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

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Abstract

This paper studies how differences in employment risk across sectors affect the transmission mechanism of monetary policy. Using micro-level data, I show that households working in sectors more exposed to business cycles—i.e. experiencing higher employment risk—tend to accumulate more precautionary savings than those working in less exposed sectors. I develop a two-sector model with uninsurable, sector-specific employment risk to study how these differences affect the monetary policy transmission in a multi-sector environment. The consumption response is larger and more persistent in the more exposed sector, with a cumulative difference of approximately 30 basis points over four quarters. I identify two channels through which differences in employment risk affect sectoral and aggregate consumption responses and show how the interaction between the two channels amplifies the aggregate consumption response, highlighting the importance of accounting for sector-specific employment risk when analysing the transmission mechanism of monetary policy.

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1 Introduction

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

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

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

To motivate the analysis, I first develop a simple consumption-savings model that analytically shows how employment risk affects both the level of permanent income and the amount of precautionary savings. In this framework, employment risk is modelled as a function of a constant separation rate and a stochastic job-finding rate. I show that the level of precautionary savings depends on three key observables: (i) the separation rate, (ii) the persistence parameter of the job finding rate process, and (iii) the variance of its innovations. The model shows that households tend to accumulate more precautionary savings when they face a higher likelihood of job separation and when they experience larger, although less persistent, fluctuations in the job finding rate.

Then, I present some new empirical facts on 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 employ-

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

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

ment risk.[3]

To capture cross-sectoral differences in employment risk, I classify sectors as either cyclical or non-cyclical based on how sensitive their net worker flows are to business cycles. I then merge this sectoral employment risk information with household balance sheet data. Because I cannot directly observe the additional savings induced by precautionary motives, I propose a novel way and use the difference in net liquid asset holdings of comparable households with similar net wealth working in cyclical and non-cyclical sectors as a proxy.[4]

I find that households working in sectors more exposed to business cycles, i.e. cyclical sectors, hold larger balances of net liquid assets than otherwise similar households working in sectors less exposed to business cycle fluctuations, i.e. non-cyclical sectors. Moreover, this difference is larger among poorer households and decreases with net wealth. These findings are consistent with a stronger precautionary saving motive of households working in more "risky" cyclical sectors.

In the following section, I build a two-sector HANK model to analyse the macroeconomic implications of my empirical findings. The model incorporates two additional elements relative to a standard HANK model with search and matching frictions. First, I introduce *labour market segmentation*. In the model, households work in either a cyclical or a non-cyclical sector, facing different employment risks that depend on the characteristics of each labour market segment and the state of the business cycle. Second, I adopt a *multi-sector framework*. While having more than one sector is standard in the representative agent models, it is less common in heterogeneous agent contexts. This enables me to study how shifts in sectoral demands interact with standard features of HANK models, such as MPC heterogeneity and the precautionary saving motive.

I calibrate the model to capture differences in employment risk between the cyclical and non-cyclical sectors in the US. In particular, I set separation rates to match the observed transition rates from employment to unemployment in each sector. Households in the cyclical sector face separation rates that are more than three times higher than those in the non-cyclical sector.

Following an expansionary monetary policy shock, the consumption response is larger and more persistent in the cyclical sector than in the non-cyclical sector. Over four quarters, the cumulative difference between the two sectors is around 30 basis points, with a peak difference of more than 10 basis points on impact. I identify two main channels through which employment risk affects these responses.

The first channel is the *Employment Risk Channel*. A higher separation rate raises the

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

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

sectoral MPC in two ways. First, it makes the consumption function more concave, mechanically increasing MPCs. Second, it reduces household wealth. Together, these effects lead to a higher asset-weighted MPC in the cyclical sector.

The second channel is the *Sectoral Reallocation Channel*. The separation rate also affects labour market tightness, which determines wages, hiring costs, and real marginal costs. In the more rigid non-cyclical sector, labour market tightness rises sharply, driving up wages and hiring costs. This makes production relatively more expensive, shifting goods and labour demand toward the cyclical sector. The additional income in the high-MPC cyclical sector further amplifies sectoral and aggregate consumption through the Keynesian multiplier.

Then, I show that the sectoral reallocation channel plays a crucial role in driving business cycles by shifting resources to the high-MPC sector, boosting aggregate consumption by roughly 10 basis points over four quarters. When wages in this sector are stickier—reflecting its historically higher unionisation—the effect intensifies, reaching roughly 15 basis points over one year. Moreover, when sectors are closer substitutes, the reallocation is stronger and more persistent, amplifying aggregate consumption with less pressure on aggregate inflation. In contrast, greater complementarity between sectors results in more uniform responses across sectors and higher aggregate inflation.

Finally, I compare the two-sector HANK model to a two-sector Representative Agent New Keynesian (RANK) model with search and matching frictions. In the RANK model, households are fully insured against employment risk, so the only channel driving sectoral differences is the sectoral reallocation channel. I show that the RANK model produces larger differences in sectoral outputs than the HANK model. With incomplete markets, households self-insure by accumulating assets, which dampens labour reallocation and reduces asymmetries in sectoral responses. From a policy perspective, this finding suggests that optimal sector-specific stabilisation policies might be less necessary than suggested by the RANK model.

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

Empirical labour literature has found that workers face very heterogeneous employment risk over the business cycle (e.g. Hall (2005); Elsby, Hobijn, and Sahin (2010); Davis and Haltiwanger (2014); Elsby, Hobijn, and Şahin (2015); Haltiwanger, Hyatt, and McEntarfer (2018)).[5] In particular, Hobijn, Sahin, and Song (2010) and Hoynes, Miller, and Schaller (2012) document that workers in cyclical industries experience steeper rises in

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

unemployment rates during economic downturns, indicating that they face higher unemployment risk. More recently, Chapuis and Coglianese (2024) use a nonparametric machine learning approach on millions of workers in the US and find that workers in cyclical industries experience higher unemployment risk. They also find that the difference in unemployment risk between the most and least exposed workers is larger in these industries.

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

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

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

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

Sterk (2020) among others). The literature generally finds that the effectiveness of monetary policy and the determinacy of equilibrium in HANK models crucially depend on the cyclical properties of income risk. Empirical evidence suggests that the skewness of income growth rates is procyclical—in booms, large positive income shocks are more likely than large negative ones.[8]

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

The paper also discusses the role of sectoral demand spillovers in the amplification of aggregate demand. Caramp, Colino, and Restrepo (2017) find that employment in durable manufacturing industries is more cyclical than in other industries and that this cyclicality is amplified in general equilibrium at the commuting zone level. They identify a potential source of propagation operating via demand spillovers; lower consumption by laid-off workers working in durable industries may affect demand in non-durable industries, which further reduces employment in durable industries.[9] In my model, sectoral spillovers are driven by demand effects and differences in labour market characteristics across the two sectors. A higher separation rate in the cyclical sector makes production relatively cheaper than in the non-cyclical sector. As a result, there is a labour and goods spillover from the non-cyclical towards the cheaper cyclical sector, increasing households' income and consumption in the cyclical sector.

My findings relate to a growing literature on how sectoral heterogeneity interacts with incomplete markets to shape macroeconomic outcomes (e.g., Guerrieri, Lorenzoni, Straub, and Werning (2022); Baqaee and Farhi (2022); Baqaee and Rubbo (2023)). Whereas these works emphasise input-output linkages, I focus on the labour-market side and highlight how differences in employment risk can substantially amplify or dampen the standard HANK transmission channels.

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

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

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 the models. First, they have a unified labour market, and in my framework, the labour market is segmented. Second, they have endogenous separations and sluggish vacancy creation, whereas I have a constant exogenous separation rate and free-entry condition for new vacancies. Finally, I do not impose zero liquidity, meaning that employment risk in my model is not mapped one-to-one to consumption risk because households have access to an additional savings vehicle.

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

2 Employment Risk and Precautionary Savings

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

Time is discrete, denoted as $t = 1, 2, 3, \ldots$. Consider a household that was employed at the end of period $t-1$. At the beginning of each subsequent period t, there is an exogenous probability $\delta \in [0, 1]$ that the household will be separated from its current job. If separated, then a household immediately engages in a job search. The probability of finding a new job is given by the job finding rate M_t. If a household fails to secure a new job within the same period, it becomes unemployed with probability $s_t \equiv \delta(1 - M_t)$. A household remains employed with probability $(1 - s_t) \equiv 1 - \delta(1 - M_t)$.[11]

Each period, a household solves the following maximisation problem

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

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

[11] This reduced form framework mirrors the labour market structure in the quantitative model in Section 4.1 but treats the job-finding rate as an exogenous process rather than endogenous.

subject to

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

Here, the felicity function $u(c)$ is a standard constant elasticity of substitution (CES) function, with $u' > 0$, $u'' < 0$, and $u''' > 0$, c_t is consumption in period t, and a_t are asset holdings at the beginning of period t. If employed, a household earns a constant wage $\overline{w}$ and, if unemployed, then receives an unemployment benefit $b\overline{w}$, where $b \in [0, 1]$ is the replacement rate.

The (interior) solution to the problem yields the standard Euler equation

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

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

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

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

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

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

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

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

Employment risk is captured through a stochastic job finding rate $\{M_t\}$, with $M_t \in [0, 1]$.

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

I assume that the job finding rate follows an AR(1) process

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

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

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

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

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

PROOF: *See appendix A.1.* □

Proposition 1 shows that in this stylised framework, two parameters of the job finding rate process determine the amount of precautionary savings—households accumulate more precautionary savings when exposed to large but transitory changes in the job finding rate. Intuitively, a higher variance of the innovation term means that the household faces larger shocks to the job finding rate, increasing uncertainty about future income. As a result, the household wants to save more to self-insure against these income fluctuations. Similarly, a lower persistence of the job finding rate makes the current job finding rate less informative about the future job finding rate, which increases uncertainty about future income and strengthens the precautionary saving motive.[14]

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

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

[14]Note that the persistence parameter plays a dual role in the model since it also affects permanent income—more persistent shocks have a larger effect on the permanent part of income. Appendix A.2 explores this in more detail. Constantinides and Duffie (1996); Blundell, Pistaferri, and Preston (2008); Kaplan and Violante (2022), among others, discuss how more persistent income shocks make self-insurance through precautionary savings less effective.

helpful when discussing the results.

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

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

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

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

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

3 Sector-specific Employment Risk and Net Liquid Asset holdings

In the previous section, I show how employment risk affects precautionary savings using a stylised model with a homogeneous labour market. However, literature has found that the labour market is far from homogeneous, and there are significant differences in employment risk across sectors over the business cycle.[16] Yet, it is less clear whether these differences in employment risk also translate into differences in precautionary savings. For example, do households working in sectors with high employment risk accumulate more precautionary savings than those working in sectors with low employment risk? If

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

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

so, are these differences in precautionary savings smaller for wealthier households, as the theory suggests?

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

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

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

3.1 Data description

3.1.1 Survey of Consumer Finances.

In the analysis, I use the survey waves between 1989 and 2016. I focus on households with at least two members who are either married or live together, who obtain labour income from the same sector—where one member could be unemployed or not in the labour force—and the household head is between 25 and 55 years old. These restrictions allow me to focus on households in their prime working age, who pool income risk and are exposed to the same sector-specific employment risk.[18]

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

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

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

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

3.1.2 Survey of Income and Program Participation.

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

Net liquid assets. Data on the (net) wealth of households are part of topical modules and thus available only at certain waves.[21] Focusing on these waves provides information on households' balance sheets for years between 2001–2005, 2009–2011, and 2013–2016. In total, this yields 12 years of observations. For surveys before 2014 Panel Waves, I calculate

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

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

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

net liquid assets as the sum of municipal or corporate bonds and/or US government securities, interest-bearing checking accounts, savings accounts, money market, certificate of deposit, and non-interest checking accounts minus store bills or credit card debt. In 2014, the US Census Bureau redesigned the SIPP and changed some variables I use to calculate net liquid assets. Therefore, for 2014 Panel Waves 1–4, I calculate net liquid assets as the sum of the value of assets held at financial institutions (checking and savings account, CDs, non-interest checking account), the value of other interest-earning assets (municipal or corporate bonds and/or US government securities) minus store bills or credit card debt.

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

3.1.3 Longitudinal Employer-Household Dynamics.

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

I calculate two measures of net worker flows, depending on the definition of nonemployment. The first measure of net worker flows uses flows to and from *persistent nonemployment*. The second measure uses flows to and from *full-quarter nonemployment*. The difference between persistent and full-quarter nonemployment is whether nonemployment also includes workers who have single-quarter jobs in the quarters following a separation from the main job. For example, workers with transitory jobs are included in persistent nonemployment but not in full-quarter nonemployment.[26] Both measures of net worker

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

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

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

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

[26] Note that for the LEHD data, nonemployment is defined as the lack of a main job, not the lack of a job. Moreover, the lack of a 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

flows are expressed as a share of average employment within the sector. The summary statistics of the LEHD sample are shown in the top panel of Table B.2.2 in the appendix.

3.1.4 Job Openings and Labor Turnover Survey.

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

3.2 Employment risk in Cyclical and Non-cyclical sectors

To determine whether households in the SCF sample belong to cyclical or non-cyclical sectors, I first need to classify which industries are cyclical and which are non-cyclical. However, I cannot directly infer industry cyclicality from the SCF data itself because the survey is triennial, and one needs information at a business cycle frequency to capture differences in cyclicality. To address this, I rely on the Longitudinal Employer-Household Dynamics (LEHD) data. However, the LEHD and the SCF data set are not fully comparable in terms of industries; in the publicly available SCF data, the standard four-digit North American Industry Classification System (NAICS) industries are merged into seven distinct SCF-industry groups for confidentiality reasons. To bridge this gap and relate the SCF data with the LEHD data, I establish a correspondence between 20 two-digit NAICS industries from the LEHD dataset and the seven industry groups defined in the SCF. The mapping is relatively straightforward in most cases, as each two-digit NAICS industry from the LEHD dataset aligns with a single SCF-industry group. However, there are instances where an industry spans two SCF groups. In such cases, I assign the industry to the SCF-industry group, where this industry has the largest employment share. For a more detailed discussion on how I map LEHD industries into SCF groups, see appendix B.1.1.

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)).

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

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

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

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

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

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

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

[28] 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.

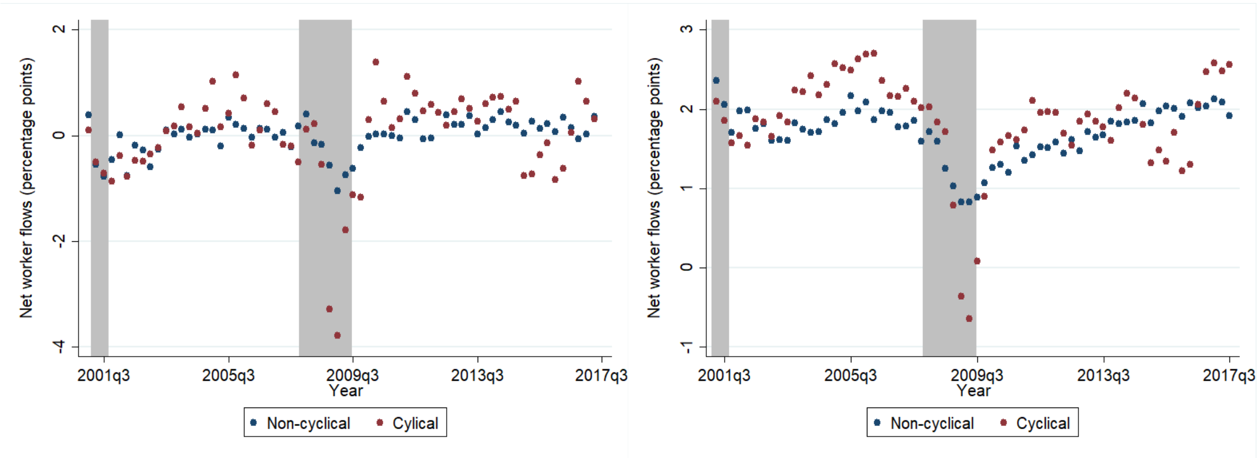
3.2.2 Employment risk in cyclical and non-cyclical sectors

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

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

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

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

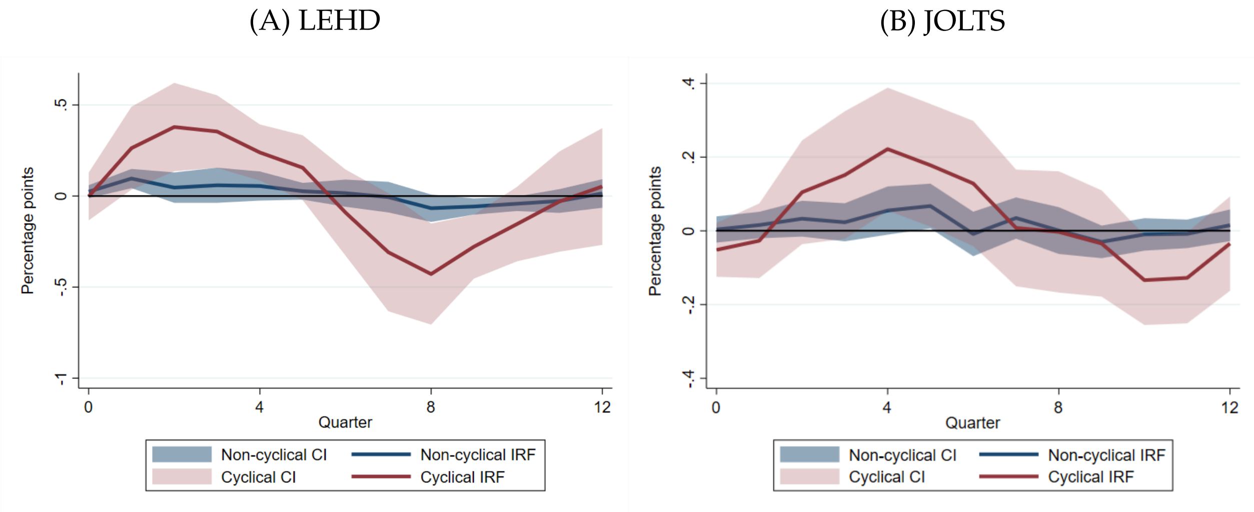
flows on a US monetary policy shocks series, its lagged values, and additional controls.[30] The US monetary policy shocks come from the work by Bu, Rogers, and Wu (2021).[31] The data is quarterly, seasonally adjusted, and covers the period 2001q2–2017q3.

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

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

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 ($K = Q = 4$).[32] The impulse responses are constructed based on the estimated coefficient φ_h. Standard errors are adjusted for heteroskedasticity and autocorrelation (Newey–West standard errors).

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



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

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

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

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

is defined as an annualised 1 standard deviation decrease in the monetary policy shock series.[33] I find that in both samples, net worker flows in non-cyclical sectors are much less responsive than in cyclical sectors, conditional on a monetary policy shock. While the timing and the size of peaks in cyclical sectors are somewhat different in the two samples, the dynamic of net worker flows is surprisingly similar.[34]

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

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

Do households working in cyclical sectors and experiencing higher employment risk have a stronger precautionary savings motive than otherwise similar households who work in non-cyclical sectors? If so, is this motive stronger for poorer households? Standard incomplete-markets literature suggests that households with greater income risk should hold more liquid assets for a precautionary reason. Moreover, this self-insurance motive should be even more important for poor households because they are more likely to be borrowing-constrained. In this section, I empirically test these predictions: (i) are there differences in net liquid asset holdings between sectors, and (ii) do these differences in net liquid asset holdings between sectors vary across the wealth distribution?

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

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

where $Y_{i,q,c,t}$ is the amount of net liquid assets held by household i, who is in quintile q of net wealth distribution, working in sector c, at time t. γ is an intercept, γ_c is a dummy variable for working in a cyclical sector, γ_q is a dummy for being in quintile q, γ_t are year-

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

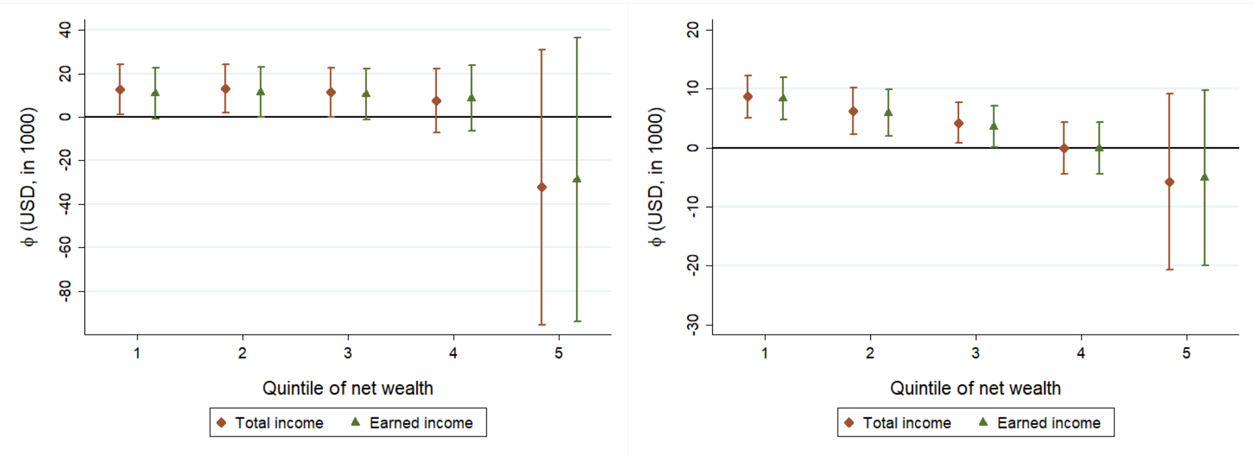
[34] Hubert and Savignac (2023) use French data and find that flows into unemployment, conditional on identified monetary policy shocks, are larger for more cyclical sectors.

fixed effects, γ_s are US state-fixed effects, $\tau_{t,s}$ are state-by-year fixed effects, allowing for unobserved state-level heterogeneity to vary over time, and $X_{i,t}$ is a vector of household characteristics.[35]

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

Figure 3: Differences in net liquid assets across sectors

(A) SCF (B) SIPP



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

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

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

measure used.

The differences in net liquid assets presented here are in levels. Alternatively, one can also express net liquid assets as a share of household income, making the interpretation somewhat more intuitive.[36] Figure C.5.1 in the appendix presents results where net liquid assets are normalised by annual income. For the SCF sample, the difference in normalised net liquid assets is statistically significant for the second quintile of the net wealth distribution. I find that households working in cyclical sectors hold approximately 10 percentage points more normalised net liquid assets than comparable households working in non-cyclical sectors, with the difference being the largest for the second quintile of the net wealth distribution. For the SIPP sample, the difference in normalised net liquid assets is similar to that of the SCF sample but statistically significant only when net liquid assets are normalised by earned income.

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

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

3.4 Testing predictions of Proposition 1

Proposition 1 predicts that households facing larger and less persistent changes in job finding rates are more inclined to save for self-insurance. To test this prediction, I construct job finding rates f_t, using matched monthly Current Population Survey (CPS) data. The

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

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

[38] This does not mean that they face the same employment risk. On the contrary, households in cyclical sectors might still experience a larger employment risk than households in non-cyclical sectors. However, they have enough liquid wealth to smooth their consumption path.

sample spans from March 2002 to October 2017, and the data is both seasonally adjusted and corrected for time aggregation (see Shimer (2012)).[39]

I estimate the following model both at monthly and quarterly frequencies

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

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

As shown in Table 2, the job finding rate in cyclical sectors exhibits lower persistence and higher volatility of its innovations compared to non-cyclical sectors. These findings suggest that households in cyclical sectors face more uncertain job prospects and, as a result, exhibit a stronger precautionary saving motive.[40]

Table 2: Estimation of sectoral job finding rates

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

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

A back-of-the-envelope calculation using the estimated values implies that, at a quarterly frequency, the precautionary saving component in cyclical sectors is approximately 1.5 times larger than in non-cyclical sectors, holding all other factors constant. Moreover, because precautionary savings scale quadratically with the separation rate, the higher separation rates observed in cyclical sectors would amplify this difference even further.

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

[40] These results are robust to specifications with linear and quadratic time trends.

4 A two-sector Heterogeneous Agent New Keynesian model

The empirical evidence reveals pronounced differences in employment risk and precautionary savings across sectors. Specifically, households working in cyclical sectors face greater job uncertainty and, as a result, accumulate more precautionary savings than those in less cyclical sectors. This finding suggests that sector-specific employment risk is a crucial determinant of household consumption behaviour and aggregate economic activity in response to shocks. In the following section, I develop a two-sector HANK model to examine how these differences in employment risk impact the transmission of monetary policy.

Environment Time is discrete, and the horizon is infinite. The economy consists of a continuum of households employed either in the Cyclical or Non-Cyclical sector, facing two sources of uninsurable risk: (i) sector-specific employment risk, with exogenous job separation rates and endogenous job finding rates, and (ii) idiosyncratic income risk in the form of productivity shocks when employed. Households consume a final good produced by a representative competitive firm that aggregates bundles of intermediate goods from both sectors into the final consumption good. Intermediate goods in each sector are produced by a continuum of monopolistically competitive firms facing Rotemberg (1982) price adjustment costs and search frictions as in Blanchard and Galí (2010). 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.

4.1 Households

While ex-ante identical, households differ ex-post in their sector-specific employment outcomes $e_{it}^{x} \in \{0, 1\}$, where $x \in \{C, NC\}$ denotes the respective sector. When employed, they face idiosyncratic income risk due to productivity shocks k_{it}^{x}, with $\mathbb{E}\left[k_{it}^{x}\right] = 1$.[41] Households derive utility from consuming the final good and supply one unit of labour when employed.[42] Households share a common CES utility function

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma}, \tag{13}$$

where γ^{-1} is the elasticity of intertemporal substitution.

A household i working in sector x with asset position a, employment status e, and

[41] Both, the sector-specific employment process and productivity shocks follow a first-order Markov chain.

[42] Inelastic labour supply is consistent with very low estimates of marginal propensities to earn (MPEs) observed in microdata (e.g., see Cesarini, Lindqvist, Notowidigdo, and Östling (2017)).

productivity level k solves the following problem

$$V_t\left(a^x_{it-1}, e^x_{it}, k^x_{it}\right) = \max_{c^x_{it},\, a^x_{it}} u\left(c^x_{it}\right) + \beta \mathbb{E}_t\left[V_{t+1}\left(a^x_{it}, e^x_{it+1}, k^x_{it+1}\right)\right] \tag{14}$$

subject to

$$c^x_{it} + a^x_{it} = (1+r_t)a^x_{it-1} + I^x_{it}, \tag{15}$$

$$a^x_{it} \geq 0 \,. \tag{16}$$

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 real disposable income, which depends on the employment status e

$$I^x_{it} = \begin{cases} \left(1-\tau^x_t\right)\left(z^x_{it}\right)^{\theta} + D^x_{it} & \text{if employed } (e=1) \\ b^x\left(1-\tau^x_t\right)\left(z^x_{it}\right)^{\theta} & \text{if unemployed } (e=0) \end{cases} \tag{17}$$

Pre-tax labour income is equal to $z^x_{it} = w^x_t k^x_{it}$, where w^x_t is sector-specific real wage and k^x_{it} is idiosyncratic productivity level. Employed households receive after-tax labour income $\left(1-\tau^x_t\right)\left(z^x_{it}\right)^{\theta}$ and real dividends D^x_{it} from intermediate goods-producing firms.[43] Parameter $\theta \in [0,1]$ measures the progressivity of labour income tax, with higher values indicating a more progressive tax system. Unemployed households receive unemployment benefits equivalent to a replacement rate b^x of the labour income they would have earned if employed. Income tax progressivity and the replacement rate are important as they affect income risk and determine the strength of the precautionary saving motive.

Labour market. The labour market structure closely follows the framework introduced by Blanchard and Galí (2010). In this approach, labour market frictions are captured through hiring costs that rise with labour market tightness. The idea is that the expected cost of hiring a household increases when the labour market becomes tighter.[44]

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

$$U^x_t = U^x_{t-1} + \delta^x N^x_{t-1}, \tag{18}$$

[43] Dividends are distributed to employed households in proportion to their productivity levels.

[44] 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.

where U^x_{t-1} is the mass of unemployed households from the period $t-1$, and N^x_{t-1} is the mass of employed households before separations occur at the beginning of period t.[45] From this pool of unemployed households, firms hire H^x_t of households who become productive in the same period they are matched with a firm.[46] Sectoral hiring in period t evolves according to

$$H^x_t = N^x_t - (1-\delta^x)N^x_{t-1}. \tag{19}$$

Labour market tightness. Labour market tightness is defined as the ratio of hires to the number of unemployed $M^x_t \equiv H^x_t / U^x_t$.[47] Substituting (18) and (19) in the labour market tightness definition yields

$$M^x_t \equiv \frac{H^x_t}{U^x_t} = \frac{N^x_t - (1-\delta^x)\, N^x_{t-1}}{U^x_{t-1} + \delta^x N^x_{t-1}}. \tag{20}$$

Job loss rate. The job loss rate, which is my measure of employment risk, is defined as the probability that an employed household becomes unemployed without being re-hired within the same period

$$s^x_t = \delta^x\,(1 - M^x)\,. \tag{21}$$

Hiring costs. Hiring is costly. The cost per hire in a sector x is given by

$$\psi^x_1\,(M^x_t)^{\psi^x_2}\,, \tag{22}$$

where $\psi^x_1 > 0$ is the level of hiring costs expressed in terms of final consumption good, and ψ^x_2 is the elasticity of hiring costs with respect to labour market tightness. The sectoral hiring costs are equal to the product of a cost per hire (22) and aggregate sectoral hiring (19)

$$\psi^x_1\,(M^x_t)^{\psi^x_2}\,H^x_t. \tag{23}$$

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

$$w^x_t = \overline{w}^x \left(\frac{M^x_t}{\overline{M}^x}\right)^{\zeta}, \tag{24}$$

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

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

[47] 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.

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

$$Y_t = \left[\alpha^{1-\eta}\left(Y_t^C\right)^{\eta} + (1-\alpha)^{1-\eta}\left(Y_t^{NC}\right)^{\eta}\right]^{\frac{1}{\eta}}. \tag{25}$$

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.[48] Both bundles of sectoral intermediate goods are themselves CES aggregates

$$Y_t^C = \left(\int_0^1 y_{jt}^{\frac{1}{\mu_C}}\, dj\right)^{\mu_C} \qquad Y_t^{NC} = \left(\int_0^1 y_{kt}^{\frac{1}{\mu_{NC}}}\, dk\right)^{\mu_{NC}}, \tag{26}$$

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

$$y_{jt} = \left(\frac{p_{jt}}{P_t^C}\right)^{-\mu_C/(\mu_C-1)} \left(\frac{P_t^C}{P_t}\right)^{-1/(1-\eta)} \times \alpha Y_t \qquad \forall\, j, \text{ and} \tag{27}$$

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

$$y_{kt} = \left(\frac{p_{kt}}{P_t^{NC}}\right)^{-\mu_C/(\mu_C-1)} \left(\frac{P_t^{NC}}{P_t}\right)^{-1/(1-\eta)} \times (1-\alpha)\, Y_t \qquad \forall\, k. \tag{28}$$

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

$$P_t^C = \left(\int_0^1 p_{jt}^{\frac{1}{1-\mu_C}}\, dj\right)^{1-\mu_C} \qquad P_t^{NC} = \left(\int_0^1 p_{kt}^{\frac{1}{1-\mu_{NC}}}\, dk\right)^{1-\mu_{NC}}, \tag{29}$$

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

and the price index of the final good is

$$P_t = \left[\alpha \left(P_t^C \right)^{\frac{\eta}{\eta-1}} + (1-\alpha) \left(P_t^{NC} \right)^{\frac{\eta}{\eta-1}} \right]^{\frac{\eta-1}{\eta}} . \tag{30}$$

Benchmark specification. As my benchmark specification, I consider a special case of (25), where the final good is being bundled together using Cobb-Douglas aggregator ($\eta = 0$)

$$Y_t = \kappa \left(Y_t^C \right)^{\alpha} \left(Y_t^{NC} \right)^{1-\alpha} , \tag{31}$$

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

$$y_{jt} = \left(\frac{p_{jt}}{P_t^C} \right)^{-\mu_C/(\mu_C-1)} \left(\frac{P_t^C}{P_t} \right)^{-1} \times \alpha Y_t \qquad \forall\, j, \text{ and} \tag{32}$$

$$y_{kt} = \left(\frac{p_{kt}}{P_t^{NC}} \right)^{-\mu_C/(\mu_C-1)} \left(\frac{P_t^{NC}}{P_t} \right)^{-1} \times (1-\alpha) Y_t \qquad \forall\, k. \tag{33}$$

Price indices in the two sectors are the same as in (29), while the price index of the final good simplifies to

$$P_t = \left(P_t^C \right)^{\alpha} \left(P_t^{NC} \right)^{1-\alpha} . \tag{34}$$

Dividing both sides of (34) by P_{t-1} and defining $\pi_t \equiv P_t / P_{t-1}$, one obtains aggregate inflation

$$\pi_t = \left(\pi_t^C \right)^{\alpha} \left(\pi_t^{NC} \right)^{1-\alpha} . \tag{35}$$

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

$$y_{mt} = Z_t \, n_{mt} , \tag{36}$$

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

$$n_{mt} = (1 - \delta^x) \, n_{mt-1} + h_{mt} , \tag{37}$$

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 $\psi_1^C \left(M_t^C\right)^{\psi_2^C}$ and quadratic price adjustment costs $\Theta_t^C = \frac{\alpha\vartheta}{2}\left(\frac{p_{jt}}{p_{jt-1}} - 1\right)^2 Y_t$, with $\vartheta > 0$. The latter costs are measured in terms of the final good and proportional to the sector size. The profit maximisation problem of a firm reads

$$\max_{\{p_{js}, n_{js}, y_{js}, h_{js}\}} \mathbb{E}_t \sum_{s \geq t} \left(\frac{1}{1+r}\right)^{s-t} \left\{ \frac{p_{js}}{P_s} y_{js} - w_s^C n_{js} - \psi_1^C \left(M_s^C\right)^{\psi_2^C} h_{js} - \frac{\alpha\vartheta}{2} \left(\frac{p_{js}}{p_{js-1}} - 1\right)^2 Y_s \right\}, \tag{38}$$

subject to (32), (36), and (37). As shown in appendix D.1, the solution to this problem yields the New Keynesian Phillips curve in the cyclical sector

$$\pi_t^C \left(\pi_t^C - 1\right) = \frac{1}{\vartheta\left(\mu_C - 1\right)} \underbrace{\left[\mu_C \frac{P_t}{P_t^C} mc_t^C - 1\right]}_{\widetilde{mc_t}^C} + \frac{1}{1+r} \mathbb{E}_t \, \pi_{t+1}^C \left(\pi_{t+1}^C - 1\right) \frac{Y_{t+1}}{Y_t}, \tag{39}$$

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

$$\pi_t^{NC} \left(\pi_t^{NC} - 1\right) = \frac{1}{\vartheta\left(\mu_{NC} - 1\right)} \underbrace{\left[\mu_{NC} \frac{P_t}{P_t^{NC}} mc_t^{NC} - 1\right]}_{\widetilde{mc_t}^{NC}} + \frac{1}{1+r} \mathbb{E}_t \, \pi_{t+1}^{NC} \left(\pi_{t+1}^{NC} - 1\right) \frac{Y_{t+1}}{Y_t}. \tag{40}$$

4.3 Government

The government runs a balanced budget on a constant level of real debt B, adjusting τ_t^x to satisfy

$$\sum_x N_t^x \int \left(z_{it}^x - \left(1 - \tau_t^x\right) \left(z_{it}^x\right)^\theta\right) di = r_t B + \sum_x U_t^x \int b^x \left(1 - \tau_t^x\right) \left(z_{it}^x\right)^\theta di. \tag{41}$$

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

$$1 + r_t = \frac{1 + i_{t-1}}{\pi_t}. \tag{42}$$

4.4 Monetary authority

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

$$r_t = \bar{r} + \rho_R (r_{t-1} - \bar{r}) + \epsilon_t \, , \tag{43}$$

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.[49]

4.5 Equilibrium

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

$$\Gamma_{t+1}^x \left(\mathcal{A}, e_{t+1}^x\right) = \int_{\{(a^x,\, e^x): g_t(a^x, e^x) \in \mathcal{A}\}} \Pi_{ee'}^x \; d\Gamma_t^x \left(a^x, e^x\right) \, , \qquad x \in \{C, NC\} \tag{44}$$

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

$$B = \sum_x \int g_t \left(a^x, e^x\right) \, d\Gamma_t^x \left(a^x, e^x\right) \, . \tag{45}$$

Using (36) in (32) and (33), 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

$$Y_t^C \equiv \alpha \left(\frac{P_t^C}{P_t}\right)^{-1} Y_t = Z_t \, N_t^C \, , \tag{46}$$

and

$$Y_t^{NC} \equiv (1-\alpha) \left(\frac{P_t^{NC}}{P_t}\right)^{-1} Y_t = Z_t \, N_t^{NC} \, . \tag{47}$$

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

$$D_t^x = \frac{1}{N_t^x} \left(Y_t^x - \psi_1^x \left(M_t^x\right)^{\psi_2^x} H_t^x\right) - w_t^x \, . \tag{48}$$

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

$$L_t = \sum_x L_t^x = \sum_x \int d\Gamma_t^x \left(a^x, 1\right) = 1 - \left(U_t^C + U_t^{NC}\right) = 1 - U_t \, , \tag{49}$$

[49]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

$$N_t = \sum_x N_t^x = N_t^C + N_t^{NC}, \tag{50}$$

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

$$N_t = L_t \equiv 1 - U_t\,. \tag{51}$$

The goods market clearing condition requires

$$Y_t = C_t + \psi M_t H_t + \Theta_t\,, \tag{52}$$

where Y_t *is aggregate output from (31),* $C_t \equiv \sum_x \int c_t\,(a^x, e^x)\, d\Gamma_t^x\,(a^x, e^x)$ *is aggregate consumption,* $\psi M_t H_t \equiv \sum_x \psi_1^x\,(M_t^x)^{\psi_2^x}\, H_t^x$ *are aggregate hiring costs, and* $\Theta_t \equiv \sum_x \Theta_t^x$ *are aggregate price adjustment costs, both expressed in terms of a final consumption good. In equilibrium, all decision rules and value functions satisfy all optimality conditions, definitions, and budget constraints.*

4.6 Model calibration

I calibrate the model at a quarterly frequency to the US economy. Table 3 presents the baseline calibration. I set household elasticity of intertemporal substitution to $\gamma = 0.5$, which is a standard value in the literature. The discount factor β is set to target the steady state annual real interest rate of $r = 3\%$. To model income risk, I calibrate idiosyncratic productivity shocks to the persistent component of log earnings of employed workers in the US. The parameter values are taken from Braxton, Herkenhoff, Rothbaum, and Schmidt (2021). Since I have no information on sectoral estimates, I use these values for both sectors.

The sector size parameter $\alpha = 0.24$ is set to match the employment share of the cyclical sector.[50] The substitution parameter between sectors η is set to 0 to match the unitary elasticity of substitution between the sectoral bundles of intermediate goods. The steady-state markup for intermediate firms to $\mu = 1.2$, as in Christiano, Eichenbaum, and Rebelo (2011). The Rotemberg price adjustment cost is set to match the average price duration of 3 quarters (Nakamura and Steinsson (2008)).

The steady-state unemployment rate is set to $U = 6.3\%$, the average unemployment rate in the US over the period 2001q2–2017q3. Sectoral job separation rates are calibrated to match empirical counterparts calculated from CPS microdata (see Table B.2.3 in the ap-

[50]This is based on BLS sectoral employment data from 2001 to 2016, with the cyclical sectors defined as described in Section 3.2.1. BLS data can be found here `https://www.bls.gov/emp/data/industry-out-and-emp.htm`.

Table 3: Baseline calibration

Description	Parameter	Value: Cyclical	Value: Non-cyclical	Target
HOUSEHOLDS				
Discount factor	β	0.98054		Annual real interest rate of 3%
EIS	$1/\gamma$	0.5		Standard
Idiosyncratic productivity				See text
Persistence	ρ_k	0.9401		
Standard deviation	σ_k	0.2261		
PRODUCTION				
Sector size	α	0.24		Cyclical sector employment share
Substitutability btw. sectors	η	0		Cobb-Douglas
Markup	μ	1.2		See text
Price adj. costs	ϑ	30		Avg. price duration of 3 qtr.
LABOUR MARKET				
Unemployment rate	U	0.063		Unempl. rate: 2001q2–2017q3
Job separation rate	δ	0.266	0.076	See text
Level of hiring costs	ψ_1	0.031	0.048	McKay and Reis (2021)
Elasticity of hiring costs	ψ_2	1		Blanchard and Galí (2010)
Elasticity of wages w.r.t. labour market tightness	ζ	1		See text
GOVERNMENT				
Bond supply	B	1.803		Avg. liq. assets to income = 0.55
Progressivity parameter	θ	0.181		See text
Replacement rate	b	0.4		Avg. repl. rate: 2001q2–2017q3

pendix). This delivers a job separation rate of $\delta^{NC} = 0.075$ in the non-cyclical sector and $\delta^{C} = 0.266$ in the cyclical sector. Following McKay and Reis (2021), the hiring cost parameter ψ_1 is calibrated to match recruiting costs of 3% of quarterly wages, as reported by Barron, Berger, and Black (1997). This results in $\psi_1 = 0.031$ for the cyclical sector and $\psi_1 = 0.048$ for the non-cyclical sector. The elasticity of hiring costs is set to $\psi_2 = 1$, ensuring consistency with a matching function elasticity with respect to unemployment of 0.5 in a standard DMP model (Petrongolo and Pissarides (2001)).[51] In the baseline calibration, wages are flexible, with a unitary elasticity of wages to labour market tightness.

Bond supply B is calibrated to match annual household net liquid assets to income ratio of 0.55, as observed in the data.[52]. Two key parameters determine income risk and, therefore, the strength of the precautionary saving motive: the replacement rate for unemployed households and the tax progressivity for employed households. Given the limited evidence on sector-specific replacement rates, a uniform replacement rate of $b = 40\%$ is applied to both sectors, corresponding to the average US replacement rate during that period.[53] The progressivity parameter for labour income tax is set to 0.181 for both sectors, based on estimates from Heathcote, Storesletten, and Violante (2017).

4.6.1 Calibration results

Table 4 presents baseline calibration results. The model predicts higher job finding $\overline{M}$ and job loss rates $\bar{s}$ in a steady state for the cyclical sector. Although households in the cyclical sector have a higher probability of finding a job when unemployed, a higher separation rate means that more households lose their jobs in the first place, which leads to a higher overall job loss rate. This indicates that households face greater employment risk and thus exhibit a stronger precautionary saving motive. While the model does a good job of predicting lower pre-tax income and less wealth for households in the cyclical sector, it underestimates the differences in income and wealth levels between the two sectors (see Table B.2.1 in the appendix).

The model delivers an aggregate MPC of 0.085 at a quarterly frequency, corresponding to an annual value of approximately 0.33, with higher values in the cyclical sector than in the non-cyclical sector.[54] Figure 4 shows the average MPCs across quintiles of sectoral wealth distribution. As one can observe, the MPC difference between the two sectors is

[51]See Blanchard and Galí (2010) for the mapping between hiring costs elasticity ψ_2 and the elasticity of matching function with respect to unemployment in a canonical DMP model.

[52]This is known as the "liquid wealth calibration". The target is the average of the SIPP estimate (0.61) and the SCF estimate (0.48) over the period 2001–2016. The definitions of net liquid assets and income follow those outlined in Section 3.1.

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

[54]This value is consistent with other models and empirical estimates. For example, Parker (1999), Jappelli and Pistaferri (2010), Parker, Souleles, Johnson, and McClelland (2013), and Kaplan and Violante (2022) report annual MPCs ranging from 0.1 to 0.4. A higher average MPC in the cyclical sector relative to the non-cyclical sector is consistent with Patterson (2020), who shows that individuals working in industries more exposed to the Great Recession shock, i.e. more cyclically sensitive industries, have higher MPCs.

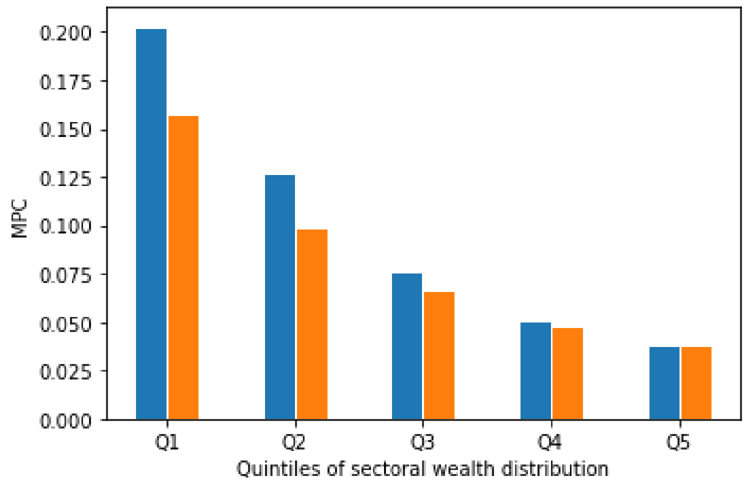
Table 4: Steady-state results

Description	Parameter	Aggregate	Cyclical	Non-cyclical
Job finding rate	$\overline{M}$	0.643	0.798	0.528
Job loss rate	$\bar{s}$	0.043	0.054	0.035
Labour income (in USD)	$\bar{z}$	10,568	10,522	10,582
Pre-tax total income (in USD)		12,689	12,644	12,704
– After-tax total income		12,268	12,224	12,283
– Unemp. benefits		4,907	4,889	4,913
Average wealth (in USD)		23,250	19,625	24,395
Average MPC (quarterly)	$\overline{MPC}$	0.084	0.097	0.080
– Employed			0.087	0.070
– Unemployed			0.247	0.233

Notes: Household income in USD is expressed in terms of the average US GDP between 2001 and 2016. Total income includes labour income and dividends from the intermediate goods-producing firms.

largest for the poorest households and decreases as wealth increases.

Figure 4: MPCs across quintiles of sectoral wealth distribution



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

What drives the differences in MPC across the two sectors? In the model, the separation rate has two main effects. First, it affects employment risk; a higher separation rate raises the probability of job loss, increasing income uncertainty. Second, it makes employed, asset-poor households more likely to hit the borrowing constraint. Carroll, Holm, and Kimball (2021) show that both factors lead to a more concave consumption function and higher MPCs.[55]

Sectoral and aggregate MPCs also depend on sectoral wealth distributions, which are also affected by the sectoral separation rates. As discussed in Section 2, a higher separation rate reduces the level of permanent income. Moreover, a high separation rate also increases the probability of job loss every period, forcing households to draw down their savings more frequently and making it more difficult to accumulate large asset holdings. As a result, households in the cyclical sector tend to be poorer and exhibit higher MPCs. This is also what I observe in the data (see Table B.2.1 in the appendix).[56] While households in the cyclical sector exhibit stronger precautionary saving motives due to higher employment risk, these additional savings are insufficient to compensate for their lower *target wealth levels* associated with their lower permanent income (Carroll, 2004).[57]

Taken together, the combination of a more concave policy function and lower wealth among households in the cyclical sector, compared to those in the non-cyclical sector, results in a higher sectoral MPC. As the next section shows, these differences in sectoral MPCs matter for both sectoral and aggregate responses following an expansionary monetary policy shock.

5 Sectoral Exposure to Aggregate Shocks and Propagation of Business Cycles

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

The monetary policy shock is modelled as an annualised 1 percentage point decrease in the real interest rate r_t. The resulting IRFs are presented in Figure 5. 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). This stronger response reflects two factors: (i) higher MPCs among households in the cyclical sector, and (ii) more procyclical income in that sector. Over four quarters, the cumulative difference between the two sectors is approximately 30 basis points, with a peak difference of more than 10 basis points at impact.

The basic mechanism driving the impulse responses is as follows. Following an ac-

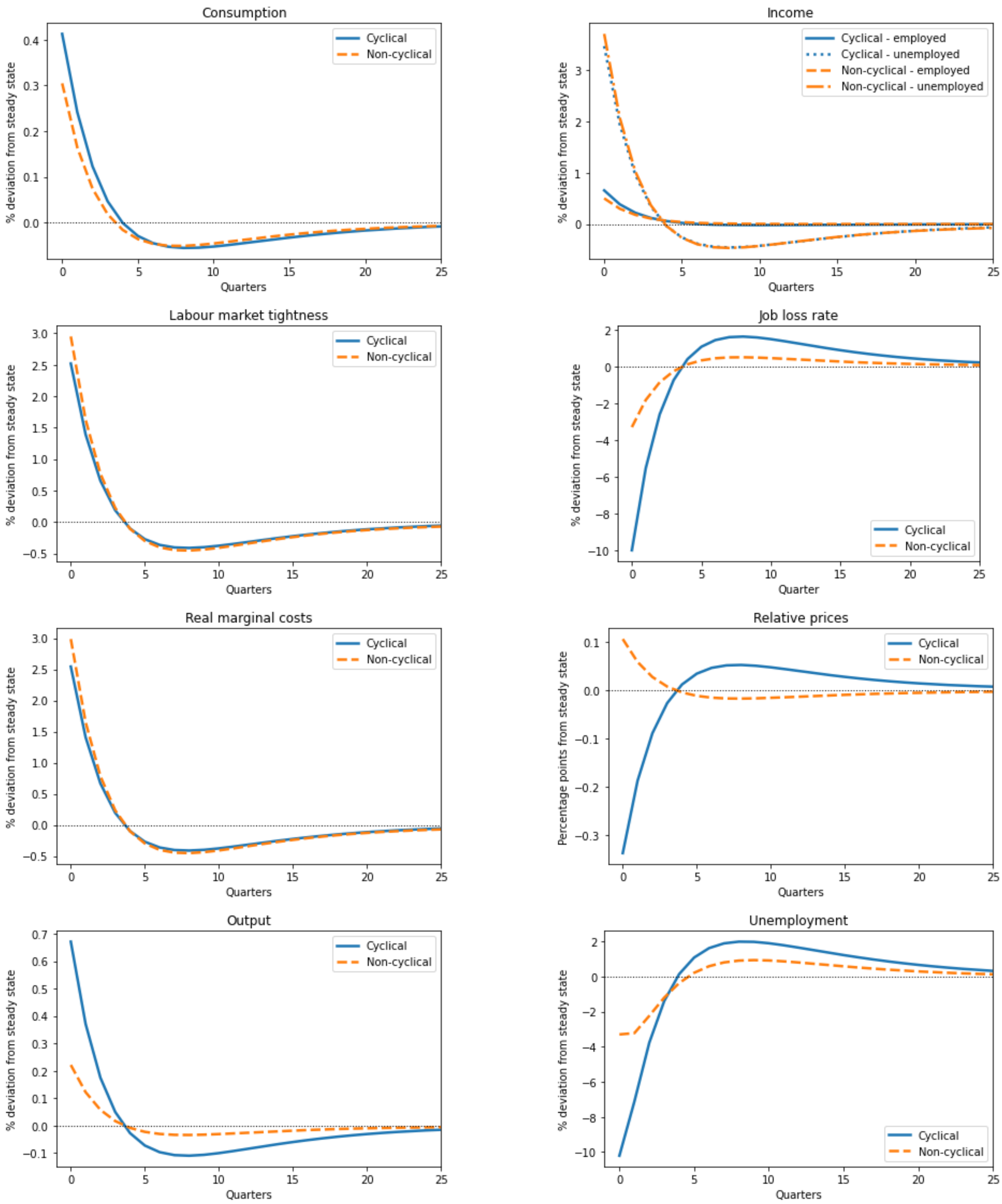
[55] Kaplan and Violante (2022) quantify the contributions of income risk and borrowing constraints to the rise in average MPC relative to the certainty-equivalent MPC. They find that borrowing constraints account for over two-thirds of the increase, while uninsurable income risk explains the remaining one-third.

[56] In Section 2, the job finding rate $\overline{M}$ is exogenous, whereas, in the model, it is endogenous and depends on the separation rate. Using the steady-state value of the job finding rate (20) in equation (8) delivers the same result, i.e., permanent income is decreasing in the separation rate.

[57] Compared with a zero-liquidity setting in which all savings arise purely from precautionary motives, my model incorporates a positive stock of government bonds and includes savings proportional to permanent income. Consequently, households not only save for precautionary reasons but also maintain wealth in line with their expected long-term income.

commodative monetary policy shock, demand for a final consumption good increases. To meet this increased demand, firms in both cyclical and non-cyclical sectors increase production and hire additional workers, thereby increasing employment (reducing unemployment) and income in both sectors. However, the extent to which employment and income in each sector increase depends critically on the “fluidity” of the respective labour market. Following Blanchard and Galí (2010), a labour market with a high separation rate and large worker flows is characterised as *"fluid"*, while a labour market with a low separation rate and low worker flows is characterised as *"rigid"*.

Figure 5: The effect of a monetary policy shock



Notes: The figure shows impulse responses to a monetary policy shock with persistence $\rho_R = 0.6$. Sectoral relative prices are expressed relative to the aggregate price level, specifically as P^C/P and P^{NC}/P.

Because the labour market in the non-cyclical sector is more rigid, the initial increase in labour market tightness is larger than in the cyclical sector. 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] As labour market tightness increases, both wages and hiring costs rise, which in turn increases real marginal costs, making goods produced in the non-cyclical sector relatively more expensive.[59] This increase in real marginal costs reallocates production and labour demand toward the less expensive cyclical sector, further increasing employment, income and consumption of households in the cyclical sector. I refer to this channel as the *Sectoral Reallocation Channel* and operates even without employment risk as long as there are differences in production costs across sectors.

As shown in the previous section, households in the cyclical sector face higher employment risk and thus exhibit higher MPCs on average. This means that for the same increase in income, consumption rises more in the cyclical sector than in the non-cyclical sector. This amplification, driven by differences in employment risk, is referred to as the *Employment Risk Channel*. In addition to the separation rate, the strength of this channel is influenced by two parameters: the replacement rate for unemployed households and the tax progressivity for employed households. Both parameters affect income risk and the strength of the precautionary saving motive, hence sectoral MPCs. For example, higher replacement rates and more progressive labour income taxes reduce income risk, leading households to save less for precautionary reasons, thereby increasing the average assets-weighted MPC.

With incomplete markets, the sectoral reallocation channel has an additional effect on consumption responses because it also affects the cyclicality of income risk and, hence, precautionary savings. The literature shows that countercyclical income risk amplifies aggregate demand responses following an accommodative monetary policy shock, while procyclical income risk dampens them.[60] Following Acharya and Dogra (2020), I define the *income gap* as the difference between employed and unemployed households' incomes. In the model, employed households receive procyclical after-tax labour income and countercyclical dividends.[61] Unemployed households receive unemployment benefits proportional to their after-tax labour income only. As a result, income risk in both sectors is countercyclical—the income gap narrows during booms and widens during re-

[58]Observe from (20) 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, $\mathcal{E}_{M,N}$ increases as δ decreases, that is, when the labour market is more rigid.

[59]Real marginal costs include wages as well as current and future hiring costs. See equation (D.23) in the appendix for details. 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.

[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, refer to McKay, Nakamura, and Steinsson (2016).

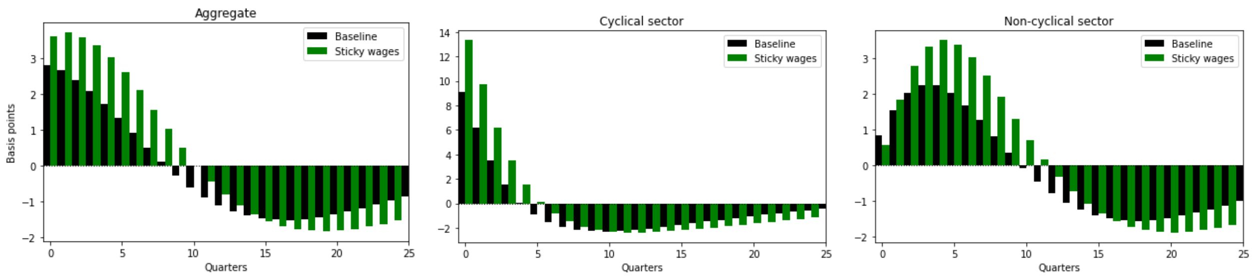
[61]Dividends decline during economic expansions due to sticky prices and flexible wages. As discussed by Broer, Harbo Hansen, Krusell, and Öberg (2019) and Auclert, Bardóczy, and Rognlie (2023), among others, this setting might have undesirable consequences on the labour supply. However, this might be less of a concern given my assumption of inelastic labour supply.

cessions—consistent with empirical findings in the literature (starting with Storesletten, Telmer, and Yaron (2004)). Due to the countercyclical nature of income risk, the precautionary saving motive is weaker during booms, thereby amplifying sectoral and aggregate consumption responses.

5.1.1 How Important Are Demand Spillovers for the Amplification of Business Cycles?

To quantify the role of the sectoral reallocation channel in driving business cycle fluctuations, I compare consumption responses in the full model—where relative prices adjust endogenously—to those in a counterfactual where relative prices are fixed at their steady-state values. As an additional experiment, I also consider a calibration with more rigid wages in the cyclical sector, reflecting historically higher unionisation rates in industries more exposed to business cycles, such as construction or manufacturing.

Figure 6: The Sectoral Reallocation Channel



Notes: The bars show the strength of the sectoral reallocation channel under different calibrations. The channel is calculated as the difference between the baseline response and the response in which the relative price is at its steady-state value. The channel is computed as the difference between the baseline consumption response and the response from a model in which the relative price is fixed at its steady-state value. In the "sticky wages" calibration, the elasticity of wages to labour market tightness in equation (24) is set to $\zeta^C = 0.5$.

In the baseline calibration (black bars in Figure 6), the channel raises consumption in both sectors, but the increase is much larger in the cyclical sector. Because the non-cyclical sector has a more rigid labour market, its real marginal costs rise sharply with additional hiring, pushing up production costs and relative prices. As a result, production and labour demand shift toward the cheaper cyclical sector, boosting employment, income, and consumption there. Moreover, because the cyclical sector has a higher MPC, this reallocation further amplifies aggregate consumption. Overall, the channel delivers a cumulative effect of around 10 basis points over four quarters.

Interestingly, despite production and income shifting toward the cyclical sector, there is still positive demand spillover to the non-cyclical sector. The multiplier effect from higher income in the cyclical sector is strong enough to boost non-cyclical consumption beyond what it would be if this reallocation channel were absent. This shows the importance of this channel in enhancing the overall effectiveness of monetary policy.

The channel becomes even more potent in the sticky wages calibration (green bars). Stickier wages in the cyclical sector moderate the rise in real marginal costs, making production there even cheaper. This cost advantage intensifies the shift in production and labour demand toward the cyclical sector, leading to a larger increase in consumption. As before, the accompanying income redistribution to the high-MPC sector amplifies the overall consumption response by approximately 15 basis points cumulatively over one year.

5.1.2 The Role of Sectoral Substitutability in Monetary Policy Transmission

Baqaee and Farhi (2022), among others, shows that substitutability in production plays an important role in determining how shocks propagate both at the aggregate level and across sectors. In the baseline model, a Cobb-Douglas aggregator is used, implying a unitary elasticity of substitution. Here, I explore how varying the elasticity of substitution between goods produced in the cyclical and non-cyclical sectors affects the transmission of a monetary policy shock. Specifically, I vary this elasticity to capture two distinct cases—in the left panel of Figure 7, the sectors are *gross complements*, whereas in the right panel, they are *gross substitutes*.

When the two sectors are more substitutable, the initial consumption increase in the cyclical sector is larger and more persistent relative to a baseline calibration. Intuitively, a higher elasticity of substitution amplifies the sectoral reallocation channel. Once the cyclical good becomes relatively cheaper, the final goods producer quickly reallocates spending away from the more expensive non-cyclical inputs toward cheaper cyclical ones. This reallocation boosts production, labour demand, income, and consumption for households in the cyclical sector. Given that the cyclical sector is the high-MPC sector, this further amplifies aggregate consumption. In contrast, demand for the non-cyclical sector's goods rises less, resulting in lower income and consumption gains in that sector.

On the other hand, if the two sectors' outputs are gross complements, the final-goods producer is far less responsive to changes in relative prices.[62] In this scenario, the sectoral reallocation channel weakens, and output, employment, and income across the two sectors move much more closely. As a result, the consumption responses of households in both sectors also become more similar, and the amplification arising from differences in MPCs is effectively diminished.

[62] Because of the strong complementarity in production, shifts in aggregate demand affect real marginal costs and inflation without inducing significant changes in sectoral outputs.

Figure 7: Sectoral Substitutability

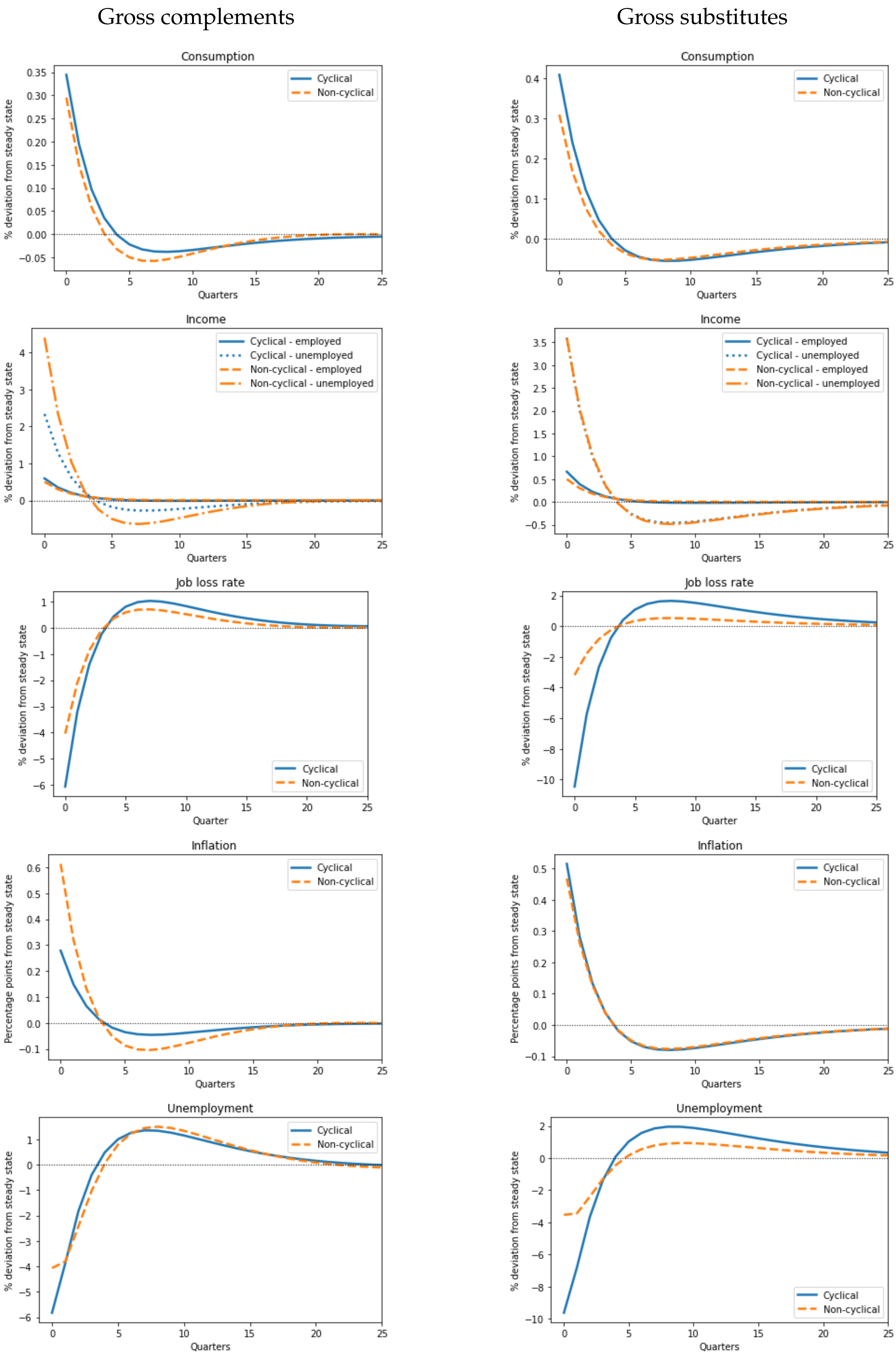
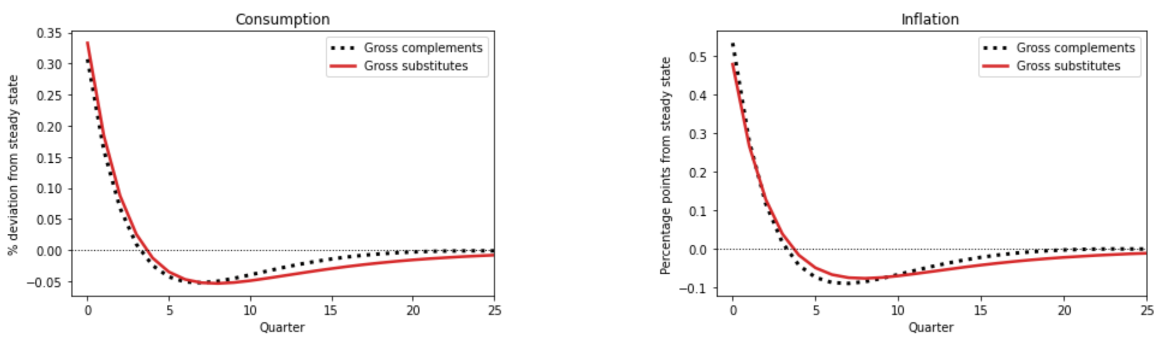


Figure 8 shows how the elasticity of substitution affects aggregate consumption and inflation. When sectors are closer substitutes, there is a stronger amplification of aggregate consumption responses and less pressure on aggregate inflation, as demand shifts toward the cheaper, high-MPC cyclical sector. In contrast, when sectors are more complementary, relative price adjustments are muted, leading to more uniform cost pressures across the economy. This dampens the sectoral reallocation channel, resulting in less amplification of aggregate consumption and higher aggregate inflation. Over a year horizon, the cumulative difference between the two consumption responses is almost 10 basis points, with a peak difference of approximately 3 basis points on impact.

Figure 8: Sectoral Substitutability and Amplification

Gross complements | Gross substitutes



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

5.2 A two-sector Representative-Agent New Keynesian model

To understand how incomplete markets affect monetary policy transmission in an economy with sectoral differences in employment risk, I compare the HANK model's responses with those from an otherwise identical two-sector RANK model. The main difference between the two models is that households in the HANK model are not insured against idiosyncratic risk, while households in the RANK are. As a result, the only operative channel in the RANK model is the Sectoral Reallocation Channel.[63]

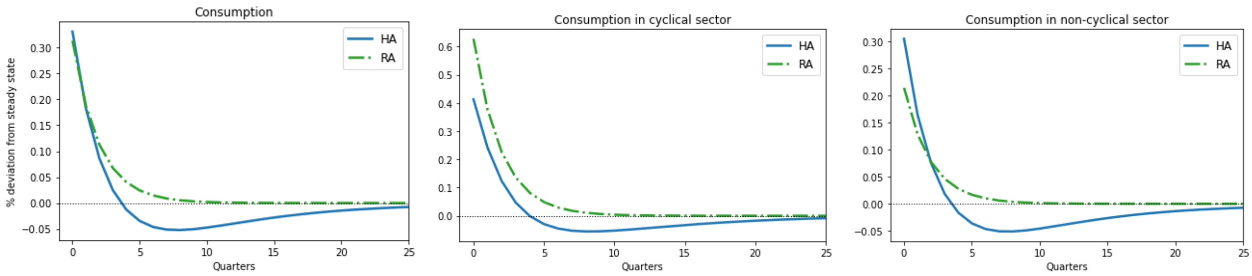
For brevity, I only focus on consumption responses.[64] Figure 9 shows both aggregate and sectoral consumption responses for the two models. In the short run, aggregate consumption behaves similarly in both frameworks. However, after about two quarters, the HANK aggregate response falls below the response in the RANK model and only gradually recovers. This shortfall mainly reflects precautionary savings behaviour by households facing uninsurable employment risk—when households receive extra income, they

[63]The calibration is otherwise identical for both models.

[64]Figure **??** in the appendix shows impulse responses in the RANK model for other variables.

save part of it to insure against potential future job losses, muting the consumption increase relative to a fully insured representative household.

Figure 9: Monetary policy shock, HANK vs RANK

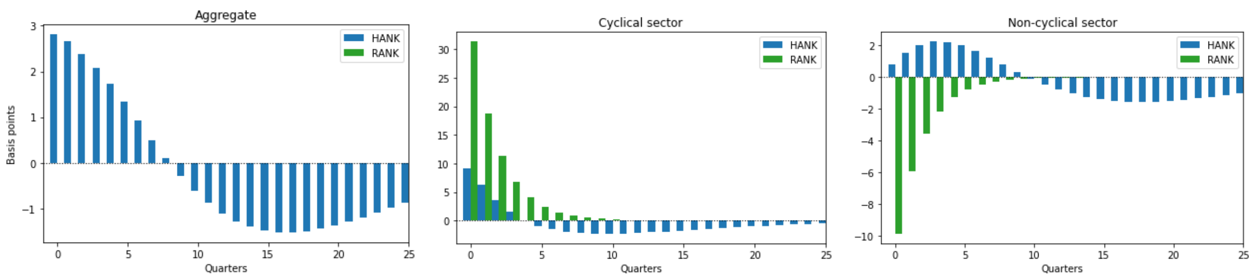


Notes: The solid blue line shows impulse responses from the baseline HANK model, and the dash-dotted green line shows responses from the corresponding RANK model.

The middle and right panels of Figure 9 depict consumption responses in the cyclical and non-cyclical sectors and show significant differences between the HANK and RANK models. In the cyclical sector, where employment risk is higher, households save a larger share of any additional income rather than spending it immediately, so the HANK response remains below that of the RANK model. Although the cyclical sector also experiences a larger decline in its job loss rate during economic expansions, this reflects its overall volatility, as it tends to deteriorate more sharply in downturns.

In contrast, in the non-cyclical sector, the HANK response initially exceeds that of the RANK but falls below it after about three quarters. On impact, these households dissave to finance their consumption—briefly "overshooting" the RANK response—before gradually rebuilding their assets, eventually pulling consumption below the RANK level.

Figure 10: The Sectoral Reallocation Channel, HANK vs RANK



Notes: The bars show the strength of the sectoral reallocation channel in the HANK and RANK models. The channel is calculated as the difference between the baseline response and the response in which the relative price is at its steady-state value. The channel is computed as the difference between the baseline consumption response and the response from a model in which the relative price is fixed at its steady-state value.

Figure 10 shows how demand spillovers affect consumption responses in the HANK vs the RANK model. The RANK framework shows a much larger spike in the cyclical sector (middle panel), reflecting a bigger demand shift toward the cheaper cyclical sector. In contrast, in the HANK model, precautionary savings dampen this effect—despite the price drop, households do not fully spend additional income, which results in a more muted response.

Turning to the non-cyclical sector (right panel), in the RANK model, non-cyclical consumption declines as households substitute away from relatively more expensive goods. In HANK, however, income redistribution into the high-MPC cyclical sector amplifies aggregate consumption, and some of this additional aggregate demand spills over into the non-cyclical sector, increasing consumption in that sector.

Finally, in contrast to the HANK model, demand spillovers do not impact the aggregate consumption in the RANK model. This is because households in cyclical and non-cyclical sectors have identical MPCs, and income redistribution does not affect the aggregate consumption response—i.e., there is no amplification via the multiplier.

6 Conclusion

This paper studies how differences in employment risk across sectors affect the transition mechanism of monetary policy. I show that households in more cyclical, high-risk sectors accumulate higher precautionary savings, reflecting more uncertain job prospects. Using a two-sector HANK model with search and matching frictions, I show that the consumption response is larger and more persistent in the cyclical sector.

The reason for a more pronounced 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 makes the labour market more fluid, shifting labour demand towards the cyclical sector. Moreover, this sectoral reallocation of demand amplifies sectoral and aggregate consumption via the multiplier effect. This amplification increases with more rigid wages in the cyclical sector or when goods from the two sectors are closer substitutes.

A two-sector RANK framework with full insurance tends to overestimate sectoral asymmetries. This suggests that self-insurance against job losses dampens labour reallocation and reduces the need for potential sector-specific stabilisation measures. These findings highlight the importance of considering the heterogeneity of employment risk across sectors when analysing the transmission mechanism of monetary policy, as it significantly affects both sectoral and aggregate dynamics.

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A Appendix to Section 2

A.1 Proof of proposition 1

Start with (6)

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

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

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

Expand and distribute the terms in the previous equation

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

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

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

$$
\begin{aligned}
c \approx & -\frac{\beta R-1}{\beta R} A(c)^{-1}+\bar{w}[1-\delta(1-\bar{M})(1-b)] \\
& -\frac{1}{2} \gamma(c)\left[\mathbb{E}\left[\left((1-\rho) \bar{M}+(\rho-1)\left(\bar{M}+\sum_{j=0}^{\infty} \rho^j \epsilon_{t-j}\right)\right)^2\right]+\sigma_\epsilon^2+0\right] \delta^2(1-b)^2 \bar{w}^2 \qquad \text{(A.5)} \\
\approx & -\frac{\beta R-1}{\beta R} A(c)^{-1}+\bar{w}[1-\delta(1-\bar{M})(1-b)] \\
& -\frac{1}{2} \gamma(c)\left[\mathbb{E}\left[\left((\rho-1) \sum_{j=0}^{\infty} \rho^j \epsilon_{t-j}\right)^2\right]+\sigma_\epsilon^2\right] \delta^2(1-b)^2 \bar{w}^2 \qquad \text{(A.6)} \\
\approx & -\frac{\beta R-1}{\beta R} A(c)^{-1}+\bar{w}[1-\delta(1-\bar{M})(1-b)] \\
& -\frac{1}{2} \gamma(c)\left[(\rho-1)^2 \frac{\sigma_\epsilon^2}{1-\rho^2}+\sigma_\epsilon^2\right] \delta^2(1-b)^2 \bar{w}^2 . \qquad \text{(A.7)}
\end{aligned}
$$

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

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

□

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

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

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

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

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

Note that in comparison to the consumption equation (8) in the main text, the steady-state value of the job finding rate now reads $\bar{M} \equiv \mathbb{E}[M_t]=\frac{\mu_M}{1-\rho}$. The dual nature of the persistence parameter can be observed by comparing the second ($\mathcal{PI}$) and the third term ($\mathcal{S}$) in (A.10).

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

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

B Data appendix

B.1 Further sample restrictions

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

Here, I describe how I relate the LEHD industry data with the SCF industry data and clarify the necessary adjustments to ensure their comparability. As described in Section 3.2.1, mapping the LEHD data to the SCF data is relatively straightforward, however, there are instances that require a more detailed analysis. For example, when a LEHD industry is in more SCF–industry groups, I disaggregate the LEHD industry to the four-digit NAICS level and assign it to the SCF-industry group, which has the largest employment share of that industry.[65]

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

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

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

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

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

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

B.1.2 Employment history in the SCF sample

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

Note that the SCF has no explicit information on households' employment history. However, there is information on the household's tenure with the current employer, which I use as a proxy for the employment history. In my analysis, I include only households whose tenure in that sector is above some threshold value in the analysis.[66]

I proceed as follows. First, I normalise the household's tenure by the total work experience.[67] Then, I use this information to calculate the sector-specific median value of normalised tenure for each survey year. In the last step, I restrict the sample to households that are above the median value of the normalised tenure.

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

To compute sectoral job finding rates, I use publicly available Current Population Survey (CPS) microdata. [68] This is a monthly survey that allows for the estimation of the transition rates between employment, unemployment, and inactivity (see, e.g., Blanchard, Diamond, Hall, and Murphy (1990), Shimer (2005), Elsby, Hobijn, and Sahin (2010), among many others).

[66] 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.

[67] 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.

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

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

Two further restrictions are imposed to ensure comparability with the SCF and SIPP samples. First, I exclude "switchers", that is, workers switching sectors (industries) during survey waves.[69] Second, I only consider workers who are between 25 and 55 years old. Selection into the cyclical and the non-cyclical sectors is based on results in Section 3.2.1.

Following Shimer (2012), I first calculate instantaneous transition rates between employment states to correct for time aggregation bias.[70] From these, I calculate monthly and quarterly job finding rates. The transformation between the instantaneous transition rate and monthly job finding rate is as follows

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

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

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

Similarly, one can calculate monthly and quarterly separation rates

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

and

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

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

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

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

B.2 Summary statistics

B.2.1 Household balance sheets

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

Table B.2.1: Summary statistics

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

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

B.2.2 Labour market flows

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

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

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

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

B.2.3 Job finding and separation rates

Table B.2.3 presents summary statistics of job finding and separation rates, as explained in section B.1.3, using CPS data. Job finding rates f_t in cyclical sectors are lower, whereas separation rates s_t are higher than in non-cyclical sectors. This implies that workers in cyclical sectors are more likely to lose their jobs than those in non-cyclical sectors, and it takes longer for them to find another job if unemployed.

Table B.2.3: Summary statistics – CPS sample

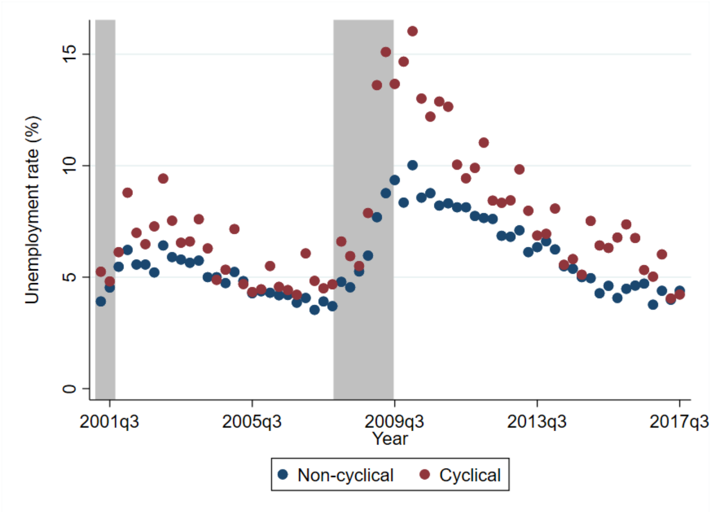
	Cyclical		Non-cyclical	
Description	Mean	SD	Mean	SD
Monthly				
f_t^m	0.219	0.055	0.241	0.050
s_t^m	0.021	0.006	0.011	0.001
Observations	187	187	187	187
Quarterly				
f_t^q	0.516	0.089	0.556	0.079
s_t^q	0.062	0.016	0.034	0.005
Observations	63	63	63	63

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

C Additional figures

C.1 Unemployment rate

Figure C.1.1: Unemployment rate

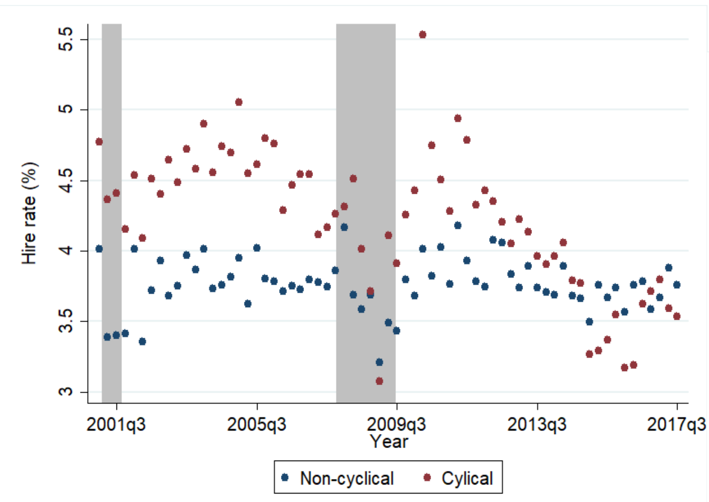


Notes: This figure plots the unemployment rate in cyclical and non-cyclical sectors. The panel covers the period 2001q2–2017q3. Selection into cyclical and non-cyclical sectors is based on results in Section 3.2.1.

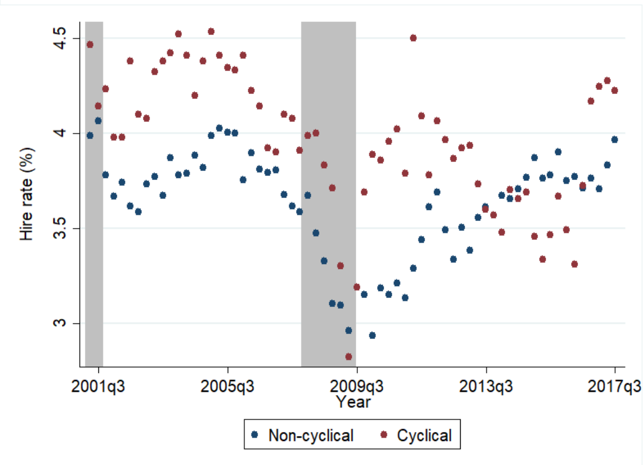
C.2 Worker flows over the business cycle

Figure C.2.1: Hiring rate

(A) LEHD



(B) JOLTS

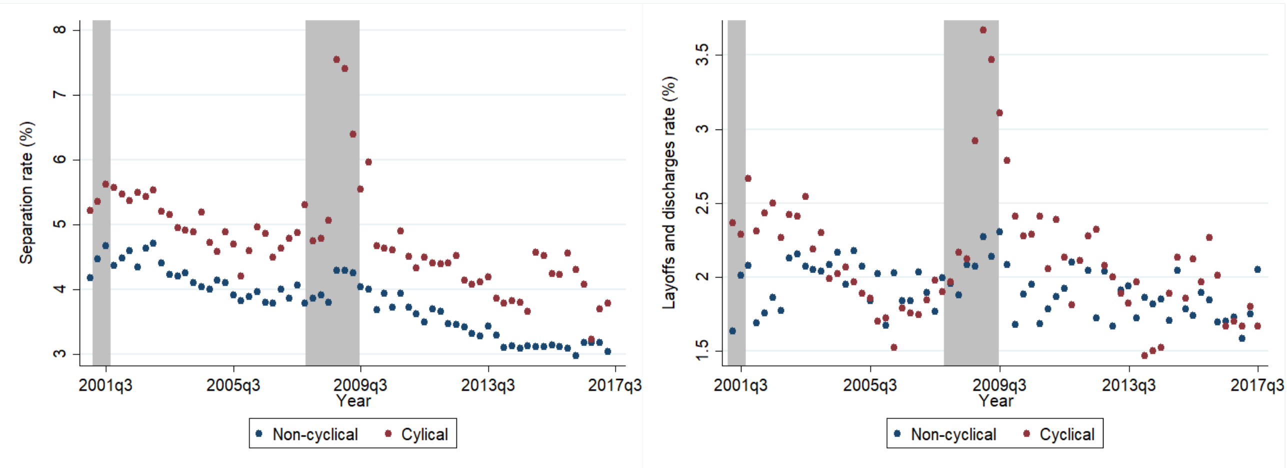


Notes: PANEL (A): The hiring rate is defined as hires from persistent nonemployment, expressed as a share of employment and multiplied by 100. PANEL (B): The hiring rate is defined as hires from unemployment, expressed as a share of employment and multiplied by 100. Both panels cover the period 2001q2–2017q3.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

Figure C.2.2: Separation rate

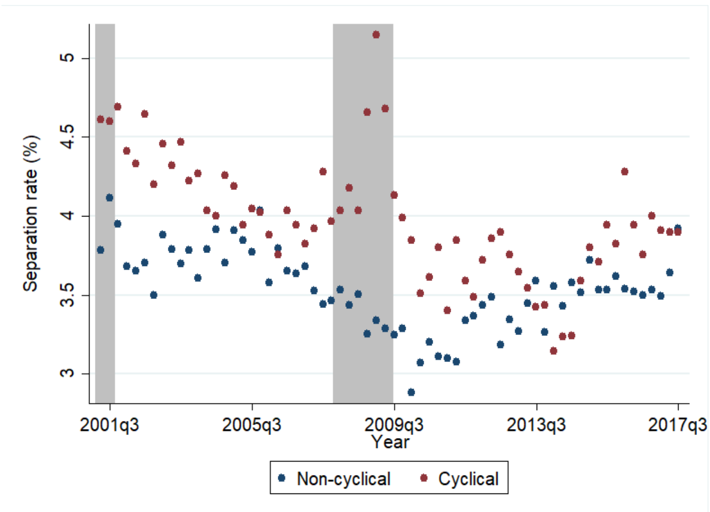
(A) LEHD

(B) JOLTS



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

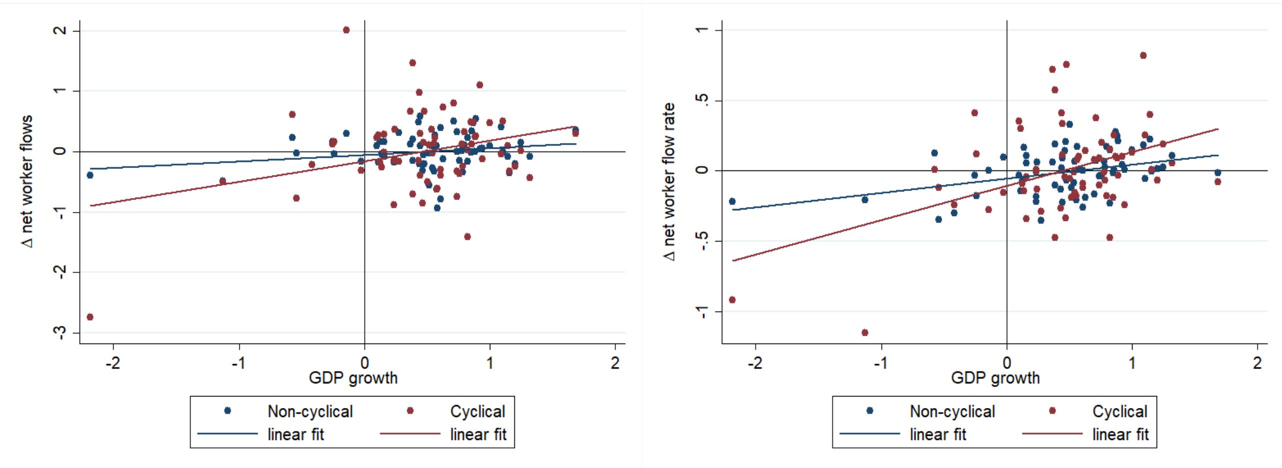
Figure C.2.3: Total separations rate in the JOLTS data



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

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

(A) LEHD (B) JOLTS



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

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

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

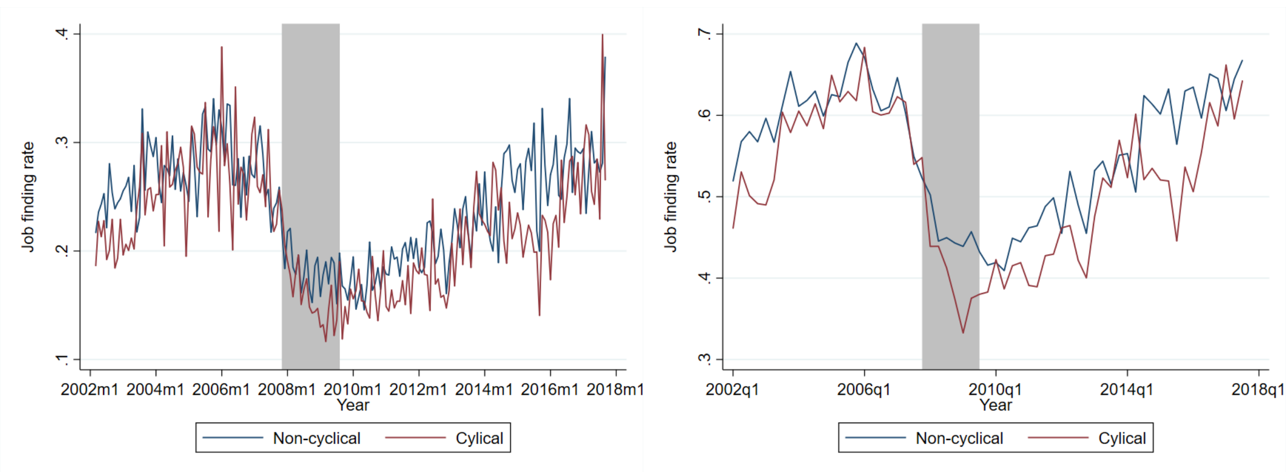
Figure C.3.1 plots job finding rates at monthly and quarterly frequencies, which I use to test Proposition 1 in Section 3.4. Monthly data displays high volatility in job finding rates for both sectors, making it hard to identify cyclical patterns. However, quarterly data shows that job finding rates in cyclical sectors fluctuate much more over the business cycle compared to 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.

Figure C.3.1: Job finding rate

(A) Monthly

(B) Quarterly

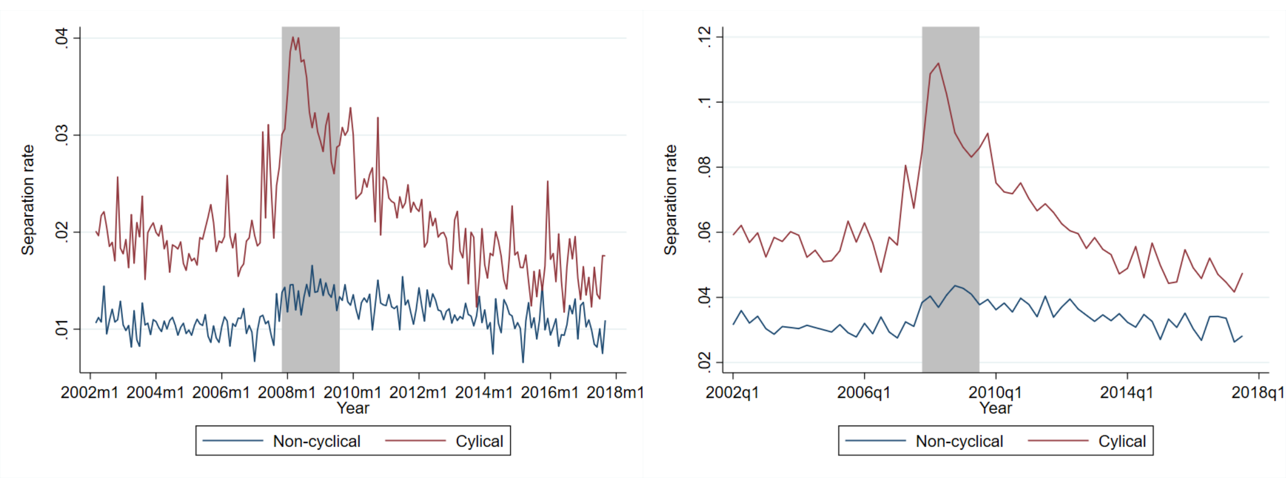


Notes: PANEL (A) shows job finding rates using monthly data. PANEL (B) shows job finding rates at a quarterly frequency. To obtain quarterly data, I rescale instantaneous transition rates to a quarterly frequency and then average them within a quarter. The data in both panels is seasonally adjusted and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

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

Figure C.3.2: Separation rate

(A) Monthly (B) Quarterly



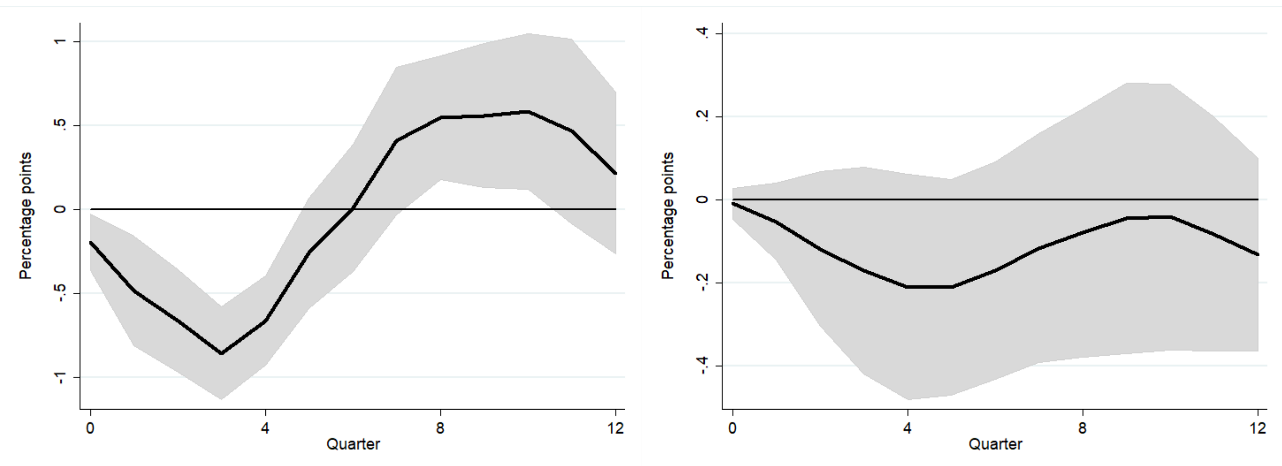
Notes: PANEL (A) shows separation rates using monthly data. PANEL (B) shows separation rates at a quarterly frequency. To obtain quarterly data, I rescale instantaneous transition rates to a quarterly frequency and then average them within a quarter. The data in both panels is seasonally adjusted and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

C.4 Robustness of Local Projections approach

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

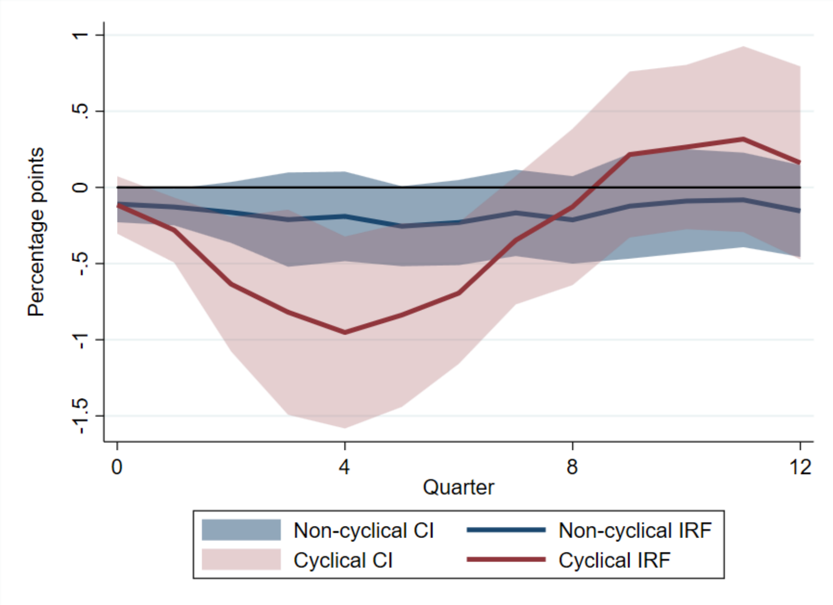
Figure C.4.1: The response of the real interest rate and the aggregate unemployment rate

(A) Real interest rate (B) Unemployment rate



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

Figure C.4.2: The responses of sectoral unemployment rates

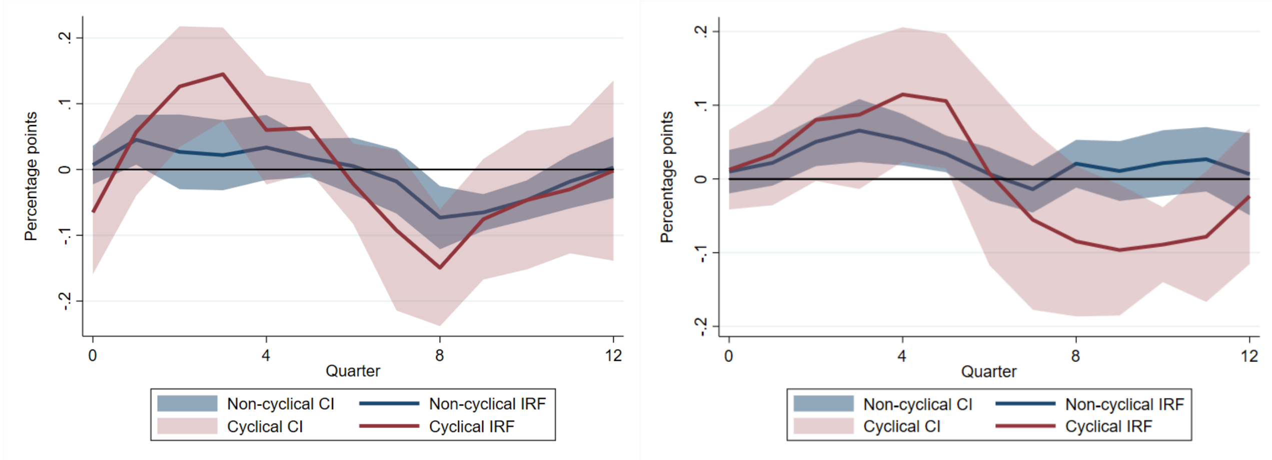


Notes: This figure shows the impulse response of sectoral unemployment rates following expansionary monetary policy shocks. Selection into the cyclical and the non-cyclical sectors is based on results in Section 3.2.1. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity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

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

Figure C.4.3: Hiring rate

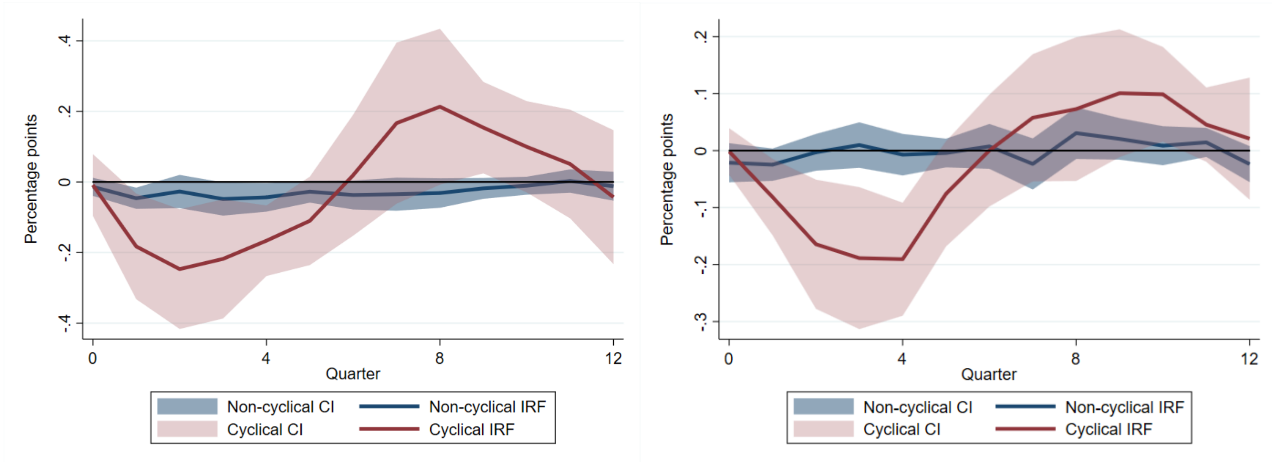
(A) LEHD (B) JOLTS



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

Figure C.4.4: Separation rate

(A) LEHD (B) JOLTS



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

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

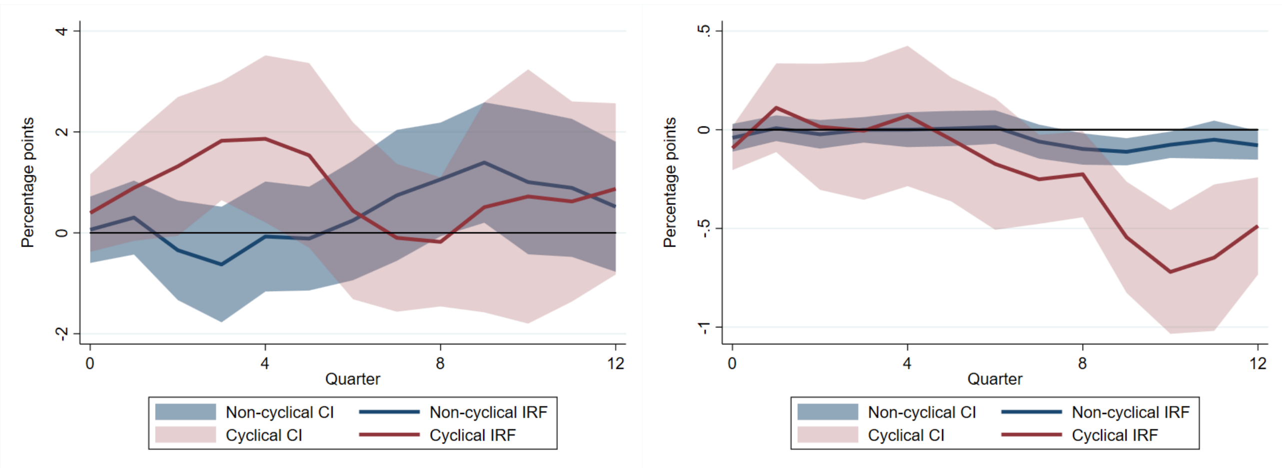
Here, I re-estimate the model in (10) with the job finding and separation rate calculated from CPS data. Results are shown in Figure C.4.5. The left panel displays job finding rate responses across the two sectors following an expansionary monetary policy shock. In the short run, the job finding rate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

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

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

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

(A) Job finding rate (B) Separation rate



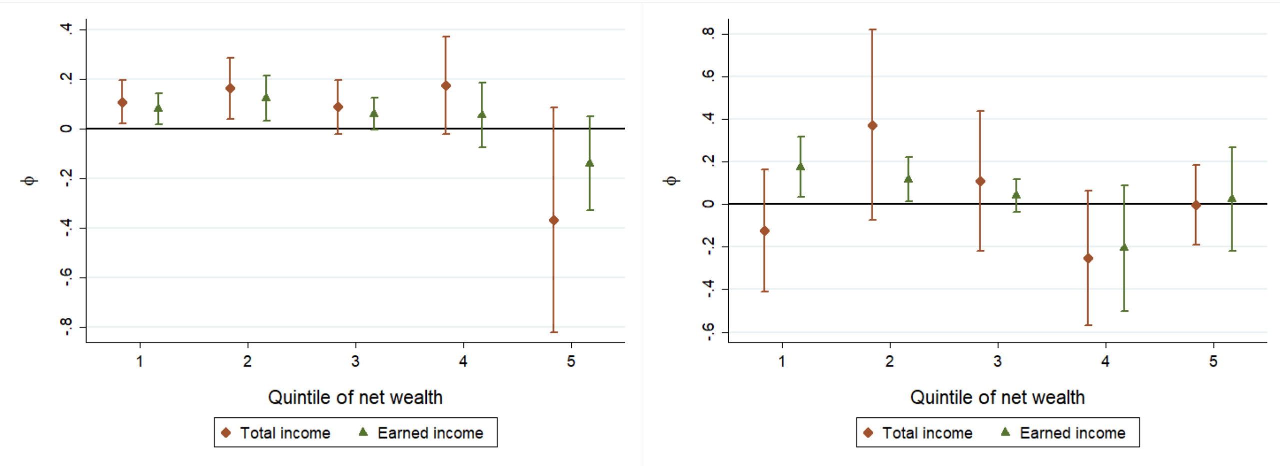
Notes: This figure shows impulse responses following an expansionary monetary policy shock. Shaded areas are 90 percent confidence bands. Standard errors are corrected for heteroskedasticity and autocorrelation (Newey–West standard errors). The data in both panels is seasonally adjusted and covers the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

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

C.5.1 Net liquid assets to income ratio

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

(A) SCF (B) SIPP



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

D Model appendix

D.1 Derivation of (39) in Section 4.2.2

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

$$\max_{\{p_{js},n_{js},y_{js},h_{js}\}} \mathbb{E}_t \sum_{s\geq t} \left(\frac{1}{1+r}\right)^{s-t} \left\{ \frac{p_{js}}{P_s} y_{js} - w_s^C n_{js} - \psi_1^C \left(M_s^C\right)^{\psi_2^C} h_{js} - \frac{\alpha\vartheta}{2}\left(\frac{p_{js}}{p_{js-1}} - 1\right)^2 Y_s \right\}, \tag{D.15}$$

subject to

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

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

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

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

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

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

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

$$-\psi_1^C\left(M_t^C\right)^{\psi_2^C} + \lambda_{2t} = 0\,. \tag{D.22}$$

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

$$mc_t^C \equiv \lambda_{3t} = \frac{w_t^C + \psi_1^C\left(M_t^C\right)^{\psi_2^C} - \frac{1}{1+r}\mathbb{E}_t\left[\left(1-\delta^C\right)\psi_1^C\left(M_{t+1}^C\right)^{\psi_2^C}\right]}{Z_t}\,. \tag{D.23}$$

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

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

Since in equilibrium all firms in the sector are identical, they charge the same price and produce the same output, hence $p_{jt}=P_t^C$. Furthermore, define price inflation in the cyclical sector as $\pi_t^C\equiv P_t^C/P_{t-1}^C$, one can rewrite (D.24) to obtain the New Keynesian Phillips curve (39) in the main text.

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

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

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