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

Uroš Herman†

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Abstract

This paper studies the role of sector-specific employment risk for the transmission of monetary policy within a two-sector Heterogeneous Agent New Keynesian model. I start with the observation that sectoral net worker flows can be informative about sectoral employment risk and, thus, the strength of the sectoral precautionary saving motive. I find that households working in cyclical sectors, which are more exposed to business cycles and feature higher employment risk, tend to accumulate more net liquid assets than households working in sectors less exposed to business cycle fluctuations. This difference in net liquid assets is larger at low wealth levels. Then, I build a two-sector HANK model in which sectors differ in terms of endogenous employment risk and analyse the transmission mechanism of monetary policy. The consumption response following an expansionary monetary policy is larger and more persistent in the sector with higher employment risk. I identify two channels through which employment risk affects sectoral and aggregate consumption responses.

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

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†Aix-Marseille University, CNRS, AMSE, France. E-Mail: uros.herman@univ-amu.fr.

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.

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 and generates heterogeneous MPCs, which affect the transmission mechanism of monetary policy. Most heterogeneous agent literature assumes that all households work in one sector and face the same employment risk. However, as labour literature has found, and as I show in this paper, the labour market is far from homogeneous, and there are large differences in employment risk across sectors over the business cycle. Yet, it remains largely unexplored how these differences in employment risk affect monetary policy transmission.

There are two main contributions of the paper. The first contribution is to show that sectoral net worker flows can be informative about sectoral employment risk and, therefore, the strength of the precautionary savings motive.[2] My second contribution is to build a two-sector Heterogeneous Agent New Keynesian (HANK) model augmented with labour market frictions, allowing me to study the role of sectoral employment risk in the monetary policy transmission mechanism.

I proceed as follows. To motivate the analysis, I use a simple consumption-savings model to show 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, households tend to accumulate more precautionary savings when they are more likely to be separated from a current job and when they are exposed to large and more transitory changes in the job finding rate.

The following section presents some new empirical facts about sectoral employment risk and precautionary savings. My measure of employment risk is based on net worker flows over the 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. To capture cross-sectoral differences in employment risk, I categorize all sectors into two groups; cyclical and non-cyclical sectors, depending on the sensitivity of sectoral net worker flows to business cycles. Then, I merge information on the sectoral em-

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

[2] Net worker flows are expressed in terms of rates and are defined as the difference between hire and separation rates, where the denominator is employment. For brevity, I use the term net worker flows.

ployment 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.[3] 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.

Then I build a two-sector HANK model to analyse the macroeconomic implications of the 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. 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.[4]

I calibrate the model to capture some of the main 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 nonemployment observed in the data. I find that households in the cyclical sector face almost twice as high separation rates as households 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. I identify two channels through which employment risk affects consumption responses in my model. 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. Both factors together contribute to a higher sectoral MPC. As a result, the consumption increase will be larger for a given income increase. Second, the separation rate also

[3] 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.

[4] Auclert, Rognlie, Souchier, and Straub (2021) include similar elements in their model. However, they focus on exchange rates and the real income channel in a small open economy model. In contrast, I focus on differences in labour market segments in a closed economy.

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 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.[5] This second channel is the "relative labour demand channel" and is operative even if there is no employment risk. However, with incomplete markets, this channel has an additional effect on consumption responses; additional income in the cyclical sector makes income risk more procyclical, strengthening the precautionary savings motive and restraining the consumption response.

As a sensitivity analysis, I study how the results and the importance of the two channels change when I vary (i) the coefficient of elasticity of substitution between the two sectors and (ii) the persistence of the monetary policy shock. Regarding the first exercise, I find that the elasticity of substitution operates mainly via the relative labour demand channel; when the two sectors are substitutes, labour demand spillovers from the non-cyclical sector to the cyclical one are much larger than when the two sectors are complements. Concerning the second exercise, I show that persistence affects the cyclicality of income risk and the strength of the precautionary savings motive. A transitory shock mostly affects poor hand-to-mouth households, and the effect of the cyclicality of income risk on consumption responses is limited. However, with a persistent shock, the importance of the cyclicality of income risk increases, making the precautionary saving motive much more important for sectoral consumption responses.

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)).[6] 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 (un)employment risk.

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

[5] 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.

[6] 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)).

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.[7] 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.[8]

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.[9] 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

[7] 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).

[8] 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.

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

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 (2018) 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—high MPC individuals. This mechanism is operative in my model; households in the cyclical sector have higher MPCs, 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 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.[10] 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,

[10] 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.

Section 5 discusses the results, and Section 6 concludes.

2 Employment Risk and Precautionary Savings

I start by showing how employment risk affects the amount of precautionary savings. To do this, I introduce a stylized consumption-savings model in which 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.

Time is discrete, denoted as $t = 1, 2, 3, \ldots$. Consider a household that was employed 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 the household immediately engages in a job search. The probability of finding a new job is given by the job finding rate M_t. If the 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—without unemployment spell at the beginning of period t—with probability $(1 - s_t) \equiv 1 - \delta(1 - M_t)$.[11]

Each period, a household solves the following maximization problem

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

subject to

$$c_t + a_{t+1} \leq R a_t + (1 - s_t)\, \overline{w} + s_t\, 0\,. \tag{2}$$

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, a_t are asset holdings at the beginning of period t. A household income, if employed, is given by $(1 - s_t)\, \overline{w}$, where $(1 - s_t)$ is the probability of remaining employed and $\overline{w}$ is a constant wage. With probability s_t, a household becomes unemployed and does not receive any income.

The solution to the problem yields the standard Euler equation

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

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

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

[11] This setup follows the labour market structure used in the quantitative model, which is explained in detail in Section 4.1.

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 analyse the effect of employment risk on precautionary savings, I simplify the analysis and assume that a household chooses to hold zero assets in period t.[12] In this case, expected consumption is equal to expected income, $\mathbb{E}(c_{t+1}) = \mathbb{E}\left[(1 - s_{t+1})\, \overline{w}\right] \equiv \mathbb{E}\left[(1 - \delta\,(1 - M_{t+1}))\, \overline{w}\right]$. Using this fact in (5) yields

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

Employment risk is captured through a stochastic job finding rate $\{M_t\}$. The job finding rate follows an AR(1) process

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

where $\overline{M} \geq 0$ is the unconditional mean (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) yields

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

where the last term determines the amount of precautionary saving S.[13] As seen from (8), the amount of precautionary saving S depends on the separation rate δ and on two parameters describing the job finding rate process: the variance of innovations σ_ϵ^2 and 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 $\gamma(c)$, a constant wage $\overline{w}$, and an exogenous separation rate δ, the amount of precautionary savings S is larger when (i) the variance of innovations of the job finding*

[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.

[13] There are two additional factors in (8) which affect household's consumption level at time t. The first term on the right-hand side is associated with the intertemporal substitution motive βR and absolute risk aversion $A(c)$. The second term on the right-hand side, i.e. $\overline{w}\left[1 - \delta\left(1 - \overline{M}\right)\right]$, is akin to households's permanent income.

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 they are exposed to large and transitory changes in the job finding rate. Intuitively, a higher innovation variance means that the household faces larger shocks to the job finding rate, which increases the uncertainty and volatility of future income. Thus, the household will want to save more to protect against these fluctuations. On the other hand, a higher persistence implies that the current job finding rate is more informative about the future job finding rate, which reduces uncertainty about future income and the need for precautionary savings.[14]

In Section 4, I build a quantitative model and analyse how differences in employment risk across sectors affect the monetary policy transmission mechanism. There, differences in employment risk across sectors are modelled as differences in separation rates. The following corollary establishes a relationship between the separation rate and the amount of precautionary saving.

Corollary 1.1 (Separation rate and precautionary savings)**.** *For a given parameter of absolute prudence $\gamma(c)$, a constant wage $\overline{w}$, and a job finding rate process $\{M_t\}$, the amount of precautionary saving S in (8) 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 S. This relationship arises because a higher separation rate implies a higher probability of job loss and income uncertainty. As households face a greater risk of unemployment, they have a stronger incentive to save as a precautionary measure to mitigate the potential adverse effects of job separation. Therefore, an increase in the separation rate intensifies the precautionary saving motive, leading to a higher value of S in (8). Observe that 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 $\overline{w}$.

3 Sector-specific Employment Risk and Net Liquid Asset holdings

In the previous section, I showed how employment risk affects precautionary savings using a stylised model with a homogeneous labour market. However, literature has found that the labour market is far from homogeneous, and there are significant differences in employment

[14] With more persistent income shocks, self-insurance through precautionary savings becomes less effective and more difficult, see, for example, Constantinides and Duffie (1996); Kaplan and Violante (2022), among others.

risk across sectors over the business cycle.[15] 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?

This section attempts to provide 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.[16]

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 test the prediction of Proposition 1.

3.1 Data description

Survey of Consumer Finances. I use the survey data for the period between 1989–2016. In the analysis, I focus on households with at least two members, who are either married or live together, who obtain labour 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 enable me to focus on households in their prime working age, who pool income risk and are exposed to the same sector-specific employment risk.[17]

[15]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.

[16]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.

[17]Restricting the sample to households where both members work in the same sector is very restrictive and reduces the sample quite a bit. Therefore, I also allow for instances where one household member is working,

The definition of net liquid assets is the same as in Bayer, Luetticke, Pham-Dao, and Tjaden (2019). Specifically, net liquid assets comprise money market, checking, savings, and call accounts, certificates of deposit, private loans, and bond holdings minus credit card debt.[18] The data is measured in real terms, i.e. CPI adjusted to 2016 dollars. From the survey, I also construct two measures of income that differ in terms of income type households receive. The first measure includes only earned income, i.e., wages and salary income plus income from a business, sole proprietorship, and farm.[19] This is my benchmark income measure. The second measure is broader and includes all earned and unearned income plus transfers. Both income measures are expressed in real terms, before tax, and annualised. The left panel of Table B.2 in appendix presents summary statistics from the SCF sample.

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.

Data on the (net) wealth of households are part of topical modules and thus available only at certain waves.[20] 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 mutual funds and/or stocks, municipal or corporate bonds and/or US government securities, interest-bearing checking accounts, savings accounts, money market, certificate of deposit, and non-interest checking account 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), and value of stocks and mutual funds minus store bills or credit card debt. Income is calculated as in the SCF sample.[21] The data is CPI ad-

and the other one is not doing any work for pay.

[18] 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.

[19] Note that income from sole proprietorship and/or business can be negative, which could cause that earned income becomes negative. In my sample, the share of households with a negative earned income is less than 0.5 percent of the sample.

[20] 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.

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

justed to 2016 dollars. Summary statistics of the SIPP sample can be found in the right panel of Table B.2.

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.[22] I define net worker flows as the difference between hire and separation rates to nonemployment.[23] 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.[24] 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 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.[25] 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.3.

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. Therefore, I use layoffs instead of separations to calculate net worker flows. To make The JOLTS sample comparable to the LEHD sample, I average the monthly

[22]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.

[23]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.

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

[25]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)).

data to quarterly frequency and restrict the sample to the period between 2001q2–2017q3. The data is seasonally adjusted. As before, net worker flows are expressed as a share of average employment within the sector. The bottom panel of Table B.3 presents some summary statistics of the JOLTS sample.

3.2 Employment risk in Cyclical and Non-cyclical sectors

Before I allocate households in the SCF sample to cyclical or non-cyclical sectors, I need to define which industries are cyclical and which are non-cyclical. Because I can not infer the cyclicality of industries directly from the SCF data, I use the LEHD data. However, the LEHD and the SCF data set are not fully comparable in terms of "industry groupings"—in the publicly available version of the SCF data, the standard four-digit NAICS industries are merged into seven distinct SCF-industry groups for confidentiality reasons. Therefore, to relate the SCF with the LEHD data, I match 20 two-digit NAICS industries from the LEHD sample with the seven industry groups defined by the SCF. The mapping is rather straightforward for most industries, as the two-digit NAICS industry from the LEHD sample is only in one SCF-industry group. However, there are instances where an industry maps into two SCF groups. In this case, I assign the industry to the SCF-industry group, where this industry has the largest employment share. See also appendix B.1 for a detailed discussion about the mapping of LEHD industries into SCF groups.

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 different business cycle measures X_t and various controls

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

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. X_t is a measure of the business cycle (I consider the change in (the negative of) the log of real GDP, the change in the log of unemployment, and NBER recession episodes), SCF_{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 net worker flows.

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, and in columns 3 and 6, I use changes in the log of unemployment level. I find that for all specifications, net worker flows in SCF-industry groups 2 and 3 are consistently more sensitive to business cycle fluctuations than the US as a whole. In contrast, net worker flows in SCF-industry groups 6 and 7 are consistently less sensitive. Changes in net worker flows in other SCF-industry groups are not statistically significantly different from the US average.

Considering results 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.[26] 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.

[26]Geremew and Gourio (2018) study the cyclicality of US employment across industries using the Current 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.

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.

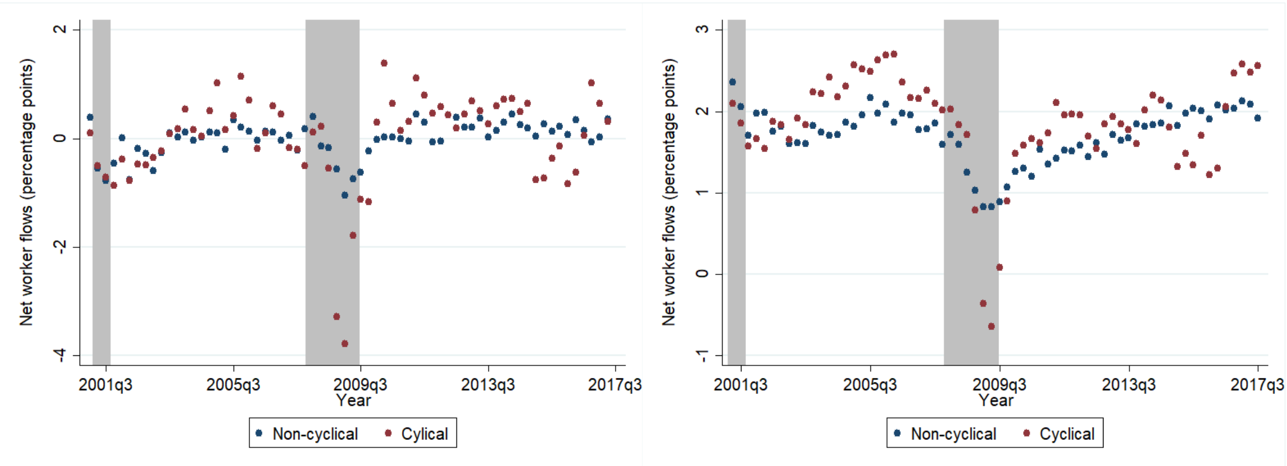
3.2.2 Employment risk in cyclical and non-cyclical sectors

Figure 1 plots 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 large differences in 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, relative to workers working in non-cyclical sectors. There is also substantial variation in net worker flows across sectors. For example, the standard deviation of net worker flows in cyclical sectors is almost twice as large as in non-cyclical sectors. This implies that workers in cyclical sectors experience higher employment risk than those in non-cyclical sectors.[27] My results 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.[28]

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.

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.[29] The US monetary policy shocks series comes from the work by Bu, Rogers, and Wu (2021).[30] The

[27] As a robustness check, I have tried different measures of net worker flows, hires and separations separately, including other demographic controls, controlling for two-digit industries. The results remain robust across all specifications. Moreover, Section C.2 in appendix shows gross worker flows (hires and separations) over the business cycle.

[28] The most exposed workers are working in Construction and Durable Manufacturing, whereas the least exposed are workers in Transportation, Health and Education.

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

[30] 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`.

data is quarterly, seasonally adjusted, and covers the period 2001q2–2017q3.

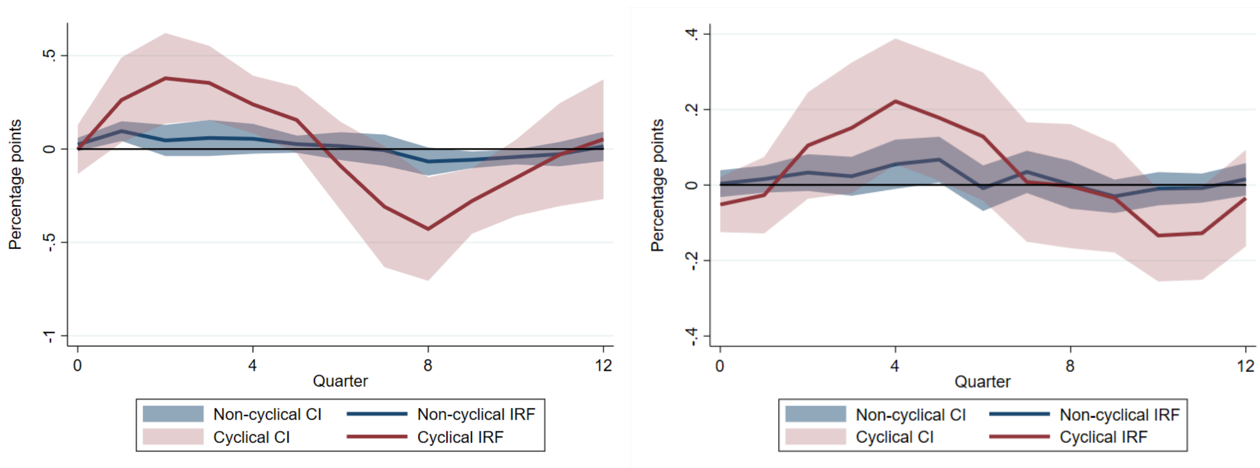
I estimate the following LP model for cyclical and non-cyclical sectors separately

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

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 ($K = Q = 4$).[31] 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: 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.

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.[32] 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 timing and the size of peaks in cyclical sectors are somewhat different in the two samples, the dynamic of

[31] 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.

[32] Figures C.8A and C.8B in appendix plot the effect of expansionary monetary policy shocks on the real interest rate and the unemployment rate.

net worker flows is surprisingly similar.[33]

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.9 and C.10 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 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

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

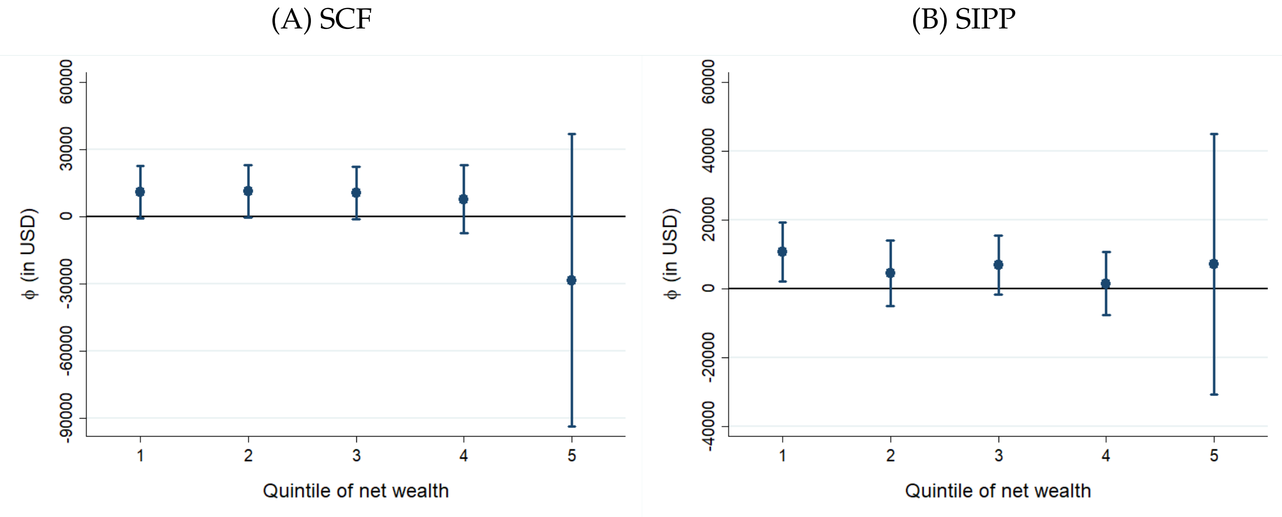
where $Y_{i,q,c,t}$ is the amount of net liquid assets held by a household i, who is in quintile q of net wealth distribution, working in sector c, at time t. γ_c is a dummy variable for working in a cyclical sector, γ_q is a dummy for being in quintile q, γ_s are US state fixed effects, $\tau_{t,s}$ 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.[34] I am interested in the parameter ϕ, which measures the difference in net liquid asset holdings in quintile q between households

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

[34] I include gender, age and age squared, race bins, educational attainment bins, occupation bins, tenure, number of kids, households earnings, 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.

working in cyclical sectors and those working in 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.

Figure 3: Differential holdings of net liquid assets across sectors



Notes: In PANEL (A) are point estimates together with 90 percent confidence intervals from estimating (11) using the SCF sample. The regression includes year-fixed effects. PANEL (B) shows point estimates and 90 percent confidence intervals from estimating (11) 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.

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.[35] I find that households working in cyclical sectors hold, on average, more net liquid assets than households with similar characteristics and similar wealth working in non-cyclical sectors and the difference in net liquid asset holdings is statistically significant for poor households. The results for wealthy households are statistically insignificant, and even different signs for the top quintile, reflecting large uncertainty regarding the point estimates due to the imprecise measurement of the wealthiest households.

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.[36] Households would like to avoid the situation where they have to reduce their

[35]As a robustness check, Figure C.12 in appendix shows results using only year fixed effects when estimating the SIPP sample.

[36]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. Yet, there is no consensus on the importance of the precautionary saving motive in terms of additional savings. A paper studying the strength of precautionary saving motive using some type of cross-sectoral differences

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.[37] 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)). 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 all this information on sectoral employment risk and precautionary savings at hand, I can now test the prediction of Proposition 1 in the data. According to the proposition, households exposed to large and less persistent changes in the job finding rate should accumulate more precautionary savings for self-insurance. However, given the data limitation, I cannot calculate job finding rates as typically defined in the literature. Instead, I construct quarterly *job finding rate proxies* P_t using the LEHD and the JOLTS data. To construct the LEHD proxy, I take quarterly flows from persistent nonemployment to employment in period t and divide them by the number of unemployed workers in period $t-1$. Similarly, for the JOLTS sample, I divide quarterly hires in period t by the number of unemployed workers in period $t-1$.[38] Then, I estimate the following equation

$$P_t = \mu + \rho P_{t-1} + \varepsilon_t \,, \tag{12}$$

where μ is the constant, ρ is the persistence parameter, and σ_ϵ is the standard deviation of the innovation ε_t.

in income risk is by Fuchs-Schündeln and Schündeln (2005). Authors test whether civil servants exposed to lower income risk have significantly lower wealth holdings than individuals in other jobs. They find that after German reunification, the savings rate of most East Germans increased, but the savings rates of civil servants (income risk for them almost did not change after reunification) did not. In West Germany, there was no such difference in savings rates between civil servants and the private sector.

[37]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, they have enough (liquid) wealth to smooth their consumption path.

[38]More details on the construction of proxies, what are limitations, and comparison with the job-finding rate compiled by Shimer (2012) can be found in Section C.4 in appendix.

Table 2: Estimation of job finding rate proxies

	LEHD		JOLTS	
	Cyclical	Non–cyclical	Cyclical	Non–cyclical
μ	0.944	0.971	0.526	0.549
	(0.17)	(0.17)	(0.13)	(0.12)
ρ	0.876	0.910	0.884	0.954
	(0.06)	(0.05)	(0.07)	(0.03)
σ_P	0.156	0.115	0.094	0.055
	(0.02)	(0.01)	(0.01)	(0.01)
Observations	66	66	66	66

Notes: This table shows results from ML estimation of $P_t = \mu + \rho P_{t-1} + \varepsilon_t$, where μ is the constant, ρ is the persistence parameter, and σ_P is the standard deviation of the innovation ε_t. 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. Standard errors are corrected for heteroskedasticity.

Table 2 presents estimates of the job finding rate proxies. I find that the proxy in cyclical sectors is less persistent, and the standard deviation of its innovation is larger than in non-cyclical sectors. According to Proposition 1, both time-series properties of job finding rate proxies—low persistence and large shocks—are associated with a stronger precautionary savings motive in cyclical sectors.[39] Of course, given the short sample, results should be interpreted with caution.

4 A two-sector Heterogeneous Agent New Keynesian model

I now build a two-sector HANK model with search and matching frictions. The model builds on and 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

[39]Using the estimated values from Table 2 in equation (8) delivers precautionary savings S_t between 0.013 (LEHD) and 0.005 (JOLTS) in cyclical sectors, and 0.007 (LEHD) and 0.002 (JOLTS) in non-cyclical sectors. Moreover, the results are robust to various specifications: including linear time trend, quadratic time trend, controlling for heteroskedastic and autocorrelated (Newey-West) standard errors.

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

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

Employed households receive real wage w^x_{it} and real dividends from intermediate goods firms D^x_{it}, net of taxes τ^x_t. Households who do not find jobs become unemployed and receive unemployment benefits b^x. Unemployment benefits in each sector are equal to the replacement rate rr^x of the sectoral steady state wage $\overline{w}^x$.

[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.

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

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

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

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

[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.

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.

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

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

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

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 measured in terms of the final good $\Theta_t^C = \frac{\vartheta}{2}\left(\frac{p_{jt}}{p_{jt-1}}-1\right)^2 Y_t$, with $\vartheta > 0$. The profit maximisation problem of a firm is

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

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

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

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

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

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

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

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. $\Gamma_t^x(a^x, e^x)$ *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

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

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

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

[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.

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* $L_t^x = N_t^x$*. 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),* $C_t \equiv \sum_x \int c_t\,(a^x, e^x)\, d\Gamma_t^x\,(a^x, e^x)$ *is aggregate consumption,* $\psi M_t H_t \equiv \sum_x \psi^x M_t^x H_t^x$ *are aggregate hiring costs, and* $\Theta_t \equiv \sum_x \Theta^x$ *are aggregate price adjustment costs. 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 on sectoral worker flow rates. 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).

The steady state unemployment rate is set to $\overline{U} = 6.3\%$ in both sectors, which is the average unemployment rate in the US for the period 2001q2–2017q3. I calibrate the job separation rate to match average sectoral worker flow rates from employment to nonemployment in the LEHD sample (see Table B.3 in appendix). This delivers a job separation rate of $\delta^{NC} = 0.086$

[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.

Table 3: Baseline calibration

Description	Parameter	Value: Cyclical	Value: Non-cyclical	Target
Sector size	α	0.5		Symmetric sectors
Discount factor	β	0.989		Real annual interest rate of 3%
Substitutability between sectors	η	0		Cobb-Douglas aggregator
EIS	$1/\gamma$	0.5		Standard
Markup	μ	1.2		Standard
Price adjustment cost	ϑ	55		Average price duration of 4 qtr
Bond supply	B	1.803		Average liq. assets to income = 0.55
LABOUR MARKET				
Unemployment rate	$\overline{U}$	0.063		Unempl. rate: 2001q2–2017q3
Job separation rate	δ	0.164	0.086	See text
Vacancy posting cost	ψ	0.031		McKay and Reis (2021)
Replacement rate	rr	0.4		Average repl. rate: 2001q2–2017q3
Elasticity of wages w.r.t. labour market tightness	ζ	1		See text

in the non-cyclical sector and $\delta^C = 0.164$ in the cyclical sector. The replacement rate in both sectors equals $rr = 40\%$ to match the average replacement rate in the US in that period.[49] In the baseline calibration, wages are flexible, and the elasticity of 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 shows results from my baseline calibration. The model delivers higher job finding rates $\overline{M}$ and lower wages $\overline{w}$ in the steady state for the cyclical sector. Both calibration outcomes are qualitatively in line with what I observe in the data (see Table B.2 and Table B.3 in appendix). The job loss rate—my measure of employment risk—is larger in the cyclical sector than in the non-cyclical one.[50] Moreover, the model predicts the aggregate $\overline{MPC}$ of 0.052 at a quarterly frequency, corresponding to an annual value of approximately 0.21, with higher values in the cyclical sector than in the non-cyclical sector.[51] 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

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

[50] In the model, the job loss rate is equal to the probability of being separated and not being rehired in the same period, i.e. $s_t \equiv \delta^x(1 - M_t^x)$.

[51] The fact that households in the cyclical sector have higher average MPCs holds across the wealth distribution. Figure E.13 in appendix plots average MPCs across sectors for different quintiles of the sectoral wealth distribution.

more exposed to the Great Recession shock, i.e. more cyclically sensitive industries, have higher MPCs.[52]

Table 4: Steady state results

Description	Parameter	Aggregate	Cyclical $\delta^C = 0.164$	Non-cyclical $\delta^{NC} = 0.086$
Job finding rate	$\overline{M}$	0.670	0.745	0.594
Job loss rate	$\bar{s}$	0.046	0.051	0.041
Wage	$\overline{w}$	0.830	0.829	0.831
Average MPC (quarterly)	$\overline{MPC}$	0.052	0.056	0.048
– Employed			0.050	0.042
– Unemployed			0.146	0.136
Bond holdings (% of total)			43.89	56.11
Lower bond supply				
Average MPC		0.073	0.078	0.068
Lower unemployment benefits				
Average MPC		0.056	0.06	0.052

What explains these differences in MPC across the two sectors? In the model, the job separation rate determines employment risk and, therefore, income risk. With a higher separation rate, households are more likely to become unemployed and receive unemployment benefits, increasing their income risk.[53] In addition, a higher separation rate also makes households more likely to hit borrowing constraints if they are poor. Carroll, Holm, and Kimball (2021) shows that both effects—income risk and borrowing constraints—make the consumption function more concave, heightening the prudence and strengthening the precautionary saving motive.[54] 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.[55] MPCs are much larger among unemployed households—some of them being poor hand-to-mouth

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

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

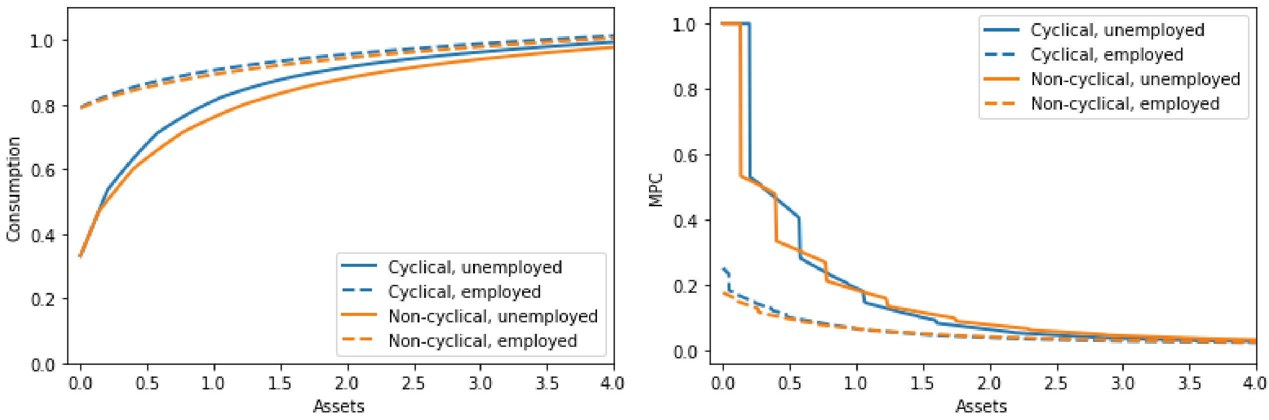
[54]Kaplan and Violante (2022) quantifies how much income risk and borrowing constraints contribute to the increase in an average MPC relative to the certainty MPC. They find that borrowing constraints explain more than two-thirds of the increase, while uninsurable income risk explains one-third.

[55]Figures E.14 and E.15 in appendix plot consumption functions and MPC for different values of the separation rate. As one can see, the concavity of the consumption function is increasing in the separation rate, and so are MPCs. When $\delta = 0$, there is no employment risk and hence income risk, consumption functions are linear, and the MPC is equal to the MPC under certainty.

consumers with MPC equal to 1. When households become wealthier, MPCs in both sectors quickly converge to the MPC, which would prevail under complete markets.

Figure 4: Consumption functions and MPCs

(A) Consumption functions (B) MPCs



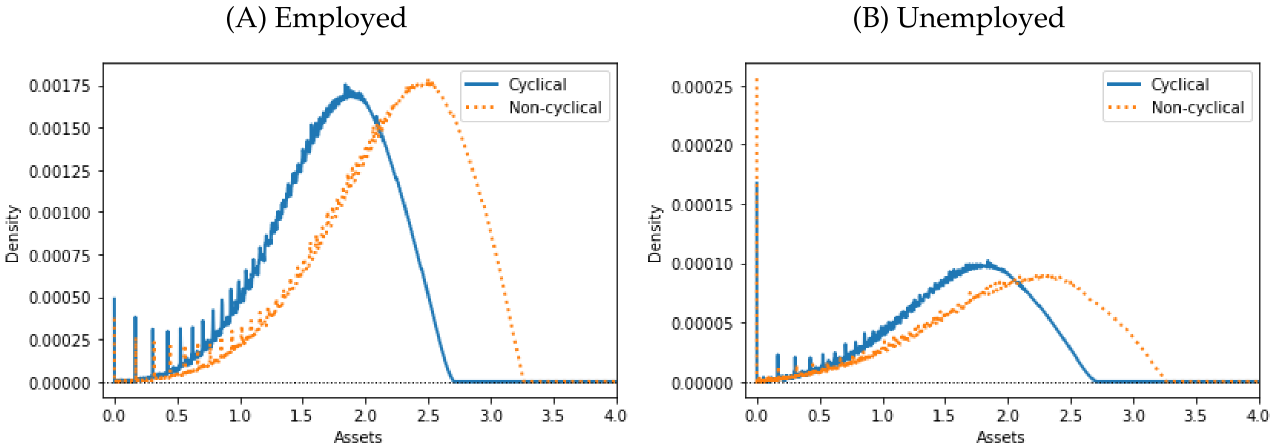
Notes: This figure shows consumption functions and MPCs across sectors and employment statuses, calibrated as shown in Table 3.

Note that sectoral MPCs and the aggregate MPC also depend on stationary wealth distributions of households in each sector, and these distributions themselves 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 in appendix). Interestingly, there are more unemployed households at the borrowing constraint in the non-cyclical sector than in the cyclical one. One explanation for this result would be that due to a lower separation rate, the unemployment state in the non-cyclical sector is more persistent—once a household is unemployed, it is likely that this state will persist for a longer time than in the cyclical sector.[56] This implies that a household is more likely to be at the borrowing constraint, which we see in panel (B). However, a high separation rate also makes it more difficult to accumulate large asset holdings since there is a higher probability of losing a job and depleting previously accumulated assets.[57] This would explain why households in the cyclical sector are less wealthy.

[56] In other words, with lower separation rates, it is more likely to stay poor (rich) if you start as a (poor) rich household, generating more bimodal-looking distributions. See wealth distributions for different values of the separation rate in Figure E.17 in appendix.

[57] Low, Meghir, and Pistaferri (2010) finds that the rate of wealth accumulation decreases with a higher job destruction rate because unemployment spells reduce opportunities to accumulate wealth.

Figure 5: Stationary distributions



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

Next, I explore how the availability of government bonds and the generosity of unemployment benefits affect MPCs in the economy. I find that MPCs increase when the supply of government bonds is lower. When I reduce the supply of bonds by 25%, the aggregate MPC increases to 0.073. With a lower bond supply, there is less self-insurance coming from government bonds. As a result, the wealth distribution in both sectors will shift to the left and (mechanically) increase the average MPCs in both sectors. In addition, with fewer outside assets available, the precautionary savings motive becomes stronger (more households in the high-MPC part of the distribution). Both factors contribute to higher MPCs. When I reduce the replacement rate by 10 percentage points, from 40% to 30% of the steady-state wage, the aggregate MPC increases to 0.056. Lower unemployment benefits imply that the income one receives when unemployed is lower. This increases income risk and makes the precautionary channel more potent (again, this generates more mass at low wealth levels). As a result, average MPCs in the economy increase.

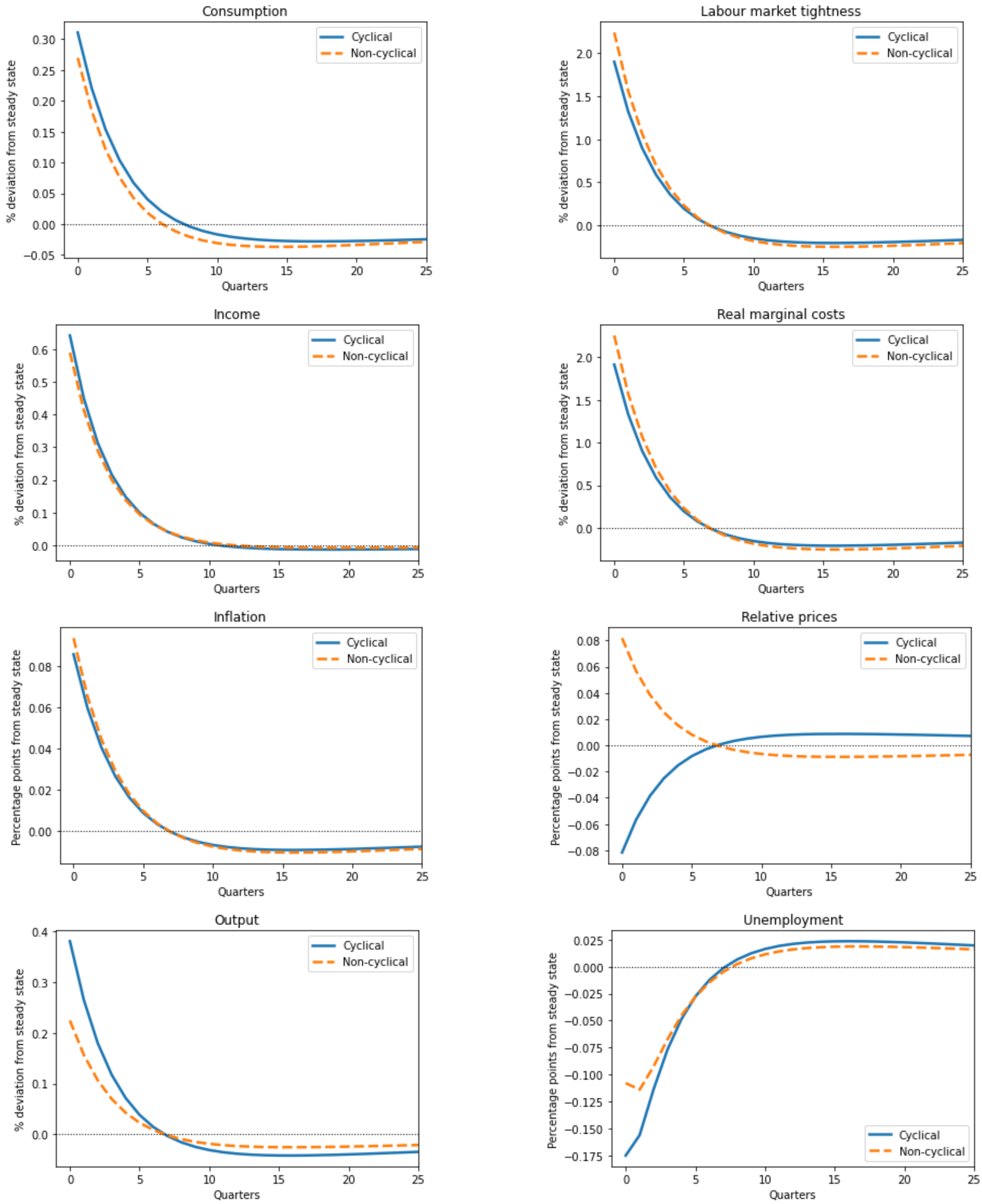
5 Sectoral Exposure to Aggregate Shocks and Propagation of Business Cycles

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").

5.1 The effect of a monetary policy shock in a two-sector HA 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.

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.

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*.

However, 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 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.[58]

Because both 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.[59] 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.

With incomplete markets, this channel has an additional effect on consumption responses because it also affects the cyclicality of income risk and the precautionary savings motive. The literature found that countercyclical income risk amplifies aggregate demand responses

[58] To see this formally, 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, with a more rigid labour market.

[59] Real marginal costs include wages, and current and future hiring costs. See equation (D.17) 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.

(dynamic amplification) in HANK models following an accommodative monetary policy shock. In contrast, procyclical income risk dampens them (dynamic discounting).[60] Following Acharya and Dogra (2020), I use the "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 income comprising wages and dividends, net of taxes, whereas unemployed households receive constant unemployment benefits.[61] However, the model also incorporates employment risk that is countercyclical; households in both sectors are more likely to be employed and be in a high-income state during a boom than during a downturn. This means that households' expected income and hence income gap depend on the probability of being employed or unemployed. To take this into account, I multiply households' income by the (sector-specific) corresponding job finding and job loss probabilities.[62]

Figure 7 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. However, the additional income in the cyclical sector—due to the relative labour demand channel—makes income risk even more procyclical. This strengthens the precautionary savings motive and dampens the consumption response in the cyclical sector. As I show in Section 5.3.2, this effect becomes stronger with a more persistent monetary policy shock.[63]

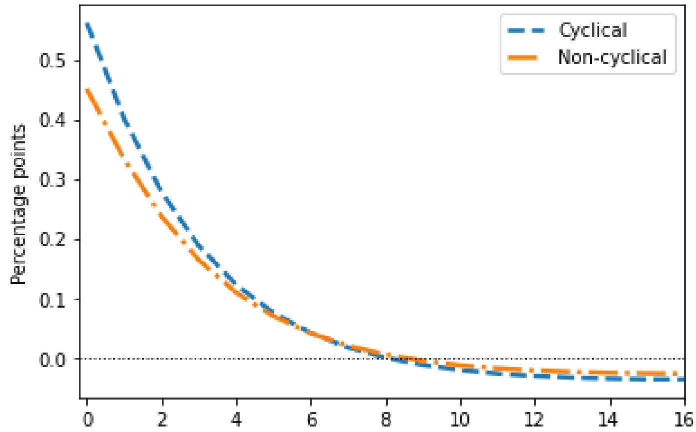
[60] See Acharya and Dogra (2020) for a detailed discussion about the role of the cyclicality of income risk in HANK models. For countercyclical income risk see Werning (2015); Den Haan, Rendahl, and Riegler (2017); Acharya and Dogra (2020); Ravn and Sterk (2020), among others. For procyclical income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

[61] Wages are procyclical, while dividends are countercyclical due to sticky prices. The overall after-tax income is procyclical.

[62] 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, $1-M_t^x$.

[63] 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 wealth 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 also Hagedorn, Luo, Manovskii, and Mitman (2019) how changes in interest rate lead to a redistribution of wealth 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.

Figure 7: 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).

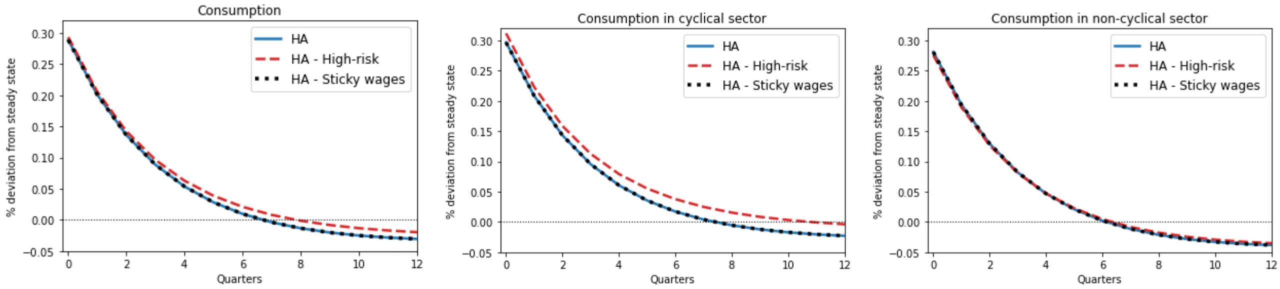
5.2 A further look into the market incompleteness channel and the relative labour demand channel

In what follows, I do some experiments to study the two channels and their importance in the transmission mechanism of monetary policy in more detail. In the first experiment, I make wages in the cyclical sector more sticky than in the non-cyclical sector, which would be consistent with higher unionisation rates in cyclical sectors.[64] To do this, I reduce the parameter that governs wage stickiness in the wage equation (22) to $\zeta^C = 0.5$. I refer to this experiment as the "Sticky wages" calibration. In the second experiment, I increase employment risk in the cyclical sector so that the separation rate is three times larger than in the baseline calibration while leaving all other parameters unchanged. I refer to it as the "High-risk" calibration.

[64]For more direct evidence on wage stickiness across sectors, see https://www.frbsf.org/economic-research/indicators-data/nominal-wage-rigidity.

5.2.1 The market incompleteness channel

Figure 8: Market incompleteness channel



Notes: The solid blue line shows impulse responses from the baseline HANK model, the dash-dotted red line shows impulse responses from the HANK model with the high-risk cyclical sector calibration ($\delta^C \approx 0.5$), and the dotted black line shows results from the HANK model with more sticky wages in the cyclical sector. The relative labour demand channel being "switched off" in all models, i.e. $P^C/P = P^{NC}/P = 1$.

Figure 8 plots consumption responses from the three models. To avoid any confounding effect from the relative labour demand channel, I fix relative prices in all models to its steady state value $P^C/P = P^{NC}/P = 1$. Responses from the baseline calibration are in the solid blue line, responses from the “High-risk” calibration are in the dash-dotted red line, and the responses with more sticky wages in the cyclical sector are in the black dotted line. With the high-risk calibration, the aggregate consumption response is larger than in the baseline model—a high separation rate in the cyclical sector increases employment risk and households’ MPCs, and, therefore, the consumption response is stronger for a given (proportional) income increase. A higher sectoral MPC also increases aggregate MPC, pushing aggregate consumption response above the response in the baseline calibration. In this setup, 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. However, as we see next, wage stickiness plays an important role in the relative labour demand channel.

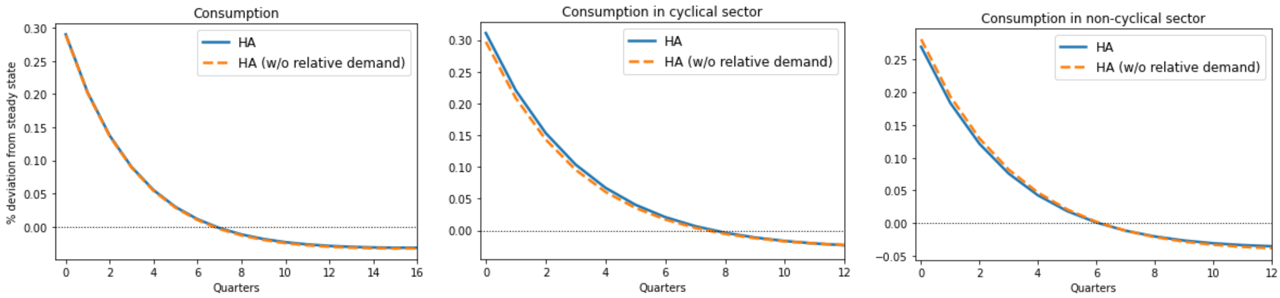
5.2.2 The relative labour demand channel

To isolate the relative labour demand channel, Figure 9 compares consumption responses from the baseline HANK model (solid blue line) with responses from the HANK model, in which relative prices are fixed to the steady state value $P^C/P = P^{NC}/P = 1$ (dashed orange line). The difference between the two responses measures the strength of the channel.

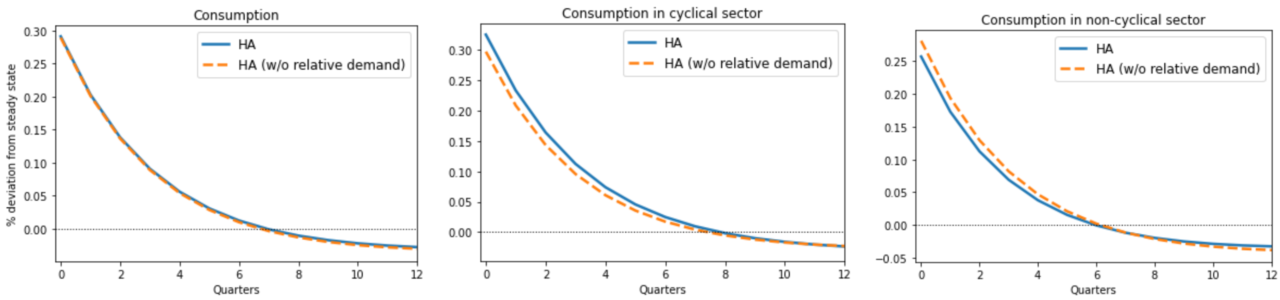
The top panel in Figure 9 shows results from the baseline calibration. I find that the relative labour demand channel increases consumption in the cyclical sector and reduces consumption in the non-cyclical sector. As discussed above, a more rigid labour market in the non-cyclical sector makes real marginal 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.

Figure 9: The relative labour demand channel

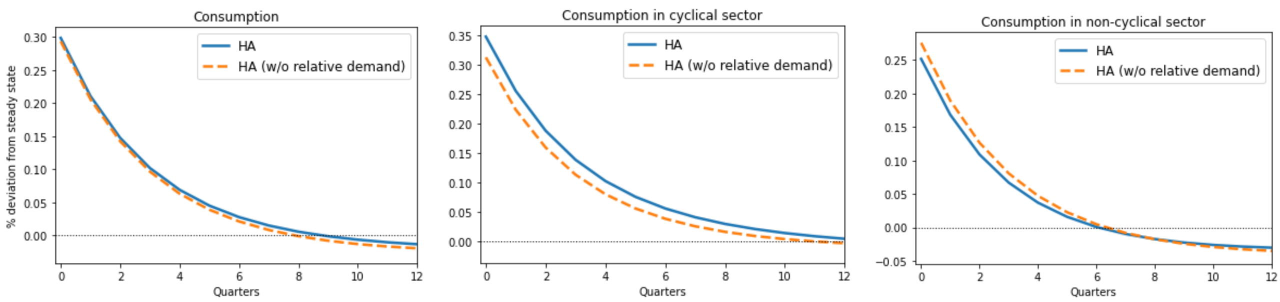
(A) Baseline



(B) Sticky wages



(C) High-risk



Notes: The solid blue line in all panels shows impulse responses from the baseline two-sector HANK. The dashed orange line shows responses from the HANK model when the relative labour demand channel is "switched off", i.e. when relative prices are fixed to steady state values $P^C/P = P^{NC}/P = 1$.

For the aggregate consumption response, it seems that the channel does not play any role; a reduction in the non-cyclical sector is compensated by the increase in the cyclical sector, and there is no effect on the aggregate response.[65] However, this is because, in the baseline calibration, differences in MPCs across sectors are too small to have a quantitatively significant effect on aggregate consumption responses. I show in the "High-risk" calibration, where differences in employment risk across sectors are large, that this channel affects the aggregate consumption response.

With more sticky wages in the cyclical sector, the channel becomes stronger, and the consumption increase in the cyclical sector is even larger (see panel (B)). This is because, with

[65]This would be the case if MPCs in both sectors were identical, and therefore it would not matter which households receive additional income.

more sticky wages in the cyclical sector, an increase in real marginal costs in the cyclical sector becomes more restrained.[66] This makes production in the cyclical sector even cheaper, which amplifies the relative demand channel and further increases consumption in the cyclical sector. Although wage stickiness makes the relative demand channel more potent, differences in MPCs across sectors are too small to have a sizeable effect on the aggregate response.

Panel (C) shows results from the "High-risk" cyclical sector 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 also increases employment risk and the sectoral MPC. Both factors together generate a much stronger consumption response in the cyclical sector than in the non-cyclical sector. Moreover, the income redistribution into the high MPC sector increases aggregate consumption response above the aggregate response in which this channel is not present. This shows how the interaction of the relative labour demand channel and high MPCs can amplify the aggregate consumption response via the Keynesian multiplier.

5.3 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.

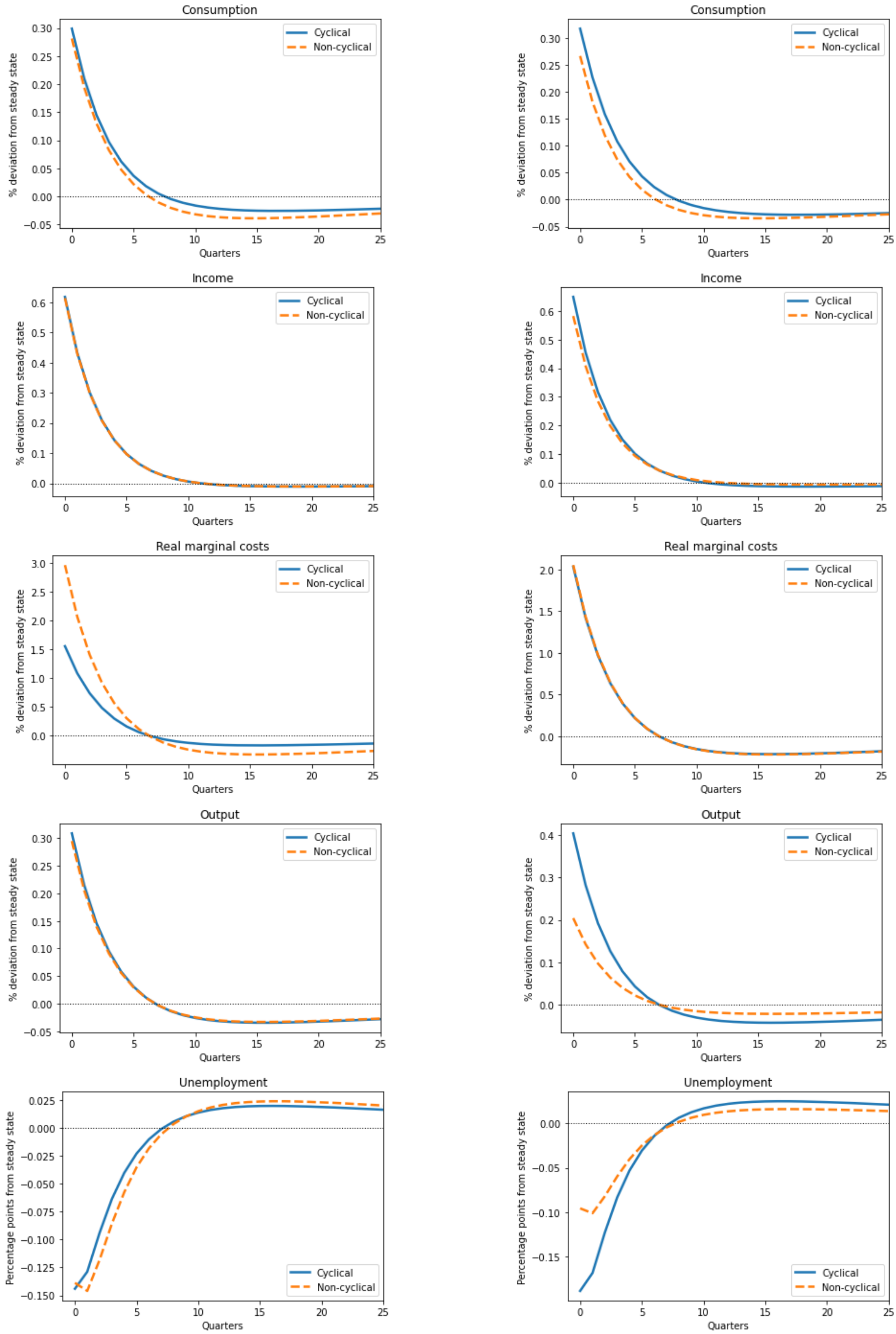
5.3.1 The role of elasticity of substitution between sectors

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 10. In the left panel, the two sectors are *gross complements* with the elasticity of substitution of 0.2. In the right panel, sectors are *gross substitutes* with the elasticity of substitution equal to 2.

[66]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 actually increase real marginal costs. In my model, this can not happen because wages represent by far the biggest component of real marginal costs.

Figure 10: Elasticity of substitution between sectors

Gross complements | Gross substitutes



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 the final good are gross complements, the final-good producer is less responsive to changes in relative prices. 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. As a result, consumption responses in the two sectors become more similar.

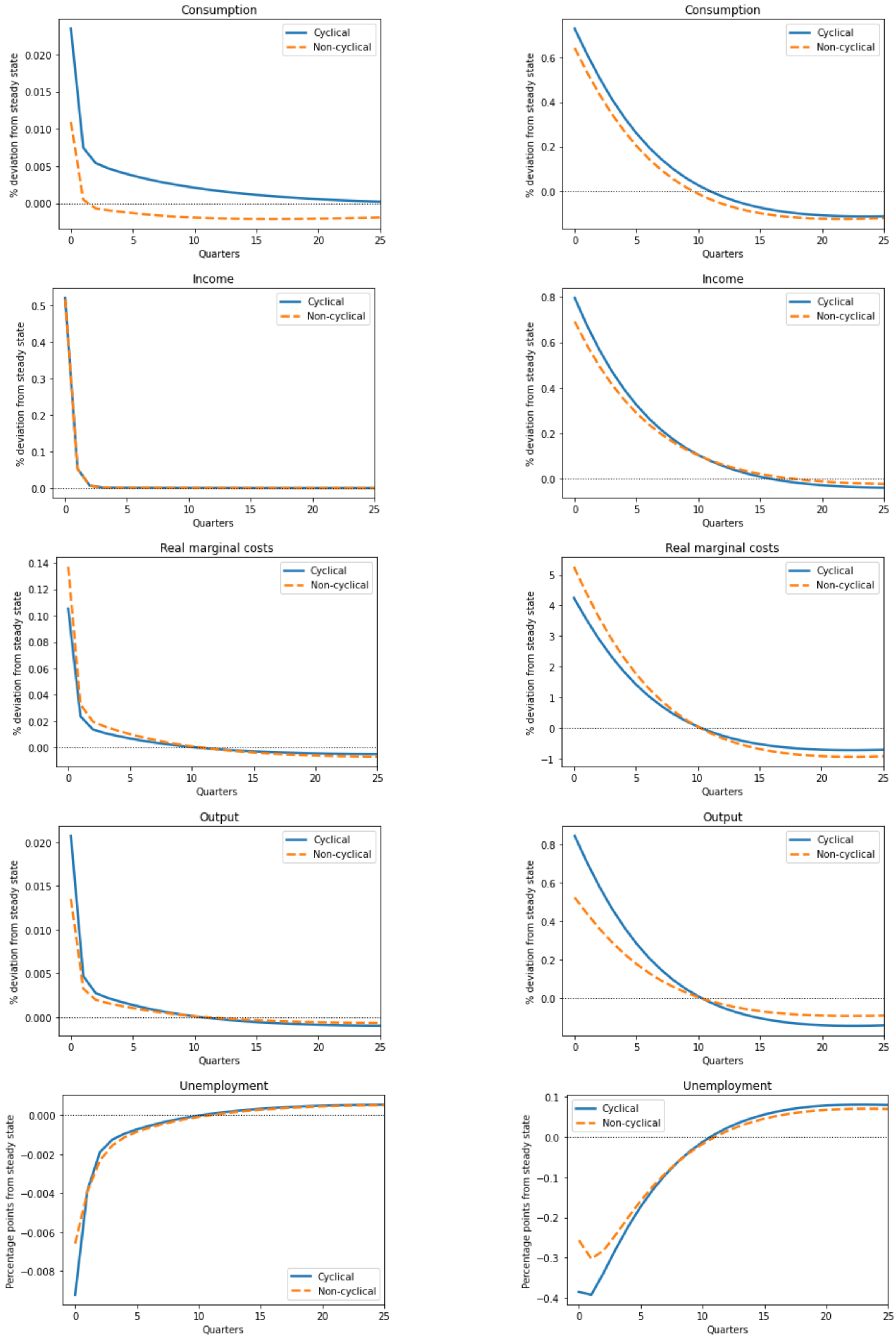
5.3.2 The role of persistence

Here, I analyse the role of the persistence of the monetary policy shock in the transmission of monetary policy. The left column in Figure 11 in appendix shows impulse responses for a transitory shock $\rho_R = 0.1$, and the right column shows the responses for a persistent shock with $\rho_R = 0.9$. In both columns, consumption increases the most in the cyclical sector, as in the baseline, with the overall magnitude depending on the persistence of the shock. Moreover, the difference between consumption responses in the two sectors depends on the persistence parameter; for a transitory shock, the consumption response in the cyclical sector is much larger than in the non-cyclical sector, while for a persistent shock, the two sectoral consumption responses become more alike.

The degree of persistence of monetary policy shock is important because it determines which households, wealthy or poor, are more affected by the shock. Kaplan, Moll, and Violante (2018) argue that with a more persistent monetary policy shock, a large portion of the income increase due to the interest rate cut occurs in the future. As a result, hand-to-mouth households receive a smaller share of additional income on impact, which weakens the consumption response. Note that differences in MPCs across sectors in the model are largest precisely at low wealth levels (see Figure E.13 in appendix). This could explain why, for a transitory shock, the consumption response in the cyclical sector is well above the response in the non-cyclical sector.

Figure 11: Shock persistence

Low persistence ($\rho_R = 0.1$) High persistence ($\rho_R = 0.9$)



Conversely, a more persistent shock makes the relative labour demand channel more powerful, further increasing employment and income in the cyclical sector. As a result, there is redistribution between sectors; households in the cyclical sector become wealthier, while households in the non-cyclical sector become poorer. This effectively reduces MPC differences across sectors and generates more similar sectoral consumption responses.[67]

6 Conclusion

This paper investigates the role of differential employment risk across sectors for 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).

Then 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.

Finally, I analyse how the elasticity of substitution between sectors and the persistence of a monetary policy shock affect the transmission mechanism of monetary policy. I show that the elasticity of substitution operates mainly via the relative labour demand channel, whereas more persistent shocks affect the cyclicality of income risk and the strength of the precautionary savings motive.

[67]Because there are fewer poor households in the cyclical sector, the average MPC decreases. In contrast, with less labour demand from the non-cyclical sector, households become poorer, and the average MPC increases.

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A Proofs of results

A.1 Proof of proposition 1

Start with (6)

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

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

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

Expand and distribute the terms in the previous equation

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

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

Applying the unconditional expectation operator

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

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

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

Finally, rearrange the last term to obtain (8) in the main text

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

□

B Data appendix

B.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 what adjustments are needed to make them comparable. 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.[68]

Table B.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 Management 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 group 6. Second, net worker flows in the industry are very cyclical and drive results in the SCF-industry

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

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.2 Further sample restrictions

B.2.1 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.[69]

I proceed as follows. First, I normalise the household's tenure by the total work experience.[70] 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.

[69] 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.

[70] 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.

B.3 Summary statistics of household balance sheets

Table B.2 presents summary statistics from the SCF and SIPP survey.

Table B.2: Summary statistics – SCF and SIPP samples

	SCF		SIPP	
Mean	Cyclical	Non–cyclical	Cyclical	Non–cyclical
Wages and salaries (annualised)	85,038	115,895		
Earned income (annualised)	101,309	138,048	76,953	103,947
Total income (annualised)	109,628	146,286	82,699	110,250
Net liquid assets	34,524	58,846	35,627	50,121
Net wealth	539,691	635,425	146,253	205,436
Median				
Wages and salaries (annualised)	62,765	86,588		
Earned income (annualised)	66,229	94,274	60,748	81,309
Total income (annualised)	69,147	96,606	65,520	86,193
Net liquid assets	1,939	6,261	355	2,033
Net wealth	87,657	167,769	17,096	33,622
Observations	6,802	15,818	13,868	35,789

Notes: This table shows mean and median values of selected variables calculated from the household balance sheet data. Net liquid assets comprise 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. All statistics are computed using survey weights.

B.4 Summary statistics of labour market flows

Table B.3 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.3: Summary statistics – LEHD and JOLTS samples

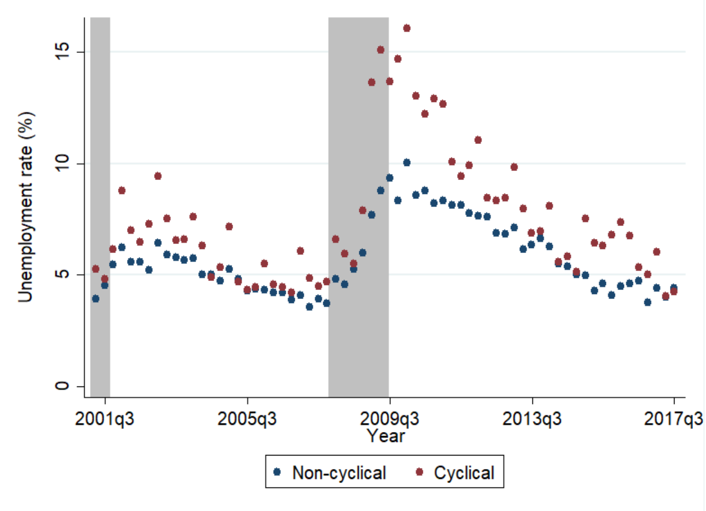
	Cyclical		Non-cyclical	
Description	Mean	SD	Mean	SD
LEHD				
Hire rate (%)	4.226	0.499	3.762	0.193
Separation rate (%)	4.772	0.770	3.785	0.481
Net worker flows (pp)	-0.017	0.887	-0.064	0.331
Job finding rate proxy	0.879	0.316	0.893	0.269
JOLTS				
Hire rate (%)	3.958	0.365	3.627	0.277
Separation rate (%)	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
Job finding rate proxy	0.466	0.185	0.464	0.148
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. For a definition of job finding rate proxies and how they are calculated, see Section C.4. Data is quarterly, seasonally adjusted, and covers the period 2001q2–2017q3.

C Additional figures

C.1 Unemployment rate

Figure C.1: Unemployment rate

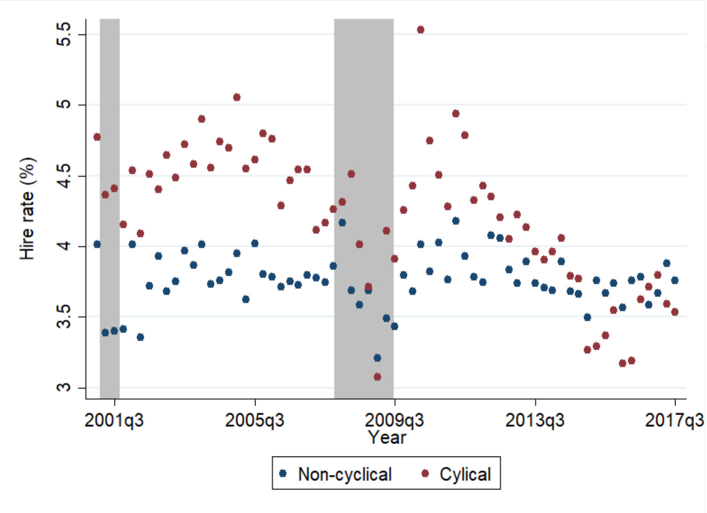


Notes: This figure plots the unemployment rate in cyclical and non-cyclical sectors. The panel covers the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1.

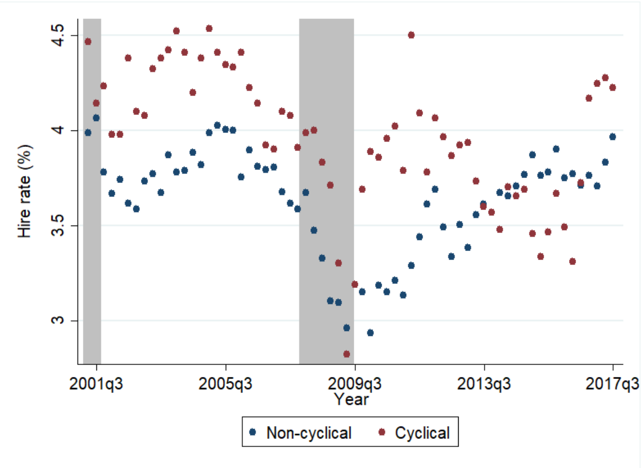
C.2 Worker flows over the business cycle

Figure C.2: Hiring rate

(A) LEHD



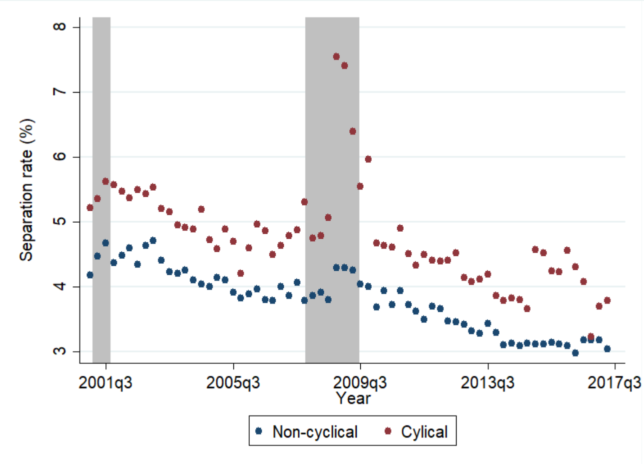
(B) JOLTS



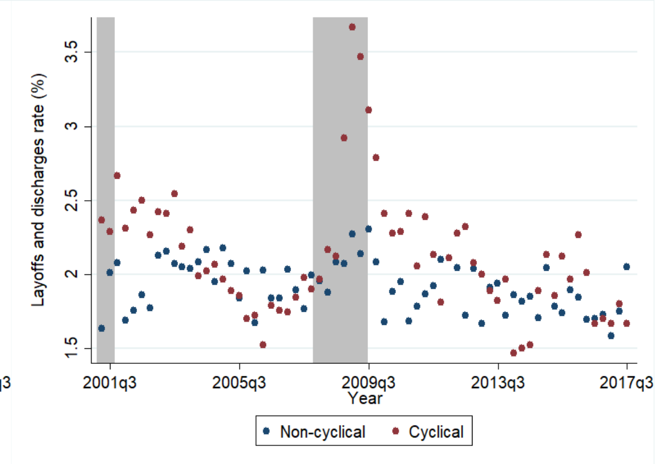
Notes: PANEL (A): The hiring rate is defined as hires from persistent nonemployment, expressed as a share of employment and multiplied by 100. PANEL (B): The hiring rate is defined as hires from unemployment, expressed as a share of employment and multiplied by 100. Both panels cover the period 2001q2–2017q3.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

Figure C.3: Separation rate

(A) LEHD

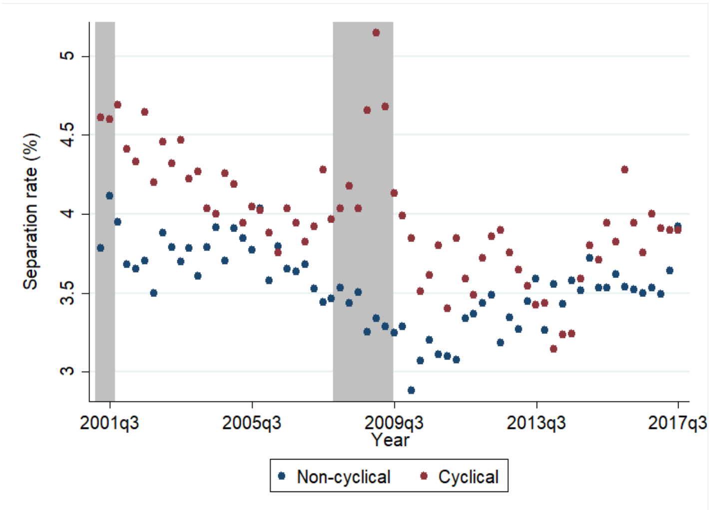


(B) JOLTS



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.4: Total separations rate in the JOLTS data

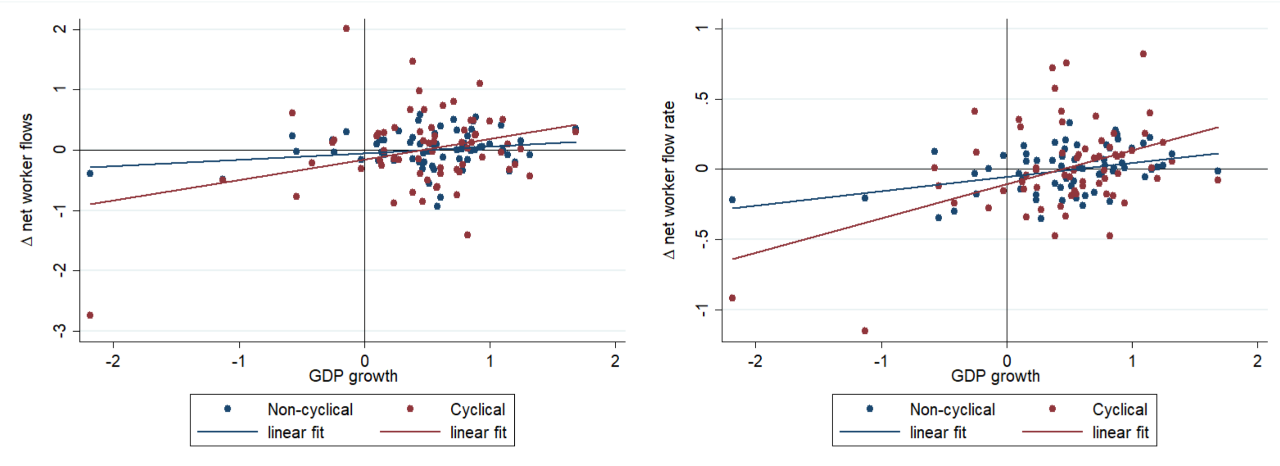


Notes: The separation rate is defined as total separations to unemployment, expressed as a share of total employment and multiplied by 100. The panel covers the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1.

C.3 Variability of net worker flows

Figure C.5: Variability of net worker flows in cyclical and non-cyclical sectors

(A) LEHD (B) JOLTS



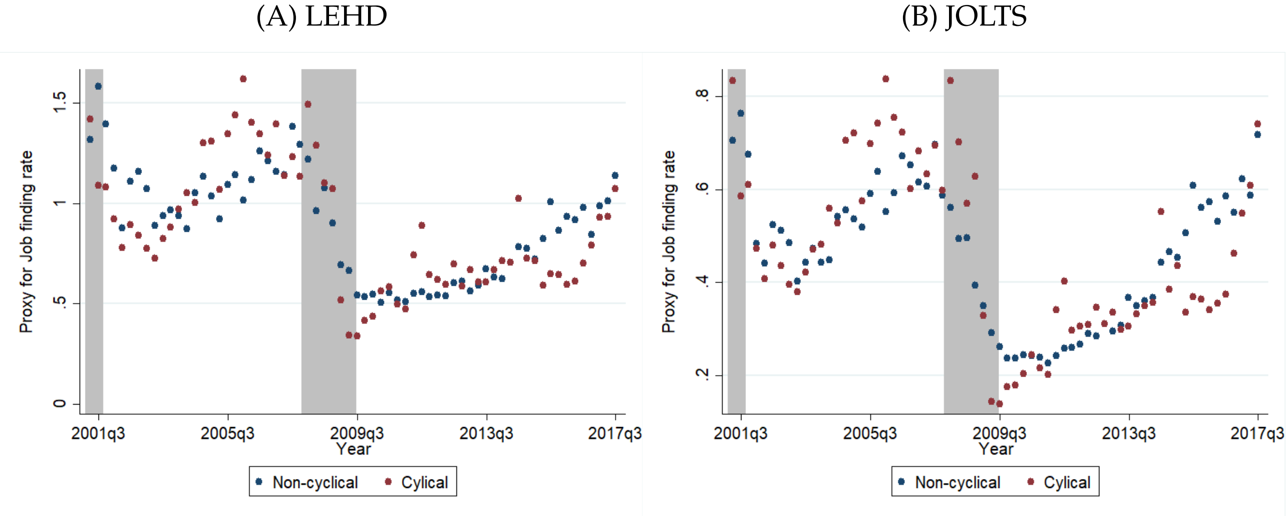
Notes: Variability of net worker flows is calculated as the change in net worker flows between t and $t-1$. GDP growth is calculated as the quarterly difference in the log of the real GDP and multiplied by 100. Both panels cover the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors 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.5 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.[71] 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.

[71] 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.

C.4 Job finding rate proxies across sectors

Figure C.6: Job finding rate proxies

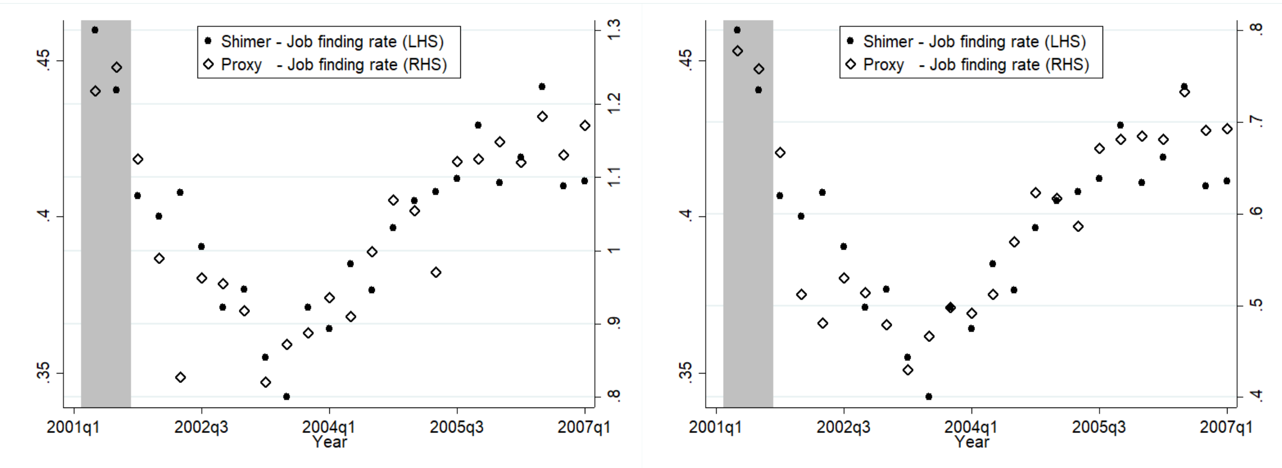


Notes: The data in both panels is seasonally adjusted and covers the period 2001q2–2017q3. Selection into the cyclical and the non-cyclical sector is based on results in Section 3.2.1. Shaded areas denote NBER recession episodes. PANEL (A) shows a proxy for a job finding rate using LEHD data. To construct the proxy, quarterly flows from persistent nonemployment to employment in period t are divided by the number of unemployed workers in period $t-1$. The number of unemployed workers across industries comes from the CPS. PANEL (B) shows a proxy for a job finding rate using JOLTS data. To construct the proxy, quarterly hires in period t are divided by the number of unemployed workers in period $t-1$. As before, the number of unemployed workers across industries comes from the CPS.

Figure C.6 shows job finding rate proxies for the two samples. In the LEHD data, the value of the proxy is sometimes above one, which theoretically does not make any sense. The reason is that with the LEHD data, we observe hires from nonemployment, which is a broader concept than unemployment because it also includes workers that are not in the labour force. As a result, the proxy can be larger than one. However, Proposition 1 shows that the relevant parameters determining the amount of the precautionary savings are the persistence parameter ρ and the variance of innovations σ_ε^2 of the job finding rate process M_t.

Figure C.7: Job finding rate proxies vs Shimer (2012) job finding rates

(A) LEHD (B) JOLTS



Notes: The figure plots the two proxies of the job finding rate together with the job finding rate constructed by Shimer (2012). The latter can be found on his home page (`https://sites.google.com/site/robertshimer/research/flows`).

There is a concern that my job finding rate proxies are incompatible with job finding rates in the literature (see, for example, Hobijn and Şahin (2009)). To address this issue, I plot my proxies against the job finding rate series by Shimer (2012) for 2001q2–2007q1. That is the period when the data is available for all the series.[72] The results are in Figure C.7. Although the levels are different, the dynamics between the two series for this short sample is surprisingly similar.

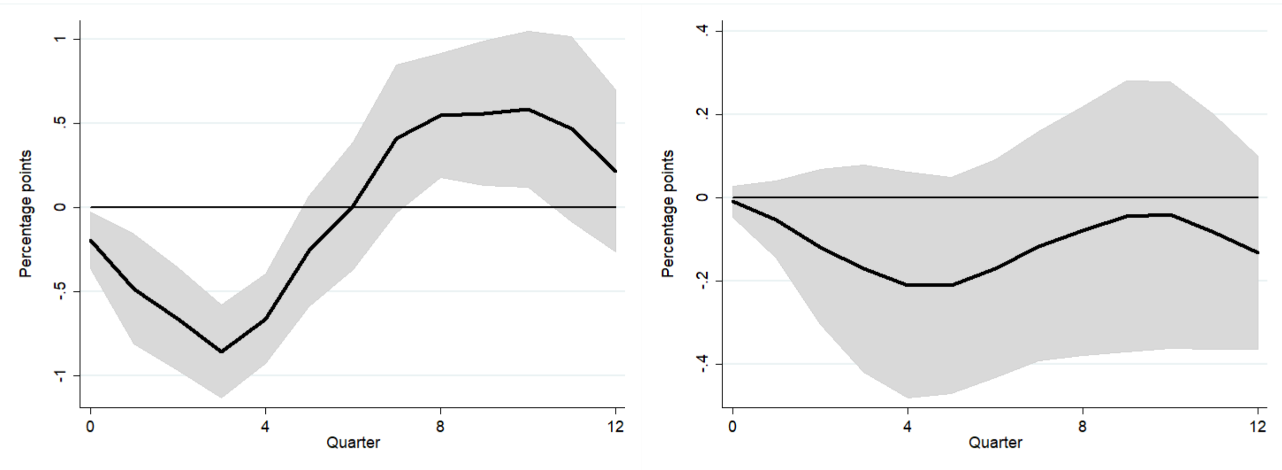
[72] I use job finding rate series constructed by Shimer (2012) because the data is readily available online. Other estimates of the job finding rate have similar dynamics, but the levels are different. See, Figure 4 in Hobijn and Şahin (2009) for comparison.

C.5 Robustness of Local Projections approach

C.5.1 The response of real interest rate and the unemployment rate to an expansionary monetary policy shock

Figure C.8: The response of real interest rate and unemployment rate

(A) Real interest rate (B) Unemployment rate

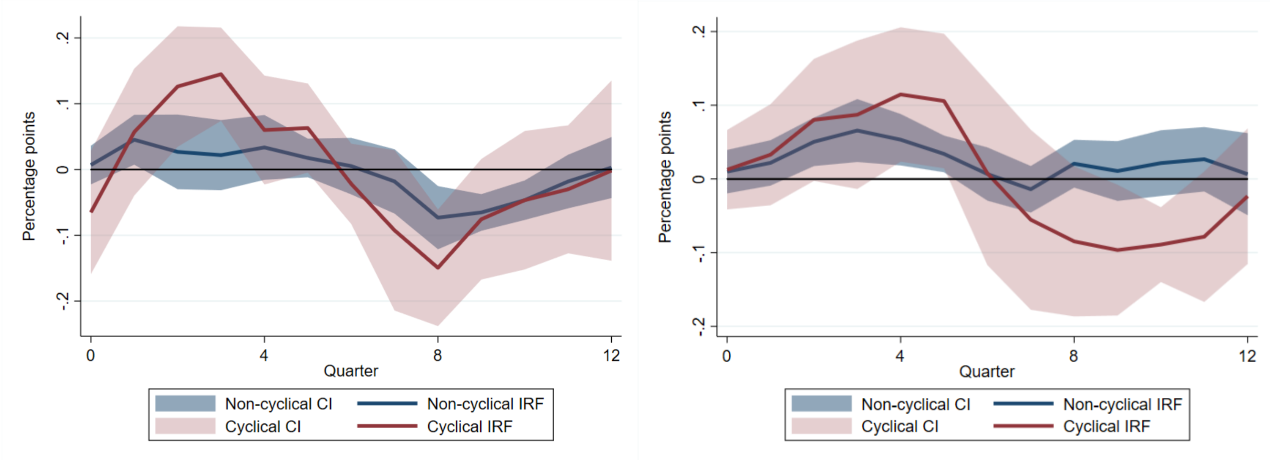


Notes: This figure shows impulse responses following an expansionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors). The data is seasonally adjusted and covers the period 2001q2–2017q3. 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).

C.5.2 Worker flows conditional on a monetary policy shock

Figure C.9: Hiring rate conditional on a monetary policy shock

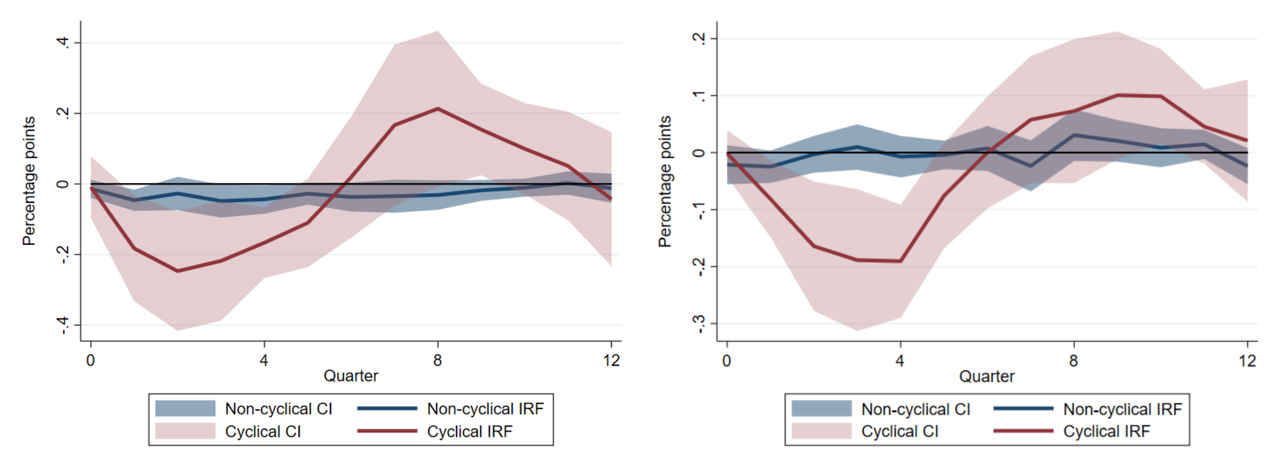
(A) LEHD (B) JOLTS



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). 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.10: Separation rate conditional on a monetary policy shock

(A) LEHD (B) JOLTS



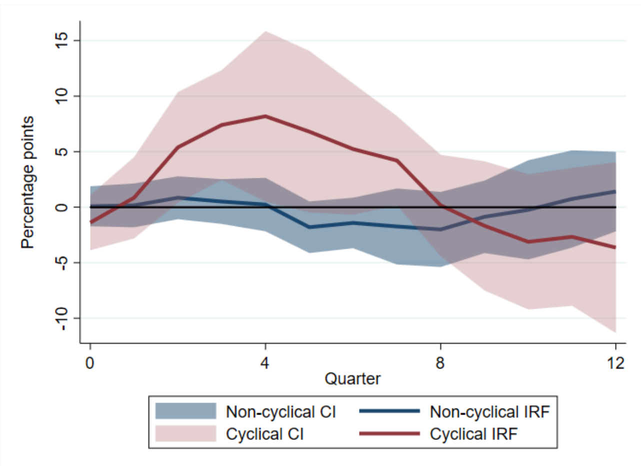
Notes: This figure shows impulse responses following an expansionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected and heteroskedasticity and autocorrelation (Newey–West standard errors). The data is seasonally adjusted and covers the period 2001q2–2017q3. Selection into the cyclical and non-cyclical sector is based on results in Section 3.2.1. PANEL (A): The 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.5.3 Job finding rate proxies conditional on identified monetary policy shocks

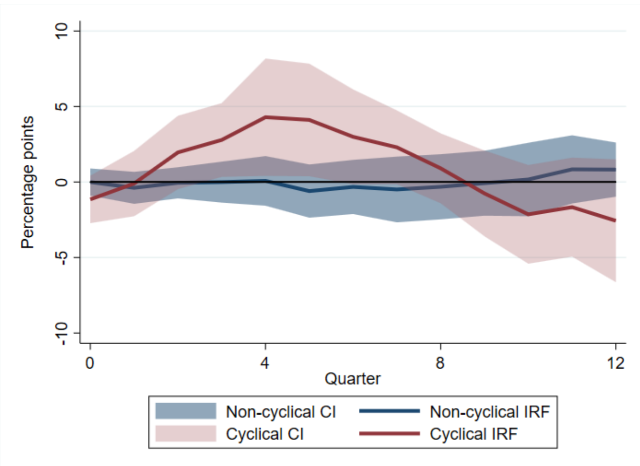
Here, I examine if the job finding rate proxies are informative about the sectoral employment risk conditional on an identified monetary policy shock. If they are indeed informative about the sectoral employment risk, then one would expect similar impulse responses as in Figure 2. To test this, I re-estimate the model in (10) with the job finding rate proxy as the dependent variable. Results are shown in Figure C.11. I find that the job finding rate proxy in cyclical sectors fluctuates much more than in non-cyclical sectors at a business cycle frequency. In contrast, in non-cyclical sectors, the response of the proxy is almost flat. These results are in line with my findings in Section 3.2.3.

Figure C.11: Responses of job finding rate proxies to a monetary policy shock

(A) LEHD



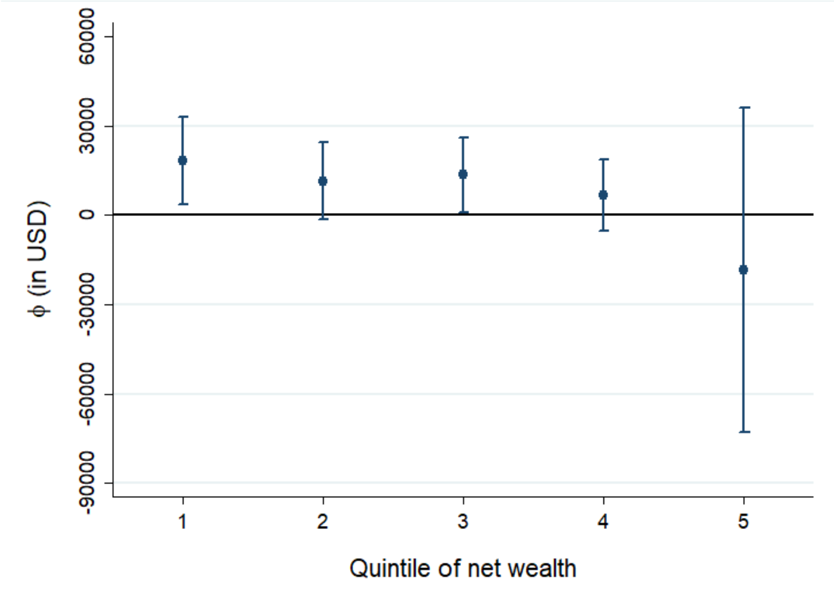
(B) JOLTS



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). The data in both panels is seasonally adjusted and covers the period 2001q2–2017q3. Selection into the cyclical and non-cyclical sectors is based on results in Section 3.2.1. For more details on the construction of proxies, see Section C.4 in appendix.

C.6 Holdings of net liquid assets across sectors (alternative specification)

Figure C.12: SIPP



Notes: This figure plots point estimates from estimating (11) together with 90 percent confidence intervals. In contrast to panel A in Figure 3, regressions here include only year fixed effects. All regressions are computed using survey weights, and standard errors are clustered at the household level. I use observations from 2001 to 2016. All nominal variables are adjusted to 2016 dollars.

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

$$\max_{\{p_{js}, n_{js}, y_{js}, h_{js}\}} \mathbb{E}_t \sum_{s \geq t} \left(\frac{1}{1+r} \right)^{s-t} \left\{ \frac{p_{js}}{P_s} y_{js} - w_s^C n_{js} - \psi^C M_s^C h_{js} - \frac{\vartheta}{2} \left(\frac{p_{js}}{p_{js-1}} - 1 \right)^2 Y_s \right\}, \tag{D.9}$$

subject to

$$y_{jt} = \left(\frac{p_{jt}}{P_t^C} \right)^{-\mu_C/(\mu_C - 1)} \left(\frac{P_t^C}{P_t} \right)^{-1} \times \alpha Y_t \,, \tag{D.10}$$

$$n_{jt} = \left(1 - \delta^C \right) n_{jt-1} + h_{jt} \,, \tag{D.11}$$

$$y_{jt} = Z_t n_{jt} \,. \tag{D.12}$$

Let λ_{1t}, λ_{2t}, and λ_{3t} be multipliers on the three constraints (D.10)–(D.12). First order conditions with respect to choice variables are

$$\begin{aligned} &\frac{y_{jt}}{P_t} + \lambda_{1t} \left(\frac{\mu_C}{1-\mu_C} \right) \left(\frac{p_{jt}}{P_t^C} \right)^{\frac{\mu_C}{1-\mu_C} - 1} \left(\frac{1}{P_t^C} \right) \left(\frac{P_t^C}{P_t} \right)^{-1} \alpha Y_t \\ &\quad - \vartheta \left(\frac{p_{jt}}{p_{jt-1}} - 1 \right) \left(\frac{1}{p_{jt-1}} \right) Y_t + \frac{1}{1+r} \mathbb{E}_t \left[\vartheta \left(\frac{p_{jt+1}}{p_{jt}} - 1 \right) \left(\frac{p_{jt+1}}{p_{jt}^2} \right) Y_{t+1} \right] = 0 \,, \end{aligned} \tag{D.13}$$

$$-w_t^C - \lambda_{2t} + \frac{1}{1+r} \mathbb{E}_t \left[(1 - \delta^C) \, \lambda_{2t+1} \right] + \lambda_{3t} Z_t = 0 \,, \tag{D.14}$$

$$\frac{p_{jt}}{P_t} - \lambda_{1t} - \lambda_{3t} = 0 \,, \tag{D.15}$$

$$-\psi^C M_t^C + \lambda_{2t} = 0 \,. \tag{D.16}$$

Observe that real marginal costs is the multiplier on (D.12)

$$mc_t^C \equiv \lambda_{3t} = \frac{w_t^C + \psi^C M_t^C - \frac{1}{1+r} \mathbb{E}_t \left[(1-\delta^C) \psi^C M_{t+1}^C \right]}{Z_t} \,. \tag{D.17}$$

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.15) and (D.10) in (D.13) and using the definition of real marginal costs, the price setting optimality condition reads

$$\left(\frac{p_{jt}}{P_t^C}\right)^{\frac{\mu_C}{1-\mu_C}}\left(\frac{P_t^C}{P_t}\right)^{-1}\frac{\alpha Y_t}{P_t}+\left(\frac{p_{jt}}{P_t}-mc_t^C\right)\left(\frac{\mu_C}{1-\mu_C}\right)\left(\frac{p_{jt}}{P_t^C}\right)^{\frac{\mu_C}{1-\mu_C}-1}\left(\frac{P_t^C}{P_t}\right)^{-1}\frac{\alpha Y_t}{P_t^C}$$
$$=\vartheta\left(\frac{p_{jt}}{p_{jt-1}}-1\right)\left(\frac{1}{p_{jt-1}}\right)Y_t-\frac{1}{1+r}\mathbb{E}_t\left[\vartheta\left(\frac{p_{jt+1}}{p_{jt}}-1\right)\left(\frac{p_{jt+1}}{p_{jt}^2}\right)Y_{t+1}\right]. \quad \text{(D.18)}$$

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.18) to obtain the New Keynesian Phillips curve (37) in the main text.

$$\pi_t^C(\pi_t^C-1)=\frac{\alpha}{\vartheta(\mu_C-1)}\left[\mu_C\frac{P_t}{P_t^C}mc_t^C-1\right]+\frac{1}{1+r}\mathbb{E}_t\,\pi_{t+1}^C(\pi_{t+1}^C-1)\frac{Y_{t+1}}{Y_t}, \quad \text{(D.19)}$$

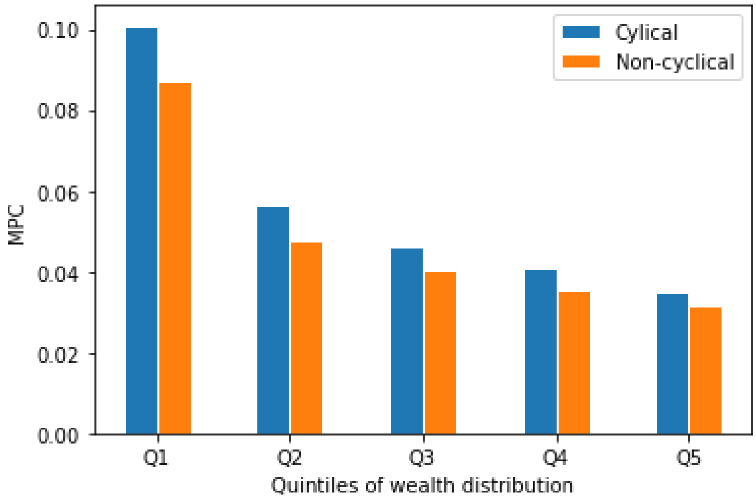
Similarly, one solves for the New Keynesian Phillips curve in the non-cyclical sector

$$\pi_t^{NC}(\pi_t^{NC}-1)=\frac{1-\alpha}{\vartheta(\mu_{NC}-1)}\left[\mu_{NC}\frac{P_t}{P_t^{NC}}mc_t^{NC}-1\right]+\frac{1}{1+r}\mathbb{E}_t\,\pi_{t+1}^{NC}(\pi_{t+1}^{NC}-1)\frac{Y_{t+1}}{Y_t}. \quad \text{(D.20)}$$

E Additional figures and tables from the model

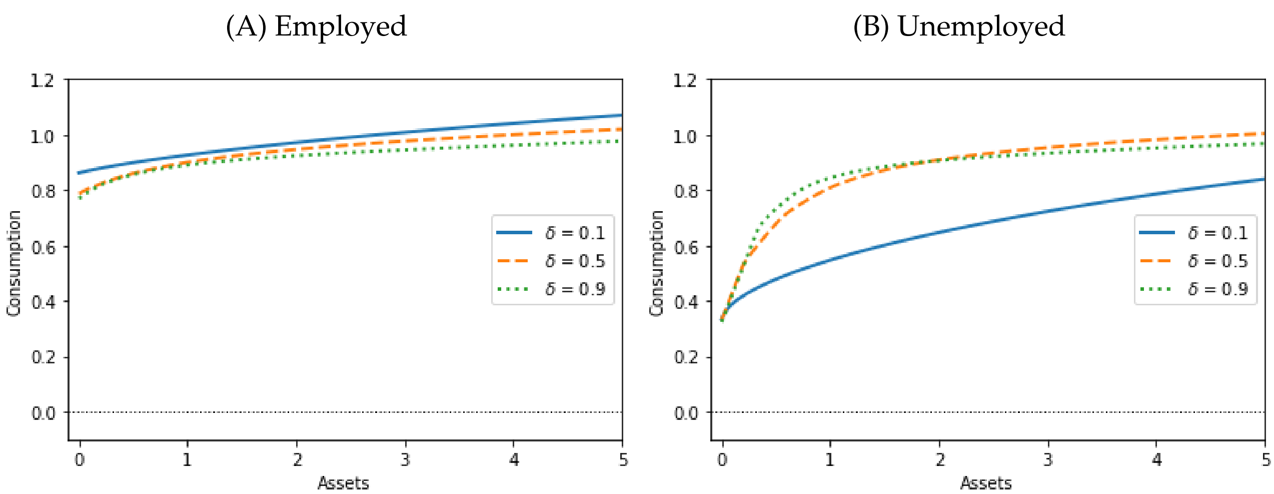
E.1 Consumption functions and MPCs

Figure E.13: MPCs across quintiles of sectoral wealth distribution



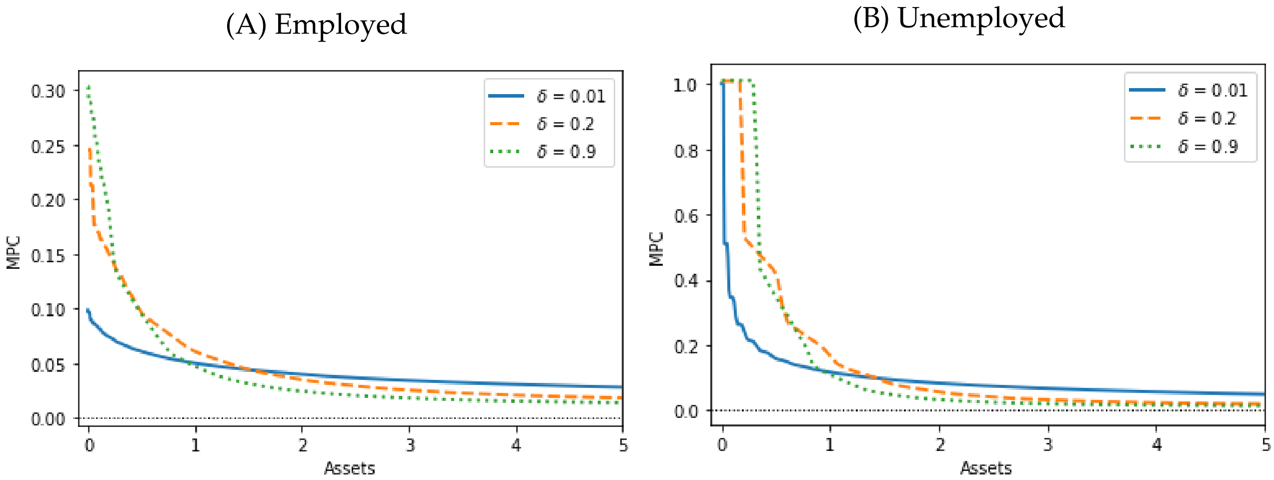
Notes: This figure plots average quarterly (asset-weighted) MPCs across quintiles of sectoral wealth distribution.

Figure E.14: Consumption functions for different values of the separation rate



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.15: 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.16: CDF of bond holdings

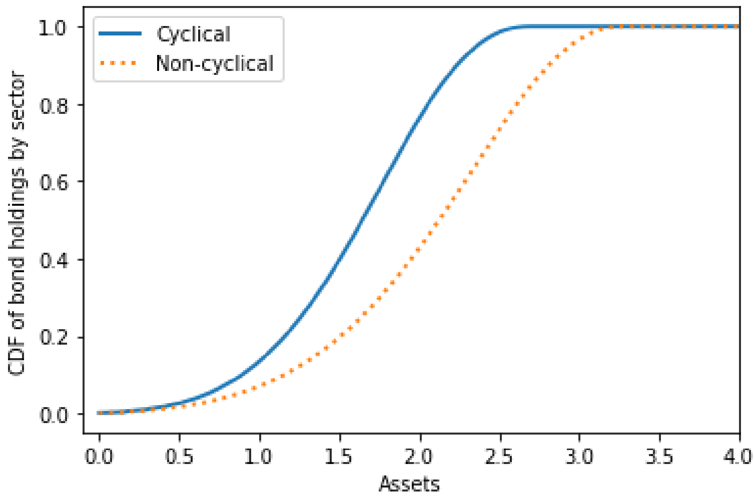
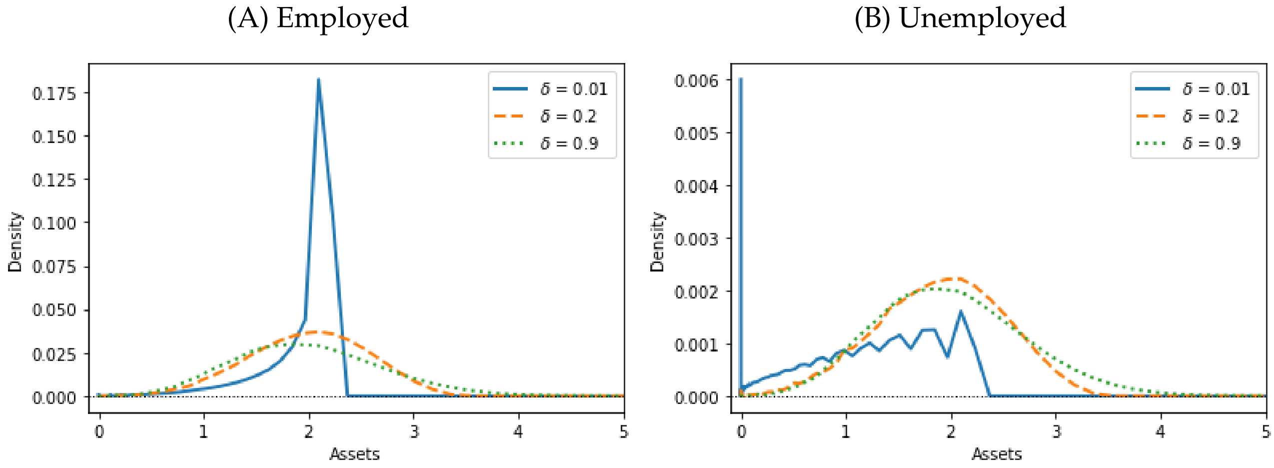


Figure E.17: Stationary wealth distribution for different values of the separation rate

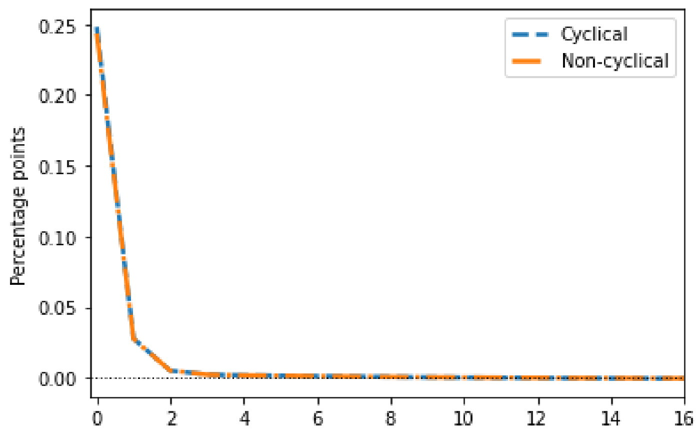


Notes: This figure shows stationary wealth distributions for different values of the separation rate δ. All other parameters are calibrated as in Table 3.

F Additional results from Section 5

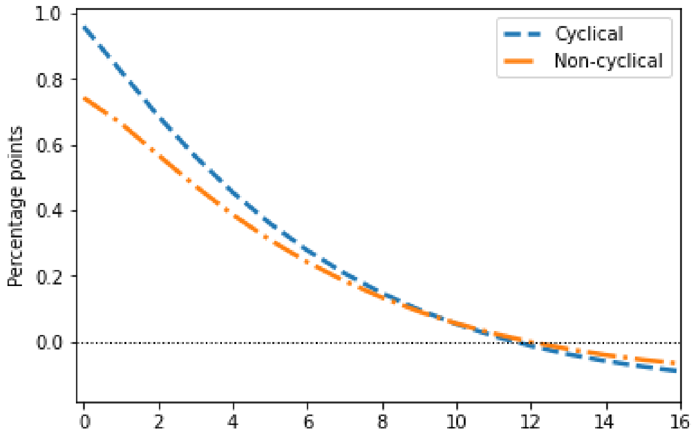
F.1 Income gap(s)

Figure F.18: Income gap for a transitory shock ($\rho_R = 0.1$)



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).

Figure F.19: Income gap for a 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).