Université de Montréal

Essays in Financial Economics

Par Zerbo Souleymane

Département de sciences économiques
Faculté des arts et sciences

Thèse présentée à la Faculté des études supérieures
en vue de l'obtention du grade de Philosophiæ Doctor (Ph.D.)
en sciences économiques

Juillet, 2021

Université de Montréal
Faculté des Études Supérieures et Postdoctorales

Cette thèse intitulée :
Essays in Financial Economics

présentée par :
Zerbo Souleymane

a été évaluée par un jury composé des personnes suivantes :

René Garcia, président rapporteur
Benoît Perron, directeur de recherche
Raphaël Godefroy, membre du jury
Dimitris Papanikolaou, examinateur externe

Thèse déposée en Juillet 2021

à mes parents Kandey et Boureima

Remerciements

J’ ai une profonde gratitude envers ma directrice de recherche Vasia Panousi, pour son soutient et sa contribution tout au long de cette thèse.

J’ aimerais envoyer mes remerciements à René Garcia, Dimistris Papanikolaou, Guillaume Sublet pour leur aide, soutien multiformes et générosité. Je remercie aussi Vasia Panousi, René Garcia, Dimistris Papanikolaou, Guillaume Sublet, Louphou Coulibaly, Hervé Zeida pour leurs soutiens durant mon marché de travail.

Je remercie particulièrement mes amis Koné N’ golo, Magnim Farouh, Idriss Tsafack, Emel Pokam, Karelle Mbapte, Stéphane N’ dri, Goudou Félicien pour leur soutien et leur disponibilité continue. Je ne saurais oublier tous les autres colles diants de doctorat du département de sciences économiques qui ont fait de mon chemininiment une unique expence ponctuée de moments mémorables.

Je suis également très reconnaissant envers mes proches et amis restés au pays, qui malgré la distance n’ ont pas manqué de m’ encourager jusqu’ au bout. Ma reconnaissance et mes pensées vont particulièrement à mes parents Kandey et Boureima, mes frères pour le soutien.

Mes remerciements sont également adressés aux enseignants, chercheurs et au personnel administratif du département des sciences économiques et du CIREQ. Pour finir, je tiens mercier le département de finance de l’ Université de Northwestern Kellogg pour leur hospitalité.

Résumé

Cette thèse passe en revue certains facteurs de risques économiques (risque de revenu, risque de la finance parallèle, et risque carbone) en utilisant de nouvelles sources de données et méthodologies.

Le premier chapitre examine comment la réponse de la consommation face au risque de capital humain affecte la finance des ménages. A partir de données conjointes sur la consommation, les revenus et les actifs des ménages américains, ce papier documente le lissage excessif de la consommation comme un facteur essentiel pour le choix de portefeuille et montre qu'il peut expliquer les énigmes financières observées chez les ménages américains. Par ailleurs, le papier formalise l'effet du lissage excessif sur le choix de portefeuille à l'aide d'un modèle de cycle de vie où un ménage est confronté à un risque de revenu salarial idiosyncratique. Le modèle est calibré de façon à correspondre aux observations sur le cycle de vie de la détention d'actifs risqués des ménages américains.

Le deuxième chapitre évalue le transfert de risques des banques dans les activités bancaires non réglémentées. En exploitant les variations dans les risques discutés par les banques dans leur rapports financiers et en utilisant les outils de l'analyse textuelle, ce document fournit une nouvelle mesure de l'activité bancaire non-réglementée. Le papier montre empiriquement que (1) les banques sont plus susceptibles de contourner les régulations lorsque leurs leviers de fonds propres deviennent contraignantes, (2) il existe une relation positive entre le transfert de risque et le risque extrême des banques. Par la suite, le papier rationalise ce transfert de risque en utilisant un modèle macroéconomique avec un secteur financier. Dans le modèle, l' événement de défaut de paiement et la présence d'externalités dues à une application imparfaite de la réglementation encourage les banques à s'engager dans une stratégie de transfert des risques. Enfin, le papier utilise ce cadre pour étudier la régulation optimale. On montre qu'une taxe sur l'activité sectorielle réduit efficacement le transfert des risques des banques par rapport à d'autres politiques comme la réglementation des fonds propres de la banque.

Enfin, le troisième chapitre aborde l'effet du risque carbone sur la stabilité économique. Nous étudions ce risque à l'aide de données de panel constituées de 50 États américains aucours des années 1998 à 2018. De plus, nous supposons une dépendance transversale des facteurs communs non observés (par exemple, les liens commerciaux, l'intégration financiére) entre les états. En utilisant une approche d' émissions de carbone basée sur la consommation, ce chapitre montre qu'une diminution d'une unité des émissions de carbone est associée, à long terme, à une croissance de la production logarithmique par habitant de 4,5 points de pourcentage. En outre, nous trouvons des impacts différentiels dans la distribution du revenu par habitant des États. Ces résultats éclairent le débat sur la voie de transition optimale vers une économie sobre en carbone.

Mots-clés: Risque de revenus, couverture du risque, consommation, finance parallèle, régulation bancaire, analyse textuelle, consommation carbone, risque carbone.

Abstract

This thesis reviews some economic risk factors (labor income risk, shadow banking risk, and carbon risk) using new data sources and novel methodologies.

The first chapter investigates how the response of consumption to human capital risk affects household finance. Using joint data on consumption, income, and assets of representative US households, I document the excess smoothness of consumption as an essential factor for portfolio choice and show that it can explain household finance puzzles. Furthermore, I formalized the effect of the excess smoothness on the portfolio choice using a structural life-cycle model where a household faces an idiosyncratic wage income risk. The model is calibrated to match relevant aspects of the dynamics and the life cycle of risky asset holding from the PSID.

The second chapter assesses banks' risk-shifting in the non regulated banking activity, also called shadow banking. Exploiting variations in risks disclosed by banks in their financial reports and using textual analysis tools, this document provides a new measure non regulated banking activity. The paper empirically documents that (1) banks are more likely to shift risk out of the regulator's reach when their risk-based capital constraints become binding, (2) there is a positive relationship between risk-shifting and tail risk of banks. The paper then rationalizes banks' risk-shifting behavior using a macroeconomic model with a financial sector. In the model, the event of default on debt and the presence of externality due to imperfect regulation enforcement encourage banks to engage in risk-shifting strategies. As a result, banks behave as cross-sector arbitrageurs. Finally, the paper uses this framework to study optimal regulation. We show that a tax on sectoral activity effectively reduces banks' risk-shifting compared to other bank's equity regulation policies.

Finally, the third chapter studies the effect of carbon risk on economic stability using a consumption-based carbon emissions approach for 50 U.S. states over the years 1998 - 2018. The paper assumes a cross-sectional dependence from unobserved common factors (e.g., trade linkage, financial integration) between the states. Under this assumption, we find that one unit decreases in carbon emissions is associated with 4.5 percentage points decrease in the per capita output growth over the long run. Besides, we find differential impacts across the distribution of per capita states income. These findings inform the debate over the optimal transition path toward a low carbon economy.

Keywords: Income risk, hedging, consumption, shadow banking, financial regulation, textual analysis, carbon consumption, carbon risk.

Contents

List of Tables

List of Figures

Chapter 1

Excess smoothness of consumption and household finance

1.1 Introduction

How does the pattern of consumption response to human capital risk affect household finance? Uninsurable labor income risk is very important for households' portfolio decisions (Angerer and LAM (2009), Betermier et al. (2012), Bonaparte et al. (2014), Fagereng et al. (2018), Chang et al. (2018)), which in turn have general equilibrium asset pricing implications through their effects on consumption. However, considering only labor income risk fails to explain the unconditional capital asset pricing model (CAPM) (as documented by Fama and Schwert, 1977), whereas the conditional CAPM with labor income risk is successful in explaining the cross-section of expected returns (as documented by Jagannathan and Wang, 1996). A potential reason for this failure stems from a common assumption that uninsurable income risk leads one for one to consumption risk. As a result, risk factors related to labor income and consumption in calibrating asset pricing models has been developed in isolation. Put differently, less attention has been paid to the linkage between consumption risk and income risk as a single factor for investment decisions.

Yet, an important feature of household consumption in the data is the excess smoothness meaning that consumption does not fully respond to permanent income shocks. Moreover, novel influential empirical studies have documented the ability of households to insulate their consumption from permanent income shocks. In particular, those studies have shown a substantial role of second-earners'[0] and labor-supply adjustment as an important source of household self-insurance and therefore a tools for consumption insurance (Blundell et al. (2016)[1], Attanasio et al. (2005), Kaplan and

[0] Women's labor-force participation has stabilized at 75% since the early 1990s

[1] For example Blundell et al. (2016) estimate that 39 percentage point (p.p) of consumption is insured against the shock to the first earner's wage. More specifically, of this 39 p.p; 25 p.p (65 percent of the total insurance effect) come from family labor supply (she increases her labor supply when his wages fall permanently).

Violante (2010)[2] and Ortigueira and Siassi (2013)).

Inspired by these empirical facts, this paper revisits the literature on household's uninsurable idiosyncratic income risk and portfolio choice. I show that a single factor representing consumption response to wage income risk can rationalize three important puzzles observed in household finance: The limited market participation (unconditional stocks share), the smaller level of stocks share held by US household (conditional stock share) and the weaker incentive for income hedging demand [3] for stocks. These puzzles account for the conditional and unconditional stocks holding by households. To reach our goal, the paper develops a structural dynamic life-cycle model for a potential two-earner household facing idiosyncratic wage-income risk and making jointly endogenous portfolio and labor supply decisions. Specifically, by exploiting the self-insurance mechanism available at the household level against income shock, I incorporate the resulting consumption dynamics into a portfolio choice model.

The model is solved analytically and draws intuitive conclusions. The optimal portfolio allocation derived from the above framework can be decomposed in three channels. The first channel is related to the risk premium on risky assets over consumption risk. The second channel captures the role of consumption insurance which is defined as the fraction of the variance of the income shock that does not translate into a corresponding change in consumption. Finally, the third channel is related to the income risk hedging demand. The particularity of the optimal portfolio choice derived in this paper is that households are both concerned about consumption and income risks and are willing to hedge these risks. Households hedge their consumption not only against labor income risk but also against income flow from financial risky assets (dividends and capital gains)[4]. Whereas this consumption hedging manifests itself as an effective risk aversion over consumption risk, income hedging is captured by a covariance term. Whenever this covariance is positive (negative), there is a negative (positive) hedging demand for stocks. It is through the income hedging motives that consumption response to wage income shocks transmits its effect on households' portfolio choice. When this response is almost close to zero, households are no longer concerned with income hedging demand using financial assets. This mechanism can explain the low correlation between income risk and stock market return observed in the data. However, the consumption risk is still present and households relate most of their portfolio choice to this risk. This mechanism can be viewed as the direct effect of consumption risk on portfolio allocation. The indirect effect can be analyzed by looking at the adjustment of labor supply in response to income shocks. A complementary effect of household members' labor supply

[2] Kaplan and Violante (2010) show that households in the US data have access to more self insurance, thereby to more consumption smoothing against permanent labor income shocks, compared to households in a standard Bewley model. In their calibrated standard incomplete model, they find that the fraction of permanent shocks that doesn't pass trough into consumption (consumption insurance) in on average the same in economies with zero borrowing limit and natural borrowing limit.

[3] Heaton and Lucas (2000), Cocco et al. (2005) document that, the correlation between stock market returns and labor income shocks is close to zero.

[4] Maggio et al. (2019) show that household optimize their consumption with respect capital gains and dividend income from the stocks they hold.

in the face of income shocks is tantamount to a lack of consumption insurance. As a result, the household is still subject to permanent income shocks and adopts a strong income risk hedging strategy using financial assets. In this case, both consumption and income risks hedging will be present in household's investment decisions. Based on this mechanism, it can be argued that the strength of the consumption risk hedging channel (direct effect) and the income risk hedging channel (indirect effect) are the key elements for household optimal portfolio choice.

The paper then proceeds to an empirical analysis, which takes the model as a guide. Thus, using income, consumption and wealth data from the U.S. Panel Study of Income Dynamics (PSID) for the post-1999 period, the paper provides a testable implication of households' consumption and income dynamics linkages on their financial risk-taking. The main result of the paper is that a one-standard-deviation decrease in the pass-through of permanent-wage income shocks to consumption increases the risky-asset share by 0.8%. The intuition underlining this result is as follows: when a wage shock does not transmit to consumption, the income hedging component of the optimal portfolio shuts down and the portfolio decision is mainly driven by household's effective risk aversion. When this effective risk aversion is low, then household increases its risky asset holding. Conversely, I find that a one-standard-deviation increase in the adjustment of labor supply to permanent-income shocks increases the risky-asset share by 0.4%. The net effect of shock transmission to consumption and labor supply—interpreted as the total consumption insurance with respect to a permanent wage income shock—on portfolio allocation is determined by the degree of household risk aversion preference and the elasticity of substitution between labor supply and consumption.

Moreover, to provide a deep analysis of the consumption risk channel on portfolio choice, the paper complements the previous analysis by looking into factors that may potentially affect household's effective risk aversion. In this regard, the paper investigates households' consumption commitments meaning goods (durables goods (housing, vehicles) and some services (education, childcare, insurance, utilities,...) that involve costly transactions in response to households' income risks. Indeed, in the presence of consumption commitments, there is an excess-smoothness of consumption and the equilibrium implication of the income hedging demand derives from the model still holds. More importantly, Chetty and Szeidl (2016) show that consumption commitments provide a micro-foundation for internal habit formation like behavior and therefore an instrument that modifies household's effective risk aversion. To measure this effective risk aversion, I consider household's risk bearing capacity proxies by the ratio of housing loan to income stemming from housing consumption commitment. I find that an increase in the risk bearing capacity reduces the intensity in absolute terms of the relation between the consumption sensitivity to shocks and risky asset holding.

Taken together, the results above provide evidence that after taking into account the endogeneity of the participation decision, household portfolio composition re-balancing away from stocks is driven by consumption response to wage income shocks.

Finally, the paper conducts a simulation exercise of the portfolio choice over the life cycle and investigates the income risk hedging demand in the data. First, I find a negative co-movement between wage-income growth and stock-holding returns for households. Second, numerical simulations reveal that a combination of consumption response to wage income shocks and a relatively small risk aversion can well explain the shape and location of the life cycle profile of the average household's risky share. In fact, with a relative risk aversion of $\sigma = 2.3$, the model matches the average equity share and can explain its decline over the life-cycle.

Related Literature

This paper contributes to the literature on household finance, which is currently scant in results about the implication of labor income dynamics on life-cycle consumption and portfolio choice (Chai et al. (2011), Gomes et al. (2008), Farhi and Panageas (2007), and Fagereng et al. (2018)) and the income risk hedging demand (Heaton and Lucas (2000), Cocco et al. (2005), Vissing-Jorgensen (2002), Davis and Willen (2000), Betermier et al. (2012), Massa and Simonov (2006), Bonaparte et al. (2014), and M. Addoum et al. (2019)). Contrary to prior works, this paper explicitly studies the joint effect of consumption and income dynamics and their linkage on household portfolio allocation. Closely related is the paper by Addoum et al. (2019) who provide a model where the households derive utility from both consumption and income. However, In their paper, the consumption measure captures only food expenditures at and away from home and their focus is on the excess sensitivity property of consumption in analyzing household's portfolio choice problem. Moreover, there is no life cycle in their model.

Second, the paper is related to the literature on excess smoothness of consumption (Chetty and Szeidl (2007), Chetty and Szeidl (2016), Luo et al. (2017)). A leading explanation of the excess smoothness of consumption is the added worker effect. In fact, recent studies have scanned the within-household risk-sharing and the role of secondary-earner labor supply for consumption insurance. Some examples here include Kaplan and Violante (2010), Blundell et al. (2016), Daminato and Pistaferri (2017), Attanasio et al. (2005), Chunzan and Dirk (2020), Mazzocco (2004), Ortigueira and Siassi (2013), and Vasia et al. (2019). The model of Blundell et al. (2016) is particularly relevant. They provide a structural model to analyze the family labor supply as an insurance mechanism. However, their model includes only a risk-free asset, thereby missing the insights provided here about the effects of household risk sharing on portfolio allocation. Chunzan and Dirk (2020) provides a calibrated version of Blundell et al. (2016) framework and study optimal progressive taxation. Also, the work by Ortigueira and Siassi (2013) investigates the impact of within-household risk-sharing on household labor supply and savings decisions. However, the model includes only idiosyncratic unemployment risk and he didn't address a portfolio-choice analysis.

The remainder of the paper is organized as follows. Section 1.2 presents model. Section 3.3 presents the data and some facts regarding household finance puzzles and the joint dynamic of consumption and labor income. Section 1.4 presents testable implications of the model. Section 1.5 streamlines a simulation exercise over the lifecycle.

Finally, section 2.6 concludes.

1.2 Model

A potential challenge in this study is how to measure the excess smoothness of consumption. To do so one needs to distinguish the consumption response to transitory income shock from its response to permanent income shock. In this section, I lay out a structural model that can address that issue.

1.2.1 Setting

Time is discrete and denoted by t. Each household i consists of two earners or spouses. A primary earner or head of the family, $j = 1$, who always works except in cases of involuntary unemployment. A secondary earner, $j = 2$, who faces a probability of non-participation in the labor market each period. Let $\tilde{p}_{i,t}$ be the probability that the secondary earner i participates in the labor market in year t. Finally, the two earners make joint decisions about provision of labor supply, allocation of income across consumption and savings, and allocation of savings or portfolio across a risky and a risk-free asset.

Wage income process. For each spouse j in household i and in year t, real log wage income, after removing the effect of observables, $x_{i,j,t}$, is decomposed in two components, a fully permanent component and a transitory component. The permanent component of real residual income is denoted by $F_{i,j,t}$ and is subject to shocks $\upsilon_{i,j,t}$ from a distribution $\upsilon_{i,j,t} \rightarrow iid(0, \sigma^2_{\upsilon_j})$. In the literature, these shocks are known as permanent-income shocks. The transitory component of real residual income is subject to shocks $u_{i,j,t}$ from a distribution $u_{i,j,t} \rightarrow iid(0, \sigma^2_{u_j})$. In the literature, these shocks are known as transitory-income shocks. For the case of a secondary earner, the probability of labor-market participation is also a determining factor of real wage income. Putting everything together, during the working life of ages 25-65, the real wage income process for each spouse is characterized by:

$$log(W_{i,j,t}) = \begin{cases} x'_{i,j,t}\beta^j_W + \epsilon_{i,j,t} & \text{if j=1} \\ x'_{i,j,t}\beta^j_W + \beta_W \tilde{p}_{i,t} + \epsilon_{i,j,t} & \text{if j=2} \end{cases} \tag{1.1}$$

where residual income, $\epsilon_{i,j,t}$, is decomposed into:

$$\begin{aligned} \epsilon_{i,j,t} = & F_{i,j,t} + u_{i,j,t} \\ F_{i,j,t} = & F_{i,j,t-1} + \upsilon_{i,j,t} \end{aligned} \tag{1.2}$$

For each spouse, the own permanent shocks and the own transitory shocks are serially uncorrelated. However, both types of shocks are allowed to be correlated across spouses. In particular, the covariance of permanent shocks across spouses is denoted by $\sigma_{\upsilon_1\upsilon_2}$, while the covariance of transitory shocks across spouses is denoted by $\sigma_{u_1u_2}$.

Financial assets. Markets are incomplete. There are two assets. First, a riskless asset, B_t, with gross return R_f that is constant over time. Second, a risky asset, S_t, with random gross return R^s_t. The law of motion for the excess return required for investment in the risky asset is given by:

$$R^s_t - R_f = \rho(R^m_t - R_f) + \eta^s_t \tag{1.3}$$

where ρ is the market beta, R^m is the market return, and $\eta^s_t \rightarrow iid(0, \sigma^2_{\eta t})$. Let $0 \leq \alpha^s_{i,t} \leq 1$ be the share of wealth that household i invests in the risky asset in period t $(0 \leq \alpha^s_{i,t} \leq 1)$. Then, the return to the household's portfolio between t and $t+1$, denoted by $R^p_{i,t+1}$, is given by:

$$R^p_{i,t+1} = R_f + \alpha^s_{i,t}(R^s_{i,t+1} - R_f) \tag{1.4}$$

Preferences. Household preferences depend on total consumption, C_{it}, and on hours worked by each spouse, L_{1t} and L_{2t}. The discount factor is $\beta \in (0,1)$. The following regular assumption is made about the utility function: U is strictly increasing in C_t, strictly decreasing in L, strictly concave and twice differentiable. In order to allow for interaction between spouses, preferences are assumed non-separable between consumption and labor. Let $A_{it} = B_{it} + S_{it}$ denote total household assets, i.e. the sum of riskless- and and risky-asset holdings. Then, for each age $t \in \{t_0, t_0+1, ..., T_r\}$, where T_r is retirement age, a household solves the following problem:

$$\begin{aligned}
\max_{C_{it}, L_{1t}, L_{2t}, \alpha_{it}} E_t & \sum_{k=0}^{T_r - t} \beta^{t+k} U(C_{t+k}, L_{1,t+k}, L_{2,t+k}) \\
& \text{s.t.} \\
& A_{i,t+1} = R^p_{i,t+1}\{A_{i,t} + \sum_{j=1}^{2} W_{j,t} L_{j,t} - C_{it}\} \\
& A_{i,t} = B_{i,t} + S_{i,t} \\
& B_{i,t} \geq 0, S_{i,t} \geq 0
\end{aligned} \tag{1.5}$$

1.2.2 Solving the model

This section first presents an analytic solution to the optimal consumption-saving problem of a household. Then, under a specific but very common assumption about preferences, it presents an analytic solution about a household's optimal portfolio allocation problem across risky and riskless assets.

1.2.2.1 Optimal consumption and labor supply

To derive the optimal path of consumption and labor supply, the paper follows Blundell et al. (2016) methodology. Let λ_t be the multiplier on the household-budget constraint.

Hence, $\Delta ln\lambda_{it}$ will denote the change in the marginal utility of wealth. Then, the first-order conditions of problem (2.12) with respect to consumption, work hours and assets are given by:

$$\begin{aligned} U_c(C_t, L_{1t}, L_{2t}) = \lambda_t \\ -U_{l_1}(C_t, L_{1t}, L_{2t}) = \lambda_t W_{1t} \\ -U_{l_2}(C_t, L_{1t}, L_{2t}) = \lambda_t W_{2t} \\ E_t[\lambda_{t+1} R^p_{t+1}] = \lambda_t/\beta \end{aligned} \tag{1.6}$$

The solution to the household problem proceeds in two steps. First, a Taylor approximation is applied to the first-order conditions from (1.6). This step yields expressions for the growth rates of consumption and work hours in terms of income shocks (permanent and transitory) and the marginal utility of wealth. Second, log-linearization of the inter-temporal budget constraint is used to establish the links between asset returns and the shocks in income and in the marginal utility of wealth. In what follows, each step is described in turn.

First step. Let $\eta_{x,y}$ be the Frisch elasticities, which denote the change in variable x in response to a change in the price y, such that the marginal utility of wealth remains unchanged. For example, $\eta_{c,p}$ is the Frisch elasticity of consumption with respect to the risk premium, $\eta_{l1,w1}$ is the Frisch elasticity of husband work hours with respect to the first earner's wage, and so on.

A log linear approximation of the first-order condition for consumption from (1.6) yields:

$$\Delta lnC_{i,t} = (-\eta_{c,p} + \eta_{c,w1} + \eta_{c,w2})\Delta ln\lambda_{it} + \eta_{c,w1}\Delta lnW_{1,t} + \eta_{c,w2}\Delta lnW_{2,t} \tag{1.7}$$

Similarly, a log linear approximation of the first-order conditions for work hours from (1.6) yields:

$$\Delta lnL_{i,j,t} = (\eta_{l_j,p} + \eta_{l_j,w_j} + \eta_{c,w_{-j}})\Delta ln\lambda_{it} + \eta_{l_j,w_j}\Delta lnW_{j,t} + \eta_{l_j,w_{-j}}\Delta lnW_{l_{-j},t} \tag{1.8}$$

Then, the log-linearization of the Euler equation in (1.6) yields:

$$\Delta ln\lambda_{i,t+1} \approx \psi_t + \epsilon_{i,t+1} \tag{1.9}$$

where $\epsilon_{i,t+1}$ is the innovation in the growth of the marginal utility of wealth. Because $\lambda_{i,t+1}$ is not observable, a log-linearization of the inter-temporal budget constraint is used to determine $\epsilon_{i,t+1}$ as a function of shocks to wages and risky-asset returns.

Second step. By repeated substitution on the household budget, the present-value budget constraint is obtained:

$$E_t \sum_{k=0}^{T_r-t} \frac{C_{t+k}}{(1+R^p_{t+k})^k} = A_t + E_t \sum_{k=0}^{T_r-t} \frac{W_{1,t+k}L_{1,t+k}}{(1+R^p_{t+k})^k} + E_t \sum_{k=0}^{T_r-t} \frac{W_{2,t+k}L_{2,t+k}}{(1+R^p_{t+k})^k} \tag{1.10}$$

The following definitions will be useful in what follows. First, let $H_{i,j,t}$ be spousal human wealth, i.e. the net present discounted value of future wages for that spouse. Let $H_{i,t}$ be the human wealth of the household, i.e. the sum of human wealth for each spouse. Let $s_{j,t}$ denote the relative share of each spouse's human wealth in total household human wealth:

$$s_{j,t} \approx \frac{H_{i,j,t}}{H_{i,t}} \tag{1.11}$$

For each household, define the ratio of financial wealth over total wealth, π_{it}, as:

$$\pi_{it} \approx \frac{A_{i,t-1}}{A_{i,t-1} + H_{i,t}} \tag{1.12}$$

Using the above, a log linearization of (1.10) yields:

$$\epsilon_{i,t} = \frac{\sum_{j=1}^{2}[\eta_{c,w_j} - (1-\pi_t)(s_{jt} + \overline{\eta_{l,w_j}})]\upsilon_{j,t} - \alpha_{t-1}[(1-\pi_t)\frac{T_r - t}{2} - \pi_t]\eta_{i,t}^s}{(1-\pi_t)s_t[\overline{\eta_{l,p}} + \overline{\eta_{l,w_1}} + \overline{\eta_{l,w_2}} + \eta_{c,p} - (\eta_{c,w1} + \eta_{c,w2})]} \tag{1.13}$$

where $\overline{\eta_{x,y}} = \sum_{j=1}^{2} s_{jt}\eta_{x,y}$.

Lastly, define $\kappa_{x,z}$ as the sensitivity coefficient that captures the response of variable x to shock z. Using equations (1.7), (1.8), (A.2) and (1.13), the dynamics of consumption and labor supply as functions of the different shocks are:

$$\begin{pmatrix} \Delta lnC_{i,t} \\ \Delta lnL_{i,1,t} \\ \Delta lnL_{i,2,t} \end{pmatrix} \approx \begin{pmatrix} \kappa_{c,u_1} & \kappa_{c,u_2} & \kappa_{c,\upsilon_1} & \kappa_{c,\upsilon_2} & \alpha_{i,t-1}^s\kappa_{c,\eta^s} \\ \kappa_{l_1,u_1} & \kappa_{l_1,u_2} & \kappa_{l_1,\upsilon_1} & \kappa_{l_1,\upsilon_2} & \alpha_{i,t-1}^s\kappa_{l_1,\eta^s} \\ \kappa_{l_2,u_1} & \kappa_{l_2,u_2} & \kappa_{l_2,\upsilon_1} & \kappa_{l_2,\upsilon_2} & \alpha_{i,t-1}^s\kappa_{l_2,\eta^s} \end{pmatrix} \times \begin{pmatrix} \Delta u_{i,1,t} \\ \Delta u_{i,2,t} \\ \upsilon_{i,1,t} \\ \upsilon_{i,2,t} \\ \eta_{i,t}^s \end{pmatrix} \tag{1.14}$$

For example the parameter $\kappa_{c,\upsilon}$ determines the degree of permanent-income shocks transmission to household's consumption stream. This parameter is between the range 0 and 1. When $\kappa_{c,\upsilon} = 0$ income shocks are not transmitted to consumption. In contrary when $\kappa_{c,\upsilon} = 1$, income shocks are fully are transmitted to consumption.

Along the same lines, the sensitivity of labor supply to permanent-wage income shocks is $\kappa_{l,\upsilon}/\Delta log(L_t)\upsilon$. This parameter determines the magnitude of the adjustment of work hours in response to wage-income shocks. When $\kappa_{l,\upsilon} < 0$ there is a substitution effect which is good for insurance purpose. For example, labor supply increase when worker faces negative wage income shocks. However, when $\kappa_{l,\upsilon} > 0$ there is a complementary effect i.e. wage income shocks and change in labor supply go in the same direction.

In general, the sensitivity parameters are not only function of time varying variables which include the ratio of financial-to-human wealth for (π_{it}) and the shares of spousal human wealth in total household human wealth (s_{1t}, s_{2t}), but also of fixed parameters which are elasticities($\boldsymbol{\eta}$).

$$\kappa_{x,z,t} = F(\pi_{it}, s_{1t}, s_{2t}; \boldsymbol{\eta}) \tag{1.15}$$

Appendix *A.1.4* provides the expression of the function F.

1.2.2.2 Optimal portfolio allocation

This section presents results under the often-used assumptions of Cobb-Douglas preferences and unitary elasticity of substitution between consumption and leisure.[5] Specifically, preferences are given by:

$$U(C, L_1, L_2) = \frac{\{C[(1-L_1)^{\zeta}(1-L_2)^{1-\zeta}]^{\omega}\}^{1-\sigma} - 1}{1-\sigma} \tag{1.16}$$

where σ is the coefficient of relative risk aversion, ω parametrizes the preferences for leisure, and ζ is the weight of husband's leisure relative to the secondary earner's leisure. The parameters of the utility function are calibrated to the micro-elasticities estimated by Blundell et al. (2016).

Using this particular functional form, the Euler equation from (1.6) can be written as:

$$E_t\left[\beta \frac{U_c(C_{t+1}, L_{1,t+1}, L_{2,t+1})}{U_c(C_t, L_{1,t}, L_{2,t})} R_{p,t+1}\right] = 1 \tag{1.17}$$

In addition, define the parameters $\hat{\gamma_1} = (1-\zeta)\omega(1-\sigma)$, $\hat{\gamma_2} = \zeta\omega(1-\sigma)$. For each spouse j, let $-Q_j$ be the ratio of expected work hours to expected leisure hours:

$$Q_j \approx \frac{-\overline{L}_j}{(1-\overline{L}_j)} \tag{1.18}$$

Because $L \in [0, 1]$, it follows that $Q_j < 0$.[6]

Using these definitions and the second-order approximation techniques of Chan and Viceira (2000), equation (1.17) can further be written as:

$$E_t(r_{s,t+1} - r_f) + \frac{1}{2} var(r_{s,t+1}) = -cov(r_{s,t+1}, \sum_{j=1}^{2} \hat{\gamma}_j Q_j \Delta ln L_{j,t+1} + \sigma \Delta ln C_{j,t+1}) \tag{1.19}$$

where $r_{s,t+1}$ is the logarithm of the risky return in period $t+1$ and r_f is the logarithm of the (constant) riskless return. So, the left-hand-side depends on the expected risk premium and on the variance of the return to the risky asset. The right-hand-side depends on the covariance between the risky return and the sum of the growth rates of work hours and consumption. Assume zero correlation between the transitory shocks in wages and stock returns. Then, using equations (1.14) and (1.19), the following proposition is obtained:

Proposition 1 Letting $\Lambda_j = -\hat{\gamma}_j Q_j$ a fixed parameter in $[0, 1]$ and $\Gamma = \sigma\kappa_{c,\eta^s} + \sum_{j=1}^{2} \Lambda_j \kappa_{l_j,\eta^s}$ the consumption risk hedging term, the optimal share of stocks out of liquid wealth each period t is approximately:

[5] Cobb-Douglas preferences have been used in many portfolio allocation studies, such as Chai et al. (2011), Gomes et al. (2008) and Farhi and Panageas (2007), among others. A unitary elasticity of substitution between consumption and leisure is consistent with the evidence in Chai et al. (2011).

[6] For details on the derivations see A.1.5.

$$\alpha^{opt} = \underbrace{\frac{E_t(r_{s,t+1} - r_f) + \frac{1}{2}\sigma^2_{\eta^s}}{\Gamma\sigma^2_{\eta^s}}}_{\text{Sharpe-Ratio}} - \sum_{j=1}^{2} \underbrace{\left[\Lambda_j(\kappa_{l_j,\upsilon_j} + \kappa_{l_{-j},\upsilon_j}) + \sigma\kappa_{c,\upsilon_j}\right]}_{\text{Consumption insurance}} \times \underbrace{\frac{cov(\eta^s, \upsilon_j)}{\Gamma\sigma^2_{\eta^s}}}_{\text{Income risk hedging}} \tag{1.20}$$

Equation (1.20) shows that, the optimal portfolio share invested in the risky asset depends on three components. The first component, called Sharpe-Ratio per consumption risk hedging, essentially captures the effect on α^{opt} of the Sharpe ratio, i.e. of the excess return, $(r_s - r_f)$, per unit of risk, $\sigma^2_{\eta^s}$, undertaken by household and a consumption risk hedging term Γ. All else equal, an increase in the risk premium renders the risky asset more attractive, compared to the riskless asset, and therefore tends to increase the share of wealth invested in the risky asset. The consumption risk hedging reflects consumption risk related to risky-asset. In this framework, it plays a role of an effective risk aversion over consumption risk. That is because, as households accumulate financial assets over the life cycle; they consume out of financial wealth. As a consequence, consumption also reacts to shock on financial assets. More precisely, Γ captures the transmission of return shocks to consumption, and it further consists of two terms. One, the direct effect of a return-shock on consumption, captured by the sensitivity parameter κ_{c,η^s}. Two, the indirect effect on consumption resulting from the adjustment of work-hours in response to the market shock, captured by the sensitivity parameter κ_{l,η^s}. In other words, the adjustment of hours can be used to offset some part of the direct effect of a market shock on consumption.

The second component called consumption-insurance and characterized by the role of households formation and labor supply adjustment for the optimal risky-asset investment. Suppose that a the secondary earner can adjust his/her labor supply in response to a shock in the risky-asset return. Then, the first earner enjoys a degree of risk-sharing of the asset shock that he would not have been able to obtain, had he been without the secondary earner. In other words, this term captures wealth effects on risky investment, induced by the potential of sharing risks with a partner, via the adjustment of the partner's work hours in response to adverse shocks in financial-income sources. A number of observations are in order. If the household consisted of only one earner or of two earners who did not share risks (in which case $\kappa_{l_1,\upsilon_{-2}} = \kappa_{l_2,\upsilon_{-1}} = 0$), then the optimal portfolio rule would drop out by the terms affected by $\kappa_{l_1,\upsilon_{-2}}$ and $\kappa_{l_2,\upsilon_{-1}}$. By contrast, $\kappa_{l_1,\upsilon_{-2}} \neq 0$ and $\kappa_{l_2,\upsilon_{-1}} \neq 0$, then the possibility of adjustment in spousal work hours emerges as an additional consumption-smoothing device.

The third component, called the income risk hedging, reflects the role of income hedging on the optimal risky investment. This term depends on the covariance between the risky return, η^s, and the changes to the permanent component of household wage income. When $cov(\eta^s, \upsilon_j) \neq 0$, income risk generates a hedging demand for stocks. For example, suppose that household i faces a negative covariance between shocks to the risky return, η^s, and permanent shocks to spouse j's wage income, υ_j. This is desirable from the viewpoint of hedging shocks to different income sources. Hence, it reduces the effective risk aversion and tends to increase investment in the risky asset.

Overall, one of the main novel contributions of this paper is the analytical solution and identification of the two main channels via which the demand for hedging shocks across wage- and financial-income influences the decision to invest in a risky asset and the optimal portfolio allocation at the household level. First, the sign of the correlation of the shocks across the two income sources affects the hours worked by each spouse. Second, the sign of this correlation may result in an adjustment of hours worked by the spouse's partner, thereby opening up a source of risk-sharing that would not have been available in the absence of the partner. Hence, either the spouse or the spouse's partner (or both) can flexibly adjust hours worked to reduce exposure to wage-income shocks that are positively correlated with asset-return shocks.

1.3 Data and Facts

To test the implication of the model presented in the previous section, the paper relies on the Panel Study of Income Dynamics (PSID). The data contains 10 waves of a representative family sample of the US population. Starting in 1999 the survey became biennial. It collects information on seven categories of household consumption expenditures, including food, childcare, health, utilities, gasoline, car maintenance, transportation, education, and housing[7] It also collects information on wage income, pensions, cash, bonds, stocks. Also, the data has demographic information which include age, marital status, education, and the number of children. For the analysis, the paper select continuously married couples, with spousal ages $25-65$ years old, without missing information on key demographics. I use this sample to build variables related to risky asset, safe asset, financial asset, and total net worth. The *Risky asset* is defined as directly-held stocks, i.e., the sum of stockholdings in publicly-held corporations, mutual funds, investment trusts, and IRA accounts. I exclude business income from the risky asset. The *safe asset* is defined as the sum of bank deposits, cash, bonds, and pensions. The *Financial asset* is defined as the sum of the variables for risky and safe investments. Finally, the *Total net worth* is defined as the sum of financial assets, earnings, and real estate net of debt.

Table (A.1), Table (A.2) and Table (A.3) display sample summary statistics on demographics, incomes, assets and consumption in real 2000 dollars.

[Table (A.1) here]

[Table (A.2) here]

[Table (A.3) here]

[7] The consumption data in the PSID covers 70% of consumption items available in the Consumer Expenditure Survey (CEX), see Blundell and al.(2016).

In the sample, the head of the household earns on average $\$48,708$ in annual wage income, while the secondary earner earns $\$33,476$. Besides, the labor force participation of the secondary earner in the sample is about 72%. Next I show some facts about the joint dynamic between consumption and the household finance puzzles.

1.3.1 Joint dynamic of consumption and income

This section highlights facts at the household level about the linkage between income and consumption.

First, household-level consumption is relatively uncorrelated with her income over the life cycle.

[Figure (A.1) here]

As shown in Figure (A.1), the average correlation between the change in consumption ($\Delta log(C_t)$) and the change in total labor income ($\Delta log(I_t)$) across age groups is very small and exhibits an inverted U-shape over the life cycle. Besides, consumption appears to be far less correlated with income than what predicted by standard models of one earner household. This suggests that consumption volatility is disconnected from income volatility.

Second, consumption is less volatile than wage income over the life cycle. Figure A.2 plots the average ratio between dispersion of consumption ($\sigma(\Delta log(C_t)$) and dispersion of wage income ($\sigma(\Delta log(w_t)$) across age groups.

[Figure (A.2) here]

These two empirical facts highlighted above provide evidence on excess smoothness of consumption.

1.3.2 Household finance puzzles: Conditional and unconditional stock holding

An important function of stock market is to allow household to hedge their labor income risk. Nevertheless, the average annual stock market participation rate for households is about 21%. Furthermore, conditional on participation, households in the sample hold about 11% of their total financial wealth in stocks. Figure (A.3) presents information on stock market participation and risky share by income quartiles. Stock-market participation is monotonic in household's income. Furthermore, conditional on stock-market participation, the distribution of the risky share is approximately the same across income quartiles.

[Figure (A.3) here]

Figure (A.4) paints the stock-market participation and the conditional risky share over the life cycle. Despite an increase in the stock participation rate over the working life cycle, the conditional risky share does not change too much and sticks on average around 42% of the total assets over the life cycle. The previous pattern also holds across the income distribution, as shown in Figure (A.3).

[Figure (A.4) here]

Next, I study how the joint dynamic of consumption and income can explain the observed conditional and unconditional stocks held by households.

1.4 Testable implications for portfolio allocation

1.4.1 Consumption response to wage income shocks: Evidence from labor supply adjustment

To estimate empirically, the consumption and labor supply linkages to wage income shocks, I rely on the structural approach provided in section (1.2.2.1)[8]. In order to compute the consumption response to wage income shock ($\kappa_{c,.}$) and the labor supply response to wage income shock ($\kappa_{l,.}$), one needs to compute workers' human wealth ($H_{j,t}$). By definition, the human wealth is the expected value of the discounted future labor income stream of a worker. For simplicity, I argue that human wealth can be view as an implicit risk-less asset, therefore it can be discounted at the inverse of the gross interest rate $(1 + r_f)$. Finally, the human wealth for each spouse i in household j can be definied as follows:

$$H_{i,j,t} = Y_{ijt} + \sum_{k=1}^{T_r} \frac{E_t(Y_{ij,t+k})}{(1 + r_f)^k}$$

To compute the lifetime wealth $E_t(Y_{ij,t+k})$, spouse's earning is regressed on deterministic characteristics (q^d) that either do not change over time (such as race, education) and characteristics (q^f) that change in the future(such as a polynomial age). Hence, the expected earnings at age $(t + k)$ given information at time t is:

$$E_t(Y_{i,j,t+k}) = \begin{cases} q_i^d \hat{\theta}_1 + q_{i,j,t+k}^f \hat{\theta}_2 & \text{if j=1 (First earner)} \\ P_t[q_i^d \hat{\theta}_1 + q_{i,j,t+k}^f \hat{\theta}_2] & \text{if j=2 (Second eaner)} \end{cases}$$

P_t is the predicted probability of the secondary earner being employed.

With, the human wealth in hand, I then compute the income shocks transmission to consumption and labor supply. Figure (A.5) above depicts the distribution of consumption insurance conditional on household net worth being above the 75^{th} versus below

[8] See appendix ($A.1.4$) for the complete analytical expression

the 25^{th} percentile. The difference in the distribution of these two groups is evident and consistent with the fact that less wealthy households rely more on intra-household risk sharing to smooth out consumption against permanent income shocks than top wealthy households.

[Figure (A.5) here]

A similar analysis is performed for the adjustment of labor supply to permanent-income shocks. As shown in Figure (A.6), there is a larger margin of adjustment in labor supply for households with lower net worth, compared to households at the top of the wealth distribution.

[Figure (A.6) here]

1.4.2 Empirical Analysis

This section presents the empirical strategy. To begin with, let's defined the total consumption response to permanent wage income shocks by the following expression

$$CWS_{it} = \sum_{j=1}^{2} \kappa_{c_i, v_j, t} \tag{1.21}$$

CWS measures the direct channel of consumption insurance in Equation (1.20). A decrease in CWS means an increase in household's consumption insurance. Similarly, the indirect channel capturing the total labor supply response to wage income risk can be expressed as follows

$$LWS_{it} = \sum_{j=1}^{2} \sum_{k=1}^{2} \kappa_{l_j, v_k, t} \tag{1.22}$$

Next, I run the following regression where the dependent variable is the risky share and the main explanatory variable is the consumption response to labor income shocks.

$$RS_{it} = \beta_a A_a + \beta_t T_t + \delta_1 Z_{it} + \beta_c CWS_{it} + \beta_l LWS_{it} + \epsilon_{1,it} \tag{1.23}$$

Where A_a, T_t are dummies for age and time, Z_{it} is a set of controls that include income, wealth, age, number of children, and unemployment. Finally, $\epsilon_{1,it}$ is the error term.

1.4.2.1 Unconditional stock share

Table (A.4) reports the estimates from the Tobit model where the dependent variable is the unconditional stock share. The sample in this model includes both nonstockholders and stockholders

[Table (A.4) here]

As reported in column (1), consumption response to income shocks exerts an effect on household's portfolio choices. In column (3), I include a set of control variables and the positive correlation still hold. The result shows that 1 percentage point (pp) decrease in consumption response to income shocks (or an increase in consumption insurance) implies a decrease of stock holding by about 0.658 pp. In terms of economic magnitude, it means that 1 standard deviation increase in consumption insurance reduces stock holding about $(0.245 * 65.8\% * 0.24) = 3.87\%$. I also find that education is positively correlated with stock holding although having kids reduces the likelihood of investing in stock market. These results are consistent with many other studies.

1.4.2.2 Conditional stock share

In the previous section, I assume that the decision to participate in the stock market is exogenous. Here, I perform the same asset allocation specification. However, I argue that households' stock-market participation is endogenous. Then, I investigate the relation between the conditional risky-investment decisions and consumption insurance. The endogeneity concerns are addressed using the Heckman (1977) selection model. For instance, Fagereng et al. (2017) to address this issue, argues that since participation in stock market implies fixed costs, household participation decisions depends on household's wealth. In this paper, I used a dummy variable characterizing the presence of a secondary earner to generate a wealth effect. Thus, the empirical strategy is as follows a two-step equation. First, the stock-market participation equation is estimated with a sample that includes both non-stockholders and stockholders.

$$\begin{aligned} prob(P_{it} = 1|x) =& prob(P^*_{it} > 0|x) \\ =& prob(\delta_a A_a + \delta_t T_t + \delta_1 Z_{it} + \delta_2 \mathbb{1}(2^{nd} \text{ earner working})_{it} + \epsilon_{1,it} > 0) \end{aligned} \tag{1.24}$$

The above regression provides an estimate for the probability of participating, which is used in the second stage estimation for equity share regression. In this stage, the equity-share regression is estimated using data for stockholders only.

$$RS_{it} = \beta_a A_a + \beta_t T_t + \delta_1 Z_{it} + +\beta_c CWS_{it} + \beta_l LWS_{it} + \theta_p \lambda_{it} + \epsilon_{2,it} \tag{1.25}$$

where λ_{it} is the inverse Mills ratio computed from the participation Equation (1.24). The error terms of the regressions are captured by $\epsilon_{1,it}$ and $\epsilon_{2,it}$.

Table (A.5) shows the estimates from the Heckman selection model.

[Table (A.5) here]

The most interesting results from the Heckman specification are those related to the stock holding decisions. The results indicate that household's portofolio allcation is significantly affected by the degree of consumption insurance and labor supply adjustment in response to permanent-income shocks. The result suggests that a 1% increase in labor-supply adjustment to a permanent wage income shocks increases the risky share about 2%. In order words, a one-standard-deviation increase in labor-supply adjustment to permanent wage shocks increases the stock share by about $0.3 \times (2\%) \times 0.979 = 0.4\%$. These results show that these effects are economically important. Surprisingly, I find that conditional on stock market participation, a 1% decrease in the consumption response permanent wage income shock increases the risky share about 11%. Put differently, a one-standard-deviation increase in consumption insurance increases the stock share by about $0.3 \times (11\%) \times 0.245 = 0.8\%$. This result stands in contrast with the estimates in Table (A.4) and implies that consumption insurances of the non-stockholders in the Tobit regression are the driving force of the non participation in stock. Moreover, the economic magnitude from the Heckman specification, in absolute term, is much smaller than the 3.56% obtain in the unconditional stock share regression. From this analysis, it can be argue that, conditional on participation the availability of consumption insurance provides a little incentive for stock holding. This results can rationalized our second puzzle which characterizes the low level of stock held by households conditional on their participation. One potential explanation of this small and positive effect on stock holding could be household's effective risk aversion. Indeed, as consumption is smooth, the household likely builds internal habits which may affect its risk preferences. To better understand this mechanism, I investigate households' consumption commitment. Besides, Chetty and Szeidl (2007) show that consumption commitments can explain the behavior of labor supply decisions within the households, the added worker effect and the self-insurance that arises from it. Also, with the consumption commitment, the equilibrium effect of consumption response to income shock on portfolio decision still holds. Figure (A.7) provides the adjustment rate of durables goods and services. As shown by the figure, housing consumption exhibits the lowest adjustment rate. Intuitively, this lower adjustment rate implies a high internal habit formation and subsequently an increase in risk aversion.

[Figure (A.7) here]

Table (A.6) reports the estimates of Equation (1.25) with housing commitment.

[Table (A.6) here]

When accounting for housing commitment, the relation between stock holding and the consumption response to wage income shock remains statistically significant. In addition, the effect in absolute magnitude is greater than the one reported in Table (A.5). The reason being that housing commitment increases household's effective risk aversion. As a result, households portfolio allocations are more sensitive to their effective risk aversion. Next, I look more closely at household's effective risk aversion. Since the PSID doesn't have a direct measure of household's risk preference, I use as proxy the risk bearing capacity measured by Loan to income ratio (LTI). In fact, with the LTI, household is prone to fluctuation on interest rate risk, swing in house price affecting collateral value, deleveraging risk or other risks affecting the real economy. In this context, a higher LTI implies a higher risk bearing by a household. Using this insight, I find that the relation between stock holding and the consumption response to wage income shock becomes more important, in absolute magnitude, when the LTI decreases. This result shows that the commitment of having to make future mortgage payments amplifies household's risk aversion and reduces her risky asset holding. Hence the positive impact of the consumption insurance on the conditional risky share decreases when the household's risk-bearing capacity i.e. the LTI increases. This result is consistent with Becker and Shabani (2010)'s finding on the effect of mortgage interest rate on households' portfolio allocation.

1.5 Life-cycle analysis

This section presents a simulation exercise for stock allocation over the life-cycle while taking into account the consumption insurance mechanism. Let us recall that Equation (1.20) allows us to identify three components from the optimal portfolio allocation: the Sharpe-ratio, the consumption insurance, and the income hedging demand. In order to address the life cycle analysis, the paper estimates the hedging demand and calibrates the unknown preference parameters.

1.5.1 Income hedging demand

To measure the correlation between income shock and stock return, prior studies used the market return to proxy households' stock return. The reason is that there is a lack of detailed information on stocks held by households. However, since 1999 the PSID has been redesigned and more information about stocks held by household such as capital gain and dividend payment are made available. Here, the paper relies directly on these information to compute stock returns held by the households.

Thus, to compute this return, the analysis begins with an approach similar to Fagereng et al. (2016). Specifically, the return on the risky assets is defined as the sum of dividend yield plus capital gains:

$$R^s_{it} = \frac{d_t}{P_t} + I_{it}\frac{P_{t+1}}{P_t} \tag{1.26}$$

where d_t is the dividend per share, P_t is the price per share, and I_{it} is a *dummy* that takes the value 1 if the household sold stock and realized capital gains. However, a drawback is that the heterogeneity in returns is driven only by I_{it}, because d_t is the market dividend yield and P_t is the market price index. By contrast, here, the richer household-level data of the PSID can be used. In particular, the PSID variables about the dollar-amount of the dividends received by a household and the dollar-amount of stocks sold by the household. Hence, equation (1.26) can be re-written as:

$$R^s_{i,t} = \frac{d_{it}Q_{it}}{P^s_t Q^s_{it}} + I_{it}\frac{P^s_{t+1}Q^s_{it}}{P^s_t Q^s_{it}} \tag{1.27}$$

where Q_{it} is the quantity of stocks held by the household. Next, we can write:

$$R^s_{i,t} \approx \frac{Dividend_{it}}{Stock_{it}} + I_{it}\frac{Stock\_Sell_{it}}{Stock_{it}} \tag{1.28}$$

Because information about the risky asset (dividends received, assets sold, total assets) is only for the end of each period, the timing of households' investment decisions and the flow of dividends received is unknown. To correct this problem, asset returns are redefined as:

$$R^s_{i,t} \approx \frac{Dividend_{it}}{\frac{1}{2}(Stock_{it} + Stock_{i,t-1})} + I_{it}\frac{Stock\_Sell_{it}}{\frac{1}{2}(Stock_{it} + Stock_{i,t-1})} \tag{1.29}$$

Next, using capital asset pricing models (CAPM), the excess return on risky assets can be decomposed into a market risk component and an idiosyncratic-risk component:

$$r^s_{i,t} - r_f = \phi_1 \underbrace{(r^m_t - r_f)}_{Market\_risk} + \underbrace{\eta^s_{i,t}}_{Idiosyncratic\_risk} \tag{1.30}$$

where $r^s_{i,t} = ln(1 + R^s_{i,t})$ is the log return to stockholdings, $r_f = ln(1 + R_f)$ is the log risk-free return, and $r^m_t = ln(1 + R^m_t)$ is the log market portfolio return.[9] In the spirit of Cocco et al. (2005), the correlation structure between wage-income shocks and the innovation in the return to the risky asset can be characterized via the OLS regression:

$$\Delta lnW_{i,j,t} = \beta(r^s_{i,t} - r_f) + \epsilon_{st} \tag{1.31}$$

Here, the idiosyncratic component estimated in equation (1.30) is used to measure the correlation .[10]. Next, I transform all the wage shock and stock return to have a unit variance and run the following regression.

$$\Delta lnW_{i,j,t} = \rho_j \eta^s_{i,t} + \epsilon_{st} \tag{1.32}$$

Where $\hat{\rho}_j$ captures the correlation between a spousal j wage innovation and stock return.

The results are reported in Table A.8. The details about the estimation procedure is provided in Appendix (A.1.2).

[Table (A.8) here]

[9] The idiosyncratic component in equation (1.30) indicates households' level of sophistication. That is, a more sophisticated household carries little idiosyncratic risk in its financial wealth. Another point is that idiosyncratic risk in stock returns will likely be correlated with household wage-income risk if it refers to geographically or professionally similar sources.

[10] To additional correlation structures are also tested: (1) $R^s_{i,t} \approx \frac{D_{it}}{S_{it}} + I_{it}\frac{Stock\_Sell_{it}}{S_{it}}$ (2) $R^s_{i,t} \approx \frac{D_{it}}{S_{i,t-1}} + I_{it}\frac{Stock\_Sell_{it}}{S_{i,t-1}}$.

The result shows a positive and significant correlation between spouses wage shocks and the return on stocks. In other words, there is a positive hedging demand for stock and household exploit the income hedging benefits offered by the stock market. This results, corroborates Davis and Willen (2000) finding[11].

Also, I provide an estimate of the variance of spouse's permanent wage shock, transitory wage shock, and the covariance structure of these shocks. The estimation method of the permanent-transitory of wage shocks follow closely the variance decomposition method of Meghir and Pistaferri (2004). The estimation shows that there is no insurance through the occupational choice of spouses. This result is due to the positive correlation of the transitory and the permanent component of the two spouses. Likely, this positive covariance structure reflects the fact that spouses tend to work in sectors or occupations that are subject to similar aggregate shocks.

1.5.2 Life-cycle investment profiles

To provide the life cycle pattern of stocks allocation, the paper relies on a plausible parametrization of the Cobb-Douglas preference (σ, ω, ζ), the labor supply (Q_1, Q_2), the assets returns (r^s, r_f) and the retirement horizon (T_r). To compute the average ratio of labor/leisure of the head (Q_1) and the spouse (Q_2), a time endowment of 100 hours per week is assumed as in Gomes et al. (2008) and the average hours of work in the in Table (A.1) is used to compute Q_1 and Q_2 (conditional on the spouse labor market participation). In addition, ζ and ω are calibrated to match the elasticity parameters $(\boldsymbol{\eta})$ reported in table (A.9). The risk aversion σ is used as a target for the calibration exercise. The calibration strategy is described in more details in appendix (A.1.6). Finally, I assume that households are only compensated with the market risk, not the idiosyncratic risk. Hence, the stock market information is used to calibrate the excess premium and the volatility of the stock market. Table (A.10) provides an overview of the parameters in the quantitative model, along with the calibrated parameters.

Based on these parameters, Figure (A.9) below paints the life cycle profile of household portfolio allocation.

[Figure (A.9) here]

The average risky share derives from the model is 40.2%, whereas the average portfolio share in the data is 42.2%. Moreover, the simulated model provides a decreasing stock share over life-cycle. Specifically, in the earlier working life, young households (age between 30 and 35) optimally allocate all financial wealth to stocks, since they have a high human wealth and no financial asset yet. Indeed, the human wealth is viewed as a portfolio of risk-free assets, perturbed with an idiosyncratic risk factor. Furthermore, the ratio of human wealth and financial wealth determines household's effective risk aversion. When young, this effective risk aversion is low because future income

[11] Davis and Willen (2000) correlation between aggregate equity returns/own-industry equity and labor income shocks ranges from $-.25$ to $.25$ over most of the life-cycle.

is discounted at the expected risk-free rate and it increases the ratio of human wealth to financial wealth. As a result, young households tend to have an important myopic strategy (Sharpe-Ratio) for stock holding. This optimal portfolio rule at younger age is a common feature of life-cycle portfolio choice models (Gomes et al. (2008), Cocco et al. (2005), Dahlquist et al. (2018)). In the remaining life cycle period (age between 35 and 65), human capital decreases which in turn raises household's effective risk aversion. Consequently, the myopic strategy falls and the household tilts its portfolio toward risk-free assets and away from stock.

1.6 Other explanation of the excess smoothness of consumption

Among other potential explanations of the excess smoothness of consumption, rational inattention and credit-driven consumption are important candidates.

1.6.1 Rational Inattention

The idea behind rational inattention in explaining the excess smoothness of consumption is that households process signals slowly therefore appear to respond sluggishly to innovations in permanent income. This sluggish delivers smaller responses to permanent income changes (Luo and Young (2010)). This inattention behavior could provide an answer for the limited stock market participation puzzle observed in the US data because investors with a very low degree of attention might face extremely large long-term consumption risk, which restricts their participation in the stock market (Luo (2010)).

1.6.2 Debt-driven consumption

The excess smoothness of consumption can also be explain by the flow of debt and the looser lending constraints in the economy. In fact, falling interest rates have characterized advanced economies over the past 40 years, especially in the US. As a result, consumption is affected positively on many financial products such as mortgage, credit card, and auto loans therefore allowing household to shield their consumption against human capital risk. For example, Favilukis et al. (2017) show that a loosening of borrowing constraints, together with lower transaction costs for housing, increases home prices and improves the ability of households to insure against income risk.

1.7 Conclusion

In this paper, I find that a single factor capturing the degree of household's excess smoothness of consumption can rationalize numerous puzzles in household finance, including the limited market participation, the lower level of stock held by households conditional on their participation, and the weaker evidence of income hedging demand. These results are driven by the importance of consumption insurance provided by a secondary earner in the household. The paper validates these results empirically using consumption, income, and portfolio data from the PSID. Then, I formalize these findings with a realistic structural model of consumption, income risk, and household investment decision. The results here suggest avenues for further research. For example, It would be interesting to test the aggregate implication of the excess the smoothness of consumption on aggregate asset prices.

Chapter 2

Systemic risk-shifiting

2.1 Introduction

> "*...Banks direct exposures to credit risk have declined as banks have shifted from an originated to retain business model to an originate to distribute business model, but it has increased the complexity and opacity of credit markets, possibly introducing new risks transmission channel..."*
>
> Global Financial Stability Report 2020

This paper studies how banks' risk-shifting strategy in non-regulated banking activity affects financial stability. After the 2008 financial crisis, non-regulated banking, also called shadow banking[0], has been the center of policy debates. Indeed, the sector represents a large part of the financial intermediation, and it keeps growing. As of 2017, the shadow banking sector's size almost doubled in Canada and accounted for approximately 110% of its GDP. However, the examination of banks' risk-taking strategy in that sector is very challenging. Part of the reason is that we lack appropriate balance sheet information on financial instruments that pass-through and pay-through the shadow banking.

This paper tackles this challenge using novel data and a new methodology based on machine learning techniques. Specifically, the paper exploits exogenous variation in bank's risk disclosure using their financial reports. Indeed, textual data provide direct information on how banks describe, among other aspects of their business, the use of financial instruments. To reach our goal, the paper begins by constructing a

[0] The shadow banking sector is composed of special investment vehicle (SIVs) and special purpose vehicles (SPVs) that intermediate credit through securitization, and secured funding techniques such as asset-backed commercial paper (ABCP), asset-backed securities (ABS), and collateralized debt obligations (CDOs). In other words, one can think of the shadow banking as a capital or a trading sector which is lightly regulated or unregulated. The terms "shadow banking" and "non-regulated activity" are used interchangeably throughout the paper

training set of annual reports of publicly-traded and non-bank[1] Canadian financial institutions. Next, using a non-supervised algorithm—the Latent Dirichlet allocation (LDA)—the training sample is transformed into a set of topics representing various banking activities. Using these topics, the paper identifies a lexicon of keywords that implicitly translate shadow banking activities. Finally, each bank is scored based on the lexicon using the cosine similarity metric. Besides, compared to other measures of risk exposure that relies on the balance sheet data[2], the textual-based approach is more appealing because of its informativeness and simplicity.

Looking at the cross-section of the shadow banking index, the paper finds that banks behave strategically. Specifically, banks engage in shadow banking when their regulatory risk-based capital constraints become bindings. Moreover, this behavior is more pronounced in a tighter regulatory regime than in a looser regime. Besides, the empirical estimate shows that 10 percentage points (pp) drop in a bank's regulatory risk-based capital is associated with 3 pp increase in its shadow banking index. Also, the paper finds that the shadow banking index is linked positively to different bank-level systemic risks measured by the change in the Conditional value at risk ($\Delta CoVaR$) and the Marginal expected shortfall (MES). These results confirm the theoretical prediction in Acharya (2009), Wagner (2010), Wagner (2011), and Allen et al. (2012) that the risk-shifting channel may result in a higher systemic risk when banks are prone to high level of vulnerability in the economy. Additionally, the paper analyzes the dynamic relationship between the shadow banking index and the systemic risk measures and finds a non-linear dependence. This finding is consistent with the recent literature on occasional financial crises (He and Krishnamurthy (2019), Gertler et al. (2020), Paul (2020)). This paper is the first to investigate the empirical association between banks' risk-shifting and their tail risk utilizing big data and machine learning tools to the best of our knowledge.

Afterward, the paper presents a partial equilibrium model of risk-shifting. The model builds on the macroeconomic model with a financial market (Brunnermeier and Sannikov (2014) and He and Krishnamurthy (2019)), in which there are two types of investors: bankers and a representative household. In the model, I assume risk mispricing in the financial market, which provides an incentive for risk reallocation across financial sectors (shadow banking and traditional banking). Although investors are risk-averse, they differ in their degree of financial sophistication. Bankers play a key role in this environment since they are the most sophisticated investors in the financial market. Thus, the household delegates her portfolio choices to banks by investing in their debt and equity. As sophisticated investors, bankers have incentives for risk-shifting by choosing

[1] According to the Financial stability Board, the term "shadow bank" refers to non-bank (non-depository) lenders that are not subject to the same regulatory supervision as traditional banks

[2] In risk management, there exist numerous methods that rely on balance sheet approach or statistical methods such as copula, common mixture, component, and dependence models. Another way to measure a potential risk exposure is to compute the distance between two portfolio structures. To apply these methods one need to collect information on different class of assets which are not always available on bank's balance sheet.

endogenously sectoral risk exposures. In the model, bankers' incentive for risk-shifting results from the combination of two elements. First, debt is risky, and the bank can default on their debt holder. In particular, in crisis risk, the debt holder takes the downside risk, and the equity holder takes the upside. Second, there is an externality in the financial market due to imperfect regulation across the banking sectors.

I start by analyzing the optimal risk-shifting strategy by banks in this environment. Within the framework, it is shown that at the optimality, banks choose their risk-shifting strategy such that the cross-market arbitrage opportunity is equal to the riskiness of their portfolio. The intuition is that under the equilibrium risk-shifting allocation, banks profit by exploiting the risk-pricing discrepancies between sectors. While banks may fail to take a socially optimal level of market arbitrage position by way of their risk-shifting choices, the availability of an entity-based regulation is insufficient on its own to mitigate risk exposure. On that account, the complementary policy takes the form of sectoral Sharpe-ratios targeting that limits the cross-sector arbitrage. Under this policy, bankers are indifferent toward risk-shifting strategy. Finally, the paper compares the equilibrium allocation in which banks freely take the arbitrage position to the no-arbitrage allocation. The ability to resort to activity-based regulation, meaning a tax on banking activity, effectively reduces risk-shifting strategy and leads to some Pareto improvement associated with the less sophisticated investor's welfare (household).

Related Literature

This paper first contributes to the growing literature on the unintended consequences of financial regulations. For example, Erol and Ordoñez (2017) and Anderson et al. (2019) provide a theoretical model to study how the interbank network reaction to financial regulation affects systemic risk. The empirical literature, however, is more limited and our paper provide a contribution by bringing a new data on the table. Moreover, other researchers have focused on the consequences of financial regulation on shadow banking sector. For instance, in Begenau and Landvoigt (2018), households' liquidity preferences are at the heart of the model. These preferences are critical to analyze the effect of the changes in capital requirements on the banking structure especially the shadow banking sector. Also Bengui and Bianchi (2018) in their model discuss the desirability and the effectiveness of financial regulations when they are imperfectly enforced. Finally, Buchak et al. (2018a) (respectively Irani et al. (2018)) document in the context of residential mortgage (respectively the market for syndicated corporate loans) that regulatory constraints may create a risk-shifting strategy from a balance sheet retention activity to an originate-to-sell activity. Also, Becker and Ivashina (2015) provide recent evidence of risk shifting in the bond market from the insurance sector. Relative to those works, this paper study the implications of risk-shifting for financial stability.

This paper also adds to the literature that studies risk-shifting behavior (Acharya (2009), Huang et al. (2011), Elliott et al. (2018)). Acharya (2009) argues that limited liability and the presence of a negative externality of one bank's failure on the health of other banks give rise to a systemic risk-shifting where all banks undertake correlated investments. Using this argument, the author develops a model of optimal regulation. Similarly, Elliott et al. (2018) to go along with systemic risk-shifting mechanism, provide an empirically fact on banks' correlated risk exposure where banks with more similar real exposures tend to lend more to each other. They endogenize this stylized fact into a network model where limited liability encourage banks to engage in risk-shifting. The present paper differs from the aforementioned studies. Instead of the above externality, I focus on the role plays by market failure meaning externality due to imperfect regulation enforcement. Broadly speaking, the literature has mostly ignored institutional elements that may potentially be responsible for risk-shifting incentive. An exception is the work by Farhi and Tirole (2012). The latter provide an alternative mechanism where systemic risk-shifting arises in response to a non-targeted monetary policy.

In addition, this paper is related on macroeconomic model augmented with financial sector. Seminal contribution includes He and Krishnamurthy (2013), He and Krishnamurthy (2019), and Brunnermeier and Sannikov (2014). This literature gained prominence following the global financial crisis, with several papers looking to understand the origins of financial crisis. For example He and Krishnamurthy (2019) focus on a single baking sector and study stabilization policies in crisis (equity injection, interest rate cuts, asset-purchasing programs by the central bank). Brunnermeier and Sannikov (2014) also rely on a single banking sector setting to study prophylactic policies (open market operation, leverage constraint, restrictions on dividends) and their affect on overall system stability. The contribution of this paper is the analysis of a financial sector with imperfect regulation enforcement. Specifically, I consider a multi-banking sector with the existence of risk evasion or risk shifting. This allows the model to characterize banks' risk-shifting decision and to study optimal policy.

Lastly, this paper shares common elements with a stream of research that uses text as data (Gentzkow et al. (2019), Hanley and Hoberg (2019), Hoberg and Phillips (2018)). Despite their high dimensionality, banks' disclosures are useful for understanding issues in corporate finance and they provide additional rich information. Closely related paper using similar methodology as in the present paper is Hanley and Hoberg (2019). They use textual information to detect dynamic emerging risk the financial sector and study how the commonality in banks' risk disclosures can explain commonality in their stock market returns. We differ from their work by focusing on a systemic risk aspect.

The rest of the paper is organized as follows. Section 2.2 provides background information on the evolution of the financial landscape. Section 2.3 presents the data and the textual-based methodology. Section 2.4 introduces our econometric methodology and discusses the result. Section 2.5 streamlines a stylized model of risk-shifting behavior. Section 2.6 concludes.

2.2 Motivating aggregate facts

This section introduces the motivating aggregate observations on the evolution of the Canadian financial market. The first observation is related to the growing importance of shadow banking activity. Figure A.12 below depicts this evolution.

[Figure A.12 here]

According to the Financial Stability Board, the shadow banking system is a collection of non-bank institutions (money market funds, broker-dealers, and mortgage companies) that conduct maturity, credit, and liquidity transformation outside the traditional commercial banking system. These financial intermediaries face much less regulations or none. Meanwhile, these institutions rely heavily on special-purpose entities and special-purpose vehicles to refund themselves in the capital market. Since the financial crisis, the shadow banking's size has grown 1.7 times. Between 2015 and 2017 alone, this sector grew by about 30%. In fact, the growing shadow banking's size in the decade has been influenced by a broad range of external forces including regulatory arbitrage[3](Ordoñez (2018), Bengui and Bianchi (2018)), unconventional monetary policy(Xiao (2019)) and technology (Buchak et al. (2018b), Fuster et al. (2019), Tang (2019)).

Turning our attention entirely to traditional banks, the second observation highlights their search for margins in shadow bank-like activity. Like non-bank institutions, traditional banks provide credit intermediation in the financial system. Besides, they are the primary provider of financial services. However, they are regulated by the government. The regulations are setup to curb excessive risk-taking and can take various forms among which holding of loss-absorbing capital, short-term and long-term liquidity management and positions, activity restrictions, enhanced risk management standards, and expectations. Throughout the paper, the terms traditional banks and regulated banks will be used interchangeably. Although they are regulated, traditional banks expose themselves also to shadow banking activity by financing the non-bank institutions. Figure A.13 provides a glimpse of this exposure.

[Figure A.13 here]

Indeed, regulated banks have stepped forward into market-making activity by increasing their exposure to security distribution activity. More precisely, they borrow security for diversification purposes and lend security for risk hedging purposes. The former arises as a search for margins and the latter as a collateral transformation[4] for

[3] Buchak et al. (2018b) empirically estimates that 2/3 of the rising in shadow banking is due to a change in the regulatory system and 1/3 in technology.

[4] In the collateral transformation activity, the lenders of security swap less-desired security for preferred security.

risk hedging purposes in the shadow banking sector. Taking together, regulated banks became net security borrowers which allowed them to escape potentially restrictive regulatory constraints and enhance their profitability.

To summarize, the aggregate facts from the above reveal that (*i*) shadow banks' assets have substantially increased as well as (*ii*) regulated banks exposition to the shadow banking sector. Consequently, there is a growing role for the market-based financial system, since some claims or short-term items of the shadow banking activity are marked to market. From this financial configuration, it appears there is a systemic risk -shifting buildup. Yet, the balance sheet treatment related to shadow banking is often opaque and may depends on many factors. For instance, the balance treatment can depends on the rights of re-hypothecation (Jesse et al. (2019)) and collateral re-use. With rehypothecation right, borrowers can use for their purposes, securities that have been posted as collateral by their clients. Therefore, they have to disclose transactions related to those securities in their balance sheet. Without rights of rehypothecation, data are made available only in the event of a default. Consequently, it is challenging to have an accurate banks' linkage in the shadow activity through balance sheet information.

2.3 Risk-shifting strategy: Evidence from textual data

2.3.1 Data

This study employs an extensive data set of textual information to measure shadow banking activity. The textual data information is more available and usually implies more abundant information and intuition senses. In fact, since 1997, it has been mandatory for Canadian financial institutions to file electronically through a system called the System for Electronic Document Analysis and Retrieval (SEDAR[5]). The latter was put in place by the Canadian Securities Administrators (CSA) for the transmission, review, and dissemination of financial documents. The paper builds a training sample of banks to identify and measure discourse related to correlated risk exposure with such information. To do so, the paper applies a web-crawling algorithm on the SEDAR system to download 715 annual reports. The training set includes textual data from 92 financial institutions of which 14 are regulated banks (traditional banks), and 78 are non-regulated banks (shadow banks). Moreover, the data covers the period 1997 to 2017. Besides, a bank's classification into a regulated bank or a shadow bank is done based on the Canadian Bank Act3 of the Office of Superintendent of Financial Intermediaries (OSFI). In each annual report, there is a section called "*Management Discussion and Analysis* (MD&A)". The *MD&A* section accounts for more than 2/3 of the document, and it represents the section where financial institutions discuss their

[5] SEDAR is the equivalent of the Securities and Exchange Commission's (SEC) Electronic Data-Gathering, Analysis, and Retrieval (EDGAR) in the US.

balance sheets, liquidity needs, and ongoing contractual arrangement and networking. Nonetheless, the textual data are unstructured and high-dimensional. Accordingly, as typical in the computational linguistic analysis and before estimation, the raw texts of financial documents are cleaned and then taxonomized into sets of words. For example, cleaning involves dropping words that appear very frequently across papers, such as common words, numbers, and names. After the pre-processing, the final training set has 20 million words describing different banking activities with a vocabulary of 2,432 unique keywords. The textual information are complemented with balance sheet and stock price information. The balance sheet information are obtained from Statistics Canada while the stock prices information are obtained from the Center for Research in Security Prices (CRSP). Table A.19 in appendix (A.2.4) presents a descriptive statistic of the data use for the analysis.

2.3.2 Banking activity risk disclosure

The challenge with the training set using its "bag-of-words" form is its high dimensionality (20 million words), making information retrieval hard to process. To address this issue, one can proceed by using the Latent Dirichlet Allocation (LDA) model. More precisely, the LDA is an unsupervised learning technique, introduced by Blei et al. (2003), which views documents as topics and requires to choose only one input: The number of topics. In order words, without a strong prior regarding the relevant keywords, it summarizes documents into a set of important topics. Moreover, the LDA model can be looked upon as a factor model applied to text, where a factors in this case are topics where each topic is treated as a probability distribution of words. However, a drawback of the LDA model is that it gives sometimes results that are not interpretable since it adds non-informative words that add noise to the determinaiton of topics. To reduce these noise, the paper applies other processing tools before running the LDA algorithm. Explicitly, this paper uses in tandem the 2-grams and 3-grams collocation models (e.g., "mutual fund", "mortgage backed security") and the part-of-speech tagger to improve the interpretability of LDA output. Note that the entire process just described is fully automated and 20 topics are extracted from the cleaned training sample. Because LDA puts high probability weights on two-word and three-word that are present in the risks disclosed by many banks, these bigrams and trigrams are systemically important and not idiosyncratic. The application of the LDA on the training set results in potentially informative topics that can be gleaned from the financial reports, as shown in figure A.10 below.

[Figure A.10 here]

For example, the words in Topic 16 from such unsupervised topic modeling appear to be associated with capital and clearing house activity; whereas the words that constitute Topic 10 are associated with mortgage brokerage activity. To identify shadow banking activity, I started with seed words from the Financial Reporting Standards

Board (FSRB) and the Basel Committee of Banking Supervision (BCBS). These seed words are then used to obtain all adjacent two-word and three-word combinations containing one of the seed words from the entire keywords of the 20 topics. Finally, this approach allows to obtain a comprehensive training dictionary of shadow banking activity that contains a total of 36 keywords. Table A.2.4 in the appendix provides the full list of the keywords of the shadow banking activity. In fact, the identified keywords are related to direct participation (trading) and indirect participation (sponsorship to non-consolidated financial entities, liquidity enhancement, Step-in-risk[6], guarantees, and committed liquidity provision) in the unregulated activity. In particular, the indirect participation arises when banks provide liquidity support to less-regulated or unregulated legal entities. In the next step, the paper converts the lexicon into bank-year numerical term counts.

2.3.3 Shadow banking index

Our primary shadow banking index aims to achieve a simple objective: to measure the importance of banks' discourse regarding shadow banking risk exposure. Besides, providing such a measure is not as straightforward a task as it appears for many reasons. In fact, the semantic meanings of the related keywords in the lexicon have evolved during the past decade as well as banks' activities disclosure rules. As a result, using a simple term frequency count as weighting scheme could be misguiding. To deal with those issues, the paper uses the cosine similarity metric. Specifically, the cosine similarity scores the lexicon at each bank level by taking into account not only how important is the lexicon in a financial report but also how important is the lexicon between banks. This approach allows to generate a continuous score for each bank and a more informative degree of shadow banking exposure. The cosine similarity metric proceeds as follows:

2.3.3.1 Incremental Tf-IDf

The paper begins by transforming the financial lexicon into numerical values using the Term Frequency (Tf) and Inverse document frequency (IDF) weighting scheme. Specifically, Tf-IDf seeks to grant lexical relevance to a term within a broader collection of documents. In other words, the Tf-IDf reflects the importance of a word in a document, expressing both the occurrence (Tf) and the scarcity (IDF) of the word.

Still, the Tf-IDf weighting scheme is not ideal because it ignores the temporal flow of new investment vehicles. For instance the *'multi-seller conduits'*, a pay-trough and pass-trough investment vehicle, become mainstream in the financial system before the 2008 crisis. The standard IDf would sharply de-emphasize this term in the $TfIDf$

[6] Step-in risk exists when banks are connected to unconsolidated entities and provide implicit credit or liquidity support to securitization conduits, structured investment vehicles(SIVs), and money market funds(MMFs).

because so many financial entities subsequently used this phrase so intensively. To overcome this issue, this paper uses a modified version of the traditional IDF measure. In particular, in place of the IDf, this paper instead construct a "point-in-time" version of the inverse document frequency denoted by Incremental Inverse Document Frequency ($IIDf$). In addition, the $IIDf$ weighting scheme can account for changes in the accounting standard (IAS 39, IRFS 7, IRFS 9, IRFS 13)[7]. Intuitively, the $IIDf_t$ related to a given word in a year t is defined as the scarcity of the bag of words in all banks' reports prior to year t (past documents and the documents of the current year).

$$\text{Tf-IIDf}_{it} = \underbrace{Tf_{it}}_{\text{Term frequency}} \times \underbrace{IIDf_t}_{\text{Scarcity in financial system}} \tag{2.1}$$

With

$$Tf_{it} = \begin{cases} \frac{1+log(T_{it})}{1+log(a_{it})} & \text{if} \quad T_{it} \geq 1 \\ 0 & \quad \text{otherwise} \end{cases}$$

Specifically, for each document i, let TF_{it} be the raw count of a word w in the i^{th} document and a_{it} is the average word count in the i^{th} document.
The $IIDf$ is defined as follow:

$$IIDf_t = log(\frac{\sum_{\text{i prior to t}}}{\sum_{\text{i prior to t}} \mathbb{1}_{w \in i}})$$

2.3.3.2 Cosine similarity

The cosine similarity metric[8] is widely used in computational linguistic analysis. The advantage of the measure is that it views a bank not in isolation but in relation to other banks, which allows putting into perspective the banking organization. Following Hoberg and Maksimovic (2014), the paper uses an approach defined as the local cosine similarity measure. The latter is motivated by the concept of "cliques" in social networks. In order words, the local similarity is based on words that tend to appear with a collective group of related words (i.e., they appear in word "cliques"). Intuitively, financial words are likely to have this property. For example, the lexicon of financial terms obtained in the previous section is strongly represented by words that are unique to shadow banking activity. Thus, to compute the local cosine similarity, first, the $tfiidf$ is not computed based on a single word but on the lexicon of shadow banking terms. Second, the $tfiidf$ is transformed to have unit length. Finally, bank $i's$ normalized $tfiidf$ score is loaded on bank $j's$ score to have a pairwise similarity score. The local cosine similarity (CosSim) based on the lexicon is given by

$$CosSim_{ij,t} = V_{it} \times V_{jt} \tag{2.2}$$

[7] IRFS (International Financial Reporting Standards, IAS (International Accounting Standards)

[8] Technically, the cosine similarity is the angle between the characteristic vectors of two neighborhoods or entities

Where $V_{it} = \frac{\text{Tf-IIDf}_{it}}{||\text{Tf-IIDf}_i||}$ is the normalized term frequency-inverse incremental document frequency of bank i.

To obtain a continuous score for each bank, in particular for banks designed as systemically important banks, the normalized *tfiidf* score is mapped rather to the aggregate *tfiidf* score of banks in the training set. To do so, let's define by $\overline{V}_{t,Training}$ the aggregation based on equally-weighted average of the normalized *tfiidf* score.

$$V_{t,Training} = \frac{\overline{\text{Tf-IIDf}}_t}{||\overline{\text{Tf-IIDf}}||} \tag{2.3}$$

where $\overline{\text{Tf-IIDf}}_t$ is the average value of $\text{Tf-IIDf}_{i,t}$ across all banks in the training set for year t and $\overline{\text{Tf-IIDf}}$ its vector representation. Finally, the cosine similarity of a bank i is given by

$$CosSim_{i,t} = V_{it}.V_{t,Training} \tag{2.4}$$

Besides, note that as the $TfIIDf$ is nonnegative therefore the cosine similarity ranges from 0 to 1. In particular, an increase in the cosine similarity[9] metric means that banks are more likely to engage in shadow banking activity. Yet, there is a caveat to keep in mind regarding the cosine similarity approach. There is no perfect score, meaning it is hard to obtain a measure of cosine similarity close to one. In the appendix, figure A.14 paints the histogram of the shadow banking index across banks and figure A.15 provides the aggregate evolution over time.

2.3.4 Validating the Shadow banking Index

Thus far the objective has been to produce an index of shadow banking activity. In this section, the paper provides external validations of the index via two mechanisms : Regulatory arbitrage and income diversity.

2.3.4.1 Regulatory arbitrage

In the first validation exercise, the paper shows whether the shadow banking index is related to regulatory arbitrage. Indeed, risk-taking in traditional banking is constrained by simple regulations. However, there is a regulatory arbitrage when these regulations become not only stringent but also imperfectly enforced across the banking sector. At the end the banks take advantage of these regulations. The paper provides insight on this mechanism by visualizing how the shadow banking index moves over periods of significant change in the regulatory regime. In particular, a commonly used regulatory constraint is the required level of equity that banks must hold to back their risky assets so called the risk-weighted capital requirements (*Tier1 Capital*). The latter imposes minimum levels of capital ("skin in the game") that banks should hold as a fraction of their risk-weighted assets. Figure (A.16) paints the link between the Tier1 ratio

[9] From the perspective of network approach, the cosine similarity metric can be considered as a similarity-based network property.

and the shadow banking index in two different regulatory capital regimes: a looser regime where the minimum capital is set to 4% and a tighter regulatory regime with a minimum capital set to 8.5%. In fact, after the 2008 crisis, the Basel capital regulation guidelines became stringent. The rules have doubled the minimal capital ratio, and directed banks to hold excess capital as conservation and countercyclical buffers above the minimum. Concretely, the Tier1 capital increased from 4% to 6% of risk-weighted assets at all times. In addition a Tier 1 capital conservation buffer[10] of 2.5% was set and has to be maintained at all times, bringing the total requirement to 8.5%. Banks that fall below this threshold will be constrained in their ability to distribute earnings. The graph below shows the spillover effect of change in the minimum capital requirement on banks' shadow banking activity. At the cross-sectional level, there is a mixed relation between the Tier1 capital and the shadow banking index across two regulatory regimes.

[Figure A.16 about here]

On the one hand, shadow banking index is relatively small for all banks in the looser regulatory regime. In addition, there is a positive link between banks' capital requirements and the shadow banking activity. The reason for this positive relationship is that banks with high regulatory capital potentially put to risk their capital. Consequently, they increase their exposition to unregulated activity. On the other hand, the passage of a minimum capital ratio from 4% to 8.5% reshapes the financial landscape and offers the opportunity to observe the structural evolution of banks' shadow banking exposure. We observe that the shadow banking index increases a lot for all banks during the tighter regulatory regime. This pattern arises because of the additional regulatory capital. However, there is a reverse in the slope. In fact, the more banks are close to the minimum capital requirement, the further their shadow banking indexes rise. Put differently, banks near the minimum capital requirement transfer their risks in non-regulated activity for risk-sharing. As a result, those banks increase their activity outside regulatory umbrella.

To test the above relations more formally, the shadow banking index is regressed on the regulatory capital, controlling for fixed bank and year effects. The results are reported in Table (A.13).

[Table (A.13) here]

In all specifications (1) and (2), the shadow banking index is negatively linked to the regulatory capital ratio. The result in (2) shows that a 1 pp drop in the regulatory capital is associated with 0.29 pp increase in the shadow banking index. This suggest that banks are more likely to risk shift in the shadow banking when their regulatory risk-based capitals constraint become binding. This finding provides support of the regulatory arbitrage as a source of risk-shifting incentive.

[10] The capital conservation buffer is designed to be used in times of crisis.

2.3.4.2 Income diversity

Another explanation of a potential shit to the shadow banking activity is bank's portfolio diversification strategy. In fact, Wagner (2010), Wagner (2011) and Allen et al. (2012) argue that portfolio diversification may potentially lead them to provide intermediation outside the regulatory umbrella. Using this insight, the paper investigates if a bank's income diversification strategy into core (interest income) and non-core (non-interest income) business is positively related to the shadow banking index. Table (A.14) reports the empirical connection between bank's shadow banking index and its income diversity. Column (1) demonstrates the regression result with only bank fixed effect while column (2) controls both for bank and time fixed effect variables. As demonstrated, different specifications yield consistent results, with the R^2 improving slightly by the inclusion of more controlling factors (On average, the R^2 with only bank fixed effect is just 0.41 , and the R^2 with both bank and time fixed effects is 0.60). All regressors are significant and falls below the 5% significance threshold.

[Table (A.14) here]

In all specifications, the coefficients of income diversity are positive and statistically significant, suggesting that an increase in income diversity leads to a higher the shadow banking index. In specification (2), the coefficient of the income diversity is 0.047 with a standard error of 0.014. This suggests that a 10 pp increase in bank's is income diversity is associated with 47pp increase of its shadow banking index. This finding is consistent with the idea that bank's portfolio diversification increases common shock likelihood. Regarding the size of banks, one can see that the log of assets is significant for all specifications. The positive sign on log of assets suggests the size of bank may increase its similarity with other banks to activity outside regulatory sight.

After the textual-based index passes these initial validation checks, the paper investigates in the next section its implication on bank-level portfolio riskiness.

2.4 Shadow banking activity and Portfolio riskiness

Thus far, this paper provides a text-based measure capturing shadow banking activity from regulated banks. This section investigates the empirical relation between shadow banking activity and bank portfolio risk metrics, including bank level idiosyncratic risk and systemic risk.

2.4.1 Measuring idiosyncratic and systemic risk metrics

A broad set of variables are used in the financial literature to capture different aspects of banks' exposure to systemic risk. This exposure can arise through two fundamental channels.

First, banks can be thought as *risk-recipients*. As such their exposure to systemic risk can be measured with the Marginal expected shortfall (MES). The latter is developed by Acharya et al. (2017). Specifically, the MES measures co-movement between an individual bank and the rest of the banking sector based on the drop in the market return conditional on a sector-wide downturn.

Letting R be the daily index return of the aggregate banking sector or the overall economy and r_i be the daily (log) stock return of bank i; the marginal expected shortfall at risk level of $\alpha\%$ is measure as follows:

$$MES_{i,\alpha} = -E\left[r_i | R \leq -VaR(\alpha)\right] \tag{2.5}$$

where the value at risk (VaR) is the most that the system loses with confidence $1-\alpha$, that is, $P(R < -VaR(\alpha)) = \alpha$.
Conceptually, the MES estimation follows two steps. In the first step the $\alpha\%$ worst days for the market returns ($VaR(\alpha)$) in a given year is computed using an estimation window size of 260 trading days. For that purpose a non-parametric approach is used to compute the distribution of the market return and calculate the ($VaR(\alpha)$) of the market. In the second step, an equal-weighted average return r_i on bank i is computed for the days were the market is in it $VaR(\alpha)$. Thus, the bank level systemic risk is given by:

$$MES_{i,t,\alpha} = \frac{1}{\#days}\sum_{d \in I} r_{i,d}, \quad \text{I=\{Stock Market in its 5\% tail in a given year t\}} \tag{2.6}$$

The system is compute as the index of S&P/TSX composite banks Index return.

Second, the bank is considered as *risk-inducer* and its contribution to systemic risk is measured following Adrian and Brunnermeier (2016). In this case, the systemic risk of bank is measured as the change in its conditional value at risk ($\Delta CoVaR$). $\Delta CoVaR$, defined as the difference between the $CoVaR$ conditional on the distress of an institution and the CoVaR conditional on the normal state of the institution, measures the marginal contribution of an institution to the overall systemic risk. The CoVaR is the conditional value at risk of the financial system. Specifically the calculation is as follows:

First, a quantile regressions of market returns on individual bank returns is applied:

$$r_{mt} = \alpha_{system|i} + \beta_{system|i} r_{it} + \epsilon_{it} \tag{2.7}$$

where r_{it} is the weekly stock returns of bank i, and r_{mt} is the weekly market returns. Then CoVaR is defined as the predicted value from the quantile regressions:

$$CoVaR = \hat{\alpha}^q_{system|i} + \hat{\beta}^q_{system|i} VaR^q_{it} \tag{2.8}$$

where VaR^q_{it} is the q percentile value at risk of bank i at time t which directly from its past equity returns using one-year rolling windows. In the second step, the $\Delta CoVaR$ is computed as the difference between the CoVaR conditional on the distress of an institution i ($q = 5\%$, that is, using the worst 5% financial system returns in the quantile regression) and CoVaR conditional on the normal state of the institution ($q = 50\%$). According to the above definition, $\Delta CoVaR$ can be written as

$$\Delta CoVaR_{it}^{5\%} = CoVaR_{it}^{5\%} - CoVaR_{it}^{50\%} \tag{2.9}$$

The $\Delta CoVaR$ is estimated at weekly frequency. To merge them with all other variables included in the analysis, the resulting estimates are collapsed to yearly frequency by taking averages.

The summary statistics for the different systemic risk measures described above is presented in the appendix (see Table (A.12)). The mean and the median of the $\Delta CoVaR$ (5.35% and 5.045%) are higher than the one of the MES (1.47% and 1.12%). Besides, these measures also account for episodes of high financial fragility that did not necessarily result in a crisis. Larger values of $\Delta CoVaR$ and MES correspond to a higher systemic risk contribution.

To measure bank's idiosyncratic risk, the paper utilizes bank's distance to insolvency captures by the Z-Score. The latter was developed by Laeven and Levine (2007) and defined as the probability that bank's losses exceed its capital. More precisely, the Z-score is defined as the ratio between a bank's buffer (Return on Assets (ROA) + Capital-Asset-Ratio (CAR)) and its stock return volatility.

$$Z - score = \frac{ROA + CAR}{\sigma_r} \tag{2.10}$$

2.4.2 Main Empirical Results

In this section, the paper proceeds by regressing the portfolio risk metrics on the shadow banking index while controlling for several bank-specific variables.

$$\text{Portfolio Risk}_{it} = \beta_1 + \beta_2 \text{Shadow banking Index}_{it} + \beta_3 Z_{it} + \upsilon_i + \mu_t + \epsilon_{it} \tag{2.11}$$

Where Z_{it} captures bank balance sheet information. The estimation contains a set of fixed effects to control for unobserved heterogeneity such as banks idiosyncratic characteristics captured by υ_i and μ_t which refers to change in economic environment. Finally, the variable ϵ_{it} is the error term with the standard exogeneity assumption.

[Table (A.15) here]

The regression predicts a positive link between bank's shadow banking index and its systemic risk measures. In contrast, this paper finds that bank's size is not significant.

Furthermore, columns (2) and (4) present the estimated when controlling fixed effects for banks and years. These specifications yield consistent results and an improvement in R^2. As shown in column (2), a 10 pp increase in the index is associated with 11.6 pp increases in bank-level systemic risk measured by the MES. The coefficients of log(Asset) are very small and positive but not statistically significant. Also, looking at the relation between shadow banking index and the idiosyncratic risk, column (5) shows a negative and statistically significant correlation.

Also, another property of systemic risk that has gained considerable momentum in theoretical studies[11] (He and Krishnamurthy (2019), Gertler et al. (2020), Paul (2020)) recently. In fact, financial crises are rare events. They are usually preceded by prolonged boom periods and a buildup of financial fragility. When booms go bust, a deep economic contraction follows. Thus, a valid concern is whether the impact[12] of the shadow banking index on bank-level systemic risk varies across economic states. In this latter regard, the paper runs the benchmark specification on two sub-samples: a pre-crisis sample (1997-2008) and a post-crisis sample (2009-2017). Table A.18 presents the dynamic relation between the shadow banking index and systemic risk conditional to the state of the economy.

[Table (A.18) here]

In particular, when considering banks as risk-takers, column (1) indicates that 10 p.p increases in the shadow banking index is associated with 2.91% p.p in the MES. In the contrary in column (3), a bank's MES decreases by 2.5% p.p when its shadow banking index increases by 10% p.p. These findings suggest a nonlinear dependence of the shadow banking index and systemic risk. The reason for this dichotomy is that risk-shifting to shadow banking tends to strengthen in booms and may weaken in recessions. Specifically, when the sample is restricted to the post-crisis period, the shadow banking index is linked negatively to bank-level systemic risk. This is because shadow banking plays a role of risk-sharing mechanism that shields banks against the fall in their market capitalization in the boom period while this role amplifies shocks during crisis risk.

Though these estimates are correlational rather than causal; they are strongly suggestive and consistent with theories linking the interbank network's effect on financial stability and the non-linearity aspect of financial crises. In the appendix, the paper provides additional robustness checks by looking at other risk transmission mechanisms such as asset commonality, loan commonality, and changes in the training set. Overall, these findings have important implications for how regulation should address systemic risk concerns.

2.5 A model of Risk-Shifting

In this section, the paper provides a framework to study bank's risk-shifting behavior and proposes a normative analysis for regulation design.

[11] Non linearity is captured in these works by occasionally binding constraint, precautionary saving motive and bank runs

[12] The theoretical literature on shadow banking articulates two views: A positive view that consider this activity as an innovation and a negative view that consider the activity as a nuisance.

2.5.1 Setting

Consider an economy with a banking sector and three types of agents: A representative household, a set of $N = \{1, ..., n\}$ heterogeneous banks and a social planner. Each bank intermediates credits but finance them using different liabilities[13] and may face or not a regulator contract. Moreover, the financial market subsumes an traditional banking sector and a shadow banking sector (trading/capital market). Finally, the planner objective is to maximize the welfare of the representative household net of any social costs of financial distress.

The timing of the model is as follows: There are two dates $t = 0, 1$. All agents make their decisions at $t = 0$ and investments pay off at $t = 1$. In the interim date between $t = 0$ and $t = 1$, news about the aggregate economic state of the world arrives. News can be either good(no crisis risk) or bad(crisis risk). In crisis period bank can default on debt with probability p and debt-holder take the downside risk but not equity holder.

2.5.1.1 Household

The representative household is endowed with Y unit of capital at time 0 and has preference over consumption(C). She is risk-averse and would like to smooth her consumption across periods. However, the household does not have direct access to investment projects because she is less efficient in searching, evaluating, and monitoring them[14]. As a less sophisticated investor, the household faces limited financial market participation and therefore invests in bank i' s deposits D_i as well as bank's equity E_i. Holding a bank's equity yield a stochastic gross return R_i^e while a bank's deposit yields a risk-free gross return R^d. Finally, the household's claims deliver $\beta < 1$ unit of utility from expected future consumption C_1. The corresponding household's problem is as follows.

$$\max_{C_0,C_1,D_i,E_i} U(C_0) + \mathbb{E}\left[\beta U(C_1)\right] \quad \text{s.t.} \tag{2.12}$$

$$C_0 + \sum_{i=1}^{N} D_i + \sum_{i=1}^{N} E_i = Y \tag{2.13}$$

$$C_1 = \sum_{i=1}^{N} R_i^e E_i + \sum_{i=1}^{N} R D_i \tag{2.14}$$

[13] Let's recall that in this model, the shareholder claim reflecting limited liability is rule-out. This is because, household is both debt holder and shareholder.

[14] This assumption akin to the intermediaries asset pricing literature which assumes that the marginal investor in the financial market is only banks. See He and Krishnamurthy (2013), He et al. (2017), Adrian et al. (2014)

2.5.1.2 Banks and Financial markets

Banks are highly sophisticated investors. It is assumed that, unlike the household, the banks do not derive utility from consumption, but from their "*reputation*". More precisely, a bank's reputation can be considered as the return on equity delivering to the household. Thus, each bank manages an intermediary financial technology intending to maximize its equity value. Banks' portfolio choices in the financial market at time $t = 0$ is captured as follows.

Traditional banking (TB): There is $K_1, ..., K_N$ aggregate capital in the economy that yields a stochastic return R^k at time $t = 1$ for every unit of investment at time $t = 0$. The distribution of R^k is denoted by F, with mean μ, standard deviation σ_k. Each bank$i$ finance the aggregate capital K_i .

Shadow banking (SB): In this sector, banks can transform their asset into securities which are marked by the capital market. More precisely, bank $i's$ asset can be slice into two tranches, where a share λ^s can be traded with a different risk pricing kernel because the sector is less regulated or unregulated. Since the financial markets are segmented, the regulator can faces a moral hazard problem. where each bank can takes excessive risks in this sector at his expense. Finally, bank i's net worth a time 0 is

$$\hat{E}_i = \underbrace{(1-\lambda_i^s)K_iR^k}_{\text{TB profit}} + \underbrace{\lambda_i^s K_i R^s}_{\text{SB profit}} - \underbrace{R^d D_i}_{\text{Deposit cost}} \tag{2.15}$$

In the above equation, the first expression captures the retail banking sector profit while the second expression captures the bank's profit from risk-shifting sector. Also, assets in the risk-shifting sector yield a return R^s which follow a distribution G independent of F, with mean μ_s ($\mu_s > \mu_k$) and standard deviation $\sigma_s(\sigma_s > \sigma_k)$.

Proposition 1. From bank's balance sheet condition and the evolution of their net worth (2.15)*, the equity return of each bank is given by*

$$R_i^e = (R^k - R^d)\underbrace{(1-\lambda_i^s)\frac{K_i}{E_i}}_{\text{TB leverage}} + (R^s - R^d)\underbrace{\lambda_i^s\frac{K_i}{E_i}}_{\text{SB leverage}} + R^d$$

Looking at the proposition, the first term on the right-hand side shows how the bank can use leverage to amplify its return on net worth whenever the return on its assets exceeds the deposit rate. The second term indicates the reallocation effect of imperfect risk regulation. It is captured by the leverage on security times the excess return on a security.

$$\tilde{R}_i^e = (R^k - R^d)(1-\lambda_i^s)\frac{K_i}{E_i} + (R^s - R^d)\lambda_i^s\frac{K_i}{E_i} + R^d \tag{2.16}$$

Default: At time 0.5, there is an interim news event about the future economic state. In a crisis risk state, banks can default on their debt in which case debt holder receives zero. However, equity holder receive the residual banks' equity value during the crisis state.

$$R^d = \begin{cases} 0 & \text{with probability p} \\ R & \text{otherwise} \end{cases}$$

Thus, with the possibility of default on debt, banks can shift risk by searching for yield through equity return. To see this mechanism let's consider the expected return on equity using equation(2.24).

$$\mathbb{E}(\tilde{R}_i^e) = \frac{K_i}{E_i}[(1-\lambda_i^s)(\mathbb{E}(R^k) - R) + \lambda_i^s(\mathbb{E}(R^s) - R)] + pR$$

$$\frac{\partial \mathbb{E}(\tilde{R}_i^e)}{\partial p} = R \tag{2.17}$$

Equation(2.17) shows that the expected equity return is positively correlated with the probability of default on debt. This result implies that banks will have an incentive to shift risk in favor of the equity holder.

Finally, banks are risk-adverse and each one solves a simple mean-variance objective over R_i^e.

$$\max_{\lambda_i^s} \quad \mathbb{E}(R_i^e) - \frac{\gamma_i}{2} Var(R_i^e) \tag{2.18}$$

where $\gamma_i > 0$ parametrizes the constant relative risk aversion of the bank.

2.5.2 Equilibrium

2.5.2.1 Laissez-faire equilibrium with risk reallocation

In this section, the focus in on a bank's risk-shifting choice. The equilibrium is defined as follows.

Definition 1(Risk-shifting equilibrium). An equilibrium consists of prices $\{R^k, R^s, R\}$, assets holding decision of the representative household $\{E_i, D_i\}_{i=1...N}$ and banks' risk-shifting decision λ^s, such that given prices

i) The representative household solves the problem as described by (2.12)
ii) Banks solve the problem as described by (2.18)
iii) Market clears

Given the inter-temporal preferences of household over consumption, the optimal consumption path related equity investment decision satisfies

$$U'(C_0) = \mathbb{E}\left[\beta R_i^e \, U'(C_1)\right] \qquad for \quad i \in 1...N$$

This condition describes the Euler equation for equity holding. It states that the cost of reducing consumption today is equal to the expected value of reallocating consumption to the next period times the capital gain as an equity holder. A similar equation holds for deposit position.

In equilibrium, bank i's risk-shifting position affects R_i^e and the future consumption it delivers to the household. Due to banks' crucial role in this framework, the solution of the model revolves around equation (**??**).

Proposition 2. *Given bank's problem* (2.18)*, the optimal risk-shifting strategy* λ_i^s *satisfies:*

$$\underbrace{\frac{\mathbb{E}(R^k - R^d)}{\sigma_k} - \frac{\sigma_s}{\sigma_k}\frac{\mathbb{E}(R^s - R^d)}{\sigma_s}}_{\text{Cross-sector arbitrage}} = \underbrace{\frac{K_i}{E_i}\sigma_k\left[1 - \lambda_i^s\left(\frac{\sigma_s}{\sigma_k}\right)^2 - \lambda_i^s\right]\gamma_i}_{\text{Portfolio riskiness}} \tag{2.19}$$

Optimality requires that bank i chooses λ_i^s such that the cross-sector arbitrage opportunity is equal to the riskiness of its portfolio times the risk aversion of γ_i. In particular, the proposition determines how much banks adjust their risk-shifting decisions to the cross-sector arbitrage opportunity. The left-hand side (LHS) of equation (2.22) is the difference between sectoral Sharpe-ratios. The latter is defined as the risk premium on an investment divided by its risk. The right-hand side (RHS) describes the riskiness of a bank's portfolio is captured by terms relative to regulation, leverage, and sectoral risks.

Besides, the relation in equation (2.22) deviates from the traditional result of the Capital asset pricing model (CAPM)[15]. Indeed, this equation implies that banks could bear less risk on their portfolio holding constant γ_i, while the equilibrium Sharpe ratio in a sector rises. As a result, banks could take more risk in both sectors, leading to excessive risk-taking in the financial system. Thus, risk-shifting might be less desirable from a social planner's perspective, whose objective is to curb excessive risk-taking in the financial system.

2.5.2.2 Equilibrium with regulatory capital constraint

Let's consider now that banks face an equity capital constraint in the retail banking sector that constraint their investment opportunity. This constraint is model as follow:

$$E_{it} \leq \hat{E}_{it} \tag{2.20}$$

The capital constraint states that each banker i should holds equity up to the bank capital capacity $\hat{E}_{it}$ and the rest of banker fund is raised through debt financing. Under this constraint, a banker's problem becomes

[15] The CAPM model states that if agents bear more risk in its portfolio and/or has a higher risk aversion, the equilibrium Sharpe ratio rises. The reason is that, in the CAPM, the agent holds the market portfolio, which does not permit arbitrage opportunity.

$$\begin{array}{ll} \max\limits_{\lambda_i^s} & \mathbb{E}(R_i^e) - \frac{\gamma_i}{2} Var(R_i^e) \\ \text{s.t.} & \\ & E_{it} \leq \hat{E}_{it} \end{array} \tag{2.21}$$

The optimality condition for risk-shifting is given by the following proposition.

Proposition 3. Given bank's problem (2.25) and the Lagrangian multiplier($\mu \geq 0$), the optimal risk-shifting strategy λ_i^s satisfies:

$$\underbrace{\frac{\mathbb{E}(R^k - R)}{\sigma_k} - \frac{\sigma_s}{\sigma_k}\frac{\mathbb{E}(R^s - R)}{\sigma_s}}_{\text{Cross-sector arbitrage}} + \mu \underbrace{\frac{K_i(R^s - R^d)}{\sigma^s}}_{\geq 0} = \underbrace{\frac{K_i}{E_i}\sigma_k \left[1 - \lambda_i^s \left(\frac{\sigma_s}{\sigma_k}\right)^2 - \lambda_i^s\right]\gamma_i}_{\text{Portfolio riskiness}} \tag{2.22}$$

If we look at the first-order condition, if regulatory capital constraint didn't bind ($\mu = 0$), we would have an equilibrium similar to the laissez-faire equilibrium. If the constraint binds ($\mu > 0$), the portfolio riskiness is equal to the cross-sector arbitrage plus an additional positive term representing the shadow price of relaxing the capital constraint. Under the regulatory capital constraint, risk-shifting is not reduced, and bankers still take on more risk.

2.5.3 Optimal regulation and welfare

In this section, I study optimal regulation in the presence of risk-shifting and the associated welfare. Indeed, the social planner faces three sources of market inefficiency. First, the risk mispricing across banking sectors leading to an increase in risk-shifting. Second, potential financial market disruption and the ex-post cost of the financial market bailout. Finally, the deadweight costs of crisis risk on household's consumption in period $t = 1$. Aside from the first source, the two other sources of inefficiency are well established in the literature. Overall, these sources of inefficiency provide an argument for social planner's intervention. Like banks, the planner is constraint. He knows the probability distribution of shocks G and F, but not their realizations. However, unlike banks, the constrained planner internalizes aggregate asset fire sales on bank's equity. Additionally, the planner can set some risk management tools affecting agents' asset positions and ensuring that reallocation of resources leads to a Pareto improvement in the economy. Thus, the focus in this section is on the first[16] source of inefficiency and the focal point of policy intervention is on banks' risk-shifting positions.

To achieve an equilibrium with a less risk-shifting strategy, the social planner should target cross-sector arbitrage. This intervention can be thought of as an activity-based regulation that implies a consistent risk pricing across sectors and subsequently providing a no-arbitrage condition. The following equation defines this no-arbitrage condition

$$\frac{\mathbb{E}(R^k - R)}{\sigma_k} = \frac{\mathbb{E}(R^s - R)}{\sigma_s} \tag{2.23}$$

[16] Intervention at the first source of inefficiency accounts for a prudential policy.

.

It is worth noting that equation(2.23) is reminiscent of the Arbitrage Pricing Theory[17](APT) where asset risk premiums should be "consistent", in that they can be derived from a single risk premia. By keeping sectoral Sharpe-ratios the same via an activity regulation, the social planner could affect banks' investment decisions and limit risk-shifting. Let's define by τ a tax set to regulate an activity rather than regulating banker's capital. For simplicity, let's consider τ, the activity-based tax of the traditional banking sector relative to the activity-based tax of the shadow banking sector.

$$\tilde{R}_i^e = (R^k - R^d)(1-\lambda_i^s)\frac{K_i}{E_i} + \tau(R^s - R^d)\lambda_i^s\frac{K}{E_i} + R^d \tag{2.24}$$

The planner solves the following program

$$\begin{aligned} \max_{\lambda_i^s} \quad & \mathbb{E}(R_i^e) - \tfrac{\gamma_i}{2}Var(R_i^e) \\ \text{s.t.} \quad & \tilde{R}_i^e = (R^k - R^d)(1-\lambda_i^s)\tfrac{K_i}{E_i} + \tau(R^s - R^d)\lambda_i^s\tfrac{K_i}{E_i} + R^d \\ & \tfrac{\mathbb{E}(R^k - R)}{\sigma_k} = \tfrac{\mathbb{E}(R^s - R)}{\sigma_s} \end{aligned} \tag{2.25}$$

The optimal tax τ^* satisfied

$$\tau^* = \frac{\sigma_k}{\sigma_s} \tag{2.26}$$

Intuitively, the social planner sets the optimal tax τ in a way to put back the risk-pricing of the traditional banking sector into the shadow banking sector and vice versa. This tax allows the planner to narrow the gap between asset prices and their fundamentals. The next result characterizes the bank's risk-shifting position under the no-arbitrage condition.

Corollary 1. Under the no-arbitrage condition: i) the optimal risk-shifting strategy $\hat{\lambda}_i^s$ is given by

$$\hat{\lambda}_i^s = \frac{\sigma_k^2}{\sigma_k^2 + \sigma_s^2} \tag{2.27}$$

ii) There exist an equilibrium outcome where banks are indifferent toward risk-shifting.

The results above are intuitive. Under the no-arbitrage condition, the risk is consistently priced across sectors, and banks face a tradeoff. While banks may be willing to trade their risk away in another sector ($\frac{\partial \hat{\lambda}_i^s}{\partial \sigma_k} > 0$), they may find less attractive to do so. The reason is to do with the additional risk-premia their portfolios have to bear

[17] Unlike the CAPM which assumes only one factor model, the ATP allows a risk pricing with multiple factors.

($\frac{\partial \hat{\lambda}_i^s}{\partial \sigma_s} < 0$). As a result, there exists an equilibrium outcome where banks are indifferent to systemic risk-shifting under the no-arbitrage condition.

On top of its effect on the market-wide risk, the activity-based regulation prevents banks from excessive risk-shifting and might imply a scope of welfare improvement. To see that, the welfare under the equilibrium allocation is compared to one of the no-arbitrage opportunity allocations. To this end, the paper builds on Gromb and Vayanos (2002) welfare evaluation procedure[18].

Suppose that the social planner can change banks' date-0 risk-shifting choices from their equilibrium value by affecting the market arbitrage opportunity through the activity-based regulation. The planner affects only the risk-shifting positions and lets the market determines all other(debt and equity holders) positions and prices. As a result, the social planner might reduce or increase the cross-market arbitrage position and might achieve a Pareto improvement for household consumption in the next period. Formally, the welfare evaluation can be implement as follow: First, date-0 risk-shifting positions, $\lambda^s = (\lambda_1^s, \lambda_2^s, ..., \lambda_N^s)$ are treated as exogenous parameters. Broadly speaking, the purpose of this ex-ante intervention is to mitigate excessive risk-shifting in period 0. Second, for each value of λ_i^s, a "λ^s *equilibrium*" is defined by adding to *Definition 1* the requirement that a bank's position at date-0 be λ_i^s. Finally, the household expected utility over consumption in this "λ^s *equilibrium*" is computed, and the derivative at the value of λ^s that corresponds to the original equilibrium is evaluated. Whether λ^s involves a desirable level of risk-shifting depends on the derivative sign.

Since the bankers do not consume, the social planner maximizes date-1 welfare function $W(\lambda^s)$ of the representative household defines below, subject to the resource constraints of the economy in equations (2.14) and (2.24). This welfare function corresponds to one of the crisis periods.

$$W(\lambda^s) = \mathbb{E}\left[U(C_1)\right]$$

The benefit involved in affecting ex-ante the arbitrage positions is discussed by examining the derivative of the welfare function with respect to λ_i^s

$$\frac{\partial W(\lambda^s)}{\partial \lambda_i^s} = \mathbb{E}\left[\left\{(R^s - R^d) - (R^k - R^d)\right\}\lambda_i \frac{K_i}{E_i} U'(C_1)\right] \quad (2.28)$$

A change in λ_i^s has a direct effect on bank i's reputation, meaning the capital gain it must deliver to household. Changing λ_i^s changes this capital gain by $\left\{(R^s - R^d) - (R^k - R^d)\right\}$. Therefore, household's consumption at date-1 changes by that amount. The resulting change in expected utility is the expectation, with respect to the capital gain, leverage and the marginal utility of consumption of date-1. Moreover, depending on the sign of $\left\{(R^s - R^d) - (R^k - R)\right\}$, the arbitrage positions of banks from date-0 may fail to be

[18] Gromb and Vayanos (2002) show that while arbitrage activity is Pareto improving, arbitrageurs might fail to take a socially optimal level of risk.

socially optimal given that their positions sometimes involve too much and sometimes too little risk-shifting, and hence a consumption risk for household especially during a crisis risk state. Thus, to illustrate the effect of the activity-based supervision on household's welfare, the paper performs a comparative static to establish a monotonicity of the equilibrium risk-shifting with respect to the policy parameter τ. The following result is obtained

Proposition 3. The welfare sensitivity to the equilibrium risk-shifting strategy is decreasing under the activity-based regulation (τ).

Proof: This result is a direct consequence of the observation that under the no-arbitrage condition from equation (2.23), the derivative with respect to the risk-shifting equilibrium of the date-1 welfare $W(\lambda^s)$ is now given by

$$\frac{\partial W(\lambda^s)}{\partial \lambda_i^s} = \mathbb{E}\left[\left\{(R^k - R^d)(\frac{1}{\tau} - 1) - \phi\right\}\lambda_i \frac{K}{E_i} U^{'}(C_1)\right]$$

Next taking the derivative with respect to τ yields

$$\frac{\partial^2 W(\lambda^s)}{\partial \tau \partial \lambda_i^s} = -\mathbb{E}\left[\left\{\frac{(R^k - R^d)}{\tau^2}\right\}\lambda_i \frac{K_i}{E_i} U^{'}(C_1)\right]$$

$$\frac{\partial^2 W(\lambda^s)}{\partial \tau \partial \lambda_i^s} < 0 \tag{2.29}$$

The result above shows that the equilibrium risk-shifting is decreasing in the activity-based supervision τ. Regulating activities limit banks temptation to shift their risk across sectors which limit bank's excessive risk taking and reduces the household's risk bearing cost ex-post. Furthermore, such ex ante policy intervention may reduce financial market bailout or untargeted policies ex post during crisis risk.

2.6 Conclusion

The 2008 financial crisis has led to an increased interest in banks' business models, financial shock propagation, and regulations design to contain systemic risk. Since this crisis, the financial landscape has changed profoundly, with more banks engaging in risk-shifting behavior toward lightly regulated or unregulated financial intermediaries and networking outside the regulatory umbrella. Imperfect risk enforcement provides an incentive for such risk-shifting behavior. The present paper contributes both empirically and theoretically to the literature on banks' risk-shifting actions. Despite extensive studies on risk-shifting sources, little has been done looking into the contribution of banks' risk-shifting behaviors on systemic risk. This paper provides a computational linguistic-based approach to such risk-shifting behavior and empirically finds a non-linear relationship between the risk-shifting behavior and systemic risk at the bank level.

Moreover, this paper models banks' risk-shifting decisions depending upon imperfect risk pricing across financial sectors. From this perspective, our approach is compatible with the idea that financial intermediaries can take arbitrage positions by participating in several banking activities or asset classes where the risk pricing differs. The theoretical model shows that regulator intervention that achieves a no-arbitrage condition in the market by targeting Sharpe ratios can reduce risk-shifting behavior and welfare improvement.

Besides, in the ongoing COVID-19 crisis, central banks have shielded financial institutions from the pandemic's full cost and became a market-maker of last resort. However, central banks' involvement in providing liquidity to new markets could shift the risk perception in the future and distort future behavior by banks. In particular, the moral hazard problem could emerge when banks may have incentives for risk-shifting toward new markets. Consequently, new regulator oversights are needed, and the activity-based rule proposed in this paper may fit into the context of the post-COVID-19 crisis. It is clear that banks' industrial organization is vital to identify the buildup of risk and regulation design. There are some avenues for future research. For instance, studying the centrality, the concentration, and the sparsity of a holdings-based banking network and their implications on systematic risk reflected in equilibrium asset prices is an exciting agenda for future research.

Chapter 3

Carbon risk and the macroeconomy

3.1 Motivation

What are the effects of carbon shocks on the economy? The production process of firms depends heavily on carbon. Yet, the impact of unexpected changes in carbon on economic activity is currently unknown and has received much less attention in academia[0]. The main reason for this inattention stems from the measurement issues relative to carbon footprint at the firm level. In particular, most of the emissions occur outside the firm making it challenging to analyze the effect of carbon risks on the economy. This paper fills the gap using a consumption-based carbon emissions approach. Specifically, this approach measures carbon emissions at the point of consumption, attributing all the emissions in production and distribution to the final consumers of goods and services. The main benefit of the consumption-based approach is that it measures carbon emissions in a given boundary (city, county, state, country) and therefore can account for potential carbon leakages (Jakob et al. (2014), Franzen and Mader (2018)).

The contribution of this paper is twofold. First, this paper builds novel data by combining carbon footprint information from the Economic Input-Output Life Cycle Assessment and household consumption data from the Bureau Economic Analysis (BEA). More precisely, we tie carbon emissions to household consumption. Indeed, households stand at the end of the life cycle of goods and services produced in the economy. As such, carbon emissions embodied in households' consumption appear to be good candidates to assess the nexus between carbon risk and the macroeconomy.

Second, we implement our research question building on a growth model adapted

[0] A survey conducted by the Bank of International Settlement in April 2020 states that climate physical risk and transition risk could have a systemic risk implication to the economy(https://www.bis.org/bcbs/publ/d502.pdf).

Another report of the European Systemic Risk Board shows that the transition to a low-carbon economy could affect systemic risk through two channels. First, a sudden transition away from fossil-fuel energy could harm GDP, as alternative sources of energy would be restricted in supply and more expensive at the margin. Second, there could be a sudden repricing of carbon-intensive assets, which are financed in large part by debt (https://www.esrb.europa.eu/pub/pdf/asc/Reports$_A SC_{61}602.pdf$)

to a setting with a dirty sector that intensively used carbon and, a labor intermediate input (Gerlagh (2008), Acemoglu et al. (2016), Fried (2018)). We extend this model by considering an economy of multiple states with similar production technology but facing different exposures to the dirty sector. Moreover, we argue that there is dependence across the states. Such dependence can arise from common factors such as trade linkage, financial integration, and exposures to common shocks. Owing to this dependence, the impact of carbon shock in one state can spill over to another state and subsequently create a contagion mechanism. This pattern can lead to a systemic carbon risk and might be amplified by the climate transition policy. To capture such dependence, the paper relies on the Cross-sectional Autoregressive Distributed Lag (CS-ARDL) estimation strategy. Specifically, the CS-ARDL accounts for three key features of the data: dynamics, heterogeneity, and cross-sectional dependence. Armed with the CS-ARDL approach, we find that one unit decrease in the consumption-based carbon emissions is associated, in the long run, with lower per capita log output growth of 4.5 percentage points. Furthermore, we show that our empirical findings do not apply equally to the top 25%, and the bottom 25% per capita income states. In addition, our study sheds light on the impact of carbon emissions on temperature at the state level. Indeed, we find evidence of positive lag effect of consumption based-carbon emissions on the deviation of temperature from its historical norm over the past 30 years $(1988-2018)$. The lag effects is consistent with the climate econometrics (Hsiang (2016)). To the best of our knowledge this is the first paper to provide empirical estimates of the relation between carbon emissions and temperature deviation.

Related literature

This paper contributes to the growing literature on climate-economy and climate-finance that analyzes the physical risk and transition risk aspects of climate change. There is growing research on how physical climate shocks affect the economic growth (Dell et al. (2012), Dell et al. (2014), Kahn et al. (2019), Hsiang (2016), Jones and Olken (2010), Colacito et al. (2019)), innovations in quantitative general equilibrium models of climate change (Nordhaus et al. (1992), Nordhaus and Boyer (2000), Gerlagh (2008), Acemoglu et al. (2016), Fried (2018)),and adaptations (Barreca et al. (2016), Gourio and Fries (2020)). For instance, Kahn et al. (2019) study the long-term impact of climate change on economic activity across countries, using a stochastic growth model where labor productivity is affected by country-specific climate variables defined as deviations of temperature and precipitation from their historical norms. Acemoglu et al. (2016) develop an endogenous growth model in which clean and dirty technologies compete in production. They show that if dirty technologies are more advanced, the transition to clean technology can be difficult. Our paper differs from the studies above by accounting for the systemic implication of climate shocks.

While there are substantial empirical works on the physical risk, studies on the transition risk are limited. The small existing studies rely on general equilibrium models of climate-economy and calibration exercises (Fried et al. (2020), Baldwin et al. (2020), Bansal et al. (2016)). In these studies, transition risk is very often proxied with climate variables like temperature or precipitation. Other works focus exclusively on the regulatory climate change risks on firms and financial markets (Krueger et al. (2020), Choi et al. (2020), Bolton and Kacperczyk (2020), Brown et al. (2020), De Haas and Popov (2019)). Nonetheless, their approach comes with several shortcomings and cannot capture the real emission due to carbon leakage. For instance, these studies use the Environmental, Social, and Governance (ESG[1]) score as a proxy of firm-level carbon emissions or use emissions embodied in production by the industrial sector. This paper complements all the studies mentioned above using a consumption-based carbon emissions approach.

The rest of the paper is organized as follows. Section 3.2 provides background information on the climate policy, especially the transition to a low carbon economy. Section 3.3 presents the data. Section 3.4 introduces our econometric methodology and discusses the results. Section 3.5 concludes.

3.2 Background

The Paris Agreement in 2015 allowed policymakers to define climate goals and associated policies. One of these goals is to keep the global temperature rise below 2 degrees Celsius. Reaching such goal requires a substantial reduction of the global greenhouse gas emissions or a global transition to a low-carbon economy. To satisfy this requirement, policymakers set a Nationally determined contributions (NDCs) that foresee different decarbonization scenarios. In addition, the NDCs include unconditional and conditional commitments on other countries' actions and/or financial or other assistance types. Figure A.24 below shows different global greenhouse emissions reduction scenarios.

[Figure A.24 here]

For example, the NDCs would result in 53-56 giga tons of CO_2 emissions ($GtCO_2e$) of global emissions in 2030, whereas to keep temperature grown below 2°C of the pre-industrial level, emissions should be less than 40 $GtCO_2e$ by 2030. Also, for a 66% chance of keeping warming below 1.5°C in 2100, emissions in 2030 should not exceed 24 $GtCO_2e$, much less than the NDC projected emissions of 53-56 $GtCO_2e$.

Nevertheless, there is a high uncertainty surrounding the optimal path (timing and speed) of emissions reduction. Part of the reason is due to the long time horizons over which reductions are promised combined with the short-term costs of immediate action. Moreover, models that estimate these carbon costs provided a substantial uncertainty

[1] ESG score evaluate companies and countries on how far advanced they are with sustainability.

over the optimal price. The figure A.24 shows the histogram of the social cost of carbon across models. There are over 200 estimates of the price of carbon from roughly 50 different studies.

[Figure A.24 here]

As a result, whether the shift to a low-carbon economy will be slow, gradual, benign or late, abrupt, and costly are sources of uncertainty. Thus, an understanding of the relationship between carbon emissions and economic growth is critical for any ambitious emissions reduction program, as implied by the Paris Agreement.

3.3 Carbon emissions: Evidence from household consumption

This section presents the carbon emissions from the household consumption perspective. Our analysis combines greenhouse gas emissions data from the Economic Input-Output Life Cycle Assessment (EIO-LCA) with the Bureau Economic Analysis (BEA) data on household aggregate consumption.

3.3.1 Carbon emission factors

The data on carbon emissions is obtained from the EIO-LCA database which estimates the materials and energy resources required for the environmental emissions resulting from different activities. More precisely, the EIO-LCA traces out the various GHG emissions [2] (including all the various manufacturing, transportation, mining, and related requirements) required for producing a particular product or service. Moreover, the EIO-LCA provides the economic transactions of GHG emissions per dollar for each product in 428 sectors. Specifically, the database allows to know the quantity of GHG consumed when purchasing $\$1000K$ of a good produced in a given sector. As households stand at the product usage stage where they control the product, we limit the analysis to household goods. To tie carbon emissions to household consumption, we consider the “2002 model," which uses the input-output table provided by the Bureau of Economic Analysis of the Department of Commerce. Another model, the “2007 model" was developed by US Environmental Protection Agency (EPA) in 2017 and used the official 2007 benchmark input-output table from BEA. The comparison [3] of the 2002-model and the 2007-model reveals no large differences between the life cycle GHG emissions results of the two models. This comparison shows that the emission

[2] Carbon dioxide equivalents are defined as the quantity of carbon dioxide that for a given amount of greenhouse gas or a mixture of greenhouse gas would generate the same global warming potential. The covered GHG are Carbon Dioxide, Methane, Nitrous Oxide, and Fluorinated GHGs.

[3] A Comparison of Methods and Results from the 2007 Benchmark USEEIO model and the 2002 EIO-LCA Model

factor collected is not significantly affected by the change in the year. Therefore, we use the 2002-model uniquely, and we identify fifty production sectors out of the 428 sectors related to household goods and services. Then, we collect carbon footprint information for 28 two-digit household goods produced in these 50 sectors. The complete list of the 28 two-digit goods is provided in appendix A.3.5. These goods can be summarized into 11 consumption categories: food, clothing, housing, furniture, health, transportation, communication, recreation, education, food services and accommodation, financial services and insurances. Figure A.25 above shows the carbon emission factors per millions dollars of goods purchase.

[Figure A.24 here]

3.3.2 Consumption-based carbon emissions

Using BEA data, we collected aggregate information on consumption over the sample period of 1998 to 2018. We then map this aggregate information to the carbon emission factors. Since the carbon emission factors per million dollars are related to 2002 price, we deflate our sample using the 2002 consumer price index. Overall, we covered 28 two-digit good categories out of 44 in the BEA table. This coverage represents 87% of household aggregate consumption. For a given consumption category j, the consumption-based carbon is defined as the product of expenditure C_j ,and the carbon emission factor F_j. Finally, the total carbon-based consumption (E_t) at each period t is obtained by summing over the 11 consumption categories.

$$E_t = \sum_{j=1}^{11} C_{jt} * F_j$$

We complement the carbon data with the per capita GDP, per capita income, and employment from the BEA to build panel data for 50 U.S. states over 1998-2018. Figure A.20 shows the evolution across time of the per capita consumption-based carbon emission in the US. Figure A.21 provides a spatially-concentrated chart of the consumption-based carbon across the US.

3.4 Carbon risk

3.4.1 Empirical framework

To demonstrate the channel through which a shock to carbon might affect the economy, the paper adapts a standard growth model to a setting with a dirty sector (D) that intensively uses carbon and labor (L) intermediate input. Examples of such models include the seminal work of Gerlagh (2008), Acemoglu et al. (2016), Fried (2018). We extend this class of model by considering an economy composed of $N = \{1, ..., n\}$ states with similar production technology but facing different exposures to the dirty sector.

In each state i, a final consumption good Y_i is produced according to a Cobb-Douglas technology using carbon, and labor inputs. For each state i, the final good production follows

$$Y_{it} = A_{it} D_{it}^{\theta} L_{it}^{1-\theta} \tag{3.1}$$

where $A_{it} = \exp^{-a_i t}$ is the productivity, θ denotes the factor share of carbon intermediaries.

Taking the logs in the good production function and differencing with respect to time, we have the dynamic growth equations

$$\Delta y_{it} = a_i + \theta \Delta d_{it} \tag{3.2}$$

Δy_t represents the growth rate of per-capita output. The growth equation in ((3.2)) allows identifying shock to the dirty sector on the state level output, which appears through θ. However, it's essential to consider two aspects of how this shock may play out. First, carbon shocks could potentially have a short-term and long-term impact of economic growth shock. Second, there could be a systemic risk due to potential dependence across states, such as trade linkage, financial integration, and exposure to standard shocks, which may amplify carbon shock.

To reach our goals, we rely on the Cross-sectional Auto-Regressive Distributed Lag model (CS-ARDL) developed by Chudik et al. (2017) and use the consumption-based carbon emission as a proxy for the dirty sector. Thus, we can rewrite equation (3.2) as follow:

$$\varphi_i(L)\Delta y_{it} = a_i + \Gamma_i(L)\Theta' \Delta e_{it} + \epsilon_{it} \tag{3.3}$$

$$\epsilon_{it} = b_i' f_t + u_{it} \tag{3.4}$$

For $i = 1, 2, ..., N$ and $t = 1, 2, ..., T$ where $\varphi_i(L)$ and $\Gamma_i(L)$ are power series in L, the lag functions. Finally, a_i is the fixed effect, e_{it} is the per capita carbon emission and, ϵ_{it} is a serially uncorrelated shock across i. While Equation (3.3) captures the ARDL component, Equation (3.4) captures the cross-sectional dependencies . In equation (3.4), f_t is an unobserved common factor that could lead to cross-sectional error dependencies between the states. These global factors are mostly unobserved and can simultaneously affect both growth and carbon emission and may lead to badly biased estimates if the unobserved common factors are indeed correlated with the regressors. Therefore, this estimation strategy considers three key features of the panel (i.e., dynamics, heterogeneity, and cross-sectional dependence) jointly. On top of that, the CS-ARDL approach has the merit to be robust *i)* to the possibility of unit roots in regressors, *ii)* to omitted variables bias, *iii)* to reverse causality, *iv)* finally, it is applicable irrespective of whether the short and/or long-run coefficients are heterogenous or homogeneous.

To filter out the effects of the unobserved common factors from Equation (3.4), Equation (3.3) is augmented with the cross-sectional(CS) averages of the dependent and explanatory variables, as well as their lags. Finally, we estimate the following equation.

$$\Delta y_{it} = \sum_{l=1}^{q} \varphi_{il} \Delta y_{i,t-l} + \sum_{l=0}^{p} \theta_{il} \Delta e_{i,t-l} + \sum_{l=0}^{m} \psi_{il} \bar{z}_{i,t-l} \tag{3.5}$$

Where $\bar{z}_t = [\overline{\Delta y_t}, \overline{\Delta e_t}]'$ the vector of the averages of per capita GDP growth ($\overline{\Delta y_t}$) and emission growth ($\overline{\Delta e_t}$) across states. Given the estimate of the short run coefficients $\{\hat{\theta}, \hat{\varphi}\}$, the CS-ARDL estimates of the mean lon-grun effects are computed as mean level coefficients for the long-run individual effect:

$$\hat{\omega} = \frac{1}{N} \sum_{i=1}^{N} \frac{\sum_{l=0}^{p} \hat{\theta}_{il}}{1 - \sum_{l=1}^{p} \hat{\varphi}_{il}} \tag{3.6}$$

3.4.2 Empirical results

In this section, we estimate the equation (3.5) to obtain the level short-run and long-run estimates for different truncation lag orders, p = 1, 2. For the cross-sectional averages component, the number of lags is also fixed for different values m=1,2. Table A.23 reports estimates from the mean groups of the short-run and long run impact of carbon emissions on economic growth for two other CS-ARDL specifications.

[Table A.23 here]

The estimated long-run risk coefficients are statistically significant and positive for all specifications. In term of magnitude, we find that one unit decreases in carbon emissions is associated with lower per capita log GDP growth of 4.5 percentage point for CS-ARDL(1,1,1) specification and 5.5 percentage point for a CS-ARDL(2,2,2) specification. Besides, short term coefficients are also positive and statistically significant (for e_t and e_{t-1}).

The CS-ARDL specification could be biased in the presence of a small sample as it is in our case (T=20). To account for this bias we follow Chudik et al. (2016). We estimate a CS-DL specification by removing the lagged component of the dependent variable in the specification (3.5). While the CS-DL estimator can deal with additional modeling issues (cross-sectional dependence, robustness to different lag-orders, serial correlations in errors, sample size), it leaves the reverse causality problem unresolved. However, Chudik et al. (2016) argue that even with this reverse causality bias, CS-DL's performance in terms of RMSE is much better than that of the CS-ARDL approach when T is moderate. Our estimates for the CS-DL specification are summarized in table A.24 below.

[Table A.24 here]

The results suggest that the long-run relationship between log per capita GDP growth and carbon emission is not undermined by potential bias due to the sample size. The coefficients of the long-run effects remain positive and statistically significant.

Moreover, we investigate the long-run effect by controlling for within U.S. income inequality. Specifically, we consider the top quartile and the bottom quartile of the per capita income distribution across states and the following panel model:

$$\Delta y_{it} = a_i + \sum_{l=0}^{p} \theta_{il} \Delta e_{i,t-l} + \sum_{l=0}^{p} \lambda_{il} \Delta e_{i,t-l} \times \mathbb{1}_{i \in Dist} + \sum_{l=0}^{m} \psi_{il} \bar{z}_{i,t-l} + \epsilon_{it} \tag{3.7}$$

where "$Dist$" refers to the top 25% per capita income distribution or the bottom 25% per-capita income distribution. The results from estimating specification (3.7) is reported in table A.25.

[Table A.25 here]

The estimated coefficients for the interaction terms are statistically significant especially when considering more lags. As a result, we cannot reject the hypothesis that there are differential effects of consumption-based carbon emission across the per-capita income states. Moreover, looking at the long-run variable $\hat{\omega}$, the associated coefficient remains positive and statistically significant for all the specifications. Furthermore, the long-run effect for the top per capita income states is more important than the bottom.

Although our results from the CS-ARDL and the CS-DL have pros and cons, we note that the sign of the long-run relationship between carbon-based consumption and growth $\hat{\omega}$ is always positive and statistically significant. The estimated mean-group value of the long-run coefficient, is negative and statistically significant in all specifications, ranging from 0.032 to 0.055 across different specification and lag orders.

3.5 Conclusion

This paper studies the long-term effect of carbon risk on the economy using a consumption-based approach. Precisely, we measure carbon emissions at the point of consumption, attributing all the emissions in production and distribution to the final consumers of goods and services. The paper finds that one unit decreases in carbon emissions is associated, in the long run, with lower per capita log output growth of 4.5 percentage points. Moreover, the paper finds differential impacts across the distribution of per capita states income. For future research, we would like to explore the effect of soft and abrupt de-carbonization policies on the economy and the optimal de-carbonization policy.

Bibliography

Acemoglu, Daron, Ufuk Akcigit, Douglas Hanley, and William Kerr, "Transition to clean technology," *Journal of Political Economy*, 2016, *124* (1), 52–104.

Acharya, Viral V, "A theory of systemic risk and design of prudential bank regulation," *Journal of financial stability*, 2009, *5* (3), 224–255.

_ , Lasse H Pedersen, Thomas Philippon, and Matthew Richardson, "Measuring systemic risk," *The Review of Financial Studies*, 2017, *30* (1), 2–47.

Addoum, Jawad M., George M. Korniotis, and Alok Kumar, "Income Risk, Dynamic Style Preferences, and Return Predictability," *Forthcoming Journal of Finance*, 2019.

Addoum, Jawad M, Stefanos Delikouras, and George M Korniotis, "Consumption-income sensitivity and portfolio choice," *The Review of Asset Pricing Studies*, 2019, *9* (1), 91–136.

Adrian, Tobias and Markus K. Brunnermeier, "CoVaR," *American Economic Review*, July 2016, *106* (7), 1705–41.

_ , Erkko Etula, and Tyler Muir, "Financial intermediaries and the cross-section of asset returns," *The Journal of Finance*, 2014, *69* (6), 2557–2596.

Allen, Franklin, Ana Babus, and Elena Carletti, "Asset commonality, debt maturity and systemic risk," *Journal of Financial Economics*, 2012, *104* (3), 519–534.

Anderson, Haelim, Mark Paddrik, and Jessie Jiaxu Wang, "Bank Networks and Systemic Risk: Evidence from the National Banking Acts," *American Economic Review*, 2019, *109* (9), 3125–61.

Angerer, Xiaohong and POK-SANG LAM, "Income risk and portfolio choice: An empirical study," *The Journal of Finance*, 2009, *64* (2), 1037–1055.

Attanasio, Orazio, Hamish Low, and Virginia Sánchez-Marcos, "Female labor supply as insurance against idiosyncratic risk," *Journal of the European Economic Association*, 2005, *3* (2-3), 755–764.

Baldwin, Elizabeth, Yongyang Cai, and Karlygash Kuralbayeva, "To build or not to build? Capital stocks and climate policy," *Journal of Environmental Economics and Management*, 2020, *100*, 102235.

Bansal, Ravi, Dana Kiku, and Marcelo Ochoa, "Price of long-run temperature shifts in capital markets," Technical Report, National Bureau of Economic Research 2016.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro, "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century," *Journal of Political Economy*, 2016, *124* (1), 105–159.

Becker, Bo and Victoria Ivashina, "Reaching for yield in the bond market," *The Journal of Finance*, 2015, *70* (5), 1863–1902.

Becker, Thomas A and Reza Shabani, "Outstanding debt and the household portfolio," *The Review of financial studies*, 2010, *23* (7), 2900–2934.

Begenau, Juliane and Tim Landvoigt, "Financial regulation in a quantitative model of the modern banking system," *Available at SSRN 2748206*, 2018.

Bengui, Julien and Javier Bianchi, "Macroprudential policy with leakages," Technical Report, National Bureau of Economic Research 2018.

Betermier, Sebastien, Thomas Jansson, Christine Parlour, and Johan Walden, "Hedging labor income risk," *Journal of Financial Economics*, 2012, *105* (3), 622–639.

Blei, David M, Andrew Y Ng, and Michael I Jordan, "Latent dirichlet allocation," *Journal of machine Learning research*, 2003, *3* (Jan), 993–1022.

Blundell, Richard, Luigi Pistaferri, and Itay Saporta-Eksten, "Consumption inequality and family labor supply," *The American Economic Review*, 2016, *106*, 387–435.

Bolton, Patrick and Marcin Kacperczyk, "Do investors care about carbon risk?," Technical Report, National Bureau of Economic Research 2020.

Bonaparte, Yosef, George M Korniotis, and Alok Kumar, "Income hedging and portfolio decisions," *Journal of Financial Economics*, 2014, *113* (2), 300–324.

Brown, James R, Matthew Gustafson, and Ivan Ivanov, "Weathering cash flow shocks," *Available at SSRN 2963444*, 2020.

Brunnermeier, Markus K and Yuliy Sannikov, "A macroeconomic model with a financial sector," *American Economic Review*, 2014, *104* (2), 379–421.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Beyond the balance sheet model of banking: Implications for bank regulation and monatary policy," Technical Report, National Bureau of Economic Research 2018.

_ , _ , _ , **and** _ , "Fintech, regulatory arbitrage, and the rise of shadow banks," *Journal of Financial Economics*, 2018, *130* (3), 453–483.

Chai, Jingjing, Wolfram Horneff, Raimond Maurer, and Olivia S Mitchell, "Optimal portfolio choice over the life cycle with flexible work, endogenous retirement, and lifetime payouts," *Review of Finance*, 2011, *15*, 875–907.

Chan, Yeung and Luis Viceira, "Asset allocation with endogenous labor income: the case of incomplete markets," 2000.

Chang, Yongsung, Jay H Hong, and Marios Karabarbounis, "Labor market uncertainty and portfolio choice puzzles," *American Economic Journal: Macroeconomics*, 2018, *10* (2), 222–62.

Chetty, Raj and Adam Szeidl, "Consumption commitments and risk preferences," *The Quarterly Journal of Economics*, 2007, *122* (2), 831–877.

_ **and** _ , "Consumption commitments and habit formation," *Econometrica*, 2016, *84* (2), 855–890.

Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, "Attention to global warming," *The Review of Financial Studies*, 2020, *33* (3), 1112–1145.

Chudik, Alexander, Kamiar Mohaddes, M Hashem Pesaran, and Mehdi Raissi, *Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors*, Emerald Group Publishing Limited, 2016.

_ , _ , _ , **and** _ , "Is there a debt-threshold effect on output growth?," *Review of Economics and Statistics*, 2017, *99* (1), 135–150.

Chunzan, Wu and Kruger Dirk, "Consumption Insurance Against Wage Risk: Family Labor Supply and Optimal Progressive Income Taxation," *AEJ: Macroeconomics(forthcoming)*, 2020.

Cocco, Joao F, Francisco J Gomes, and Pascal J Maenhout, "Consumption and portfolio choice over the life cycle," *The Review of Financial Studies*, 2005, *18* (2), 491–533.

Colacito, Riccardo, Bridget Hoffmann, and Toan Phan, "Temperature and growth: A panel analysis of the United States," *Journal of Money, Credit and Banking*, 2019, *51* (2-3), 313–368.

Dahlquist, Magnus, Ofer Setty, and Roine Vestman, "On the asset allocation of a default pension fund," *The Journal of Finance*, 2018, *73* (4), 1893–1936.

Daminato, Claudio and Luigi Pistaferri, "Family labor supply and asset returns," 2017.

Davis, Steven J and Paul Willen, "Using financial assets to hedge labor income risks: Estimating the benefits," Technical Report, Citeseer 2000.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, 2012, *4* (3), 66–95.

_ , _ , and _ , "What do we learn from the weather? The new climate-economy literature," *Journal of Economic Literature*, 2014, *52* (3), 740–98.

Elliott, Matthew, Jonathon Hazell, and Co-Pierre Georg, "Systemic risk-shifting in financial networks," *Available at SSRN 2658249*, 2018.

Erol, Selman and Guillermo Ordoñez, "Network reactions to banking regulations," *Journal of Monetary Economics*, 2017, *89*, 51–67.

Fagereng, Andreas, Charles Gottlieb, and Luigi Guiso, "Asset Market Participation and Portfolio Choice over the Life-Cycle," *The Journal of Finance*, 2017, *72*, 705–750.

_ , Luigi Guiso, and Luigi Pistaferri, "Portfolio choices, firm shocks, and uninsurable wage risk," *The Review of Economic Studies*, 2018, *85* (1), 437–474.

_ , _ , Davide Malacrino, and Luigi Pistaferri, "Heterogeneity and persistence in returns to wealth," *The American Economic Review: Papers & Proceedings*, 2016, *106* (5), 651–655,.

Farhi, Emmanuel and Jean Tirole, "Collective moral hazard, maturity mismatch, and systemic bailouts," *American Economic Review*, 2012, *102* (1), 60–93.

_ and Stavros Panageas, "Saving and investing for early retirement: A theoretical analysis," *Journal of Financial Economics*, 2007, *83*, 87–121.

Favilukis, Jack, Sydney C Ludvigson, and Stijn Van Nieuwerburgh, "The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium," *Journal of Political Economy*, 2017, *125* (1), 140–223.

Franzen, Axel and Sebastian Mader, "Consumption-based versus production-based accounting of CO2 emissions: Is there evidence for carbon leakage?," *Environmental science & policy*, 2018, *84*, 34–40.

Fried, Stephie, "Climate policy and innovation: A quantitative macroeconomic analysis," *American Economic Journal: Macroeconomics*, 2018, *10* (1), 90–118.

— , **Kevin Novan, and W Peterman**, "The Macro Effects of Climate Policy Uncertainty," Technical Report, Mimeo, March 2020.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery, "The role of technology in mortgage lending," *The Review of Financial Studies*, 2019, *32* (5), 1854–1899.

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy, "Text as data," *Journal of Economic Literature*, 2019, *57* (3), 535–74.

Gerlagh, Reyer, "A climate-change policy induced shift from innovations in carbon-energy production to carbon-energy savings," *Energy Economics*, 2008, *30* (2), 425–448.

Gertler, Mark, Nobuhiro Kiyotaki, and Andrea Prestipino, "A macroeconomic model with financial panics," *The Review of Economic Studies*, 2020, *87* (1), 240–288.

Gomes, Francisco J, Laurence J Kotlikoff, and Luis M Viceira, "Optimal life-cycle investing with flexible labor supply: A welfare analysis of life-cycle funds," *American Economic Review*, 2008, *98*, 297–303.

Gourio, Francois and Charles Fries, "Adaptation and the Cost of Rising Temperature for the US Economy," 2020.

Gromb, Denis and Dimitri Vayanos, "Equilibrium and welfare in markets with financially constrained arbitrageurs," *Journal of financial Economics*, 2002, *66* (2-3), 361–407.

Haas, Ralph De and Alexander A Popov, "Finance and carbon emissions," 2019.

Hanley, Kathleen Weiss and Gerard Hoberg, "Dynamic interpretation of emerging risks in the financial sector," *The Review of Financial Studies*, 2019, *32* (12), 4543–4603.

He, Zhiguo and Arvind Krishnamurthy, "Intermediary asset pricing," *American Economic Review*, 2013, *103* (2), 732–70.

— **and** — , "A macroeconomic framework for quantifying systemic risk," *American Economic Journal: Macroeconomics*, 2019, *11* (4), 1–37.

— , **Bryan Kelly, and Asaf Manela**, "Intermediary asset pricing: New evidence from many asset classes," *Journal of Financial Economics*, 2017, *126* (1), 1–35.

Heaton, John and Deborah Lucas, "Portfolio choice and asset prices: The importance of entrepreneurial risk," *The journal of finance*, 2000, *55* (3), 1163–1198.

Heckman, James J, "Sample selection bias as a specification error (with an application to the estimation of labor supply functions)," 1977.

Hoberg, Gerard and Gordon M Phillips, "Text-based industry momentum," *Journal of Financial and Quantitative Analysis*, 2018, *53* (6), 2355–2388.

_ **and V. Maksimovic**, "Redefining Financial Constraints: A Text-Based Analysis," *Corporate Finance: Capital Structure Payout Policies eJournal*, 2014.

Hsiang, Solomon, "Climate econometrics," *Annual Review of Resource Economics*, 2016, *8*, 43–75.

Huang, Jennifer, Clemens Sialm, and Hanjiang Zhang, "Risk shifting and mutual fund performance," *The Review of Financial Studies*, 2011, *24* (8), 2575–2616.

Irani, Rustom M, Rajkamal Iyer, Ralf R Meisenzahl, and Jose-Luis Peydro, "The rise of shadow banking: Evidence from capital regulation," 2018.

Jakob, Michael, Jan Christoph Steckel, and Ottmar Edenhofer, "Consumption-versus production-based emission policies," *Annu. Rev. Resour. Econ.*, 2014, *6* (1), 297–318.

Jesse, Johal, Roberts Joanna, and Sim John, "Canadian Securities Lending Market Ecology," 2019.

Jones, Benjamin F and Benjamin A Olken, "Climate shocks and exports," *American Economic Review*, 2010, *100* (2), 454–59.

Kahn, Matthew E, Kamiar Mohaddes, Ryan NC Ng, M Hashem Pesaran, Mehdi Raissi, and Jui-Chung Yang, "Long-term macroeconomic effects of climate change: A cross-country analysis," Technical Report, National Bureau of Economic Research 2019.

Kaplan, Greg and Giovanni L Violante, "How much consumption insurance beyond self-insurance?," *American Economic Journal: Macroeconomics*, 2010, *2* (4), 53–87.

Krueger, Philipp, Zacharias Sautner, and Laura T Starks, "The importance of climate risks for institutional investors," *The Review of Financial Studies*, 2020, *33* (3), 1067–1111.

Laeven, Luc and Ross Levine, "Is there a diversification discount in financial conglomerates?," *Journal of financial economics*, 2007, *85* (2), 331–367.

Luo, Yulei, "Rational inattention, long-run consumption risk, and portfolio choice," *Review of Economic dynamics*, 2010, *13* (4), 843–860.

_ **and Eric R Young**, "Risk-sensitive consumption and savings under rational inattention," *American Economic Journal: Macroeconomics*, 2010, *2* (4), 281–325.

— , **Jun Nie, Gaowang Wang, and Eric R Young**, "Rational inattention and the dynamics of consumption and wealth in general equilibrium," *Journal of Economic Theory*, 2017, *172*, 55–87.

Maggio, Marco Di, Amir Kermani, and Kaveh Majlesi, "Stock market returns and consumption," *Forthcoming Journal of finance*, 2019.

Massa, Massimo and Andrei Simonov, "Hedging, familiarity and portfolio choice," *The Review of Financial Studies*, 2006, *19* (2), 633–685.

Mazzocco, Maurizio, "Saving, risk sharing, and preferences for risk," *American Economic Review*, 2004, *94* (4), 1169–1182.

Meghir, Costas and Luigi Pistaferri, "Income variance dynamics and heterogeneity," *Econometrica*, 2004, *72*, 1–32.

Moyer, Elisabeth J, Mark D Woolley, Nathan J Matteson, Michael J Glotter, and David A Weisbach, "Climate impacts on economic growth as drivers of uncertainty in the social cost of carbon," *The Journal of Legal Studies*, 2014, *43* (2), 401–425.

Nordhaus, William D and Joseph Boyer, "Warming the world," 2000.

— **et al.**, "The'dice'model: Background and structure of a dynamic integrated climate-economy model of the economics of global warming," Technical Report, Cowles Foundation for Research in Economics, Yale University 1992.

Ordoñez, Guillermo, "Sustainable shadow banking," *American Economic Journal: Macroeconomics*, 2018, *10* (1), 33–56.

Ortigueira, Salvador and Nawid Siassi, "How important is intra-household risk sharing for savings and labor supply?," *Journal of Monetary Economics*, 2013, *60* (6), 650–666.

Paul, Pascal, "A macroeconomic model with occasional financial crises," *Journal of Economic Dynamics and Control*, 2020, *112*, 103830.

Tang, Huan, "Peer-to-peer lenders versus banks: substitutes or complements?," *The Review of Financial Studies*, 2019, *32* (5), 1900–1938.

Vasia, Panousi, De Backer Jason, and Ramnath Shanti, "The Covariance Structure of Household-Level Income," 2019.

Vissing-Jorgensen, Annette, "Towards an explanation of household portfolio choice heterogeneity: Nonfinancial income and participation cost structures," Technical Report, National Bureau of Economic Research 2002.

Wagner, Wolf, "Diversification at financial institutions and systemic crises," *Journal of Financial Intermediation*, 2010, *19* (3), 373–386.

_ , "Systemic liquidation risk and the diversity–diversification trade-off," *The Journal of Finance*, 2011, *66* (4), 1141–1175.

Xiao, Kairong, "Monetary transmission through shadow banks," *Forthcoming Review of Financial Studies*, 2019.

Appendix A

Annnexes

A.1 Appendix Chapter 1

A.1.1 Tables and Figures

Table A.1: Summary statistics for household's members demographics and labor market characteristics

var	Mean	Median	$25^{th} percentile$	$75^{th} percentile$	SD
Primary earner (head)					
Age	44	44	35	53	10.98
Earnings	82327	57172	35103.37	94602.29	147178.7
Hours worked	2060	2100	1880	2500	873.94
Share with some college	.65	1	0	1	.48
Second earner					
Labor Participation rate	77%	1	0	1	.42
Age	42	42	33	51	10.98
Earnings (conditional on participation)	44226	34000	17880.78	56365.71	44559.61
Hours worked (conditional on participation)	1368	1653	466	2024	935.11
Share with some college	67%	1	0	1	.47
#Observations			26001		

Note: 10 biennial PSID waves (*1999-2016*). This table shows summary statistics for key demographics and labor market condition. Income variables are deflated by the consumer price index (CPI) into 2002 dollars.

Table A.2: Summary statistics for financial assets

	Mean	Median	$25^{th}percentile$	$75^{th}percentile$	SD
Total Financial Assets	158224.6	13163.76	1333.3	89294.2	1180352
Safe Assets	102894.8	10998.19	1266.3	67817	369912.7
Stock Market Participation	.26	0	.	.	.44
Unconditional Risky Share	11%	0	.	.	.24
Conditional Risky Share	42%	0	.	.	.31
Total Net Worth	309516.6	122651.7	36608.43	322658.3	1818947
#Observations			26001		

Note: 10 biennial PSID waves (*1999-2016*). This table shows summary statistics for household's financial assets. Assets variables are deflated by the consumer price index (CPI) into 2002 dollars.

Table A.3: Summary statistics of durable consumption and services

	Mean	Median	$25^{th} percentile$	$75^{th} percentile$	Sd
Total Insurance	5614.47	4080.96	2216.14	7230.87	10693.23
Utilities	10046.04	5383.98	2790.69	11847.39	12732.19
Housing	25354.36	12543.92	7423.78	21446.47	78667.04
Transport	362.63	0	0	0	2177.53
Education	2794.97	0	0	687.39	9218.58
Health	4720.27	2795.84	840.29	6376.19	6635.53
#Observations			26001		

Note: 10 biennial PSID waves (*1999-2016*). This table shows summary statistics for household's financial assets. Assets variables are deflated by the consumer price index (CPI) into 2002 dollars.

Table A.4: Consumption smoothness and unconditional risky share

	Unconditional Risky Share		
	(1)	(2)	(3)
CWS_{it}	0.821*** (0.044)		0.658*** (0.172)
LWS_{it}	-	-0.203*** (0.002)	0.019 (0.012)
age			-0.0107*** (0.003)
agew			0.013*** (0.003)
educ			0.107*** (0.032)
educw			0.209*** (0.027)
Kids			-0.041*** (0.010)
Year Fe	yes	yes	yes
State Fe	yes	yes	yes
Pseudo R^2	0.082	0.084	0.104
# Observations	7161	11773	7161

The estimation period consists of the 10 biennial PSID waves (*1999-2016*). Each regression includes time, age and state fixed effects and controls for household characteristics. Standard errors are in parentheses and are robust to heteroscedasticy. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$.

Table A.5: Consumption smoothness and conditional risky Share: Heckman Selection

	Stock Participation	Conditional Risky Share	Conditional Risky Share
$2^{nd} earnerworking4$	0.07*** (0.00)		
CWS_{it}		-0.11*** (0.04)	
LWS_{it}			0.02*** (0.007)
Year FE	yes	yes	yes
State FE	yes	yes	yes
Age FE	yes	yes	yes
R^2	0.05	0.07	0.03
#Obsevations	23247	1544	3314

This table shows the two-stage Heckman (1979) regressions for portfolio allocation. The estimation period consists of the 10 biennial PSID waves (*1999-2016*). Each regression includes time, age and state fixed effects and controls for household characteristics. Standard errors are in parentheses and are robust to heteroscedasticy. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$.

Table A.6: Conditional risky share and effective risk aversion: evidence from housing consumption commitment

	Dependent variable: conditional risky share			
	Homeowner+Renter	Homeowner with mortgage		
		$25^{th}pctile < LTI$	$50^{th}pctile < LTI < 75^{th}pctile$	LTI>$75^{th}pctile$
CWS_{it}	-0.12*** (0.04)	-0.26*** (0.09)	-0.15* (0.08)	0.002 (0.001)
Housing commitment	0.02* (0.01)	0.03 (0.02)	0.02 (0.03)	0.06 (0.05)
Year FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Age FE	yes	yes	yes	yes
R^2	0.07	0.23	0.17	yes
#Obsevations	1521	295	498	282

This table shows the two-stage Heckman (1979) regressions in the presence of housing consumption commitment. The parameter LTI captures households leverage and it is define as the ratio of mortgage to total income. The estimation period consists of the 10 biennial PSID waves (*1999-2016*). Each regression includes time, age and state fixed effects and controls for household characteristics. Standard errors are in parentheses and are robust to heteroscedasticy. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$.

Table A.7: Conditional risky share and effective risk aversion: evidence from housing consumption commitment

	Dependent variable: Conditional Risky Share		
	Homeowner+Renter	Homeowner with mortgage	
		LTI<20%	LTI>80%
LWS	0.018*** (0.007)	0.03*** (0.01)	0.011 (0.02)
Housing Commitment	0.017* (0.01)	0.02 (0.01)	0.034* (0.01)
Year FE	yes	yes	yes
State FE	yes	yes	yes
Age FE	yes	yes	yes
R^2	0.03	0.14	0.05
#Obsevation	3272	759	1876

This table shows the two-stage Heckman (1979) regressions in the presence of housing consumption commitment. The parameter LTI captures households leverage and it is define as the ratio of mortgage to total income. The estimation period consists of the 10 biennial PSID waves (*1999-2016*). Each regression includes time, age and state fixed effects and controls for household characteristics. Standard errors are in parentheses and are robust to heteroscedasticy. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$.

Table A.8: Wages variance estimates and hedging demand

		First earner (Head)	Secondary earner
Wage shocks	Transitory (σ_u^2)	0.0374*** (0.028)	0.0469*** (0.095)
	Permanent (σ_v^2)	0.0180*** (0.05)	0.022 (0.155)
Covariance of Wage Shocks	Transitory ($\sigma_{u_1 u_2}$)	0.049** (0.0243)	
	Permanent ($\sigma_{v_1 v_2}$)	0.074* (0.041)	
Hedging demand ($\hat{\rho}$)		-0.181*** (0.0386)	-0.145*** (0.043)

Note:This table reports estimates of the variance of permanent and transitory labor wage-income shocks. The estimation is based on the error terms from estimating the wage income process. Wage process are estimated using GMM. The estimation period consists of the 10 biennial PSID waves (*1999-2016*). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. Standard error are in parenthesis.

Table A.9: Elasticities

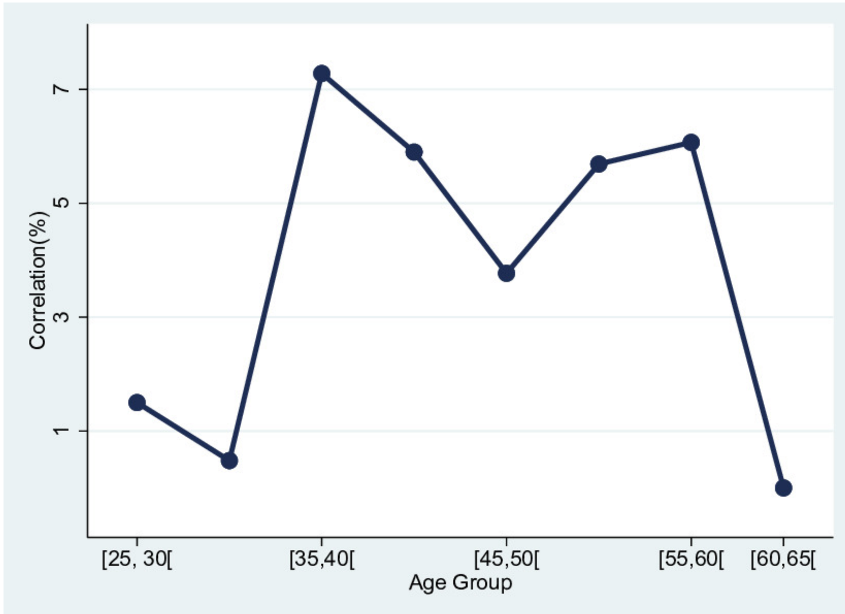
BPS Model			
Preference Parameters (Frisch elasticities)		Insurance parameters (cross-elasticities)	
$\eta_{c,p}$	0.372	η_{c,w_1}	-0.148
η_{l_1,w_1}	0.594	η_{c,w_2}	-0.030
η_{l_2,w_2}	0.871	$\eta_{l_1,p}$	0.085
	-	$\eta_{l_2,p}$	0.035
	-	η_{l_1,w_2}	0.104
	-	η_{l_2,w_1}	0.212

Note: BPS(Blundell et al. (2016)). The values of the elasticity parameters correspond to the model without taxes in BPS model.

Table A.10: Parameterization

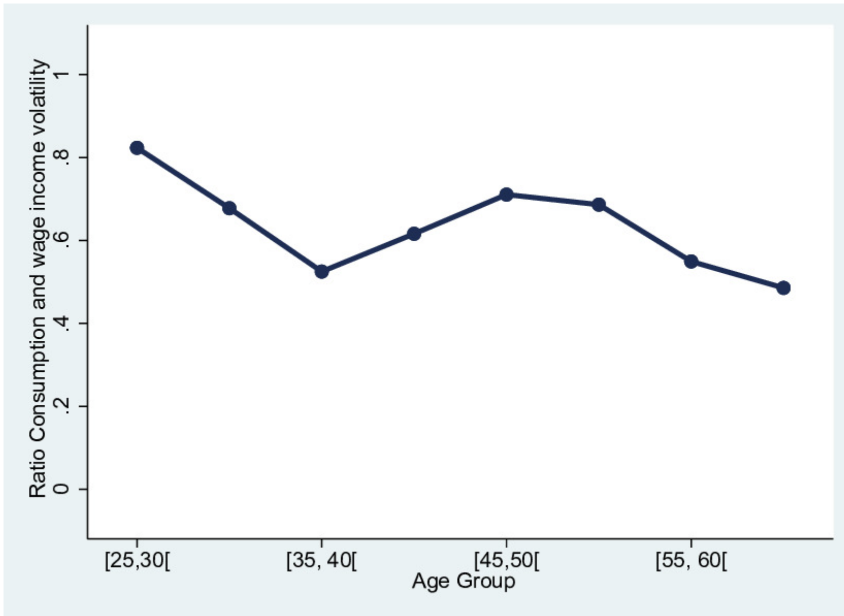
Parameter		Value	Source
Preferences and demographics			
Retirement Age	T_r	65	US law
Weight of spouses leisures	ω	0.26	Calibrated (target $\hat{\sigma}$)
Weight of First /Second earner leisure	ζ	0.22	Calibrated (target $\hat{\sigma}$)
Risk aversion	$\hat{\sigma}$	2.69	Blundell et al. (2016)
Ratio labor/leisure of first earner	$\mid Q_1 \mid$	0.59	PSID
Ratio labor/leisure of Second earner	$\mid Q_2 \mid$	0.42	PSID
Risk-free return	r_f	0.02	Blundell et al. (2016)
Technology parameters			
Risk Premiums	$E(r^s - r_f)$	0.04	Gomes et al. (2008)
Std.Stock Market	σ_m	0.205	Gomes et al. (2008)

Figure A.1: Correlation between consumption and total labor income $corr\left(\Delta log(C_t), \Delta log(I_t)\right)$



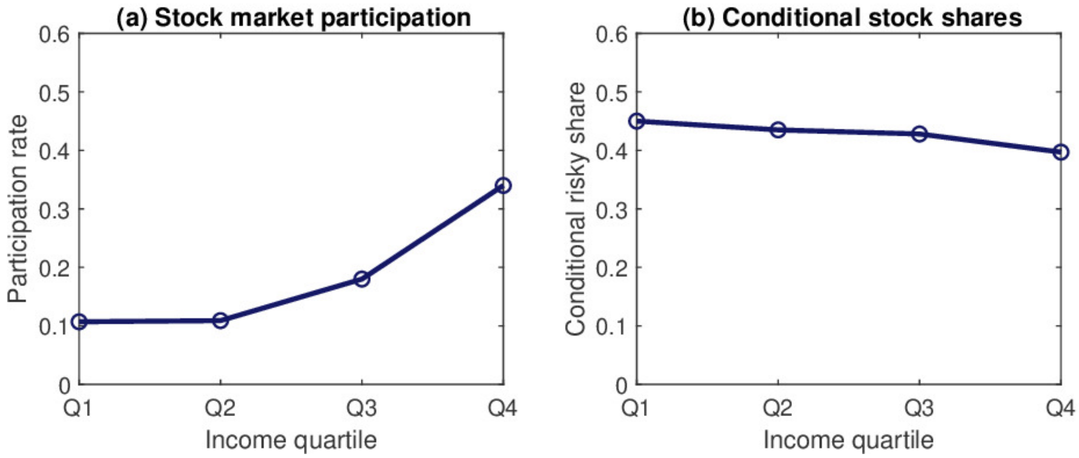
Note: This figure shows by age group the correlation between the change in consumption and the change in total labor income. The estimation period uses 10 biennial PSID waves spanning the time period(*1999-2016*). The consumption expenditure contains exclusively durable goods and services(Housing, Transports, Insurance, health , education, utilities).

Figure A.2: Relative consumption dispersion $\frac{\sigma_{\Delta log(C_t)}}{\sigma_{\Delta log(w_t)}}$



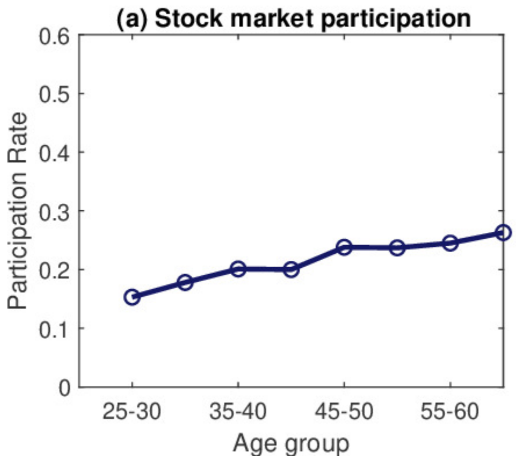
Note: This figure shows by age group the ratio between the volatility of change in consumption and the volatility of change in wage income.The estimation period uses 10 biennial PSID waves spanning the time period (*1999-2016*). The consumption expenditure contains exclusively durable goods and services(Housing, Transports, Insurance, health , education, utilities).

Figure A.3: Participation and conditional risky share by income quartiles



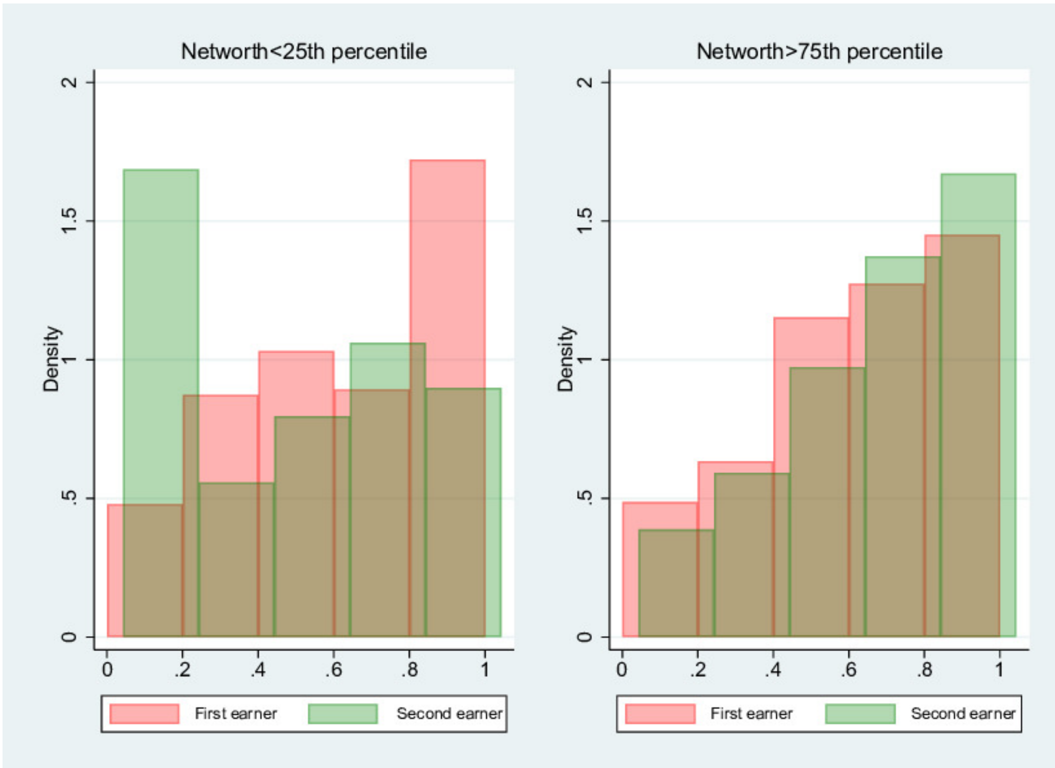
Note: The estimation period uses 10 biennial PSID waves spanning the time period *1999-2016*. (a) shows the participation rate (fraction of households owing stock) and (b) shows the conditional (on participation) risky shares

Figure A.4: Participation and conditional stock share across age groups



Note: The line with circles represents a 5-year average. (a) shows the participation rate (fraction of households owing stock) and (b) shows the conditional (on participation) risky shares. The estimation period uses 10 biennial PSID waves spanning the time period *1999-2016*.

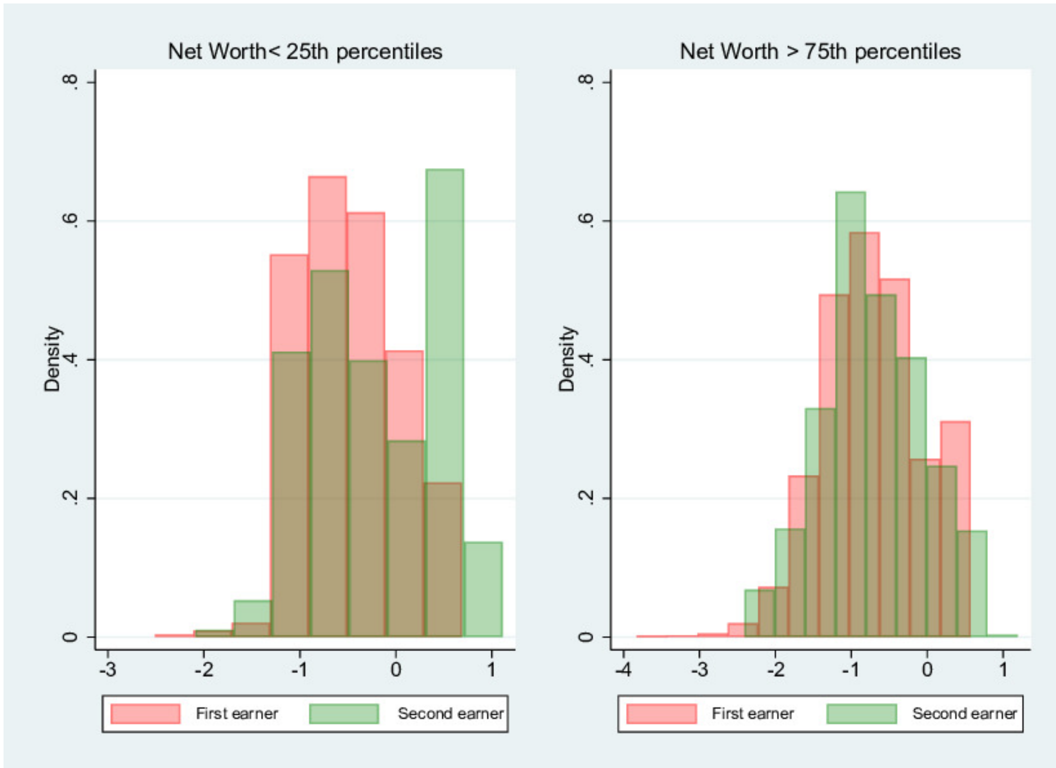
Figure A.5: Consumption insurance against permanent income shocks conditional on household net worth



.

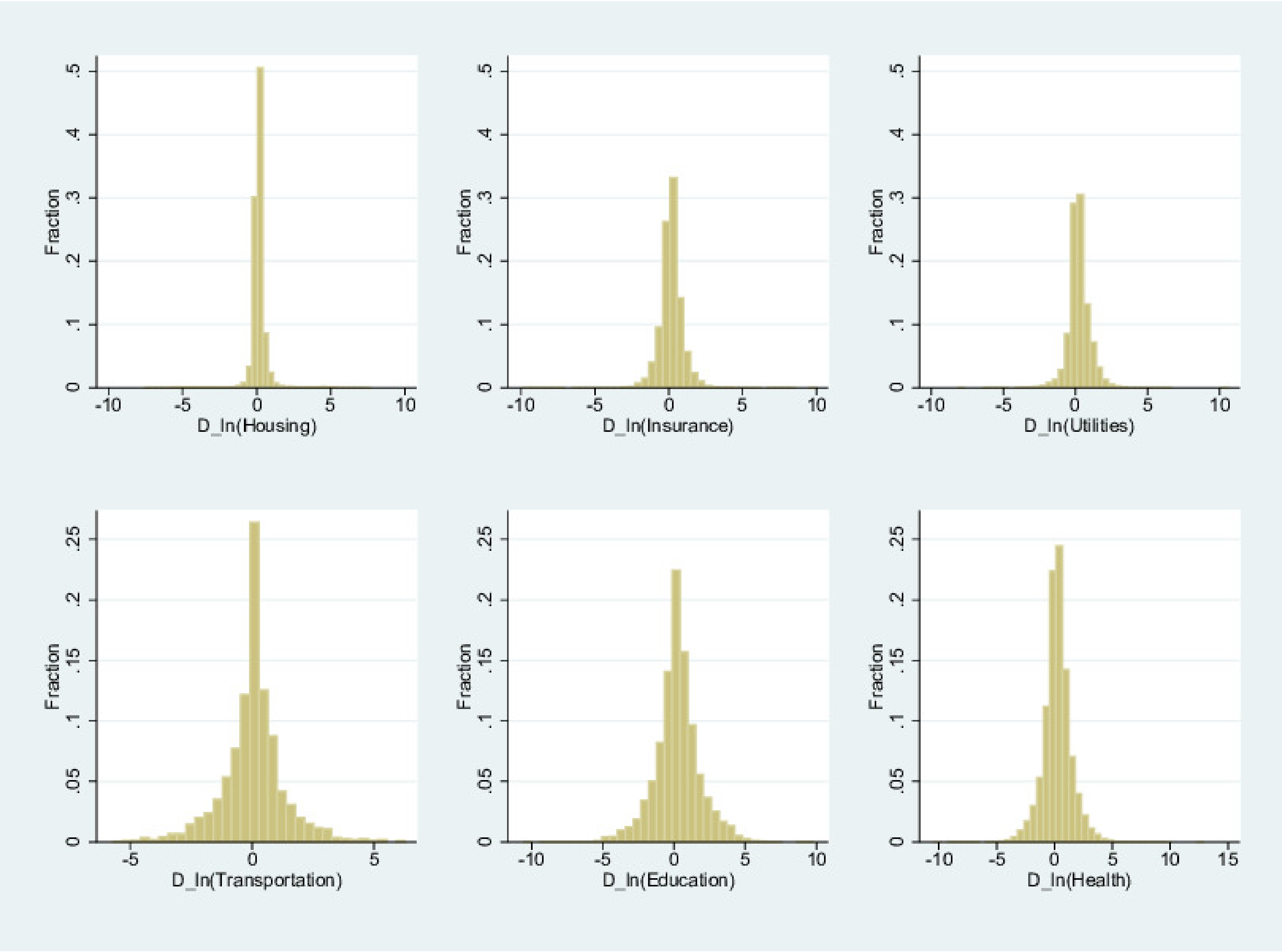
Note: This figure shows the distribution of consumption insurance of households in the first and fourth quartiles of the net worth distribution. The estimation period uses 10 biennial PSID waves spanning the time period *1999-2016*.

Figure A.6: Labor supply insurance against permanent income shocks conditional on household net worth



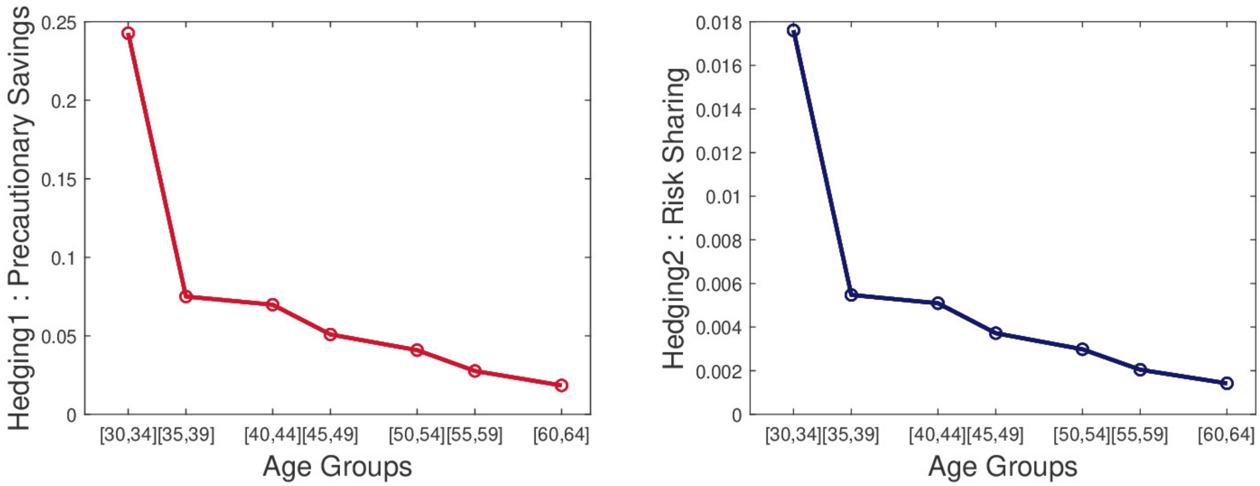
Note: This figure shows the distribution of labor supply insurance of households in the first and fourth quartiles of the net worth distribution. The estimation period uses 10 biennial PSID waves spanning the time period *1999-2016*.

Figure A.7: Durable consumption and service commitments



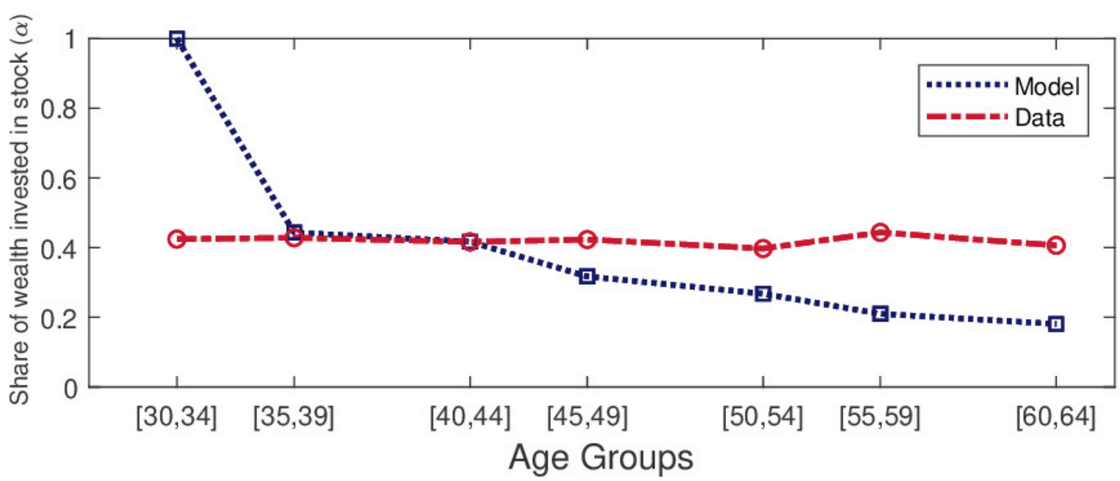
Note: This figure shows the histogram of durable consumptions and services adjustment by category. The estimation period uses 10 biennial PSID waves spanning the time period *1999-2016*.

Figure A.8: Household income hedging-induced investments through risk-sharing and Precautionary Savings channels



Note: This figure displays the implication of the negative Hedging demands for stocks. The Hedging-induced investments are calculated for different age group. The left panel represents the hedging-induced investments driven by the precautionary savings and the right panel represents the hedging demand driven by intra-household Risk-Sharing.

Figure A.9: Calibration and model fit



Note: The figure shows the household portfolio choices over the Working life and the fit of the model to the data.

A.1.2 Wage shock parameters

We estimate our time invariant income process by pooling observation of all ages (25-65). Thus we estimate only 6 parameters for the wage process ($\sigma^2_{u_1}, \sigma^2_{u_2}, \sigma^2_{\upsilon_1}, \sigma^2_{\upsilon_2}, \sigma_{u_1u_2}, \sigma_{\upsilon_1\upsilon_2}$). Following Meghir and Pistaferri (2004), the key moment that identifies the variance of the permanent and transitory shocks are :

$$\begin{aligned}
\sigma^2_{u_j} &= -E(\Delta w_{j,t}\Delta w_{j,t+1}) \\
\sigma^2_{\upsilon_j} &= E(\Delta w_{j,t}(\textstyle\sum_{k=-1}^{1}\Delta w_{j,t+k})) \\
\sigma_{u_1,u_2} &= -E(\Delta w_{1,t}\Delta w_{2,t+1}) \\
\sigma_{\upsilon_1,\upsilon_2} &= E(\Delta w_{j,t}(\textstyle\sum_{k=-1}^{1}\Delta w_{2,t+k}))
\end{aligned}$$

Where $\Delta w_{j,t} = \Delta u_{j,t} + \upsilon_{j,t}$
The identification strategy implies that the model is over-identified. Thus, we estimate the wage process, preference and insurance parameters using the minimum distance estimator (MDE[1]) method which relies on a weighting[2] minimization of the scaled deviation between each data and theoretical moment to find the parameters

A.1.3 Preference and Insurance Parameters (BPS model)

We have 9 preference and insurance parameters($\eta_{c,p}, \eta_{l_1,p}, \eta_{l_2,p}, \eta_{c,w1}, \eta_{c,w2}, \eta_{l_1,w1}, \eta_{l_1,w2}, \eta_{l_2,w1}, \eta_{l_2,w2}$) estimated in the **BPS** model. Considering the following moments :

$$\begin{aligned}
m_1 &= E(\Delta w_{1,t}\Delta y_{1,t+1}) = -(1+\eta_{l_1,w1})\sigma^2_{u_1} - \eta_{l_1,w2}\sigma_{u_1u_2} \\
m_2 &= E(\Delta w_{2,t}\Delta y_{1,t+1}) = -(1+\eta_{l_1,w1})\sigma_{u_1u_2} - \eta_{l_1,w2}\sigma^2_{u_1} \\
m_3 &= E(\Delta w_{1,t}\Delta w_{1,t+1}) = -\sigma^2_{u_1} \\
m_4 &= E(\Delta w_{2,t}\Delta w_{2,t+1}) = -\sigma^2_{u_2} \\
m_5 &= E(\Delta w_{2,t}\Delta w_{1,t+1}) = -\sigma_{u_1u_2}
\end{aligned}$$

Combining those moments we obtain the following elasticity and cross elasticity :

$$\begin{aligned}
\eta_{l_1,w_1} &= \tfrac{m_1m_4 - m_2m_5}{m_3m_4-(m_5)^2} \\
\eta_{l_1,w_2} &= \tfrac{m_2m_3 - m_1m_5}{m_3m_4-(m_5)^2}
\end{aligned}$$

The parameters $\eta_{l_1,w2}$ and $\eta_{l_2,w1}$ can be obtain by symmetric. To identify the extent of non-separability between consumption and hours, the same approach above can be apply:

$$\begin{aligned}
m_6 &= E(\Delta w_{1,t}\Delta c_{i,t+1}) = -\eta_{c,w1}\sigma^2_{u_1} - \eta_{c,w2}\sigma_{u_1u_2} \\
m_7 &= E(\Delta w_{2,t}\Delta c_{i,t+1}) = -\eta_{c,w1}\sigma_{u_1u_2} - \eta_{c,w2}\sigma^2_{u_2}
\end{aligned}$$

[1] The MDE estimator solves the following minimization problem :

$$\min_{\Theta}[M - F(\Theta)]'W[M - F(\Theta)]$$

[2] Altonji and Segal (1996) with a Monte-Carlo simulation show that one of the optimal weighting matrix (W) is the identity matrix.

Hence we can show that :

$$\begin{aligned}\eta_{c,w_1} &= \tfrac{m_6 m_4 - m_7 m_5}{m_3 m_4 - (m_5)^2}\\ \eta_{c,w_2} &= \tfrac{m_7 m_3 - m_6 m_5}{m_3 m_4 - (m_5)^2}\end{aligned}$$

To identify $\eta_{l_1,p}$, $\eta_{l_2,p}$, the symmetry of the Frisch substitution matrix can be applied. It represents the matrix of behavioral responses which is written as follow:

$$\begin{pmatrix} \frac{dc}{dp} & \frac{dc}{dw_1} & \frac{dc}{dw_2} \\ \frac{dl_1}{dp} & \frac{dl_1}{dw_1} & \frac{dl_1}{dw_2} \\ \frac{dl_2}{dp} & \frac{dl_2}{dw_1} & \frac{dl_2}{dw_2} \end{pmatrix} = \begin{pmatrix} \eta_{c,p}\frac{c}{p} & \eta_{c,w_1}\frac{c}{w_1} & \eta_{c,w_2}\frac{c}{w_2} \\ -\eta_{l_1,p}\frac{l_1}{p} & -\eta_{l_1,w1}\frac{l_1}{w_1} & -\eta_{l_1,w2}\frac{l_1}{w_2} \\ -\eta_{l_2,p}\frac{l_2}{p} & -\eta_{l_2,w1}\frac{l_2}{w_1} & -\eta_{l_2,w2}\frac{l_2}{w_2} \end{pmatrix}$$

Imposing symmetry of the matrix above we have :

$$\begin{cases} \eta_{l_j,p} = -\eta_{c,w_j}\frac{pc}{w_j h_j} \quad for \quad (j = 1, 2) \\ \eta_{l_2,w1} = \eta_{l_1,w2}\frac{w_1 h_1}{w_2 h_2} \end{cases}$$

A.1.4 Shock transmission coefficients

This appendix shows how to derive equation (1.7), (1.8), (A.2) in the main text. We follow the strategy in the online appendix of Blundell et al. (2016)

Step1 : Approximation of the Euler equation

$$E_t[\lambda_{t+1} R_{p,t+1}] = \frac{\lambda_t}{\beta}$$

Applying a second order Taylor approximation to $exp(ln\lambda_{t+1} + R_{p,t+1})$ around $ln\lambda_t + E_t[R_{p,t+1}]$ we have:

$$\Delta ln\lambda_{i,t+1} \approx \psi_t + \epsilon_{i,t+1} \tag{A.1}$$

$$\begin{aligned} exp(ln\lambda_{t+1} + R_{p,t+1}) = exp(ln\lambda_t + E_t[R_{p,t+1}])\,[1 + (\Delta ln(\lambda_{t+1}) + (R_{p,t+1} - E_t[R_{p,t+1}]) \\ + \frac{1}{2}(\Delta ln(\lambda_{t+1}) + (R_{p,t+1} - E_t[R_{p,t+1}])^2 \end{aligned}$$

$$\begin{aligned} -E_t[\Delta ln\lambda_{t+1}] \approx 1 - exp(\frac{1-\beta}{\beta} + E_t[R_{p,t+1}]) + E_t[R_{p,t+1} - E_t[R_{p,t+1}]) \\ + \frac{1}{2}Var(\Delta ln(\lambda_{t+1})) + \frac{1}{2}Var(R_{p,t+1}) + \alpha_t Cov(\Delta ln(\lambda_{t+1}), \eta_{s,t+1}) \end{aligned}$$

It is assumed that $1 - exp(\frac{1-\beta}{\beta} + E_t[R_{p,t+1}]) = 0$ in equilibrium, and $E_t[R_{p,t+1}]) + E_t[R_{p,t+1} - E_t[R_{p,t+1}]) = 0$. Then, we can then write

$$\Delta ln\lambda_{i,t+1} \approx \psi_t + \epsilon_{i,t+1} \tag{A.2}$$

where $\psi_t = \frac{1}{2}Var(\Delta ln(\lambda_{t+1})) + \frac{1}{2}Var(R_{p,t+1}) + \alpha_t Cov(\Delta ln(\lambda_{t+1}), \eta_{s,t+1})$

Step2 : Approximation of the first order conditions

Given the first order condition:

$$\begin{gathered} U_c(C_t, L_{1t}, L_{2t}) = \lambda_t \\ U_{l_1}(C_t, L_{1t}, L_{2t}) = \lambda_t W_{1t} \\ U_{l_2}(C_t, L_{1t}, L_{2t}) = \lambda_t W_{2t} \end{gathered}$$

the second step is to take a first order approximation for $U_x(C_t, L_{1t}, L_{2t})$ around lnC_t, lnL_{1t}, lnL_{2t} where $x \in \{c, l_1, l_2\}$. Thus we have:

$$\begin{gathered} \Delta lnU_c(.) \approx \frac{U_{cc}C_t}{U_c}\Delta lnC_t + \frac{U_{cl_1}L_{1t}}{U_c}\Delta lnL_{1t} + \frac{U_{cl_2}L_{2t}}{U_c}\Delta lnL_{2t} \\ \Delta lnU_{l_1}(.) \approx \frac{U_{l_1c}C_t}{U_{l_1}}\Delta lnC_t + \frac{U_{l_1l_1}L_{1t}}{U_c}\Delta lnL_{1t} + \Delta lnL_{2t} \\ \Delta lnU_{l_2}(.) \approx \frac{U_{l_2c}C_t}{U_{l_2}}\Delta lnC_t + \frac{U_{l_2l_1}L_{1t}}{U_c}\Delta lnL_{2t} + \frac{U_{l_1l_1}L_{2t}}{U_{l_1}}\Delta lnL_{2t} \end{gathered} \tag{A.3}$$

From the first order condition can derive that:

$$\begin{gathered} \Delta lnU_c(.) = \psi_t + \epsilon_{i,t} \\ \Delta lnU_{l_1}(.) = \psi_t + \epsilon_{i,t} + \Delta lnW_{1,t} \\ \Delta lnU_{l_2}(.) = \psi_t + \epsilon_{i,t} + \Delta lnW_{2,t} \end{gathered} \tag{A.4}$$

Combining equations (24) and (25) and after some algebra, we have:

$$\begin{pmatrix} \Delta ln\lambda_t \\ \Delta ln\lambda_t + \Delta lnW_{1t} \\ \Delta ln\lambda_t + \Delta lnW_{2t} \end{pmatrix} \approx \begin{pmatrix} \frac{U_{cc}}{U_c}C_t & \frac{U_{cl_1}}{U_c}L_{1t} & \frac{U_{cl_2}}{U_c}L_{2t} \\ \frac{U_{l_1c}}{U_{l_1}}C_t & \frac{U_{l_1l_1}}{U_c}L_{1t} & \frac{U_{l_1l_2}}{U_{l_1}}L_{2t} \\ \frac{U_{l_2c}}{U_{l_2}}C_t & \frac{U_{l_2l_1}}{U_c}L_{1t} & \frac{U_{l_1l_1}}{U_{l_1}}L_{2t} \end{pmatrix} * \begin{pmatrix} \Delta lnC_t \\ \Delta lnL_{1t} \\ \Delta lnL_{2t} \end{pmatrix} \tag{A.5}$$

Hence we have :

$$\begin{pmatrix} \Delta lnC_t \\ \Delta lnL_{1t} \\ \Delta lnL_{2t} \end{pmatrix} \approx \begin{bmatrix} -\eta_{c,p} & \eta_{c,w_1} & \eta_{c,w_2} \\ \eta_{l_1,p} & \eta_{l_1,w_1} & \eta_{l_1,2} \\ \eta_{l_2,p} & \eta_{l_2,w_1} & \eta_{l_2,w_2} \end{bmatrix} * \begin{pmatrix} \psi_t + \epsilon_{i,t} \\ \psi_t + \epsilon_{i,t} + \Delta lnW_{1t} \\ \psi_t + \epsilon_{i,t} + \Delta lnW_{2t} \end{pmatrix} \tag{A.6}$$

Step3 : Approximation of the intertemporal budget constraint

As the marginal utility of wealth (λ_t) is unobserved, in this step we used the present value budget constraint in order to eliminate the change in the marginal utility of wealth from equation (A.6). To do so , the idea is to link the innovation of the marginal utilities of wealth $\epsilon_{i,t}$ with measurable shocks to wages and to risky assets.

The present value budget constraint can be written as follow:

$$E_t \sum_{k=0}^{T_r - t} \frac{C_{t+k}}{(1+r_{p,t+k})^k} = A_t + E_t \sum_{k=0}^{T_r - t} \frac{W_{1,t+k}(1-L_{1,t+k})}{(1+r_{p,t+k})^k} + E_t \sum_{k=0}^{T_r - t} \frac{W_{2,t+k}(1-L_{2,t+k})}{(1+r_{p,t+k})^k} \tag{A.7}$$

Applying a Taylor approximation technique (see **Blundell, Low and Preston (2013)** for the general Taylor rule) to the LHS, we obtain :

$$
\begin{aligned}
E_I[ln \sum_{k=0}^{T_r-t} \frac{C_{t+k}}{(1+r_{p,t+k})^k} &= ln \sum_{k=0}^{T_r-t} exp[E_{t-1}lnC_{t+k} - kE_{t-1}ln(1+r_{p,t+k})] \\
+ \sum_{k=0}^{T_r-t} \theta_{t+k}[E_IlnC_{t+s} &- E_{t-1}lnC_{t+s} - k\{E_Iln(1+r_{p,t+k}) - E_{t-1}ln(1+r_{p,t+k})\}]
\end{aligned} \tag{A.8}
$$

Where

$$
\theta_{t+k} = \frac{exp[E_{t-1}lnC_{t+k} - kE_{t-1}ln(1+r_{p,t+k})]}{\sum_{j=0}^{T_r-t} exp[E_{t-1}lnC_{t+j} - kE_{t-1}ln(1+r_{p,t+j})]}
$$

From equation() we can derive:

$$
lnC_{t+k} = lnC_{t+k-1} + (-\eta_{c,p} + \eta_{c,w1} + \eta_{c,w2})(\psi_t + \epsilon_{i,t}) + \eta_{c,w1}\Delta lnW_{1,t} + \eta_{c,w2}\Delta lnW_{2,t}
$$

Also, we neglected ψ_t since it does not cannot carry any stochastic terms. For $I = t$ and applying a recursive analyze on k; we can show that:
if $k = 0$ then

$$
E_tlnC_{t+k} - E_{t-1}lnC_{t+k} = (-\eta_{c,p} + \eta_{c,w1} + \eta_{c,w2})\epsilon_{i,t} + \eta_{c,w1}(\nu_{it} + u_{it}) + \eta_{c,w2}(\nu_{it} + u_{it})
$$

if $k \geq 0$ then

$$
E_tlnC_{t+k} - E_{t-1}lnC_{t+k} = (-\eta_{c,p} + \eta_{c,w1} + \eta_{c,w2})\epsilon_{i,t} + \eta_{c,w1}\nu_{it} + \eta_{c,w2}\nu_{it}
$$

Hence we have :

$$
\begin{aligned}
\sum_{k=0}^{T_r-t} \theta_{t+k}[E_IlnC_{t+s} - E_{t-1}lnC_{t+s}] \approx &\sum_{k=0}^{T_r-t} \theta_{t+k}[(-\eta_{c,p} + \eta_{c,w1} + \eta_{c,w2})\epsilon_{i,t} + \eta_{c,w1}\nu_{it} + \eta_{c,w2}\nu_{it}] \\
&+ \theta_t(\eta_{c,w1}u_{it} + \eta_{c,w2}u_{it})
\end{aligned} \tag{A.9}
$$

Further

$$
\begin{aligned}
\sum_{k=0}^{T_r-t} \theta_{t+k}[E_Iln(1+r_{p,t+k}) - E_{t-1}ln(1+r_{p,t+k})] &\approx \sum_{k=0}^{T_r-t} \theta_{t+k}[E_Ir_{p,t+k} - E_{t-1}r_{p,t+k}] \\
&\approx \sum_{k=0}^{T_r-t} \theta_{t+k}k\alpha_{t-1}\eta_t^s
\end{aligned} \tag{A.10}
$$

Assuming that $\theta_t \approx 0$ and $\sum_{k=0}^{T_r-t} \theta_{t+k}k \approx \frac{T_r-t}{2}$ and taking the difference between expectation $I = t$ and $I = t-1$, we have :

$$
\begin{aligned}
&E_t[ln \sum_{k=0}^{T_r-t} \frac{C_{t+k}}{(1+r_{p,t+k})^k}] - E_{t-1}[ln \sum_{k=0}^{T_r-t} \frac{C_{t+k}}{(1+r_{p,t+k})^k}] \approx \\
&(-\eta_{c,p} + \eta_{c,w1} + \eta_{c,w2})\epsilon_{i,t} + \eta_{c,w1}\nu_{it} + \eta_{c,w2}\nu_{it} - \frac{T_r-t}{2}\alpha_{t-1}\eta_t^s
\end{aligned} \tag{A.11}
$$

Now we turn on the analysis of the RHS of equation (A.7). The previous approach is apply to the right hand side of the intertemporal budget constraint. In particular, the approximation procedure to the right hand side is similar to that in Blundell et al.(2016) with a stochastic portfolio returns. We then define. Let's define by :

$$D_1 = \sum_{j=0}^{T-t} exp[E_{t-1}ln[L_{1,t+j}W_{1,t+j} - jE_{t-1}ln(1+r_{p,t+j})] \tag{A.12}$$

$$D_2 = \sum_{j=0}^{T-t} exp[E_{t-1}ln[L_{2,t+j}W_{2,t+j} - jE_{t-1}ln(1+r_{p,t+j})] \tag{A.13}$$

$$D_3 = exp[E_{t-1}ln(A_t)] \tag{A.14}$$

$$\pi_t = \frac{expE_{t-1}ln(A_t)}{D_1 + D_2 + D_3} \tag{A.15}$$

$$s_t = \frac{D_1}{D_1 + D_2} \tag{A.16}$$

Then, following the approximation procedure detailed for the left-hand side, the approximated right-hand side of the intertemporal budget constraint is given by:

$$A_t + E_t \sum_{k=0}^{T_r - t} \frac{W_{1,t+k}(L_{1,t+k})}{(1+r_{p,t+k})^k} + E_t \sum_{k=0}^{T_r - t} \frac{W_{2,t+k}(L_{2,t+k})}{(1+r_{p,t+k})^k} \approx$$

$$(1-\pi_t)[(s_t\eta_{l_1,\lambda}+(1-s_t)\eta_{l_1,\lambda})\epsilon_{it}+(s_t\eta_{l_1,w_1}+(1-s_t)\eta_{l_1,w_2})v_{1t}+(s_t\eta_{l_1,w_1}+(1-s_t)\eta_{l_2,w_2})v_{2t}-\frac{T-t}{2}\alpha_{t-1}\eta^s_t] \tag{A.17}$$

Equating the approximation of the left hand side(equation ??) of the budget constraint with that for the right hand side(equation A.17), we can solve for ϵ_t:

$$\epsilon = \frac{[\eta_{c,w_1} - (1-\pi_t)(s_t + \bar{\eta}_{l,w_1})]v_{1,t}}{(1-\pi_t)[\bar{\eta}_{l,p} + \bar{\eta}_{l,w_1} + \bar{\eta}_{l,w_2}] + \eta_{c,p} - (\eta_{c,w_1} + \eta_{c,w_2})}$$
$$\frac{[\eta_{c,w_2} - (1-\pi_t)(s_t + \bar{\eta}_{l,w_1})]v_{2,t}}{(1-\pi_t)[\bar{\eta}_{l,p} + \bar{\eta}_{l,w_1} + \bar{\eta}_{l,w_2}] + \eta_{c,p} - (\eta_{c,w_1} + \eta_{c,w_2})}$$
$$\frac{((1-\pi_t)\frac{T-t}{2} - \pi_t)\alpha_{t-1}\eta^s_t}{(1-\pi_t)[\bar{\eta}_{l,p} + \bar{\eta}_{l,w_1} + \bar{\eta}_{l,w_2}] + \eta_{c,p} - (\eta_{c,w_1} + \eta_{c,w_2})} \tag{A.18}$$

for $j \in \{1, 2\}$ we have:

$$\kappa_{c,v_j} = \eta_{c,w_j} + \frac{(-\eta_{c,p} + \eta_{c,w_1} + \eta_{c,w_2})[\eta_{c,w_j} - (1-\pi_{it})(s_{jt} + \overline{\eta_{l,w_j}})]}{(1-\pi_{It})[\overline{\eta_{l,p}} + \overline{\eta_{l,w_1}} + \overline{\eta_{l,w_2}} + \eta_{c,p} - (\eta_{c,w1} + \eta_{c,w2})]}$$

$$\kappa_{l_j,\upsilon_j} = \eta_{l_j,w_j} + \frac{(-\eta_{l_j,p} + \eta_{l_j,w_1} + \eta_{l_j,w_2})[\eta_{c,w_j} - (1-\pi_{it})(s_{jt} + \overline{\eta_{l,w_j}})]}{(1-\pi_{it})[\overline{\eta_{l,p}} + \overline{\eta_{l,w_1}} + \overline{\eta_{l,w_2}} + \eta_{c,p} - (\eta_{c,w1} + \eta_{c,w2})]}$$

$$\kappa_{l_j,\upsilon_{-j}} = \eta_{l_j,w_j} + \frac{(-\eta_{l_j,p} + \eta_{l_j,w_1} + \eta_{l_j,w_2})[\eta_{c,w_j} - (1-\pi_{it})(s_{jt} + \overline{\eta_{l,w_j}})]}{(1-\pi_{it})[\overline{\eta_{l,p}} + \overline{\eta_{l,w_1}} + \overline{\eta_{l,w_2}} + \eta_{c,p} - (\eta_{c,w1} + \eta_{c,w2})]}$$

$$\kappa_{c,\eta^s} = \frac{[\pi_{it} - (1-\pi_{it})\frac{T-t}{2}](-\eta_{c,p} + \eta_{c,w_1} + \eta_{c,w_2})}{(1-\pi_{it})[\overline{\eta_{l,p}} + \overline{\eta_{l,w_1}} + \overline{\eta_{l,w_2}} + \eta_{c,p} - (\eta_{c,w1} + \eta_{c,w2})]}$$

$$\kappa_{l_j,\eta^s} = \frac{[\pi_{it} - (1-\pi_{it})\frac{T-t}{2}](\eta_{l_j,p} + \eta_{l_j,w_1} + \eta_{l_j,w_2})}{(1-\pi_{it})[\overline{\eta_{l,p}} + \overline{\eta_{l,w_1}} + \overline{\eta_{l,w_2}} + \eta_{c,p} - (\eta_{c,w1} + \eta_{c,w2})]}$$

A.1.5 Optimal portfolio allocation

Given the Euler Equation of the household problem:

$$E_t\left[\beta\frac{U_c(C_{t+1}, L_{1,t+1}, L_{2,t+1})}{U_c(C_t, L_{1,t}, L_{2,t})}R_{p,t+1}\right] = 1$$

A log linear approximation yield to:

$$E_t\left[exp\left\{log(\beta) + r_{i,t+1} + \sum_{j=1}^{2}\hat{\gamma}_j ln(\frac{1-L_{j,t+1}}{1-L_{j,t}}) - \sigma\Delta lnC_{j,t+1}\right\}\right] = 1 \tag{A.19}$$

Where $\hat{\gamma}_1 = (1-\zeta)\omega(1-\sigma)$ and $\hat{\gamma}_2 = \zeta\omega(1-\sigma)$. Note that

$$ln(\frac{1-L_{j,t+1}}{1-L_{j,t}}) = ln(1-exp(l_{j,t+1})) - ln(1-exp(l_{j,t}))$$

An approximation of the expression $ln(1-exp(l_{j,t})$ around $E(l_{j,t})$ is:

$$ln(1-exp(l_{j,t})) = ln(1-exp(E(l_{j,t}))) - \frac{exp(E(l_{j,t}))}{1-exp(E(l_{j,t}))}(l_{j,t} - E(l_{j,t})) \tag{A.20}$$

Let denotes by :

$$Q_j = -\frac{exp(E(l_{j,t}))}{1-exp(E(l_{j,t}))} \approx \frac{-\overline{L_j}}{(1-\overline{L_j})}$$

Substituting (A.20) into (A.19), we have :

$$E_t\left[exp\left\{log(\beta) + r_{i,t+1} + \sum_{j=1}^{2}\hat{\gamma}_j Q_j\Delta lnL_{j,t+1} - \sigma\Delta lnC_{j,t+1}\right\}\right] = 1$$

Using a second-order Taylor approximation around the conditional means $E_t(r_{i,t+1})$, $E_t(\Delta lnL_{j,t+1})$, $E_t(\Delta lnC_{t+1})$

$$\begin{aligned}1 = &\left[1 + log(\beta) + E_t(r_{i,t+1}) + E_t(\sum_{j=1}^{2}\hat{\gamma}_j Q_j \Delta lnL_{j,t+1}) - \sigma E_t(\Delta lnC_{t+1})\right] \\ &- \frac{1}{2}var(r_{i,t+1} + \sum_{j=1}^{2}\hat{\gamma}_j Q_j \Delta lnL_{j,t+1} - \sigma \Delta lnC_{j,t+1})\end{aligned} \tag{A.21}$$

For

$$r_f \approx \sigma E_t(\Delta lnC_{t+1}) - E_t(\sum_{j=1}^{2}\hat{\gamma}_j Q_j \Delta lnL_{j,t+1}) - log(\beta) + \frac{1}{2}var(\sum_{j=1}^{2}\hat{\gamma}_j Q_j \Delta lnL_{j,t+1} - \sigma \Delta lnC_{j,t+1})$$

The equation (A.20) above can be written as follow:

$$E(r_{i,t+1}) - r_f + \frac{1}{2}var(r_{i,t+1} + \sum_{j=1}^{2}\hat{\gamma}_j Q_j \Delta lnL_{j,t+1} - \sigma \Delta lnC_{j,t+1}) = 0$$

$$E(r_{i,t+1}) - r_f + \frac{1}{2}var(r_{i,t+1}) = -cov(r_{i,t+1}, \sum_{j=1}^{2}\hat{\gamma}_j Q_j \Delta lnL_{j,t+1} - \sigma \Delta lnC_{j,t+1})$$

Using the transition matrix derived with the **BPS** model and after some algebra with the assumption that the transitory component is not correlated to the return to stock, we have :

$$\begin{aligned}E(r_{i,t+1}) - r_f + \frac{1}{2}var(r_{i,t+1}) = &\sum_{j=1}^{2}[\hat{\sigma}\kappa_{c,\upsilon_j} - \hat{\gamma}_j Q_j \kappa_{l_j,\upsilon_j}]cov(r_{i,t+1}, \upsilon_{i,j,t+1}) \\ &- \sum_{j=1}^{2}\hat{\gamma}_j Q_j \kappa_{l_j,\upsilon_{-j}} cov(r_{i,t+1}, \upsilon_{i,-j,t+1}) \\ &+ \alpha_{it}[\sigma\kappa_{c,\eta^s} - \sum_{j=1}^{2}\hat{\gamma}_j Q_j \kappa_{l_j,\eta^s}]var(r_{i,t+1})\end{aligned}$$

By definition we can approximate $cov(r_{i,t+1}, \upsilon_{i,j,t+1}) \approx \rho_j \sigma_r \sigma_{\upsilon_j}$, where ρ_j is the correlation structure estimated in section **??**. Rearranging, we obtain equation (**??**) in the main text.

A.1.6 Calibration details

Using the first stage of the procedure describes in section2.1.1, we can write ω, ζ as function of the preference and insurance parameters.

$$U_c = C^{-\sigma}[(1 - L_1)^{\zeta}(1 - L_2)^{1-\zeta}]^{\omega(1-\sigma)} = \lambda$$

$$U_{l_1} = -(1-L_1)^{\zeta\omega(1-\sigma)-1}[C(1-L_2)^{(1-\zeta)\omega}]^{(1-\sigma)} = -\lambda W_1$$

$$U_{l_2} = -(1-L_2)^{(1-\zeta)\omega(1-\sigma)-1}[C(1-L_1)^{\zeta\omega}]^{(1-\sigma)} = -\lambda W_2$$

A Log linearization approximation of the first order conditions yield to :

$$G * \begin{pmatrix} \Delta lnC \\ \Delta ln(1-L_1) \\ \Delta ln(1-L_2) \end{pmatrix} \approx \begin{pmatrix} \Delta ln\lambda \\ \Delta ln\lambda + \Delta lnW_1 \\ \Delta ln\lambda + \Delta lnW_2 \end{pmatrix} \tag{A.22}$$

Yet we have :

$$ln(1-L_j) \approx Q_j(lnL_j - E(lnL_j))$$

Hence

$$\Delta ln(1-L_j) \approx Q_j \Delta ln(L_j)$$

Thus equation(A.22) can be rewrite as follow:

$$\widetilde{G} * \begin{pmatrix} \Delta lnC \\ \Delta lnL_1 \\ \Delta lnL_2 \end{pmatrix} \approx \begin{pmatrix} \Delta ln\lambda \\ \Delta ln\lambda + \Delta lnW_1 \\ \Delta ln\lambda + \Delta lnW_2 \end{pmatrix}$$

Where

$$\widetilde{G} = \begin{bmatrix} -\sigma & Q_1(1-\sigma)\omega\zeta & Q_2(1-\zeta)\omega(1-\sigma) \\ 1-\sigma & Q_1((1-\sigma)\omega\zeta-1) & Q_2(1-\zeta)\omega(1-\sigma) \\ 1-\sigma & Q_1(1-\sigma)\omega\zeta & Q_2((1-\zeta)\omega(1-\sigma)-1) \end{bmatrix}$$

and

$$\widetilde{G}^{-1} = \begin{bmatrix} -\eta_{c,p} & \eta_{c,w_1} & \eta_{c,w_2} \\ \eta_{l_1,p} & \eta_{l_1,w_1} & \eta_{l_1,2} \\ \eta_{l_2,p} & \eta_{l_2,w_1} & \eta_{l_2,w_2} \end{bmatrix}$$

Given the functional form in this paper, the Frisch elasticities matrix ($\widetilde{G}$) is derived as functions of preference parameters and average ratio hours worked leisure of males (Q_1) and females (Q_2). However, there are some technical issue arising in the calibration strategy. To some extent, we have to choose between the fitness of own-elasticities (preference parameters) and cross-elasticities (insurance parameters).

A.2 Appendix Chapter 2

A.2.1 List of Financial Institutions

Shadow banks: Broker Dealer and MMF	
Absolute Life inc	Marvix Fund
Addenda Capital inc	Midas Capital Corporation
Atlantis systems corps	Minorco Canada Limited
B.C. Pacific Capital Corporation	Montrusco Bolton Inc
Bedford Capital Financial Corp	Mount Real Corporation
Benvest Capital	NCE flow Trough Limited Partnership
Benvest Capital inc	New west energy service
Brascan Financial Corporation	Odonnell1996 Limited Partnership
BRL Enterprises Inc	Oceanic Iron Ore Corp
Canadien Fist Financial Group	Optimum General Inc
Capvest income corp	Pacrim International Capital Inc
Cartier Partners Financial Group	Pender financial Group corporation
Central Capital Corporation	RealCap Holdings Limited
Clarington Limited Partenership	SPEQ Alliance Medical
Cornor Clark Ltd	Sprott Inc
CVF Technologies Corporation	Street Capital Group Inc
Diversified Private Equity Corp	Sunwah International Limited
Flow Capital Corp	Thomas Weisel Partners Group
FT Capital	Trimin enterprises inc
Gluskin Sheff	Wells Fargo Canada Corporation
Groupe Demeter	Western Pacific Trust Company
Guardian Capital Group	Westfield Minerals Limited
Hawker Siddeley Canada	YMG Capital Management inc
Home equity income Trust	Jovian Capital Corporation
HomeQ Corporation	Legg Mason Canada Holdings
IPC Financial Network	Loring Ward International

Shadow banks: Trust and Loan	
Canada Trusco Mortgage	Firm capital Mortgage Investment trust
Central 1 Bank	MCAP Corporation
CT Financial Services	Western Pacific
Eaton Credit Card	CHIP
MTCMIC Mortgage	MCAP Corporation
Surrey Metro Savings	Assibone
Home Capital	Coast Capital
National Trust	First West
Desjardins Trust	Innovation credit Union
Credit insustriel Desjardins Bank	Uni
Mandate national Mortgage Corporation	Vancity
Independent Factors	Capital One
TD Mortgage investment corporation Bank	Ferratum
Equisure financial management limited	Mogo
Assante Corporation	OnDesk
Heller financial	BT Alex Brown Canada

Regulated banks
Bank of Nova Scotia*
Canadian Imperial Bank of Commerce
Canadian Western Bank
National Bank of Canada*
Royal Bank of Canada*
Equitable Bank Group Inc Bank
PWC Capital Inc
VersaBank
First Nation Financial Corporation Bank
The Toronto Dominion Bank*
Bank of Montreal*
Laurentian Bank Canada*

Note: * Systemically important banks.

A.2.2 Text cleaning

As is customary in the Natural Language Processing (NPL) literature, some steps are taken to clean and reduce the raw dataset before estimation. The preprocessing of the data is done using the natural language toolkit (NLTK) in Python. First, I "tokenize" each financial document into a sequence of words. Second, we clean out all non-alphabetic characters from the tokens, including removing all punctuation and numerical characters. Third, a stop-word list is employed. This is a list of common words not expected to have any information relating to the subject of an article. Stop words come from the following source *https://pypi.python.org/pypi/stop-words*. Examples of such words are the, is, are, and this. In total, the stop-word list together with the list of common surnames, locations, dates, and given names removed roughly 1800 unique tokens from the corpus. Fourth, an algorithm known as collocation algorithm is run. The objective of this algorithm is to use the part-of-speech tagger from the NLTK Python library. This allows to focus on the parts of the document most likely to contain relevant information. Finally, we retain descriptive bigram and trigram words nouns and remove all other tokens.

A.2.3 LDA

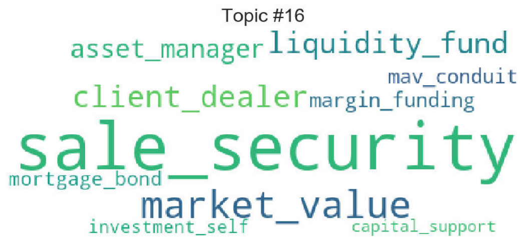
The "cleaned", but still unstructured, data-sets are decomposed into topics using a Latent Dirichlet Allocation (LDA). The LDA model is one of the most popular clustering algorithms in the NPL literature because of its simplicity, and because it has proven to classify text in much the same manner as humans would do The LDA is an unsupervised topic model that clusters words into topics, which are distributions over words, while at the same time classifying articles as mixtures of topics. An unsupervised learning algorithm is an algorithm that can discover an underlying structure in the data without being given any labeled samples to learn from. The term "latent" is used because the words, which are the observed data, are intended to communicate a latent structure, namely the subject matter (topics) of the article. The term "Dirichlet" is used because the topic mixture is drawn from a conjugate Dirichlet prior. More technical expositions of the LDA approach can be found in Blei et al. (2003).

A.2.4 Textual Data and Descriptive Statistics

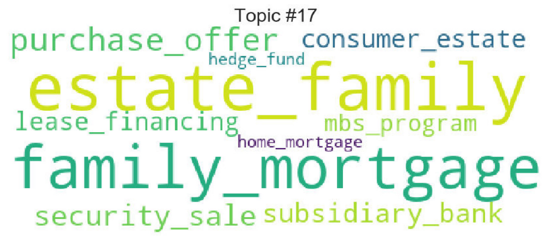
Table A.11: Lexicon of shadow banking activity

Lexicon	
mortgage_broker_services	security_distribution_service
mortgages_trades_services	client_dealer
liquidity_facility	third_party_guaranty
securities_lending_transactions	bank_sponsored
security_purchase_commitments	multi_seller_conduit
asset_purchase_agreement	credit_enhancement
co_ownership_interests	backstop_liquidity_facility
indemnification_contract	liquidity_support
obligation_securities_lent	liquidity_provider
mav_conduit	loan_substitute_securities
margin_funding_facilities	special_purpose_entity
Lending_agreements	structured_vehicle
third_party_asset	special_purpose_vehicle
standby_facility	securities_resale_agreements
	acceptances_obligation_security

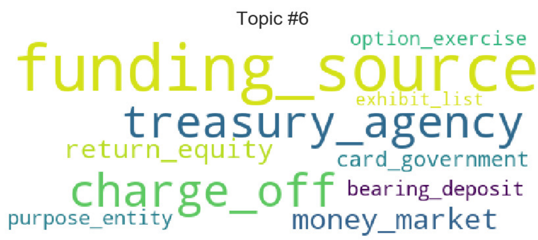
Figure A.10: 2-word and 3-word LDA model



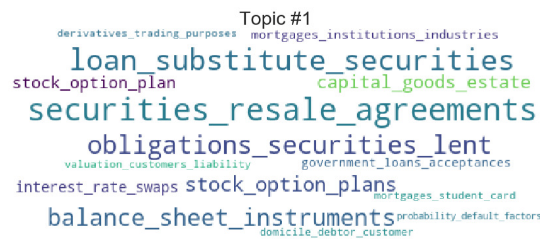
(a) Capital Market and Clearing house



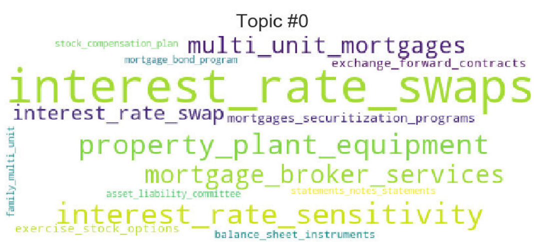
(b) Housing



(c) Funding source



(d) Security and Loan settlements

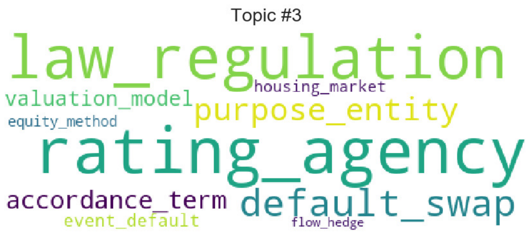


(e) Mortgage Brokerage

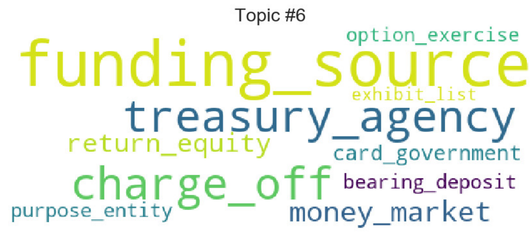
(f) Trading

Note: The topics are obtained from the training sample. The topic is represented as a word cloud and the word cloud is created based on the 10 most important words in the topic. The size of a word reflects the probability of this word occurring in the topic.

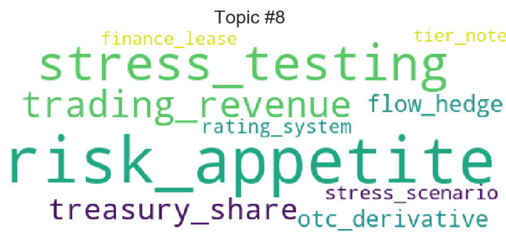
Figure A.11: Additional Topics



(a) Regulation



(b) Funding source



(c) Stress test

(d) Non-interest Revenu

Note: The topics are obtained from the training sample. The topic is represented as a word cloud and the word cloud is created based on the 10 most important words in the topic. The size of a word reflects the probability of this word occurring in the topic.

Figure A.12: Rising shadow banking sector

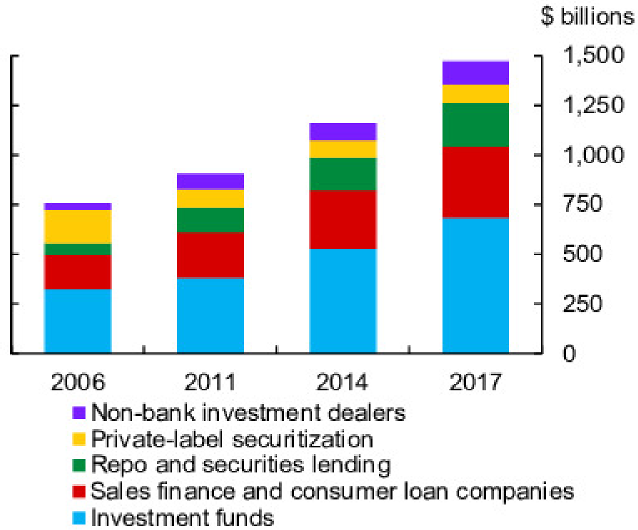
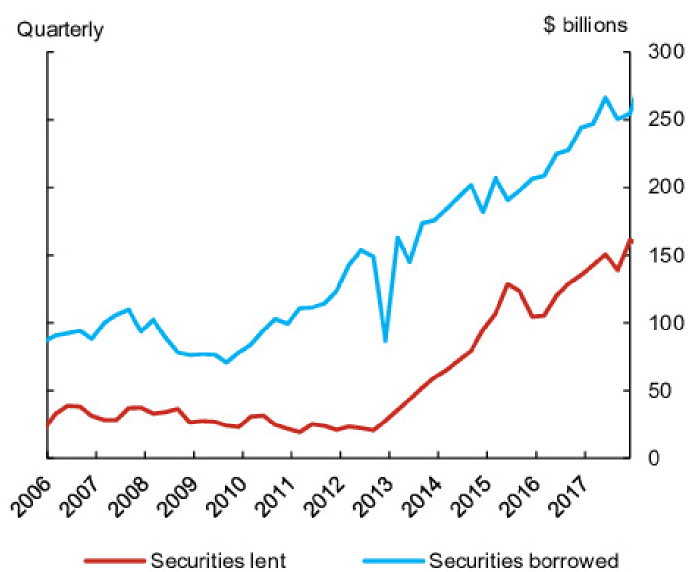
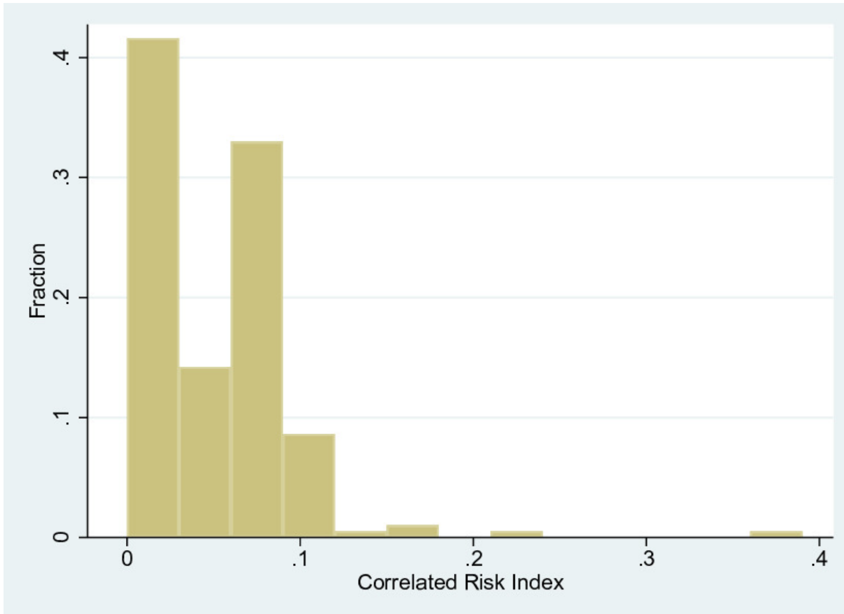


Figure A.13: Rising regulated banks' financing to the shadow banking sector



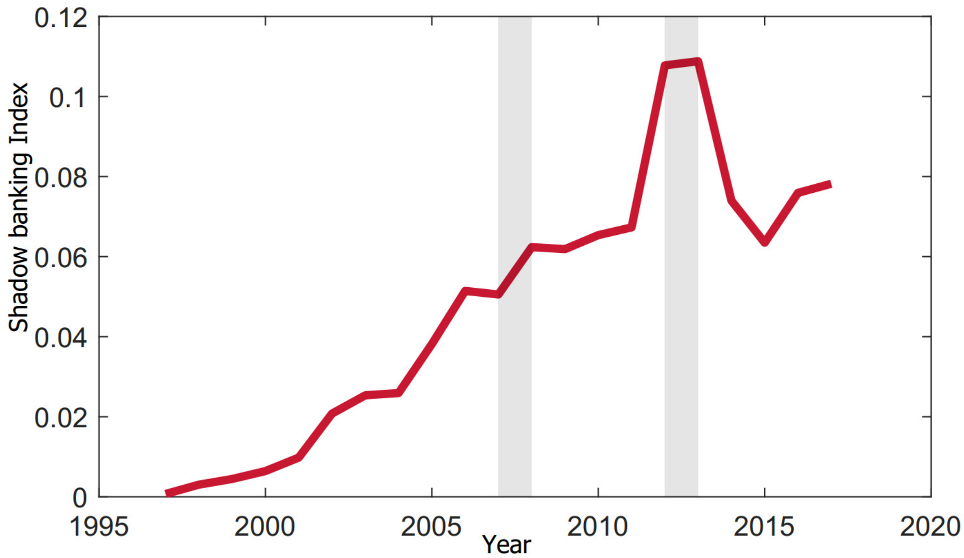
Source: Bank of Canada

Figure A.14: Histogram of shadow banking Index



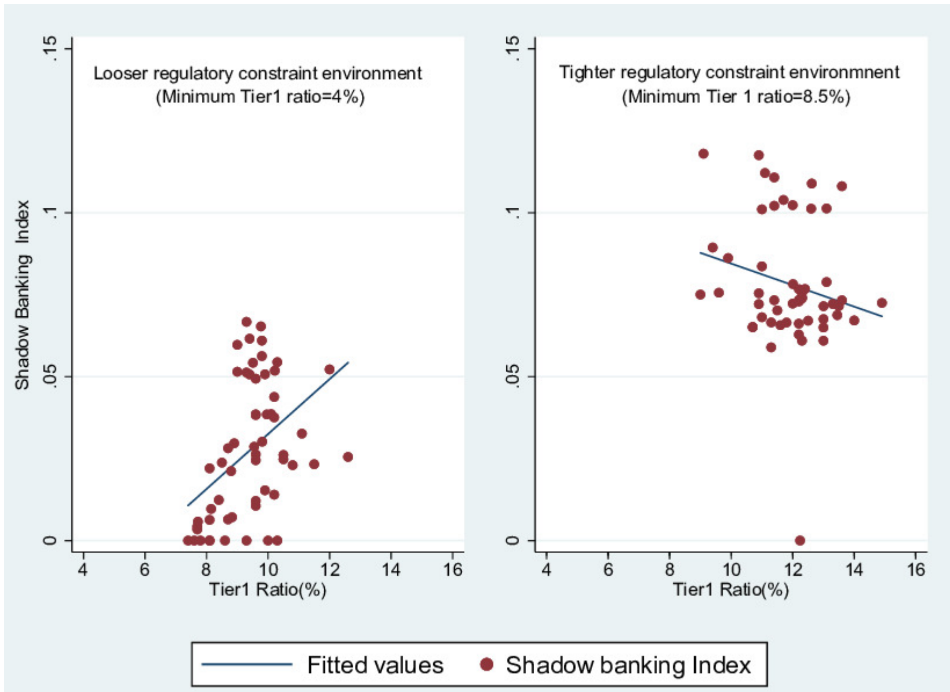
Note:This figure shows histogram of textual correlated risk index measures on the date level for systemically important banks. Values closer to one (zero) mean that the bank correlates more (less) its risk from outside regulatory umbrella.

Figure A.15: Evolution of the shadow banking index over time



Note: This figure plots the average shadow banking index as a function of time. The first shaded gray line represents concern about house price decline in U.S and the second gray line is related to concern about global growth and declining oil prices in Canada.

Figure A.16: Shadow banking Index and Regulatory arbitrage



Note: This figure depicts the scatter plot of banks' risk-based capital ratio (*Tier 1 Capital*) against shadow banking index for systemically important regulated banks in two different regulatory regimes. The left panel plots observations in a looser capital requirement regime (pre-crisis) where the minimum regulatory capital was set to 4%. The right panel plots observations in a tighter capital requirement regime(post-crisis) where the minimum regulatory capital is set to 8.5%

A.2.5 Variable definitions and data sources

Variable	Definition	Source
Balance Sheet data		
Deposit		OSFI
Log Asset	Logarithm of total asset	OSFI
Deposit/Asset	Ratio of stable funding	OSFI
Non interest income	Income from trading and securitization, investment banking and advisory fees, brokeragecommissions, venture capital and gains on non-hedging derivatives.	OSFI
Net Interest income	Income from loan	OSFI
Income Diversity	Income diversification measured by the inverse of the Hirfindal Index	
Tier 1 Capital	Ratio of Tier 1 capital to risk-weighted assets	OSFI
Return on asset(ROA)	Net interest income/ Total asset	OSFI
Risk Indicators		
$\Delta CoVaR$	Change in the conditionl value at risk	CRPS
MES	Marginal expected shortfall	CRPS
Shadow banking index	Textual based measure of discussions related to shadow banking activity	SEDAR

A.2.6 Descriptive Statistics

A.2.7 Textual data

	Mean	Median	Std	#Documents
Regulated Banks				197
Total words	39755	35282	23321	-
Unique words	2219	2402	615	-
Shadow Banks				514
Total words	14100	7883	23474	-
Unique words	1263	1204	718	-

Note: Reported summary statistics of financial documents after text processing and cleaning. The sample period consists of (*1997-2017*).

Table A.12: Summary statistics

Variable	N	Mean	Median	Std	p25	p75	p95
Textual information							
Shadow banking Index(%)	127	4.7	5.1	4.5	0.34	7.29	11.07
Balance Sheet Information							
Total Asset($billions)	126	2,933.9	1,880	3,661.2	121.5	4,240	8,260
Net interest income($millions)	126	4,918.3	3,400	5,894.2	171.5	7,110	13,020
Non interest income($millions)	126	4,883.3	2,960	6,137	32.85	7,055	13,940
ROA(%)	117	1.63	1.62	0.30	1.43	1.86	2.08
Capital Cost(%)	126	20.68	13.2	10.4	11.9	14.2	16.22
Tier 1 Capital ratio(%)	126	10.6	10.2	2.42	8.9	12.2	13.5
Idiosyncratic risk and Systemic risk measures							
log(Z-Score)	117	1.20	1.22	0.55	0.70	1.53	2.12
MES(%)	117	1.47	1.12	1.11	0.59	2.01	4.10
$\Delta CoVaR$(%)	117	5.35	5.04	0.95	4.61	5.87	7.27

Note: This table provides summary statistics of banks balance sheet information and different risk measures. The sample ranges from 1997 to 2017. ROA is bank return on asset measure by the ratio of net interest income and total asset. The correlated risk index variable is explain in section3. The $tier1$ ratio is the risk-weighted regulatory capital. $Capitalcost$ is the total capital adequacy cost. $Z - score = \frac{ROA+CAR}{\sigma_r}$ is the ratio between a bank's buffer and its stock volatility MES is the marginal expected shortfall, defined as the average stock return of a bank when the market return is in its 5% lower tail in a given year. $\Delta CoVaR$ is computed as the difference between $CoVaR$ conditional on the distress of a bank and $CoVaR$ conditional on the normal state of the institution, based on a 1-year forward-looking window.

A.2.8 Empirical results

Table A.13: Shadow banking Index and Regulatory capital constraint

	Shadow banking Index$_{it}$ (1)	(2)
Tier1 Capital	-0.405** (0.215)	-0.296*** (0.12)
size		0.109** (0.052)
size^2		-0.002* (0.001)
Bank Fe	Yes	Yes
Year Fe	Yes	Yes
R^2(*overall*)	0.91	0.85
# Observations	128	

Note.

$$\text{Shadow banking Index}_{it} = \beta_0 + \beta_1 \text{Tier1 Capital}_{it} + \beta_2 \text{size}_{it} + \beta_3 \text{size}^2_{it} + \epsilon_{it}$$

The estimation period consists of (*1997-2017*). Bank size is measured by the logarithm of total asset. Standard errors are in parentheses and are clustered at the bank level. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$.

Table A.14: Shadow banking Index and Income diversity

	Shadow banking Index$_{it}$	
	(1)	(2)
Income Diversity	0.055*** (0.015)	0.047*** (0.014)
size	0.043*** (0.004)	0.025*** (0.011)
Constante	-1.12*** (0.11)	-0.68*** (0.27)
Bank Fe	Yes	Yes
Year Fe	No	Yes
R^2	0.41	0.60
# Observations	195	

Note.

$$\text{Shadow banking Index}_{it} = \beta_0 + \beta_1 \text{Income Diversity}_{it} + \beta_2 \text{size}_{it} + \epsilon_{it}$$

The bank's income diversity is measured by the inverse of the Herfindahl-Hirschmann index(HHI) (Income Diversification$_{it} = \left[\sum_{k=1}^{2} w_{itk}^2\right]^{-1}$, w_{itk} is the weight of income type k). The Dependent variable is the textual based measure of risk disclosure from shadow banking activity. The estimation period consists of (*1997-2017*). Each regression controls for year and bank fixed effects. Standard errors are in parentheses and are robust to heteroscedasticy. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$.

Table A.15: Shadow banking Index and Portfolio riskiness

	MES		$\Delta CoVaR$		log(Z-score)
	(1)	(2)	(3)	(4)	(5)
Shadow banking Index	0.084*** (0.028)	0.116*** (0.055)	0.107*** (0.018)	0.006 (0.03)	-2.60*** (1.09)
size		0.006 (0.041)		0.004 (0.04)	-0.04 (0.13)
Deposit/Asset		-0.0130 (0.009)		0.04*** (0,009)	0.66*** (0.29)
Bank Fe	No	Yes	No	Yes	Yes
Year Fe	No	Yes	No	Yes	Yes
R^2	0.16	0.83	0.12	0.61	0.90
#Observations			117		

Note: The dependent variables are the marginal expected shortfall (MES) and the $\Delta CoVaR$ and the explanatory variable of interest is the textual-based measure of shadow banking activity. $Deposit_{it}/Asset_{it}$ measures bank's stable funding. The estimation period consists of (*1997-2017*). Each regression includes control for year and bank fixed effects. Standard errors are in parentheses and are robust to heteroscedasticy. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. The sample of banks consists of systemically important institution.

Table A.16: Dynamic effect of the Shadow banking Index

	Pre-Crisis Sample		Post-Crisis Sample	
	MES (1)	$\Delta CoVaR$ (2)	MES (3)	$\Delta CoVaR$ (4)
Shadow banking Index	0.291*** (0.094)	0.1782*** (0.060)	-0.252*** (0.03)	0.309*** (0.05)
R^2	0.26	0.23	0.40	0.32
#Obsevations	63		54	

Note: All specifications are estimated with a simple OLS regression. The dependent variable bank level systemic risk measures. The explanatory variables of interest is the textual based measure of shadow banking activity. The estimation periods for the pre-crisis is from 1997 to 2008 the post-crisis is from 2009 to 2017. Standard errors are in parentheses and are robust to heteroscedasticy. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. The sample of banks consists of systemically important institutions.

A.2.9 Robustness checks and alternative measures

In this Appendix, the paper conducts some robustness checks for the econometric results provided in table *A*.15 by controlling for other correlated risk exposure mechanisms and using alternative training sets.

A.2.9.1 Controlling for other risk measures

Here, the paper provides a robustness check for table A.15 by controlling for other contagion mechanisms emphasis in numerous theoretical studies (Wagner (2010), Wagner (2011) and Allen et al. (2012)) such as loan commonality and asset commonality between banks. ks. The common asset holdings may expose banks to common shocks, which in turn increase the probability of joint liquidation and cascading failures. The commonality can be thought as the distance between two portfolio and can be computed using the cosine similarity expression of equation(2.4).

Table A.17: Shadow banking Index and systemic risk

	MES (1)	$\Delta CoVaR$ (2)
Shadow banking index	0.117*** (0.032)	0.0038 (0.036)
Loan similarity	0.068 (0.065)	-0.128* (0.073)
Asset similarity	0.004 (0.192)	-0.151 (0.169)
Controls	Yes	Yes
$R^2(Overall)$	0.94	0.88
#Obsevations	117	

Note. This table reports results from the following regression

$$SystemicRisk_{it} = \beta_1+\beta_2*\text{Shadow banking Index}_{it}+\beta_3*\text{Loan similarity}_{it}+\beta_5*\text{Asset similarity}_{it}+\beta_4*Z_{it}+\epsilon_{it}.$$

The dependent variables are the marginal expected shortfall(MES) and the $\Delta CoVaR$. The explanatory variable of interest is the textual-based measure of correlated risk outside regulatory umbrella. $Deposit_{it}/Asset_{it}$ measures bank's stable funding. The estimation period consists of (*1997-2017*). All the specifications, the controls include time fixed effect, bank fixed effect and explanatory variables. Standard errors are in parentheses and are robust to heteroscedasticty. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. The sample of banks consists of systemically important institution.

A.2.9.2 Alternative training sample to measure the Shadow banking index

Here, the paper repeats the main analysis using two different training set: A training set with only regulated banks(Training set I) and a training set with only shadow banks(Training set II).

Table A.18: Shadow banking Index and Systemic risk

	Training set I		Training set II	
	MES (1)	$\Delta CoVaR$ (2)	MES (3)	$\Delta CoVaR$ (4)
Shadow banking Index	0.107*** (0.003)	0.008 (0.035)	0.117*** (0.031)	0.009 (0.036)
Controls	yes	yes	yes	yes
$\mathrm{R}^2(Overall)$	0.26	0.23	0.40	0.32
#Obsevations	117		117	

Note: The dependent variables are the bank level systemic risk measures. The explanatory variables of interest is the textual based measure shadow banking index.7. Standard errors are in parentheses and are robust to heteroscedasticy. $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. All the specifications, the controls include time fixed effect, bank fixed effect and explanatory variables. The sample of banks consists of systemically important institutions.

A.3 Appendix Chapter 3

A.3.1 Descriptive Statistics

Table A.19: Summary statistics

var	N	Mean	Median	p25	p75	p95	Std
Per capita GDP($US)	1029	48784.63	47182.5	41636	54270	68195	9645.62
Per capita Income($US)	1029	38646.8	37620	31362	44676	56314	97129.7
Carbon emission(tC02)							
Total carbon consumption	1029	99.47	100.14	70.06	122.96	155.3	32.81
Direct carbon emission	1029	22.97	22.73	15.3	28.37	37.98	9.36
Indirect carbon emission	1029	77.61	75.65	55.91	95.52	123.92	25.82
Services carbon consumption	1029	25.41	24.21	17.52	31.68	43.65	9.72
Durable goods Carbon consumption	1029	32.86	31.55	23.86	40.22	53.68	11.4
Non Durable goods Carbon consumption	1029	43.4	44.62	29.41	53.43	68.18	14.82

Note: This table provides summary statistics of carbon emissions and the growth rate of log per capita GDP across U.S. states. The sample ranges from 1998 to 2018. All the monetary values are defalted using the 2002 consumer price index (CPI).

A.3.2 Relation between consumption-based carbon emission and temperature

In the computable general equilibrium DICE[3] model of Nordhaus et al. (1992), faster economic activity increases the stock of greenhouse gas (GHG) emissions and thereby the average temperature. We present a state level evidence of this mechanism by assuming a delayed effect of carbon emissions on temperature.

Table A.20: Effect of carbon emissions on temperature deviation

	$\left\|T_{it} - \bar{T}_{30}\right\|$		
	1 lag	2 lags	3 lags
$\Delta e_{i,t-l}$	3.87*** (1.43)	3.585*** (1.45)	2.293 (1.57)
State FE	√	√	√
Year FE	√	√	√
R^2(*Overall*)	0.40	0.40	0.39
#Observations	931	882	833

Note.

$$\left|T_{it} - \bar{T}_{30}\right| = a_i + b_t + \theta_l \Delta e_{i,t-l} + \epsilon_{it}, \qquad l = 1, 2, 3$$

The dependent variable is $\left|T_{it} - \bar{T}_{30}\right|$ is the deviation of temperature T_{it} from its historical norm $\bar{T}_{30}$. The historical norm is computed as the average temperature over the period 1988-2018. The explanatory variable is the growth rate of consumption-based carbon emissions($\Delta e_{i,t}$). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. Standard errors are in parentheses.

[3] Dynamic Integrated Climate Economic

Table A.21: Effect of carbon emissions on temperature deviation

	$\left(T_{it} - \bar{T}_{30}\right)^+$		
	1 lag	2 lags	3 lags
$\Delta e_{i,t-l}$	1.96 (0.288)	5.43*** (0.016)	1.769 (0.247)
State FE	$\surd$	$\surd$	$\surd$
Year FE	$\surd$	$\surd$	$\surd$
R^2(*Overall*)	0.47	0.47	0.45
#Observations	535	517	479

Note.

$$\left(T_{it} - \bar{T}_{30}\right)^+ = a_i + b_t + \theta_l \Delta e_{i,t-l} + \epsilon_{it}, \qquad l = 1, 2, 3$$

The dependent variable is $\left(T_{it} - \bar{T}_{30}\right)^+$ is the positive deviation of temperature T_{it} from its historical norm $\bar{T}_{30}$. The historical norm is computed as the average temperature over the period 1988-2018. The explanatory variable is the growth rate of consumption-based carbon emissions($\Delta e_{i,t}$). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. Standard errors are in parentheses.

Table A.22: Effect of carbon emissions on temperature deviation

	$\left(T_{it} - \bar{T}_{30}\right)^{-}$		
	1 lag	2 lags	3 lags
$\Delta e_{i,t-l}$	-8.24*** (2.47)	-2.49 (2.28)	1.26 (2.28)
State FE	√	√	√
Year FE	√	√	√
$R^2(Overall)$	0.40	0.40	0.39
#Observations	931	882	833

Note.

$$\left(T_{it} - \bar{T}_{30}\right)^{-} = a_i + b_t + \theta_l \Delta e_{i,t-l} + \epsilon_{it}, \qquad l = 1, 2, 3$$

The dependent variable is $\left(T_{it} - \bar{T}_{30}\right)^{-}$ is the negative deviation of temperature T_{it} from its historical norm $\bar{T}_{30}$. The historical norm is computed as the average temperature over the period 1988-2018. The explanatory variable is the growth rate of consumption-based carbon emissions($\Delta e_{i,t}$). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. Standard errors are in parentheses.

A.3.3 Results

Table A.23: Mean Group(MG) estimates of the effect of carbon emission on GDP growth

Dependent variable	Log per capita GDP growth(Δg_t)	
	(q,p,m)=(1,1,1)	(q,p,m)=(2,2,2)
Mean Short run estimate		
Δg_{t-1}	-0.094** (0.046)	-1.013** (0.05)
Δg_{t-2}		-1.16*** (0.05)
Δe_t	0.044*** (0.009)	0.047*** (0.009)
Δe_{t-1}	0.01 (0.006)	0.012 (0.007)
Δe_{t-2}		0.018* (0.011)
Mean long-run estimate		
$\hat{\omega}$	0.045*** (0.01)	0.055*** (0.019)
N	50	50
N*T	950	900
$R^2(MG)$	0.57	0.59

Note:

$$\Delta y_{it} = a_i + \sum_{l=1}^{q} \varphi_{il} \Delta y_{i,t-l} + \sum_{l=0}^{p} \theta_{il} \Delta e_{i,t-l} + \sum_{l=0}^{m} \psi_{il} \bar{z}_{i,t-l} + \epsilon_{it}$$

The dependent variable is the output growth (Δg_t) and the explanatory variable is the growth of consumption-based carbon emission(Δe_t). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. N refers to the number of states. Standard errors are in parentheses.

Table A.24: Mean Group(MG) estimates of the effect of carbon emission on GDP growth

Dependent variable	Log per capita GDP growth(Δg_t)	
	(q,p,m)=(0,1,1)	(q,p,m)=(0,2,2)
Mean long-run estimate		
$\hat{\omega}$	0.033*** (0.007)	0.038*** (0.007)
N	50	50
N*T	950	900
R$^2(MG)$	0.54	0.58

Note:

$$\Delta y_{it} = a_i + \sum_{l=0}^{p} \theta_{il} \Delta e_{i,t-l} + \sum_{l=0}^{m} \psi_{il} \bar{z}_{i,t-l} + \epsilon_{it}$$

The dependent variable is the output growth (Δg_t) and the explanatory variable is the growth of consumption-based carbon emission(Δe_t). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. N refers to the number of states. Standard errors are in parentheses.

Table A.25: Mean Group(MG) estimates of the effect of consumption-based carbon emission on GDP growth

Dependent variable	Log per capita GDP growth(Δg_t)			
	(q,p,m)=(0,1,1)		(q,p,m)=(0,2,2)	
	(1)	(2)	(3)	(4)
Mean long run estimate				
$\hat{\omega}$	0.0359*** (0.007)	0.039*** (0.007)	0.0354*** (0.011)	0.052*** (0.0102)
$\hat{\omega} \times Top25\%$	0.004** (0.002)		0.0072** (0.011)	
$\hat{\omega} \times Bottom25\%$		0.001 (0.001)		0.0057* (0.0031)
N	50	50	50	50
N*T	950	950	900	900
R	0.46	0.48	0.38	0.43

Note: The dependent variable Δg_t is the log output growth and the explanatory variable is the growth rate of consumption-based carbon emission(Δe_t). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. N refers to the number of states. Standard errors are in parentheses.

A.3.4 Additional results

This section provides additional results of carbon emissions on the output growth by breaking the consumption-based emission in three categories: Services, durable goods and, non-durable goods.

A.3.4.1 Services

Table A.26: Consumption-based carbon emission from Services and Log output growth

Dependent variable	Log per capita GDP growth(Δg_t)	
	(q,p,m)=(0,1,1)	(q,p,m)=(0,2,2)
Mean long-run estimate		
$\hat{\omega}$	0.024*** (0.005)	0.025*** (0.007)
N	50	50
N*T	950	900
$R^2(MG)$	0.53	0.57

Note.

$$\Delta y_{it} = a_i + \sum_{l=0}^{p} \theta_{il} \Delta e_{i,t-l} + \sum_{l=0}^{m} \psi_{il} \bar{z}_{i,t-l} + \epsilon_{it}$$

The dependent variable $\Delta g_t$is the log output growth and the explanatory variable is the growth rate of consumption-based carbon emission from services($\Delta e_{service,t}$). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. Standard errors are in parentheses.

A.3.4.2 Durable goods

Table A.27: Consumption-based carbon emissions from Durable goods and Log output growth growth

Dependent variable	Log per capita GDP growth(Δg_t)	
	(q,p,m)=(0,1,1)	(q,p,m)=(0,2,2)
Mean long-run estimate		
$\hat{\omega}$	0.026*** (0.007)	0.035*** (0.008)
N	50	50
N*T	950	900
$R^2(MG)$	0.47	0.52

Note.

$$\Delta y_{it} = a_i + \sum_{l=0}^{p} \theta_{il} \Delta e_{i,t-l} + \sum_{l=0}^{m} \psi_{il} \bar{z}_{i,t-l} + \epsilon_{it}$$

The dependent variable $\Delta g_t$is the log output growth and the explanatory variable is the growth rate of consumption-based carbon emission from durable goods($\Delta e_{Durablegoods,t}$). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. Standard errors are in parentheses.

A.3.4.3 Non-Durable goods

Table A.28: Consumption-based carbon emission from Non-durable goods and Log output growth

Dependent variable	Log per capita GDP growth(Δg_t)	
	(q,p,m)=(0,1,1)	(q,p,m)=(0,2,2)
Mean long-run estimate		
$\hat{\omega}$	0.017*** (0.005)	0.021*** (0.006)
N	50	50
N*T	950	900
$R^2(MG)$	0.52	0.54

Note.

$$\Delta y_{it} = a_i + \sum_{l=0}^{p} \theta_{il} \Delta e_{i,t-l} + \sum_{l=0}^{m} \psi_{il} \bar{z}_{i,t-l} + \epsilon_{it}$$

The dependent variable Δg_t is log output growth and the explanatory variable is the growth rate of consumption-based carbon emission from non-durable goods($\Delta e_{Non-Durablegoods,t}$). $*p < 10\%$, $**p < 5\%$, $***p < 1\%$. Standard errors are in parentheses.

A.3.5 Household's consumption categories whose carbon footprint has been identified with the EIO-LCA database

Household consumption categories (2 digit level)	Carbon Footprint Coverage
1-Food and beverages purchased for off-premises consumption	
Food and nonalcoholic beverages purchased for off-premises consumption	√
Alcoholic beverages purchased for off-premises consumption	x
Food produced and consumed on farms	√
2-Clothing, footwear, and related services	
Clothing	√
Footwear	√
3-Housing, utilities, and fuels	
Housing	√
Household utilities and fuels	
Water supply and sanitation	√
Electricity, gas, and other fuels	x
Electricity	√
Natural gas	√
Fuel oil and other fuels	
4-Furnishings, household equipment, and maintenance	
Furniture, furnishings, and floor coverings	√
Household textiles	√
Household appliances	√
Glassware, tableware, and household utensils	√
Tools and equipment for house and garden	x
5-Health	
Medical products, appliances, and equipment	x
Outpatient services	√
Hospital and nursing home services	
Hospital	√
Nursing home services	√
6-Transportation	
Motor vehicles	√
Motor vehicle operation	√
Public transportation	
Ground transportation	√
Air transportation	√
Water transportation	√
7-Communication	
Telephone and related communication equipment	√
Postal and delivery services	√
Telecommunication services	√
Internet access	x
8-Recreation	
Video and audio equipment, computers, and related services	√
Sports and recreational goods and related services	√
Membership clubs, sports centers, parks, theaters, and museums	√
Magazines, newspapers, books, and stationery	√
Gambling	x
Pets, pet products, and related services	x
Photographic goods and services	x
Package tours	x
9-Education	
Educational books	x
Higher education	√
Nursery, elementary, and secondary schools	√
Commercial and vocational schools	√
10-Food services and accommodations	
Food services	√
Accommodations	√
11-Financial services and insurance	
Financial services	√
Insurance	√

A.3.6 Figures

A.3.6.1 Example

Figure A.17: Greenhouse gases footprints in one million dollars purchase of fruit and vegetable

Sector #311420: Fruit and vegetable canning, pickling and drying
Economic Activity: $1 Million Dollars
Displaying: Greenhouse Gases
Number of Sectors: Top 10

Change Inputs (Click here to view greenhouse gases, air pollutants, etc...)

Documentation:
The sectors of the economy used in this model.
The environmental, energy, and other data used and their sources.

Frequently asked questions about IO-LCA (or EEIO) models.

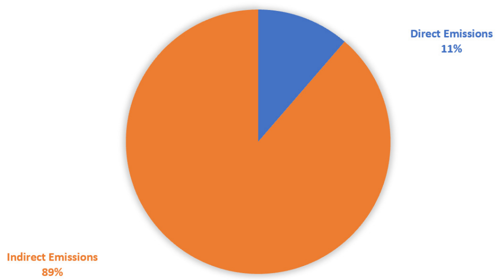
This EIO-LCA data model was contributed by Green Design Institute.

	Sector	Total t CO2e	CO2 Fossil t CO2e	CO2 Process t CO2e	CH4 t CO2e	N2O t CO2e	HFC/PFCs t CO2e
	Total for all sectors	*745.*	*527.*	*29.2*	*90.1*	*92.0*	*6.94*
221100	Power generation and supply	219.0	216.0	0.000	0.593	1.34	1.39
311420	Fruit and vegetable canning, pickling and drying	68.7	68.7	0.000	0.000	0.000	0.000
1121A0	Cattle ranching and farming	49.7	3.25	0.000	28.2	18.2	0.000
484000	Truck transportation	40.8	40.8	0.000	0.000	0.000	0.000
1111B0	Grain farming	38.2	5.63	0.000	3.12	29.4	0.000
211000	Oil and gas extraction	28.3	7.97	5.18	15.1	0.000	0.000
331110	Iron and steel mills	21.7	8.20	13.4	0.132	0.000	0.000
325310	Fertilizer Manufacturing	15.4	3.81	5.14	0.000	6.41	0.000
324110	Petroleum refineries	15.0	14.9	0.000	0.046	0.000	0.000
111200	Vegetable and melon farming	14.7	5.88	0.000	0.000	8.77	0.000

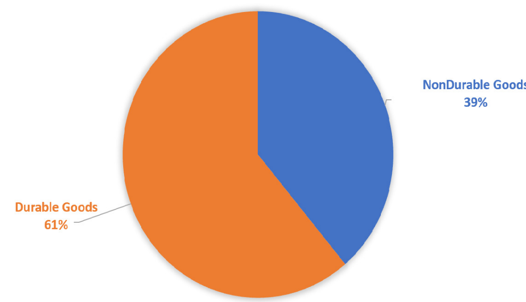
A.3.6.2 Direct and Indirect carbon emission factors

This figure shows the carbon footprint from direct emission, indirect emisision, durable consumption and, non-durable consumption. The direct emissions stem from goods such as natural gaz, motor oil , lubricant grass while the indirect emissions are embedded emissions from the production of goods and services consumed. The durable consumption good category includes housing, transport and furniture while in the non durable consumption basket we include food, health, food services and accommodation, clothing, education and recreation.

Figure A.18: Fraction of carbon footprint by consumption type and emission type

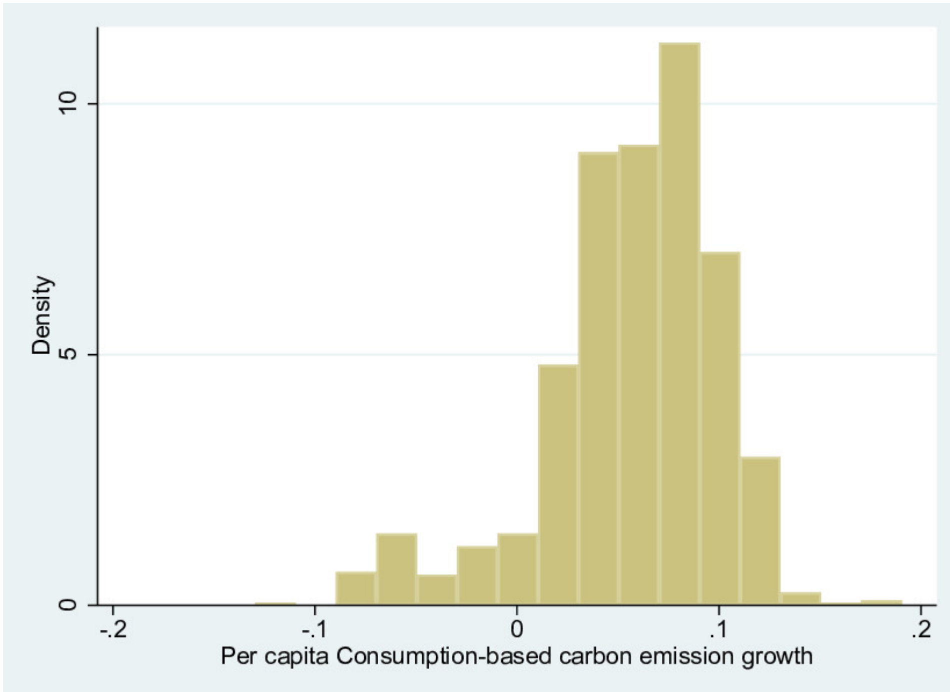


(a) **Emission type**



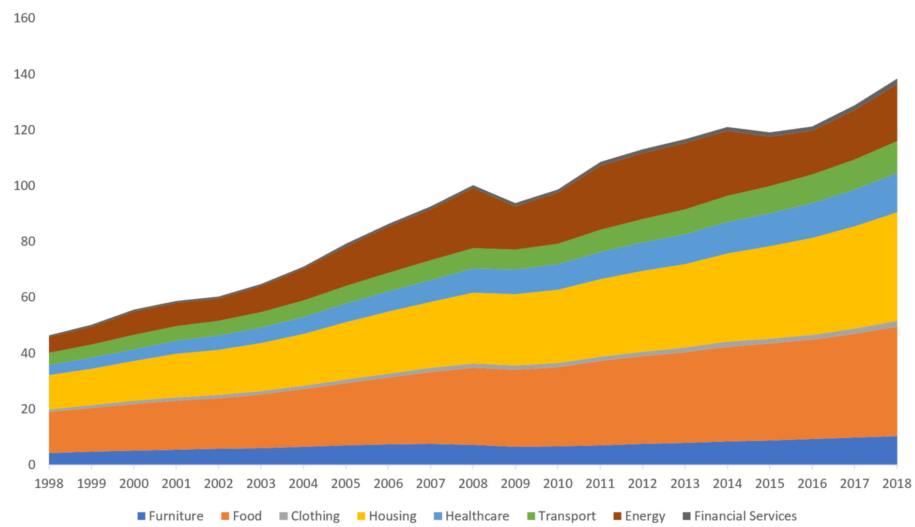
(b) **Consumption type**

Figure A.19: Distribution of carbon emissions across the U.S. States



A.3.6.3 Consumption-based carbon emission

Figure A.20: Evolution of consumption-based carbon emission by type of goods



A.3.7 Geographical concentration of the per capita consumption-based carbon emissions across across U.S.

Figure A.21: Geographical concentration of the per capita consumption-based carbon emissionsin 2015

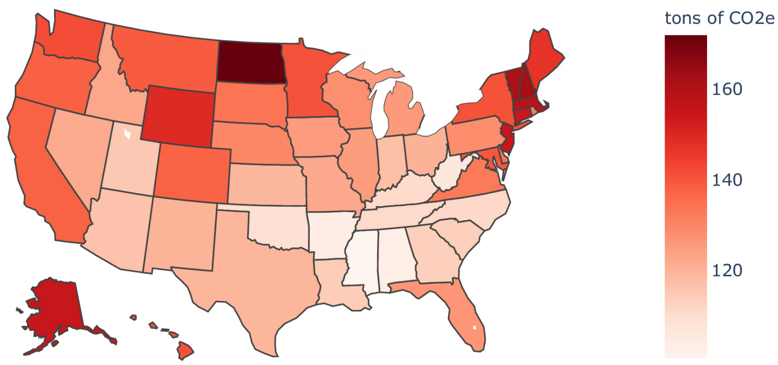
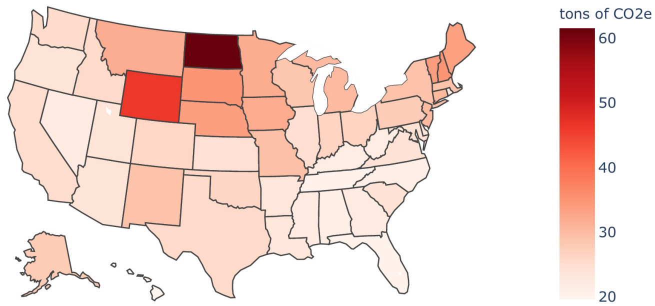
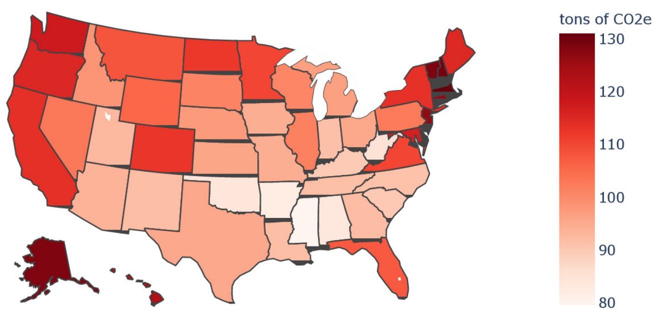


Figure A.22: Geographical concentration of the per capita consumption-based carbon emissions in 2015

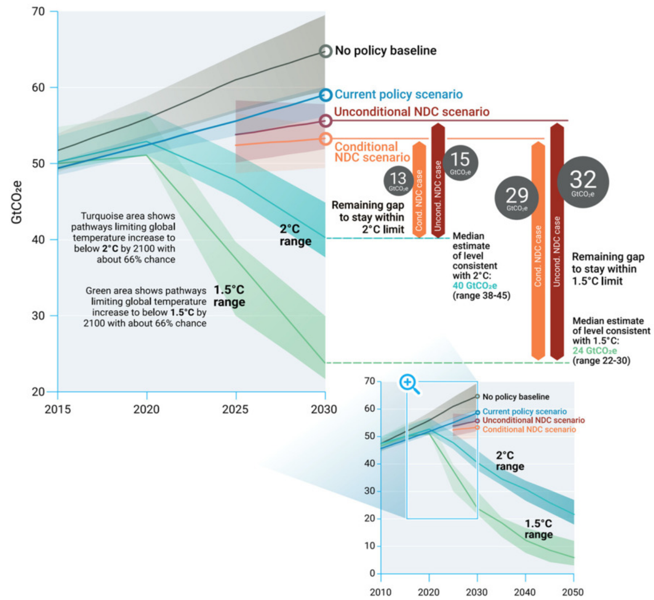


(a) **Indirect consumption-based carbon emissions:** Emission embedded in consumption related natural gaz, motor oil and lubricant grass



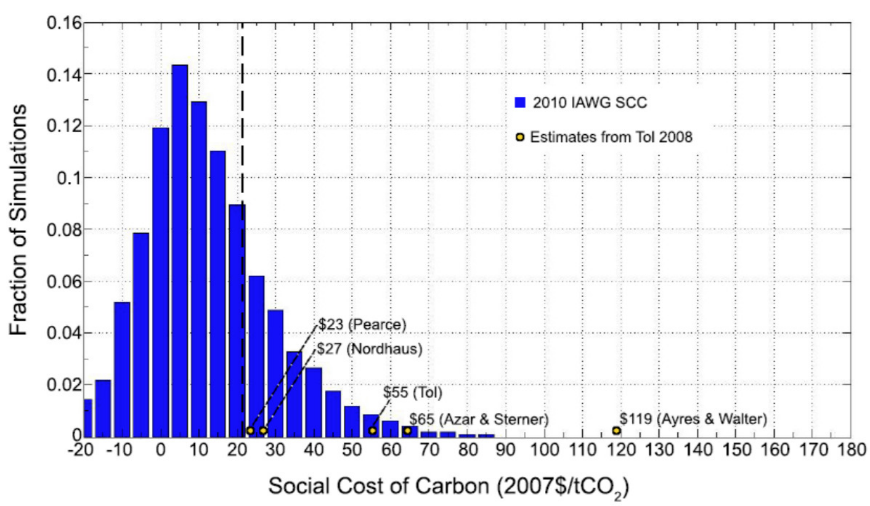
(b) **Indirect consumption-based carbon emissions:** Emissions embedded in goods such as housing and utilities, transport services, food, health, food services and accommodation, clothing, education and recreation financial and insurance services.

Figure A.23: Global greenhouse emissions under different scenarios and the emissions gap in 2030



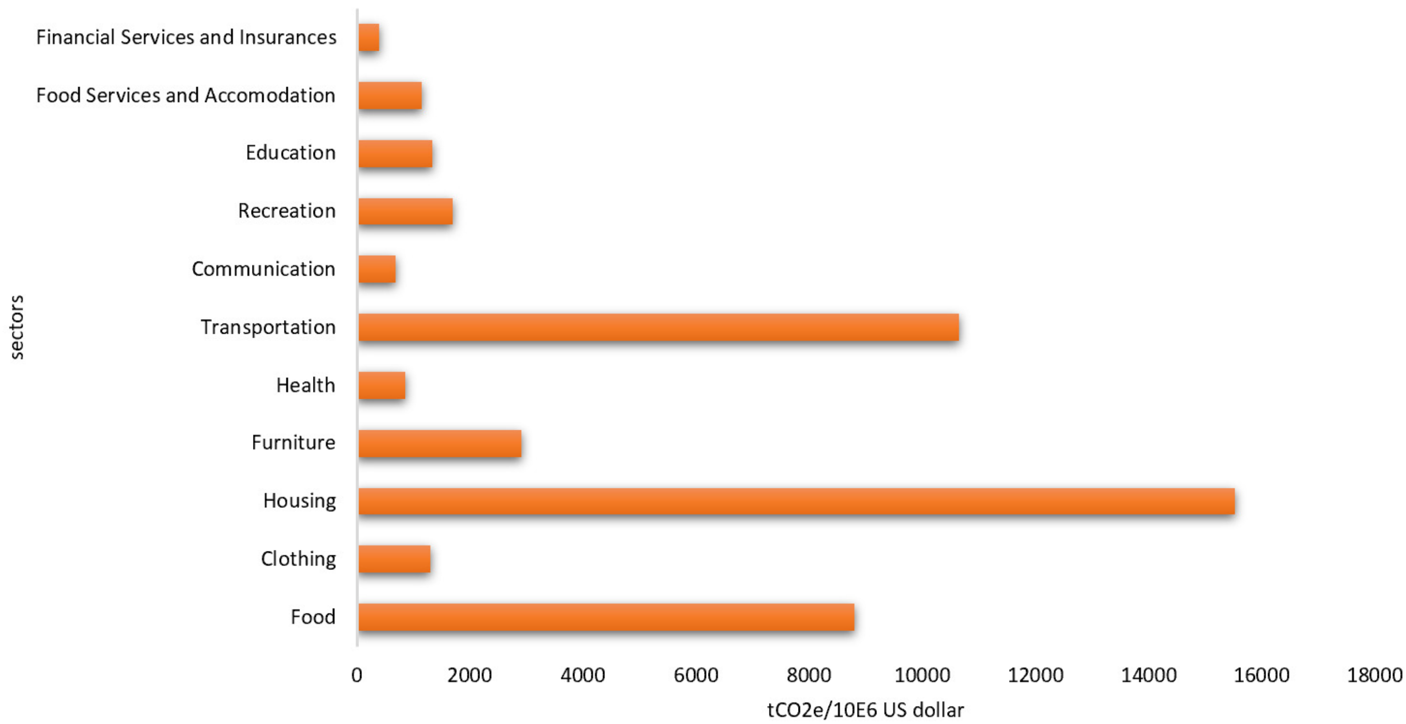
Source: *United Nations Environment Program, 2018.*

Figure A.24: Social cost of emissions reduction



Source: Moyer et al. (2014)

Figure A.25: Carbon footprint by household expenditure category



Note: The x-axis captures the tons of CO_2 emission (tCO_2e) per million of US dollars. As shown in the figure above, transport, food and housing account for the large part of carbon footprint in household consumption. They represent a total of 77% of US household dioxide carbon emission. Among household consumption basket, housing contributes the most (30%) in carbon footprint followed by transportation (21%) and food (19%).