Three papers on Macroeconomics, Asset Pricing, and International Trade

by

Sadaf Yalinejad

M.A. (Economics), Simon Fraser University

Thesis Submitted in Partial Fulfillment of the
Requirements for the Degree of
Doctor of Philosophy

in the
Department of Economics
Faculty of Arts and Social Sciences

SIMON FRASER UNIVERSITY
Fall 2023

Declaration of Committee

Name: **Sadaf Yalinejad**

Degree: **Doctor of Philosophy**

Thesis title: **Three papers on Macroeconomics, Asset Pricing, and International Trade**

Committee: **Chair:** Bertille Antoine
Professor, Economics

Kenneth Kasa
Supervisor
Professor, Economics

Lucas Herrenbrueck
Committee Member
Associate Professor, Economics

Alexander Karaivanov
Examiner
Professor, Economics

Zhenzhen FAN
External Examiner
Assistant Professor, Economics and Finance
University of Guelph

Abstract

This paper develops a multi-asset Intermediary Asset Pricing model. As in Haddad and Muir (2022), assets differ in their 'complexity', modeled here as an asset-specific information cost. More complex assets are more likely to be handled by intermediaries. As in Di Tella (2017), intermediaries and households are allowed to contract on observable aggregate TFP shocks, but not on idiosyncratic 'uncertainty shocks'. Following Di Tella (2017), uncertainty shocks are modeled as innovations to the cross-sectional variance of firm-specific productivity shocks. The model makes two key predictions: (1) Idiosyncratic risk contributes more to risk premia than aggregate TFP shocks, and (2) Idiosyncratic risk is more important for complex assets.

This paper shows that idiosyncratic risk plays a significant role in asset pricing, particularly for more complex assets such as options, commodities, and foreign exchange. Idiosyncratic risk is measured using balance sheet data for 22 large financial intermediaries and quantified as the cross-sectional variance of the residuals from time-series regressions of individual firm equity ratios on the industry average equity ratio. I find that idiosyncratic risk varies significantly over time, jumping up during NBER recessions. Based on the work of Di Tella (2017) and Haddad and Muir (2022), I then include idiosyncratic risk as an additional pricing factor using a standard Fama-MacBeth panel data methodology. Seven asset categories are considered, ranging from the simple (e.g., stocks and bonds) to the more complex (e.g., options and CDSs). I find that idiosyncratic risk prices vary significantly over time, and are larger for more complex securities.

This paper develops a multi-asset Intermediary Asset Pricing model. As in Haddad and Muir (2022), assets differ in their 'complexity', modeled here as an asset-specific information cost. More complex assets are more likely to be handled by intermediaries. As in Di Tella (2017), intermediaries and households are allowed to contract on observable aggregate TFP shocks, but not on idiosyncratic 'uncertainty shocks'. Following Di Tella (2017), uncertainty shocks are modeled as innovations to the cross-sectional variance of firm-specific productivity shocks. The model makes two key predictions: (1) Idiosyncratic risk contributes more to risk premia than aggregate TFP shocks, and (2) Idiosyncratic risk is more important for complex assets.

Keywords: Macroeconomics; Finance; Asset Pricing; Financial Intermediaries; Idiosyncratic Risk; Information Cost; International Investment

Dedication

To my family.

Acknowledgements

The last five years working towards my PhD degree have been intellectually challenging but also enormously fruitful. I could have not done it without the help of many people who gave me guidance, support, understanding, and encouragement. I would like to take a moment to thank those who greatly contributed to my completion of the degree.

I am mostly indebted to my senior supervisor, Kenneth Kasa, who cares so much about my work, always responds to my inquiries promptly, taught me tremendous knowledge in macroeconomics and finance, guided me through all the ups and downs during the entire journey, provided me with support whenever I needed, and greatly inspired and reinforced my passion to be a good economist. I learned from him the importance of doing original and rigorous research, focusing on priorities, and more importantly, being a generous person.

I also benefited from Professor Lucas Herrenbrueck, who gave lots of attention to my work and my papers. I am also grateful to Daniel Schwanen for his advice and influence on me to become a rigorous researcher and for his comments on my work on international trade.

I benefited greatly from other faculty members too. I would like to thank Brian Krauth who gave me useful feedback on my teaching performance and supported me whenever I needed it as the department chair, Alexander Karaivanov who was always available for help and advice, Bertille Antoine and Simon Woodcock, graduate chairs, who were supportive and helpful to me during my PhD journey. Lastly, I wish to acknowledge and thank all the other faculty members who have contributed to my growth and learning. Your collective wisdom and support have made a profound impact on my academic journey.

I am deeply grateful to my husband and my parents for providing unconditional love and support. I gratefully acknowledge the financial support of the Daniel Janzen Memorial Grad Scholarship and Lang Wong Memorial Schol Award, and thank all the staff and faculty of the Department of Economics at Simon Fraser University, especially Lisa Agosti and Sarah Turner. Finally, I want to take the chance to thank the C.D. Howe Institude and Innovation, Science and Economic Development Canada, Department of Strategy and Innovation Policy Sector for providing me with the opportunity of doing internships during 2022 and 2023 summers. I benefited greatly from interaction with many good economists there. I want to particularly thank Daniel Schwanen, Parisa Mahboubi, Jiang Beryl Li, Jianmin Tang, etc. for taking the time and providing feedback for my research work.

Table of Contents

List of Tables

List of Figures

Chapter 1

Asset Complexity and Idiosyncratic Risk

Abstract

This paper develops a multi-asset Intermediary Asset Pricing model. As in Haddad and Muir (2022), assets differ in their 'complexity', modeled here as an asset-specific information cost. More complex assets are more likely to be handled by intermediaries. As in Di Tella (2017), intermediaries and households are allowed to contract on observable aggregate TFP shocks, but not on idiosyncratic 'uncertainty shocks'. Following Di Tella (2017), uncertainty shocks are modeled as innovations to the cross-sectional variance of firm-specific productivity shocks. The model makes two key predictions: (1) Idiosyncratic risk contributes more to risk premia than aggregate TFP shocks, and (2) Idiosyncratic risk is more important for complex assets.

Keywords: Macroeconomics, Finance, Asset Pricing, Financial Intermediaries, Idiosyncratic Risk, Information Cost, International Investment

1.1 Introduction

Conventional asset pricing models link risk premia to the covariance of returns with the marginal utility of consumption (Lucas(1978)). Early tests of these models were not successful (Hansen and Singleton (1983), Mehra and Prescott (1985)). The problem is that aggregate consumption is not very volatile and not highly correlated with asset returns. Recent extensions that link the marginal utility of consumption to either past or expected future consumption have been somewhat more successful (Campbell and Cochrane (1999), Bansal and Yaron (2004)). Questions remain, however, about the plausibility of these so-called 'exotic preferences' models (Beeler and Campbell (2012), Epstein, Farhi, and Strzalecki (2014)).

Following the 2008 Financial Crisis, an alternative approach to asset pricing emerged, often referred to as Intermediary Asset Pricing (IAP). This literature was motivated by the observed connection between the financial health of intermediaries and risk premia in financial markets (Adrian, Etula and Muir (2014), He, Kelly and Manela (2017)). It was also motivated by the growing importance of portfolio delegation and the wealth management industry (Greenwood and Sharfstein (2013)). The key assumption in IAP models is to postulate the existence of two distinct classes of agents - 'experts' and 'households', and to suppose that assets yield higher returns when held by experts. At the same time, contractual frictions arising from imperfect information and moral hazard require intermediaries to retain some 'skin in the game'. This capital constraint endogenously binds during downturns, and provides a source of amplified and countercyclical risk premia. Early versions of these models were called 'financial accelerator' models (Kiyotaki and Moore (1997), Bernanke and Gertler (1989)), and like the Lucas model, were not very successful empirically (Kocherlakota (2000), Cordoba and Ripoll (2004)). In a pair of influential papers, He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) argue that the problem with first-generation financial accelerator models arose from log-linear solution methods, which only considered small mean-reverting perturbations around a unique steady state. They show that continuous-time formulations can capture the full global dynamics in these models, and lead to much more interesting and empirically consistent dynamics.

This paper attempts to combine these two approaches. It does so by combining two recent papers, one by Di Tella (2017) and one by Haddad and Muir (2022). A common criticism of IAP models is that the results are often sensitive to seemingly arbitrary assumptions concerning agents' ability to pool and share risks. For example, Krishnamurthy (2003) shows that if state-contingent contracts can be traded on observable and verifiable aggregate output, then the feedback and amplification effects of financial accelerator models disappear. The more recent continuous-time models are subject to the same drawback. In response, Di Tella (2017) extends these models by introducing 'uncertainty shocks'. Although he allows agents to share the risk of aggregate TFP shocks, which in practice could be accomplished simply by trading something like an S&P500 index contract, he assumes the dispersion of idiosyncratic, expert-specific productivity shocks are correlated with aggregate TFP. The variance of idiosyncratic shocks increases during recessions. Since the skin-in-the-game constraint limits the ability of agents to pool idiosyncratic risk, by requiring experts to maintain a minimum capital level, uncertainty shocks are priced in equilibrium, despite washing out in the aggregate.[1]. Di Tella's (2017) key result is that experts voluntarily *choose* ex ante to be relatively exposed to aggregate risk when the income effect of countercyclical asset returns dominates the substitution effect, which occurs in the empirically realistic case when the coefficient of relative risk aversion exceeds unity. Of course, since households have the same preferences, they too would like to have greater net worth during booms, when asset returns are low, but due to the capital constraint, the investment opportunities of experts improve relative to those of households, so in equilibrium, experts choose to bear a disproportionate share of aggregate risk, and the balance sheet channel is ignited.

A second criticism of the IAP literature focuses on its foundational assumption, i.e., the distinction between experts and households. After all, if experts weren't more productive, households would simply invest for themselves, and moral hazard, uncertainty shocks, and balance sheets would be irrelevant. Haddad and Muir (2022) address this criticism. They argue that the importance of intermediaries depends on the type of asset being considered. Experts likely have little comparative advantage investing in mundane securities, like stocks and bonds. However, for relatively complex assets, like derivatives and commodities, experts are arguably more productive, as assumed in the IAP literature. Haddad and Muir (2022) formalize expertise by supposing households must pay an information cost when investing. They assume this information cost is asset-specific, and is greater for more complex assets. The cross-sectional variation in the role of intermediaries helps to resolve a troublesome identification problem. Just because risk premia are negatively correlated with intermediary capital does not imply variations in intermediary capital are *causing* variations in risk premia. This is because intermediary capital is positively correlated with the state of the economy, and therefore households' *willingness* to bear risk. When omitted variables that produce the same effect on the dependent variable are positively correlated with the variable being considered, estimates of the effect of the included variable are overstated. The obvious response is to simply include both causal factors in the same regression. The problem, however, is that in practice both are measured with error, so the problem persists. Haddad and Muir (2022) show that because the importance of intermediary capital and household risk aversion move in opposite directions as asset complexity varies, one can derive asset-specific *lower bounds* on the relative importance of intermediary capital. Their empirical results show that these lower bounds are higher for more complex securities.

[1]A similar mechanism is at work in the idiosyncratic labor income risk model of Constantinides and Duffie (1996)

By formalizing expertise and considering multiple assets, Haddad and Muir (2022) significantly advance the IAP literature. However, their interest is primarily empirical. There is no explicit, quantifiable modeling of the underlying reasons why both intermediary capital and household risk aversion matter. That's why they are only able to derive bounds. The goal here is to provide these missing structural elements. I do this by introducing Haddad and Muir's (2022) information cost into the idiosyncratic risk model of Di Tella (2017). Not surprisingly, my results are a mixture of theirs. As in Di Tella (2017), I find that it is not intermediary capital per se that matters, but rather its cross-sectional variance. As in Haddad and Muir (2022), I find that idiosyncratic risk matters more for more complex securities, where households confront higher information costs.

Endogenous information choice has a long history in financial economics, going back to the pioneering work of Grossman and Stiglitz (1980). Veldkamp (2011) provides a survey. One of the first extensions of Grossman and Stiglitz (1980) was to allow agents to pay more for more informative signals (Verrecchia (1982)). Lei (2019) shows that these models can help explain the recent increase in wealth inequality. The households in my model can only indirectly influence the quantity of information they acquire. In particular, I assume the cost of information scales linearly with the amount invested. If you invest twice as much, your information cost is twice as high. Although in practice one can certainly point to fixed cost elements that invalidate this assumption, linearity makes the model *much* easier to solve. The result of the model is robust to a fixed cost function as it prohibits households from entering the market. More importantly for the questions addressed here, since the constant marginal information cost is assumed to vary across assets, households can influence their information costs by altering which assets they invest in. This is the key mechanism in my model. Investment in high-cost/complex assets will be largely delegated to experts.[2]

The remainder of the paper is organized as follows. Section 2 develops the model. It shows that the mechanism highlighted by Di Tella (2017) is operative in high information cost markets, but not necessarily in markets featuring low information costs. For simple securities like stocks and bonds, neither the relative wealth of intermediaries nor idiosyncratic risk are very important. This suggests that IAP models may not provide a convincing explanation of the equity premium puzzle, which focuses on stock returns. Section 3 provides concluding remarks, and outlines a couple of possible extensions. In particular, it briefly summarizes the results from Chapter 2 of my thesis, which takes this model to the data. Finally, the Appendix contains proofs and derivations of some technical results.

[2] I make no effort here to explain *why* some assets are more complex and have higher information costs. Lester, Postlewaite and Wright (2012) discuss one possibility, associated with asymmetric information and the lemons problem. From the perspective of their model, complex assets could be interpreted as those that embody greater information asymmetry between buyers and sellers. This seemed to be part of the problem associated with mortgage-backed securities during the Financial Crisis.

1.2 Model

The model closely follows Di Tella (2017), which in turn is closely related to He and Krishnamurthy (2012) [3] and Brunnermeier and Sannikov (2014). Experts are assumed to be more productive, and so households would like to delegate their investment to them. However, it is assumed that experts can either shirk or divert funds to a private account. The cost of shirking depends on the expert's exposure. To prevent shirking the expert must retain a minimum amount of 'skin-in-the-game'. This endogenously binding capital constraint is the key mechanism in these models. As in Di Tella (2017), agents are free to contract on any observable variable. This allows agents to separate risk sharing from capital investment. However, unlike Di Tella (2017), here households can also directly hold capital, but must pay a linear information cost that varies across assets (depending on the assets' complexity).

1.2.1 Model Setup

There are two types of agents: households and experts. They can both trade capital, but following Haddad and Muir (2021), the costs vary based on the asset type. k_t represents the aggregate efficiency units of capital, and k_{it} represents capital held by each agent i, either household or expert.[4] This capital is used to produce output according to the following production function:

$$y_t = [a - \iota(g_{i,t})]\ k_{i,t} \tag{1.1}$$

where ι is an investment cost function that depends on the growth rate of capital, $g_{i,t}$. Efficiency units of capital evolve stochastically, and are driven by two Brownian motion shocks:

$$\frac{dk_{i,t}}{k_{i,t}} = g_{i,t}dt + \sigma dZ_t + \nu_t dW_{i,t} \tag{1.2}$$

where dZ is an aggregate shock, and dW_i is an idiosyncratic shock to the capital held by agents (not the productivity of that agent). Aggregate risk exposure σ is a constant but

[3] In He and Krishnamurthy (2012) capital constraint is added to the model due to market imperfection. In this paper, market imperfection could be a moral hazard and to avoid it, it is assumed that agent cannot sell out their equity entirely and they are required to hold a portion of that (ϕ).

[4] A crucial simplifying assumption in these models arises from the linearity of production functions and the homotheticity of preferences, which imply that we do not need to keep track of wealth heterogeneity among households and firms. All that matters is the relative wealth *between* households and firms.

idiosyncratic risk exposure changes according to the following exogenous Cox-Ingersoll-Ross process (which ensures non-negativity):

$$d\nu_t = \lambda(\bar{\nu} - \nu_t)dt + \sigma_\nu \sqrt{\nu_t} dZ_t \tag{1.3}$$

where $\bar{\nu}$ is the long-run mean and λ is a mean reversion parameter. The negative loading of the idiosyncratic volatility of capital on aggregate risk, $\sigma_\nu < 0$, is empirically motivated, and implies positive aggregate shocks (like a TFP shock) decrease idiosyncratic risk.

Agents can trade capital continuously at a competitive price $p > 0$, which we conjecture follows an endogenously determined Ito process:

$$\frac{dp_t}{p_t} = \mu_{p,t}dt + \sigma_{p,t}dZ_t \tag{1.4}$$

Total wealth in the economy is $p_t k_t$ and $x_t = \frac{n_t}{p_t k_t}$ is the fraction of wealth held by experts and $1 - x_t$ is the fraction held by households. Financial markets are complete, with an endogenously determined stochastic discount factor process (SDF), η_t, which follows the Ito process:

$$\frac{d\eta_t}{\eta_t} = -r_t dt - \pi_t dZ_t \tag{1.5}$$

where r_t is the endogenous risk free rate, and π_t is the endogenous price of aggregate risk. Since idiosyncratic risk is wiped out in the aggregate, its equilibrium price is zero. Of course, idiosyncratic risk is still important, since due to the capital constraint, it influences the hedging demands of experts and households. The return from investing a dollar in the capital by agent i (could be an expert or a household) is as follows:

$$dR^k_{i,t} = [\frac{a - \iota(g_{i,t})}{p_t} + g_{i,t} + \mu_{p,t} + \sigma\sigma^{'}_{p,t}]dt + (\sigma + \sigma_{p,t})dZ_t + \nu_t dW_{i,t} \tag{1.6}$$

The term in brackets represents $E_t[dR^k_{i,t}]$, and the second and third terms represent aggregate and idiosyncratic risk, respectively. Experts can write contracts on any observable variables, including the shocks. Hence, they would share the risk concentrated on their balance sheets by selling equity. However, due to the moral hazard problem, they must keep a fraction ϕ which makes them face aggregate and idiosyncratic risks proportionally. Since the aggregate risk has a price of π_t, experts can write contracts on the aggregate state of the economy to eliminate exposure to aggregate risk. However, they still face idiosyncratic risk proportional to the fraction of the equity they must hold, ϕ.

Preferences of experts and households are identical. To enable a separation between risk aversion and intertemporal substitution, they are assumed to take the form of Duffie and Epstein's (1992) stochastic differential utility (SDU)[5]

$$U_t = E_t \int_t^{\infty} f(c_s, U_s) ds$$

where the (normalized) aggregator takes the homothetic/isoelastic form

$$f(c, U) = \frac{1}{1-\psi} \left\{ \frac{\rho c^{1-\psi}}{[(1-\gamma)U]^{(\gamma-\psi)/(1-\gamma)}} - \rho(1-\gamma)U \right\}$$

where ψ^{-1} is the elasticity of intertemporal substitution and γ is the coefficient of relative (static) risk aversion. If $\gamma = \psi$ one can verify that these preferences become time- and state-seperable. When solving the model I assume $\psi = 1$ and $\gamma > 1$, which implies a preference for the early resolution of uncertainty (Epstein, Farhi, and Strzalecki (2014)). The parameter ρ influences the rate of time preference, but the actual rate of time preference is endogenous.

The expert's problem can now be stated as follows:

$$\max_{\hat{e}\geq 0,\ g,\ k\geq 0,\ \theta} U(e)$$

$$subject\ to: \ \frac{dn_t}{n_t} = (\mu_{i,n,t} - \hat{e}_{i,t})\ dt + \sigma_{i,n,t}\ dZ_t + \tilde{\sigma}_{i,n,t}\ dW_t \tag{1.7}$$

where:

$$\mu_{i,n,t} = r_t + p_t \hat{k}_{i,t} \left(E_t[dR^k_{i,t}] - r_t \right) - (1-\phi_e) p_t \hat{k}_{i,t} (\sigma + \sigma_{p,t}) \pi_t + \theta_{i,t} \pi_t \tag{1.8}$$

$$\sigma_{i,n,t} = \phi_e p_t \hat{k}_{i,t} (\sigma + \sigma_{p,t}) + \theta_{i,t} \tag{1.9}$$

[5]SDU preferences are the continuous-time counterpart of the more familiar discrete-time recursive preferences of Epstein-Zin (1989).

$$\tilde{\sigma}_{i,n,t} = \phi_e p_t \hat{k}_{i,t} \nu_t \tag{1.10}$$

Given homotheticity, it is convenient to scale things by net worth. In what folllows, let n_t denote the net worth of experts and let hatted variables be divided by n_t. Experts invest in capital and sell $(1-\phi)$ of their equity to the market. The market does not mind idiosyncratic risk (because it averages out in the aggregate), but requires π_t for each unit of aggregate risk. Due to moral hazard, experts must maintain a portion ϕ of the risk on the capital they purchase. Since they can contract on aggregate risk, they will remove some aggregate risk from their portfolio. The parameter θ_t determines how much aggregate risk experts choose to keep on their balance sheet.

Optimal contracts can be decentralized as in Di Tella (2017). Experts create a firm with $p_t k_t$ and sell equity to raise funds except for a fraction of the capital they must hold (ϕ) to avoid moral hazard. Also, they trade aggregate securities and receive a payment as CEO of the firm as compensation for the idiosyncratic risk they hold on the fraction of their firms' equity. We can think of $\theta_{i,t}$ as the fraction of the expert's wealth invested in a set of aggregate securities that span Z (normalized to have an identity loading on Z). In the special case with only one aggregate shock, $d = 1$, we can think of this security as a normalized market index. More generally, we can consider the intermediate case in which contracts may be written only on a linear combination of aggregate shocks $\tilde{Z}_t = B_t Z_t$ for some full rank matrix $B_t \in R^{d' \times d}$ with $d' < d$. In this case, we will be restricted to choosing $\theta_{i,t} = \tilde{\theta}_{i,t} B_t$. In particular, with $B_t = 0$, contracts cannot be written on Z.

Since experts can not contract on the idiosyncratic risk on their balance sheets, they are exposed to idiosyncratic risk proportional to the fraction of equity they hold. This is the fundamental source of the vulnerability of the financial sector and why uncertainty shocks become amplified.

The household's problem is quite similar to an expert's. The key difference is that they also face an information cost when they trade in asset markets:

$$\max_{\hat{c} \geq 0,\ g,\ k^h \geq 0,\ \theta} U(c)$$

$$subject\ to: \ \frac{d\omega_t}{\omega_t} = [\mu_{i,\omega,t} - \hat{c}_{i,t} - \frac{I_t}{2}(\sigma^2_{i,\omega,t} + \tilde{\sigma}^2_{i,\omega,t})]\ dt + \sigma_{i,\omega,t}\ dZ_t + \tilde{\sigma}_{i,\omega,t}\ dW_t \tag{1.11}$$

where:

$$\mu_{i,\omega,t} = r_t + p_t \hat{k}^h_{i,t} \left(E_t[dR^k_{i,t}] - r_t \right) - (1 - \phi_h) p_t \hat{k}^h_{i,t} (\sigma + \sigma_{p,t}) \pi_t + \theta_{i,t} \pi_t \tag{1.12}$$

$$\sigma_{i,\omega,t} = \phi_h p_t \hat{k}^h_{i,t}(\sigma + \sigma_{p,t}) + \theta_{i,t} \tag{1.13}$$

$$\tilde{\sigma}_{i,\omega,t} = \phi_h p_t \hat{k}^h_{i,t}\nu_t \tag{1.14}$$

As in the case of experts, $\hat{c}$ and $\hat{k}^h$ are normalized by household net wealth, denoted by ω_t [6]. Unlike experts, households do not manage firms and invest on the behalf of others, so moral hazard does not constrain their ability to pool idiosyncratic risk. If risk pooling among households were perfect, we would have $\phi_h = 0$. However, any sort of friction to perfect risk sharing would imply $\phi_h > 0$. For added generality, I allow $\phi_h > 0$, and then consider the limit, $\phi_h \to 0$, as household risk-pooling becomes perfect.

The household's problem also differs from experts' in the information cost they face. Like experts, households can trade aggregate risk, and that is why θ appears in their budget constraint. This term enables households to separate the decision on how much capital to hold from how much risk to take. I is the information cost to households which could take any positive value depending on the complexity of the asset market. If $I = 0$, the household does not face any cost when they want to trade in an asset market and they trade just like an expert. However, if I is high in an asset market for a household, it makes them much less efficient than an expert in trading, which may cause households to decide not to trade in that asset market. The key implication of this model is that the impact of idiosyncratic risk in pricing assets is greater in asset markets that are costly for households to enter and trade. However, if they face low costs, they may enter and trade, then experts may not be the only participant matter in pricing the asset and Di Tella's conclusions about the effects of experts' balance sheets and idiosyncratic risk may no longer be valid.

1.2.2 Solving the Model

Di Tella (2017) starts solving the model by first proving that an expert's investment opportunity set relative to a household's is increasing with respect to idiosyncratic risk. In other words, in states with greater idiosyncratic risk, experts get better investment opportunities, as compensation for the additional risk they must bear. He then argues that this causes experts to accumulate *more* risk on their balance sheets, in order to be able to better smooth marginal utility across states. For example, during downturns wealth falls, which raises the marginal value of wealth. However, the equilibrium return to investing also increases, which helps to offset the wealth reduction. If $\gamma > 1$ this latter effect domi-

[6] In experts' budget constraint (equation 1.8), $(1-\phi)p_t\hat{k}_{i,t}(\sigma + \sigma_{p,t})\pi_t$ is what experts pay to households for selling their equity. This term could be added to households' constraints as what they receive from experts. However, it is not the households' control variable and is not going to change the result. Hence, for simplicity, this term is dropped from households' budget constraints.

nates, and experts *choose* the have relatively low wealth during downturns. However, in my model, because households may choose to invest for themselves, an expert's relative investment opportunity may not be increasing with respect to idiosyncratic risk, and therefore idiosyncratic risk might not matter.

In Di Tella's model with SDU preferences, when $\gamma > 1$ financial losses are (optimally) concentrated on experts' balance sheets.[7] Also, when $EIS > 1$, an intertemporal substitution effect dominates, and agents prefer to consume when capital is unattractive because of high idiosyncratic risk and weak balance sheets. This causes the price of capital and investment to go down when risk premia go up after an uncertainty shock. Di Tella notes that $\gamma > 1$ is supported by much empirical evidence, while evidence regarding EIS is more mixed. In this paper, for simplicity purposes, I assume $EIS = 1$.

It is useful to consider a simplified model, in which ν is characterized by a one-time shock at time-0, after ν is realized, the only shock in the economy would be a TFP shock. This implies σ_x is zero and therefore σ_ξ, σ_ζ, and σ_p are zero where ξ is experts investment opportunity and ζ is households investment opportunity. Experts HJB will then be:

$$\rho \; log \; \xi = \max_{\hat{e},g,\hat{k},\theta} \rho \; log \; \hat{e} + \mu_n - \hat{c} - \frac{\gamma}{2}\sigma_n^2 - \frac{\gamma}{2}\tilde{\sigma}_n^2 + \frac{\xi_x^{'}}{\xi}\mu_x \tag{1.15}$$

subject to the budget constraint in equation 1.7. Households HJB is similar but has additional terms due to the information costs.[8]:

$$\rho \; log \; \zeta = \max_{\hat{c},g,\hat{k},\theta} \rho \; log \; \hat{c} + \mu_\omega - \hat{c} - \frac{\gamma}{2}\sigma_\omega^2 - \frac{\gamma}{2}\tilde{\sigma}_\omega^2 - \frac{I}{2}\sigma_\omega^2 - \frac{I}{2}\tilde{\sigma}_\omega^2 + \frac{\zeta_x^{'}}{\zeta}\mu_x \tag{1.16}$$

subject to the budget constraint in equation 1.11. The first-order conditions with respect to g, c, and e are as follows, respectively:

[7] The word 'optimal' here is a bit misleading. It is indeed *individually* optimal for experts to choose to have aggregate risk concentrated on their balance sheets, but this does not imply it is *socially* optimal. That is, a benevolent social planner could produce a Pareto improvement, due the the well known market externalities associated with these models. That is, individual experts do not consider the market equilibrium responses of their collective choices.

[8] One might argue that incorporating information costs in this way does not differentiate risk-aversion from information costs. In general, if households want to trade more complex assets, they must first acquire the necessary information (if they didn't need to, they would be considered an expert!). Hence, this way of incorporating information cost is not expected to change the results while providing more simplification in the model.

$$\iota^{'}(g_t) = p_t \tag{1.17}$$

$$\hat{c} = \hat{e} = \rho \tag{1.18}$$

Based on the market clearing equation for consumption ($\hat{e}px + \hat{c}p(1-x) = a - \iota(g)$), anything produced each period minus those used for investment ($\iota(g_t)$), will be consumed by households and experts:

$$\hat{e}xp_t + \hat{c}(1-x)p_t = \rho\ p_t = a - \iota(g_t)$$

which delivers the following equilibrium price of capital,

$$p_t = \frac{a - \iota(g_t)}{\rho} \tag{1.19}$$

The first-order conditions for σ_n and σ_ω:

$$\sigma_n = \frac{\pi_t}{\gamma}, \quad \sigma_\omega = \frac{\pi_t}{\gamma + I} \tag{1.20}$$

and the market clearing conditions for standard deviations:

$$\sigma_n x + \sigma_\omega(1-x) = \sigma$$

then deliver the following equilibrium price of aggregate risk,

$$\pi_t = \frac{\sigma\gamma(\gamma + I)}{xI + \gamma} \tag{1.21}$$

Note that it depends on the distribution of wealth. As in all IAP models, the risk premium rises as the relative wealth of experts declines. According to the capital market clearing condition ($p\hat{k}x = 1$) and the first-order condition for $\hat{k}$ in experts' problem and incorporating equation 1.6:

$$\frac{a - \iota(g_t)}{p_t} + g_t + \mu_{p,t} - r_t = \sigma\pi_t + \gamma\phi_e^2 \ \frac{\nu_t^2}{x} \tag{1.22}$$

Likewise, from the household's problem we have $p\hat{k}^h(1-x) = 1$ (note that $\hat{k}^h$ in households equation is divided by ω and in expert equation is divided by n.), same equation for $\hat{k}^h$ from households' problem is as follows:

$$\frac{a - \iota(g_t)}{p_t} + g_t + \mu_{p,t} - r_t = \sigma\pi_t + \gamma\phi_h^2 \ \frac{\nu_t^2}{1-x} \tag{1.23}$$

In equation 1.23 if I is zero, which means households do not face any information cost when they trade in that asset market, households are the same as experts and they could be considered as an expert. Adding equations 1.22 and 1.23 gives the following equation for equilibrium asset excess returns:

$$\frac{a - \iota(g_t)}{p_t} + g_t + \mu_{p,t} - r_t = \frac{\sigma^2\gamma(\gamma + I)}{xI + \gamma} + \left[\frac{\gamma\phi_e^2}{x} + \frac{(\gamma + I)\phi_h^2}{1-x}\right] \ \frac{\nu_t^2}{2} \tag{1.24}$$

Equation 1.24 is analogous to equation 10 in Di Tella (2017). Adding information costs produces an additional term in how idiosyncratic risk and experts' balance sheets impact excess returns. Compared to the Di Tella model, here the aggregate risk price is a function of information costs (I), which increases the impact of x on risk premia. An increase in idiosyncratic risk still increases the risk premium in the way that Di Tella's model does. But here, the size of the effect is greater due information costs. As usual, the risk premium is a decreasing function of the expert's relative wealth, x. However, in this model when $I \neq 0$, as the experts' wealth ratio decreases (which is the case following an idiosyncratic shock), the risk premium increases and the magnitude of this increase increases with I. This means experts and their balance sheets matter more in asset markets that are hard for households to trade in. Suppose I were zero in a market, meaning households could trade freely in that market and they do not face any information cost. In that case, idiosyncratic risk impacts excess returns by $\frac{\gamma\phi_e^2}{2x} + \frac{(\gamma+I)\phi_h^2}{2(1-x)}$. In such a market, as the expert's balance sheet becomes weaker (lower x), the impact of idiosyncratic risk on excess return increases. In the extreme case, when $x \to 0$ then $\frac{\gamma\phi^2}{2x} \to \infty$. The impact of x on risk premium is similar to Di Tella's model since when $I = 0$ the first term in equation 1.24 has no x. On the other hand, when I is very large, which is the case in markets that are very hard for households to trade in, the impact of x on risk premium increases accordingly, especially when $\phi_h = 0$. This happens because in markets with high information costs, households are less efficient than experts (in the following, we will see that in markets with high information costs, if households trade, their relative investment opportunity set does not increase when idiosyncratic risk increases.).

To summarize, in markets with high information costs for households, experts matter more for asset pricing than in markets with low information costs. To show how x influences excess return, the following equation is the derivative of the left-hand side of equation 1.24 with respect to x:

$$\frac{d(E(R^k_{i,t}) - r_t)}{dx} = -\frac{1}{2}\sigma^2\gamma\frac{I(\gamma + I)}{(xI + \gamma)^2} + \left[-\frac{\gamma\phi_e^2}{x^2} + \frac{(\gamma + I)\phi_h^2}{(1 - x)^2}\right]\frac{\nu_t^2}{2} \tag{1.25}$$

In equation 1.25, in the market with greater information cost (I), the first term will be greater. Hence, in markets with higher information costs, weaker experts' net wealth increases excess returns, while in markets with no information cost, equation 1.25 is smaller. This means as the information cost increases for households, a weaker balance sheet of experts, plays a more important role in excess returns, and all discussions of Di Tella (2017) around the role of experts' balance sheets and idiosyncratic risks in excess returns would be valid. In the appendix, equations 1.25 and 1.24 are derived when $\phi_h = \phi_e$ for households. As shown in equations A6 and A7, even if we assume households face a moral hazard problem as experts face, results concerning the impact of idiosyncratic risk and the relative wealth of experts on the risk premium continue to hold as in Di Tella's model works when information costs for households are high enough and expert relative wealth is low.

Figure 1.1 depicts how the derivative of excess returns varies with the information cost according to equation 1.25, when $\phi_e > 0$ and $\phi_h = 0$ [9]. There are two highlights in the graph. First, when the information cost is zero, while households can now also trade risky assets, the derivative goes to zero when the expert wealth ratio is greater than 0.5. This means excess return increases when experts' balance sheets become weaker only if they hold less than 50 percent of the wealth in the economy. This could be significant in Di Tella's conclusion considering how lower experts' wealth ratio plays a role in the model. As is explained later in this paper, when there is a negative idiosyncratic shock, experts' relative investment opportunities increase and this leads to lower experts' wealth ratio. However, according to figure 1.1, if experts have already more than 50 percent of the economy's wealth, a drop in experts' wealth ratio does not increase asset risk premium that much and

[9] The value of $\phi_e = 0.2$ for experts comes from Di Tella (2017) and He and Krishnamurthy (2012). He and Krishnamurthy (2012) discuss that Hedge fund contracts typically pay the manager 20% of the fund's return in excess of a benchmark.

there would be no amplification effect as discussed in Di Tella (2017). However, notice that as the information cost increases the derivative becomes significantly negative, even when x goes to 1. For instance, when the information cost is 20, even when experts hold more than 50 percent of the economy's wealth, the derivative is still significantly negative, and excess return increases as experts become weaker. This is closer to Di Tella' conclusion that the derivative of excess return with respect to x is always negative regardless of how much wealth is held by experts. In this case, even a small drop in the experts' wealth ratio, could result in a considerable increase in the asset risk premium and amplification effect.

The second highlight from the graph is the magnitude of the derivative. As information cost increases, excess returns increase when x decreases and the magnitude of this increase varies depending on the information cost. This means in asset markets with higher information costs, which are more difficult for households to trade in, when x decreases by one percent, excess returns increase way more compared to asset markets with zero information cost for households. This emphasizes the role of experts in pricing assets with high information costs for households compared to assets with low information costs for households and confirms that Di Tella conclusions hold only in more complicated asset markets.

The basis of Di Tella's discussion is that experts' investment opportunities increase following an idiosyncratic shock relative to households and that is why experts choose to take more idiosyncratic risk ex-ante. To show this in the setting of this model, we now assume idiosyncratic risk has not been realized yet and the model is more general. From homothetic preferences, we know that the value function for an expert with net worth n takes the following power form:

$$V_t(n) = \frac{(\xi_t n)^{1-\gamma}}{1-\gamma} \tag{1.26}$$

for some stochastic processes, $\xi > 0$, which can be interpreted as the Stochastic Discounting Factor (SDF) that captures the forward-looking stochastic investment opportunities the expert faces. When ξ increases, experts gain greater utility for a given level of net wealth (n_t). Households have the same value function, where $\zeta > 0$ now represents households' investment opportunities. Di Tella argues that since agents are risk averse, they want to smooth marginal utility across states. Therefore, if their net wealth drops during a negative shock but at the same time their investment opportunity increases relative to households, they would leverage up to smooth marginal utility. Similarly, during an idiosyncratic shock, experts' investment opportunities increase relative to households, so they leverage up to hold all capital in the economy and this leads to lower x which makes experts and the whole economy more vulnerable [10] (experts and households' investment opportunities both drop following a negative idiosyncratic shock, however, experts' investment opportunity increases relative to households.). This means experts' relative investment opportunity ($\Omega = \frac{\xi}{\zeta}$) should be an increasing function of idiosyncratic risk (ν). To show this, all equilibrium conditions will be plugged into HJBs and then experts' HJB will be deducted from households':

$$\rho \ (log\ \xi - log\ \zeta) = \mu_n - \mu_\omega - \frac{\gamma}{2}\ \sigma_n^2 + \frac{\gamma + I}{2}\ \sigma_\omega^2 - \frac{\gamma}{2}\ \tilde{\sigma}_n^2 + \frac{\gamma + I}{2}\ \tilde{\sigma}_\omega^2 + \left(\frac{\xi_x'}{\xi} - \frac{\zeta_x'}{\zeta}\right)\ \mu_x \tag{1.27}$$

Using Ito's Lemma, we can find μ_x. From equations 1.2 and 3.2, and applying Ito's Lemma, x would follow a stochastic process [11]:

$$\mu_x = x\ [\mu_n - \mu_p - \hat{e} - g - \sigma\sigma_p + (\sigma + \sigma_p)^2 - \sigma_n(\sigma + \sigma_p)] \tag{1.28}$$

$$\sigma_x = x(\sigma_n - \sigma - \sigma_p) \tag{1.29}$$

For households $\mu_{1-x} = -\mu_x$ and the using the equations for μ_x and μ_{1-x}:

$$\mu_x = x(1 - x) \left[\mu_n - \mu_\omega - \frac{I\sigma^2}{xI + \gamma}\right] \tag{1.30}$$

From equations 1.12 and 1.8 and plugging in π from equation 1.21:

[10] Di Tella (2017), argues that relative investment opportunities do not change following an aggregate shock because investment opportunities for both household and experts change the same.

[11] considering that $x = \frac{n_t}{p_t k_t}$ and based on Ito's Lemma for the multiplication (pk):

$$\frac{dpk}{pk} = (\hat{e} + g + \mu_p + \sigma_p\sigma)dt + (\sigma + \sigma_p)dZ$$

and then using Ito's Lemma for ratio ($\frac{n}{pk}$):

$$\frac{d\frac{n}{pk}}{\frac{n}{pk}} = [\mu_n - \mu_p - \hat{e} - g - \sigma\sigma_p + (\sigma + \sigma_p)^2 - \sigma_n(\sigma + \sigma_p)]dt + (\sigma_n - \sigma_p - \sigma_k)dZ$$

$$\mu_n - \mu_\omega = \frac{1-2x}{x(1-x)} \left[\frac{\gamma\phi_e^2}{x} + \frac{(\gamma+I)\phi_h^2}{1-x}\right] \frac{\nu_t^2}{2} + \frac{I}{(I+\gamma)\gamma} \pi^2 \tag{1.31}$$

Plugging equation 1.30 into equation 1.27, provides the following function for Ω:

$$\begin{aligned} \rho \; log \; \Omega = \mu_n - \mu_\omega - \frac{\gamma}{2} \sigma_n^2 + \frac{\gamma+I}{2} \sigma_\omega^2 - \frac{\gamma}{2}\tilde{\sigma_n^2} + \frac{\gamma+I}{2}\tilde{\sigma}_\omega^2 \\ + \partial_x log\Omega \; x(1-x) \left[\mu_n - \mu_\omega - \frac{I\sigma^2}{xI+\gamma}\right] \end{aligned} \tag{1.32}$$

In equation 1.32, $\rho \; log\Omega$ is a decreasing function of $x \in (0, 0.5)$ as well as an increasing function of ν as long as I is large enough, $x \in (0,1)$ and $log\Omega$ does not change significantly with x in the intermediary values of $x \in (0, 0.5)$ (which means $\partial log\Omega$ should not be very large in the intermediary values). The proof is provided in section 5.2 of the appendix. In this case, experts' relative investment opportunities increase when their wealth decreases as long as they hold less than 50 percent of the economy's wealth and the market has high information costs for households. Also, experts relative investment opportunity increases when an idiosyncratic shock hits the market and there is a high information cost for households. Therefore, households do not have any incentive to enter markets that are more costly to them compared to experts. Notice that if I is small or zero, $log\Omega$ is not a strictly increasing function of x, which means when x drops and experts become weaker, their relative investment opportunity does not necessarily increase. In markets with low information costs the idiosyncratic channel that Di Tella emphasizes in his paper may not work. In such a market, we cannot prove experts' investment opportunity relative to households increases when idiosyncratic risk increases. In the next step, we need to show x decreases as experts' investment opportunity relative to households' increases which shows the amplification effect of an uncertainty shock in the presence of an information cost for households which is increasing with respect to the complexity of assets.

In Di Tella's paper, σ_x is a function of x_t, γ, and σ_Ω. In this paper, σ_x is still a function of these variables as well as the information cost. Taking the steps explained in section B of the appendix leads us to the following equation for σ_x:

$$\sigma_x = x(1-x) \; \frac{I}{xI+\gamma} \; (\sigma + \sigma_p) + x(1-x) \; \frac{1-\gamma}{xI+\gamma} \; \sigma_\Omega \tag{1.33}$$

where $\sigma_\Omega = \sigma_\xi - \sigma_\zeta$. The first term in equation 1.33, is the additional term, created due to the information cost that households face. In Di Tella's model, σ_x is equal to only the last term in equation 1.33 (with no information cost). The term xI appeared in the denominator of the second term, causing the impact of σ_Ω on σ_x smaller than what Di Tella estimates. Since experts have the opportunity to invest in risky assets, which is the case when the information cost for households is greater than zero, they receive greater utility per dollar of wealth compared to households which means $\Omega_t = \frac{\xi_t}{\zeta_t} > 1$. This ratio depends on the state of the economy and is not constant. This means when agents are risk averse ($\gamma > 1$) if there is an aggregate shock that increases experts' investment opportunity relative to households, experts hold a smaller share of aggregate wealth in the economy which makes the economy more vulnerable to a shock. Here is the course of events when there is a high information cost for households: (1) ν which is the idiosyncratic risk concentrated on the experts' balance sheet increases and through equation 1.32 causes an increase in experts' relative investment opportunity, (2) increase in Ω leads to a sudden drop in x from equation 1.33, (3) since $log\Omega$ is a decreasing function of x when I is high enough and experts have less than 50 percent of the wealth in the economy, experts relative investment opportunity increases and steps (2) and (3) repeat.

Note that when information costs are zero, equation 1.33 will be the same as in Di Tella (2017) (equation 13 in Di Tella's paper). However, when households trade a risky asset and do not have to pay any information cost, they are treated the same as experts in the model. Intuitively, in that case, when a negative aggregate shock hits the economy, both household's and experts' investment opportunity changes the same and the experts' relative investment opportunity does not increase. Also, as explained in equation 1.32, if information cost is not large enough, experts' relative investment opportunity is not an increasing function of ν necessarily. This may not lead to a drop in the experts' wealth ratio (x) as it drops when the information cost for households is large. Therefore, Di Tella's conclusion on the impact of an increase in experts' relative investment opportunity leading to a drop in experts' wealth ratio, holds only if households face an information cost when they want to trade in risky asset markets.

1.3 Conclusion

This paper shows that financial intermediaries play an increasing role in asset pricing as information costs increase. In markets where information costs are low, such as stocks and bonds, household risk aversion can be expected to be the dominant factor. However, in complex markets, such as derivatives and foreign exchange, the balance sheets of intermediaries become the domiinant risk pricing factor. Hence, when pricing assets, it is essential to choose the 'right tool for the job'. As in physics, there is no grand unified theory of asset pricing.

A key advantage of the theory developed in this paper is that it is relatively straightforward to estimate and test, *as long as you are willing to commit to an a priori classification* *of asset complexity*. An ambitious approach would be to estimate the full structure of the model, using maximum likelihood. This would be computationally challenging, given that an explicit expression for the likelihood function is unavailable. Still, methods based on simulated moments or indirect inference could be applied. A less ambitious approach would be to use the model's key prediction, that idiosyncratic risk becomes an increasingly important factor as asset complexity increases, as motivation for a standard linear factor pricing approach. Such an approach is implemented in Chapter 2 of my thesis.

1.4 References

Adrian, T., Etula, E., & Muir, T. (2010). Financial Intermediaries and the Cross Section of Asset Returns. Federal Reserve Bank of New York Staff Reports, No. 464.

Athey, S., & Skrzypacz, A. (2017). Yuliy Sannikov: Winner of the 2016 Clark Medal. Journal of Economic Perspectives, 31(2), 237–256.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2018). Really Uncertain Business Cycles. Econometrica, 86(3), 1031–1065.

Bocola, L., & Lorenzoni, G. (2020). Risk Sharing Externalities.

Borri, N., & Verdelhan, A. (2012). Sovereign Risk Premia. 2010 Meeting Papers 1122, Society for Economic Dynamics.

Brunnermeier, M. K., & Sannikov, Y. (2014). A Macroeconomic Model with a Financial Sector. The American Economic Review.

Brunnermeier, M., & Sannikov, Y. (2016). Macro, Money, and Finance: A Continuous Time Approach (No. w22343; p. w22343). National Bureau of Economic Research.

Cao, D., & Nie, G. (2017). Amplification and Asymmetric Effects without Collateral Constraints.

Christiano, L. J., Motto, R., & Rostagno, M. (2014). Risk Shocks. American Economic Review, 104(1), 27–65.

Cochrane, J. H. (2001). Asset Pricing. Princeton [u.a.]: Princeton Univ. Press.

Constantinides, G. M., Jackwerth, J. C., & Savov, A. (2013). The Puzzle of Index Option Returns. Review of Asset Pricing Studies, 3(2), 229–257.

DeMarzo, P. M., & Sannikov, Y. (2006). Optimal Security Design and Dynamic Capital Structure in a Continuous-Time Agency Model. The Journal of Finance, 61(6), 2681–2724.

Di Tella, S. (2017). Uncertainty Shocks and Balance Sheet Recessions. Journal of Political Economy, 125(6), 2038–2081.

Eisfeldt, A. L., Anderson, U., Lustig, H., & Zhang, L. (2022). Risk and Return in Segmented Markets with Expertise.

Foster, L., Haltiwanger, J., & Krizan, C. J. (1998). Aggregate Productivity Growth: Lessons from Microeconomic Evidence (No. w6803; p. w6803). National Bureau of Economic Research.

Haddad, V., & Muir, T. (2021). Do Intermediaries Matter for Aggregate Asset Prices?

Han, L. J., Kasa, K., & Luo, Y. (2019). Ambiguity, Information Processing, and Financial Intermediation.

He, Z., Kelly, B., & Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. Journal of Financial Economics, 126(1), 1–35.

He, Z., & Krishnamurthy, A. (2013). Intermediary Asset Pricing. American Economic Review, 103(2), 732–770.

Lester, B., Postlewaite, A., & Wright, R. (2012). Information, Liquidity, Asset Prices, and Monetary Policy. The Review of Economic Studies, 79(3), 1209–1238. https://doi.org/10.1093/restud/rds003

L. Veldkamp, L. (2011). Information Choice in Macroeconomics and Finance. Princeton University Press.

Pasquariello, P. (1999). The Fama-MacBeth Approach Revisited.

Robson, A. J., & Orr, H. A. (2021). Evolved attitudes to risk and the demand for equity. Proceedings of the National Academy of Sciences, 118(26), e2015569118.

The Impact of Uncertainty Shocks. (2009). Econometrica, 77(3), 623–685.

Yang, F. (2013a). Investment shocks and the commodity basis spread. Journal of Financial Economics, 110(1), 164–184.

Yang, F. (2013b). Investment shocks and the commodity basis spread. Journal of Financial Economics, 110(1), 164–184.

1.5 Appendix

1.5.1 The relationship between risk premium and x when $\phi_e = \phi_h$ in households' problem:

When $\phi > 0$ in households' problem, equations 1.11 to 1.14 will be as follow:

$$\max_{\hat{c}\geq 0,\ g,\ k\geq 0,\ \theta} U(c)$$

$$subject\ to: \ \frac{d\omega_t}{\omega_t} = [\mu_{i,\omega,t} - \hat{c}_{i,t} - \frac{I_t}{2}(\sigma^2_{i,\omega,t} + \tilde{\sigma}^2_{i,\omega,t})]\ dt + \sigma_{i,\omega,t}\ dZ_t + \tilde{\sigma}_{i,\omega,t}\ dW_t \tag{A1}$$

where:

$$\mu_{i,\omega,t} = r_t + p_t\hat{k}_{i,t}(E_t[dR^k_{i,t}] - r_t) - (1-\phi)p_t\hat{k}_{i,t}(\sigma + \sigma_{p,t})\pi_t + \theta_{i,t}\pi_t \tag{A2}$$

$$\sigma_{i,\omega,t} = \phi p_t\hat{k}_{i,t}(\sigma + \sigma_{p,t}) + \theta_{i,t} \tag{A3}$$

$$\tilde{\sigma}_{i,\omega,t} = \phi p_t\hat{k}_{i,t}\nu_t \tag{A4}$$

Then taking the first order condition with respect to $\hat{k}$ is:

$$\frac{a - \iota(g_t)}{p_t} + g_t + \mu_{p,t} - r_t = \sigma\pi_t + (\gamma + I)\phi^2\ \frac{\nu_t^2}{1-x} \tag{A5}$$

which substitute equation 1.23 when $\phi \neq 0$. Adding up equation 1.22 to equation A5, gives the following equation for asset excess return instead of equation 1.24:

$$\frac{a - \iota(g_t)}{p_t} + g_t + \mu_{p,t} - r_t = \sigma\pi_t + [\frac{\gamma + I}{1-x} + \ \frac{\gamma}{x}]\ \frac{\phi^2\nu_t^2}{2} \tag{A6}$$

Taking the first derivative of equation A6 with respect to x leads to equation below:

$$\frac{d(E(R^k_{i,t}) - r_t)}{dx} = -\frac{1}{2}\sigma^2\gamma\frac{I(\gamma+I)}{(xI+\gamma)^2} + [-\frac{\gamma}{x^2} + \frac{\gamma+I}{(1-x)^2}]\ \frac{\phi^2\nu_t^2}{2} \tag{A7}$$

Figure 1.2 is comparable to figure 1.1 when $\phi > 0$.

1.5.2 Proof of equation $\log\Omega(x,\ \nu)$ to increasing in ν and decreasing in x:

The first step is to show $\log\Omega(x,\ \nu)$ is decreasing in x as long as $x \in (0,1)$. If we simplify equation 1.32 more, it will be as follows:

$$\begin{aligned} \rho log\Omega = & \frac{\nu^2}{2x(1-x)}\left[-\gamma\phi_e^2\ +\ (\gamma+I)\phi_h^2\right]\ +\ \frac{1}{2}\frac{I\gamma(\gamma+I)}{(xI+\gamma)^2}\sigma^2 \\ & + \partial_x log\Omega\ x(1-x)\ \left[\mu_n - \mu_\omega - \frac{I}{xI+\gamma}\sigma^2\right] \end{aligned} \tag{A8}$$

To show equation A8 is decreasing with respect to $x \in (0, 0.5)$ we start by finding possible values for $log\Omega(x=0)$, $log\Omega(x=0.5)$. If $x=0$, then $log\Omega$ goes to positive infinity, and if $x = 0.5$, then $log\Omega$ goes to a finite number. However, one may discuss that in some x, $log\Omega$ might be increasing. In that case, $\partial_x log\Omega$ should be zero for at least one x. Between $x=0$ to $x=0.5$, $\partial log\Omega$ is not zero if I is large enough. This is because the derivative of the first two terms of equation A8 are always positive if I is large enough and the third term is zero, which has a contradiction. This means from 0 to 0.5, $log\Omega$ is strictly decreasing. enough. However, when $x \in (0.5, 1)$ we cannot prove that $log\Omega$ is strictly decreasing with x. In this case, experts' relative investment opportunity decreases with experts' wealth ratio only if they hold less than 50 percent of the economy's wealth.

Second, we need to show $log\Omega$ is increasing with ν. Simplifying equation A8 results in the following equation:

$$\begin{aligned} \rho log\Omega = & \frac{\nu^2}{2x(1-x)}\left[-\gamma\phi_e^2\ +\ (\gamma+I)\phi_h^2\right]\ +\ \frac{1}{2}\frac{I\gamma(\gamma+I)}{(xI+\gamma)}\sigma^2 \\ & + \partial_x log\Omega\ x(1-x)\ \left[\frac{1-2x}{x(1-x)}\ \left(\frac{\gamma\phi_e^2}{x} + \frac{(\gamma+I)\phi_h^2}{1-x}\right)\frac{\nu^2}{2} + \frac{I\pi}{\gamma(\gamma+I)}\left(\pi-\sigma\right)\right] \end{aligned} \tag{A9}$$

ν is appeared in two terms in equation A9. In the first term as long as I is large, the derivative with respect to ν is positive $(-\gamma\phi_e^2\ +\ (\gamma+I)\phi_h^2\ >\ 0)$. The second term con-

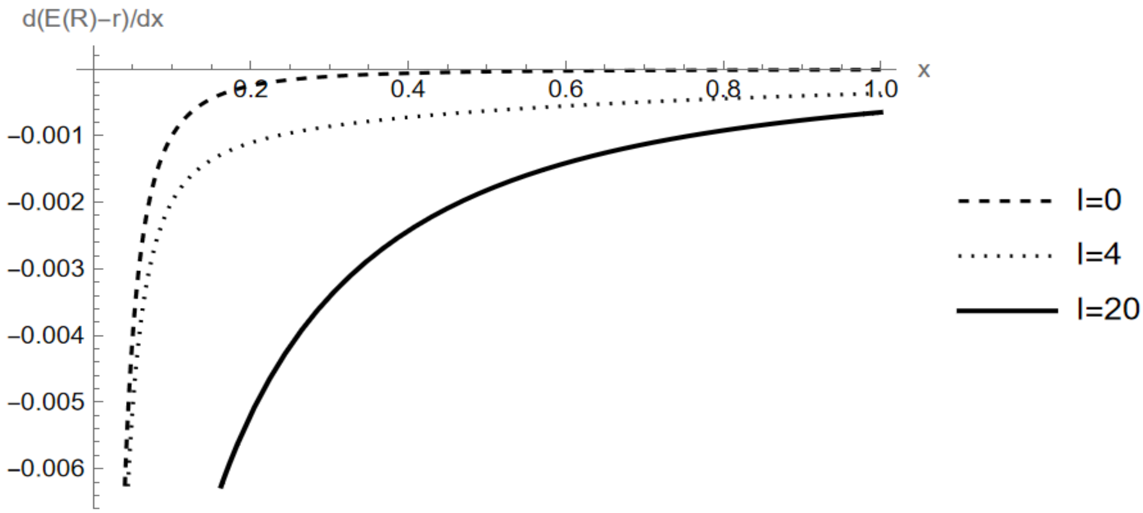

Figure 1.1: This graph shows how the right-hand side of equation 1.25 changes with information costs (I) across assets. The solid line corresponds to $I = 20$ (high information cost), the dotted line corresponds to $I = 4$ (medium information cost), and the dashed line corresponds to $I = 0$ (no information cost). The vertical line represents the derivative of excess return with respect to x, the experts' wealth ratio. The parameters calibration has been taken from Di Tella (2017), such that $\sigma = 1.25$ percent, $\gamma = 5$, $\phi_e = 0.2$ for expert, $\phi_h = 0$ for households, and $\nu = 0.01$.

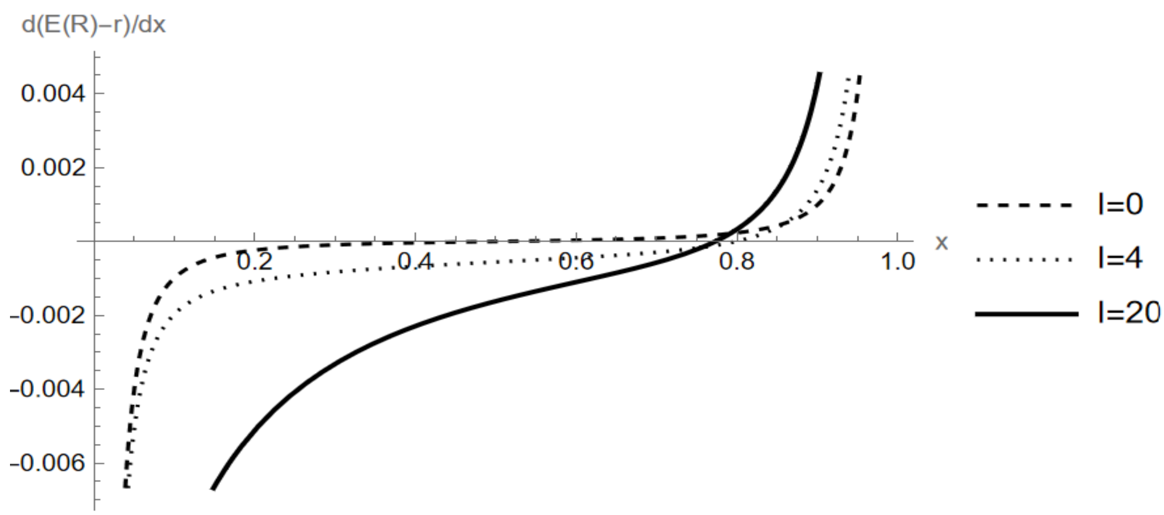

Figure 1.2: This graph shows how the right-hand side of equation A7, in which $\phi > 0$, changes with information costs (I) across assets. The solid line corresponds to $I = 20$ (high information cost), the dotted line corresponds to $I = 4$ (medium information cost), and the dashed line corresponds to $I = 0$ (no information cost). The vertical line represents the derivative of excess return with respect to x, the experts' wealth ratio. The parameters calibration has been taken from Di Tella (2017), such that $\sigma = 1.25$ percent,$\gamma = 5$, $\phi = 0.2$, and $\nu = 0.01$

taining ν is also increasing with ν, as long as $x > 0.5$ and since we already proved $\partial_x log\Omega$ is negative ($\partial_x log\Omega\ (1-2x)\ \left(\frac{\gamma\phi_e^2}{x} + \frac{(\gamma+I)\phi_h^2}{1-x}\right) > 0$). For the derivative to be positive with respect to ν when $x < 0.5$ we need I to be large enough and the following equation to hold:

$$\frac{\nu^2}{2x(1-x)} \left((\gamma+I)\phi_h^2\right) > \partial_x log\Omega\ (1-2x)\ \left(\frac{(\gamma+I)\phi_h^2}{1-x}\right)$$

Simplifying the above leads to the following equation:

$$\frac{\phi_h^2\nu^2(\gamma+I)}{2(1-x)}\ \left(\frac{1}{x}\ +\ \partial_x log\Omega\ (1-2x)\right) > 0$$

Which means if $\partial_x log\Omega$ is smaller than $\frac{1}{x(1-2x)}$ in absolute term for $x < 0.5$, then $log\Omega$ is increasing with respect to ν for values of x.

1.5.3 Proof of Equation 1.32:

In equation 1.26, ξ is a stochastic discount factor capturing forward-looking investment opportunities. When ξ_t is high, the expert is able to obtain a large amount of utility from a given net worth n_t, as if his actual net worth was $\xi_t n_t$. It depends only on the history of aggregate shocks Z and must be determined in equilibrium. It follows Ito's process as below:

$$\frac{d\xi_t}{\xi_t}\ =\ \mu_{\xi,t}dt\ +\ \sigma_{\xi,t}dZ \tag{A10}$$

Households SDF (ζ) also follows similar Ito's process:

$$\frac{d\zeta_t}{\zeta_t}\ =\ \mu_{\zeta,t}dt\ +\ \sigma_{\zeta,t}dZ \tag{A11}$$

Unlike the simplified environment, here it is assumed that $EIS \neq 1$. Hence, the Hamilton-Jacobi-Bellman (HJB) equation associated with experts' problems after some algebra is:

$$\begin{aligned}\frac{\rho}{1-\Psi}\ =\ &\max_{\hat{e},g,\hat{k},\theta} \frac{\hat{e}^{1-\Psi}}{1-\Psi}\rho\ \xi^{\Psi-1}\ +\ \mu_n\ -\ \hat{e}\ +\ \mu_\xi \\ &-\frac{\gamma}{2}\left(\sigma_n^2\ +\ \sigma_\xi^2\ -\ 2\frac{1-\gamma}{\gamma}\sigma_n\sigma_\xi^{'} + \tilde{\sigma}_n^2\right)\end{aligned} \tag{A12}$$

Subject to constraint described in equation 1.8. Households' HJB is similar to experts' but it has additional terms for information cost:

$$
\begin{aligned}
\frac{\rho}{1-\Psi} \;&=\; \max_{\hat{c},g,\hat{k},\theta} \;\frac{\hat{c}^{1-\Psi}}{1-\Psi}\rho\;\zeta^{\Psi-1} \;+\; \mu_\omega \;-\; \hat{c} \;+\; \mu_\zeta \\
-\;\frac{\gamma}{2}\left(\sigma_\omega^2 \;+\; \sigma_\zeta^2 \;-\; 2\frac{1-\gamma}{\gamma}\sigma_\omega\sigma_\zeta^{'} + \tilde{\sigma}_\omega^2\right) \;&-\; \frac{I}{2}\sigma_\omega^2 \;-\; \frac{I}{2}\tilde{\sigma}_\omega^2
\end{aligned}
\tag{A13}
$$

Subject to constraint described in equation 1.11. Taking the first order condition with respect to θ in experts and households problem leads to the following equations, respectively:

$$\sigma_{n,t} = \frac{\pi_t}{\gamma} - \frac{\gamma-1}{\gamma}\sigma_{\xi,t} \tag{A14}$$

$$\sigma_{\omega,t} = \frac{\pi_t}{\gamma+I} - \frac{\gamma-1}{\gamma+I}\sigma_{\zeta,t} \tag{A15}$$

Now, two equations above are incorporated into the market clearing condition for standard deviation, $\sigma_n x + \sigma_\omega(1-x) = \sigma + \sigma_p$ and the using equation 1.29:

$$\sigma_x = x(1-x)\;[\frac{I}{\gamma(\gamma+I)}\;\pi\;-\;\frac{\gamma-1}{\gamma}\;\sigma_\xi\;+\;\frac{\gamma-1}{\gamma+I}\;\sigma_\zeta] \tag{A16}$$

π also comes from the first order conditions with respect to σ_n in experts' problem and σ_ω in households' problem. Using the first-order conditions:

$$\sigma_n = \frac{\pi + (1-\gamma)\sigma_\xi}{\gamma} \tag{A17}$$

$$\sigma_\omega = \frac{\pi + (1-\gamma)\sigma_\zeta}{\gamma+I} \tag{A18}$$

Then using the market clearing condition for standard deviations:

$$\pi = \frac{\gamma(\gamma+I)}{\gamma+Ix}\;[\sigma + \sigma_p + \frac{\gamma-1}{\gamma}\sigma_\xi x \;+\; \frac{\gamma-1}{\gamma+I}\sigma_\zeta(1-x)] \tag{A19}$$

Incorporating equation A19 into equation A16 and after some simplifications:

$$\sigma_x = x(1-x)\;\frac{I}{xI+\gamma}\;(\sigma+\sigma_p) + x(1-x)\;\frac{1-\gamma}{xI+\gamma}\;(\sigma_\xi - \sigma_\zeta) \tag{A20}$$

Since $\Omega = \frac{\xi}{\zeta}$ and $\sigma_\Omega = \sigma_\xi - \sigma_\zeta$, equation 1.33 can be derived.

Chapter 2

Asset Complexity, Idiosyncratic Risk, and the Cross-Section of Expected Returns

Abstract

This paper shows that idiosyncratic risk plays a significant role in asset pricing, particularly for more complex assets such as options, commodities, and foreign exchange. Idiosyncratic risk is measured using balance sheet data for 22 large financial intermediaries and quantified as the cross-sectional variance of the residuals from time-series regressions of individual firm equity ratios on the industry average equity ratio. I find that idiosyncratic risk varies significantly over time, jumping up during NBER recessions. Based on the work of Di Tella (2017) and Haddad and Muir (2022), I then include idiosyncratic risk as an additional pricing factor using a standard Fama-MacBeth panel data methodology. Seven asset categories are considered, ranging from the simple (e.g., stocks and bonds) to the more complex (e.g., options and CDSs). I find that idiosyncratic risk prices vary significantly over time, and are larger for more complex securities.

Keywords: Macroeconomics, Finance, Asset Pricing, Financial Intermediaries, Idiosyncratic Risk, Information Cost, International Investment

2.1 Introduction

Much research has been conducted to investigate changes in asset risk premia and how they evolve through time. Figure 2.1 displays the evolution of the US equity premium from the 1920s until the Covid pandemic. Notice that the equity premium surges during recessions. Not surprisingly, the largest spike occurs during the Great Depression. There is also considerable cross-sectional variation in risk premia, which of course has been the focus of the finance profession. Simultaneously accounting for both the time-series and cross-sectional variation in risk premia is a challenging task. Traditional models like the CAPM were developed to explain cross-sectional variation, and do less well explaining time-series variation. Recently developed Intermediary Asset Pricing models, inspired by the 2008 Financial Crisis (He and Krishnamurthy (2012), Brunnermeier and Sannikov (2014), focus on time-series variation in risk premia, but thus far, relatively few empirical studies examine their cross-sectional implications (Adrian, Etula, and Muir (2014), He, Kelly and Manela (2017), Haddad and Muir (2022)). The goal of this paper is to contribute to this emerging literature exploring the cross-sectional implications of IAP models.

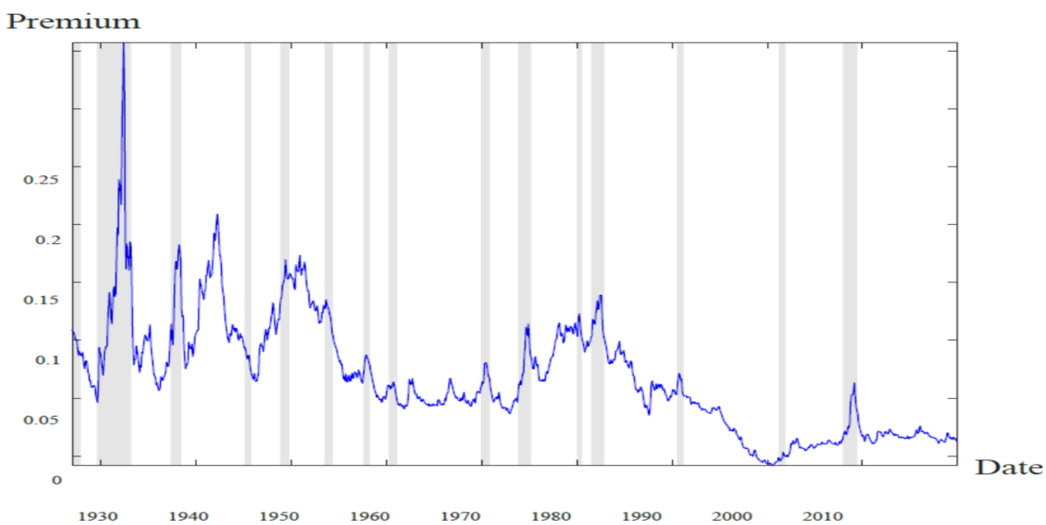

Figure 2.1: The graph illustrates US Equity Risk Premium 1927-2019. The data are from Shiller (`econ.yale.edu/shiller/data.htm`) and the bars are NBER-dated recessions. The ex-ante equity premium is the fitted value from the regression of the 1-year ahead excess return on the current dividend yield. It has an average value of 6.8%. Source: The figure is provided by Dr. Kenneth Kasa in AJ Robson and H. Allen, Evolved attitudes to risk and the demand for equity. PNAS January 20, 2021.

I address the following questions: (1) To what extent do financial intermediaries play a role in asset pricing? (2) What characteristics of intermediaries' balance sheets impact risk premia? and (3) In which assets should their role be highlighted? Di Tella (2017) proposes an asset pricing model in which idiosyncratic risk is endogenously concentrated on the balance sheets of financial intermediaries. That is, intermediaries actually *choose* to be exposed to market downturns.This study empirically investigates Di Tella's prediction and explores the significance of idiosyncratic risk in asset pricing for seven asset classes.

This study makes two contributions to the literature. First, an empirical proxy for idiosyncratic risk is constructed using a panel data set of 22 financial intermediaries' balance sheets from 1970 through the end of 2021. This proxy varies as one would expect, exhibiting sharp spikes during NBER recessions. To estimate idiosyncratic risk, the percentage change in the sum total of primary dealers' equity over the sum of primary dealers' assets is measured as aggregate risk. The percentage change in equity over assets of individual primary dealers is then regressed on aggregate risk. Idiosyncratic risk is then proxied by the cross-sectional standard deviation of the regressions residuals. Second, I estimate idiosyncratic risk prices using a two-step Fama-MacBeth methodology applied to seven asset categories. The assets span from simple assets like stocks and bonds to more complex assets such as options, CDS, commodities, and foreign currency. The key distinction between simple and complicated asset classes is that households do not participate in more complicated asset markets but are more involved in simple asset markets. This means financial intermediaries are expected to play a more important role in more complicated asset markets than in markets for simple assets. The study's findings indicate that idiosyncratic risk on the balance sheets of intermediaries has a greater effect in asset markets where intermediaries engage more than households, such as commodities and foreign exchange. Therefore, idiosyncratic risk premia are higher in markets where financial intermediaries are more involved. Also, using the FamaMac-Bath time-varying procedure, the time-varying price of idiosyncratic risk is estimated. The estimated time-varying idiosyncratic risk premium for all classes of asset pooled increases during NEBR recessions but on average is constant over time.

The literature on asset pricing and risk premia may be divided into two groups. The first highlights the importance of household risk aversion. The challenge is to explain why households appear to be so risk averse, and why risk aversion varies so much over time. Leading contributions are the backward-looking habit persistence model of Campbell and Cochrane (1999), the forward-looking long-run risk model of Bansal and Yaron (2004), and the heterogeneous risk aversion models of Chan and Kogan (2002) and Garleanu and Panageas (2015). Inspired by the 2008 Financial Crisis, the second group argues that since households do not participate in highly complicated asset markets, they cannot influence risk premia. This group focuses on the share of financial intermediaries in asset markets and emphasizes their significance in asset pricing. As an early example, Bernanke and Gertler (1989) investigated how financially constrained entrepreneurs respond to a macroeconomic shock and how this amplifies the shock. Given that entrepreneurs' net worth falls when a shock hits the economy, their external financing is restricted, resulting in insufficient investment in the economy, which magnifies the shock impact in a feedback loop. Extensions by Kiyotaki and Moore (1997) and Bernanke, Gertler, and Gilchrist (1999) develop dynamic models in which lenders require collateral, leading to credit restrictions for borrowers owing to financial frictions. Procyclical variation in collateral values leads to the amplification and propagation of exogenous productivity shocks.

Papers that use a time-continuous approach have been shown to better capture the global dynamics of these (nonlinear) models. Brunnermeier and Sannikov (2014) were among the first to apply a time-continuous approach to asset pricing and the balance sheets of financial intermediaries. When an aggregate shock strikes the economy, asset values fall first, causing experts' (financial intermediaries') net worth to decline, forcing risk premia to rise and asset prices to fall further. They also found that financial innovations encourage experts to borrow more, causing their balance sheets to deteriorate further. This makes the economy more sensitive to even minor aggregate shocks. In the article, this is referred to as the 'volatility paradox', because while financial innovations are meant to stabilize the economy, they instead make it more vulnerable since leverage endogenously increases in response.

There are empirical studies aiming to estimate the role of financial intermediaries in asset pricing with historical data. Adrian, Etula, and Muir (2014) show that shocks to securities broker-dealers' leverage, defined as assets over equity, have explanatory power in stock and bond prices. He et al. (2017) broaden the assets considered to include seven asset classes ranging from stocks to more complex assets and use aggregate shocks to equity capital ratios to explain a significant amount of cross-sectional variation in assets' expected returns, particularly in more complicated asset classes such as corporate and sovereign bonds, derivatives, commodities, and currencies. Besides differences in the asset classes used, AEM and HKM appear to arrive at contradictory empirical results in that AEM found a positive risk price for broker-dealer leverage shocks (in which leverage is defined as the dealer's asset over equity), while HKM showed a positive price for primary dealer capital ratio shock (in which capital ratio is equity over asset). HKM argue that the difference arises from whether you focus on subsidiary or holding company level. HKM also examines the AEM pricing factor for all seven classes of assets. They find the AEM factor plays a significant role in more sophisticated assets such as options, CDS, and FX market. This finding is consistent with most intermediary-based asset pricing models in which intermediaries play a larger role in more complicated asset markets that are difficult for households to trade in (Shleifer and Vishny (1997)).

Haddad and Muir (2020) is another intriguing empirical paper in this literature. They simultaneously consider the risk aversion of households and intermediaries in asset pricing and find that variations in the ability of intermediaries to bear risk is more important than households' willingness to bear risk in more complicated asset markets where households do not participate. The empirical results of my paper are comparable to HM, AEM, and HKM. In terms of the classes of assets used in this paper, it is similar to the seven classes of assets in the HKM paper. However, the HKM data only runs until 2012, but in this paper whenever data is available (FF25, US bonds, Options, and foreign exchange), it is updated until 2020. Also, my paper is different from all three papers in terms of the variable from financial intermediaries' balance sheets that plays a role in pricing assets. HKM and AEM both test the explanatory power of *aggregate* risk concentrated on the intermediary's balance sheet. HM also examines to what extent intermediaries play a role in pricing different classes of assets relative to households, but they do not investigate the specific factor from intermediaries' balance sheet that has the most explanatory power. Unlike all three papers, this study is based on the structural model of Di Tella (2017) and tests the explanatory power of *idiosyncratic* risk concentrated on the intermediaries' balance sheets in pricing assets. Nonetheless, this paper does find financial intermediaries play a significant role in pricing more complicated assets, which is consistent with the aforementioned papers' results. Also, as in HM, this paper distinguishes asset markets where households participate actively, from asset markets which are more complicated for households to trade in. Considering the complexity across assets, this paper concludes financial intermediaries are marginal investors in more complicated asset markets compared to less complicated ones.

Returning to the theoretical models on the role of intermediaries in asset pricing, a significant feature missed in the Brunnermeier and Sannikov (2014) paper is that there is no ability for experts to contract on aggregate risk. According to Krishnamurthy (2003), the amplification channel from the financial sector disappears if experts can trade state-contingent securities. Di Tella (2017) constructs a model based on Brunnermeier and Sannikov (2014) that allows experts to contract on any observable variable. He concludes that aggregate shocks will be shared with households, resulting in no amplification impact of an aggregate shock. In contrast, idiosyncratic risk, such as uncertainy shocks, remains concentrated on the experts' balance sheets, causing endogenous risk that amplifies idiosyncratic shocks. He explains that experts take more idiosyncratic risk ex-ante in order to take advantage of better investment opportunities provided by downturns. Because experts have the choice to share their aggregate risk with households, this opportunity is only activated after an idiosyncratic shock rather than an aggregate shock. If there is an aggregate shock, both households' and experts' investment prospects are affected equally. In contrast, following an idiosyncratic shock, experts' investment opportunities improve relative to the household investment opportunities.

Regarding idiosyncratic risk estimation, Bloom (2009) and, more recently, Bloom et al. (2012) study the significance of uncertainty shocks in business cycles. They found that an uncertainty shock can induce a 2.5 percent decline in business cycles. Christiano et al. (2014) conclude that idiosyncratic shocks are a major driving force in business cycles in the presence of financial frictions and incomplete contracts. Campbell et al. (2012) investigate the explanatory power of a volatility component in asset pricing and show that it explains the growth-value gap in expected returns. This study is different from all these papers in terms of how the idiosyncratic risk is estimated. The rest of the paper describes the model, data, and related variables in section two, then the model findings and conclusion in sections three and four, respectively.

2.2 Model

2.2.1 Asset Pricing Model

Di Tella (2017) is the basis for this study. Di Tella attributes financial frictions to moral hazard, and allows financial intermediaries to contract on observable variables. As a result, experts share aggregate risk. Households and experts are two agents in the model with equal degrees of risk aversion [1]. Households do not trade capital and instead lend to experts. However, experts trade capital and create a larger return than households. Experts sell equities to households in order to share the risks with them. To avoid moral hazard, they must retain a portion of their equity. Aggregate risk and idiosyncratic risk are endogenously concentrated on the experts' balance sheet in proportion to the equity they maintain. Di Tella proves that if experts are allowed to contract, they would contract (for example, using a market index) to share aggregate risk on their balance sheets. When agents may contract on the aggregate state of the economy, the choice of how much capital to acquire (leverage) is separated from the choice of aggregate risk sharing, and optimal contracts hedge the market's (endogenously) stochastic investment opportunities. However, due to the capital constraint idiosyncratic risk remains concentrated on their balance sheet in proportion to the equity they retain.

The hedging motive of experts compared to households determines aggregate risk sharing in equilibrium. Brownian TFP shocks have no effect on experts' or households' relative investment possibilities. Therefore they share aggregate risk proportionally to their wealth. TFP shocks have a direct influence on output in equilibrium, but they are not amplified through the balance-sheet channel and have no magnified effect on the price of capital, investment, or the financial market. Unlike Brownian TFP shocks, uncertainty shocks induce an endogenous hedging motive, increasing experts' investment opportunities relative to households. If experts were risk neutral, they would retain more wealth during downturns to maximize utility per unit of net worth, potentially mitigating the balance sheet impact. When experts are relatively risk-averse, so that the income effect of return variation dominates the substitution effect, they choose to hold less wealth during downturns and more wealth during booms to smooth the level of utility, resulting in more risk exposure in downturns. As a result, experts choose a high exposure to aggregate risk. Intuitively, downturns, appear to be periods of high idiosyncratic risk, with reduced asset prices and increased risk premia. Experts who invest in these assets and earn risk premia have greater investment opportunities during downturns and acquire more utility per dollar than households. Empirical data suggests that the income effect dominates the substitution effect. Additionally,

[1] As long as households' risk aversion is greater or equal to the experts', Di Tella's model works well theoretically. However, if experts are more risk-averse than households, then the idiosyncratic risk should be large enough to activate the amplification channel.

this paper focuses on downturns when agents' risk-bearing capacity typically decreases and they effectively become more risk-averse. Therefore, the latter situation dominates the former and this is why, during downturns, experts leverage up, increasing the idiosyncratic risk concentrated on their balance sheets and making them further vulnerable. As a result, financial losses following an uncertainty shock are concentrated on experts' balance sheets, further reducing asset values and increasing risk premia, thus driving experts to take even more aggregate risk ex-ante in a two-way feedback loop.

The purpose of this paper is to examine empirically the theoretical mechanism highlighted by Di Tella (2017), and to thereby quantify how an idiosyncratic shock is amplified by experts' balance sheets. The model used here is comparable to Haddad and Muir (2020) in that both use financial sector health in asset pricing. However, Haddad and Muir's (2020) primary goal is to determine if experts matter at all for asset pricing. They jointly assess the role of financial intermediaries and households in asset returns. They do not consider what specific variables or mechanisms produce their influence on asset returns. In contrast, here only idiosyncratic risk concentrated on the experts' balance sheets influences asset prices. Aggregagte capital by itself is irrelevant. To summarize, Haddad and Muir (2020) studied whether the balance sheets of financial intermediaries matter for asset pricing. In this study, we presume this is true, and take one step forward by seeking to demonstrate empirically that only idiosyncratic risk is concentrated on the expert balance sheet, and this is the element that influences asset returns.

To derive the theoretical pricing kernel in general equilibrium, assume experts maximize the following utility function:

$$E\left[\int_o^\infty e^{-\rho t}\frac{c_t^{1-\gamma}}{1-\gamma}\,dt\right]$$

where ρ is the rate of time preference and $\gamma > 1$ is the coefficient of relative risk aversion. From the envelope theorem, the marginal utility of wealth is equal to the marginal utility of consumption. Given that only experts can trade capital and an uncertainty shock changes experts' investment opportunities more than households, experts' marginal utility of wealth matters for pricing assets. Hence, in equilibrium, the marginal utility of wealth ($\wedge_E$) is:

$$c_t = \alpha n_t \tag{A1}$$

$$\wedge_E = e^{-\rho t}(\alpha n_t)^{-\gamma} \tag{A2}$$

where n_t is the experts' net worth and α is a constant. Given that $n_t = x_t W_t$, where x_t is the net worth share of experts and W_t is the total wealth in the economy, equation A2 can be rewritten as:

$$\wedge_E = e^{-\rho t}(\alpha x_t W_t)^{-\gamma} \tag{A3}$$

The intuition behind the above equation is that W_t relates to a persistent aggregate productivity shock, which appears in all asset pricing models and impacts all economic fundamentals. When an economy's aggregate wealth falls, agents' marginal value of wealth rises. The share of experts' net worth (x_t) is the second key factor. If experts' net worth falls in comparison to the rest of the economy, their marginal utility of wealth rises, influencing asset prices. x_t, on the other hand, is a decreasing function of idiosyncratic risk, ν_t. During a downturn, ν_t rises, and because this risk is concentrated on the experts' balance sheet, experts' net worth falls. Idiosyncratic risk averages out in the aggregate and has no effect on aggregate wealth. As a result, when idiosyncratic risk rises, just the numerator of x_t declines while the denominator remains the same, and so experts' marginal utility of wealth rises accordingly.

An aggregate shock, on the other hand, has no effect on experts' net worth ratio, x_t. Given that experts can write contracts and share aggregate risk with households if the economy suffers a negative aggregate shock, it will squeeze both households' and experts' net worth equally. This means that experts' net worth ratios do not change, and so their marginal utility of wealth and investment opportunities do not change, and the aggregate shock is not amplified through their balance sheets.

Therefore, experts' marginal utility of wealth will be a function of aggregate wealth and idiosyncratic risk:

$$\wedge_E \propto e^{-\rho t}(\nu_t W_t)^{-\gamma} \tag{A4}$$

Based on equation A4, a standard asset pricing Euler equation is used to derive a two-factor asset pricing model. We assume experts' marginal value of wealth matters in determining expected excess returns:

$$E_t(dR_t^i) - r_t^f dt = -E_t(dR_t^i \,.\, \frac{d\wedge_t}{\wedge_t}) \tag{A5}$$

Where dR_t^i is the instantaneous return of asset i and r_t^f is the risk-free rate. Using equation A4 we can rewrite equation A5 as follow:

$$E_t(dR_t^i) - r_t^f dt = \gamma \ E_t(dR_t^i \ . \ \frac{dW_t}{W_t}) + \gamma \ E_t(dR_t^i \ . \ \frac{d\nu_t}{\nu_t}) \tag{A6}$$

According to the time-continuous approach and using Ito's lemma for R_t^i, W_t, and ν_t:

$$E_t(dR_t^i) - r_t^f dt = \frac{\sigma_{R^i}}{\sigma_w} dt \gamma \sigma_W^2 \ + \ \frac{\sigma_{R^i}}{\sigma_\nu} dt \gamma \sigma_\nu^2 \tag{A7}$$

where $\frac{\sigma_{R^i}}{\sigma_w} = \beta_{Wt}^i$ is the aggregate wealth risk loading, $\frac{\sigma_{R^i}}{\sigma_\nu} = \beta_{\nu t}^i$ is the idiosyncratic risk loading, $\gamma\sigma_W^2$ is the price of aggregate wealth risk and $\gamma\sigma_\nu^2$ is the price of idiosyncratic risk. Hence, A7 can be rewritten as:

$$E_t(dR_t^i) - r_t^f dt = \beta_{Wt}^i dt \ . \ \lambda_W \ + \ \beta_{\nu t}^i dt \ . \ \lambda_\nu \tag{A8}$$

The empirical model used to investigate the significance of experts' balance sheets is as follows, and it consists of two steps. First, risk loadings will be estimated using time series regressions of asset portfolio excess returns on idiosyncratic risk concentrated on experts' balance sheets and market excess returns, which proxy aggregate wealth risk:

$$R_{t+1}^{i_k} - r_t^f = a^{i_k} + \beta_\nu^{i_k} \nu_{t+1} + \beta_W^{i_k}(R_{t+1}^W - r_t^f) + \epsilon_{t+1}^{i_k} \tag{A9}$$

Then the time average of portfolio excess returns in each class of asset will be regressed on the estimated betas from equation A9, to estimate risk prices as the coefficients:

$$E[R_{t+1}^{i_k} - r_t^f] = \gamma_k + \lambda_\nu^k \hat{\beta}_\nu^{i_k} + \lambda_W^k \hat{\beta}_W^{i_k} + \upsilon^{i_k} \tag{A10}$$

The main focus of this study is on λ_ν^k. If the idiosyncratic risk channel plays role in asset pricing, λ_ν^k is expected to be positive, especially for more complicated classes of assets in which financial intermediaries (experts) primarily trade.

The main restriction of the above model is that betas are presumed constant over time. However, if the true beta is time-varying, A9 and A10 are misspecified. Since primary dealer data is only available quarterly, it is insufficient for estimating time-varying betas. To address this data restriction, the Fama and MacBeth (1973) technique is adopted. According to Fama and MacBeth (1973), the excess return of each asset class is regressed on idiosyncratic risk and market risk using a rolling 5-year regression in the first stage of the model (A9). In this situation, A9 is as follows::

$$R^{i_k}_{t+1} - r^f_t = a^{i_k} + \beta^{i_k}_{t\nu}\nu_{t+1} + \beta^{i_k}_{tW}(R^W_{t+1} - r^f_t) + \epsilon^{i_k}_{t+1} \tag{A11}$$

The second step involves two regressions, first for each date and each asset class, resulting in time-varying asset prices. Second, the excess return is regressed on the time-varying betas in a panel regression to estimate a unique risk price for each asset class. The results of these regressions are provided in the section below.

2.2.2 Data

The asset classes used in the study are from He et al. (2017), which contains excess return data for seven asset classes, ranging from simple assets exchanged by households and individuals to more complicated assets traded mostly by financial intermediaries: (1) The Fama-French 25 portfolio of equities (formed by interacting 5 size and 5 book-to-market portfolios), (2) US bonds, (3) Sovereign bonds, (4) Options, (5) CDS, (6) Commodities, and (7) Foreign exchange are the assets used here in order of complexity. From the first quarter of 1970 to the last quarter of 2012, the data is available. The excess returns for the Fama-French equity portfolio, US bonds, and foreign exchange are updated through the end of 2021.

Aggregate risk is measured using He et al. (2017)'s "Intermediary Capital Risk Factor" from 1970:1 to the most recent date[2]. The data from financial intermediaries' balance sheets are required for idiosyncratic risk. Financial intermediaries are primary dealers who function as trading counterparties to the Federal Reserve Bank of New York in the implementation of monetary policy. The list of these primary dealers is provided in table 2.1 and their balance sheets at the holding company level are used. CRSP/Compustat provides data on these primary dealers. According to HKM, this small group of dealers significantly represents the financial sector in terms of trading volumes.

2.2.3 Idiosyncratic Risk[3]

The idiosyncratic risk measured in this study is an uncertainty risk on the experts' balance sheets. The risk comes from the following production function:

$$y_{i,t} = A_t z_{i,t} f(k_{i,t}, n_{i,t}) \tag{A12}$$

[2]The risk factor data is available on the Zhiguo He website at https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/

[3]Dew-Becker and Giglio (2023) provide an alternative strategy for estimating idiosyncratic risk, based on firm-level option implied volatility.

where $k_{i,t}, n_{ji,t}$ are the expert's idiosyncratic capital and labor respectively. The concept of idiosyncratic risk and the way it is estimated in this paper is similar to Campbell et al. (2001). The role that firm-level volatility plays in macroeconomic models is discussed in models of "Cleansing Recessions". An exogenous change in the arrival rate of information about management quality may reduce output as resources are reallocated from low-quality firms to high-quality firms. As another example, a recession (which happens due to other reasons) reveals information about management quality and could increase the rate of reallocation across firms. The idiosyncratic risk used in this paper is also due to an uncertainty shock (which could be accompanied or not by an aggregate shock) that may change the balance sheets of some firms more than others. To this end, idiosyncratic risk is derived from the cross-sectional variance of the residual of intermediaries' balance sheet percentage changes. Herskovic et al. (2016) measures volatility as idiosyncratic firm risk, the equally weighted average of firm-level market model residual return variance. The productivity component includes two parts, an aggregate part A_t and an idiosyncratic part $z_{i,t}$.

Two productivity components are obtained from different variables. The volatility of $z_{i,t}$ is caused by cross-sectional dispersion based on balance sheets, but the volatility of A_t is caused by the market index or GDP changing over time. This suggests that the risks captured on the experts' balance sheet are either aggregate or idiosyncratic. As a result, if we subtract aggregate risk from the volatility of experts' balance sheets, the residual risk could be interpreted as uncertainty risk.

$$\%\Delta Balance\ sheet_{i,t} = \beta Aggregate\ risk_t + \mu_{i,t}$$

In the equation above, the cross-sectional standard deviation of the error term ($\mu_{i,t}$) is used to capture uncertainty risk concentrated on the experts' balance sheets. To measure experts' balance sheets and aggregate risk the approach used here is similar to what is proposed by He et al. (2017). For the balance sheet, market structure is used which is defined as follows for each firm:

$$x_{i,t} = \frac{Market\ Equity_{i,t}}{Market\ Equity_{i,t} + Book\ Debt_{i,t}} \tag{A13}$$

For each expert, market equity is the share price multiplied by the number of outstanding shares, whereas book debt is total assets minus common equity. Market value equity accurately reflects the financial distress of financial intermediaries. The book value of debts could also be a proxy for the market value of debt. This is because debt in the financial industry is more short-term and collateralized, and hence less tied to business credit risk. In this study, the percentage change of the (aggregate) primary dealer capital ratio from

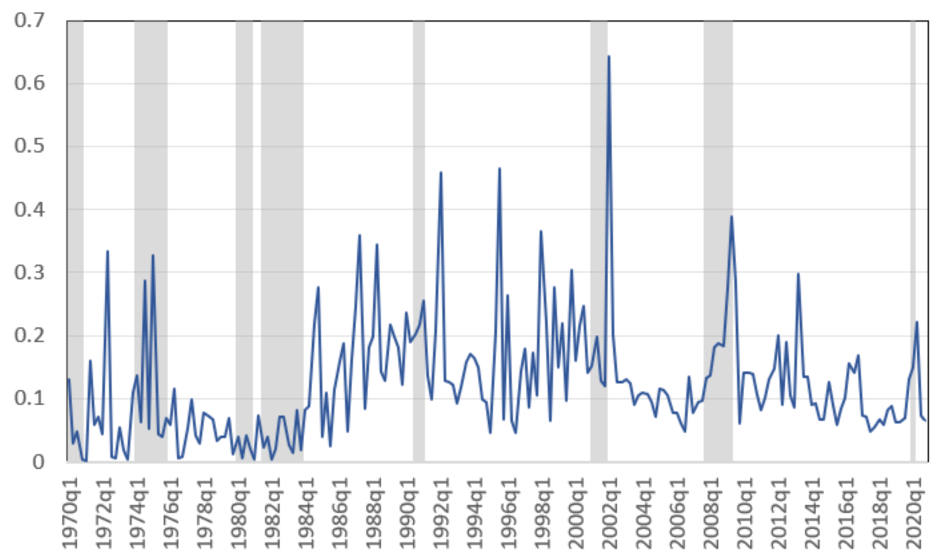

Figure 2.2: The solid blue line represents the idiosyncratic risk which is the cross-sectional standard deviation of the residual of the individual risk factor on the aggregate risk factor regression. Shaded regions indicate NBER recessions.

He et al. (2017) is used for aggregate risk [4]. In HKM, the primary dealer capital ratio is[5]:

$$x_t = \frac{\sum_i Market\ Equity_{i,t}}{\sum_i Market\ Equity_{i,t} + Book\ Debt_{i,t}} \tag{A14}$$

In figure 2.2, the estimated idiosyncratic risk is plotted against NBER recessions from the first quarter of 1970 to the first quarter of 2020. Notice that during recessions uncertainty risk increases. It also rose in 1998 when LTCM collapsed and some assets were affected, and around 1987 (Black Monday) when the stock market collapsed.

Figures 2.3 and 2.4 plot impulse responses from an exogenous idiosyncratic risk shock. There are two key state variables in this economy, (1) the exogenous level of idiosyncratic risk, ν_t, and (2) the endogenous wealth share of intermediaries, x_t. The top row in each figure shows how key variables of interest respond over time to variations in ν_t for 3 alternative (fixed) values of x_t. The bottom row then does the reverse, showing how variables respond to x_t over time, for 3 alternative (fixed) values of ν_t. These graphs are comparable to those in Di Tella (2017), which present numerical solutions to an uncertainty shock. The difference between Figures 2.3 and 2.4 and those in Di Tella (2017) is that Di Tella uses

[4] He et al. (2017) also provides the ratio of the primary dealers' total assets over all the US-based broker–dealers (BD), all banks (Banks), and all firms in Compustat (Cmpust) which shows the significant role the primary dealers have in the economy. For instance, the average total assets of all US-based primary dealers from 1960 to 2012 was 95% of all broker-dealers, 60% of all banks, and 24% of all firms in Compustat.

[5] HKM constructs the growth rate of the capital ratio by first running an auto-regressive $x_t = \rho_0 + \rho_1 x_{t-1} + u_t$ and then by dividing the residual by the lagged capital ratio $x_t^{\Delta} = \frac{u_t}{x_{t-1}}$.

Campbell et al. (2001) for the stochastic process for idiosyncratic risk ν, whereas in this study, idiosyncratic risk is the empirically measured cross-sectional standard deviation of the residuals from regressions of the individual risk factor on the aggregate risk factor.[6] The findings are consistent with those of Di Tella's work [7]. First, according to graph 2.3, a weaker balance sheet depresses asset prices further, and experts' relative investment opportunities Ω are better when idiosyncratic risk ν_t is higher and their proportion of aggregate wealth x_t is low (weak balance sheets). Second, from graph 2.4, the risk-free interest rate r_t falls (it can even become negative), while the price of aggregate risk p_t rises, both because idiosyncratic risk ν_t rises and because balance sheets x_t weaken. Therefore, while the exogenous shock simply raises idiosyncratic risk ν_t, it endogenously magnifies aggregate risk $\sigma + \sigma_{p,t}$.

2.3 Results

As discussed earlier in the model, the asset pricing test contains two steps. According to equation A9 in the first step, the excess return of each portfolio in each class of asset is regressed on the market excess return and uncertainty risk in a time series regression. The results of the first step are summarized in table 2.2 [8].

In the second phase, the average excess portfolio return over time is cross-sectionally regressed on betas derived in the first step for each portfolio in each asset class using equation A10. Table 2.3 summarizes the results of the second-stage regression. Our primary focus is on the price of idiosyncratic risk, γ_{id}^k. The first seven columns provide the price of risk for each asset class, while the last column shows the results of regressing all portfolios from all asset classes combined. The price of risk in all other asset classes is positive and ranges from 0.02 to 0.35. Moreover, the estimated idiosyncratic risk premium is not statistically significant only in US bonds and sovereign bonds, which are regarded as simple assets, as well as in CDS. This may suggest that idiosyncratic risk appears to have greater explanatory power for more complicated assets. The last column displays the risk price for all portfolios, which is 0.05 per quarter. Given that the cross-section standard deviation of idiosyncratic risk betas across all asset classes is 0.07 (table 2.2) if two assets have betas that differ by

[6] In Di Tella (2017), the idiosyncratic risk long-run mean is 0.25, the standard deviation is 0.17 and the autoregression coefficient is 1.38. Whereas in this study, the long-run mean of idiosyncratic risk is 0.12, the standard deviation is 0.27 and the autoregression coefficient is 0.26.

[7] The numerical solution used for these graphs is exactly the same as what is used in Di Tella (2017). The only difference is that in these graphs the idiosyncratic risk estimated by primary dealers' capital ratio is used. Di Tella (2017) adds a time dimension and solves the system as if there were a finite horizon T. Then it must look for p, ξ, and ζ as functions of (n, x, t). For more details regarding the solution, please refer to Di Tella (2017), "Uncertainty Shocks and Balance Sheet Recessions", Appendix B.

[8] To avoid cross-sectional correlation in the panel, a GMM regression with heteroskedasticity-and autocorrelation-consistent weighting matrix is used.

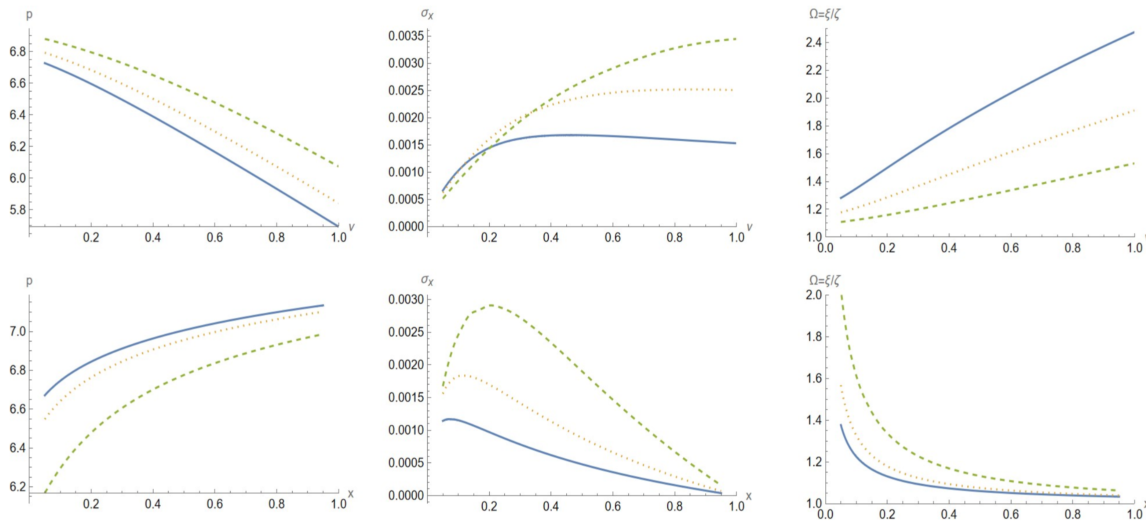

Figure 2.3: The price of capital p, volatility of x ,σ_x, and relative investment opportunities $\Omega = \frac{\xi}{\zeta}$, as functions of ν (above) for $x = 0.05$ (solid), $x = 0.10$ (dotted), and $x = 0.2$ (dashed), and as a function of x (below) for $\nu = 0.12$ (solid), $\nu = 0.25$ (dotted), and $\nu = 0.6$ (dashed).

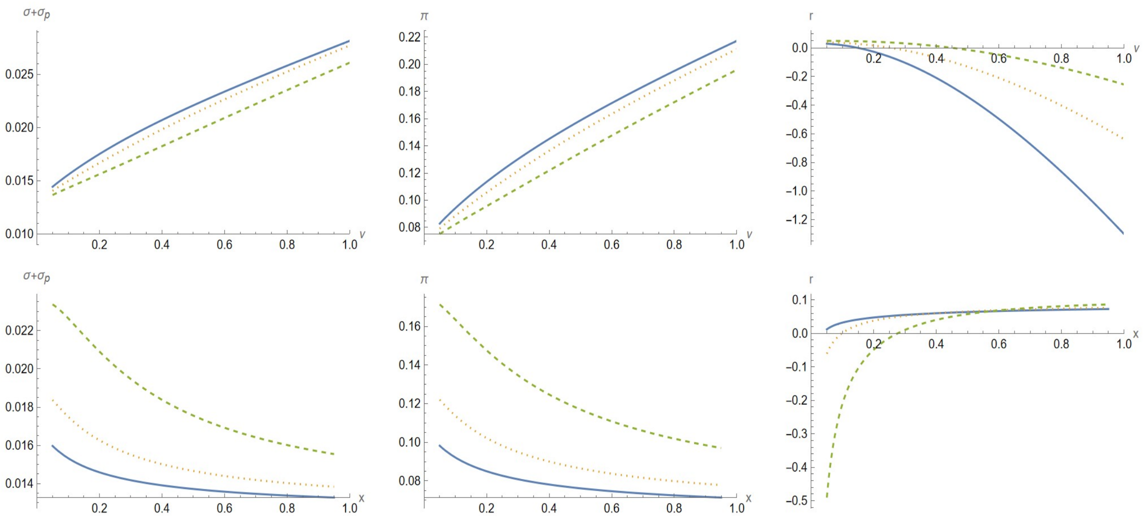

Figure 2.4: Aggregate risk $\sigma + \sigma_p$, the price of risk p, and the risk-free rate r as functions of ν (above) for $x = 0.05$ (solid), $x = 0.10$ (dotted), and $x = 0.2$ (dashed), and as a function of x (below) for $\nu = 0.12$ (solid), $\nu = 0.25$ (dotted), and $\nu = 0.6$ (dashed)..

one standard deviation, their risk premia differ by 0.07×0.05 or 0.35 percent for a quarter and 1.4 percent for a year.

Another interesting finding from the table is that the idiosyncratic risk loading (β_{idio}) appears to be higher for more sophisticated assets than for less complicated groups. Since experts are the only or principal traders in more intricate asset markets, and because the idiosyncratic risk is concentrated primarily on their balance sheets, the idiosyncratic risk loading is projected to be higher in markets where they are the only investors. Furthermore, the study's key premise is that intermediates (experts) are homogenous. Two tests are performed to determine if the loading of idiosyncratic risk is higher in more complicated assets than in less complicated ones[9]. Stocks, US bonds, and sovereign bonds are considered less complicated assets, and households make up a large majority of their traders. More complicated assets include options, CDS, commodities, and foreign exchange and households are assumed not to be present in these markets. The loading of idiosyncratic risk is greater in more complicated assets, according to tests on risk loading equality between complicated and less complicated assets. When the assumption from Di Tella's study on the idiosyncratic risk that investment opportunities are exclusively available to experts is included, this could make more sense that in the markets of more complicated assets, experts could have more investment opportunities relative to the household when there is an uncertainty shock hitting the market. But in less complicated asset markets (where households can enter and trade easily), the idiosyncratic risk may not be the only factor that plays a role in pricing assets.

The tables 2.4 and 2.5 show the results of time-varying beta in the Fama-MacBeth Procedure. In the FamaMac-Bath procedure, rolling 5-year regressions are regressed in each class of asset and for each portfolio over every 5 years. The average and standard deviation of betas for each asset class over time for market risk and idiosyncratic risk as regressors are shown in table 2.5. Table 2.5 provides the risk price for each asset class derived from regressing excess returns on time-varying betas estimated in the first step. Except for Fama French 25, the estimated risk prices are positive and statistically significant for all classes and range from 0.01 to 0.12. The last column displays the results of the second regression,

[9]One test is a Wald test with the following test statistics:

$$W = \frac{(\beta_{stocks} - \beta_{options})^2}{SE(\beta_{stocks})^2 + SE(\beta_{options})^2} + \frac{(\beta_{usbond} - \beta_{CDS})^2}{SE(\beta_{usbond})^2 + SE(\beta_{CDS})^2} + \frac{(\beta_{sovereign} - \beta_{commodities})^2}{SE(\beta_{sovereign})^2 + SE(\beta_{commodities})^2} + \frac{\beta_{FX}^2}{SE(\beta_{FX})^2}$$

Also, a t-test is used to test this assumption as follows:

$$t = \frac{(\bar{x}_1 - \bar{x}_2)}{\sqrt{(\frac{s_1^2}{3} + \frac{s_2^2}{4})}}$$

where $\bar{x}_1$ is the mean of β of the less complicated assets and $\bar{x}_2$ is the means of β of more complicated assets.

with all portfolios from all asset classes pooled into a sample. In this sample, the estimated idiosyncratic risk price is 0.03, which is not significantly different from table 2.3, which is 0.05. (this is also the case for the price of market risk).

In table 2.5, excess returns are regressed on time-varying betas for each class of asset in a panel regression (including time and all portfolios in each class of asset). However, in the FamaMac-Bath procedure, we can also regress excess return on betas on each date and derive a time-varying risk premium. This would let us look into how the price of idiosyncratic risk has changed over time across assets. To apply this concept in this model, in the second step of the procedure, instead of estimating a single panel regression with the time-varying betas of each asset, we now run a cross-sectional regression at each time period and for each asset. The estimated time-varying risk premium for each class of asset is depicted in figure 2.5. These graphs are analogous to figure 2.1, which depicts a declining risk premium of stocks over time. However, idiosyncratic risk price is only dropping over time for CDS and marginally in foreign exchange. It does not follow an increasing or negative trend for stocks (FF25), US bonds, options, and all asset classes pooled. Also, in each graph, the gray areas represent NEBR recessions. In all classes of assets, risk premia had gone up during or right after the recession, indicating higher uncertainty due to recession periods.

Graph 2.6 compares estimated returns to actual returns for each asset type. Graphs a and b are from FamaMac-Bath 5-year rolling regressions and graphs c and d The graphs on the left depict all asset classes. Except for FF25, which appears to be an exception, all asset classes are almost on the 45-degree line. To have a better grasp of the other asset classes, FF25 is removed from the right graphs. Except for FF25, the asset pricing model developed in the paper works fairly well, as seen by the graphs. It is also consistent with expectations that idiosyncratic risk does not work well in FF25. In comparison to other asset markets, households participate more in stock markets. This implies that idiosyncratic risk concentrated on the experts' balance sheet will be less important in the stock market (FF25).

2.4 Conclusion

We find that disparities in asset exposure to the standard deviation of the residual of the capital ratio of primary dealers explain variations in expected excess returns on assets markets that households are usually absent at such as US bonds, foreign sovereign bonds, options, CDS, commodities, and currencies. In the stock market, where household participates at large, the idiosyncratic risk concentrated on the experts' balance sheet may not matter as it matters for more complicated assets. The idiosyncratic risk component has a positive risk price and is strongly procyclical, which is particularly pronounced in more complex assets where only financial intermediaries play a role. Our findings provide empirical support for the view that financial intermediaries are marginal investors in many asset classes, particularly more complex assets, and, as a result, the view that the financial soundness of these intermediaries is important for understanding broad asset price behavior.

2.5 References

Adrian, T., Etula, E., & Muir, T. (2010). Financial Intermediaries and the Cross Section of Asset Returns. Federal Reserve Bank of New York Staff Reports, No. 464.

Athey, S., & Skrzypacz, A. (2017). Yuliy Sannikov: Winner of the 2016 Clark Medal. Journal of Economic Perspectives, 31(2), 237–256.

Bloom, N. (2009). The Impact of Uncertainty Shocks. Econometrica, 77(3), 623–685.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2018). Really Uncertain Business Cycles. Econometrica, 86(3), 1031–1065.

Bocola, L., & Lorenzoni, G. (2020). Risk Sharing Externalities.

Borri, N., & Verdelhan, A. (2012). Sovereign Risk Premia. 2010 Meeting Papers 1122, Society for Economic Dynamics.

Brunnermeier, M. K., & Sannikov, Y. (2014). A Macroeconomic Model with a Financial Sector. The American Economic Review.

Brunnermeier, M., & Sannikov, Y. (2016). Macro, Money, and Finance: A Continuous Time Approach (No. w22343; p. w22343). National Bureau of Economic Research.

Cao, D., & Nie, G. (2017). Amplification and Asymmetric Effects without Collateral Constraints.

Christiano, L. J., Motto, R., & Rostagno, M. (2014). Risk Shocks. American Economic Review, 104(1), 27–65.

Cochrane, J. H. (2001). Asset Pricing. Princeton [u.a.]: Princeton Univ. Press.

Constantinides, G. M., Jackwerth, J. C., & Savov, A. (2013). The Puzzle of Index Option Returns. Review of Asset Pricing Studies, 3(2), 229–257.

DeMarzo, P. M., & Sannikov, Y. (2006). Optimal Security Design and Dynamic Capital Structure in a Continuous-Time Agency Model. The Journal of Finance, 61(6), 2681–2724.

Dew-Becker, I., & Giglio, S. (2023). Cross-Sectional Uncertainty and the Business Cycle: Evidence from 40 Years of Options Data. American Economic Journal: Macroeconomics, 15(2), 65–96. https://doi.org/10.1257/mac.20210136

Di Tella, S. (2017). Uncertainty Shocks and Balance Sheet Recessions. Journal of Political Economy, 125(6), 2038–2081.

Foster, L., Haltiwanger, J., & Krizan, C. J. (1998). Aggregate Productivity Growth: Lessons from Microeconomic Evidence (No. w6803; p. w6803). National Bureau of Economic Research.

Haddad, V., & Muir, T. (2021). Do Intermediaries Matter for Aggregate Asset Prices?

Han, L. J., Kasa, K., & Luo, Y. (2019). Ambiguity, Information Processing, and Financial Intermediation.

He, Z., Kelly, B., & Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. Journal of Financial Economics, 126(1), 1–35.

He, Z., & Krishnamurthy, A. (2013). Intermediary Asset Pricing. American Economic Review, 103(2), 732–770.

Herskovic, B., B. Kelly, H. Lustig, and S. Van Nieuwerburgh. 2016. “The Common Factor in Idiosyncratic Volatility: Quantitative Asset Pricing Implications.” J. Financial Econ. 119 (2): 249–83.

Krishnamurthy A. (2003). Collateral constraints and the amplification mechanism. Journal of Economic Theory. Pasquariello, P. (1999). The Fama-MacBeth Approach Revisited.

Robson, A. J., & Orr, H. A. (2021). Evolved attitudes to risk and the demand for equity. Proceedings of the National Academy of Sciences, 118(26), e2015569118.

Shleifer, A. & Vishny, R.W. (1997). The Limits of Arbitrage. Journal of Finance 47 (4), 1343-1366.

Yang, F. (2013a). Investment shocks and the commodity basis spread. Journal of Financial Economics, 110(1), 164–184.

Yang, F. (2013b). Investment shocks and the commodity basis spread. Journal of Financial Economics, 110(1), 164–184.

Primary dealer	Holding company	Start date
Goldman, Sachs & Co.	Goldman Sachs Group, Inc., The	12/4/1974
Barclays Capital Inc.	Barclays PLC	4/1/1998
HSBC Securities (USA) Inc.	HSBC Holdings PLC	6/1/1999
BNP Paribas Securities Corp.	BNP Paribas	9/15/20
HSBC Securities (USA) Inc.	HSBC Holdings PLC	6/1/1999
UBS Securities	LLC UBS AG	6/9/2003
Credit Suisse Securities (USA) LLC	Credit Suisse Group AG	1/16/2006
Nomura Securities International,Inc	Nomura Holdings, Inc.	7/27/2009
J.P. Morgan Securities LLC	JPMorgan Chase & Co.	9/1/2010
Merrill Lynch, Pierce, Fenner & Smith	Bank Of America Corporation	11/1/2010
SG Americas Securities, LLC	Societe Generale	2/2/2011
Bank Of Nova Scotia, NY Agency	Bank Of Nova Scotia, The	10/4/2011
BMO Capital Markets Corp.	Bank Of Montreal	10/4/2011
Jefferies LLC	Jefferies LLC	3/1/2013
TD Securities (USA) LLC	Toronto-Dominion Bank, The	2/11/2014

Table 2.1: Primary dealers as of June 2020. Primary dealers, as designated by the NY Fed serve as its trading counterparties as it implements monetary policy. Primary dealers are obliged to: (i) participate consistently in open market operations to carry out US monetary policy, and (ii) provide the NY Fed's trading desk with market information and analysis. Primary dealers are also required to participate in all US government debt auctions and to make reasonable markets for the NY Fed. See `http://www.newyorkfed.org/markets/primarydealers.html` for current and historical lists of primary dealers.

	The time series regression (the first step)							
	FF25	US Bonds	Sov. Bonds	Options	CDS	Commod	FX	All
Mean (β_i^{mrk})	1.13	0.10	0.32	-0.16	0.11	0.18	0.05	0.29
Std (β_i^{mrk})	0.19	0.10	0.20	0.45	0.07	0.22	0.05	0.55
Mean (β_i^{idio})	0.03	0.01	0.11	0.02	0.03	0.01	0.01	0.02
Std (β_i^{idio})	0.03	0.01	0.04	0.13	0.03	0.09	0.03	0.07
$F(\alpha = 0)$	0.01	0.55	1.16	1.05	1.10	1.33	0.65	0.99
$p - value$	0.96	0.94	0.34	0.37	0.25	0.88	0.46	0.52

Table 2.2: The mean and variance of time series regression. The table is representing the results of regressing the excess return of portfolios for each class of asset on the idiosyncratic risk and the market excess return using GMM regression. In the GMM regressions, first, the coefficients are estimated using an identity matrix, then the estimated coefficients are used to estimate the weighting matrix. The reported coefficients are those estimated using the second weighting matrix. Then over the portfolios, an average of betas is taken which is the mean of each regressor in the table. Below the mean, the standard deviation of betas across portfolios in each asset class is also reported in the table. β_i^{mrk} is the beta of the market excess return as the regressor and β_i^{idio} is the beta of the idiosyncratic risk as the regressor for each class of asset. The last row is the test statistic on the intercepts of the regressions. The intercept should be zero meaning when there is no systemic risk, the excess return of an asset is expected to be zero. The test statistic is $\frac{T-N-K}{N}(1 + E_T(f^{'})\ \hat{\Omega}^{-1} E_T(f))^{-1}\ \hat{\alpha}^{'} \hat{\Sigma}^{-1} \hat{\alpha} \sim F_{N,T-N-K}$ where N is the number of assets, K is the number of factors, and $\Omega = \frac{1}{T}\ \sum_{t=1}^{T} [f_t - E_T(f)][f_t - E_T(f)]^{'}$.

	Cross-sectional regression (the second step)							
	FF25	US Bonds	Sov. Bonds	Options	CDS	Commod	FX	All
γ_{mrk}^{k}	0.20	0.04	0.05	0.016	0.003	-0.05	-0.10	0.02
$p(\chi^2(\gamma = 0))$	(0.00)	(0.00)	(0.00)	(0.00)	(0.79)	(0.00)	(0.00)	(0.00)
γ_{id}^{k}	0.10	0.05	0.03	0.35	0.02	0.27	0.15	0.05
$p(\chi^2(\gamma = 0))$	(0.00)	(0.46)	(0.54)	(0.00)	(0.43)	(0.00)	(0.05)	(0.04)
Portfolio size	25	20	6	18	20	23	12	124

Table 2.3: The coefficients of the cross-sectional regression. The table is representing the results of regressing the average of each portfolio's excess return on the beta estimated from the time series regression using the GMM method. In the GMM regressions, first, the coefficients are estimated using an identity matrix, then the estimated coefficients are used to estimate the weighting matrix. The reported coefficients are those estimated using the second weighting matrix. γ_{mrk}^{k} is the risk premium of the market excess return and γ_{id}^{k} is the idiosyncratic risk premium for each class of asset.

	The time series rolling 5-year regression (the first step)							
	FF25	US Bonds	Sov. Bonds	Options	CDS	Commod	FX	All
Mean (β_i^{mrk})	1.135	0.130	0.309	0.837	0.117	0.091	0.050	0.522
Std (β_i^{mrk})	0.25790	0.19455	0.30300	0.20126	0.08850	0.65357	0.18622	0.5814
Mean (β_i^{idio})	0.096	-0.038	0.094	-0.028	0.051	0.020	-0.0226	0.018
Std (β_i^{idio})	0.21964	0.14220	0.20400	0.09909	0.07299	0.49129	0.14854	0.2493

Table 2.4: The mean and variance of time series regression. The table is representing the results of regressing the excess return of portfolios for each class of asset on the idiosyncratic risk and the market excess return using GMM regression. In the GMM regressions, first, the coefficients are estimated using an identity matrix, then the estimated coefficients are used to estimate the weighting matrix. The reported coefficients are those estimated using the second weighting matrix. Then over the portfolios, an average of betas is taken which is the mean of each regressor in the table. Below the mean, the standard deviation of betas across portfolios in each asset class is also reported in the table. β_i^{mrk} is the beta of the market excess return as the regressor and β_i^{idio} is the beta of the idiosyncratic risk as the regressor for each class of asset.

	Cross-sectional regression on the time-varying Betas (the second step)							
	FF25	US Bonds	Sov. Bonds	Options	CDS	Commod	FX	All
γ_{mrk}^{k}	0.03	0.04	0.03	0.015	-0.069	-0.01	-0.02	0.01
$p(\chi^2(\gamma=0))$	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)	(0.02)	(0.00)
γ_{id}^{k}	-0.01	0.03	0.08	0.12	0.19	0.02	0.04	0.03
$p(\chi^2(\gamma=0))$	(0.37)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)
Portfolio size	25	20	6	18	20	23	12	124

Table 2.5: The coefficients of the cross-sectional regression. The table is representing the results of regressing the average of each portfolio's excess return on the beta estimated from the time series regression using the GMM method. In the GMM regressions, first, the coefficients are estimated using an identity matrix, then the estimated coefficients are used to estimate the weighting matrix. The reported coefficients are those estimated using the second weighting matrix. γ_{mrk}^{k} is the risk premium of the market excess return and γ_{id}^{k} is the idiosyncratic risk premium for each class of asset.

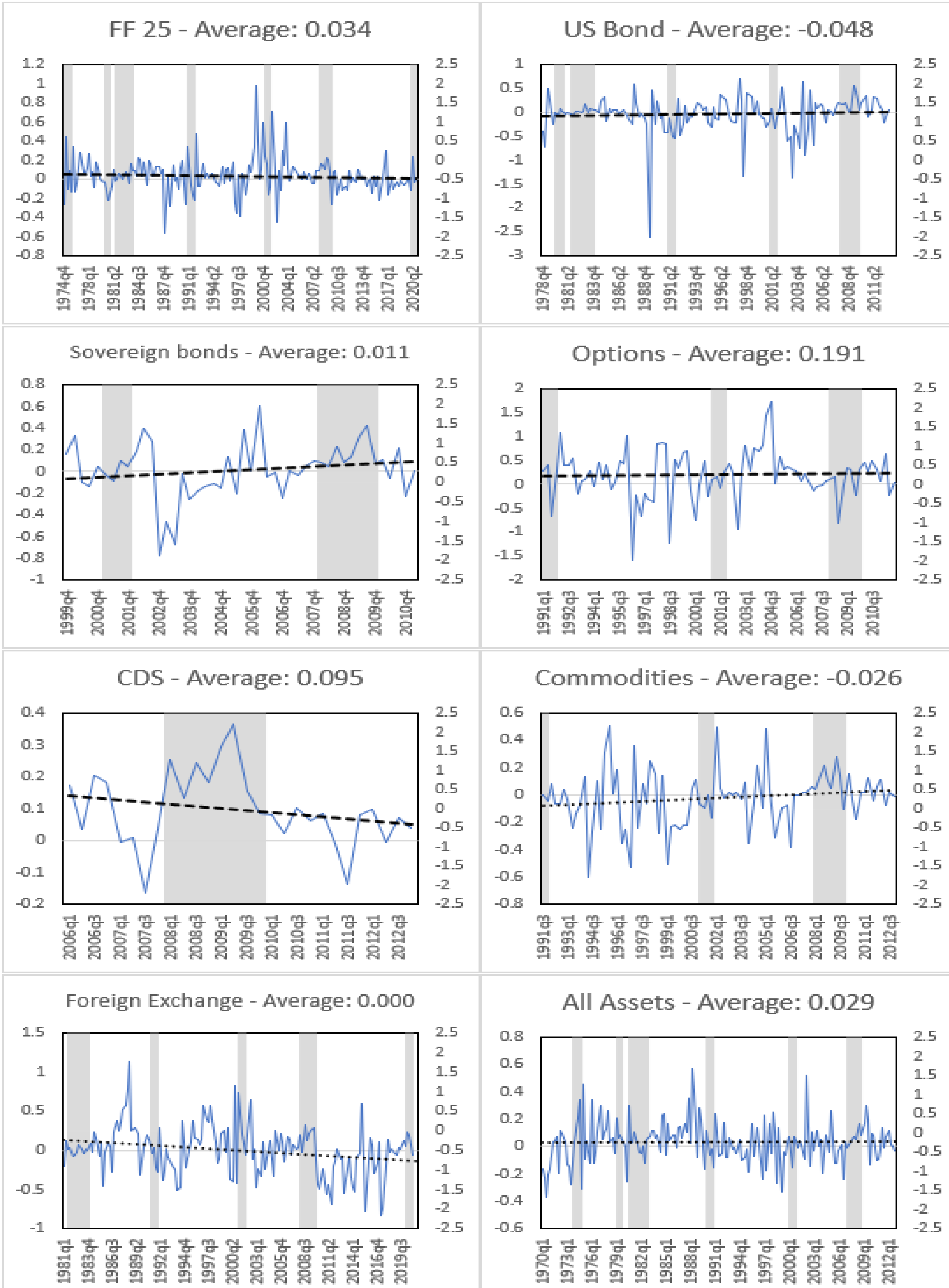

Figure 2.5: The solid blue line represents the idiosyncratic risk price at each class of asset which is the coefficient of regressing excess returns on time-varying beta for each date and each class of asset. The dashed lines are the best line fitted to the time series. The average of the risk price over time for each class of asset is written at the top of each graph. In addition, the price of risk is shown on the left vertical axis of each graph.

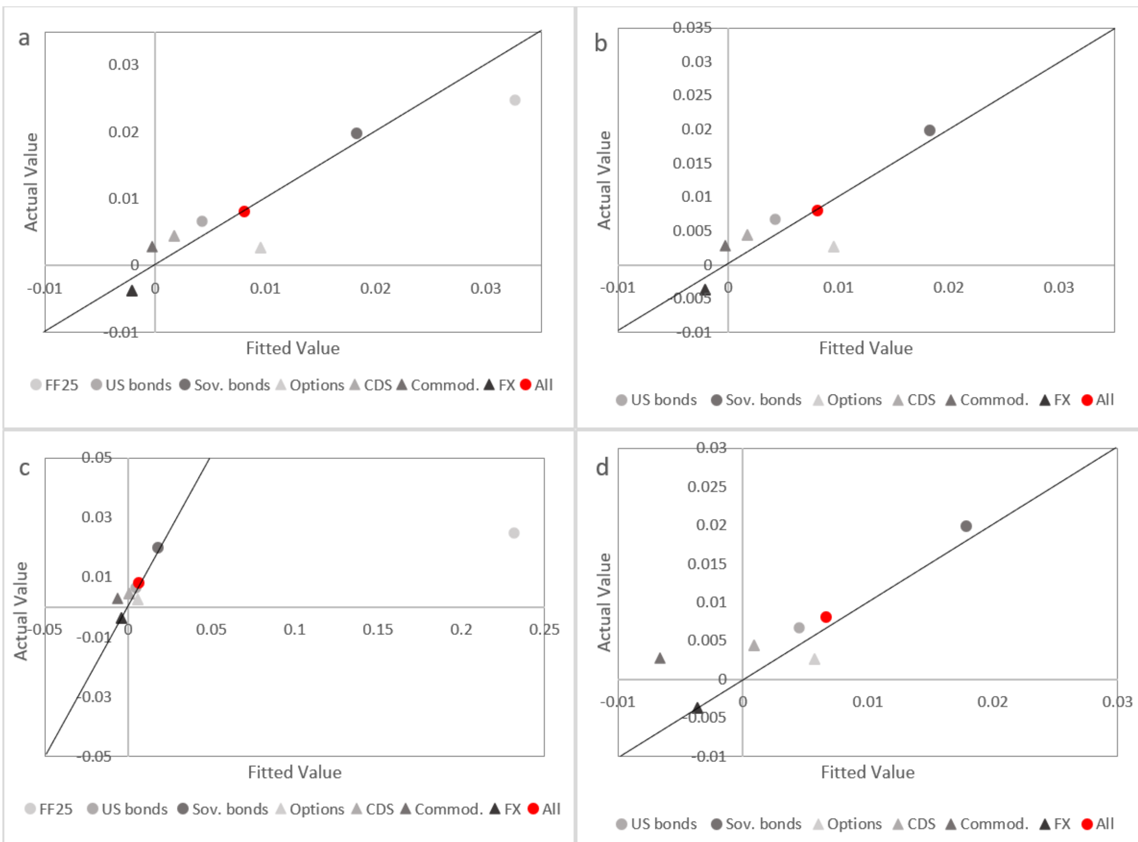

Figure 2.6: The graphs depict fitted returns from regressions in the horizontal line and the average of actual returns in the vertical axis for different asset classes. a and b are from FamaMac-Bath rolling regressions and c and d are from constant risk price regressions. The right graphs (b and d) are identical to the left ones, but FF25 has been removed. The 45-degree line is shown as a solid line in each graph.

Chapter 3

How Greater Geopolitical Risk and Global Supply Chain Disruption Change Global Investment Patterns

Abstract

This paper investigates how rising geopolitical risk and recent emphasis on reshoring and friend sharing could change the global pattern of Foreign Direct Investment (FDI) and Portfolio Investment (FPI). A Geopolitical Risk Index and an Economic Uncertainty Index are used to measure the impact of geopolitical risk and supply chain disruptions. The results indicate that as a country's geopolitical risk increases, its inflow of FDI drops while the inflow of FPI increases slightly. This suggests that a portion of FDI withdrawn returns to the country in the form of portfolio investment, probably to take advantage of the rapid economic growth of the country.

Keywords: Macroeconomics, Finance, Asset Pricing, Financial Intermediaries, Idiosyncratic Risk, Information Cost, International Investment

3.1 Introduction

Over the last two years, the terms reshoring and friend-shoring have become common in international business, particularly in North America. Reshoring happens when enterprises seek to return manufacturing activity to their home countries or surrounding countries. Globalization and international business accelerated from 1985 to 1995 as developing nations began pursuing free trade policies to address BOP imbalances. Until 2008, Canada was the largest importer into the United States. However, in 2008 China surpassed Canada to become the US's top importer. International trade has altered dramatically since 2008. Increased nationalism and efforts to "protect jobs" were key factors in US trade policies, which led to trade and tariff conflicts, with the US trading partners, throughout Trump's administration. Even before then, numerous countries were becoming concerned about their over-dependence on other countries, probability with different political views (Figure 3.1). The epidemic negatively impacted globalization in 2020 and 2021, highlighting the importance of nearshoring for businesses. Finally, the Russian invasion of Ukraine and the reactions of several Asian nations, have highlighted the necessity of maintaining a stable supply chain, and not being overly reliant on a single country.

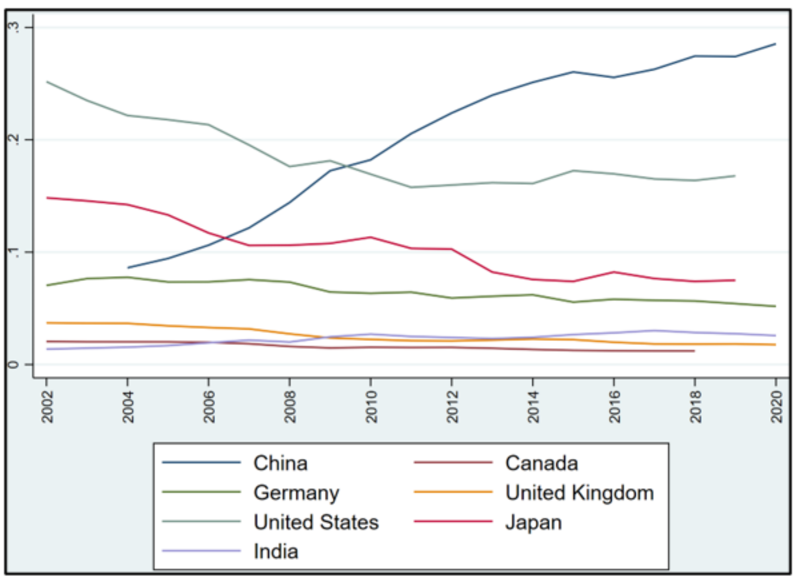

Figure 3.1: Share of the World's Manufacturing Products. Source: World Development Indicators.

Several basic difficulties have recently challenged open trade and globalization. Sustainability has risen to the top of everyone's priority list. However, the amount to which governments take this into consideration in their policies differs from country to country, and so different levels of attention to the notion of sustainability have made open trade more problematic. Security in the global supply chain (GSC) is increasingly a major problem for economies, prompting governments to focus on making their main sectors' supply chains more secure. Other significant barriers to open trade may include blocs, which are frequently mentioned by policymakers but are not always a practical and effective solution for businesses, and inconsistent global standards that primarily serve the interests of developed economies.

Aside from the higher risks and challenges to the GSC, offshoring costs have remained high after the pandemic. Freightos Baltic Index (FBX) in the global context was between \$1,100 to \$1,700 from 2017 to 2019. The Covid pandemic and worldwide lockdown limited the operation of shipping lines, which led to a significant increase in shipping costs, causing the FDX to peak at \$10,996 in September 2021. In June 2022, even though many lockdowns were over and shipping lines were back in operation, the index was still around \$7,000. An increase in shipping costs and input costs, including rising wages in emerging markets, has accelerated reshoring and has incentivized firms for supply chain reorientation.

To see how GSC disruptions could change global FDI and FPI patterns, it would be helpful to see how firms react to the risks of supply chain disruptions. Baldwin and Freeman (2021) discussed the importance of risks in the global supply chain and how firms react to these risks. They argue that by increasing supply chain flexibility, redundancy, and diversification as well as by forming long-term strategic alliances with a few of their suppliers, companies can increase their resilience to shocks. When it comes to policies, those that emphasize supply chain diversification are more effective at reducing economic volatility.

The Kearney Reshoring Index (2021) shows that due to the trade and tariff war, pandemic, and ongoing trade disruptions, American companies are becoming more serious about taking manufacturing back or closer to the US. Total manufacturing goods imports as a percentage of total output did grow in 2021, and the reshoring index became negative, which indicates that reshoring has not happened yet (Figure 3.2). But more companies are working to take their operations closer to home based on various surveys. In 2020, 78% of US manufacturing CEOs and executives answered yes or maybe to the question of whether they have considered or started reshoring their manufacturing to the US, while in 2021, 92% answered yes or maybe.

The Kearney China Diversification Index shows that the seasonally adjusted share of US LCC imports from China has dropped from 67% in the first quarter of 2018 to 50% in the second quarter of 2021. This suggests that US-based companies are becoming less dependent on China. In the third and fourth quarters of 2021, the index increased slightly, reaching 55%. Considering the war in Ukraine, the associated index for the first quarter of 2022 could be more informative. Also, the share of China in manufactured goods imported to the US has dropped constantly from 2018 to 2021, while Canada's share has risen in 2021 (probably an influence of USMCA). The share of other Asian countries has risen significantly as well. This may indicate that US businesses have abandoned some Asian countries in favor of other Asian countries (The quarterly values of imports to the US from Canada, China, and a few other countries are plotted in Figure 3.3).

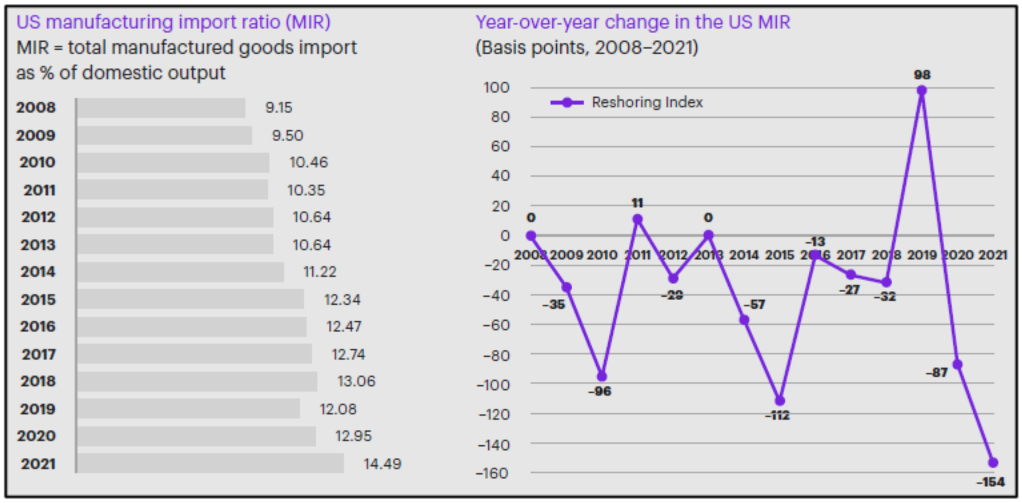

Figure 3.2: US manufacturing imports from 14 Asian low-cost countries have risen and resulted in the negative reshoring index in 2021.

Although reshoring and nearshoring do not show up clearly yet, the outlook looks promising. According to Kearney surveys (2021), 45% of CEOs said they have been approached by their stakeholders to consider reshoring or friend-shoring in their operations. In addition, 90% of CEOs answered that they are planning for nearshoring and reshoring 50% of their operations soon. This shows that they are still concerned about the availability of components and inputs for their activities. DigiTech and Automation Technology play important roles in the future of GSCs as well. In a ThomasNet survey, 55% of companies said that they are planning to invest in technologies to automate their operations. This willingness to automate technology may cause a shift toward higher-skilled workers. Baldwin and Freeman (2021) also note that the advancement of DigiTech contributes to removing GSC barriers in services and this means the future of GSCs will include services, and manufacturing goods will be produced mainly locally.

The primary purpose of this paper is to explore how GSC disruptions will affect global investment patterns, including FDI and FPI. Because measuring GSG is difficult and complicated, we employ variables that lead to GSC disruptions as proxies for GSC disruptions. Anything that feeds into GSC disruptions raises geopolitical and economic concerns as well. As a result, I use a geopolitical risk index (GPR) and an Economic Policy Uncertainty index (EPU) to assess the impact of geopolitical concerns and increased economic uncertainty on decisions to make overseas investments. The findings of the FDI and FPI models reveal that as a country's geopolitical situation worsens in comparison to other nations, more FDI is taken from the economy, but a part of that returns to the economy in the form of FPI. Section 2 develops a model for FDI, and then Section 3 develops another model for portfolio investment.

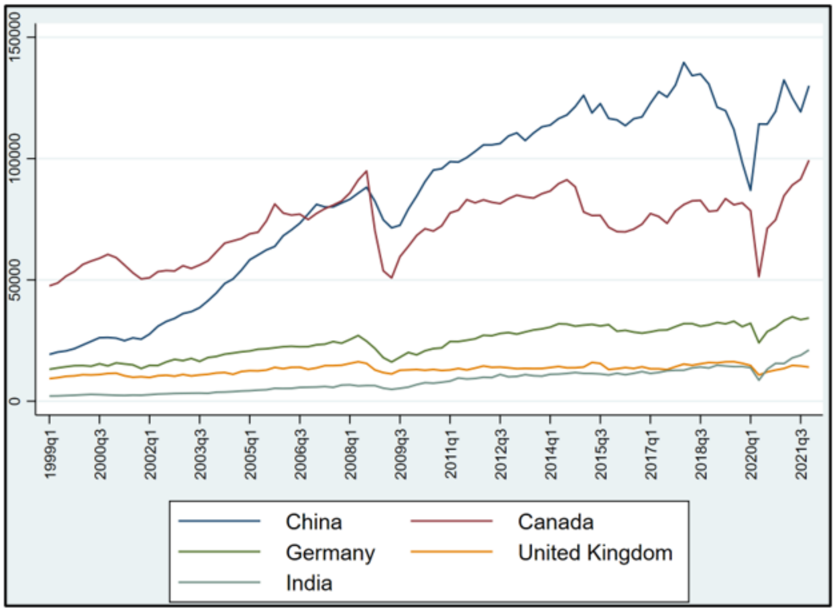

Figure 3.3: Import of Goods to the U.S., Seasonally Adjusted, In Millions of Dollars. Source: Bureau of Economic Analysis.

3.2 Foreign Direct Investment

3.2.1 Data and Model

The main purpose of this study is to capture the impact of political and economic instabilities on the intake of FDI. To this end, a reduced form econometric model is used in this study. This model incorporates several macroeconomic variables as control variables, while focusing on variables that proxy for economic policy and political risks. According to the literature, FDI and trade are highly correlated. MNEs may first start by exporting to a foreign market, and then when they become more familiar with the market, they may start taking FDI into that market and stop exporting. On the other hand, when a firm is taking FDI in another country, it may need to export components and inputs to its facilities in the host country. In this way, FDI can lead to exporting. In Hejazi and Safarian (2002) it has been discussed that due to the interaction between trade and FDI, the error term in the trade regression could change the equilibrium of FDI and the error term in FDI regression could cause changes in the trade equilibrium.

To capture this interaction, Hejazi and Safarian (2002) use Seemingly Uncorrelated Regression (SUR) and regressed trade and FDI at the same time. The same approach is applied here, and SUR is used to estimate the model. This means a change in export would change inward FDI in equilibrium and vice versa. If a drop in import is followed by an increase in inward FDI, the expected relationship is negative. But if higher inward FDI brings more import, then the expected relationship is positive. Depending on what the trade-off between these two forces could be, the sign of the FDI variable in the trade regression and the trade variable in the FDI regression could be either positive or negative. Therefore, in the export regression, the first lag of FDI is incorporated as a regressor, and in the FDI regression, the first lag of export is a regressor. The model is as follows:

$$ln(IM)_t = FDI_{t-1} + ln(GDP)_t + NEXCH_t + e_t \tag{A1}$$

$$FDI_t = ln(IM)_{t-1} + EPU_t/GPR_{t-1} + ln(HC)_t + GDPg_t + ln(W)_t + EFI_t + REXCH_t PCAP_t$$

$$+FDIWorldg_t + \nu_t \tag{A2}$$

Two regressions will be regressed together according to SUR. The variables in the model are explained in Table 3.2.1. The FDI variable used in the model is the global share of FDI for each country. Since the purpose of this study is to see the impact of economic and political instability on inward FDI patterns across the world, the share of each country's inward FDI could represent the global pattern changes more effectively. The growth rate of the world FDI is also incorporated in the regression to capture the impact of denominator change in the FDI global share. Also, in the FDI regression, EPU_t/GPR_{t-1} ($EPU_t or GPR_{t-1}$) represents economic and political instability. The Economic Policy Uncertainty Index (EPU) and Geopolitical Risk Index (GPR) are used in two different regressions to see the explanatory power of each. Since the indices are provided for the different sets of countries, inserting both indices into one regression is not technically possible.

Variable	**Description**	textbfSource
FDI	The annual global share of inward FDI	UNCTAD
IM	Log of annual real Imports of goods and services (BoP, current US$)	International Monetary Fund, Balance of Payments Statistics Yearbook, and data files.
EPU	Economic Policy Uncertainty Index divided by the global index of Economic Policy Uncertainty	Economic Policy Uncertainty [1]
GPR	Geopolitical Risk Index divided by the global index of Geopolitical Risk	Dario and Iacoviello (2022) [2]
GDP/GDPg	GDP used in the import regression is log of GDP (constant 2015 US$) per capita and GDPg in the FDI regression is the five-year GDP growth rate.	World Bank national accounts data, and OECD National Accounts data files.
REXCH	Real effective exchange rate index (2010 = 100)	International Monetary Fund, International Financial Statistics.
NEXCH	Official exchange rate (LCU per US$, period average)	International Monetary Fund, International Financial Statistics.
W	Labor Cost Per Hour	This variable is calculated using the labor share of GDP and total hours worked for each country. The labor share of GDP and total hours worked are from The Conference Board Total Economy Database.
EFI	Economic Freedom Index	Economic Freedom of the World: Annual Reports, Fraser Institute
PCAP	The price level of the capital stock, the price level of the USA in 2017=1	FebPwt - Penn World Table - international comparisons of production, income, and prices 10.0
FDIWorldg	The growth rate of world inward flow FDI.	UNCTAD

The data used for the model contains a panel of 42 countries from 1985 to 2020 in the model with a Geopolitical Risk index and 28 countries in the model with an Economic policy Uncertainty index from 1991 to 2020. Both models are on the annual and the differences between the samples and the timelines are because of the different coverage for the two indices. The variables that are interesting in this study are GPR and EPU which represent economic/political instability. If economic/political instability could cause higher risks for foreign investment, it is expected to see when GPR or EPU indices spike in a country, less inward FDI goes to the country. If this is true, the expected signs of these two indices are negative. GPR and EPU are both constructed based on the share of associated keywords in the newspapers. GPR is a measure of adverse geopolitical events and associated risks based on a tally of English-language newspaper articles covering geopolitical tensions and examining their evolution and economic effects. The percentage of times the country name and geopolitical keywords are repeated jointly in the same English-language newspapers defines the country-specific GPR. EPU is measured similarly but for country-specific measures, the media coverage is in publications written in the local language and the keywords are more economic-oriented. This makes EPU more accurate in terms of using local newspapers. However, due to the keywords that are more geopolitically focused and may suggest the current geopolitical instability, GPR is more advantageous for this research. This is why both measures are used in this study.

Exchange rates play roles both in the import and FDI models. When a country's currency depreciates, imports would be more expensive for consumers in that country, but input prices would be lower for foreign investors. Hence, there is a good chance for imports to drop and FDI to increase as the currency depreciates in a country. To capture the role of the exchange rate in the model, the nominal exchange rate is used in the import regression, and the real exchange rate is incorporated into the FDI regression. Regarding the role of GDP in the model, when the GDP growth rate is above the global average, this is an incentive for investors to take advantage of high returns and undertake FDI in a country with a high GDP growth rate. Therefore, this could impact FDI positively, and to capture this impact, the five-year growth rate of GDP, which illustrates the economy's growth rate in the long term, is used in the FDI regression. In the import regression, GDP per capita is a proxy for people's income in a country such that higher income triggers more import.

3.2.2 Result

The results of SUR model are provided in Table 3.1. The first section of the table represents the results of regressing import on FDI, and other variables and the second part contains the coefficients of FDI regressed on import, EPU/GPR, human capital, and a few other variables. The Economic Policy Uncertainty Index (EPU) model is implied in the table's second column, while the Geopolitical Risk Index (GPR) model is implied in the third column. Considering that GPR changes lead to changes in FDI and delayed comovement is observed in GPR and FDI data, the first lag of GPR works more efficiently in the model and is used in the model.

In both models, the coefficients of independent variables are shown up with the expected signs except the price of capital which is expected to be negative. EPU and GPR are both statistically significant and inversely related to the share of FDI which is consistent with the expectation [3]. As a nation's political or economic status deteriorates, EPU and GPR for that nation fall, which results in less FDI flowing into that economy. However, the sizes of the coefficients are different in the two regressions. Each 1 unit increase in EPU results in a 0.49% drop in the country's FDI share, while each 1 unit increase in GPR results in a 1.82% drop in FDI share the following year [4].

Another regression model using GPR includes bilateral inward FDI from the IMF's Coordinated Direct Investment Survey (CDIS) as a dependent variable. The advantage of bilateral data over aggregated data in Table 3.1 is that under the bilateral framework, we may use distance as a proxy for cultural differences and any other type of trade and investment cost. This data set, on the other hand, is more limited in time, beginning in 2009 and ending in 2020. This means many important events in FDI, and geopolitical situations are ignored here. The findings of this regression are comparable to those given in Table 3.1. According to the bilateral model, each unit rises in GPR results in a 0.01% decrease in FDI share the next year (Since these results are based on the bilateral data, comparing to the results in Table 3.1, this is a breakdown impact of GPR index increase on inward FDI coming from any source. Thus, to see the aggregate impact on an economy's inward FDI global share, it should be multiplied by the number of source countries.).

The Economic Freedom Index and the Human Capital Index are two more intriguing variables in the model. According to Table 3.2.1, the variable used to measure human capital for each country in the sample is the Index of human capital per person, based on years of schooling and returns to education. According to Table 3.1, as HC rises by 1%, FDI share rises by about 9.67% in the EPU and 4.12% in GPR models. Since high-tech sectors are growing fast and are in demand for more educated workers, the impact of human capital on inward FDI maybe even more substantial. In the recent ThomasNet survey[5], 55% of companies said that they are planning to invest in technologies to automate their operations. This willingness to automate technology may cause a shift toward higher-skilled workers. Baldwin and Freeman (2021) also discuss that the advancement of DigiTech contributes to removing GSCs barriers in services and this means the future of GSCs will be widely

[3] Additionally studied are GPR and EPU with lags of up to four lags, in the model. For both variables, all lags appeared with statistically significant negative coefficients. The sizes of the coefficients were almost similar to the variable shown in Table 3.1

[4] In a set of regressions for robustness checks, a SUR with log of variables and an OLS regression for FDI still confirmed the negative and statistically significant relationship between FDI share and $GPR/\ EPU$. Also, when some variables are dropped from the regression, the relationship between FDI and GPR/EPU remains the same.

[5] ThomasNet has polled more than 1,000 participants across the US to gauge their perception of manufacturing, including the industry's biggest challenges, how they view manufacturing careers, and whether they prefer to buy American products.

on services and manufacturing goods will be produced mainly locally. These discussions emphasize how crucial human capital could be to the FDI.

The importance of the Economic Freedom Index (EFI) could be in line with the impact of carbon emission restrictions on FDI. For instance, the Canadian federal government pledged to reach the carbon emission targets by 2030. Similar positions have been taken by other advanced nations as well. Aside from the long-term benefits, these activities have for economic sustainability, they might limit economies in the short run in comparison to those that are not acting so aggressively in the interest of the environment. As a result of the differences countries could have in the environmental and sustainability policies, investors may find economies with less strict environmental policies easier to take their $FDIs$ in, and with more favorable environments for investment. In the other world, committing to meet carbon emission targets makes industries more restricted and worsens the EFI of the country and could end up with lower inward FDI. As a result, policymakers should explore ways to offset the potential reduction in EFI, in addition to supporting green policies. In this model, the impact of EFI on FDI share has been estimated at 0.24 in the EPU model and 0.39 in the GPR model. This means, for instance in the GPR model if because of more strict carbon emission policies, EFI drops by 1 unit, FDI share drops by 0.4%.

The GPR index has worsened in all economies, as was previously stated in this study since 2022, but the extent of the decline varies from country to country. Given that the model includes GPR with a one-year lag, current GPR index values could be used to assess how the worldwide pattern of FDI will change over the upcoming year using the model estimated in the paper. Figure 3.4 depicts the change in the monthly global GPR index since 1985. In March 2022 the index spiked following the war in Ukraine. The spike in the index and the worsened geopolitical environment were widespread across the world. However, the degree of the increase is different in individual countries. For instance, China's GPR index has jumped over the first few months of 2022 significantly and recorded the highest number since 1985. Although the index in western nations increased in 2022 as well, it has not yet reached the levels seen in 2001 and 1991.

Figure 3.5[6] shows how the shift in the geopolitical environment and political instability might affect the global FDI share in 2021 and 2022, ceteris paribus. More or less everywhere in the world, GPR has increased as a result of the war in Ukraine. Due to the increased risk and uncertainty in the geopolitical environment, foreign investors are being more cautious when looking to make investments outside of their home countries. This caused FDI share to drop in many countries including China where FDI was increasing continuously until

[6]In the FPI model, the impact of GPR index on inward FPI global share from each source country, is measured. This means to see the aggregate impact of the geopolitical index on inward FPI global share on an economy, the GPR coefficient should be multiplied by the number of source countries which is assumed to be the same as what it was in 2020 in the sample for each country. The number of source countries in 2020 in this sample ranges from 46 to 53 for each economy.

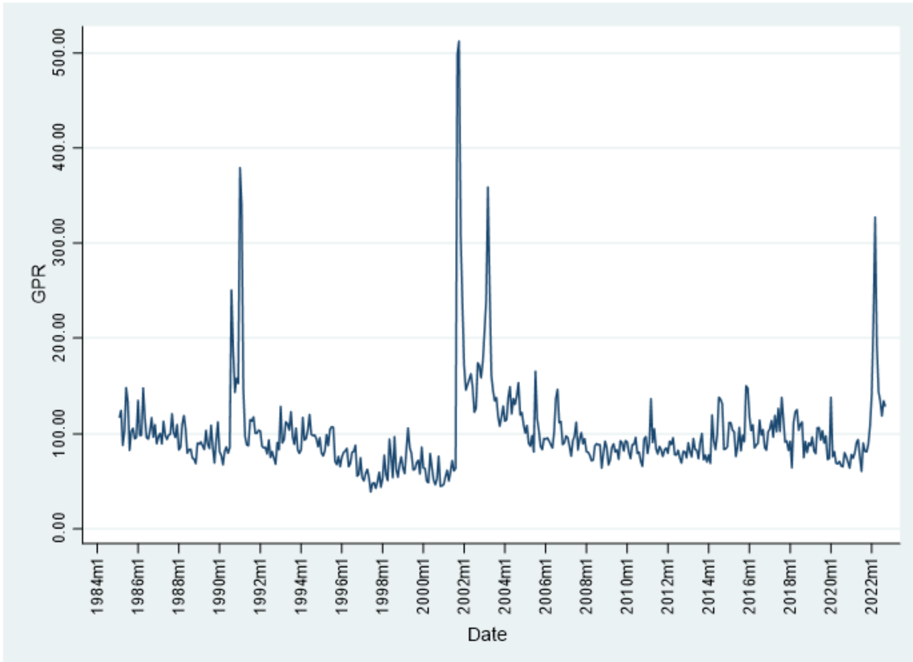

Figure 3.4: Global Geopolitical Risk Index.

2018. In comparison to the other nations, Germany and the UK would face sharper declines. This may be due to Brexit or increased risks associated with the war in Ukraine for European nations.

Despite the decline in FDI share in China and Japan, if we take the bias in the GPR index into account, this drop may indeed be far more severe in reality. The local media coverage is not used to calculate GPR for non-English speaking nations, as was previously stated in this paper. This measurement flaw may understate the actual growth that may be experienced in non-English-speaking countries' country-specific GPR indices. As per this, while GPR has raised by more than 100% in UK and Canada and about 80% in the USA in 2022, this raise was just 50% in China, 37% in India, and 60% in Japan. In contrast, more rise in China's GPR was expected given its position as Russia's ally in the war in Ukraine.

Figure 3.6 shows the forecast results of the model containing EPU. The advantage of EPU over GPR is that the index is constructed using local newspapers that would be more affected by the domestic economic situation compared with the English-language newspapers. Economic uncertainty is primarily focused on the economic situation, even if it may change slightly when the geopolitical situation changes. The graph shows that the global share of inward FDI changes for all economies when factoring into the change in EPU, ceteris paribus. The US and Canada have seen a slight boost in inward FDI share, and Germany has recorded the largest decline which could be the impact of Brexit and its consequences as well.

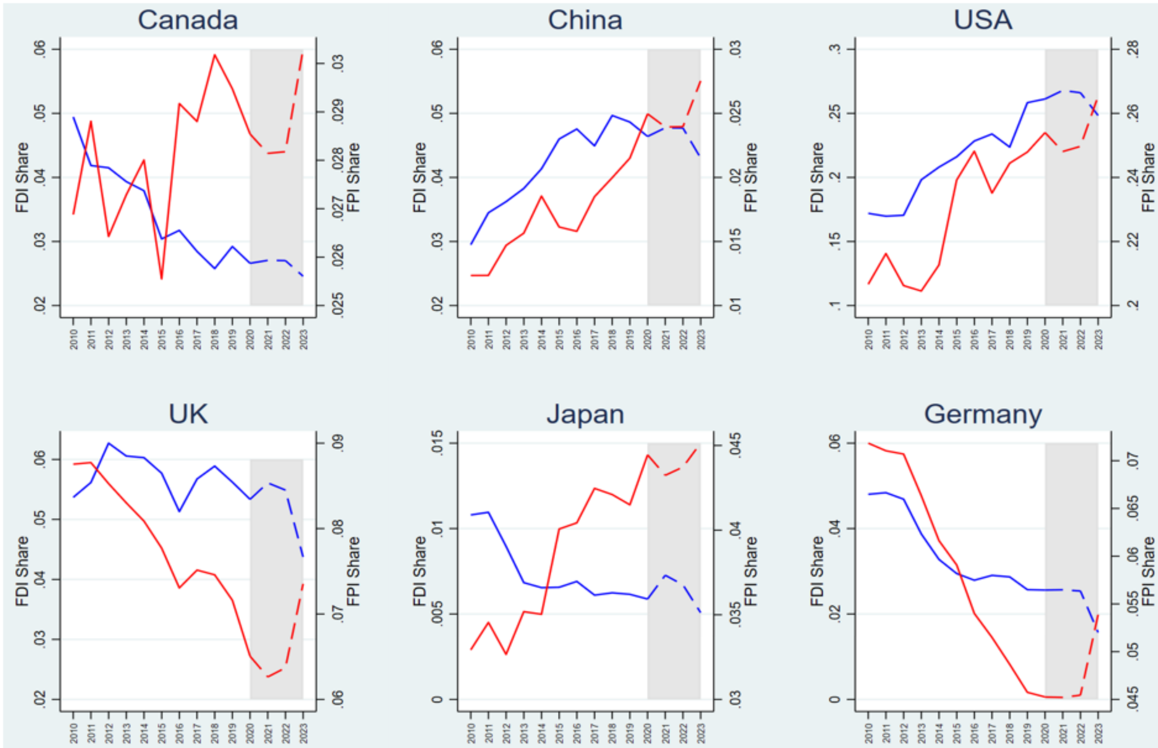

Figure 3.5: The forecast of FDI and FPI global share based on GPR changes. The graphs depict changes in FDI and FPI global share from 2010 to 2023 for a select country if the GPR index is changing, ceteris paribus. The red graph represents FPI, whereas the blue graph represents FDI. From 2010 to 2020, the graphs are historical, dada, and from 2020, they are forecasts based on the model (it is the shaded graphs and parts of the graphs in the grey region).

3.3 Foreign Portfolio Investment

3.3.1 Data and Model

The model used for FPI is a gravity model containing a distance variable. In a gravity model, transactions in equity ($T_{i,j}$) between country i and j (which is foreign portfolio investment for the purpose of this study) are related to the economic masses of two countries and trading costs as follows:

$$log(T_{i,j}) = \alpha_1 log(M_i M_j) + \alpha_2 log(\tau_{i,j}) + \alpha_3 \tag{A3}$$

Where M_i measures the economic masses of country i and M_j measures the economic masses of country j and $\tau_{i,j}$ is the trading cost. Economic mass could be measured by market capitalization. For the trading costs, the host country's financial market sophistication, distance, and Geopolitical Risk index are used. Distance could proxy information

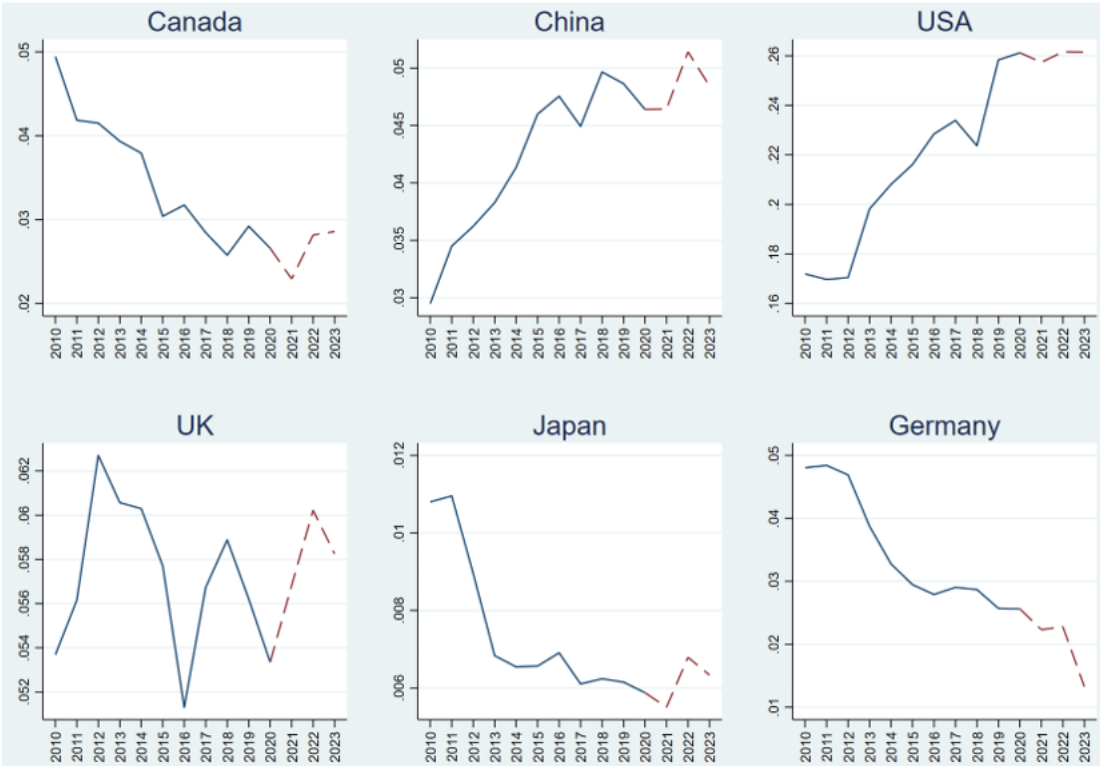

Figure 3.6: The forecast of FDI global share based on EPU changes. The Graphs illustrate how FDI global share could change over 2021 and 2022 based on changes in the economic policy uncertainty of each country, ceteris paribus. The dashed part in each graph is the forecast.

cost. Traveling is more costly to further markets and there are cultural differences that make the information cost higher for markets that are far from the home country. Also, financial market sophistication could measure the efficiency of the transaction technology. Geopolitical risk increases the political risk associated with a market and makes investors less willing to invest in that market.

Variable	**Description**	textbfSource
FPI	Bilateral annual global share of inward FPI	IMF's Coordinated Direct Investment Survey (CDIS)
Distance	Distance between capital cities, in km	Gravity data in CEPII
GPR	Geopolitical Risk Index divided by the global index of Geopolitical Risk	Dario and Iacoviello (2022)[7]
Sophistication	Financial market Sophistication Index	World Competitiveness Report by IMD
Market Capitalization	Market capitalization of listed domestic companies (current US$) deflated by GDP deflator	World Bank national accounts data

Hence, the basic estimation equation is as follows:

$$[h]FPIShare_{ijt} = ln(Distance_{i,j}) + GPR_{i,t-1} + Sophistication_{i,t}$$

$$+ln(MarketCap_i) + ln(arketCap_j) + ln(WorldFPI_t) + u_t \tag{A4}$$

The data used are described in Table A3. The data is annual and from 2001 to 2020 containing 42 FPI host countries and 53 FPI home countries (Home countries may differ from one host country to the next). The host countries are those for which the Geopolitical Risk index is measured.

3.3.2 Result

Table 3.2 shows the findings of the portfolio investment gravity model. As a dependent variable, inward portfolio investment takes the form of a percentage of the global share. To account for changes in the denominator of FDI share, the regression includes the log of global FDI as well.

The purpose of this research is to determine the GPR coefficient in FPI regression. According to Table 3.2, when a country's GPR rises by one unit, its inward FPI global share rises by 0.02%. Given the impact of the GPR index on FDI share, this is an intriguing finding (Table 3.1). When an economy's GPR index rises, indicating more geopolitical risk, its FDI share falls by 1.8%, while its FPI share climbs by 0.02% in the next year. The way FDI and FPI react to changes in geopolitical risk might mean that when a country's geopolitical risk rises, 1.8% of FDI is withdrawn, while 0.02% of investment from each source is reinvested in the country as portfolio investment [8].

The other variables in the model showed the predicted impact on FPI share. Distance has a negative impact on FPI share as a measure of cultural differences and the cost of trade and investment. If the host nation is one kilometer farther from the home country, the FPI share flowing into that country falls by 0.03% compared to the country that is one kilometer closer to the home country. The host economy's financial market sophistication has a positive but minor influence on FPI's global share. Sophisticated business procedures encourage greater efficiency in the production of products and services, which may provide a favorable environment for increased portfolio investment inflows. The market capitalization of the host and home countries illustrates the size of the capital market. As the host country's capital market grows, it may attract more portfolio investment, and as the home country's capital market grows, more portfolio investment may flow into other nations' capital markets. The significant and positive coefficients of the capital markets of the home and host economies are consistent with intuition.

Figure 3.5 depicts how the worldwide share of FDI and FPI of selected countries would vary if the countries' geopolitical risk changed while the other variables remained constant in the model. The blue graph represents FDI share (the left axis in each graph), whereas the red graph represents FPI (the right axis in each graph). Given that the GPR index has climbed in 2022 because of the war in Ukraine and other countries positions on the war, the FPI share has increased while the FDI share has decreased for countries with higher GPR and more related to war and its consequences. For instance, in European countries, geopolitical risk has grown due to conflict since there is now a greater possibility of a Russian invasion to them. This is reflected in those nations' foreign investments as lower FDI and higher FPI. Also, given China's position on the war, which has increased this country's geopolitical risk, the model forecasts that its inward FDI share will fall by 0.7% in 2023, while its inward FPI share will rise by 0.36% in 2023. As a result, it appears that increasing geopolitical risk in China will result in more FDI being withdrawn specialty in 2023, with at least some of this being returned to China in the form of portfolio investment.

3.4 Conclusion

This research aimed to examine the impact of the recent global supply chain disruption caused by the Covid-19 lockdown, which was followed by the war in Ukraine and subsequently by the leaders of Western economies emphasizing reshoring and friendshoring on the worldwide investment pattern. Since any disruption to the GSC increases geopolitical and

[8] Since in FPI model, data is bilateral, 0.02% increase in inward FPI global share because of increase in GPR index, comes from each source country. Hence, the aggregate increase in inward FPI global share for each country is the product of the number of source countries and 0.02%.

economic risk, the impact of these risks on international investment, particularly foreign direct investment and portfolio investment, is explored here.

The models' findings indicate that when an economy faces more risk in the geopolitical environment and economic policies, foreign investors are inclined to withdraw their long-term investment in the next period due to that country's increased risk. This implies that the economy will receive less FDI from global FDI. However, the situation is completely different when it comes to portfolio investment. According to the model, as an economy's geopolitical situation worsens, more FPI inflows into the economy. Putting the findings regarding FDI and FPI together suggests that when a country's geopolitical risk rises, foreign investors withdraw some of their FDI, but they may return part of it in the form of FPI. One explanation for this might be that foreign investors find the economy riskier to invest in over the long term, but they still see the economy growing quickly and do not want to miss out on benefiting from that growth. As a result, they may return to that economy in part, but with a shorter-term and less involved investment.

3.5 References

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative Politics and the Synthetic Control Method: COMPARATIVE POLITICS AND THE SYNTHETIC CONTROL METHOD. American Journal of Political Science, 59(2), 495–510. https://doi.org/10.1111/ajps.12116

Ahmad, S. Y., Cova, P., and Harrison, R. (2004). Foreign Direct Investment versus Portfolio Investment: A Global Games Approach. University of Wisconsin – Whitewater.

Alvarez, J., Krznar, I., and Tombe, T. (2019). Internal Trade in Canada: Case for Liberalization. IMF Working Paper.

Baker, S. R., Bloom, N., & Davis, S. J. (n.d.). Measuring Economic Policy Uncertainty.

Baldwin, R., Bown, C., Fried, J., González, A., Sapir, A., & Watanabe, T. (n.d.). GETTING AMERICA BACK IN THE GAME: A MULTILATERAL PERSPECTIVE.

Baldwin, R., & Freeman, R. (2022). Risks and Global Supply Chains: What We Know and What We Need to Know. Annual Review of Economics, 14(1), 153–180. https://doi.org/10.1146/annurev-economics-051420-113737

Blanchard, O., & Acalin, J. (2016). PB 16-17 What Does Measured FDI Actually Measure?

Brainard, S. L. (1993). An Empirical Assessment of the Proximity-Concentration Tradeoff between Multinational Sales and Trade (No. w4580; p. w4580). National Bureau of Economic Research. https://doi.org/10.3386/w4580

Breinlich, H., Leromain, E., Novy, D., & Sampson, T. (2020). Voting with their money: Brexit and outward investment by UK firms. European Economic Review, 124, 103400. https://doi.org/10.1016/j.euroecorev.2020.103400

Caldara, D., & Iacoviello, M. (n.d.). Measuring Geopolitical Risk.

Caliendo, L., & Parro, F. (2015). Estimates of the Trade and Welfare Effects of NAFTA. The Review of Economic Studies, 82(1), 1–44. https://doi.org/10.1093/restud/rdu035

Chen, N., & Novy, D. (2011). Gravity, trade integration, and heterogeneity across industries. Journal of International Economics, 85(2), 206–221. https://doi.org/10.1016/j.jinteco.2011.07.005

Ciuriak, D. (2022). At What Cost? The Ledger on Vladimir Putin's War. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4150006

Ciuriak, D., Ciuriak, L., Dadkhah, A., Lyu, Y., & Wen, Y. (2023). Canada's Pivot to the Indo-Pacific: The Strategic Importance of Prioritizing a Trade Agreement with ASEAN. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4393291

Ciuriak, D., Dadkhah, A., & Xiao, J. (2020). Quantifying CUSMA: The Economic Consequences of the New North American Trade Regime. C.D. Howe Institute.

D'Aguanno, L., Davies, O., Dogan, A., Freeman, R., Lloyd, S., Reinhardt, D., Sajedi, R., & Zymek, R. (2021). Global Value Chains, Volatility and Safe Openness: Is Trade a Double-Edged Sword? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3766910

Evans, K. (n.d.). FOREIGN PORTFOLIO AND DIRECT INVESTMENT.

Feils, D. J., & Rahman, M. (2008). Regional economic integration and foreign direct investment: The case of NAFTA. Management International Review, 48(2), 147–163. https://doi.org/10.1007/s11575-008-0009-9

Ghosh, M., & Wang, W. (2011). Canada and U.S. Outward FDI and Exports: Are China and India Special? The International Trade Journal, 25(4), 465–512. https://doi.org/10.1080/08853908.2011.597686

Global Affairs Canada, Office of The Chief Economist. (2012). International Trade and Its Benefits to Canada.

Goldstein, I., & Razin, A. (2006). An information-based trade off between foreign direct investment and foreign portfolio investment. Journal of International Economics, 70(1), 271–295. https://doi.org/10.1016/j.jinteco.2005.12.002

Guerin, S. S. (2006). The Role of Geography in Financial and Economic Integration: A Comparative Analysis of Foreign Direct Investment, Trade and Portfolio Investment Flows. The World Economy, 29(2), 189–209. https://doi.org/10.1111/j.1467-9701.2006.00777.x

Hejazi, W., & Safarian, A. E. (n.d.). Explaining Canada's Changing FDI Patterns.

Helliwell, J. F. (2005). Borders, Common Currencies, Trade, and Welfare: What Can We Learn from the Evidence?

Hlaing, S. W., & Kakinaka, M. (2019). Global uncertainty and capital flows: Any difference between foreign direct investment and portfolio investment? Applied Economics Letters, 26(3), 202–209. https://doi.org/10.1080/13504851.2018.1458182

Irwin, D. (2022). Explaining the trade reform wave of 1985–1995. VOX, CEPR Policy Portal

Karimo, T. M., & Tobi, D. B. (2013). Macroeconomic Uncertainty and Foreign Portfolio Investment Volatility: Evidence from Nigeria.

Körner, F. M., & Trautwein, H.-M. (2015). Sovereign Credit Ratings and the Transnationalization of Finance – Evidence from a Gravity Model of Portfolio Investment. Economics, 9(1), 20150009. https://doi.org/10.5018/economics-ejournal.ja.2015-9

Lane, P. R., and Milesi-Ferretti, G. M. (2004). International Investment Patterns. IMF Working paper.

Oldenski, L. (2015). Reshoring by US Firms: What Do the Data Say?

Pan, L., Hu, R., & Du, Q. (2022). Foreign portfolio investment patterns: Evidence from a gravity model. Empirical Economics, 63(1), 391–415. https://doi.org/10.1007/s00181-021-02133-0

Portes, R., & Rey, H. (2005). The determinants of cross-border equity flows. Journal of International Economics, 65(2), 269–296. https://doi.org/10.1016/j.jinteco.2004.05.002

Serwicka, I. (n.d.). NOT BACKING BRITAIN: FDI INFLOWS SINCE THE BREXIT REFERENDUM. The tides are turning—The 2021 Reshoring Index. (n.d.).

Tombe, T. (n.d.). Towards a More Productive and United Canada: The Case for Liberalizing Interprovincial Trade.

Tkchuk, T & A. Day, J. (2016). Tear Down These Walls: Dismantling Canada's Internal Trade Barriers, The Standing Senate Committee on Banking, Trade and Commerce.

Waqas, Y., Hashmi, S. H., & Nazir, M. I. (2015). Macroeconomic factors and foreign portfolio investment volatility: A case of South Asian countries. Future Business Journal, 1(1–2), 65–74. https://doi.org/10.1016/j.fbj.2015.11.002

Wolf, M. (n.d.). In an era of disorder, open trade is at risk.

Variable	Regression with EPU	Regression with GPR
Import Regression:		
Lag of FDI	-0.019***	-0.02 ***
	(0.003)	(0.004)
GDP	1.77***	1.71***
	(0.02)	(0.02)
NEXCH	-0.11**	-0.07***
	(0.034)	(0.018)
R-Squared	0.98	0.98
FDI Regression:		
Lag of IM	-0.71**	-0.63***
	(0.24)	(0.15)
EPU	-0.49**	-
	(0.15)	
Lag of GPR	-	-1.82***
		(0.38)
HC	9.67***	4.12***
	(1.40)	(0.88)
GDP Growth	2.20**	0.77**
	(0.70)	(0.35)
W	-4.19***	-0.88**
	(0.56)	(0.30)
EFI	0.24	0.39**
	(0.27)	(0.09)
REXCH × GDP	0.86***	0.53***
	(0.04)	(0.03)
PCAP	0.68	0.08
	(0.04)	(0.21)
Lag of FDI World Growth	-0.08	-0.11
	(0.19)	(0.13)
R-Squared	0.94	0.95

Table 3.1: The results of Seemingly Unrelated Regression as FDI and import are the dependent variables. In the first section of each model, the dependent variable is log of import and in the second section, the dependent variable is the global share of inward FDI in percentage. In both models, import and FDI are regressed using a SUR model in which the error terms are correlated contemptuously. Each row contains the coefficients followed by the significance levels. Entries marked with ** are statistically significant at 95%. Those marked with *** are significant at 99%. The figures in the parenthesizes are the standard deviations of the coefficients.

Variable	Regression with GPR
Lag of GPR	0.02***
	(0.004)
Log of distance	-0.03***
	(0.004)
Log of market cap_i	0.002**
	(0.0008)
Log of market cap_j	0.007***
	(0.001)
Sophistication	0.0002**
	(0.000)
Log of FDI World	-0.005
	(0.002)
R-Squared	0.22

Table 3.2: The result of panel regression as foreign portfolio investment is the dependent variable. The dependent variable is the global share of inward portfolio investment in percentage. i represents the host country and j represents the home country. Each row contains the coefficients followed by the significance levels. Entries marked with ** are statistically significant at 95%. Those marked with *** are significant at 99%. The figures in the parenthesizes are the standard deviations of the coefficients.