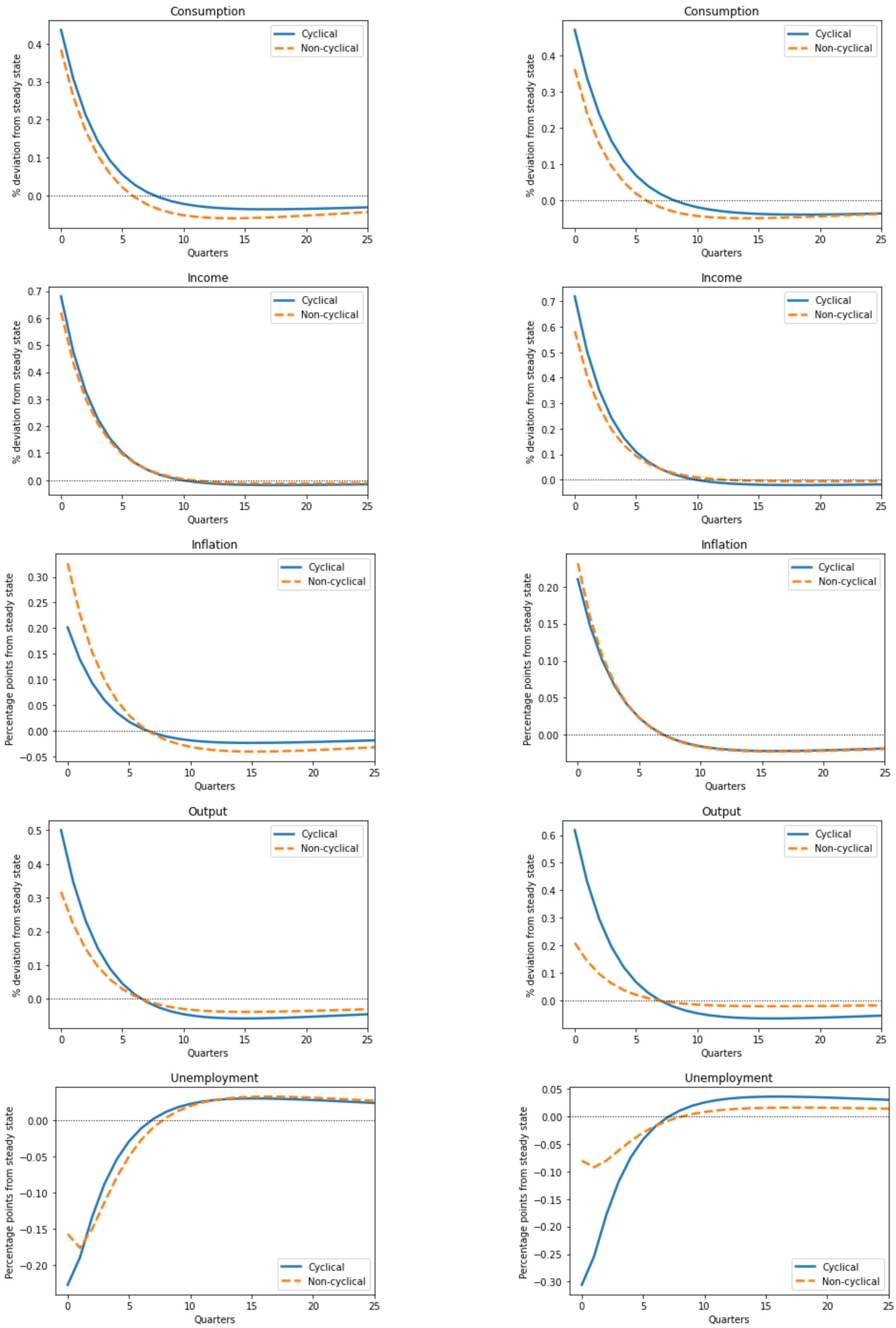
This section investigates how the models' predictions change when I vary (i) the elasticity of substitution parameter between the cyclical and the non-cyclical sector η and (ii) the persistence of the monetary policy shock ρ_R.

5.4.1 The role of elasticity of substitution between sectors

In the first exercise, I study how the substitutability of intermediate goods affects the transmission of a monetary policy shock in a two-sector framework. To do this, I vary the elasticity of substitution between the bundles of intermediate goods produced in the cyclical and the non-cyclical sectors. Results from this exercise are in Figure 11. In the left panel, the two sectors are *gross complements* with the elasticity of substitution equal to 0.2. In the right panel, they are *gross substitutes* with the elasticity of substitution equal to 2.

Figure 11: HANK

Gross complements | Gross substitutes



Notes: When sectors are gross complements, the elasticity of substitution is set to 0.2. When sectors are gross substitutes, the elasticity of substitution is set to 2. All other parameters are the same as in the baseline calibration.

When sectors are substitutes, the initial consumption increase in the cyclical sector is larger and more persistent than in the baseline. The reason is that a higher elasticity of substitution makes the relative labour demand channel more potent. When production inputs are closer substitutes, the producer of the final good is more responsive to price changes of intermediate goods and more swiftly substitutes away from the more expensive goods (produced in the non-cyclical sector) for cheaper goods (produced in the cyclical sector). This translates into higher production, labour demand, income and consumption of households working in the cyclical sector. In contrast, the demand for goods produced in the non-cyclical sector increases by less, which translates into lower income and consumption increases in the non-cyclical sector.

On the other hand, when sectoral outputs used in the production of a final good are gross complements, the final good producer is less responsive to changes in relative prices.[70] As a result, the relative labour demand channel becomes weaker, and the difference in the responsiveness of sectoral outputs is much smaller—the output, employment, and income of both sectors move very closely. Consequently, consumption responses in the two sectors become more similar. Moreover, the complementarity of sectoral goods also generates a larger inflation differential across the two sectors than when sectoral goods are close substitutes. Put differently, when sectoral outputs are gross complements, differences in inflation across sectors persist due to the complementarity of sectoral outputs used in the production of a final good. When sectoral outputs are gross substitutes, an adjustment in sectoral demands limits the extent to which inflation can diverge across sectors.

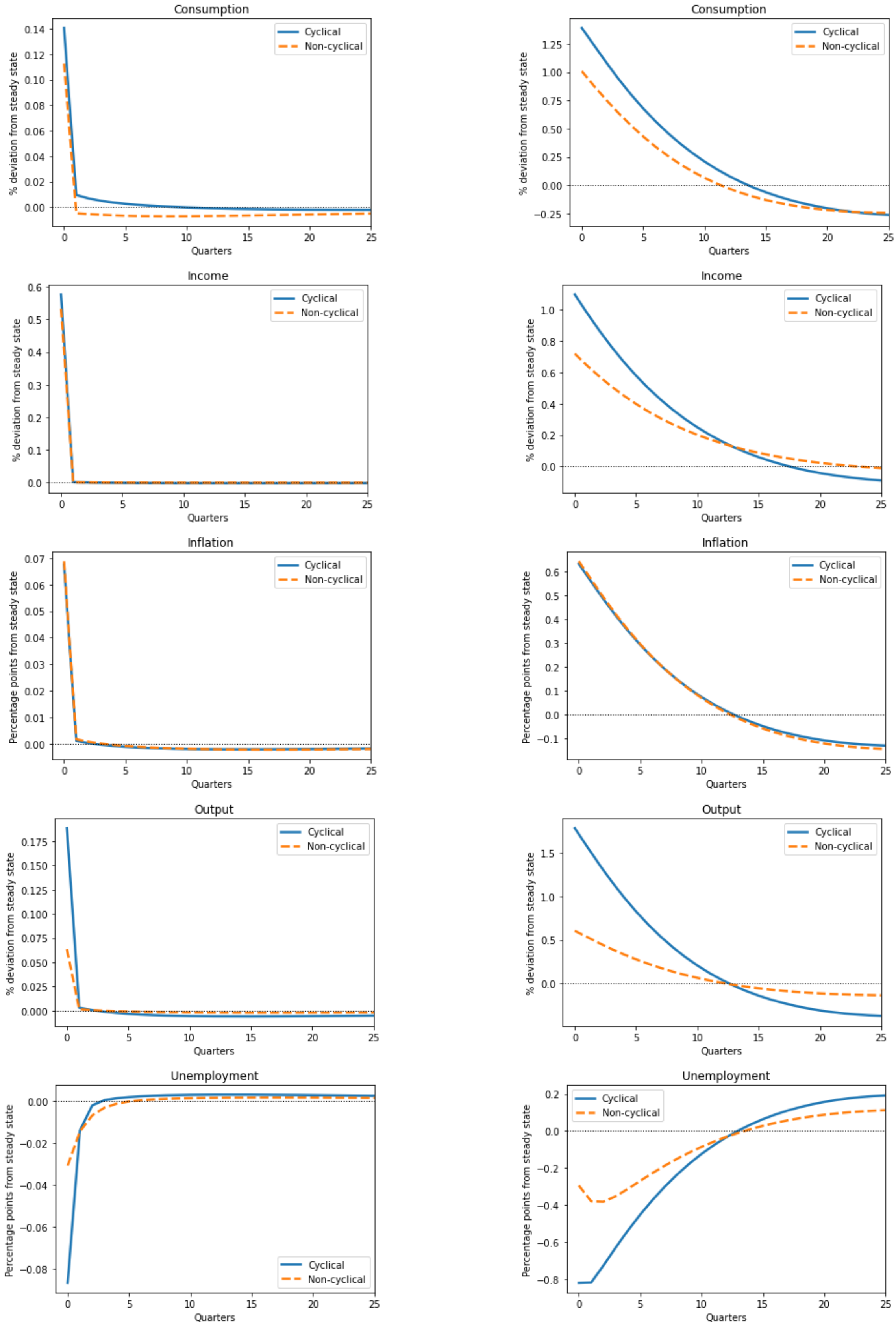
Figure F.2.2 in the appendix shows results from the same exercise using a representative agent model. I find that a higher elasticity of substitution across sectors translates into much larger differences in consumption responses relative to the HANK model. The reason is that households adjust their savings in response to income changes in the HANK model, while in the RANK, they do not. As a result, the relative demand channel is much more potent in the RANK model, generating large asymmetries across sectors.

[70]Due to the complementarity of sectoral outputs in the production of the final goods, changes in aggregate (labour) demand primarily affect sectoral real marginal costs and inflation while having little effect on sectoral outputs.

5.4.2 The role of shock persistence

Figure 12: HANK

Transitory shock ($\rho_R = 0$) Persistent shock ($\rho_R = 0.9$)



Finally, I analyse the role of the persistence of the monetary policy shock in the transmission of monetary policy. The left column in Figure 12 shows impulse responses for a *transitory* shock $\rho_R = 0$, and the right column shows the responses for a highly *persistent* shock with a persistence parameter equal to $\rho_R = 0.9$. As in the baseline, consumption increases the most in the cyclical sector, with the overall magnitude of responses depending on the persistence of the shock.

Figure F.2.3 in the appendix displays results from a representative agent model. In the presence of incomplete markets, the asymmetry in responses is significantly reduced compared to the RANK model. This effect is particularly pronounced for persistent shocks, highlighting how imperfect insurance can help stabilise the economy, even with persistent shocks.

6 Conclusion

This paper explores how differences in employment risk across sectors affect the transition mechanism of monetary policy. I start with the observation that sectoral net worker flows can be informative about sectoral employment risk and the strength of the precautionary saving motive. Using household balance sheet data, I find that households working in sectors more exposed to business cycles (i.e. cyclical sectors) accumulate more net liquid assets than comparable households working in sectors that are less sensitive to business cycle fluctuations (i.e. non-cyclical sectors).

I build a calibrated two-sector HANK model and study how differences in employment risk due to sector-specific labour market characteristics affect the transmission mechanism of monetary policy. I identify two channels determining the size of aggregate responses to a monetary policy shock. The first is the "market incompleteness channel". Because households cannot perfectly insure against employment risk, this generates heterogeneous MPCs. However, differences in labour market characteristics also affect relative prices and, through sectoral outputs, sectoral labour demand. This second channel is the "relative labour demand channel" and is operative irrespective of market incompleteness.

I show that the consumption increase is larger and more persistent in the sector with higher employment risk, which is the cyclical sector. The reason for a larger consumption increase in the cyclical sector is twofold. First, a higher separation rate increases employment risk, which increases the average sectoral MPC. Second, a higher separation rate also makes the labour market more fluid, shifting labour demand towards the cyclical sector and increasing household income. In addition, because an average MPC in the cyclical sector is higher than in the non-cyclical sector, the multiplier effect further increases sectoral and aggregate consumption.

Then, I compare how the baseline results differ from a two-sector RANK model with search and matching frictions. In a two-sector RANK model, differences in employment risk across sectors generate much larger differences in sectoral outputs than in the HANK model. Because of incomplete markets, households self-insure against unemployment spells via saving accumulation, which mutes the relative labour demand channel and reduces asymmetric responses across sectors. This should be taken into consideration when designing (optimal) policies to stabilise the economy.

As a sensitivity analysis, I examine how the elasticity of substitution between sectors and the persistence of a monetary policy shock affect the monetary policy transmission mechanism. Closer substitutes or more persistent shocks increase income redistribution, boosting consumption in the cyclical sector and reducing it in the non-cyclical sector. However, this sectoral consumption difference is less pronounced than in the representative agent framework. The attenuation occurs because additional income in the cyclical sector heightens the procyclicality of income risk, leading to increased savings and reduced consumption, while a smaller income increase in the non-cyclical sector reduces the procyclicality, resulting in decreased savings and increased consumption.

In summary, my analysis shows that the transmission mechanism of monetary policy in a multi-sector framework with incomplete markets differs substantially relative to what delivers a more standard complete markets (RANK) model. From a policy perspective, this can have important implications for the design of (optimal) sector-specific policies, as there might be less need for targeted policy interventions than suggested by the RANK model.

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A Appendix to Section 2

A.1 Proof of proposition 1

Start with (6)

$$c_t \approx -\frac{\beta R-1}{\beta R}A(c)^{-1} + \overline{w}\,\mathbb{E}\left[1-\delta\left(1-M_{t+1}\right)\left(1-\frac{\overline{b}}{\overline{w}}\right)\right] - \frac{1}{2}\gamma(c)\,\mathbb{E}\left[\left(\left(M_{t+1}-M_t\right)\left(\overline{w}-\overline{b}\right)\,\delta\right)^2\right] \tag{A.1}$$

and use the process for $\{M_t\}$ in (7), to obtain

$$\begin{aligned} c_t \approx & -\frac{\beta R-1}{\beta R}A(c)^{-1} + \overline{w}\left[1-\delta\left(1-\mathbb{E}\left[(1-\rho)\overline{M}+\rho M_t+\epsilon_{t+1}\right]\right)\left(1-\frac{\overline{b}}{\overline{w}}\right)\right] \\ & -\frac{1}{2}\gamma(c)\mathbb{E}\left[\left((1-\rho)\overline{M}+\rho M_t+\varepsilon_{t+1}-M_t\right)^2\right]\left(\overline{w}-\overline{b}\right)^2\delta^2. \end{aligned} \tag{A.2}$$

Expand and distribute the terms in the previous equation

$$\begin{aligned} c_t \approx & -\frac{\beta R-1}{\beta R}A(c)^{-1} + \overline{w}\left[1-\delta\left(1-\mathbb{E}\left[(1-\rho)\overline{M}+\rho M_t+\epsilon_{t+1}\right]\right)\left(1-\frac{\overline{b}}{\overline{w}}\right)\right] \\ & -\frac{1}{2}\gamma(c)\,\mathbb{E}\left[\left((1-\rho)\overline{M}+(\rho-1)M_t\right)^2+\varepsilon_{t+1}^2+2\left((1-\rho)\overline{M}+(\rho-1)M_t\right)\varepsilon_{t+1}\right]\left(\overline{w}-\overline{b}\right)^2\delta^2 \end{aligned} \tag{A.3}$$

$$\begin{aligned} \approx & -\frac{\beta R-1}{\beta R}A(c)^{-1} + \overline{w}\left[1-\delta\left(1-\mathbb{E}\left[(1-\rho)\overline{M}+\rho M_t+\epsilon_{t+1}\right]\right)\left(1-\frac{\overline{b}}{\overline{w}}\right)\right] \\ & -\frac{1}{2}\gamma(c)\left[\mathbb{E}\left[\left((1-\rho)\,\overline{M}+(\rho-1)M_t\right)^2\right]+\mathbb{E}\left[\varepsilon_{t+1}^2\right]\right. \\ & \left.+\,\mathbb{E}\left[2\left((1-\rho)\,\overline{M}+(\rho-1)\,M_t\right)\varepsilon_{t+1}\right]\right]\left(\overline{w}-\overline{b}\right)^2\delta^2. \end{aligned} \tag{A.4}$$

Applying the unconditional expectation operator $\mathbb{E}[\cdot]$

$$c \approx -\frac{\beta R-1}{\beta R}A(c)^{-1}+\overline{w}\left[1-\delta\left(1-\overline{M}\right)\left(1-\frac{\overline{b}}{\overline{w}}\right)\right]$$
$$-\frac{1}{2}\gamma(c)\left[\mathbb{E}\left[\left((1-\rho)\overline{M}+(\rho-1)\left(\overline{M}+\sum_{j=0}^{\infty}\rho^{j}\epsilon_{t-j}\right)\right)^{2}\right]+\sigma_{\epsilon}^{2}+0\right]\left(\overline{w}-\overline{b}\right)^{2}\delta^{2} \tag{A.5}$$

$$\approx -\frac{\beta R-1}{\beta R}A(c)^{-1}+\overline{w}\left[1-\delta\left(1-\overline{M}\right)\left(1-\frac{\overline{b}}{\overline{w}}\right)\right]$$
$$-\frac{1}{2}\gamma(c)\left[\mathbb{E}\left[\left((\rho-1)\sum_{j=0}^{\infty}\rho^{j}\epsilon_{t-j}\right)^{2}\right]+\sigma_{\epsilon}^{2}\right]\left(\overline{w}-\overline{b}\right)^{2}\delta^{2} \tag{A.6}$$

$$\approx -\frac{\beta R-1}{\beta R}A(c)^{-1}+\overline{w}\left[1-\delta\left(1-\overline{M}\right)\left(1-\frac{\overline{b}}{\overline{w}}\right)\right]$$
$$-\frac{1}{2}\gamma(c)\left[(\rho-1)^{2}\frac{\sigma_{\epsilon}^{2}}{1-\rho^{2}}+\sigma_{\epsilon}^{2}\right]\left(\overline{w}-\overline{b}\right)^{2}\delta^{2}\,. \tag{A.7}$$

Finally, rearranging the last term, we obtain (8) in the main text

$$c \approx -\frac{\beta R-1}{\beta R}A(c)^{-1}+\overline{w}\left[1-\delta\left(1-\overline{M}\right)\left(1-\frac{\overline{b}}{\overline{w}}\right)\right]-\gamma(c)\left[\frac{\sigma_{\epsilon}^{2}}{1+\rho}\right]\left(\overline{w}-\overline{b}\right)^{2}\delta^{2}\,. \tag{A.8}$$

□

A.2 The role of the persistence of the job finding rate in equation (8)

To analyse the effect of the persistence parameter on permanent income, I rewrite the process in (7) as follows

$$M_t = \mu_M + \rho M_{t-1} + \varepsilon_t\,, \qquad \varepsilon_t \sim \text{iid}\left(0, \sigma_{\varepsilon}^{2}\right) \tag{A.9}$$

where $\mu_M \geq 0$ is a constant, $\rho \in [0, 1)$ is the persistence parameter, and ε_t is the innovation term. Then equation (8) in the main text becomes

$$c \approx -\frac{\beta R-1}{\beta R}A(c)^{-1}+\underbrace{\overline{w}\left[1-\delta\left(1-\frac{\mu_M}{1-\rho}\right)\left(1-\frac{\overline{b}}{\overline{w}}\right)\right]}_{\equiv \mathcal{PI}}-\underbrace{\gamma(c)\left[\frac{\sigma_{\epsilon}^{2}}{1+\rho}\right]\left(\overline{w}-\overline{b}\right)^{2}\delta^{2}}_{\equiv \mathcal{S}}\,. \tag{A.10}$$

Note that in comparison to the consumption equation (8) in the main text, the steady-state value of the job finding rate now reads $\overline{M} \equiv \mathbb{E}[M_t] = \frac{\mu_M}{1-\rho}$. The dual nature of the persistence parameter can be observed by comparing the second ($\mathcal{PI}$) and the third term ($\mathcal{S}$) in

(A.10).

The second term, associated with the permanent income $\mathcal{PI}$, is increasing in ρ. As the shock becomes more persistent, the household consumes a larger fraction of it as part of the permanent income. This is because a more persistent shock also has a large effect on the job finding rate in the future (they are more informative about future realisations) and, thus, on permanent income. At the same time, because more persistent shocks are more difficult to self-insure against, this reduces the precautionary saving motive $\mathcal{S}$. Conversely, when the shock is transitory, the household does not consider it to be part of the permanent income. Instead, it regards it as a temporary income fluctuation, which one can self-insure against by adjusting precautionary savings.

All in all, the persistence parameter plays a dual role in the model. On the one hand, it affects the household's permanent income, with more persistent shocks having a larger effect on the permanent part of income. On the other hand, it influences precautionary savings, with transitory shocks leading to a stronger precautionary saving motive.

B Data appendix

B.1 Further sample restrictions

B.1.1 Selection of LEHD industries into SCF-industry groups

Here, I describe how I relate the LEHD industry data with the SCF industry data and clarify the necessary adjustments to ensure their comparability. As described in Section 3.2.1, mapping the LEHD data to the SCF data is relatively straightforward, however, there are instances that require a more detailed analysis. For example, when a LEHD industry is in more SCF–industry groups, I disaggregate the LEHD industry to the four-digit NAICS level and assign it to the SCF-industry group, which has the largest employment share of that industry.[71]

Table B.1.1: Mapping of LEHD industries into SCF-industry groups

SCF–ind. group	LEHD industry (two-digit NAICS code)
1	Agriculture, Forestry, Fishing and Hunting (11)
2	Mining, Quarrying, and Oil and Gas Extraction (21); Construction (23)
3	Manufacturing (31-33)
4	Wholesale Trade (42) ; Retail Trade (44-45); Accommodation and Food Services (72)
5	Finance and Insurance (52); Real Estate and Rental and Leasing (53)
6	Utilities (22); Transportation and Warehousing (48-49); Information (51); Professional, Scientific, and Technical Services (54); Management of Companies and Enterprises (55); Educational Services (61); Health Care and Social Assistance (62); Arts, Entertainment, and Recreation (71); Other Services (except Public Administration) (81)
7	Public Administration (92)

Notes: This table shows mapping of the LEHD (two-digit NAICS) industry codes into SCF-industry groups.

Moreover, I exclude the LEHD industry “Administrative and Support and Waste Man-

[71] The SCF-industry grouping is based on the four-digit NAICS level.

agement and Remediation Services (56)" from the analysis for two reasons. First, it is unclear how to allocate the industry between SCF-industry groups 5 and 6 because 60 percent of the employment falls in the SCF-industry group 5 and 40 percent in the SCF-indusrty group 6. Second, net worker flows in this industry are very cyclical and drive results in the SCF-industry group 5. The other two industries in the SCF-industry group 5 are either non-cyclical (e.g. Finance and Insurance industry), or worker flows are not statistically different from the US average flows (e.g. Real Estate and Rental and Leasing industry). Finally, there are also some differences in the coverage between these two data sources. For example, while civilian employees of the Department of Defense and members of the US Army are not included in the LEHD data, they are part of the SCF sample.

B.1.2 Employment history in the SCF sample

For the analysis, it is crucial to identify households working in cyclical and non-cyclical sectors. However, it is not sufficient to observe their current sector; one should also know their employment history because this will determine the amount of net liquid assets they hold. For example, if a household worked in a non-cyclical sector for many years and moved to a cyclical sector before the survey, then the liquidity position of this household would be more similar to a non-cyclical household than a cyclical one.

Note that the SCF has no explicit information on households' employment history. However, there is information on the household's tenure with the current employer, which I use as a proxy for the employment history. In my analysis, I include only households whose tenure in that sector is above some threshold value in the analysis.[72]

I proceed as follows. First, I normalise the household's tenure by the total work experience.[73] Then, I use this information to calculate the sector-specific median value of normalised tenure for each survey year. In the last step, I restrict the sample to households that are above the median value of the normalised tenure.

B.1.3 Calculation of Job finding and Separation rates using Current Population Survey (CPS) data

To compute sectoral job finding rates, I use publicly available Current Population Survey (CPS) microdata. [74] This is a monthly survey that allows for the estimation of the transition rates between employment, unemployment, and inactivity (see, for example, Blanchard, Diamond, Hall, and Murphy (1990), Shimer (2005), Elsby, Hobijn, and Sahin (2010) among many others).

[72]For this approach to be valid, I have to assume that the employer did not switch the sector from cyclical to non-cyclical and vice versa.

[73]Differences in tenure also reflect differential age distribution across the two sectors—households in a specific sector might be on average older, which would mechanically increase tenure. To control for this and make tenure (more) comparable across the two sectors, I normalise it by the total work experience.

[74]https://www.nber.org/research/data/current-population-survey-cps-basic-monthly-data.

Although data on transition rates between employment states are since 1976, information on the sector where households work was introduced only in January 2002. As a result, my sample starts in 2002. Moreover, for inactive households, information about sectoral employment is missing, and therefore, I restrict transitions between employment and unemployment only.

Additionally, two further restrictions are imposed to ensure comparability with the SCF and SIPP samples. First, I exclude "switchers", that is, workers switching sectors (industries) during survey waves.[75] Second, I only consider workers who are between 25 and 55 years old. Selection into the cyclical and the non-cyclical sectors is based on results in Section 3.2.1.

Following Shimer (2012), I first calculate instantaneous transition rates to correct for time aggregation bias.[76] From these, I calculate monthly and quarterly job finding rates. The transformation between the instantaneous transition rate and monthly job finding rate is as follows

$$f_t^m = 1 - \exp\left(-\lambda_t^{UE}\right), \tag{B.11}$$

where λ_t^{UE} is the instantaneous transition rate from unemployment (U) to employment (E). A quarterly job finding rate is then calculated as

$$f_t^q = 1 - \exp\left(-3\lambda_t^{UE}\right). \tag{B.12}$$

Similarly, one can calculate monthly and quarterly separation rates

$$s_t^m = 1 - \exp\left(-\lambda_t^{EU}\right), \tag{B.13}$$

and

$$s_t^q = 1 - \exp\left(-3\lambda_t^{EU}\right), \tag{B.14}$$

where λ_t^{EU} is the instantaneous transition rate from employment to unemployment.

[75] The share of switchers is small and stable throughout the sample, hovering between 1.5% and 2% of the sample per month.

[76] https://sites.google.com/site/robertshimer/research/flows.

B.2 Summary statistics

B.2.1 Household balance sheets

Table B.2.1 presents summary statistics from the SCF and SIPP survey.

Table B.2.1: Summary statistics

	SCF		SIPP	
Mean	Cyclical	Non–cyclical	Cyclical	Non–cyclical
Wages and salaries (annualised)	81,502	111,913		
Earned income (annualised)	90,406	130,238	76,960	103,946
Total income (annualised)	95,528	136,001	82,707	110,248
Net liquid assets	24,582	49,064	17,119	28,588
Net wealth	334,566	500,586	159,201	222,805
Share of HtM households	0.45	0.33	0.53	0.44
– Wealthy HtM	0.32	0.23	0.32	0.25
– Poor HtM	0.13	0.10	0.20	0.19
Median				
Wages and salaries (annualised)	62,716	86,347		
Earned income (annualised)	65,881	94,184	60,755	81,302
Total income (annualised)	68,873	96,130	65,526	86,180
Net liquid assets	1,853	6,136	254	1,354
Net wealth	86,782	165,665	19,580	38,922
Observations	5,943	14,661	13,865	35,787

Notes: This table shows the mean and median values of selected variables calculated from the household balance sheet data. Net liquid assets comprise the money market, checking, savings, and call accounts, certificates of deposit, private loans, and bond holdings minus credit card debt. Net wealth is calculated as the difference between assets and liabilities. Earned income is defined as wages and salary income plus income from a business, sole proprietorship, and farm. Total income comprises earned and unearned income plus transfers. Everything is in USD, pre-tax, and in real terms—CPI adjusted to 2016 dollars. Definitions of hand-to-mouth (HtM) households follow Kaplan, Violante, and Weidner (2014). All statistics are computed using survey weights.

B.2.2 Labour market flows

Table B.2.2 shows summary statistics of worker flows from the two data sources. While there are some differences in levels across the two samples, data suggest that households in the cyclical sector experience larger inflow and outflows to nonemployment (unemployment in the JOLTS sample) and that flows are also more volatile.

Table B.2.2: Summary statistics – LEHD and JOLTS samples

	Cyclical		Non-cyclical	
Description	Mean	SD	Mean	SD
LEHD				
Hire rate (%)	4.226	0.499	3.762	0.193
Separation rate (%)	4.772	0.770	3.785	0.481
Net worker flows (pp)	-0.017	0.887	-0.064	0.331
JOLTS				
Hire rate (%)	3.958	0.365	3.627	0.277
Separation rate (%)	3.980	0.391	3.539	0.251
Layoffs & discharges rate (%)	2.123	0.424	1.916	0.171
Net worker flows (pp)	1.835	0.629	1.711	0.331
Observations	66	66	66	66

Notes: Hire rate, separation rate, and net worker flows are expressed as a share of employment. In the JOLTS sample, net worker flows are calculated as the difference between the hire rate and the layoffs & discharges rate. Data is quarterly, seasonally adjusted, and covers the period 2001q2–2017q3.

B.2.3 Job finding and Separation rates

Table B.2.3 shows summary statistics of job finding and separation rates using CPS data. Job finding rates f_t in cyclical sectors are lower, whereas separation rates s_t are higher than in non-cyclical sectors. This implies that workers in cyclical sectors are more likely to lose their jobs than those in non-cyclical sectors, and it takes longer for them to find another job if unemployed.

Table B.2.3: Summary statistics – CPS sample

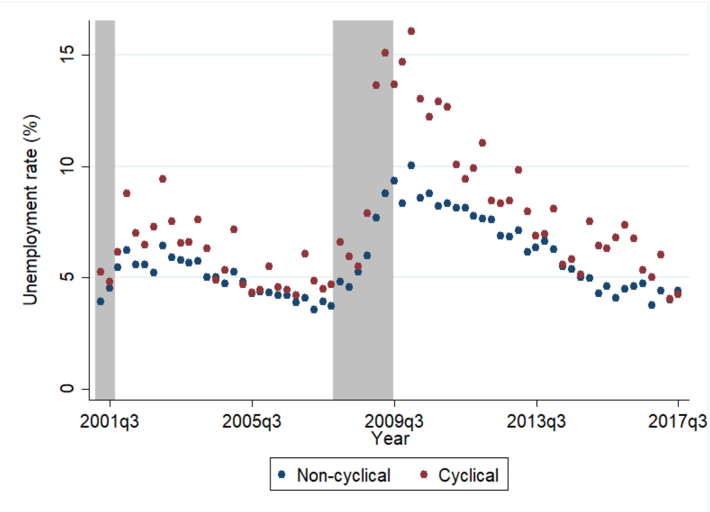
	Cyclical		Non-cyclical	
Description	Mean	SD	Mean	SD
Monthly				
f_t^m	0.219	0.055	0.241	0.050
s_t^m	0.021	0.006	0.011	0.001
Observations	187	187	187	187
Quarterly				
f_t^q	0.516	0.089	0.556	0.079
s_t^q	0.062	0.016	0.034	0.005
Observations	63	63	63	63

Notes: This table shows summary statistics of job finding (f_t) and separation rates (s_t) at monthly and quarterly frequency. To obtain quarterly data, I rescale instantaneous transition rates to quarterly frequency and then average them within a quarter. The data is seasonally adjusted and covers the period 2002q1–2017q3. Selection into the cyclical and the non-cyclical sectors is based on results in Section 3.2.1.

C Additional figures

C.1 Unemployment rate

Figure C.1.1: Unemployment rate

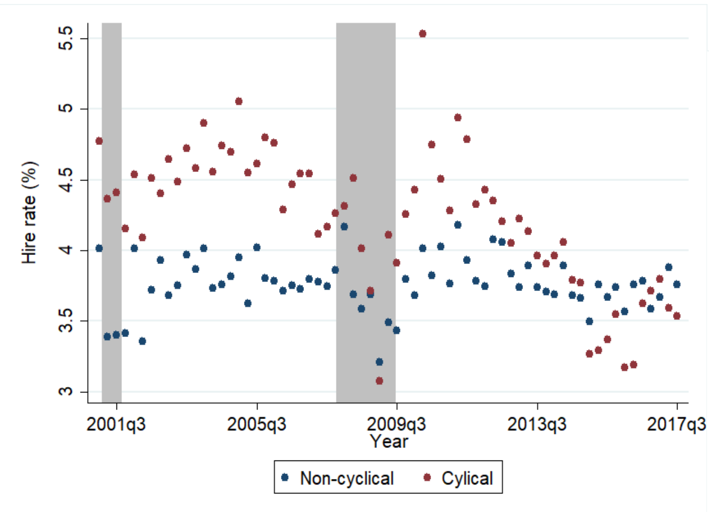


Notes: This figure plots the unemployment rate in cyclical and non-cyclical sectors. The panel covers the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1.

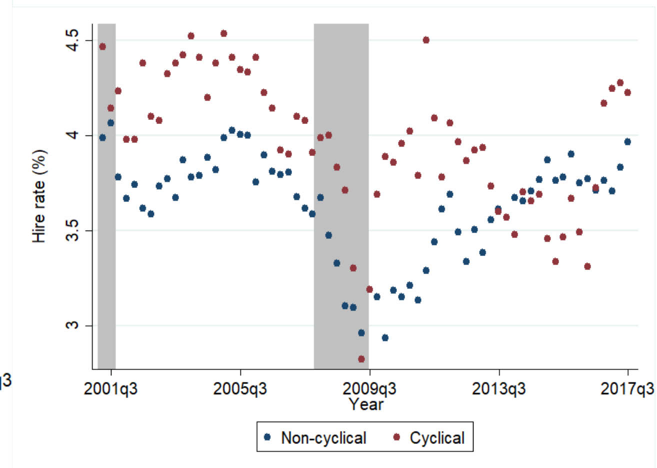
C.2 Worker flows over the business cycle

Figure C.2.1: Hiring rate

(A) LEHD



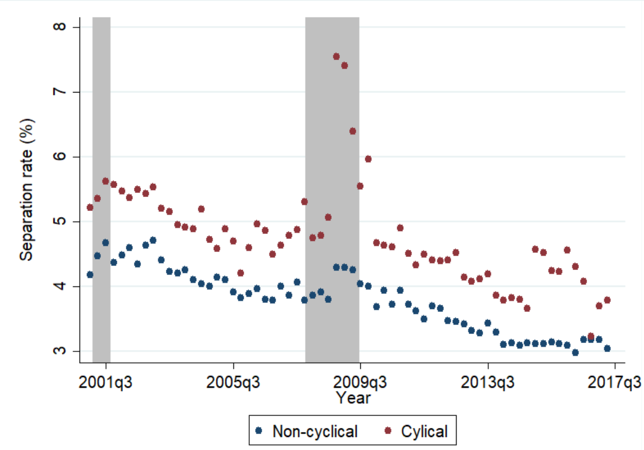
(B) JOLTS



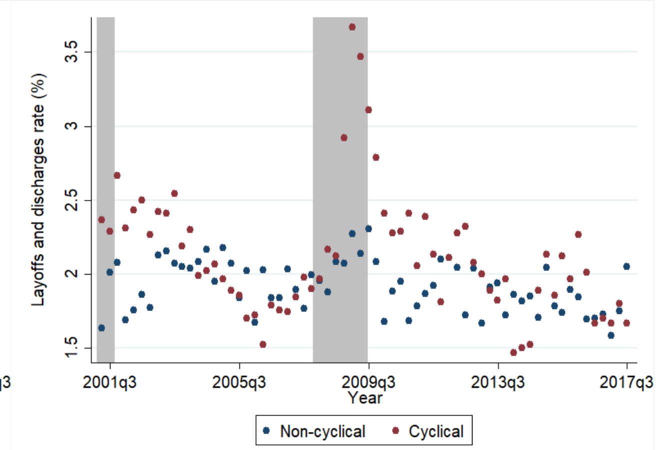
Notes: Panel (A): The hiring rate is defined as hires from persistent nonemployment, expressed as a share of employment and multiplied by 100. Panel (B): The hiring rate is defined as hires from unemployment, expressed as a share of employment and multiplied by 100. Both panels cover the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1.

Figure C.2.2: Separation rate

(A) LEHD

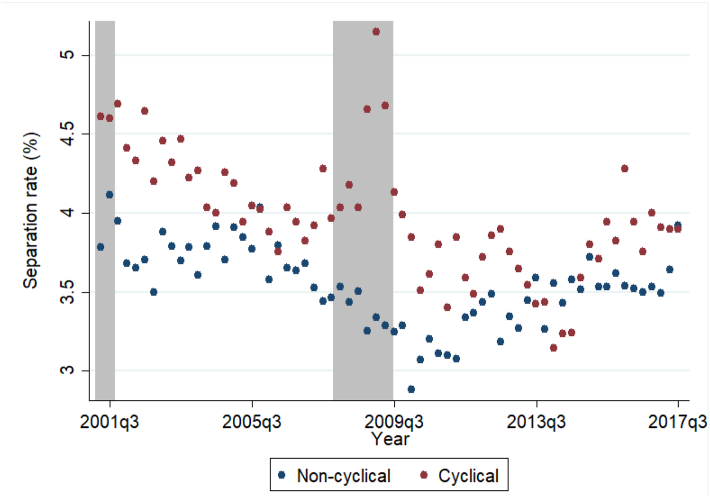


(B) JOLTS



Notes: PANEL (A): The separation rate is defined as separations to persistent nonemployment, expressed as a share of total employment and multiplied by 100. PANEL (B): The separation rate is defined as layoffs and discharges to unemployment, expressed as a share of total employment and multiplied by 100. Both panels cover the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1.

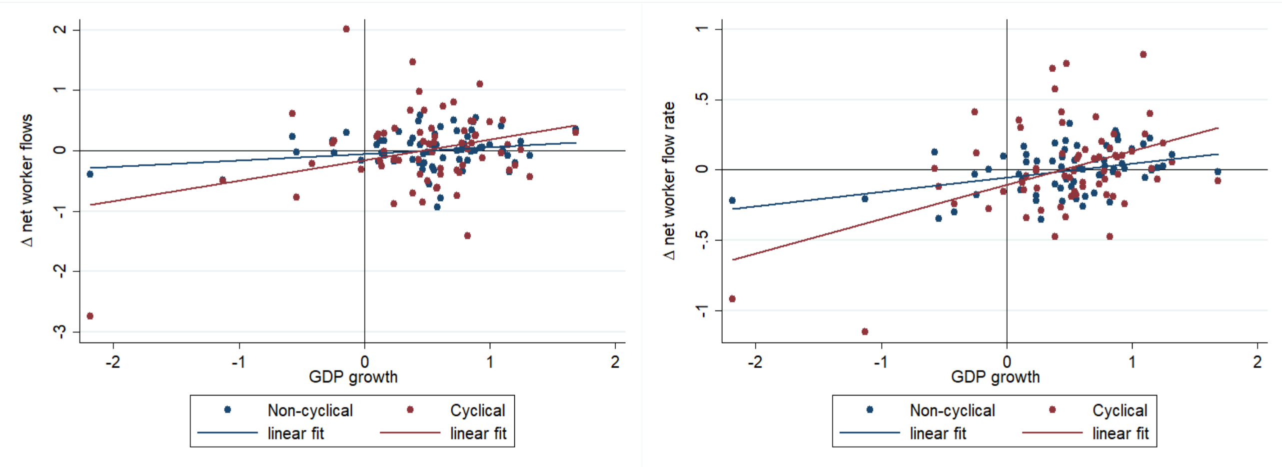
Figure C.2.3: Total separations rate in the JOLTS data



Notes: The separation rate is defined as total separations to unemployment, expressed as a share of total employment and multiplied by 100. The panel covers the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1.

Figure C.2.4: Variability of net worker flows in cyclical and non-cyclical sectors

(A) LEHD (B) JOLTS



Notes: Variability of net worker flows is calculated as the change in net worker flows between t and $t-1$. GDP growth is calculated as the quarterly difference in the log of the real GDP and multiplied by 100. Both panels cover the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1.

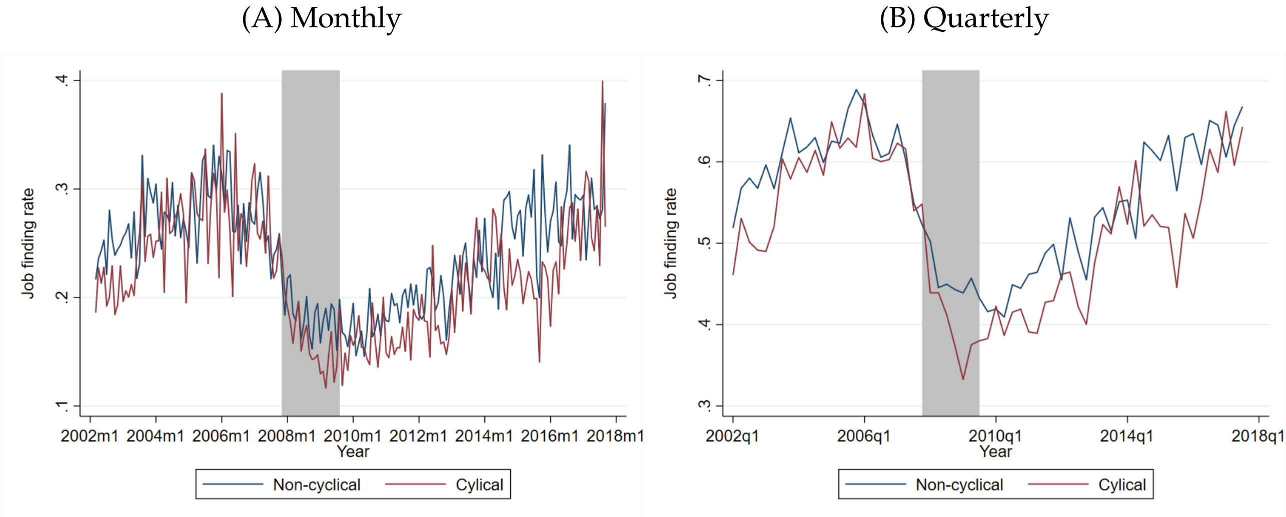
To corroborate the finding that workers in cyclical sectors indeed experience larger employment risk throughout the business cycle, Figure C.2.4 plots changes in net worker flows against the quarterly GDP growth rates. For a given GDP change, workers in cyclical sectors, on average, experience larger and more uncertain changes in net worker flows than workers in non-cyclical sectors.[77] This supports the view that workers in cyclical sectors experience more cyclical and larger (in terms of magnitude) employment risk than workers in non-cyclical sectors.

C.3 Job finding rates and separation rates using CPS data

Figure C.3.1 plots job finding rates at monthly and quarterly frequencies, which I use to test Proposition 1 in Section 3.4. At the monthly frequency, the job finding rate in both sectors is very volatile, making it difficult to see clear cyclical patterns. However, at a quarterly frequency, it is clear that the job finding rate in the cyclical sectors fluctuates much more over the business cycle than in non-cyclical sectors.

[77] Slopes of the linear fit in the two sectors confirm our previous findings that net worker flows in cyclical sectors are procyclical and (almost) acyclical in non-cyclical sectors.

Figure C.3.1: Job finding rate

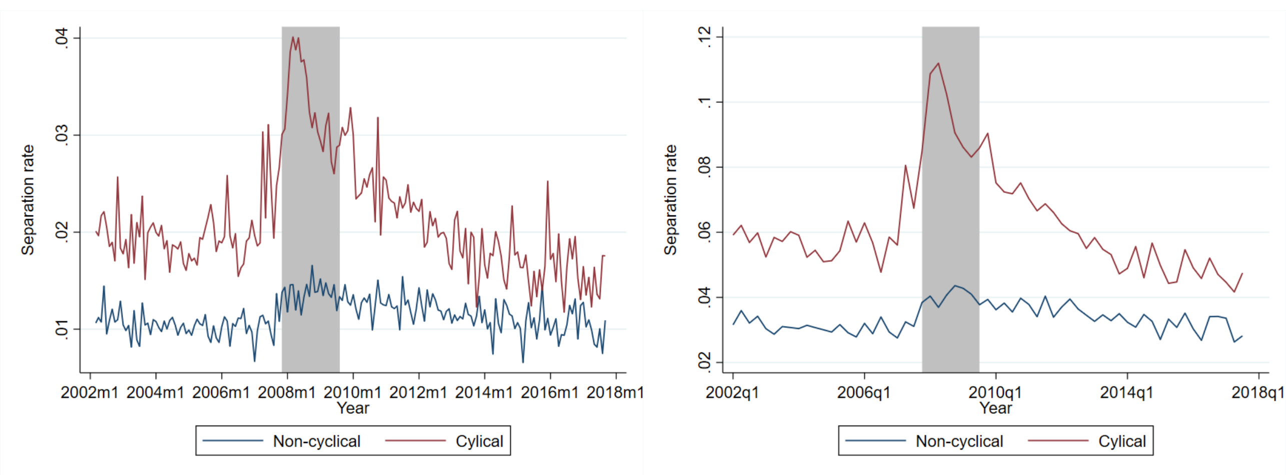


Notes: PANEL (A) shows job finding rates using monthly data. PANEL (B) shows job finding rates at a quarterly frequency. To obtain quarterly data, I rescale instantaneous transition rates to a quarterly frequency and then average them within a quarter. The data in both panels is seasonally adjusted and covers the period 2002q1–2017q3. Selection into the cyclical and the non-cyclical sectors is based on results in Section 3.2.1. Shaded areas denote NBER recession episodes.

Similarly, one can also calculate separation rates using the approach by Shimer (2012). Figure C.3.2 shows separation rates—that is, transitions from E to U—in cyclical and non-cyclical sectors. Two observations immediately stand out. Firstly, the level is much higher in cyclical sectors than in non-cyclical ones. Secondly, during a recession, households in cyclical sectors are much more likely to transition from employment to unemployment than in the non-cyclical sectors. This supports our previous finding that households in cyclical sectors are exposed to larger employment risk.

Figure C.3.2: Separation rate

(A) Monthly (B) Quarterly



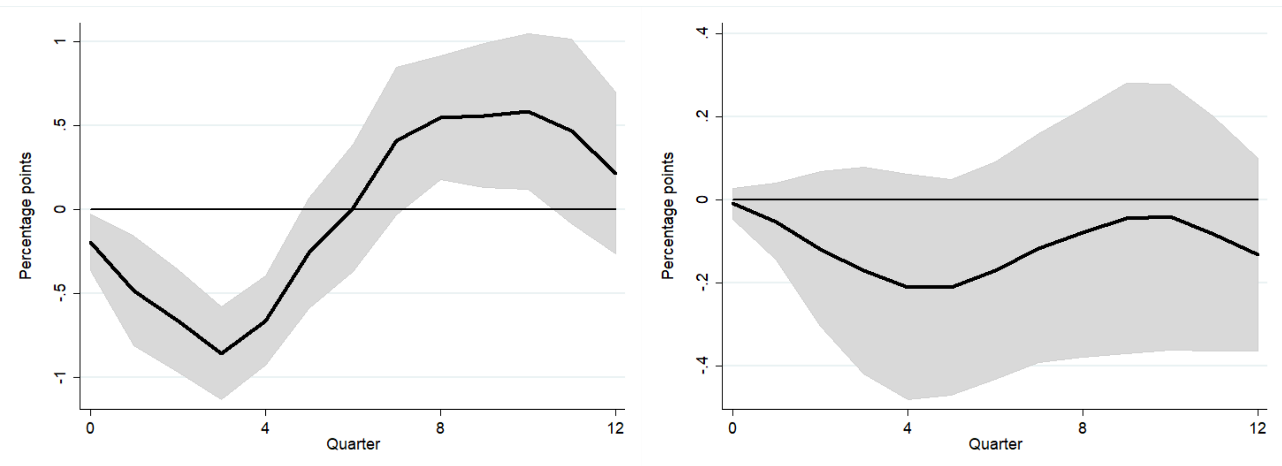
Notes: PANEL (A) shows separation rates using monthly data. PANEL (B) shows separation rates at a quarterly frequency. To obtain quarterly data, I rescale instantaneous transition rates to a quarterly frequency and then average them within a quarter. The data in both panels is seasonally adjusted and covers the period 2002q1–2017q3. Selection into the cyclical and the non-cyclical sectors is based on results in Section 3.2.1. Shaded areas denote NBER recession episodes.

C.4 Robustness of Local Projections approach

C.4.1 The response of the real interest rate and unemployment rates

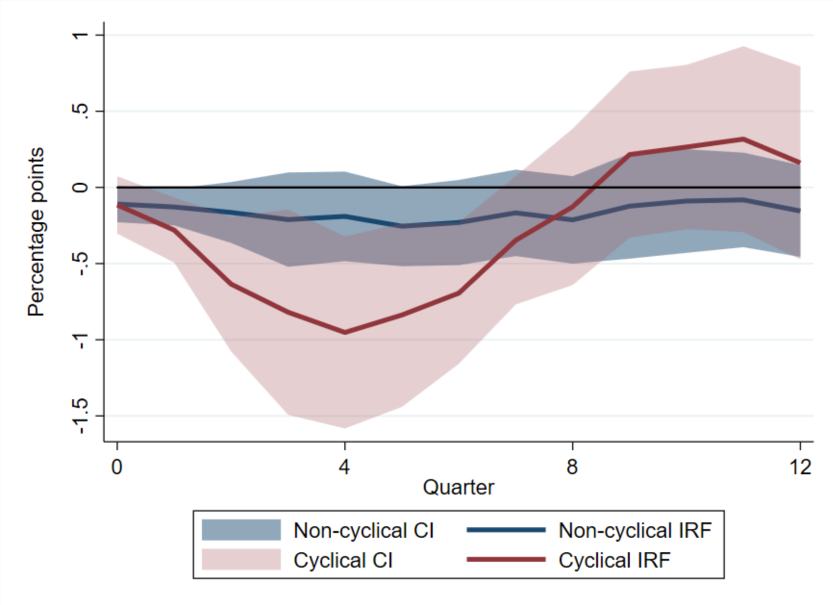
Figure C.4.1: The response of the real interest rate and the aggregate unemployment rate

(A) Real interest rate (B) Unemployment rate



Notes: This figure shows impulse responses following an expansionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors). The data is seasonally adjusted and covers the period 2001q2–2017q3. PANEL (A): The real interest rate is calculated as the market yield on US Treasury securities at 2-year constant maturity, adjusted for CPI inflation. PANEL (B): The unemployment rate (UNRATE), retrieved from FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/UNRATE).

Figure C.4.2: The responses of sectoral unemployment rates

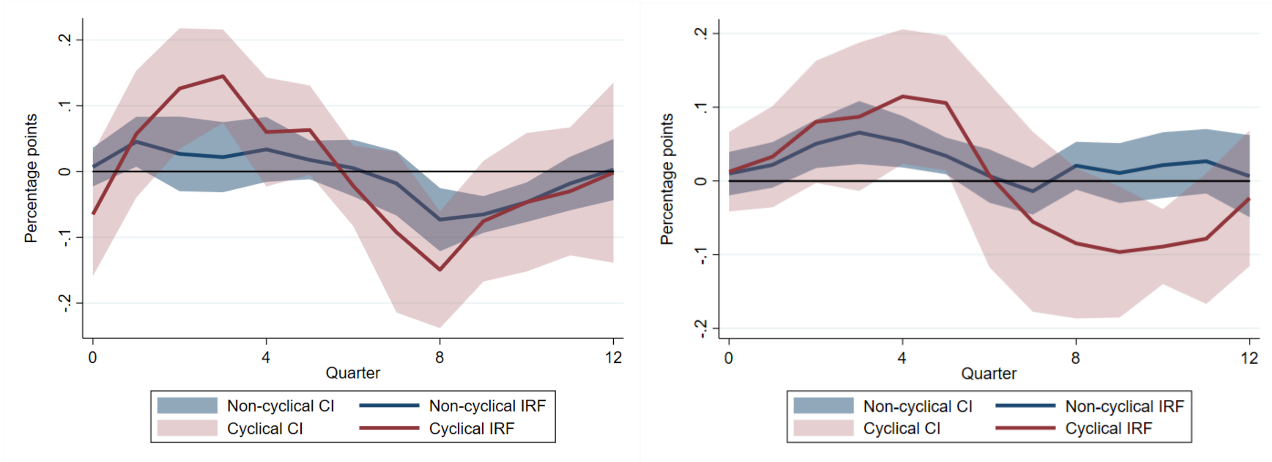


Notes: This figure shows the impulse response of sectoral unemployment rates following expansionary monetary policy shocks. Selection into the cyclical and the non-cyclical sectors is based on results in Section 3.2.1. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors).

C.4.2 Worker flows conditional on an identified monetary policy shock

Figure C.4.3: Hiring rate

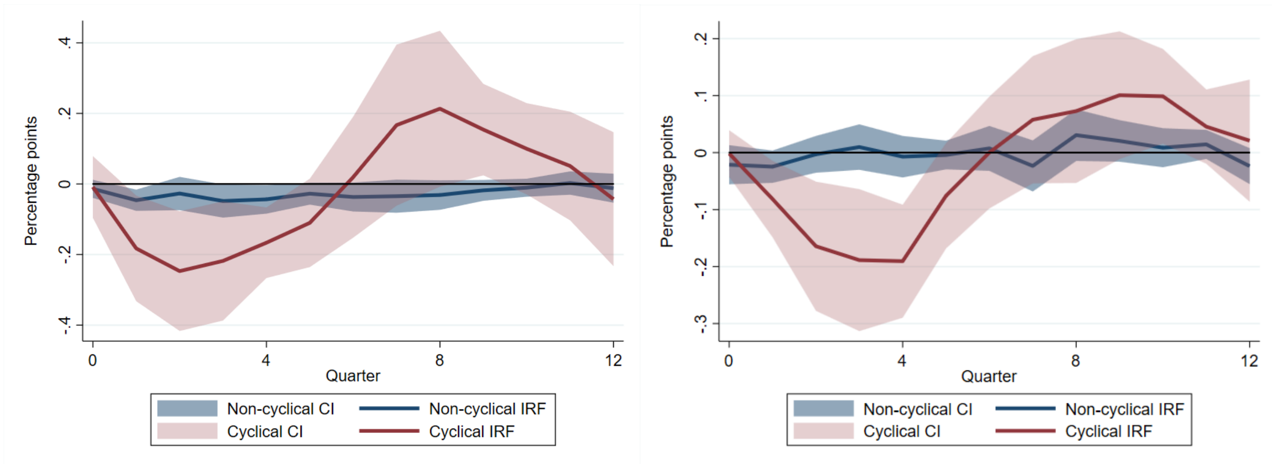
(A) LEHD (B) JOLTS



Notes: This figure shows impulse responses following an expansionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors). The data is seasonally adjusted and covers the period 2001q2–2017q3. Selection into the cyclical and non-cyclical sector is based on results in Section 3.2.1. PANEL (A): The hiring rate is defined as hires from persistent nonemployment, expressed as a share of total employment and multiplied by 100. PANEL (B): The hiring rate is defined as hires from unemployment, expressed as a share of total employment and multiplied by 100. Quarterly data are obtained by averaging monthly data of the corresponding quarter.

Figure C.4.4: Separation rate

(A) LEHD (B) JOLTS



Notes: This figure shows impulse responses following an expansionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected and heteroskedasticity and autocorrelation (Newey–West standard errors). The data is seasonally adjusted and covers the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1. PANEL (A): The separation rate is defined as separations to persistent nonemployment, expressed as a share of total employment and multiplied by 100. PANEL (B): The separation rate is defined as layoffs and discharges to unemployment, expressed as a share of total employment and multiplied by 100. Quarterly data are obtained by averaging monthly data of the corresponding quarter.

C.4.3 Job finding and separation rates conditional on an identified monetary policy shock

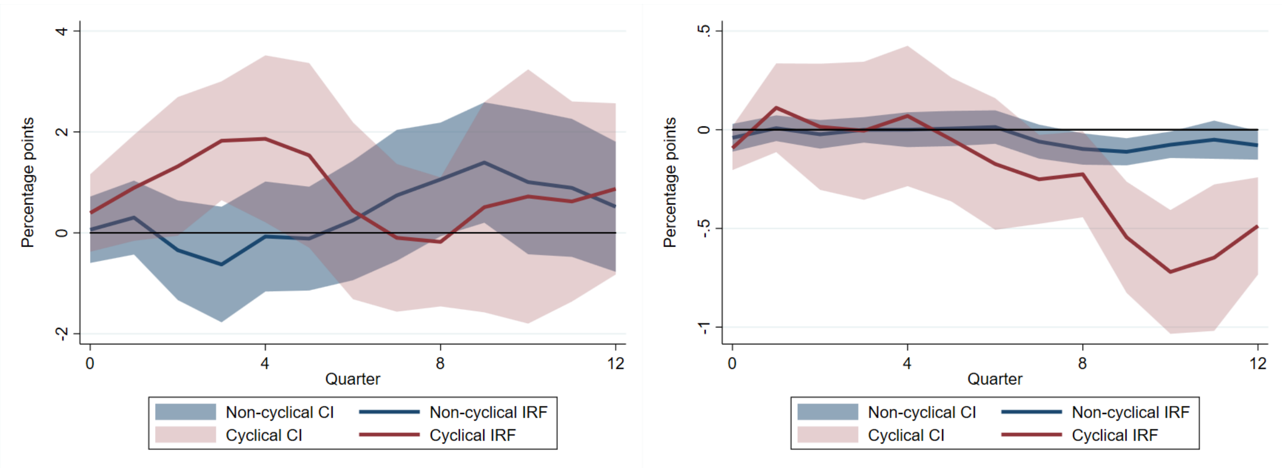
Here, I re-estimate the model in (10) with the job finding and separation rate calculated from CPS data. Results are shown in Figure C.4.5. The left panel displays job finding rate responses across the two sectors following an expansionary monetary policy shock. In the short run, the job finding rate in cyclical sectors increases much more than in non-cyclical sectors. At a longer horizon, the two responses become more alike.

The right panel of the figure shows separation rate responses across the two sectors. Expansionary monetary policy shock does not affect separation rates in the short run, and there are also no differences in sectoral responses. However, after 6 quarters, the separation rate in cyclical sectors drops, while in the non-cyclical sectors, it remains largely unresponsive.

Overall, the results suggest that the job finding rate in cyclical sectors fluctuates much more than in non-cyclical sectors at a business cycle frequency, exposing households in cyclical sectors to higher employment risk. These results align with the findings in Section 3.2.3. Nevertheless, given the short sample, the presented results should be interpreted with caution.

Figure C.4.5: Response of the job finding and the separation rate to a monetary policy shock

(A) Job finding rate (B) Separation rate



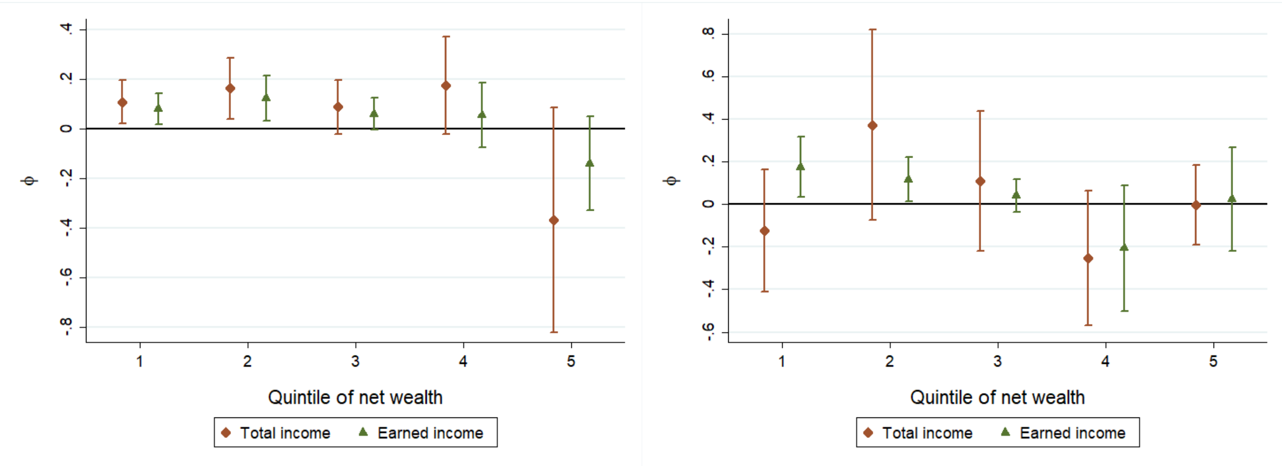
Notes: This figure shows impulse responses following an expansionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors). The data in both panels is seasonally adjusted and covers the period 2002q1–2017q3. Selection into the cyclical and the non-cyclical sectors is based on results in Section 3.2.1. For more details on the construction of job finding and separation rates from CPS data, see Section C.3 in the appendix.

C.5 Holdings of net liquid assets across sectors (alternative specifications)

C.5.1 Net liquid assets to income ratio

Figure C.5.1: Differences in net liquid assets across sectors

(A) SCF | (B) SIPP



Notes: This figure shows the net liquid assets to income ratio using the two income measures. In PANEL (A) are point estimates together with 90 percent confidence intervals using the SCF sample. The regression includes year-fixed effects. PANEL (B) shows point estimates and 90 percent confidence intervals using the SIPP sample. The regression includes state-fixed effects and state-by-year fixed effects to capture any state-specific (unobservable) characteristics and time variation common to all households within a state and year. In both panels, I use observations between 2001 and 2016. All nominal variables are adjusted to 2016 dollars. All regressions are computed using survey weights. Standard errors are clustered at the household level.

D Model appendix

D.1 Derivation of (37) in Section 4.2.2

An intermediate goods producer j operating in the cyclical sector solves the following problem

$$\max_{\{p_{js}, n_{js}, y_{js}, h_{js}\}} \mathbb{E}_t \sum_{s \geq t} \left(\frac{1}{1+r}\right)^{s-t} \left\{ \frac{p_{js}}{P_s} y_{js} - w_s^C n_{js} - \psi^C M_s^C h_{js} - \frac{\alpha\vartheta}{2} \left(\frac{p_{js}}{p_{js-1}} - 1\right)^2 Y_s \right\}, \tag{D.15}$$

subject to

$$y_{jt} = \left(\frac{p_{jt}}{P_t^C}\right)^{-\mu_C/(\mu_C - 1)} \left(\frac{P_t^C}{P_t}\right)^{-1} \times \alpha Y_t \,, \tag{D.16}$$

$$n_{jt} = \left(1 - \delta^C\right) n_{jt-1} + h_{jt} \,, \tag{D.17}$$

$$y_{jt} = Z_t n_{jt} \,. \tag{D.18}$$

Let λ_{1t}, λ_{2t}, and λ_{3t} be multipliers on the three constraints (D.16)–(D.18). First order conditions with respect to choice variables are

$$\begin{aligned} &\frac{y_{jt}}{P_t} + \lambda_{1t} \left(\frac{\mu_C}{1-\mu_C}\right) \left(\frac{p_{jt}}{P_t^C}\right)^{\frac{\mu_C}{1-\mu_C} - 1} \left(\frac{1}{P_t^C}\right) \left(\frac{P_t^C}{P_t}\right)^{-1} \alpha Y_t \\ &\quad - \alpha\vartheta \left(\frac{p_{jt}}{p_{jt-1}} - 1\right) \left(\frac{1}{p_{jt-1}}\right) Y_t + \frac{1}{1+r} \mathbb{E}_t \left[\alpha\vartheta \left(\frac{p_{jt+1}}{p_{jt}} - 1\right) \left(\frac{p_{jt+1}}{p_{jt}^2}\right) Y_{t+1}\right] = 0 \,, \end{aligned} \tag{D.19}$$

$$-w_t^C - \lambda_{2t} + \frac{1}{1+r} \mathbb{E}_t \left[(1 - \delta^C)\, \lambda_{2t+1}\right] + \lambda_{3t} Z_t = 0 \,, \tag{D.20}$$

$$\frac{p_{jt}}{P_t} - \lambda_{1t} - \lambda_{3t} = 0 \,, \tag{D.21}$$

$$-\psi^C M_t^C + \lambda_{2t} = 0 \,. \tag{D.22}$$

Observe that real marginal costs is the multiplier on (D.18)

$$mc_t^C \equiv \lambda_{3t} = \frac{w_t^C + \psi^C M_t^C - \frac{1}{1+r} \mathbb{E}_t \left[(1 - \delta^C) \psi^C M_{t+1}^C\right]}{Z_t} \,. \tag{D.23}$$

Real marginal costs are increasing in wages and hiring costs, and decreasing in expected discounted savings for keeping existing workers (not needing to hire additional workers in the next period). Substituting (D.21) and (D.16) in (D.19) and using the definition of real marginal costs, the price setting optimality condition reads

$$\left(\frac{p_{jt}}{P_t^C}\right)^{\frac{\mu_C}{1-\mu_C}}\left(\frac{P_t^C}{P_t}\right)^{-1}\frac{\alpha Y_t}{P_t}+\left(\frac{p_{jt}}{P_t}-mc_t^C\right)\left(\frac{\mu_C}{1-\mu_C}\right)\left(\frac{p_{jt}}{P_t^C}\right)^{\frac{\mu_C}{1-\mu_C}-1}\left(\frac{P_t^C}{P_t}\right)^{-1}\frac{\alpha Y_t}{P_t^C}$$
$$=\alpha\vartheta\left(\frac{p_{jt}}{p_{jt-1}}-1\right)\left(\frac{1}{p_{jt-1}}\right)Y_t-\frac{1}{1+r}\mathbb{E}_t\left[\alpha\vartheta\left(\frac{p_{jt+1}}{p_{jt}}-1\right)\left(\frac{p_{jt+1}}{p_{jt}^2}\right)Y_{t+1}\right]. \quad \text{(D.24)}$$

Since in equilibrium all firms in the sector are identical, they charge the same price and produce the same output, hence $p_{jt}=P_t^C$. Furthermore, define price inflation in the cyclical sector as $\pi_t^C \equiv P_t^C/P_{t-1}^C$, one can rewrite (D.24) to obtain the New Keynesian Phillips curve (37) in the main text.

$$\pi_t^C(\pi_t^C-1)=\frac{1}{\vartheta(\mu_C-1)}\left[\mu_C\frac{P_t}{P_t^C}mc_t^C-1\right]+\frac{1}{1+r}\mathbb{E}_t\,\pi_{t+1}^C\,(\pi_{t+1}^C-1)\frac{Y_{t+1}}{Y_t}. \quad \text{(D.25)}$$

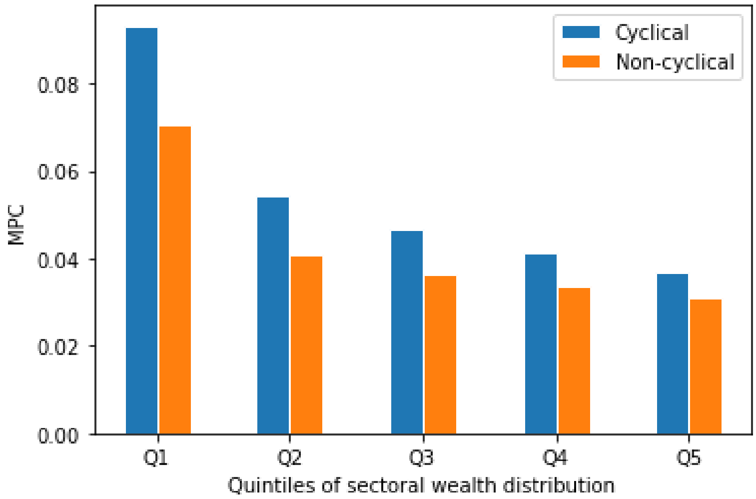
Similarly, one solves for the New Keynesian Phillips curve in the non-cyclical sector

$$\pi_t^{NC}(\pi_t^{NC}-1)=\frac{1}{\vartheta(\mu_{NC}-1)}\left[\mu_{NC}\frac{P_t}{P_t^{NC}}mc_t^{NC}-1\right]+\frac{1}{1+r}\mathbb{E}_t\,\pi_{t+1}^{NC}\,(\pi_{t+1}^{NC}-1)\frac{Y_{t+1}}{Y_t}. \quad \text{(D.26)}$$

E Additional figures and tables from the model

E.1 Consumption functions and MPCs

Figure E.1.1: MPCs across quintiles of sectoral wealth distribution

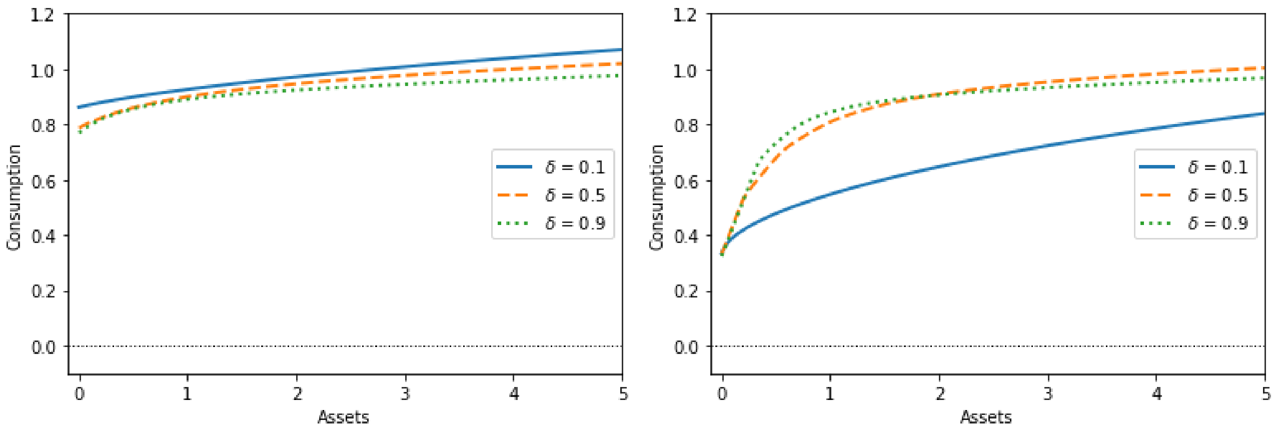


Notes: This figure plots average quarterly MPCs across quintiles of sectoral wealth distribution.

Figure E.1.2: Consumption functions for different values of the separation rate

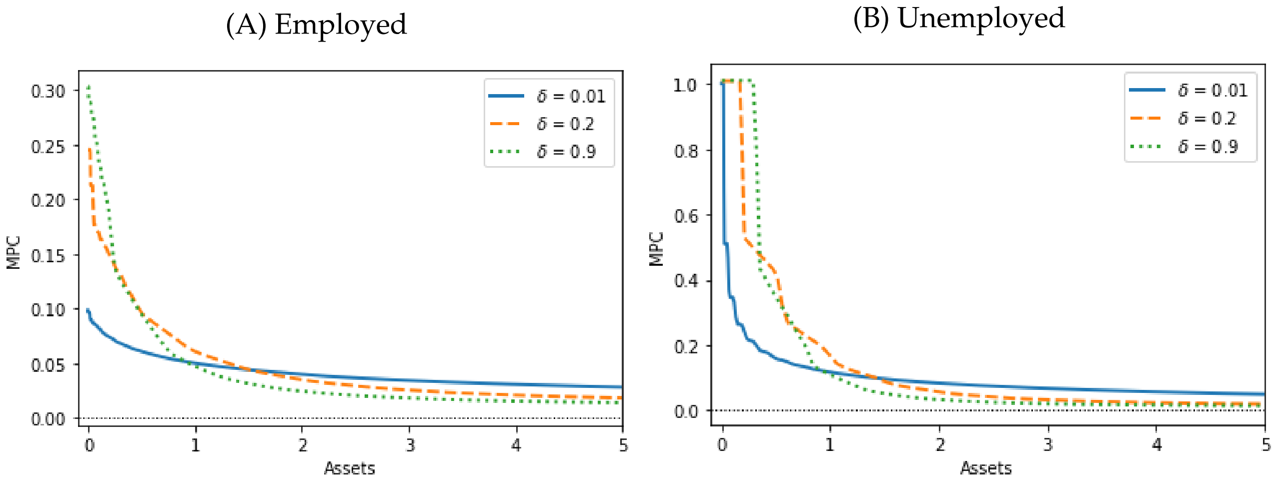
(A) Employed

(B) Unemployed



Notes: This figure shows consumption functions across employment statuses for different values of the separation rate δ. All other parameters are calibrated as in Table 3.

Figure E.1.3: MPCs for different values of the separation rate



Notes: This figure shows quarterly MPCs across employment statuses for different values of the separation rate δ. All other parameters are calibrated as in Table 3.

E.2 Some measures of wealth inequality

Figure E.2.1: CDF of bond holdings

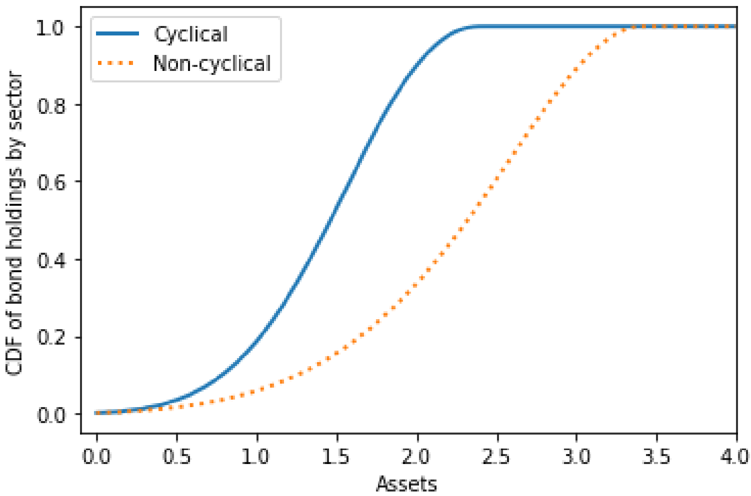
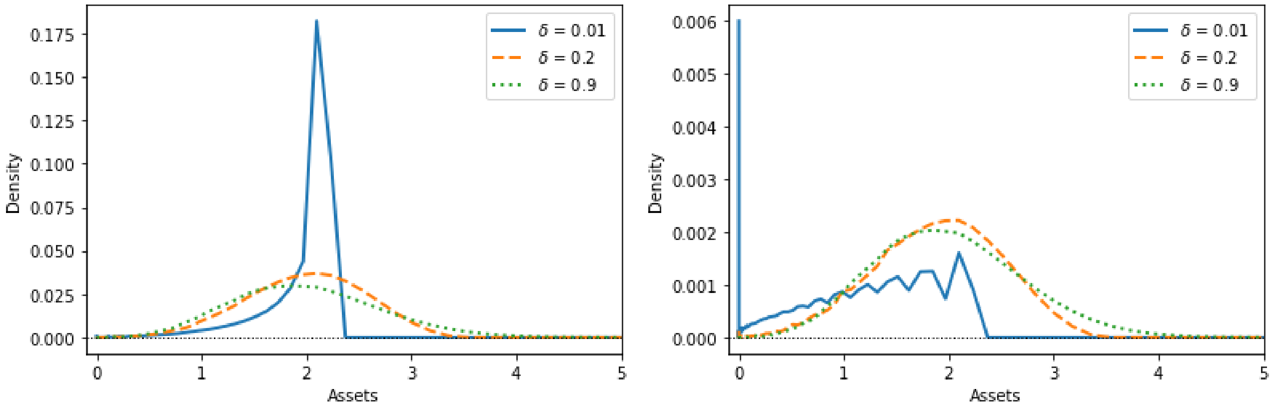


Figure E.2.2: Stationary wealth distribution for different values of the separation rate

(A) Employed (B) Unemployed

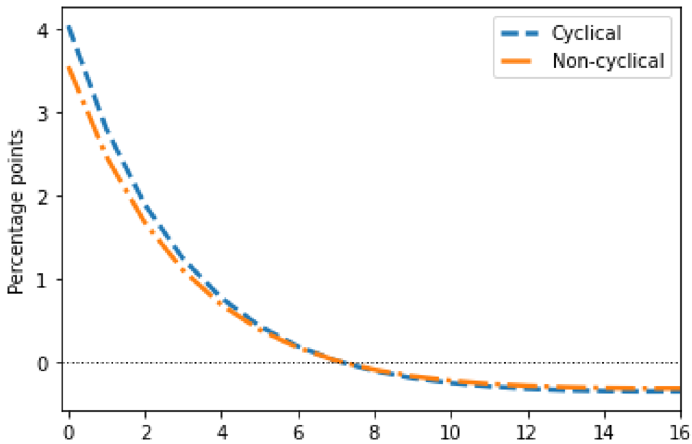


Notes: This figure shows stationary wealth distributions for different values of the separation rate δ. All other parameters are calibrated as in Table 3.

F Additional results from Section 5

F.1 Income gap(s)

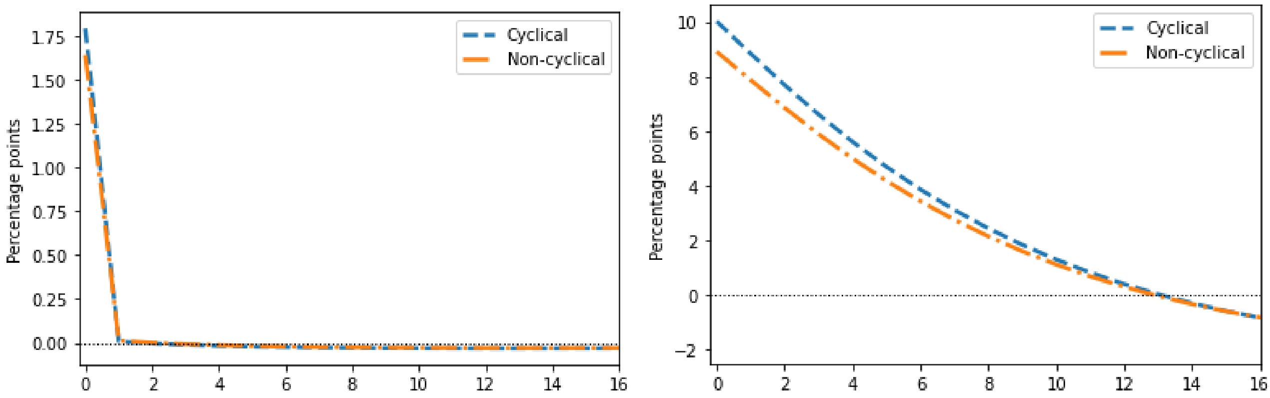
Figure F.1.1: Income gap



Notes: Income gap is calculated as the difference between household's expected income when employed (wages and dividends, net of taxes) and expected income when unemployed (unemployment benefits).

Figure F.1.2: Income gap

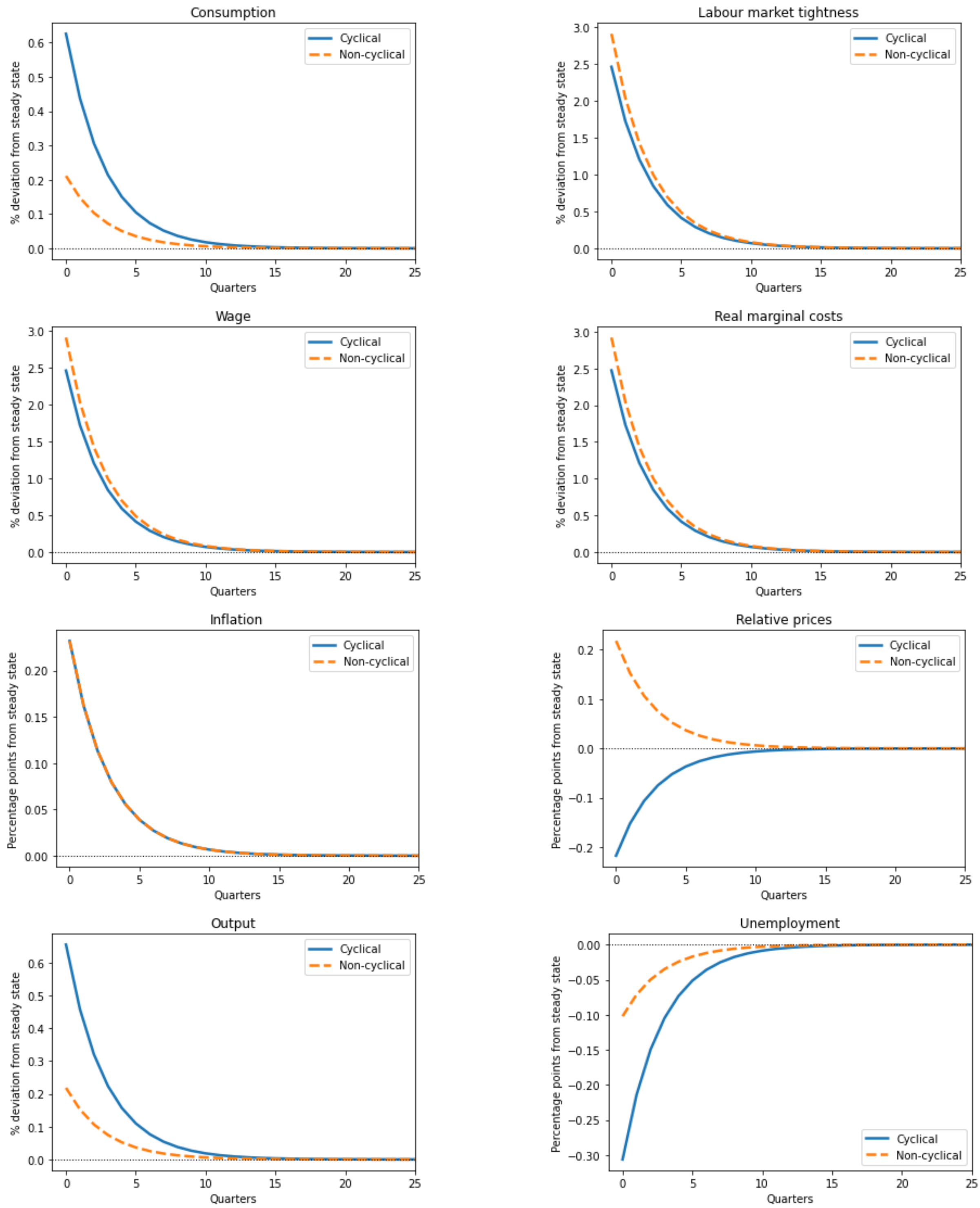
(A) Transitory shock ($\rho_R = 0$) (B) Persistent shock ($\rho_R = 0.9$)



Notes: The income gap is calculated as the difference between household's expected income when employed (wages and dividends, net of taxes) and expected income when unemployed (unemployment benefits).

F.2 Representative-Agent New Keynesian model (RANK)

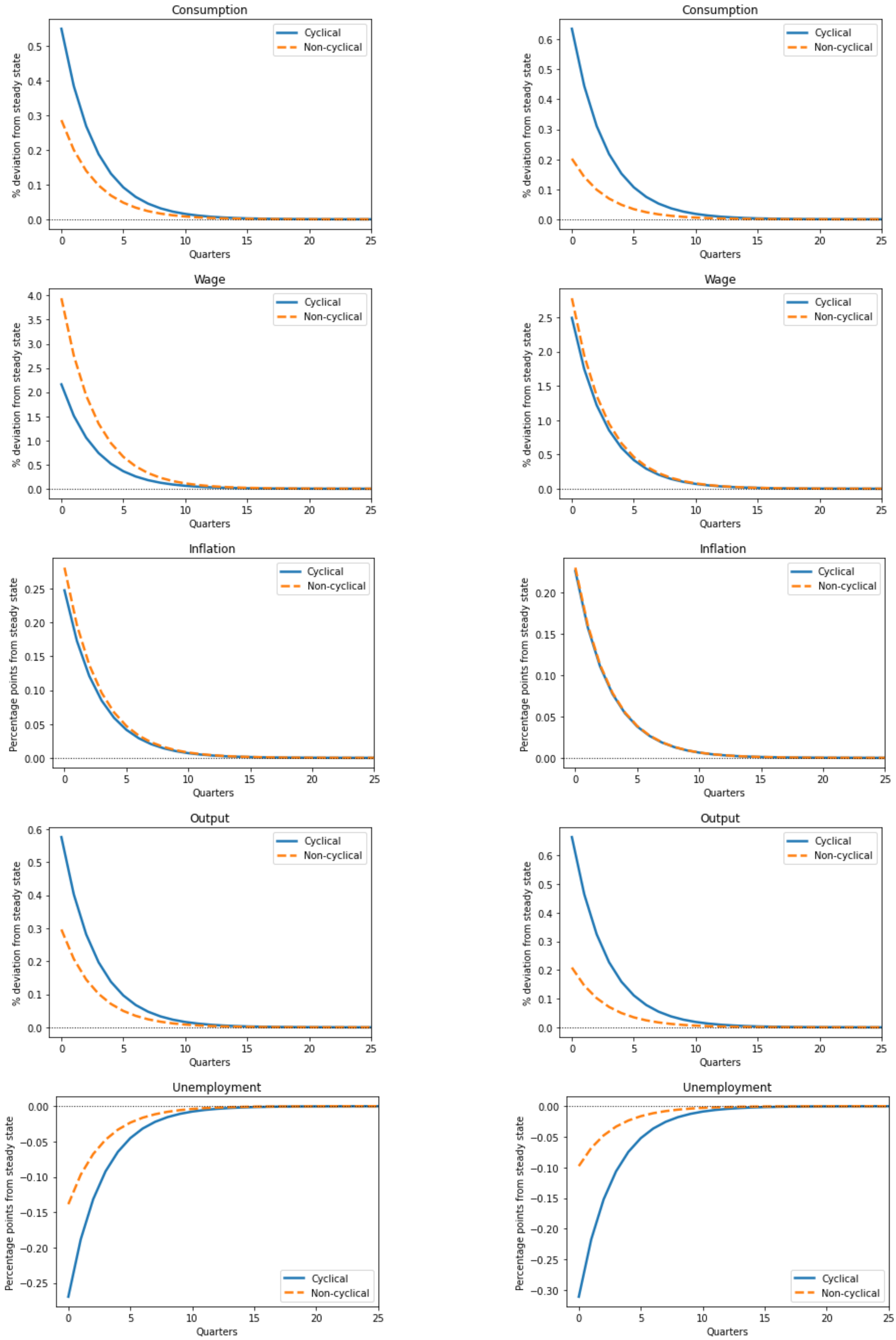
Figure F.2.1: The effect of a monetary policy shock in a two-sector RANK



Notes: The figure shows impulse responses to a monetary policy shock with persistence $\rho_R = 0.7$.

Figure F.2.2: Elasticity of substitution in RANK

Gross complements | Gross substitutes



Notes: When sectors are gross complements, the elasticity of substitution is set to 0.2. When sectors are gross substitutes, the elasticity of substitution is set to 2. All other parameters are the same as in the baseline calibration.

Figure F.2.3: Shock persistence in RANK

Transitory shock ($\rho_R = 0$) | Persistent shock ($\rho_R = 0.9$)