THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

# Essays in Financial Economics

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# Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).



I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

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**Statement of conjoint work**

I confirm that Chapter 3 were jointly co-authored with Raphael Auer, Andreas Schrimpf, and Alexander Wagner. I contributed 25% of this work.

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# Abstract

In the first chapter, I study the exchange-traded fund (ETF) market from two perspectives. First, I study its contagion, and I show that the network of the ETF market — the linkages between ETFs based on portfolio weights — catalyzes the propagation of price dislocations, the gaps between prices and their fundamental values. Arbitrage trading induces price dislocations in connected ETFs, followed by responses in returns and subsequent reversals with a sizable effect of 4-6% per year. The findings suggest that arbitragers create externalities from trading. Finally, the ETF market works as a stabilizer for price dislocations, but induced returns can incur unexpected fluctuations. Another is information embedded in ETFs. By extracting information in ETFs, I uncover the risk neutral covariance of global asset returns and currency returns to understand risk premium and exchange rate risk in the global financial market better. The measure captures some economic policy uncertainty in real time.

The second chapter studies the futures markets. The literature has documented that the inflow of institutional money into the commodity market led to so-called financialization of commodities and hence the higher correlation between equity and commodity. However, the correlation is highly time-varying, and it had decreased once before it has faced another surge. I find this time-varying correlations between equity and commodity as well as between commodity and bond are driven by the net trading positions for corresponding pair of asset classes. Exploiting this, I construct the measure that signals mispricing of large investors, and I find cross-sectional predictability for future returns with this measure. I also investigate the role of the limit to arbitrage in the currency market in a relation to return spillovers from the commodity market empirically and theoretically.

In the third chapter (co-authored with Raphael Auer, Andreas Schrimpf, and Alexander Wagner), we study how the international trade network can affect financial markets. In contrast to the earlier literature, our measure shows the trade flows in global value chains affect equity market comovements strongly. One standard deviation increase in our trade intensity measure leads to roughly 0.05 to 0.1 increase in correlations. Our results hold after controlling for financial integration and other factors that could affect the international asset market comovements.

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# Chapter 1

# Contagion and Information in the ETF Market

## 1.1 Introduction

Exchange-traded funds (ETFs) were born in the aftermath of 1987's Black Monday and were introduced into the market in 1993. Today, there are around 2,000 ETFs valued at $4 trillions in asset under management (AUM). In the United States, the number of ETFs might surpass that of stocks. As the ETF market continues to grow and replaces mutual funds, the linkages between ETFs and underlying assets, as well as those among ETFs, continue to increase. One wonders how price discovery in individual assets is affected by trading flows into and out of ETFs, once these bundled flows outweigh those targeting the underlying assets individually. Given the range of and overlap between different ETFs, arbitrage activity targeting price dislocations[1] is bound to have spill-over effects across the ETF universe.

Throughout this paper, I study how price dislocation on one fund affects other funds. I answer questions such as (i) Does arbitrage activity targeting on

[1] The difference between ETF price and NAV (net asset value, or the sum of underlying assets' values), alternatively known as mispricing, NAV deviation, or premium.

price dislocations induce contagion across ETFs? In particular, how do mispricing and return respond? and (ii) What is the nature of shock propagation in the ETF market? In the ETF market, arbitragers help the market to adjust supply and demand of ETF shares. For instance, an arbitrager in the primary market will sell its shares and buy its underlying assets to capture arbitrage opportunity when an ETF exhibits premium (ETF price > value). To sell its shares, the arbitrager receives new shares from the ETF issuer, which is called creation, in exchange for a basket of underlying securities. This increases supply of ETF shares in the market.[2] This series of actions affects underlying assets. What happens to the *other* ETFs that share common securities?

To fix ideas, let us consider a simple scenario. Suppose there are two ETFs, A and B. They share some common underlying assets. First, if a demand shock at the ETF level hits ETF B and generates a premium (ETF B price > value), the arbitrager will sell ETF B and buy the underlying assets. Then, its neighbor ETF A's value will increase due to buying pressures on common underlying assets, which leads to ETF A's discount (ETF A price < value) or a decrease in its premium. Going forward, the price of ETF A will increase so that arbitrage opportunity in A dissipates (ETF A price=value), which generates a positive return in ETF A.[3] Given this mechanism and conjecture, I study mainly two effects: Firstly, an increase in arbitrage activity in the neighbor funds creates a discount in the main fund via the adjustment in its fundamental value. Secondly, an increase in arbitrage activity in the neighbor funds leads to positive return in the main fund following an induced discount.[4]

[2]Conversely, the arbitrager will buy ETF shares and deliver it to the issuer in order to sell its underlying assets when an ETF exhibits a discount (ETF price < value). This decreases supply of its shares, which is called redemption. See Figure A1.1 and Appendix C for details.

[3]One could argue that there will be another arbitrage activity that buys ETF A, which pushes up ETF A's price.

[4]These are also described by the diagram in Section 1.3.1

I provide the first evidence on these two contagion effects and show that arbitrage activity induces mispricings to propagate through the network of the ETF market. This arbitrage-induced returns are followed by strong reversals in one to three weeks, which suggests that it is driven by trading. The effects are strong especially at longer horizons. In the short term, the effect of arbitrage activity on its own mispricing is stronger than the contagion effects from the neighbor funds. My findings are economically meaningful and statistically large. In the Equity ETF market, a one standard deviation increase in the contagion measure induces unexpected returns of 4–6% annually. Even in terms of alphas controlling Fama-French five (FF5) factors, it induces unexpected returns of around 4% annually. These results are not driven by competing explanations and can be causal. With an instrumental variable exploiting the rebalancing days of underlying portfolios, an increase in creation activity after the rebalancing induces a discount in the main fund. I quantify these effects, finding a network multiplier of 0.821 for contagion in terms of price dislocations and a network multiplier of $-1.829$ for contagion in terms of returns. These indicate that the ETF market stabilizes shocks for mispricing, while it can exacerbate shocks for returns. It can generate unexpected short-term returns with oscillating signs across ETFs. The pass-through for mispricing is 1/10, while it is 1–1.8 for returns. Further, a diff-in-diff study in the Bond ETF market reconfirms the contagion effect, finding the contagion effect of an order of 20–30 bps.

Methodologically, I directly construct a time-varying network across ETFs with more than 1 billion portfolio weights. Based on a dataset covering 37% of the U.S. ETF market, I compute a pairwise *commonality* between each pair of funds among top 100 equity ETFs to construct this network. I combine this pairwise commonalities with measures for arbitrage activities by the contracted arbitragers, APs (authorized participants) in the primary market, and other arbitragers in the secondary market. I apply this method to the Bond ETF market under the stress during the COVID-19 crisis in a subsequent empirical design.[5]

I further employ the following empirical strategies to test whether the contagion effects are driven by network interconnectedness. To differentiate the effects of arbitrage trading on mispricing of one fund from arbitrage trading on the neighbor fund, I first control arbitrage activities on the main funds' mispricing. Second, I run placebo tests to confirm that induced price dislocation and returns are in fact catalyzed by the network, not a random choice of funds and noise. Third, I support my findings with different identifications, standard instrumental variable, granular instrumental variable and diff-in-diff. Using different outcome variables, such as NAV returns and abnormal returns controlling FF5, I test to see whether the contagion effect is in fact coming from common underlying assets and arbitrage activity. Finally, I estimate a spatial autoregressive model, taking account of special dependencies across funds to eliminate the possibility of results driven by correlated shocks.

The literature has actively studied transmission of shocks by ETFs. Ben-David et al. (2018) study how ETF ownership increases the volatility of underlying stocks. Their findings support that the demand shocks in the ETF market translate into non-fundamental price changes for the underlying securities. Baltussen et al. (2019) show that the nature of index returns has changed due to index-linked products such as ETFs. Shim (2019) documents that ETF arbitragers trade underlying assets based on weights rather than fundamentals. Compared to other types of fund flows, passive ETFs' effects on underlying assets seem to have greater impact (Dannhauser and Pontiff, 2019). Given the

[5]See Figure A1.2

evidences that support a greater role of ETFs on price discoveries of underlying assets, my paper further extends this chain of propagation *across* ETFs and provides evidence at the ETF level. I propose a method to systematically capture this contagion.

The other important branch of the literature is about the roles and mechanism of ETF arbitrage. It links them to limit to arbitrage (Shleifer and Vishny, 1997, Gromb and Vayanos, 2010). For example, Pan and Zeng (2019) study the authorized participants' dual role as bond dealer and ETF arbitrager, and its conflict. Evans et al. (2019) study the implications of operational shorting. In contrast, my paper sheds light on a different consequence of arbitrage activity in the ETF market, that is, how arbitrage activity on one fund generates externalities and affects other funds' prices and fundamental values.

From more general and broader viewpoints, my paper offers a network perspective on the intertwined ETF market. Lettau and Madhavan (2018) lay out basics of ETFs and Madhavan (2014) reviews the literature and develops a canonical model of price dynamics in ETFs. Theoretically, Bhattacharya and O'Hara (2018) study how ETFs affect the informational efficiency of their underlying assets and how they induce herding behaviors. Malamud (2015) develops the general equilibrium model of the ETF market. Chinco and Fos (2019) analyse the complexity of ETFs. Anadu et al. (2018) suggest evidence of indexing on comovements and price distortions is mixed. For liquidity, Rappoport W. and Tuzun (2020) study the joint dynamics of ETF mispricing and liquidity with panel vector autoregressions. Converse et al. (2020) suggest that greater ETF ownership has amplified the global financial cycle in the emerging markets. For price deviations, Petajisto (2017) documents mispricing across different classes of ETFs; my paper partially explains how price dislocations could change.

In relation to the recent stress in the Bond ETF market due to the COVID-19 crisis, Falato et al. (2020) examine outflows of both mutual funds and ETFs and O'Hara and Zhou (2020) study the microstructure of liquidity provision in the corporate bond market. Boyarchenko et al. (2020) evaluate the corporate credit facilities and multiple dimensions of primary and secondary market functioning in a granular manner. Haddad et al. (2020) argue that it is the result of extreme selling pressure by investors in safe and liquid debt ETFs. In contrast, this paper exploits the Fed announcements of the Bond ETF purchase to reconfirm the channel I establish with the Equity ETFs.

Furthermore, I contribute to the literature in the networks and finance. Theoretical works study financial contagion extensively (e.g., Elliott et al., 2014; Acemoglu et al., 2015). The network structure of firms and industries on the stock market has been analyzed by many papers (e.g., Gofman et al., 2018; Gofman, 2013; Herskovic, 2018). Another growing strand of papers tries to link international trade networks to asset prices (e.g., Du et al., 2018; Richmond, 2019; di Giovanni and Hale, 2020; Auer et al., 2020). In contrast, this paper is the first to study the network structure of the ETF market. On the econometric side, I estimate a spatial autoregressive model, similar to those used in other papers (Herskovic et al., 2013; Denbee et al., 2018; di Giovanni and Hale, 2020).

The literature on the linkages of institutional investors' stock holdings has not considered ETFs. Anton and Polk (2014) show the degree of shared ownership forecasts cross-sectional variation in return correlation. Greenwood and Thesmar (2011) propose fragility and applies it to mutual fund ownership to study price volatility and comovements. As opposed to these papers and the studies on flow-induced contagion (e.g., Coval and Stafford, 2007; Lou, 2012), I propose *arbitrage trading–induced* contagion, which is testable only in the

ETF market.[6]

In terms of financial stability, the implication of this paper is threefold: Firstly, the network structure of the ETF market is shock-absorbing for price dislocations, while induced returns can fluctuate. Central banks need to be aware of this contagion effect. USD 289 billions of Equity ETFs are sitting on the balance sheet of the Bank of Japan, as of March 31st, 2020. An eventual tapering and unwinding of their positions must consider the interconnectedness of ETFs. Secondly, my findings highlight a role of ETF trading in contributing to the market fluctuations in a higher frequency, while Gabaix and Koijen (2020b) study the origin of the stock market fluctuation, based on quarterly data. Thirdly, Stambaugh (2014) points out that individual ownership in the equity market declined, as well as noise trading, which left less room for active management to correct prices. However, given a drastic shift from active to passive investment with ETFs, noises could arise differently in a world over which passive investment dominates. My findings indeed suggest that price discovery in the growing ETF market is distorted by contagion effects.

The paper proceeds as follows. In Section 1.2, I elaborate on methodologies and data employed to test questions. Section 1.3 describes the main channel that I exploit for analysis and presents the main results in the Equity ETF market. In Section 1.4, I provide robustness and extension from different perspectives: Section 1.4.1 to examine if the network weights really matter, Section 1.4.2 to see if it is not driven by other underlying factors or a different channel, Section 1.4.3 to support causal arguments, Section 1.4.4 to apply spatial estimation, and Section 1.4.5 to examine subsamples. Further, I document two extensions using ETFs. In Section 1.5.1, I examine the recent stress

[6]The closest form of mutual fund to a ETF is closed-end fund (CEF), which trades on the exchange. However, there is no explicit arbitrage mechanism, that is, creation/redemption by authorized participants in the primary market of ETFs. Further, sizes of those AUMs are small compared to ETFs and it is hard to claim a plausible mechanism for such contagion.

event in the Bond ETF market during the Covid-19 crisis. In Section 1.5.2, I exploit differences across types of the ETF products to examine information embedded in the ETF markets. Limitation of this version of the study are discussed in Section 1.6. Finally, Section 1.7 concludes.

## 1.2 Methodology and Data

### 1.2.1 Mind Thy Neighbor's Portfolio: A Network Approach to Contagion in the ETF Market

#### Data

The data are constructed from several sources. ETF-level variables such as price and trading volume are from Bloomberg[7], while underlying asset-level variables are from CRSP.[8] Additional data on transaction costs for underlying assets such as Daily Cost to Borrow Score are obtained from Markit. Daily portfolio weights to construct the network are from ETF Global, from 2012 to 2017.

To construct the dataset, I employ the following steps. First, I constrain the ETF sample by geography, asset class, and type. I limit it to funds in North America, equity funds, and non-synthetic vanilla funds. Therefore, some peculiar types of ETFs, such as leveraged and inverse products, are excluded from the sample for the sake of comparison and external validity. Second, I rank those equity ETFs from those that existed in 2012, based on a dollar trading volume and select the top 100 of them (therefore, there are no funds that appears or dies in the middle of the sample). This results in a coverage of 37% of the entire U.S. ETF market in terms of AUM, valued at $1.2 trillion

[7] Bloomberg (2019)
[8] Center for Research in Security Prices (CRSP®) (2019)

and consisting of 99 U.S.-listed equity funds and 1 U.S.-listed Canadian equity market fund. The issuers of ETFs and the leading market makers are shown in Figure A1.4.

For the Bond ETF sample, I use data from 2019 to July 31st, 2020. Starting with 419 U.S.-listed Fixed Income ETFs, excluding sovereign-themed funds and leveraged products leaves 292 ETFs among those that exist at the beginning of 2020 after merging with portfolio constituents data. Further, I use TRACE data to compute liquidity levels of underliers. Table 1.1 presents summary statistics for both Equity and Bond ETF samples.

**Extracting Networks**

First, I describe the methodology for the construction of the ETF network. Using portfolio weights of the top 100 Equity ETFs, I compute the time-varying network. Every $t$, I look at all the pairs of ETFs, roughly 5,000. Each ETF has approximately 300 stocks on average in its holdings, which accrues to more than 1 million weights every day and more than 1 billion weights for the entire period. For a given pair of ETFs, I construct the following commonality between fund $i$ and fund $\ell$, where $i, \ell \in \{1, 2, ..., M\}$:

$$\mathbf{d}_t(i,\ell) = \textstyle\sum_{j=1}^{N} w_{j,t}^{(i)} \log(w_{j,t}^{(\ell)})$$

$w_{j,t}^{(i)}$: holding weight of stock $j$ in ETF $i$, in period $t$

This quantity, $\sum_{j=1}^{N} w_{j,t}^{(i)} \log(w_{j,t}^{(\ell)})$, is the link between ETF A and ETF B that determines the lower bound of log deviation of net asset value in ETF A due to contagion from ETF B (see Appendix D). At the same time, this is tightly linked to cross-entropy.[9] Typically, we negate this quantity to get cross-entropy, $H(p,q) = -\sum_i p_i \log q_i$, and often use it as a loss function to minimize. High commonality

[9] A symmetry of measure is not required as the purpose of this measure is to see how trading on neighbor funds as a whole matters to fund $i$.

corresponds to low entropy and low commonality to high entropy. This measure gives high value to skewed funds and penalizes dispersed funds in the neighborhood of fund $i$. Based on this measure, I construct the following spatial matrices for every $t$.

$$\boldsymbol{D}_t = \begin{pmatrix} \mathbf{d}_t(1,1) & \dots & \mathbf{d}_t(1,M) \\ \vdots & \ddots & \vdots \\ \mathbf{d}_t(M,1) & \dots & \mathbf{d}_t(M,M) \end{pmatrix}$$

Further, after normalizing, I convert the matrices to row stochastic and later combine them with either primary or secondary market arbitrage measures. This yields Figures 1.1-a and 1.1-b, which show the topology of this ETF network and price dislocations in each ETF. Figure 1.1-a shows the price dislocations one week before the flash crash on August 24, 2015.

[Insert Figure 1.1-a here.]

Figure 1.1-b, below, shows the price dislocation after the crash; large price dislocations are in the center. Interestingly, the crash affected SPY a lot immediately after the market opened and yet the mispricing for SPY is negligible at the end of the day. In contrast, the funds in the center, which have high commonality with the other funds, exhibit large price dislocations.[10]

[Insert Figure 1.1-b here.]

The size of a node (circle) indicates the mispricing of each fund at the end of the day in percentage points; those funds, which track a large set of underlying stocks, tend to locate themselves at the periphery, e.g. SPY, IVV, and IWV, as they are balanced with large $N$ and far away from many other funds. Another observation is about the *signs* of price dislocations; the direction of numerous

[10]For instance, ITB is a home construction sector fund and VYM is a high–dividend yield fund.

price dislocations flips in many funds while large price dislocations occur. This will be explained by the empirical analysis and the estimations of network parameters that follow.

### 1.2.2 Information Embedded in ETFs

#### Data

The data are constructed from several sources. The ETF level data are from Bloomberg, while the publicly available portfolio weights are from BlackRock. Implied volatilities and option data are also from Bloomberg and OptionMetrics.[11] To compute the variance share and risk neutral FX beta, I use the MSCI Indices and options on those indices. The MSCI Indices are from Thomson Reuters Datastream.[12] It includes 13 countries and the world index for the world portfolio: Japan, United Kingdom, France, Germany, Switzerland, Australia, Hong Kong, Netherlands, Spain, Sweden, Italy, Denmark, and Singapore. Forward options on currencies are from Bloomberg. I chose the options of 1 month maturity to match with the frequencies of rebalancing in the corresponding ETFs. The sample period for returns on the MSCI indices and variance share is from 2010 up to December 31st, 2018. The sample period for the risk neutral FX beta is from January 2015 to December 31st, 2018. To construct those data, I use the following definitions and decompositions.

#### Anatomy of Hedged ETFs

Non-hedged ETF

$$\begin{aligned} P_t^{i,\$} &= E_t\left[\frac{M_{t+1}^{\$} Q_{t+1} P_{t+1}^i e_{t+1}^i}{Q_t}\right] \\ &= \frac{1}{R_{f,t}^{\$} Q_t} E_t^{Q^{\$}}[Q_{t+1} P_{t+1}^i e_{t+1}^i] \end{aligned} \tag{1.1}$$

[11] IvyDB (2019)

[12] Refinitiv (2019)

Hedged ETF

$$\begin{aligned}\tilde{P}_t^{i,\$} &= \frac{1}{R_{f,t}^{\$}\tilde{Q}_t} E_t^{Q^\$}[V_{t+1}^{EQ,i} e_{t+1}^i + V_t^{Fwd,i}(e_{t+1}^i - F_{t,T}^i)] \\ &= \frac{1}{R_{f,t}^{\$}\tilde{Q}_t} E_t^{Q^\$}[\hat{Q}_{t+1} P_{t+1}^i e_{t+1}^i + V_t^{Fwd,i}(e_{t+1}^i - F_{t,T}^i)]\end{aligned} \tag{1.2}$$

where $P_t^{i,\$}$ is a dollar price of the non-hedged instrument, $\tilde{P}_t^{i,\$}$ is a dollar price of the hedged instrument, and $e_t^i \equiv \frac{Foreign_t^i}{USD_t}$, $Q_t$ is a number of shares for the non-hedged instrument, $\tilde{Q}_t$ is a number of shares for the hedged instrument, $V_t^{EQ,i}$ is a dollar value of allocation in the non-hedged instrument in the portfolio under management of the hedged instrument. $V_t^{Fwd,i}$ is a dollar value of the notional on which an ETF issuer entered forward contracts in the hedged instrument. $\hat{Q}_t$ is a quantity of shares the issuer of the hedged instrument needs to hold in order to allocate $V_t^{EQ,i}$ to the underlying non-hedged instrument.

With these instruments, one can obtain the risk-neutral covariance of foreign equity and foreign currency returns, $Cov^{\mathbb{Q}}(R_{t+1}^i, RX_{t+1}^{i,\$})$.[13] This measure seems to capture some economic policy uncertainty, similar to Baker et al. (2016), but roughly 2-4 weeks earlier as below. I use this quantity to construct the forward-looking beta in the extension.

[Insert Figure 1.7 here.]

## 1.3 Empirical Analysis

In this section, I examine how arbitrage activity on the neighbor funds that are linked through the network affects the main fund's mispricing and its returns. To make the hypotheses explicit, I first describe the channel that I exploit

[13]This is from $\frac{1}{2\theta_t^{EQ}\theta_t^{Fwd,i}}\left\{Var^{\mathbb{Q}}(\tilde{r}_{t+1}^{i,\$}) - (\theta_t^{EQ})^2 Var^{\mathbb{Q}}(r_{t+1}^{i,\$}) - (\theta_t^{Fwd,i})^2 Var^{\mathbb{Q}}(rx_{t+1}^{i,\$})\right\}$, as long as options are available on all the undelrying assets and the hedged ETFs.

to capture this contagion. Then, I present the main findings on mispricing and returns. Further, I reconfirm the contagion effects I find in the Equity ETF market using the supplementary Bond ETF sample. In the following Section 1.4, I demonstrate robustness with a placebo test and specifications using alternative returns. I present extensions, including causal identifications; estimation of spatial models to discriminate from alternative explanations; and subsample results.

### 1.3.1 Channel of Arbitrage-Induced Contagion

The hypotheses I test are the subsequent action of an ETF arbitrager, its effect on price dislocations in ETFs, and a conjecture on responses in returns. Suppose there are two ETFs, A and B. First, if a demand shock at the ETF level hits ETF B and generates a premium (ETF B price > value), the arbitrager will sell the ETF and buy the underlying assets to capture arbitrage. Then, its neighbor ETF A's value will increase due to buying pressures on common underlying assets, which leads to ETF A's discount (ETF A price < value) or a decrease in its premium. Going forward, the price of ETF A will increase so that arbitrage opportunity in A dissipates (ETF A price=value), which generates a positive return in ETF A. This is visually captured by Figure 1.2, below.

[Insert Figure 1.2 here.]

The way the arbitrager takes on arbitrage activity has been discussed in the literature (see Appendix C for details). The focus of my examination is summarized in states (3) and (4) in the figure, that is, propagation to the neighbor fund A and its induced return as a response.

There are other possible scenarios and those are checked in the robustness excercises and with controls in the empirical analysis. For instance, an arbitrager might sell B and buy A without creating price pressures on the underlying assets if she finds a pair of very similar ETFs. In the robustness exercise, I show the main results hold even if I exclude a set of very similar funds, which track the same underlying indices and I also document that this arbitrage-induced returns take place at the NAV level, not just at the ETF price level. Another possible scenario is that the common shock hits both ETF A and B - such concerns are considered with several specifications and econometric methods in Section 1.4.

### 1.3.2 Main Results

To test the aforementioned channel, I construct two key variables using an extracted network, one for arbitrage activities in the primary market, the other for overall arbitrage activities in both the primary and secondary market (see Figure A1.1). First, I aggregate creation-redemption activities of ETF $\ell$s that are linked to fund $i$ through the network, $\mathbf{D}_t$, by pairwise commonality measure, $\mathbf{d}_t(i,\ell)$. $Creation/Redemption_{t,\ell}$ is positive when an authorized participant creates shares and negative when he redeems shares.

$$Neighbor\ AP\ Activity_{t,i} = \sum_{\ell \neq i} \mathbf{d}_t(i,\ell) * \underbrace{(Creation/Redemption_{t,\ell}) * NAV_{t,\ell}}_{\text{\$ Primary Market Activity}}$$

This variable corresponds to the primary market arbitrage. It is stated in dollars, as it is the dollar volume that creates price impact on the underlying stocks regardless of various ETFs with different numbers of outstanding shares. Throughout my exercises, I first smooth daily arbitrage activities on each fund $\ell$ over a week up to each period $t$ and further aggregate across M-1 funds using the network weights, as arbitrage activity at a daily level can be sparse or noisy.[14] Second, in a similar fashion, I aggregate mispricing in fund $\ell$ that is linked to fund $i$ through the network by pairwise measure, $\mathbf{d}_t(i,\ell)$.

$$Neighbor\,Mispricing_{t,i} = \sum_{\ell \neq i} \mathbf{d}_t(i,\ell) * \underbrace{(p^{etf}_{t,\ell} - NAV_{t,\ell}) * SharesOutstanding_{t,\ell}}_{\text{\$ Proxy for Overall Arbitrage Opportunities}}$$

Among the other covariates, $Net\,Fund\,Flow_{i,t}$ is creation/redemption shares of fund $i$, scaled by NAVs. This takes account of the ETF arbitrager's activity on the mispricing of fund $i$, not that of neighbor funds. I control the time variation and the fund heterogeneity by time fixed effect (day $t$) and ETF fixed effect (fund $i$). With this construction, the variables capture how prone each fund is to contagion (for characteristics of this contagion measure, see Figure A1.5). Using these variables, I test the following regression:

$$\begin{aligned} Mispricing_{i,t+1} = \alpha_i + \alpha_t + \theta^{NAPA} \cdot Neighbor\,AP\,Activity_{i,t} + \theta^{NMisp} \cdot Neighbor\,Mispricing_{i,t} \\ + \beta^{NFF} \cdot Net\,Fund\,Flow_{i,t} + \sum^{K} \xi^k \cdot CONTROL^k_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1.3}$$

Table 1.2 first documents the induced discount in a main fund, affected by the network. Arbitrage activities in *neighbor* funds $\ell$ create a discount in a main fund $i$. Comparing the proxy for the primary market activity, $Neighbor\,AP\,Activity_t$, and the proxy for overall arbitrage opportunities, $Neighbor\,Mispricing_t$, only the latter shows significance. This is probably because taking arbitrage in the secondary market is more frequent, while the primary market is exclusive to APs; thus, the latter probably captures overall buying pressure better than the former.

[Insert Table 1.2 here.]

[14] Authorized participants in the primary market tend to take arbitrage when mispricing becomes large enough, in comparison to arbitragers in the secondary market. This is probably because one faces a creation unit, i.e. minimum units of shares needed to run a transaction with ETF sponsor to profit from price dislocations (see Appendix C for details).

$Neighbor\,Mispricing_t$ consistently finds negative coefficients throughout all the specifications, predicting a discount in a next period. I find the same when I perform the exercise with a contemporaneous dependent variable. In terms of economic magnitude, this contagion effect has larger magnitude, daily 0.323 bps per a one standard deviation increase in the contagion measure, than the effect from net fund flow into its own fund, daily 0.195 bps. On the other covariates, first, the coefficient on $Net\,Fund\,Flow_t$ and coefficients on lagged mispricings are all positive, which suggests that mispricing persists for a while and therefore the creation of ETF shares still forecasts positive mispricing in the next period.[15] ETF-level bid-ask spread positively predicts mispricing in the next period, which suggests that lower liquidity coincides with higher mispricing, which is natural given that a higher spread will impede the profitability of ETF arbitrage. On the other hand, lower liquidity at an underlying security level negatively predicts mispricing, suggesting that the liquidity premium pushes up the NAV value, creating thinner price dislocation between the ETF price and NAV. Next, I examine response of returns after arbitrage trading on neighbor funds changes mispricing in fund $i$.

$$\begin{aligned} Return_{i,t+k} = \alpha_i + \alpha_t + \theta^{NAPA} \cdot Neighbor\,AP\,Activity_{i,t} + \theta^{NMisp} \cdot Neighbor\,Mispricing_{i,t} \\ + \beta^{NFF} \cdot Net\,Fund\,Flow_{i,t} + \beta^{Misp} \cdot Mispricing_{i,t} + \sum^{K} \xi^k \cdot CONTROL^k_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1.4}$$

I specify the regression as above. *Return* is a period return from $t+k-1$ to $t+k$, where $k \in \{1, 2, 3, 5, 7, 14, 21\}$. In addition to including fund and date fixed effects, covariates, and controls, I add $Mispricing_{i,t}$, fund $i$'s price dislocation in bps, to control responses of returns to arbitrage activities on

[15] This is in line with the point Madhavan (2014) makes, that is, the premium still exhibits positive autocorrelation that increases with staleness and the slowness with which arbitrageurs correct pricing errors.

fund $i$ as well as the net fund flow of fund $i$.

[Insert Table 1.3 here.]

Table 1.3 confirms (i) the induced discount in fund $i$ further leads to a positive response in returns, as conjectured in Figure 1.2, panel (4), and (ii) their reversals. Taking (i) and (ii) together, it suggests that this response in return is driven by trading. In detail, $Neighbor\,AP\,Activity_{i,t}$ positively predicts returns for $t+1$ and $t+2$.[16] From $t+7$, it predicts return negatively, up to $t+21$, showing reversals.[17] Similarly, $Neighbor\,Mispricing_{i,t}$ positively predicts returns in $t+2$ and up to $t+14$. In $t+21$, it predicts return negatively as a reversal. This strong reversal in return response to the arbitrage activity of the neighbor, in contrast with return response to own net fund flow, is captured in the following Figure 1.3, below.

[Insert Figure 1.3 here.]

The finding that the neighbor mispricing variable predicts an initial positive response in returns slightly later than the neighbor AP arbitrage variable suggests that the secondary market arbitrage on a linked fund $\ell$ persists for a longer period. This is in line with the fact that taking an arbitrage position in the secondary market requires the arbitrager to hold positions for a longer period than APs in the primary market, who can close NAV deviations quickly.

On the other covariates, coefficients on $Net\,Fund\,Flow_t$ are negative, which confirms the effects documented in the literature, i.e., the extra supply of

[16]One of the reasons why effects last for a while is related to the settlement operations, which can take up to 3 days in general (see Appendix C for details). Also, it is related to operational shorting. That is, APs can sell new ETF shares, while opting delay the physical share creation. Some APs create shares immediately, but some can wait to reassess the trade imbalances in the following days. They can delay even up to T+6 in some cases (see Evans et al. (2019) for details).

[17]This is consistent with the findings in Ben-David et al. (2018) that demand shocks in the ETF market generates a mean-reverting component to stock prices and the half-life of convergence of prices to the initial level is about 10 days

ETFs adjusted by APs in the primary market dampens ETF price. The sign on $Mispricing_t$, being negative, suggests that positive arbitrage opportunities, represented by mispricing, are followed by shorting of ETFs; therefore, it predicts negative returns going forward.

On economic magnitudes and time persistence of contagion effects, first, I compare the first two rows, the contagion effects from trading on neighbor fund $j$, and the third and forth rows, the effect of arbitrage activity on its own fund $i$. At $t+1$, the largest economic magnitudes shown are the result of trading on its own mispricing, daily 4.270 bps. The second is $Neighbor\,AP\,Activity_t$, arbitrage on the linked funds $\ell$, daily 1.509 bps per a one standard deviation increase in the contagion measure. This reflects a standard network propagation, that effects from neighbors are weaker than its own. In contrast, after $t+2$ and up to $t+21$, the contagion measures show consistently larger economic magnitude, 0.954 bps per a one standard deviation increase in the contagion measure, with statistical significance, whereas the effects from arbitrage activities on its own fund $i$ are weaker, 0.319 bps, with statistical significance. This contrast is even more clear if I compare $Neighbor\,Mispricing_t$ and $Mispricing_t$. The coefficients for $Mispricing_t$ have no economic significance after $t+1$, while coefficients for $Neighbor\,Mispricing_t$ have large economic significance of 1.384–2.468 bps. Importantly, those magnitudes are larger than coefficients on the contagion measure with the previous specification of mispricing as the dependent variable.

### Alternative Hypotheses

This arbitrage-induced return could be driven by other possibilities. For instance, common ETF market-level shocks might trigger changes in price dislocations and returns across ETFs. Factor structures in underlying assets may drive those results. Arbitrage opportunities might trigger trading involving only ETFs. To distinguish my findings from alternative hypotheses and explanations, I run various robustness and identifications, concluding that my findings are robust and not driven by other possibilities. See Section 1.4.1 for placebo tests to see if network weights indeed matter and are not driven by random or common shocks, Section 1.4.2 for regressions with returns replaced by different definitions (NAV Return and Alpha), Section 1.4.3 for a series of causal tests, and Section 1.4.4 for an estimation of a model considering spatial dependencies across entities.

## 1.4 Robustness

### 1.4.1 Placebo Test

In this subsection, I document placebo tests that show that the results are not driven by common shocks among ETFs or the shocks that randomly chosen funds can generate. Table 1.4, compares the coefficients obtained by placebo specifications with the baseline specification with neighbor contagion measures. *Average* variables simply take the average over all mispricing and creation/redemption of the other funds, respectively, without using commonality $d_{i,j}$. *Random* variables instead randomly pick half of the other funds at every period and average over them. This random selection of ETFs will test whether the network weights indeed matter. Using only average variables without fixed effects, the regressions in column (1) and (7) find that average mispricing across funds is *positively* related to fund $i$'s mispricing with statistical significance. This is the opposite sign of the coefficient I find on the neighbor contagion measures (columns (6) and (12)). This positive coefficient simply reflects common components of the ETF market, such as aggregate risk factors, aggregate risk appetite, and common shocks. In fact, once I control time fixed effects in columns (2) and (8), statistical significance vanishes. I find the same for different choices of explanatory variables, presented in columns (3)–(5) and columns (9)–(11). Only when a model uses the network weighted mispricing and creation/redemption variables,they are statistically significant and survive both fixed effects. This confirms that the network does indeed matter.

[Insert Table 1.4 here.]

### 1.4.2 Alternative Returns

To confirm that this response in return is driven through the channel in Figure 1.2, I test it with two alternative definitions of returns: NAV return and abnormal return after controlling Fama-French five factors. Table 1.5 presents the results. With NAV return, surprisingly, the contagion measures show *larger* economic significance, daily 1.356 bps per a one standard deviation increase in the contagion measure, than the fund $i$ Net Fund Flow, 0.507 bps, while $Mispricing_t$ shows very weak significance. This confirms that the channel of arbitrage-induced contagion takes place through adjustments in NAVs.

With abnormal return, ETF return has a similar economic significance for ETF return as baseline regressions. At $t+1$, its fund $i$ arbitrage measure, $Mispricing_t$ has a magnitude of daily 4.186 bps, whereas $Neighbor\ Mispricing_t$ is 1.178 bps. Also, $R^2$ drops significantly with abnormal return to 0.16–0.19, even with time fixed effects as compared to $R^2$ in the specification with both standard return and NAV return, around 0.69. This suggests that some portion of variability is driven by common factors, but findings suggest that this contagion effects remain strong, with daily 1.466 bps, even after taking into account factors. Comparing these results with Table 1.3 suggests that the contagion effect is indeed operates through NAV as conjectured in Figure 1.2 (3) and it is slightly weaker than the effect of the contagion measure when I use ETF return.[18] Importantly, this confirms that the response in returns is not driven by common risk factors.

[Insert Table 1.5 here.]

### 1.4.3 Causal Identification

**Instrumental Variable**

One of the possible concerns for the channel I test is that common underlying shocks drive both the mispricing of fund $i$ and the mispricing of the neighbor funds $j$. In addition to the statistical significance I find controlling aggregate risk factors and fixed effects, I further establish causal interpretation with the aid of instrumental variables. Figure A1.8 shows the relation between net fund flow and rebalancing days for the funds that rebalance and those that do not.

It indicates that the arbitrage activity of authorized participants starts plummeting first from $t = -2$ days before the rebalancing day up to a day before. On the rebalancing day, net fund flow jumps as the uncertainty about an underlying basket of portfolios resolves. This behavior of the arbitrager is in line with the mechanism of primary market arbitrage. As the arbitrager needs to trade a basket of underlying assets in the portfolio, he is less willing to do trades on days right before the rebalancing. Using this exogenous variation around rebalancing days, I construct an instrumented contagion variable, $\widehat{Neighbor\ AP\ Activity}_{t,i}$, in the following manner. The first and second stages are as follows.

[18]This is in line with the finding in Madhavan (2014) that ETF return volatility will exceed that of NAV returns.

$$Creation/Redemption_{t,\ell} * NAV_{t,\ell} = \alpha_t + \beta * \mathbb{1}_{t,\ell}\{Rebalance_{t,\ell}\} + \epsilon_t$$
$$\widehat{Neighbor\ AP\ Activity_{t,i}} = \sum_{\ell \neq i} \mathbf{d}_t(i,\ell) * \widehat{Creation/Redemption_{t,\ell} * NAV_{t,\ell}}$$

The construction of $\widehat{Neighbor\ Mispricing_{t,i}}$, corresponding to the overall arbitrage activities, simply replaces the net fund flow, the dependent variable in the first stage regression, by mispricing of the funds. By construction, these two constructed variables are relatively highly correlated ($\rho = 0.56$); although it is not optimal to run them together, they are juxtaposed in column (3).

[Insert Table 1.6 here.]

Interestingly, after using exogenous variation in rebalancing, the contagion variable corresponding to the primary market activities shows statistical significance (column (1)), in contrast to the baseline regression without an instrument in Table 1.2. The second contagion variable corresponding to the overall arbitrage activities shows somewhat weaker economic significance with an instrument, as compared to Table 1.2. These results together suggests that the arbitrage-induced price dislocations seem to be causal.

### Granular Instrumental Variable (GIV)

I employ Gabaix and Koijen (2020a) to study contagion effects in the ETF market, using the granular residual[19] and exploiting its skewed size distribution. This enables an estimation to use the idiosyncratic shocks from the large entities, which are relevant to the ETF market as a whole. First, I obtain residuals from the regression of a dependent variable on controls, $\delta_{i,t+1} = a + bX_t + e_{i,t+1}$. Controls include the same set of variables as the main regressions from Tables

[19]Granular residual has been recently used in another paper, di Giovanni et al. (2020)

1.2 and 1.3. Using residuals from the first regression, $e_{i,t}$, and the key variables, net fund flow of its own fund $i$ and net fund flow of neighbor funds, I get estimates of $\eta_t^x$, factor exposures. Further, I construct GIV as

$$Z_t^\delta = \delta_{\Gamma t} := \delta_{St} - \delta_{Et} = u_{St} - u_{Et}$$

where $\delta_{St} := \sum_{i=1}^{M} S_i \delta_{i,t}$, $S_i := \frac{AUM_i}{\sum^M AUM_i}$, $\delta_{Et} := \sum_{i=1}^{M} \frac{1}{N}\delta_{i,t}$, $X_{St} := \sum_i S_i X_{i,t}$, and $\delta_{i,t} := Mispricing_{i,t}$. The last equality comes from $\delta_{St} = \tilde{\eta}_t + u_{St}$ and $\delta_{Et} = \tilde{\eta}_t + u_{Et}$. $\tilde{\eta}_t$ is a common shock to mispricing. A key condition for the GIV estimator, $Z_t^\delta$, to work is a size distribution of the industry. In the case of the ETF market, the excess Herfindahl is, $h := \sqrt{-\frac{1}{100} + \sum_{i=1}^{100} S_i^2} \approx 0.25$ and the entities are concentrated at a relatively high level based on their AUMs (see Figure A1.9). With $Z_t^\delta$, $\eta_t^x$, and additional controls $W_t$, I estimate a multiplier, $M$, by

$$\delta_{St} = M^\delta Z_t^\delta + a'\eta_t^x + b'X_{St} + c'W_t + e_t' \tag{1.5}$$

Table 1.7, below, presents its result. From the table, $M^{misp}$ is 0.795 for the specification with mispricing in column (1). This indicates a spillover effect of $\gamma^{misp} = 1 - \frac{1}{M^{misp}} = -0.26$. To interpret, suppose the average mispricing across funds is 10 bps and some shock multiples mispricing in a particular fund by 2; an initial shock creating a positive price dislocation (premium) of 10 bps to a particular fund with a relative size of 0.5 in the ETF market could create, $\gamma^{Misp} M^{Misp} S_i u_i = -0.26 * 0.795 * 0.5 * 10bps = -1.03bps$, price discount for the other funds in the short term. This suggests that price dislocations in the ETF market are shock-absorbing and the shock to one fund induces price distortions in the opposite direction in the other funds.

[Insert Table 1.7 here.]

On the other hand, $M^{Ret}$ is $-1.008$ and $-1.829$ for the specification with ETF return as the dependent variable in columns (3) and (4), respectively. In turn, $\gamma^{Ret}$ is 1.99 and 1.54 for columns (3) and (4), respectively. This indicates that if the average return across funds is 10 bps and some shock multiplies the return by 2, the average return increases to 20 bps without contagion, whereas it changes to $-0.08$bps and $-8.29$ bps, respectively ($\mathit{\Delta Ret} = -10.08bps = M^{Ret} * 10bps * 1$ and $\mathit{\Delta Ret} = -18.29bps$) in the presence of contagion. This surprising oscillating effects of contagion is in line with what is conjectured in Figure 1.2. Further, this is in line with the reduced-form baseline regressions in Table 1.3; the contagion measure for arbitrage activity on the neighbor fund, *Neighbor AP Activity*$_t$, and the measure for arbitrage activity on its own price dislocation, *Net Fund Flow*$_t$, predict future returns with opposite signs. In other words, an initial shock of 100 bps to a particular fund with a relative size of 0.5 in the ETF market could create, $\gamma^{Ret}M^{Ret}S_iu_i = 1.99*-1.008*0.5*100bps = -100.296bps$ and $\gamma^{Ret}M^{Ret}S_iu_i = 1.546*-1.829*0.5*100bps = -144.381bps$, a shock with the opposite sign to the other funds in the market in the short term. This suggests, surprisingly, that the contagion effects in return terms can be an amplifier in contrast to mispricing, which is self-correcting. It can create an unexpected short-term return of the same magnitude or a greater relative to an initial shock, in the opposite direction.

### 1.4.4 Spatial Estimation

Some of the concerns about this type of contagion effects are the reflection problem (Manski, 1993) and correlated shocks. First, a shock to fund A can affect fund B, while a shock to fund B can affect fund A through the underlying network. Therefore, it is important to consider such spatial dependencies. Second, it can be difficult to distinguish spillover effects from fund B to fund A's return from effects on fund A's return due to correlated shocks. To address to these potential concerns, I estimate spatial models instead of using the granular instrumental variable in this section. I use the spatial autoregressive model (henceforth, SAR), described below.

$$Mispricing_{i,t} = \alpha_t^{\text{day}} + \alpha_i^{\text{fund}} + \sum_{k=1}^{K} \beta_k^{\text{fund}} x_{i,t}^k + \gamma \sum_{i \neq j} \mathbf{d}_{ij} Mispricing_{j,t} + \epsilon_{i,t}$$

$$\sim iid\, \mathcal{N}\left(0, \sigma_i^2\right), \quad i = 1, \ldots, M, \quad t = 1, \ldots, T$$

The key feature of the model is that it controls spatial correlation of a dependent variable and estimates the network parameter, $\gamma$. Rewriting in a matrix form (see Appendix E for details),

$$\mathbf{Y} = \boldsymbol{\alpha}\mathbf{F} + \mathbf{X}\boldsymbol{\beta} + \gamma \left(I_T \otimes \boldsymbol{D}_M\right) \mathbf{Y} + \varepsilon \tag{1.6}$$

For the network parameter, $\gamma$, to be identified, we need the condition that $\boldsymbol{D}$, $\boldsymbol{D}^2$, and $\boldsymbol{I}$ are linearly independent (see Bramoulle et al., 2009). This condition is met in the sample, which allows me to estimate a model by concentrated log-likelihood (Elhorst, 2003, Elhorst, 2010)

[Insert Figure 1.4 here.]

Figure 1.4 above shows a network multiplier, $M$ $(= \frac{1}{1-\gamma})$, from rolling estimations of equation 1.6. This consistently shows that the multiplier is in a range between 0.8 and 0.5, suggesting that three things. First, contagion on mispricing is intact even after taking account of spatial dependencies through the network and, therefore, correlated shocks are not driving results. Second, contagion on mispricing is consistently self-stabilizing over time, though its magnitude is time-varying. Lastly, the magnitude is in the same ballpark as multipliers estimated by the granular instrumental variable, shown in Table 1.7.

### 1.4.5 Subsamples

#### Premium vs. Discount

Table 1.8 presents the results. I split the sample into the premium sample and discount sample by an initial sign of mispricing at $t$ in each fund. Comparing the premium sample ($P_t > V_t$) in (1), (2), and (3) with the discount sample ($V_t > P_t$) in (4), (5), and (6), it suggests that the contagion effects are stronger in both statistical significance and economic magnitude in the discount sample. In (1), the contagion effect is statistically not significant, whereas the effect of creation/redemption from arbitrage activity on its own price dislocation is a daily 0.5–3.8 bps increase in the contagion measure. In contrast, in (2) and (3), the contagion effect is daily 1.3 bps, whereas the effect of arbitrage activity on its own price dislocation is less than half of that, 0.5 bps. In contrast, the discount sample already shows much stronger significance both economically and statistically already from the $t$+1 period; at $t$+1, the contagion effect is daily 3.8 bps, whereas the effect of arbitrage activity on its own price dislocation is less than that, 3.6 bps. This is because price dislocations in the discount sample get further pushed away by arbitrage-induced contagion when the linked funds exhibits positive mispricing, which creates more room for the NAV of fund $i$ to bounce back, and hence a larger move in subsequent reactions in fund $i$'s return.

[Insert Table 1.8 here.]

### Composition

Table 1.9-a presents a variant of the baseline return regression, in which the sample is split based on the category of ETFs. In each subsamples, I exclude a particular category of ETFs one by one to confirm that the findings are not driven by a particular category of ETFs. As compared to the benchmark findings in Table 1.3, where a one standard deviation increase in the contagion measure leads to a 1.509 bps increase in return, excluding the funds focused on either Sector or Growth shows higher contagion effects than the benchmark, suggesting that those funds exhibit smaller contagion effects (columns (2) and (5)). On the other hand, excluding the fund focused on Strategy, Value, or Small Caps exhibits much smaller contagion effects (columns (3), (6), and (7)). All in all, the contagion effects are robust to subsamples; this confirms that the findings are not driven by a particular subset of ETFs.

[Insert Table 1.9-a here.]

### Year

Table 1.9-b presents a variant of the main return regression, where its sample is split by year. I create the subsamples by halving the sample into two and also creating a sample that excludes 2015, the year in which there was a flash crash. (1) is without 2015, (2) is between 2012 and 2014, and (3) is between 2015 and 2017. In the first two subsamples, $Neighbor\,AP\,Activity_t$ consistently shows statistical significance. This confirms the contagion effects are not purely driven by market stresses such as the 2015 crash. In contrast, in the third subsample (3), $Neighbor\,Mispricing_t$ seems to capture the contagion effects very strongly, with a 2.789 bps increase per a one standard deviation increase in the contagion measure. This is almost as twice as the benchmark result in

Table 1.3 and suggests that the contagion effects in recent years are stronger and are coming more from arbitrage trading on the secondary market than the primary market.

[Insert Table 1.9-b here.]

### 1.4.6 Fama-Macbeth

I further confirm these results with a standard Fama-Macbeth regression in Table 1.10 and find the same pattern; the effects from arbitrage trading on its own mispricing, an induced *negative* return, come first and then the contagion effects from arbitrage trading on neighbor funds arrive later with a *positive* return.

[Insert Table 1.10 here.]

## 1.5 Extensions

### 1.5.1 Arbitrage Activities in the Bond ETF Market during the COVID-19

#### Network Effects in the Bond ETF market

In this subsection, I exploit a recent policy intervention to measures the contagion effects in the Bond ETF market. My purpose is to re-confirm the contagion effect and channel I find with the Equity ETF setting by applying the same method to the Bond ETF market, which extends the validity of the previous findings in the Equity ETF market. What I use is the differences in commonalities with the eligible ETFs among the non-eligible ETFs that were not targeted by the Fed purchase directly. Figure 1.5, below, shows the recent market reactions in the Bond ETF market in 2020.

[Insert Figure 1.5 here.]

A series of actions by the Federal Reserve is as follows: On March 15th, the Fed announced an interest rate cut, treasury bill purchase, and MBS purchase at a meeting of the Federal Open Market Committee (FOMC), on March 15th. It purchased $40 billion in Treasury inflation-protected securities (TIPS) on March 16th. In the following week, on March 23rd, it announced two additional interventions, the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF).[20] The purpose of PMCCF was to purchase bonds or portions of syndicated loans of investment grade firms. The SMCFF was to target ETFs with broad exposure to the U.S. investment grade corporate bond market and investment grade corporate bonds. On April 9th, it was expanded to include ETFs with broad exposure to the U.S. high-yield corporate bond market and corporate bonds that were rated at least BBB-/Baa3 as of March 22nd but downgraded subsequently. The initial allocation of the equity will be $50 billion toward the PMCCF and $25 billion toward SMCCF. At the announcement, actual purchases were scheduled to begin in May, but it in fact started on May 12th. The actual ETFs that the Fed purchased so far are 16 ETFs[21] and they mostly match with those eligible ETFs that were expected as below.

Many investors seemed to have front-run. What is notable is that the surge in premium is primarily around the SMCCF announcement, not the actual

[20] see `https://www.newyorkfed.org/newsevents/news/markets/2020/20200417` for details.

[21] see `https://www.federalreserve.gov/publications/reports-to-congress-in-response-to-covid-19.htm` for details.

| | Eligible ETFs |
|---|---|
| Investment Grade | LQD, VCIT, VCSH, IGSB, IGIB, SPSB, SPIB, USIG, VCLT, BSCL |
| High Yield | HYG, JNK, HYLB, USHY, SHYG, BKLN, SJNK, ANGL, HYS, BSJL |
| | ETFs purchased by the Fed (as of Aug 31st, 2020) |
| Investment Grade | LQD, IGIB, IGSB, SPSB, SPIB, VCIT, VCSH, USIG |
| High Yield | ANGL, HYG, HYLB, JNK, USHY, SHYG, SLQD, USHY |

purchase, which occurred later. Further, arbitrage activity has increased or at least redemption has stopped after the SMCCF announcement while premium surges[22] (see Figure 1.6, below).

[Insert Figure 1.6 here.]

As my main interest is in re-confirming the contagion effects rather than assessing the direct impact of the Fed purchase, I exploit this event to see how prone those non-eligible ETFs ("Others" category in Figure 1.6) that were *not* targeted but connected to the eligible ETFs ("High Yield" and "Investment Grade" categories) are to spill-overs from arbitrage activity placed on the eligible ETFs. Arbitrage activities of those ETFs are also shown in Figure A1.6, along with NAV deviations.

I use the following empirical designs. First, I apply the same method detailed in Section 1.2 to construct commonality between targeted and non-targeted ETFs and to further compare high-commonality ETFs and low-commonality ETFs among non-targeted ETFs. To separately measure both effects from the first announcement and the subsequent announcement of expansion, I use two-step tests. (i) For the March 23rd announcement, I compute each average commonality of the remaining 284 funds to the eligible investment grade ETFs

[22]Regarding arbitrage activities during these months, Laipply and Madhavan (2020) find no evidence of destabilizing arbitrage activities, that is, the AP sells ETFs *below* NAV while she delivers bonds at NAV, resulting a loss. Their findings suggest that ETFs were functioning effectively during this stress, providing price discovery. Also, they estimate intrinsic value of NAVs, instead of the official closing NAVs, and find that the absolute size of premium/discounts do not significantly differ as compared to one using the official closing NAVs.

(8 out of 10 identified are in the sample) and run a diff-in-diff study to test if high commonality non-eligible funds get larger contagion effects than low commonality non-eligible funds. The estimation period is from March 15th to April 9th, 2020. (ii) For the April 9th expansion announcement, I similarly compute each average commonality of the remaining 276 funds to the eligible high-yield ETFs (8 out of 10 identified are in the sample) and run a diff-in-diff study as the first test. The estimation period is from April 1st to May 11th, 2020. To a large extent the two groups have parallel trends before the announcement. Figure A1.7 shows the reactions of NAV deviations in the high- and low-commonality ETFs that are connected to eligible ETFs via their underlying network. Liquidity was greatly affected hugely in the corporate bond market, as documented in O'Hara and Zhou (2020). I control both liquidty at the ETF level and underlying asset level. $\textit{Composite Amihud}_{t-1}$ is an aggregated version of the Amihud measure (Amihud, 2002) for a basket of securities. The results are in Table 1.11.

[Insert Table 1.11 here.]

I find that after the announcement, non-targeted ETFs that have high commonality with the eligible ETFs had smaller price dislocations or discounts as compared to low-commonality ETFs (Panel A). This can be explained by the arbitrage activity (i.e., creation) that kicks in on the eligible ETFs as their premium surges, pushing up the NAV of non-targeted ETFs with high-commonality relative to those with low commonality. Thus, non-targeted ETFs with high-commonality get a decrease in price dislocation (i.e., a discount). These can also be confirmed in Figures 1.6 and A1.6. One might be concerned about weak creation/redemption activities after the announcement, but creation activities resumed as premium in those eligible ETFs increased, in particular in the Investment-Grade category. Creation activity did not resume in the Others category.

Further, I test again for the second announcement of expansion (Panel B) and find that statistical evidence of contagion effects in regard to the second announcement is weak. One potential reason could be that it was relatively safer products, as opposed to high-yield products, that were facing large selling pressures before the announcement and hence the reaction. Another potential reason could be that market participants might have expected high-yield ETFs were going to be included in the purchase even after the first announcement. Although it is a challenge to entirely separate out the effects of PDCF and MMLF from the effects of the SMCCF Announcement, the result in Panel A is robust to alternative designs: (a) construct commonality of non-eligible ETFs to both eligible investment grade ETFs and high-yield ETFs, (b) extending the end of the event study period up to May 11th, 2020, (c) changing the beginning of the sample from March 15th to after PDCF and MMLF. Lastly, I find that the actual purchase did not have statistically significant effects.

### 1.5.2 Information Embedded in ETFs: Forward-looking International CAPM

#### Implied Risk Neutral Covariance from ETFs

In this subsection, I exploit differences between non-hedged ETFs and hedged ETFs to retrieve risk neutral covariances and link them to international factors. First, I show we can decompose the global equity beta into several risk neutral quantities and then examine empirical implications.

### Global Equity Index and Global Beta

Starting with a dollar return of the local index relating to the world portfolio that underpins the international CAPM, $\mathbb{E}_t[R^{i,\$}_{t+1}] = \beta_{i,wp,t}\mathbb{E}_t[R^{wp,\$}_{t+1}]$, I further decompose $\beta_{i,wp,t}$ into several risk neutral components.

$$
\begin{aligned}
\mathbb{E}_t[R^{i,\$}_{t+1}] &= \beta^{\mathbb{P}}_{i,wp,t}\mathbb{E}_t[R^{wp,\$}_{t+1}] \\
&= \beta^{\mathbb{Q}}_{i,wp,t}\mathbb{E}_t[R^{wp,\$}_{t+1}] + (\beta^{\mathbb{P}}_{i,wp,t} - \beta^{\mathbb{Q}}_{i,wp,t})\mathbb{E}_t[R^{wp,\$}_{t+1}] \\
&= \Bigg(\underbrace{\boldsymbol{Var^{\mathbb{Q}}Share^{i}_{t}}}_{\substack{\text{Risk Neutral}\\ \text{Variance Share}}} + \underbrace{\boldsymbol{\beta}^{\mathbb{Q},FX}_{i,t}}_{\text{Risk Neutral FX Beta}} + \gamma^{i}_{t}\Bigg)\mathbb{E}_t[R^{wp,\$}_{t+1}] \\
&\qquad + (\beta^{\mathbb{P}}_{i,wp,t} - \beta^{\mathbb{Q}}_{i,wp,t})\mathbb{E}_t[R^{wp,\$}_{t+1}]
\end{aligned}
\tag{1.7}
$$

From the second to the third line, to decompose $\beta^{\mathbb{Q}}_{i,wp,t}$ into three components, I use the decomposition with a triangular no arbitrage relation in currencies (See Appendix. E for details). A similar decomposition can be done without a triangular no arbitrage relation. The second component in the equation 1.7, $\boldsymbol{\beta}^{\mathbb{Q},FX}_{i,t}$, can be computed by combining it with the risk neutral variance of the world portfolio and the risk neutral covariance of the hedged ETFs[23]. This risk-neutral FX beta, the second term, can be linked to some

[23] $\boldsymbol{\beta}^{\mathbb{Q},FX}_{i,t} = \frac{Var^{\mathbb{Q}}(\tilde{r}^{i,\$}_{t+1}) - (\theta^{EQ}_t)^2 Var^{\mathbb{Q}}(r^{i,\$}_{t+1}) - (\theta^{Fwd,i}_t)^2 Var^{\mathbb{Q}}(rx^{i,\$}_{t+1})}{2\theta^{EQ}_t\theta^{Fwd,i}_t Var^{\mathbb{Q}}_t(r^{wp}_{t+1})}$, where $\tilde{r}^{i,\$}_{t+1}$ is a return of the hedged ETF with weights on the underlying equities and forward contracts, $\theta^{EQ}$ and $\theta^{Fwd,i}$. For some of the currency pairs (especially cross-currency pairs not involving USD, EUR, JPY, GBP), I can use the same method as Mueller et al. (2012), $\mathrm{E}^{\mathbb{Q}}_t\left(\int_t^T \rho^{i,j}_u du\right) = \frac{\mathbb{E}^{\mathbb{Q}}_t\left(\int_t^T \gamma^{i,j}_u ds\right)}{\sqrt{\mathrm{E}^{\mathbb{Q}}_t\left(\int_t^T (\sigma^i_u)^2 du\right)}\sqrt{\mathrm{E}^{\mathbb{Q}}_t\left(\int_t^T \left(\sigma^j_u\right)^2 du\right)}}$. For the unrecoverable part directly from the ETFs with only 2 underlying assets in the sub matrix of Equity-FX pairs, I can use the same method as Buss and Vilkov (2012), $\rho^{Q}_{ij,t} = \rho^{P}_{ij,t} - \alpha_t\left(1 - \rho^{P}_{ij,t}\right)$.

macro economic intuitions. Its central quantity is

$$Cov_t^{\mathbb{Q}^\$}(R^i_{t+1}, RX^{i,\$}_{t+1}) = \underbrace{\mathbb{E}^{\mathbb{P}}_t[R^i_{t+1}RX^{i,\$}_{t+1}] - (R^\$_{f,t})^2\delta}_{\text{Premium on Exorbitant Privilege}} + \underbrace{R^\$_{f,t}Cov^{\mathbb{P}}_t(M^\$_{t+1}, R^i_{t+1}RX^{i,\$}_{t+1})}_{\substack{\approx \text{ Gourinchas-Rey(2014)} \\ \text{Exorbitant Privilege}}} \tag{1.8}$$

I establish notations as $\mathbb{Q}^\$$ for the risk-neutral measure of a dollar investor, $\mathbb{Q}^i$ for the risk-neutral measure of an investor in foreign country i, $M^\$$ for a dollar SDF, $M^i$ for a SDF in foreign country i, and lastly $\mathbb{P}$ for a physical measure.[24] This relation shows the similar economic intuition that Gourinchas and Rey (2014) argues (See Appendix. E for details). US as the global insurer receives higher expected returns when the SDF of US comoves negatively with returns in foreign countries. US gets compensated when the global equity market is in downturn and the US consumption is low, by taking an additional risk via foreign investments nevertheless. In contrast, when the global equity market is booming, US will pay the premium. The privilege captured in the FX risk-neutral covariance is even more pronounced. When the product of a foreign country return and corresponding FX return negatively comoves with the dollar SDF, US expects higher expected returns. Further, the spread between the Q and P covariances seems to capture risk levels of the market, similar to VIX. The figure below shows how it varies over time along with VIX.

[Insert Figure A1.10 here.]

As documented in the literature, the standard international CAPM framework does not work well. Let us examine how $Cov_t^{\mathbb{Q}}(R^i_{t+1}, RX^{i,\$}_{t+1})$, the central quantity in $\boldsymbol{\beta}^{\mathbb{Q},FX}_{i,t}$, stands against its physical counterparts (Table A1.10). Further, I carry out the same exercise with the risk neutral FX beta, compared with physical counterparts (Table A1.11).

[24] Brennan and Xia (2006) studied theoretical relations between $M^\$$ and $M^i$ as well as exchange rate premium to $M^\$$ and $M^i$.

## 1.6 Limitation

In this section, I elaborate on the points I have not explored in detail either because of the scope of the paper or the limitations of the data sets. First, I have not examined the formations of networks, which occurs when new ETFs are introduced into the market. In the analyses, I fixed a set of ETFs in the sample so that there is no new network formation or elimination of existing networks. Second, I take networks as given in many parts of the paper. Though I address endogeneity concerns about creation/redemption activities and price dislocations with exogenous shocks in the Equity ETF part and by fixing the network weights before the experiment in the Bond ETF part, network weights can still be affected by contagion effects.

## 1.7 Conclusion

In this chapter, I primarily study how arbitrage-induced price dislocations propagate through the ETF network and lead to responses in returns. I first show that arbitrage activity targeting on mispricing in neighbor funds induces price dislocation in the main fund with an opposite sign. I show the strong response of returns and their subsequent reversals following the induced mispricing in both the primary and secondary markets. These unexpected returns and their reversals suggest that this is driven specifically by trading.

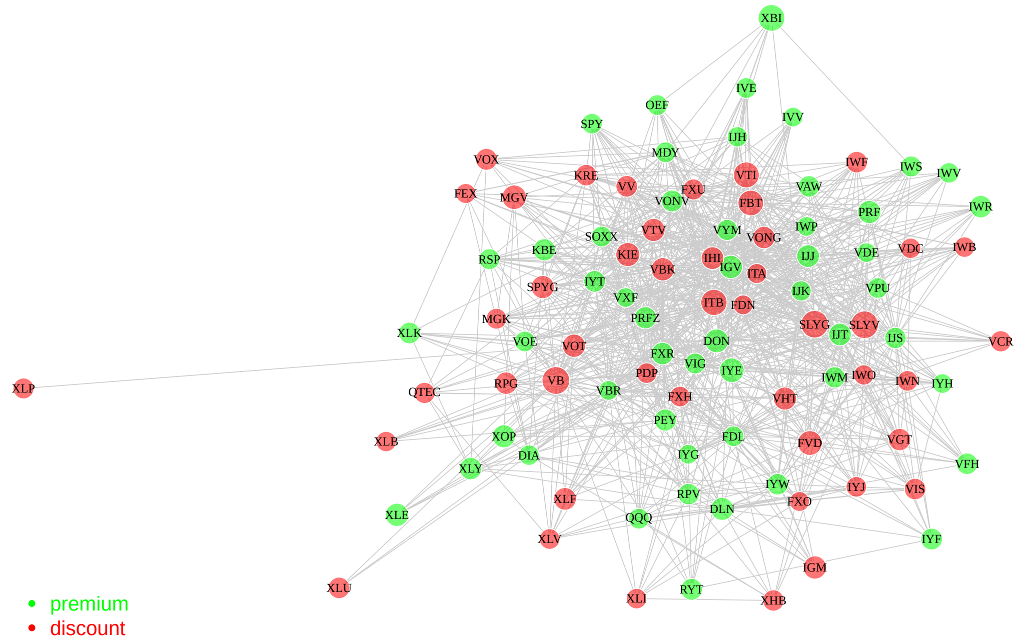
Second, I show that the underlying network does indeed matter. Without using information from the ETF network, it fails to show contagion effects. I further confirm this with NAV returns and abnormal returns, establishing that this contagion occurs via changes in the values of underlying assets. To discriminate from alternative explanations and support causality, I introduce different identifications. Regardless of identification strategies, the evidence supports the mechanism of arbitrage-induced contagion in the Equity ETF market; I reconfirm it the Bond ETF market.

While I focus on the contagion effects that stem from the proliferation of ETFs and associated tradings, other interesting venues to explore are the aspects of information and competition in the ETF market. In the extensions, I show certain types of ETFs contain useful information about the political risks of economy, which is recoverable with the novel method. There is also room to study new ETFs from the perspective of how introduction affects the market and how existing ETFs get terminated.

The notion that the ETF market is a potential systemic risk or a bubble is half wrong and half correct. A systemic risk is limited in that price dislocations in the ETF market act as a shock stabilizer, meaning that shocks wane across ETFs. In this sense, an original intention of the SEC report after 1987's Black Monday, which led to the birth of ETFs, proved correct: ETFs provide a cheaper and safer form of portfolio insurance. However, the findings also suggest that ETF prices can face short-term unexpected returns and subsequent reversals both at the ETF and the underlying asset levels. This complements the previous literature that argues volatility of underlying assets is distorted by ETFs, in that price discovery of ETFs is directionally distorted by arbitrage trading via the underlying network.

## 1.8 Figures

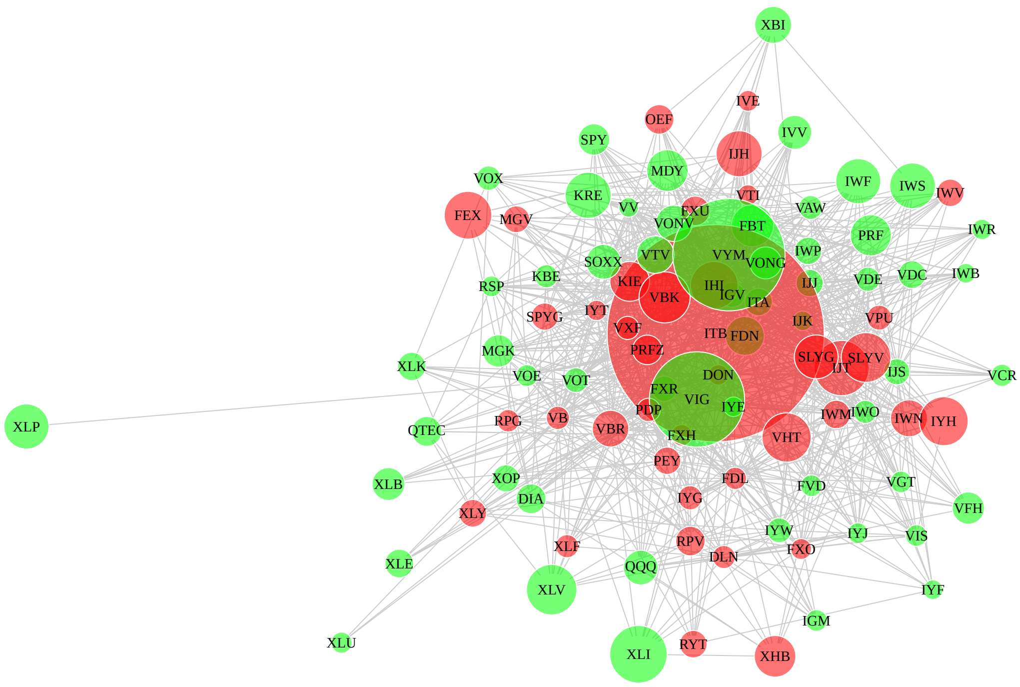
Figure 1.1: **Network Topology**




Node Size: price deviation (%)

Panel A: **Small Price Dislocation before the Crash**

This figure shows the topology of this ETF network, $\boldsymbol{D}_t$, and price dislocations in each ETF. Panel A corresponds to the price dislocations a week before the flash crash on August 24, 2015. It is drawn with the Fruchterman and Reingold algorithm.



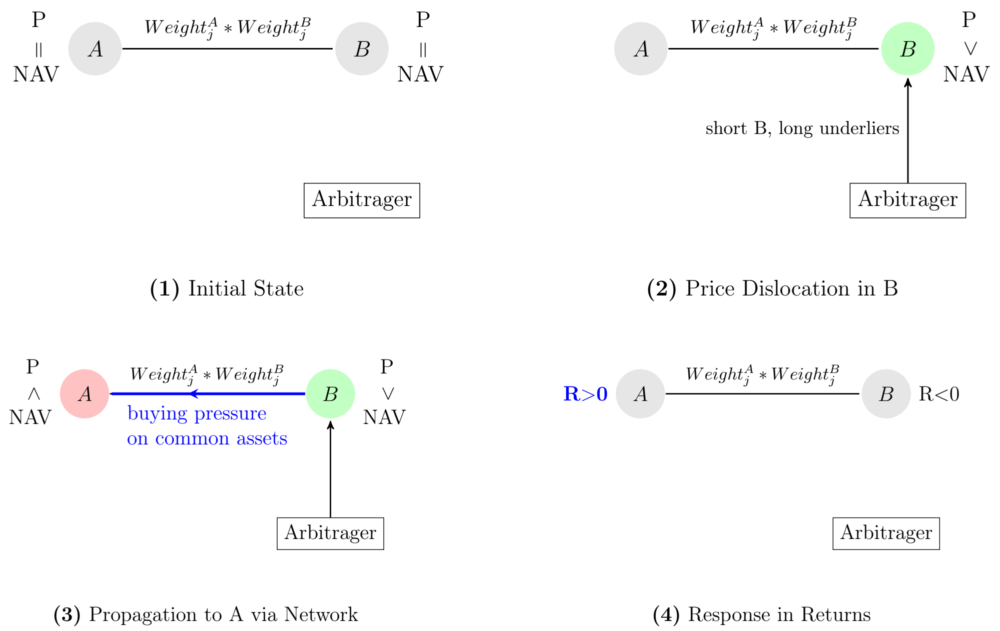

Node Size: price deviation (%)

Panel B: **Large Oscillating Price Dislocation after the Crash**

This figure shows the topology of this ETF network, $\boldsymbol{D}_t$, and price dislocations in each ETF. Panel B corresponds to the price dislocations after the flash crash on August 24, 2015. It is drawn with the Fruchterman and Reingold algorithm.

Figure 1.2: **Arbitrage Creates Propagation of Price Dislocations and Unexpected Returns**

P stands for the price of the ETF; NAV for its net asset value; and $NAV^B \equiv \sum^N Weight_j^B * Price_j$, where $Weight_j^A$ is a portfolio weight of ETF A on underlying stock $j$. Initially, a shock hits ETF B at the ETF level and creates the premium. The initial assumption of no price deviations in both ETFs is not big; deviations and changes after state (2) can be regarded as relative changes compared to the initial deviations in state (1).




**(1)** Initial State

**(2)** Price Dislocation in B

**(3)** Propagation to A via Network

**(4)** Response in Returns

Figure 1.3: **Response of Returns**

The figure shows cumulative response of returns to two independent variables, $Neighbor\,AP\,Activity_t$ and $Net\,Fund\,Flow_t$. Coefficients are estimated up to $t + 21$ in a model with the same specification as equation 1.4, except that I include only the primary market arbitrage measures and exclude the general arbitrage opportunity measure.

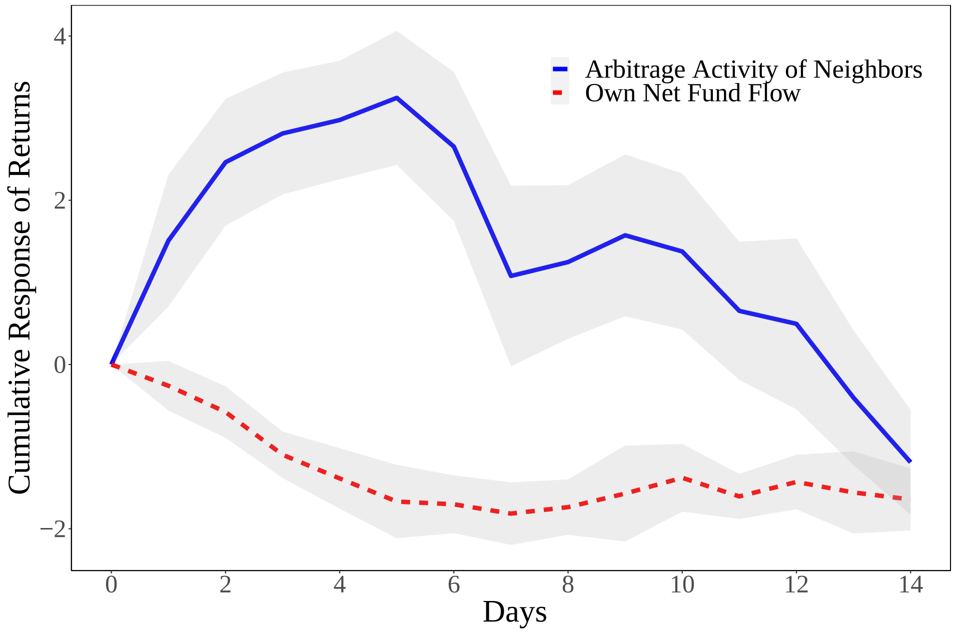



Figure 1.4: **Network Multiplier for Mispricing**

The figure shows the time-varying network multiplier, M $(= \frac{1}{1-\gamma})$, from rolling estimations of equation (4), $Y = \alpha F + X\beta + \gamma\,(I_T \otimes D_M)\,Y + \varepsilon$.

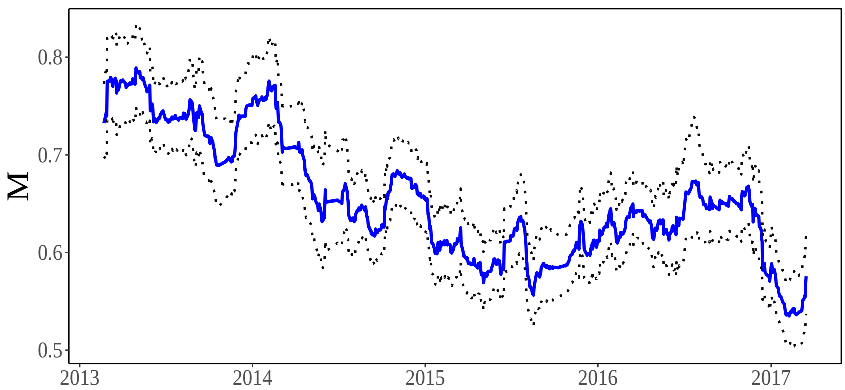


Figure 1.5: **Surge in Premium after the Fed's SMCCF Announcement**

The figure shows the market reaction of price dislocations in the Bond ETF market in 2020. The first gray dotted line shows the actions by the Fed, which consist of interest rate cuts, Treasury and MBS purchases. A second gray line shows the launch of the Primary Dealer Credit Facility (PDCF) and Money Market Mutual Fund Liquidity Facility (MMLF). A green line shows the timing of an announcement on the Secondary Market Corporate Credit Facility (SMCCF). The following two black dotted line shows the timing of the announcement on the expansion of SMCCF to high yield on April 9th and the actual purchase on May 12nd. SMCFF-eligible (blue dotted line) includes 16 eligible Bond ETFs that exist in the sample. Others (red line) include 276 non-targeted Bond ETFs.

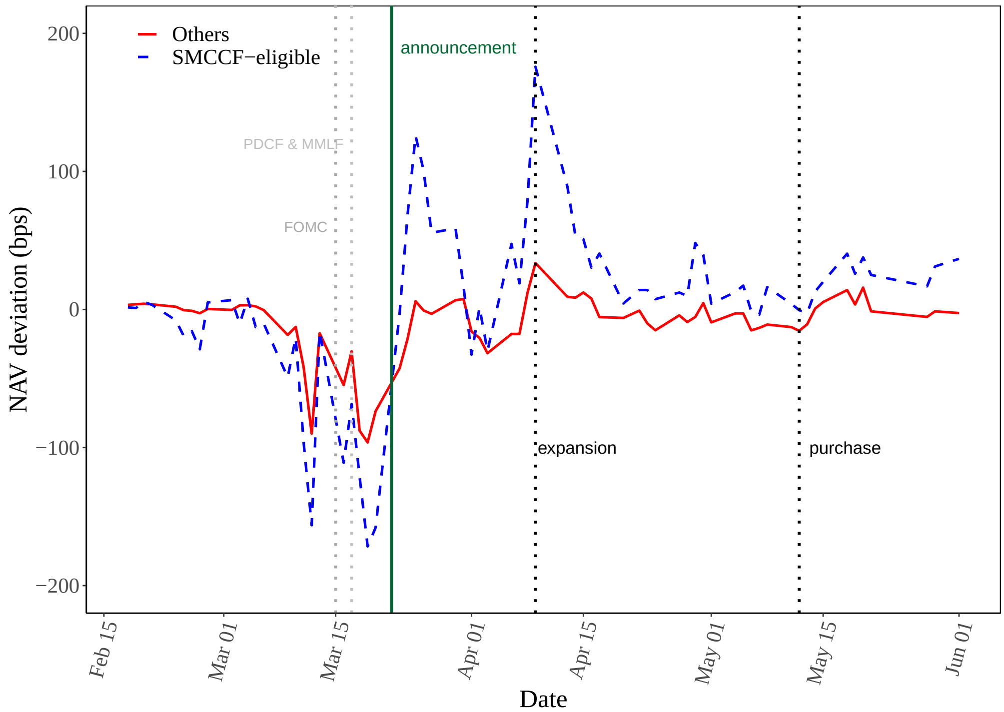


Figure 1.6: **Increase in the Creation of ETFs after the Fed's SMCCF Announcement**

The figure shows creation and redemption activities, representing primary arbitrage activities in the Bond ETF market during 2020, benchmarked to arbitrage activity throughout 2019. Eligible High Yield and Investment Grade include the eight high-yield ETFs and the eight investment grade bond ETFs that were expected to be purchased by the Fed, respectively; Others include 276 Bond ETFs in the data. FOMC–Announcement: 03/15/2020–03/22/2020; Announcement–Expansion: 03/23/2020–04/08/2020; Expansion–Purchase: 04/09/2020–05/11/2020; after Purchase: 05/12/2020 and afterwards.

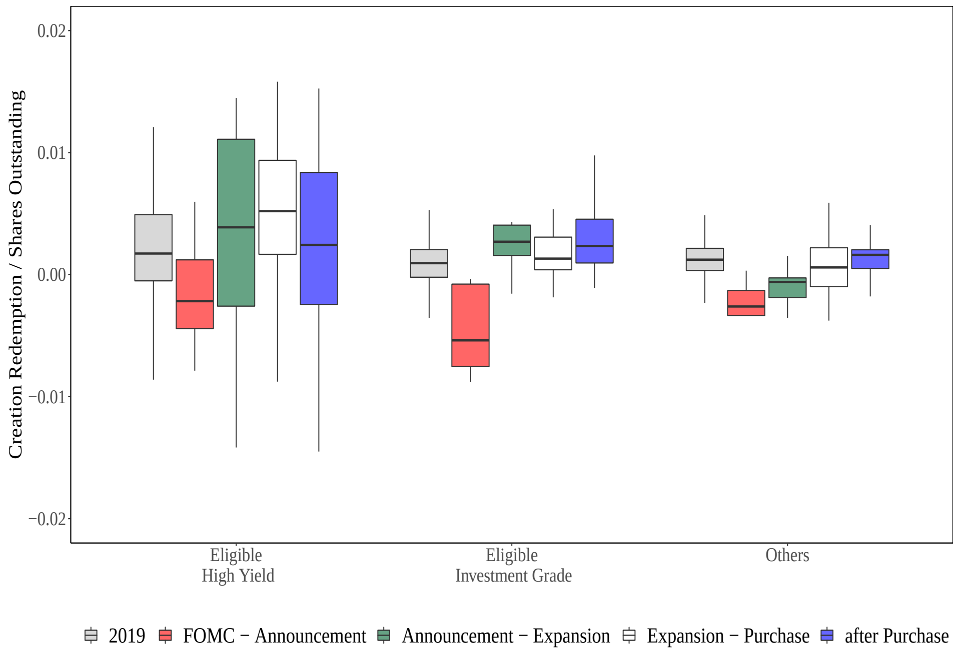
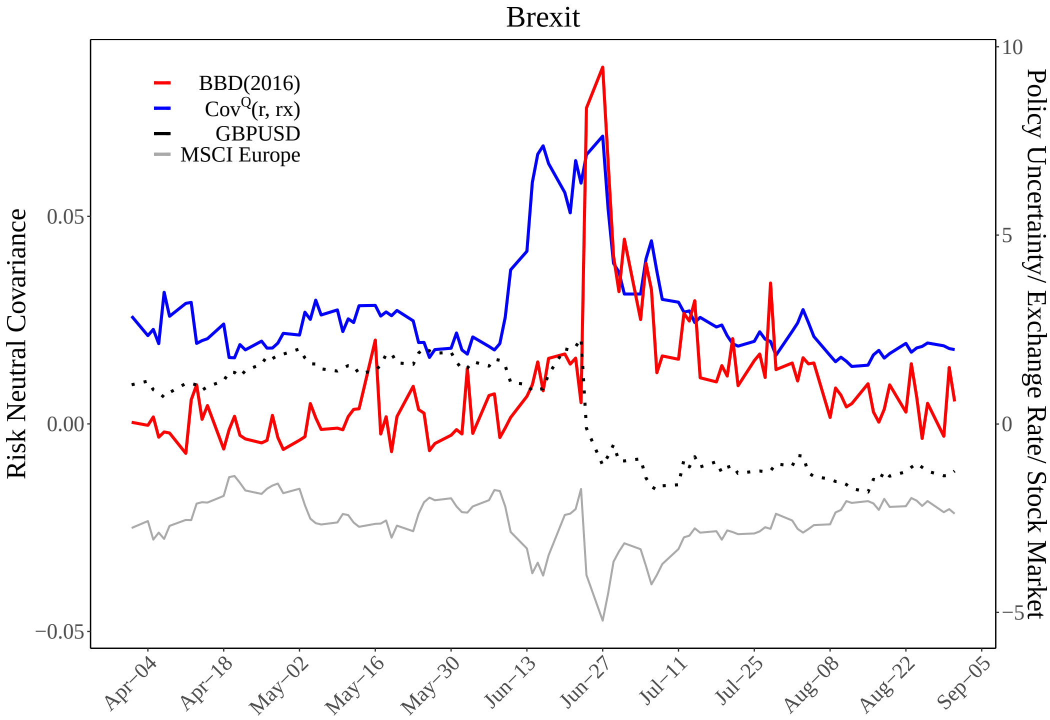


Figure 1.7: **Risk-neutral Covariance of Foreign Equity and Currency Return**

The figure shows the ETF-implied risk neutral covariance between foreign euqity return (UK) and currency return (GBP) around the Brexit, along with the exchnage rate between GBP and USD, MSCI Europe, and the economic policy uncertainty index (Baker et al., 2016).



## 1.9 Tables

Table 1.1: **Summary Statistics**

The table shows summary statistics. Mispricing is defined as $Price - NAV$. AUM is $SharesOutstanding * NAV$. Short Interest is scaled by Shares Outstanding. Net Fund Flow(EOD) is $\Delta Shares * NAV$ at the end of day, Net Fund Flow(BOD) for NAV at the beginning of the day. Bid-Ask Spread is on the fund level. Composite BAS is on the underlying asset level. Equity ETFs are in daily frequency from 2012 to 2017, for the top 100 equity ETFs. The Bond ETF sample is from 2019 to July 2020, including 292 funds.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Panel A**: Equity ETFs 2012–2017 | | | | | | | | |
| Variable | mean | SD | min | 25% | 50% | 75% | max | $n$ |
| Return (1d, %) | 0.055 | 0.983 | -13.495 | -0.420 | 0.082 | 0.586 | 13.469 | 138,162 |
| Mispricing (bps) | 0.69 | 6.69 | -241.64 | -2.26 | 0.76 | 3.54 | 462.72 | 138,162 |
| abs(Mispricing) (bps) | 4.09 | 5.33 | 0.00 | 1.38 | 2.95 | 5.21 | 462.72 | 138,162 |
| Mispricing (mil, $) | 0.26 | 6.77 | -368.38 | -0.44 | 0.08 | 0.84 | 313.60 | 138,162 |
| abs(Mispricing) (mil, $) | 2.21 | 6.40 | 0.00 | 0.22 | 0.64 | 1.82 | 368.38 | 138,162 |
| AUM (mil, $) | 7,889.89 | 20,574.86 | 37.06 | 963.50 | 2,336.12 | 6,630.30 | 279,733.19 | 138,162 |
| Creation Unit (k) | 47.01 | 20.93 | 25.00 | 50.00 | 50.00 | 50.00 | 200.00 | 137,662 |
| Bid-Ask Spread (bps) | 3.86 | 5.46 | 0.00 | 1.71 | 2.86 | 4.57 | 880.32 | 138,162 |
| Composite BAS (bps) | 3.81 | 3.57 | 0.00 | 1.92 | 2.59 | 4.32 | 169.16 | 137,905 |
| Total Expence (%) | 0.27 | 0.18 | 0.04 | 0.12 | 0.24 | 0.43 | 0.76 | 136,928 |
| Put Vol (k) | 28.58 | 180.95 | 0.00 | 0.00 | 0.00 | 0.16 | 7,007.41 | 110,034 |
| Call Vol (k) | 14.84 | 106.53 | 0.00 | 0.00 | 0.00 | 0.06 | 4,928.74 | 134,165 |
| Short Interest (%) | 0.08 | 0.18 | 0.00 | 0.00 | 0.01 | 0.06 | 3.86 | 49,585 |
| Trading Volume (mil, $) | 393.02 | 2,317.48 | 0.01 | 5.72 | 18.97 | 93.92 | 96,122.80 | 138,162 |
| Net Fund Flow (EOD, mil, $) | 3.73 | 237.09 | -10517.94 | 0.00 | 0.00 | 4.38 | 28735.68 | 137,979 |
| Net Fund Flow (BOD, mil, $) | 2.97 | 247.63 | -35,888.17 | 0.00 | 0.00 | 3.60 | 34,263.67 | 138,162 |
| **Panel B**: Bond ETFs 2019–2020 | | | | | | | | |
| Variable | mean | SD | min | 25% | 50% | 75% | max | $n$ |
| Return (1d, %) | 0.001 | 1.575 | -47.708 | -0.106 | 0.019 | 0.154 | 242.792 | 70,710 |
| Mispricing (bps) | 1.65 | 119.22 | -2,785.61 | -2.98 | 5.99 | 19.39 | 9,175.62 | 70,710 |
| abs(Mispricing) (bps) | 31.24 | 115.07 | 0.00 | 4.93 | 12.54 | 27.45 | 9,175.62 | 70,710 |
| Mispricing (mil, $) | 0.17 | 41.01 | -3,277.95 | -0.02 | 0.07 | 0.77 | 1,739.63 | 70,710 |
| abs(Mispricing) (mil, $) | 5.13 | 40.68 | 0.00 | 0.05 | 0.24 | 1.53 | 3,277.95 | 70,710 |
| AUM (mil, $) | 2,511.33 | 6,752.26 | 0.00 | 40.89 | 174.85 | 1,523.77 | 77,820.96 | 70,710 |
| Creation Unit (k) | 67.27 | 41.50 | 20.00 | 50.00 | 50.00 | 100.00 | 500.00 | 70,710 |
| Bid-Ask Spread (bps) | 2.062 | 53.799 | 0.001 | 0.093 | 0.316 | 0.936 | 9573.223 | 70,710 |
| Total Expence (%) | 0.36 | 0.34 | 0.00 | 0.13 | 0.25 | 0.48 | 2.38 | 68,118 |
| Put Vol (k) | 16.38 | 66.81 | 0.00 | 0.01 | 0.03 | 0.78 | 1160.21 | 4,861 |
| Call Vol (k) | 5.10 | 19.72 | 0.00 | 0.01 | 0.02 | 0.21 | 605.92 | 5,307 |
| Short Interest (%) | 0.01 | 0.04 | 0.00 | 0.00 | 0.00 | 0.01 | 0.58 | 28,883 |
| Trading Volume (mil, $) | 588.32 | 2,267.87 | 0.00 | 7.06 | 35.34 | 260.64 | 63,894.09 | 70,574 |
| Net Fund Flow (EOD, mil, $) | 1.74 | 61.81 | -6,375.70 | 0.00 | 0.00 | 0.00 | 2,842.84 | 70,467 |

Table 1.2: **Mispricing and Arbitrage-Induced Contagion**

The table presents regressions of a period ahead mispricing of ETFs on the contagion measures for arbitrage trading on neighbor funds (the first two rows) and on the proxies for arbitrage trading on its own mispricing (the second two rows). For liquidity, *Bid-Ask Spread*$_t$ controls for ETF-level liquidity and $Composite\,BAS_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $Average\,Mispricing_t$ and $Average\,AP\,Activity_t$ simply take averages over all mispricing and net fund flow of the other funds respectively without using commonality $d_{i,j}$. Variables are standardized. Standard errors are clustered and reported in parentheses. All specifications include day and fund fixed effects. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

| | $Mispricing_{t+1}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Neighbor\ AP\ Activity_t$ | 0.090 | 0.101 | 0.101 | 0.104 | 0.114 | 0.116 |
| | (0.068) | (0.068) | (0.068) | (0.068) | (0.070) | (0.071) |
| $Neighbor\ Mispricing_t$ | $-0.306^{***}$ | $-0.312^{***}$ | $-0.320^{***}$ | $-0.312^{***}$ | $-0.315^{***}$ | $-0.323^{***}$ |
| | (0.091) | (0.090) | (0.091) | (0.090) | (0.092) | (0.093) |
| $Net\ Fund\ Flow_t$ | | $0.198^{***}$ | $0.195^{***}$ | $0.198^{***}$ | $0.198^{***}$ | $0.195^{***}$ |
| | | (0.035) | (0.035) | (0.035) | (0.035) | (0.035) |
| $Trading\ Volume_{t-1}$ | | | $0.485^{***}$ | | | $0.493^{***}$ |
| | | | (0.123) | | | (0.123) |
| $AUM_{t-1}$ | | | $-0.344$ | | | $-0.283$ |
| | | | (0.294) | | | (0.298) |
| $Bid\text{-}Ask\ Spread_t$ | | | | $0.129^{**}$ | | $0.134^{**}$ |
| | | | | (0.054) | | (0.054) |
| $Composite\ BAS_t$ | | | | | $-0.067^{**}$ | $-0.067^{*}$ |
| | | | | | (0.034) | (0.034) |
| $Mispricing_t$ | $0.614^{***}$ | $0.599^{***}$ | $0.596^{***}$ | $0.596^{***}$ | $0.598^{***}$ | $0.592^{***}$ |
| | (0.119) | (0.119) | (0.118) | (0.118) | (0.119) | (0.118) |
| $Mispricing_{t-1}$ | $0.579^{***}$ | $0.578^{***}$ | $0.575^{***}$ | $0.576^{***}$ | $0.578^{***}$ | $0.572^{***}$ |
| | (0.075) | (0.073) | (0.073) | (0.073) | (0.073) | (0.072) |
| $Average\ AP\ Activity_t$ | $-0.265$ | $-0.037$ | $-0.050$ | $-0.036$ | $-0.060$ | $-0.071$ |
| | (0.384) | (0.284) | (0.287) | (0.283) | (0.283) | (0.285) |
| $Average\ Mispricing_t$ | 0.548 | 0.528 | 0.534 | 0.518 | 0.528 | 0.525 |
| | (0.422) | (0.423) | (0.420) | (0.422) | (0.420) | (0.416) |
| Fund FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 137,962 | 137,780 | 137,780 | 137,780 | 137,523 | 137,523 |
| Adjusted $R^2$ | 0.095 | 0.096 | 0.096 | 0.096 | 0.096 | 0.097 |

Table 1.3: **Returns and Arbitrage-Induced Contagion**

The table presents regressions of ETF returns, $R_{t+k}$, on the contagion measures for arbitrage trading on neighbor funds (the first two rows) and on the proxies for arbitrage trading on its own mispricing (the second two rows). For liquidity, $Bid\text{-}Ask\,Spread_t$ controls for ETF-level liquidity and $Composite\,BAS_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $Average\,Mispricing_t$ and $Average\,AP\,Activity_t$ simply take averages over all mispricing and net fund flow of the other funds respectively without using commonality $d_{i,j}$. Controls other than shown includes lagged return and lagged mispricing. Columns (1)–(7) vary by the number of periods ahead, $k$. Variables are standardized. Standard errors are clustered and reported in parentheses. All specifications include day fixed effects. The results are robust to adding fund fixed effects, to Fama-MacBeth specification, and to Bootstrapped standard errors. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

| | *Return* | | | | | | |
|---|---|---|---|---|---|---|---|
| | $t+1$ | $t+2$ | $t+3$ | $t+5$ | $t+7$ | $t+14$ | $t+21$ |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $Neighbor\ AP\ Activity_t$ | $1.509^{***}$ | $0.954^{**}$ | 0.350 | 0.270 | $-1.575^{***}$ | $-0.786^{**}$ | $-1.288^{***}$ |
| | (0.410) | (0.394) | (0.379) | (0.416) | (0.561) | (0.326) | (0.487) |
| $Neighbor\ Mispricing_t$ | 0.962 | $1.420^{**}$ | 0.824 | $1.384^{**}$ | $2.468^{***}$ | $1.803^{**}$ | $-2.217^{**}$ |
| | (0.603) | (0.685) | (0.713) | (0.603) | (0.654) | (0.847) | (0.886) |
| $Net\ Fund\ Flow_t$ | $-0.259^{*}$ | $-0.319^{**}$ | $-0.521^{***}$ | $-0.281$ | $-0.113$ | $-0.085$ | $-0.323^{**}$ |
| | (0.154) | (0.160) | (0.145) | (0.228) | (0.194) | (0.193) | (0.152) |
| $Mispricing_t$ | $-4.270^{***}$ | $-0.026$ | $-0.003$ | $-0.344$ | $-0.325$ | $-0.215$ | 0.261 |
| | (0.836) | (0.176) | (0.226) | (0.322) | (0.201) | (0.218) | (0.222) |
| $Bid\text{-}Ask\ Spread_t$ | $0.248^{*}$ | $-0.068$ | 0.080 | $-0.086$ | $-0.137$ | $-0.273$ | 0.126 |
| | (0.148) | (0.123) | (0.155) | (0.182) | (0.114) | (0.196) | (0.120) |
| $Composite\ BAS_t$ | $0.404^{**}$ | $0.252^{*}$ | 0.144 | 0.215 | 0.252 | 0.139 | 0.215 |
| | (0.202) | (0.133) | (0.139) | (0.174) | (0.183) | (0.165) | (0.208) |
| $Trading\ Volume_{t-1}$ | $-0.356$ | $-0.268$ | $-0.068$ | $-0.581$ | $-0.557$ | $-0.414$ | $-0.126$ |
| | (0.481) | (0.444) | (0.486) | (0.529) | (0.490) | (0.459) | (0.580) |
| $AUM_{t-1}$ | $-0.248$ | $-0.250$ | $-0.466$ | $-0.073$ | $-0.124$ | $-0.179$ | $-0.387$ |
| | (0.454) | (0.437) | (0.479) | (0.486) | (0.497) | (0.457) | (0.533) |
| $Average\ AP\ Activity_t$ | $-0.019$ | 0.404 | $-0.388$ | $-0.366$ | 0.277 | 0.799 | 0.311 |
| | (1.174) | (1.201) | (1.022) | (0.848) | (1.301) | (0.863) | (0.902) |
| $Average\ Mispricing_t$ | $-1.261$ | $-0.353$ | 0.559 | $-0.141$ | $-2.448$ | $-4.894^{*}$ | $-0.673$ |
| | (1.943) | (1.901) | (2.382) | (1.716) | (1.860) | (2.654) | (1.849) |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 137,597 | 137,597 | 137,597 | 137,597 | 137,597 | 137,597 | 137,597 |
| Adjusted $R^2$ | 0.695 | 0.690 | 0.681 | 0.675 | 0.668 | 0.641 | 0.620 |

Table 1.4: **Placebo Tests**

The table shows the results of a comparison between placebo specification and the baseline specifications for both mispricing and return. *Average* variables on the RHS simply averages quantities of the other ETFs every period, instead of using the network weights, $d_{i,j,t}$. For instance, $Average\,Mispricing_t = \sum \frac{1}{M-1}(p^{etf}_{t,\ell} - NAV_{t,\ell}) * Shares\,Outstanding_{t,\ell}$. Instead, *Random* variables randomly choose the other ETFs in the market every period and average over their mispricing and creation/redemption. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. $T$-statistics, reported in parentheses, are based on clustered standard errors. The dependent variable is in basis points.

| | $Mispricing_{t+1}$ | | | | | | $Return_{t+2}$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| *Average Mispricing$_t$* | 0.315*** | −0.004 | | | | | 2.171*** | 0.773 | | | | |
| | (17.486) | (0.000) | | | | | (8.201) | (0.000) | | | | |
| *Random Mispricing$_t$* | | | 0.005 | | | | | | −0.219 | | | |
| | | | (0.000) | | | | | | (0.000) | | | |
| *Average Cre/Redemp$_t$* | | | | 0.029 | | | | | | 1.141 | | |
| | | | | (0.000) | | | | | | (0.000) | | |
| *Random Cre/Redemp$_t$* | | | | | 0.031 | | | | | | 0.365 | |
| | | | | | (0.000) | | | | | | (0.000) | |
| *Neighbor Mispricing$_t$* | | | | | | −0.742*** | | | | | | 1.402** |
| | | | | | | (-8.214) | | | | | | (1.823) |
| *Neighbor AP Arbitrage$_t$* | | | | | | 0.054 | | | | | | 1.459*** |
| | | | | | | (0.857) | | | | | | (2.715) |
| Fund FE | | | | | | ✓ | | | | | | ✓ |
| Time FE | | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 138,062 | 138,062 | 138,062 | 138,062 | 138,062 | 138,062 | 138,162 | 138,162 | 138,162 | 138,162 | 138,162 | 138,162 |
| Adjusted $R^2$ | 0.002 | 0.055 | 0.055 | 0.055 | 0.055 | 0.079 | 0.0005 | 0.690 | 0.690 | 0.690 | 0.690 | 0.690 |

Table 1.5: **Alternative Returns**

The table presents regressions of alternative returns, $R_{t+k}$, on the contagion measures for arbitrage trading on neighbor funds (the first two rows) and on the proxies for arbitrage trading on its own mispricing (the second two rows). The LHS variable is replaced by either *NAV Return* or *Abnormal Return* controlling Fama-French five, respectively in (1)–(3) and (4)–(6). Controls not shown in the table are lagged NAV return for columns (1)–(3) and lagged abnormal return for (4)–(6). The LHS variables of columns (1)–(3) and (4)–(6), respectively, vary by the number of periods ahead, $k$, up to $t+3$. For liquidity, $Bid\text{-}Ask\,Spread_t$ controls for ETF-level liquidity and $Composite\,BAS_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $Average\,Mispricing_t$ and $Average\,AP\,Activity_t$ simply take averages over all mispricing and net fund flow of the other funds, respectively, without using commonality, $d_{i,j}$. Standard errors are clustered and reported in parentheses. All specifications include fund and day fixed effects. Variables are standardized. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

| | *NAV Return* | | | *Abnormal Return (FF5)* | | |
|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+1 | t+2 | t+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Neighbor\ AP\ Activity_t$ | 1.356*** | 0.892** | 0.354 | −0.291 | −0.102 | 0.011 |
| | (0.399) | (0.380) | (0.388) | (0.329) | (0.290) | (0.290) |
| $Neighbor\ Mispricing_t$ | 1.110* | 1.175* | 0.619 | 1.178** | 1.466** | 1.063** |
| | (0.582) | (0.675) | (0.659) | (0.540) | (0.617) | (0.526) |
| $Net\ Fund\ Flow_t$ | −0.507*** | −0.304* | −0.453*** | −0.265* | −0.392*** | −0.429*** |
| | (0.160) | (0.173) | (0.131) | (0.142) | (0.152) | (0.131) |
| $Mispricing_t$ | 1.817* | 0.067 | 0.046 | −4.186*** | 0.236 | −0.188 |
| | (0.974) | (0.172) | (0.229) | (0.891) | (0.148) | (0.259) |
| $Bid\text{-}Ask\ Spread_t$ | 0.064 | −0.084 | 0.068 | 0.175 | 0.002 | −0.101 |
| | (0.158) | (0.123) | (0.152) | (0.129) | (0.074) | (0.134) |
| $Composite\ BAS_t$ | 0.812*** | 0.419** | 0.145 | 0.438 | 0.171 | 0.194 |
| | (0.282) | (0.180) | (0.274) | (0.282) | (0.170) | (0.187) |
| $NAV\ Return_{t-1}$ | 0.206 | −0.444 | −1.155** | | | |
| | (0.442) | (0.491) | (0.489) | | | |
| $Alpha_{t-1}$ | | | | −0.613** | −1.095*** | −0.391** |
| | | | | (0.279) | (0.306) | (0.174) |
| $Trading\ Volume_{t-1}$ | 0.178 | −0.921* | −0.204 | 0.546 | −0.437 | 0.451 |
| | (0.489) | (0.505) | (0.531) | (0.461) | (0.363) | (0.403) |
| $AUM_{t-1}$ | −5.813*** | −4.829*** | −5.480*** | −4.647*** | −3.689*** | −4.500*** |
| | (0.913) | (0.913) | (0.909) | (0.802) | (0.736) | (0.756) |
| $Average\ AP\ Activity_t$ | 0.078 | 0.590 | −0.286 | 0.957 | 1.187 | 0.017 |
| | (1.164) | (1.162) | (0.958) | (0.769) | (0.779) | (0.806) |
| $Average\ Mispricing_t$ | 0.102 | 0.346 | 2.057 | −1.241 | 0.356 | 0.211 |
| | (1.961) | (1.704) | (2.807) | (1.422) | (1.163) | (1.655) |
| Fund FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 137,623 | 137,623 | 137,623 | 137,523 | 137,423 | 137,323 |
| Adjusted $R^2$ | 0.699 | 0.695 | 0.686 | 0.168 | 0.184 | 0.193 |

Table 1.6: **Instrumental Variable Regression**

The table shows results from 2SLS IV regressions exploiting the exogenous rebalancing of portfolios. Each ETF is rebalanced periodically rebalancing as are the underlying indices. Controls include net fund flow, lagged mispricing, trading volume, bid-ask spread, and AUM. Variables are standardized. Standard errors are clustered and reported in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

| | $Mispricing_{t+1}$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\widehat{NeighborAPActivity_{t,i}}$ | $-0.080^{**}$ | | $-0.032$ |
| | (0.033) | | (0.046) |
| $\widehat{NeighborMispricing_{t,i}}$ | | $-0.103^{***}$ | $-0.082^{*}$ |
| | | (0.030) | (0.044) |
| Control | ✓ | ✓ | ✓ |
| FE | ✓ | ✓ | ✓ |
| Observations | 137,778 | 137,778 | 137,778 |
| Adjusted $R^2$ | 0.044 | 0.044 | 0.044 |

Table 1.7: **Granular Instrumental Variable Estimation**

The table shows results from GIV regressions. The first two lines shows multipliers, **M**, and the coefficients estimated for $Z_t$ and $Z_t^{hetero}$ separately. $Z^{hetero}$ adjusts for heteroskedasticity. Controls include lagged dollar trading volume, lagged bid-ask spread, lagged composite bid-ask spread, lagged AUM, lagged mispricing (lagged return for (3) and (4)), and Fama-French five factors. Lagged bid-ask spread controls for ETF-level liquidity and lagged composite bid-ask spread controls for security-level liquidity. Standard errors are clustered and reported in parentheses. $\eta_1$ and $\eta_2$ are factor exposures. $^{*}p<0.1$; $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

| | $Mispricing_{t+1}$ | | $Return_{t+2}$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Z_t$ | $0.795^{***}$ | | $-1.008^{***}$ | |
| | (0.051) | | (0.313) | |
| $Z_t^{hetero}$ | | $0.821^{***}$ | | $-1.829^{***}$ |
| | | (0.056) | | (0.314) |
| $\eta_1$ | 0.052 | 0.073 | 0.145 | 0.199 |
| | (0.044) | (0.045) | (2.094) | (2.082) |
| $\eta_2$ | | | $-7.888^{***}$ | $-5.856^{***}$ |
| | | | (2.097) | (2.103) |
| Control | ✓ | ✓ | ✓ | ✓ |
| Observations | 1,399 | 1,260 | 1,399 | 1,260 |
| Adjusted $R^2$ | 0.304 | 0.634 | 0.028 | 0.077 |

Table 1.8: **Subsample: Premium vs. Discount**

The table presents a variant of the baseline return regression, where its sample is split by the directions in initial price dislocations of ETFs. Columns (1), (2), and (3) refer to the sample of funds with an initial *premium*. Columns (4), (5), and (6) refer to the sample of funds with an initial *discount*. Controls not shown in the table include lagged returns. For liquidity, $\textit{Bid-Ask Spread}_t$ controls for ETF-level liquidity and $Composite\,BAS_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $Average\,Mispricing_t$ and $Average\,AP\,Activity_t$ simply take averages over all mispricing and net fund flow of the other funds, respectively, without using commonality $d_{i,j}$. All specifications include fund and day fixed effects. Variables are standardized. Standard errors are clustered and reported in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

| | *Return* | | | | | |
|---|---|---|---|---|---|---|
| | $P_t - V_t > 0$ | | | $P_t - V_t < 0$ | | |
| | $t$+1 | $t$+2 | $t$+3 | $t$+1 | $t$+2 | $t$+3 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\textit{Neighbor AP Activity}_t$ | −0.073 | 1.267** | 1.262** | 3.794*** | 0.365 | −0.422 |
| | (0.521) | (0.554) | (0.593) | (0.763) | (0.693) | (0.703) |
| $\textit{Neighbor Mispricing}_t$ | 0.564 | −0.681 | −0.529 | 1.131 | 2.598*** | 2.220* |
| | (0.990) | (1.094) | (0.907) | (0.942) | (0.845) | (1.139) |
| $\textit{Net Fund Flow}_t$ | −0.542*** | −0.452 | −0.455*** | −0.008 | −0.185 | −0.666*** |
| | (0.192) | (0.290) | (0.164) | (0.210) | (0.235) | (0.251) |
| $\textit{Mispricing}_t$ | −3.881*** | −0.123 | −0.139 | −3.554*** | 0.365 | 0.204 |
| | (0.656) | (0.254) | (0.569) | (0.733) | (0.298) | (0.361) |
| $\textit{Trading Volume}_{t-1}$ | 1.353* | −1.444* | −0.564 | 0.401 | −0.338 | −0.049 |
| | (0.755) | (0.828) | (0.772) | (0.821) | (0.813) | (0.810) |
| $AUM_{t-1}$ | −6.373*** | −5.746*** | −4.089*** | −5.565*** | −4.188*** | −7.484*** |
| | (1.225) | (1.469) | (1.217) | (1.316) | (1.067) | (1.543) |
| $\textit{Bid-Ask Spread}_t$ | −0.010 | −0.411** | 0.083 | 0.391* | 0.153 | 0.129 |
| | (0.199) | (0.178) | (0.282) | (0.226) | (0.181) | (0.224) |
| $\textit{Composite BAS}_t$ | 0.118 | 0.348 | 0.221 | 1.268** | 0.471 | 0.093 |
| | (0.321) | (0.231) | (0.251) | (0.494) | (0.309) | (0.381) |
| $\textit{Average AP Activity}_t$ | 0.693 | 0.280 | −0.826 | −1.446 | 0.629 | 0.068 |
| | (1.186) | (1.300) | (1.453) | (1.421) | (1.395) | (1.783) |
| $\textit{Average Mispricing}_t$ | −4.083* | 2.635 | 2.356 | −2.669 | −3.840 | 2.909 |
| | (2.099) | (2.827) | (3.549) | (3.314) | (3.531) | (3.456) |
| Fund FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 73,535 | 73,535 | 73,535 | 64,088 | 64,088 | 64,088 |
| Adjusted $R^2$ | 0.705 | 0.698 | 0.695 | 0.687 | 0.683 | 0.669 |

Table 1.9-a: **Subsample: By Composition**

The table shows a variant of the baseline return regression, where its sample is split by excluding certain categories of ETFs respectively. Column (1) excludes the ETFs that are substitutes, i.e., the ETFs that tracks the same underlying indices. Exclusions: IVV, VOO, MDY, SLYG, SLYV, VTWO, VXF. Column (2) excludes the sector funds. Column (3) excludes strategy ETFs, i.e., the funds that takes specific selection strategies such as high-dividend yield stocks. Column (4) excludes the broad market ETFs that track Russel and SP500. Columns (5)–(8) exclude the growth stock-themed fund, the value stock–themed fund, the small cap stock–themed fund, and the large cap stock–themed fund, respectively. For liquidity, $\textit{Bid-Ask Spread}_t$ controls for ETF-level liquidity and $\textit{Composite BAS}_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $\textit{Average Mispricing}_t$ and $\textit{Average AP Activity}_t$ simply take averages over all mispricing and net fund flow of the other funds, respectively, without using commonality $d_{i,j}$. Controls not shown includes lagged returns. Standard errors are clustered and reported in parentheses. All specifications include fund and day fixed effects. Variables are standardized. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Dependent variable is in basis points.

| | $\textit{Return}_{t+1}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | ex. Substitutes | ex. Sector | ex. Strategy | ex. Broad Equity | ex. Growth | ex. Value | ex. Small | ex. Large |
| $\textit{Neighbor AP Activity}_t$ | 1.334*** | 1.647*** | 1.249*** | 1.493*** | 1.551*** | 1.280*** | 1.114** | 1.506*** |
| | (0.444) | (0.360) | (0.460) | (0.423) | (0.480) | (0.474) | (0.505) | (0.419) |
| $\textit{Neighbor Mispricing}_t$ | 0.776 | −0.301 | 1.099 | 0.793 | 0.814 | 0.724 | 0.838 | 0.695 |
| | (0.673) | (0.419) | (0.722) | (0.619) | (0.674) | (0.705) | (0.715) | (0.617) |
| $\textit{Net Fund Flow}_t$ | −0.301* | 0.037 | −0.203 | −0.307* | −0.364** | −0.333** | −0.332** | −0.304* |
| | (0.158) | (0.118) | (0.167) | (0.161) | (0.169) | (0.164) | (0.161) | (0.157) |
| $\textit{Mispricing}_t$ | −3.727*** | −4.147*** | −4.838*** | −4.254*** | −3.901*** | −3.897*** | −3.744*** | −4.240*** |
| | (0.918) | (1.414) | (0.271) | (0.922) | (0.958) | (0.946) | (0.932) | (0.898) |
| $\textit{Trading Volume}_{t-1}$ | 0.659 | 0.519 | 0.729 | 0.790 | 0.740 | 0.597 | 0.850 | 0.718 |
| | (0.559) | (0.433) | (0.533) | (0.557) | (0.628) | (0.585) | (0.578) | (0.554) |
| $AUM_{t-1}$ | −6.124*** | −5.300*** | −5.503*** | −6.022*** | −6.373*** | −6.452*** | −6.387*** | −6.239*** |
| | (0.982) | (0.908) | (0.955) | (1.005) | (1.055) | (1.115) | (1.008) | (1.011) |
| $\textit{Bid-Ask Spread}_t$ | 0.212 | 0.025 | 0.321** | 0.242 | 0.242 | 0.162 | 0.191 | 0.216 |
| | (0.146) | (0.173) | (0.152) | (0.152) | (0.152) | (0.160) | (0.157) | (0.148) |
| $\textit{Composite BAS}_t$ | 0.824*** | 0.038 | 0.843** | 0.819*** | 0.815*** | 0.792** | 0.907*** | 0.756** |
| | (0.299) | (0.248) | (0.332) | (0.301) | (0.316) | (0.331) | (0.315) | (0.304) |
| $\textit{Average AP Activity}_t$ | 1.232 | −0.953 | 11.905* | −0.084 | −0.145 | −0.043 | 0.245 | −0.081 |
| | (1.397) | (1.115) | (6.384) | (1.112) | (1.169) | (1.063) | (1.106) | (1.124) |
| $\textit{Average Mispricing}_t$ | −0.759 | 1.056 | −4.333 | −1.112 | −0.694 | −0.574 | −0.537 | −0.786 |
| | (1.919) | (1.494) | (7.657) | (1.901) | (1.957) | (1.932) | (1.887) | (1.857) |
| Fund & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 129,387 | 74,276 | 122,637 | 129,436 | 121,047 | 119,811 | 125,276 | 133,449 |
| Adjusted $R^2$ | 0.684 | 0.868 | 0.678 | 0.692 | 0.674 | 0.675 | 0.681 | 0.690 |

Table 1.9-b: **Subsample: By Year**

The table shows a variant of the baseline return regression, where its sample is split by time. Column (1) refer to the sample without 2015, during which a flash crash took place on August 24th. Column (2) refers to the period between 2012-2014 and (3) refers to the period between 2015 and 2017. Column (4) refers to the sample without 2017. $Bid\text{-}Ask\,Spread_t$ controls for ETF-level liquidity, while $Composite\,BAS_t$ and $Composite\,DCBS_t$ control for security-level liquidity, aggregated to each basket of underlying securities. $CompositeDCBS_t$ is not available after 2015 at my institution. $Average\,Mispricing_t$ and $Average\,AP\,Activity_t$ simply take averages over all mispricing and net fund flow of the other funds respectively without using commonality $d_{i,j}$. Controls not shown includes lagged returns. Standard errors are clustered and reported in parentheses. All specifications include fund and day fixed effects. Variables are standardized. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The dependent variable is in basis points.

| | $Return_{t+1}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | ex. 2015 | 2012-2014 | 2015-2017 | ex. 2017 |
| *Neighbor AP Activity*$_t$ | 1.391$^{***}$ | 1.697$^{***}$ | 1.103 | 2.798$^{***}$ |
| | (0.428) | (0.567) | (0.696) | (0.601) |
| *Neighbor Mispricing*$_t$ | 1.098 | −1.459$^{*}$ | 2.789$^{***}$ | 0.106 |
| | (0.770) | (0.778) | (1.005) | (0.664) |
| *Net Fund Flow*$_t$ | −0.220 | −0.392 | −0.294 | −0.312$^{*}$ |
| | (0.172) | (0.253) | (0.325) | (0.184) |
| *Mispricing*$_t$ | −4.133$^{***}$ | −5.202$^{***}$ | −3.399$^{***}$ | −4.524$^{***}$ |
| | (0.966) | (0.733) | (1.086) | (0.903) |
| *Trading Volume*$_{t-1}$ | 0.581 | −0.089 | 1.326 | 0.907 |
| | (0.577) | (0.776) | (0.814) | (0.609) |
| $AUM_{t-1}$ | −5.953$^{***}$ | −7.770$^{***}$ | −9.293$^{***}$ | −7.361$^{***}$ |
| | (1.202) | (1.792) | (1.804) | (0.978) |
| *Bid-Ask Spread*$_t$ | 0.263$^{*}$ | 0.332$^{*}$ | −0.034 | 0.242 |
| | (0.149) | (0.179) | (0.325) | (0.159) |
| *Composite BAS*$_t$ | 0.657$^{**}$ | 1.282$^{**}$ | 0.319 | 1.282$^{***}$ |
| | (0.301) | (0.504) | (0.314) | (0.480) |
| *Composite DCBS*$_t$ | | −0.326 | | |
| | | (0.467) | | |
| *Average AP Activity*$_t$ | 0.202 | 1.775 | −1.237 | 0.648 |
| | (1.332) | (2.323) | (1.558) | (1.405) |
| *Average Mispricing*$_t$ | −1.600 | −3.231 | 0.916 | −1.502 |
| | (2.516) | (3.595) | (3.932) | (2.042) |
| Fund FE | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ |
| Control | ✓ | ✓ | ✓ | ✓ |
| Observations | 113,169 | 64,933 | 72,690 | 113,444 |
| Adjusted $R^2$ | 0.678 | 0.717 | 0.676 | 0.714 |

Table 1.10: **Fama-Macbeth Regression**

The table shows the results of fama-macbeth regressions with different horizons raging from $t + 1$ to $t + 30$. The coefficients represents the relationship between cumulative returns of ETFs, $R_{t\to t+k}$, and the contagion measures (the first two rows) and the effects from arbitrage trading on its own (the second two rows), respectively. Controls include trading volume, bid ask spread (for ETF itself), composite bid-ask spread (for underlying assets), AUM, and lagged returns. Columns (1)-(8) vary by horizon, k. T statistics are reported in parentheses. Variables are standardized. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Dependent variable is in basis points.

| | $R_{t\to t+k}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | t+1 | t+2 | t+3 | t+5 | t+7 | t+14 | t+21 | t+30 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Neighbor APActivity*$_t$ | 0.248 | 0.193 | 1.180 | 0.750 | 1.506 | 5.775** | 8.945*** | 9.055** |
| | (0.53) | (0.29) | (1.42) | (0.68) | (1.18) | (3.09) | (4.1) | (3.31) |
| *Neighbor Mispricing*$_t$ | 0.434 | 0.933 | -0.413 | -0.302 | -0.608 | -0.058 | 2.775 | 2.975 |
| | (0.95) | (1.42) | (-0.51) | (-0.3) | (-0.52) | (-0.03) | (1.29) | (1.12) |
| *Mispricing*$_t$ | -3.649*** | -3.7*** | -3.632*** | -4.155*** | -4.559*** | -4.746*** | -4.161*** | -4.758*** |
| | (-17.05) | (-12.74) | (-9.23) | (-8.83) | (-8.46) | (-6.38) | (-4.49) | (-4.43) |
| *Net Fund Flow*$_t$ | -0.379 | -0.519 | -1.075 * | -1.53** | -1.824** | -1.797 | -1.772 | -1.211 |
| | (-1.43) | (-1.42) | (-2.38) | (-2.62) | (-2.68) | (-1.88) | (-1.58) | (-0.94) |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Adjusted $R^2$ | 0.131 | 0.129 | 0.128 | 0.126 | 0.121 | 0.120 | 0.118 | 0.114 |

Table 1.11: **Network Effects of Fed's SMCCF Announcement**

The table shows results from diff-in-diff-style regressions exploiting variations in commonality among non-targeted funds when SMCCF was announced in the Bond ETF market. D{*High Commonality to Eligible*} is constructed based on the same network topology construction, $\mathbf{d}_t(i,\ell) = \sum_{j=1}^{N} w_{j,t}^{(i)} \log(w_{j,t}^{(\ell)})$, as the Equity ETFs (see Section 1.2) and by ranking non-targeted ETFs based on their average commonalities to the eligible funds, $\frac{1}{\#of\,Eligible} \sum_{\ell \in Eligible} \mathbf{d}_t(i,\ell)$. The sample in Panel A is after the introduction of an interest rate cut and Treasury purchase and before the announcement of expansion, between March 15th and April 8th, 2020. The result is robust to changing the beginning of the sample to after PDCF and MMLF. The sample in Panel B is a week after the first announcement and before the purchase, between April 1st and May 11st, 2020. Controls include lagged variables of mispricing and net fund flow other than those shown below. Standard errors are clustered and reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Panel A: Announcement**

| | *Mispricing (%)* | | | | | |
|---|---|---|---|---|---|---|
| | $t$ | $t$+1 | $t$+2 | $t$+3 | $t$+7 | $t$+14 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| D{*Announcement*}*D{*High Commonality to Eligible*} | −0.273*** | −0.253 | 0.041 | −0.054 | 0.189*** | 0.099* |
| | (0.069) | (0.187) | (0.164) | (0.218) | (0.059) | (0.051) |
| D{*High Commonality to Eligible*} | 0.212*** | 0.206 | −0.002 | 0.043 | −0.209*** | −0.132*** |
| | (0.055) | (0.157) | (0.159) | (0.194) | (0.056) | (0.042) |
| *BA Spread*$_{t-1}$ | −0.008 | −0.022*** | −0.003 | −0.017 | −0.015 | −0.023** |
| | (0.006) | (0.006) | (0.008) | (0.011) | (0.013) | (0.011) |
| *Composite Amihud*$_{t-1}$ | 0.030 | 0.068 | 0.095* | 0.108* | 0.088*** | 0.067** |
| | (0.042) | (0.055) | (0.056) | (0.055) | (0.033) | (0.029) |
| *Maturity Exposure* (<1y) | 0.018 | 0.026 | 0.019 | 0.011 | −0.005 | 0.015 |
| | (0.020) | (0.022) | (0.027) | (0.021) | (0.019) | (0.012) |
| *Maturity Exposure* (1-3y) | 0.002 | −0.014 | −0.016 | −0.027 | −0.035 | −0.020 |
| | (0.028) | (0.033) | (0.035) | (0.032) | (0.034) | (0.020) |
| *Maturity Exposure* (3-5y) | −0.047 | −0.033 | −0.033 | −0.044 | −0.014 | 0.039* |
| | (0.038) | (0.041) | (0.041) | (0.041) | (0.038) | (0.021) |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 4,564 | 4,561 | 4,558 | 4,555 | 4,543 | 4,282 |
| Adjusted $R^2$ | 0.631 | 0.490 | 0.316 | 0.285 | 0.234 | 0.165 |

**Panel B: Expansion**

| | *Mispricing (%)* | | | | | |
|---|---|---|---|---|---|---|
| | t | t+1 | t+2 | t+3 | t+7 | t+14 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| D{*Expansion*}*D{*High Commonality to Eligible*} | −0.003 | −0.001 | −0.002 | −0.003 | 0.010 | 0.020** |
| | (0.019) | (0.019) | (0.017) | (0.017) | (0.014) | (0.010) |
| D{*High Commonality to Eligible*} | −0.007 | −0.013 | −0.013 | −0.014 | −0.022* | −0.029*** |
| | (0.019) | (0.018) | (0.017) | (0.018) | (0.012) | (0.008) |
| *BA Spread*$_{t-1}$ | −0.001 | −0.005*** | −0.001 | −0.001 | −0.0001 | −0.003** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| *Composite Amihud*$_{t-1}$ | 0.005 | 0.025 | 0.030 | 0.046* | 0.021 | −0.006 |
| | (0.019) | (0.023) | (0.027) | (0.023) | (0.014) | (0.009) |
| *Maturity Exposure* (<1y) | 0.009 | 0.020* | 0.028*** | 0.036*** | 0.045*** | 0.062*** |
| | (0.010) | (0.011) | (0.010) | (0.009) | (0.010) | (0.009) |
| *Maturity Exposure* (1-3y) | 0.005 | −0.001 | 0.003 | 0.001 | 0.006 | 0.002 |
| | (0.017) | (0.017) | (0.016) | (0.017) | (0.014) | (0.013) |
| *Maturity Exposure* (3-5y) | −0.001 | 0.004 | 0.007 | 0.004 | 0.003 | −0.016 |
| | (0.010) | (0.012) | (0.014) | (0.015) | (0.013) | (0.012) |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 6,174 | 5,927 | 5,925 | 5,923 | 5,915 | 5,411 |
| Adjusted $R^2$ | 0.630 | 0.511 | 0.443 | 0.392 | 0.395 | 0.277 |

# 1.10 Appendix

# A. Figures and Tables

Figure A.1: **ETF Market**

The figure illustrates how arbitrager in the ETF market, in particular Authorized Participants (APs), play roles in the primary and the secondary markets. APs are licenced entities, which are often investment banks and trading firms, and they voluntarily engage in creation/redemption activities when price dislocation between ETF price and NAV widens.

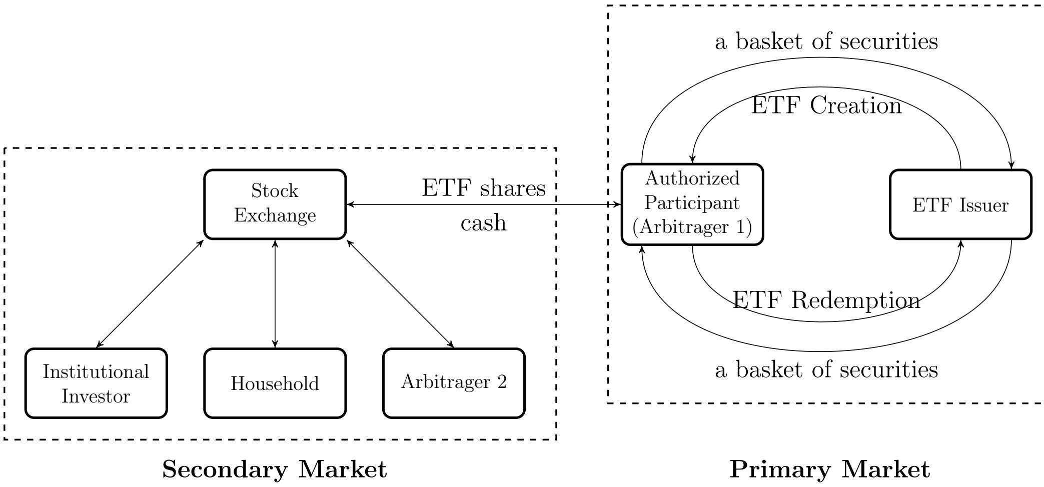
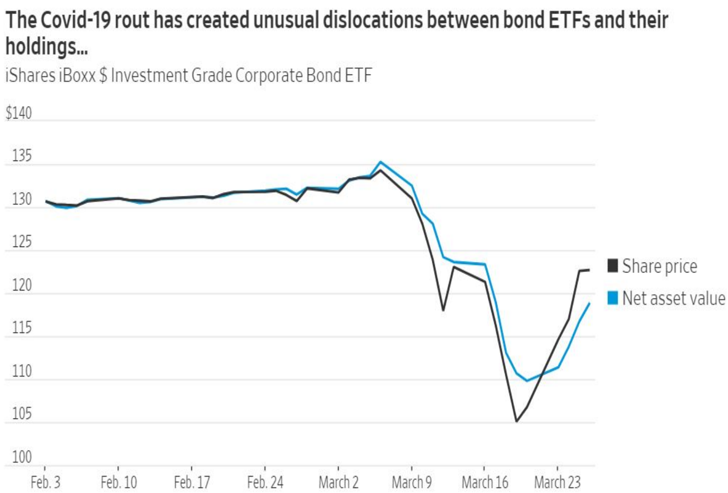



Figure A.2: **Price Dislocation during the COVID-19 Crisis**




Source: Wall Street Journal

Figure A.3: **Premium and Dispersion in Top 100 Equity ETFs**

The left panel shows the total traded premium and the premium for the top 100 Equity ETFs. Total traded premium is defined as the product of dollar trading volume and price dislocation (premium/discount), aggregated to a monthly basis. Premium per ETF is calculated as price dislocation minus bid-ask spread and aggregated with value weights based on the AUM of ETFs to a monthly basis. The right panel shows cross-sectional dispersion and volatility of return for TOP 100 ETFs. Cross-sectional dispersion is average monthly dispersion across ETFs with equal weights. Volatility of return is the value weight average of rolling time-series volatilities with 30-day windows.

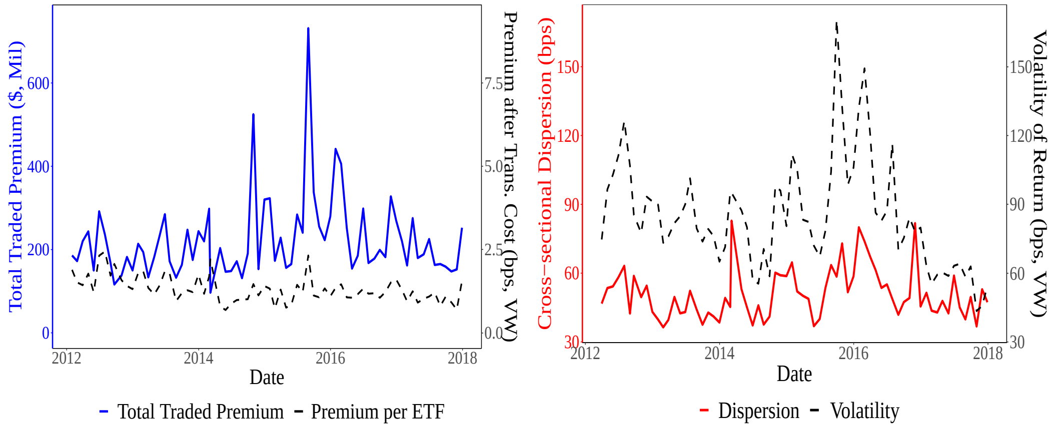



Figure A.4: **Issuer and Market Makers in Top 100 Equity ETFs**

The left panel shows how many ETFs each issuer has for the top 100 ETFs. The right panel shows the fractions of fund-date $N$, in which each entity is a lead market maker maker throughout the sample, 2012–2017.

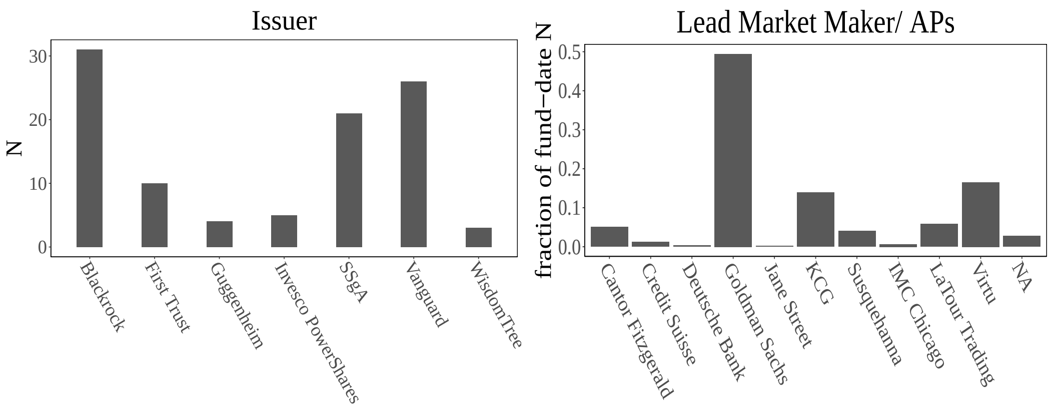


Figure A.5: **Contagion Index by Category**

The figure shows a classified presentation of the average contagion index, which captures how prone each ETF is to contagion effects from neighbor ETFs. They are classified by the category of ETFs. Style refers to mid-cap funds and those ETFs with some focus on particular sectors (but not fully limited to). Strategy refers to high-dividend yield funds and dividend-themed funds. The contagion index is defined as $\mathbf{Contagion}_i = \sum_t \sum_{\ell \neq i} \mathbf{d}_t(i,\ell) * (Creation/Redemption_{t,\ell}) * NAV_{t,\ell}$ for each ETF. All variables are standardized.

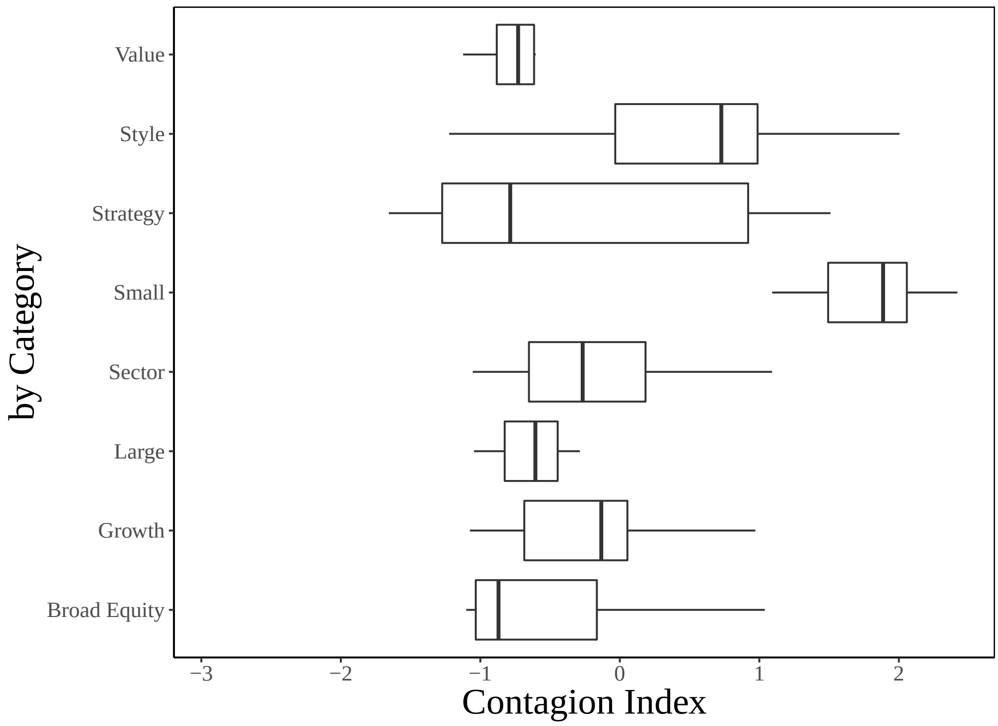


Figure A.6: **Primary Market Activity around Fed Announcement**

The figure shows market reactions of Bond ETFs before and after the SMCCF announcement by the Fed. The High Yield category includes eight major high-yield bond ETFs, eligible for the Fed purchase, and the Investment Grade category includes eight major investment-grade bond ETFs, eligible for the Fed purchase, respectively. Others include the other 276 bond ETFs.

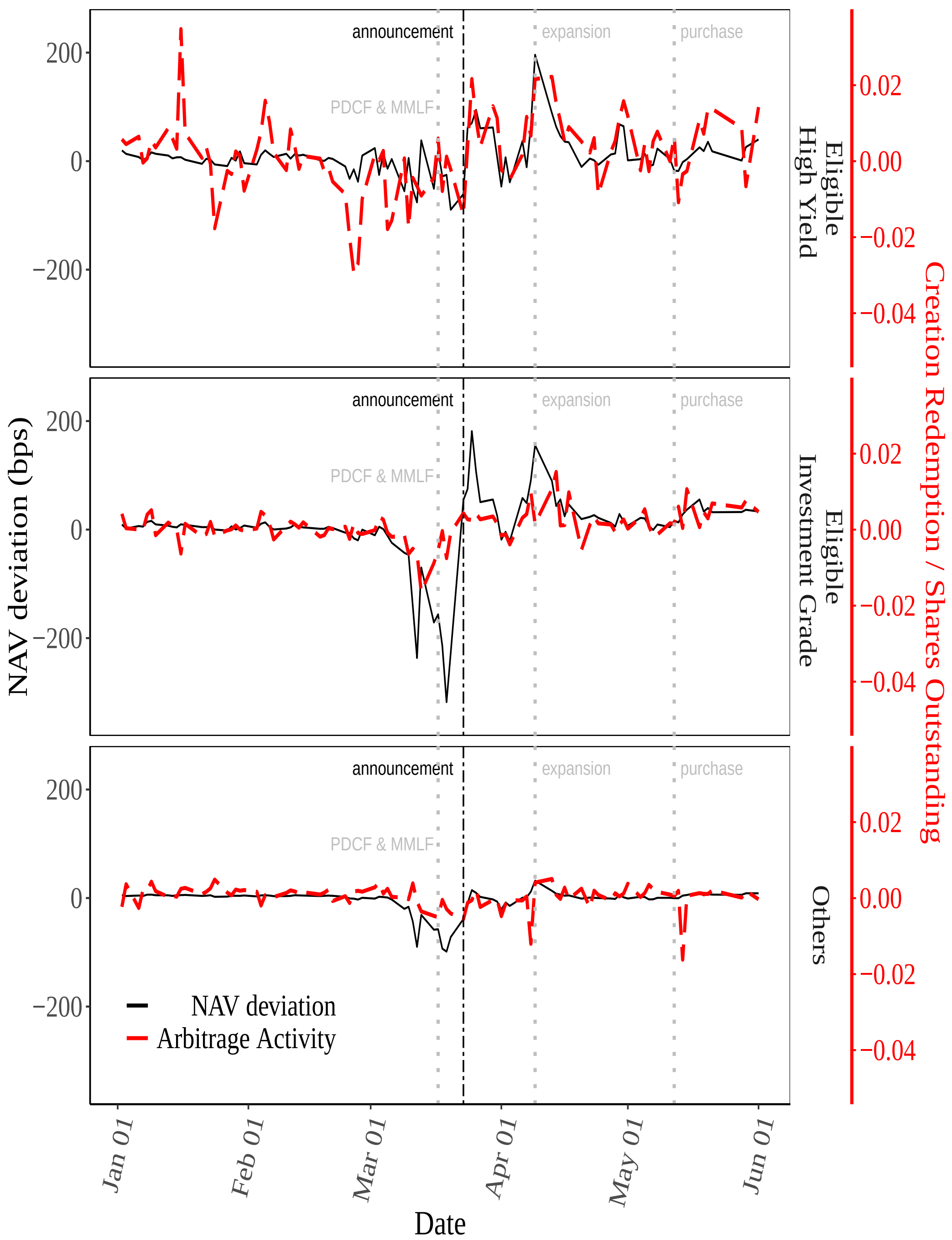
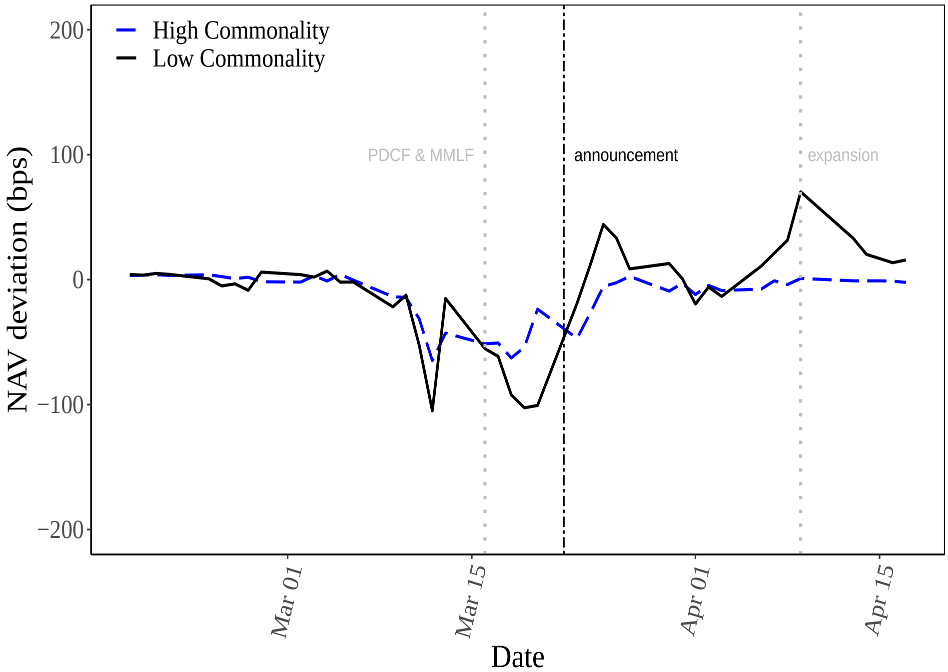


Figure A.7: **Network Effects in Non-targeted Funds**

The figure shows the market reactions of non-targeted Bond ETFs before and after the SMCCF announcement by the Fed. High-commonality and low-commonality funds are computed based on the network topology, **D**, with the same construction as the one used in the Equity ETF part. By first computing commonality, **d(i,j)**, between non-targeted funds $i$ and targeted funds $j$ and averaging over $j$, non-targeted ETFs are split into three bins. I use **d** at the beginning of the year so as to prevent the network from becoming affected by the market distress that began in March 2020.



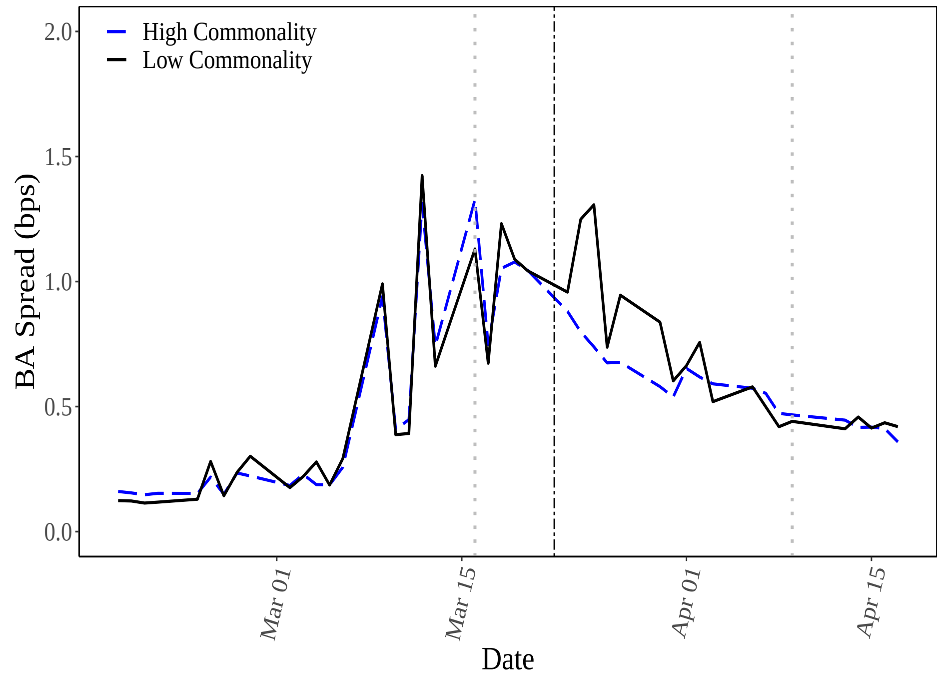



Figure A.8: **Flow Waits for Uncertainty to Resolve before Index Rebalancing**

This figure shows the average net fund flow of Equity ETFs for two groups that are split based on whether or not each fund faces rebalancing. A blue line shows the average net fund flow of rebalancing funds from five days earlier and up to five days after each rebalancing day. The sample is 2012–2017.

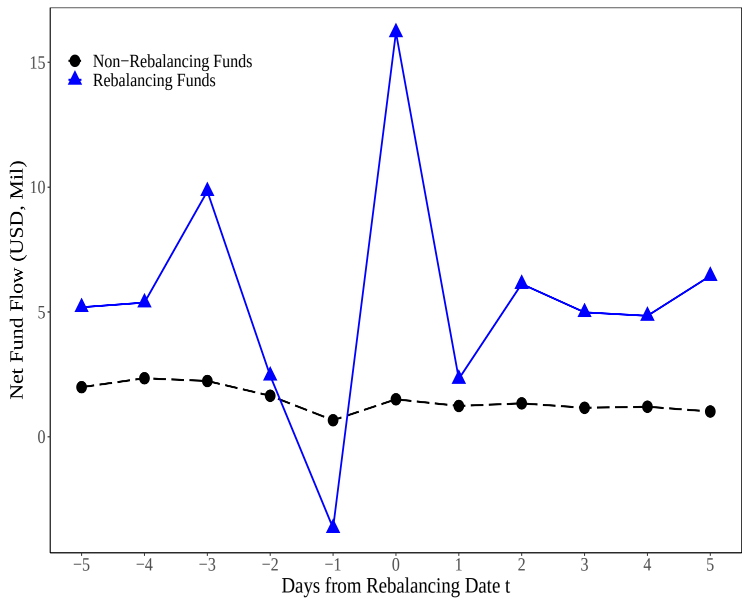
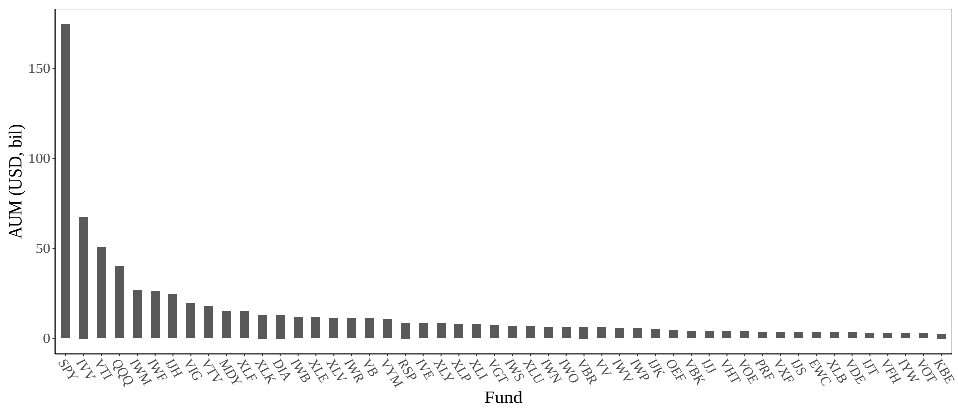



Figure A.9: **Skewed Size Distribution of Top 50 ETFs**

This figure shows the AUM of the top 50 Equity ETFs during the sample period. The excess Herfindahl is $h := \sqrt{-\frac{1}{100} + \sum_{i=1}^{100} S_i^2} \approx 0.25$ and they are concentrated at a relatively high level.



## B. Primary Market Arbitrage

This section describes the primary market arbitrage carried out by APs. It is reported that registered APs are typically 30–40 entities per one ETF and 5 are active on average at each point in time (see Blackrock (2017) for details). Authorized participants tend to be either large financial institutions or specialized market makers. The authorized participant does not have an obligation to engage in market-making activities, or AP activities.

The authorized participant takes arbitrage when the fund SPY exhibits the premium, $ETFPrice > NAV$, by gathering the basket of underlying stocks and delivering it to the ETF sponsor in return for an ETF share ("in-kind" ETF creation).[25] For this transaction, the AP needs to make orders following *creation units* specified by the ETF. In the top 100 Equity ETF sample, it is typically a block of either 25k or 50k shares. For instance,

$$\begin{aligned}\$\textit{Profit} =& (\textit{NAV of ETF})*(\ |\textit{Premium/Discount after TC}|\ )\\ &*(\textit{Creation Unit})*\mathrm{X} - \textit{Creation Fee}\end{aligned}$$

*Creation Fee* is a fee that the AP needs to pay per participating day, i.e., a day when the AP engages in creation/redemption activity. For example, a dollar profit for engaging in the creation of SPY when it exhibits 10 bps premium and is traded at USD 200 is (\$200)*(10bps)*(50K)*X − min{\$3000, 10bps*50k*\$200}, paying a creation fee. The fee is the smaller of USD 3000 or 10bps of traded price of the ETF. This creation fee is specified by the ETF issuer and documented in its prospectus.[26] The AP can scale this transaction by $X$.

[25]For a market maker, profit is not necessarily the premium, but the deviation of the ETF price from the expected value. See detailed discussion in Madhavan (2014).

[26]Source: State Street

Antoniewicz and Heinrichs (2014) write about the institutional details of settlements to a great extent as follows. According to them, it can take up to T+3 days. First, the AP submits orders to the ETF distributor, based on the portfolio composition file. This creation/redemption order will be processed via NSCC.[27] After the distribution of a file of accepted creation/redemption instructions and the checking of information of creation/redemption instructions, NSCC guarantees the settlement by the midnight of T+1. At T+2, NSCC distributes their consolidated trade summary reports and sends instructions to DTC (Depository Trust Company). Finally, from T+2 to T+3, DTC finishes the settlements. These institutional details are consistent with the findings of this chapter – in particular, the persistence of the effects from creation and redemption activities on ETF returns, which is captured by the coefficients for $Neighbor\ AP\ Activity_t$ and $Net\ Fund\ Flow_t$.

[27]Domestic fixed-income securities and some of their ETFs are also NSCC-eligible. However, many domestic fixed-income ETFs are processed outside NSCC due to their constituents which are not NSCC-eligible such as international securities and Treasuries. See Antoniewicz and Heinrichs (2014) for details.

# C. Commonality Function

Assuming linear a price impact on the price of underlying stocks when the ETF arbitrage with a dollar amount of trade, $w_j^B V_{j,t}^B$, takes place on ETF B, $p_{j,t+1} = p_{j,t} + \gamma \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}}$, the net asset value (= fundamental value) of ETF A after the arbitrage activity is

$$
\begin{aligned}
V_{t+1}^A &= \sum^N w_j^A p_{j,t+1} \\
&= \sum^N w_j^A (p_{j,t} + \gamma \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}})
\end{aligned}
$$

where $w_j^B$ is the weight on stock $j$ in ETF B, $V_{j,t}^B$ is the net asset value of ETF B, $MktCap_{j,t}$ is the market cap of stock $j$, and $\gamma$ is the parameter that represents the strength of the price impact on stock $j$. With this after-arbitrage net asset value of ETF A, $V_{t+1}^A$, expressing log deviation of $V_{t+1}^A$ relative to the value prior to the arbitrage activity yields the following expression with the aid of Taylor expansion and Jensen's inequality:

$$
\begin{aligned}
log\Big(\frac{V_{t+1}^A}{V_t^A}\Big) &= log\Big(1 + \frac{\gamma \sum^N w_j^A \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}}}{V_t^A}\Big) \\
&\approx k + (1-\rho)\Big(log\gamma \sum^N w_j^A \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}} - logV_t^A\Big) \\
&\geq k + (1-\rho)\Big( \underbrace{\sum^N w_j^A log(w_j^B)}_{\substack{\text{the link between A and B} \\ \text{that affects A's deviation}}} + log\gamma + \sum^N w_j^A log(\frac{V_{j,t}^B}{MktCap_{j,t}}) - logV_t^A\Big)
\end{aligned}
$$

where

$$\rho \equiv \frac{1}{1 + exp(log\gamma \overline{\sum^N w_j^A \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}}} - \overline{V_t^A})}$$

$$k \equiv -log\rho - (1-\rho)log\left(\frac{1}{\rho} - 1\right)$$

Therefore, a distance function used to define commonality in the paper, $d_{AB} \equiv \sum^N w_j^A \log(w_j^B)$, is the link between ETF A and ETF B that determines the lower bound of log deviation of the net asset value of ETF A due to contagion from ETF B.

# D. Definitions

$$\mathbf{F} = (I_T \otimes \mathbf{1}_M, \mathbf{1}_T \otimes I_M),$$

$$\boldsymbol{D}_M = \tfrac{1}{T}\Sigma_{t=1}^T \boldsymbol{D}_{M,t},$$

$$\boldsymbol{\alpha} := (\alpha_1^{day}, \ldots, \alpha_T^{day}, \alpha_1^{fund}, \ldots, \alpha_M^{fund})', \boldsymbol{\beta} := (\beta_1, \ldots, \beta_K)'$$

$$\mathbf{Y} := (y_{1,1}, \ldots, y_{M,1}, \ldots, y_{i,t}, \ldots, y_{1,T}, \ldots, y_{M,T})'$$

$$\text{”} := (\epsilon_{1,1}, \ldots, \epsilon_{M,1}, \ldots, \epsilon_{i,t}, \ldots, \epsilon_{1,T}, \ldots, \epsilon_{M,T})'$$

$$\mathbf{X} = \begin{pmatrix} x_{1,1}^1 & \ldots & x_{1,1}^k & \ldots & x_{1,1}^K \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m,1}^1 & \ldots & x_{m,1}^k & \ldots & x_{m,1}^K \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{M,T}^1 & \ldots & x_{M,T}^k & \ldots & x_{M,T}^K \end{pmatrix}$$

# E. Derivations for Extension 1.5.2

One can decompose $\beta^{\mathbb{Q}}_{i,wp,t}$ into three components, as follows.

$$\begin{aligned}
\beta^{\mathbb{Q}}_{i,wp,t} &= \frac{Cov^{\mathbb{Q}}_t(r^i_{t+1}, r^{wp}_{t+1})}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})} \\
&= \frac{Cov^{\mathbb{Q}}_t(r^i_{t+1}, \sum_j^N w_j r^j_{t+1})}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})} \\
&= \frac{w_i Var^{\mathbb{Q}}_t(r^i_{t+1}) + Cov^{\mathbb{Q}}_t(r^i_{t+1}, \sum_{j\neq i} w_j r^j_{t+1})}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})} \\
&= \frac{w_i Var^{\mathbb{Q}}_t(r^i_{t+1})}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})} + \underbrace{\frac{Cov^{\mathbb{Q}}_t(r^i_{t+1}, r^{RoW(i)}_{t+1})}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})}}_{\equiv \beta^{\mathbb{Q}}_{i,RoW,t}} \\
&\approx \frac{w_i Var^{\mathbb{Q}}_t(r^i_{t+1})}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})} + \frac{Cov^{\mathbb{Q}}_t(r^i_{t+1}, rx^{RoW(i),\$}_{t+1} + r^{RoW(i),EQ}_{t+1}))}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})} \\
&= \frac{w_i Var^{\mathbb{Q}}_t(r^i_{t+1})}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})} + \frac{Cov^{\mathbb{Q}}_t(r^i_{t+1}, rx^{i,\$}_{t+1})}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})} + \frac{Cov^{\mathbb{Q}}_t(r^i_{t+1}, rx^{RoW(i),i}_{t+1} + r^{RoW(i),EQ}_{t+1})}{Var^{\mathbb{Q}}_t(r^{wp}_{t+1})} \\
&\equiv \boldsymbol{Var^{\mathbb{Q}}Share^i_t} + \underbrace{\boldsymbol{\beta}^{\mathbb{Q},FX}_{i,t}}_{\equiv \text{ Risk Neutral FX Beta}} + \psi^i_t
\end{aligned}$$

Risk neutral covariance between foreign equity return and foreign currency return can be interpreted as below.[28]

$$\begin{aligned}
Cov^{\mathbb{Q}^\$}_t(R^i_{t+1}, RX^{i,\$}_{t+1}) &= \mathbb{E}^{\mathbb{Q}^\$}_t[R^i_{t+1} RX^{i,\$}_{t+1}] - \mathbb{E}^{\mathbb{Q}^\$}[R^i_{t+1}]\mathbb{E}^{\mathbb{Q}^\$}[RX^{i,\$}_{t+1}] \\
&= R^\$_{f,t}\mathbb{E}^{\mathbb{P}}_t[M^\$_{t+1} R^i_{t+1} RX^{i,\$}_{t+1}] - (R^\$_{f,t})^2 \delta \mathbb{E}^{\mathbb{P}}_t[M^\$_{t+1} RX^{i,\$}_{t+1}] \\
&= \underbrace{\mathbb{E}^{\mathbb{P}}_t[R^i_{t+1} RX^{i,\$}_{t+1}] - (R^\$_{f,t})^2\delta}_{\text{Premium on Exorbitant Privilege}} + \underbrace{R^\$_{f,t} Cov^{\mathbb{P}}_t(M^\$_{t+1}, R^i_{t+1} RX^{i,\$}_{t+1})}_{\substack{\approx \text{ Gourinchas-Rey(2014)} \\ \text{Exorbitant Privilege}}}
\end{aligned}$$

[28] $\delta = \mathbb{E}^{\mathbb{P}}_t[M^i_{t+1} R^i_{t+1} RX^{\$,i}_{t+1}]$.

# F. Figures and Tables for Extension 1.5.2

Figure A.10: **Q-P Covariance Spreads**

The figure shows the spreads between Q covariance and P covariance for several regions along with VIX: Europe, Japan, and Germany. A blue line is $Cov_{i,t}^{\mathbb{Q},FX} - Cov_{i,t}^{\mathbb{P},FX}$. The Q covariances are constructed using a combination of ETFs and options following Section 1.5.2.

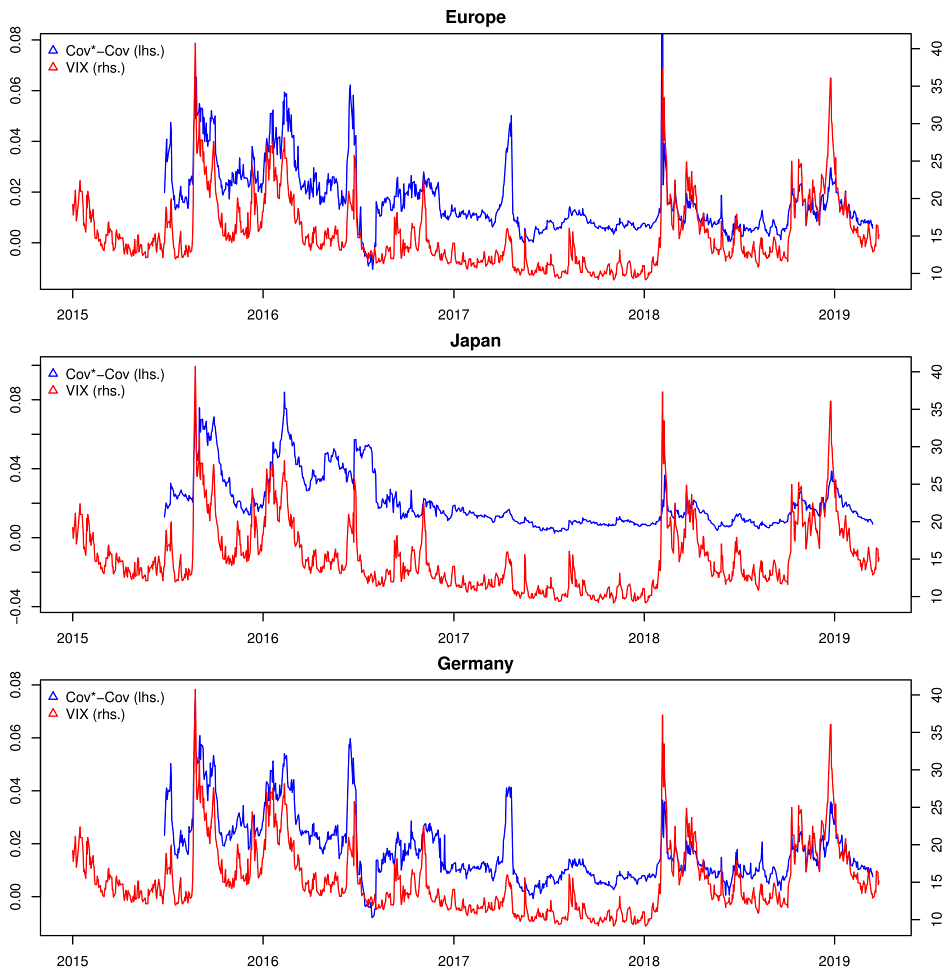


Table A.1: **Country Index Return on P and Q Covariances**

Panel A in the table shows the regressions of P covariance and Q covariance between equity and corresponding currency returns for each country, $Cov_t^{\mathbb{P}}(r_{t+1}^i, rx_{t+1}^{i,\$})$ and $Cov_t^{\mathbb{Q}}(r_{t+1}^i, rx_{t+1}^{i,\$})$. In Panel B, it documents the regression of the pooled regression with P and Q covariances of all the countries. The sample period for return on MSCI index is from 2010 up to December, 2018. The sample period for risk neutral FX beta is from January 2015 to December, 2018. Standard errors are reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

| | | *Forecast Horizon* | | | | |
|---|---|---|---|---|---|---|
| Panel A | | 1d | 1w | 2w | 3w | 4w |
| EU | P | -0.008 | 0.214 | 0.446 | 0.476 | 0.446 |
| | | (0.075) | (0.307) | (0.508) | (0.678) | (0.735) |
| | Q | -0.131*** | -0.785*** | -1.294*** | -1.523*** | -1.766*** |
| | | (0.039) | (0.142) | (0.199) | (0.266) | (0.350) |
| JP | P | 0.0004 | 0.285 | 0.928* | 1.862*** | 3.020*** |
| | | (0.067) | (0.354) | (0.514) | (0.586) | (0.618) |
| | Q | -0.168** | -1.046*** | -1.870*** | -2.609*** | -3.251*** |
| | | (0.066) | (0.275) | (0.316) | (0.297) | (0.291) |
| DE | P | 0.007 | 0.369 | 0.896 | 1.001 | 0.968 |
| | | (0.079) | (0.386) | (0.634) | (0.834) | (0.928) |
| | Q | -0.128*** | -0.890*** | -1.495*** | -1.879*** | -2.341*** |
| | | (0.044) | (0.184) | (0.228) | (0.266) | (0.337) |
| FR | P | -0.024 | 0.205 | 0.560 | 0.618 | 0.637 |
| | | (0.074) | (0.326) | (0.547) | (0.754) | (0.844) |
| | Q | -0.124*** | -0.751*** | -1.275*** | -1.533*** | -1.787*** |
| | | (0.039) | (0.170) | (0.217) | (0.263) | (0.353) |
| IT | P | -0.040 | 0.159 | 0.462 | 0.323 | 0.006 |
| | | (0.106) | (0.486) | (0.761) | (0.967) | (1.071) |
| | Q | -0.159*** | -0.966*** | -1.666*** | -1.985*** | -2.266*** |
| | | (0.053) | (0.198) | (0.293) | (0.395) | (0.507) |
| $R^2_P$ | | 0.000 | 0.003 | 0.013 | 0.022 | 0.037 |
| $R^2_Q$ | | 0.018 | 0.115 | 0.192 | 0.213 | 0.234 |
| Panel B | | | | | | |
| *Pooled* | P | -0.010 | 0.206 | 0.565** | 0.789** | 1.001*** |
| | | (0.033) | (0.162) | (0.249) | (0.316) | (0.363) |
| | Q | -0.139*** | -0.865*** | -1.477*** | -1.834*** | -2.185*** |
| | | (0.021) | (0.085) | (0.114) | (0.146) | (0.189) |
| $R^2_P$ | | 0.00003 | 0.002 | 0.010 | 0.014 | 0.017 |
| $R^2_Q$ | | 0.017 | 0.110 | 0.182 | 0.200 | 0.219 |

Table A.2: **Country Index Return on P and Q FX Betas**

Panel A in the table shows the regressions of P beta and Q beta between equity and corresponding currency returns for each country, $Cov_t^{\mathbb{P}}(r_{t+1}^i, rx_{t+1}^{i,\$})$ and $Cov_t^{\mathbb{Q}}(r_{t+1}^i, rx_{t+1}^{i,\$})$. In Panel B, it documents the regression of the pooled regression with P and Q FX betas of all the countries. The sample period for return on MSCI index is from 2010 up to December, 2018. The sample period for risk neutral FX beta is from January 2015 to December, 2018. Standard errors are reported in parentheses. $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01.

| | | *Forecast Horizon* | | | | |
|---|---|---|---|---|---|---|
| Panel A | | 1d | 1w | 2w | 3w | 4w |
| EU | P | 0.0002 | 0.004 | 0.009** | 0.014*** | 0.019*** |
| | | (0.0005) | (0.003) | (0.004) | (0.005) | (0.006) |
| | Q | 0.001 | 0.007*** | 0.012*** | 0.018*** | 0.025*** |
| | | (0.0005) | (0.003) | (0.004) | (0.004) | (0.005) |
| JP | P | -0.0004 | -0.001 | 0.001 | 0.004 | 0.010** |
| | | (0.001) | (0.004) | (0.004) | (0.004) | (0.005) |
| | Q | -0.055*** | -0.312*** | -0.493*** | -0.619*** | -0.715*** |
| | | (0.011) | (0.039) | (0.047) | (0.050) | (0.065) |
| DE | P | -0.002*** | -0.010*** | -0.011*** | -0.010* | -0.008 |
| | | (0.001) | (0.003) | (0.004) | (0.006) | (0.007) |
| | Q | -0.049*** | -0.297*** | -0.480*** | -0.580*** | -0.688*** |
| | | (0.010) | (0.041) | (0.052) | (0.054) | (0.073) |
| FR | P | -0.002*** | -0.010*** | -0.010** | -0.010* | -0.006 |
| | | (0.001) | (0.003) | (0.004) | (0.005) | (0.006) |
| | Q | -0.051*** | -0.281*** | -0.435*** | -0.531*** | -0.612*** |
| | | (0.010) | (0.037) | (0.047) | (0.051) | (0.065) |
| IT | P | -0.002*** | -0.009*** | -0.009* | -0.010 | -0.012 |
| | | (0.001) | (0.003) | (0.005) | (0.007) | (0.008) |
| | Q | -0.056*** | -0.297*** | -0.449*** | -0.539*** | -0.644*** |
| | | (0.014) | (0.047) | (0.065) | (0.085) | (0.110) |
| $R^2_P$ | | 0.0001 | 0.005 | 0.019 | 0.031 | 0.048 |
| $R^2_Q$ | | 0.002 | 0.022 | 0.041 | 0.054 | 0.071 |
| Panel B | | | | | | |
| *Pooled* | P | 0.0001 | 0.003** | 0.008*** | 0.012*** | 0.016*** |
| | | (0.0003) | (0.001) | (0.002) | (0.002) | (0.003) |
| | Q | 0.001** | 0.007*** | 0.013*** | 0.018*** | 0.024*** |
| | | (0.0003) | (0.001) | (0.002) | (0.002) | (0.003) |
| $R^2_P$ | | 0.00002 | 0.004 | 0.015 | 0.024 | 0.036 |
| $R^2_Q$ | | 0.001 | 0.017 | 0.035 | 0.047 | 0.064 |

Table A.3: **Correlation of variables (daily)**

This table shows the daily correlations of risk neutral covariances between equity and corresponding currency returns for Europe with other major variables.

| | RNC (Europe) | FX Return | Local Equity Return | BBD (2016) UK | VIX | SMB | HML | RMW | CMA | MOM |
|---|---|---|---|---|---|---|---|---|---|---|
| RNC(Europe) | 1 | | | | | | | | | |
| FX Return | 0.036 | 1 | | | | | | | | |
| Local Equity Return | -0.168 | 0.002 | 1 | | | | | | | |
| BBD(2016) UK | 0.063 | -0.023 | -0.045 | 1 | | | | | | |
| VIX | 0.692 | 0.04 | -0.176 | -0.23 | 1 | | | | | |
| SMB | 0.024 | -0.006 | -0.591 | -0.008 | 0.033 | 1 | | | | |
| HML | -0.056 | -0.01 | 0.221 | 0.02 | -0.06 | -0.171 | 1 | | | |
| RMW | 0.089 | 0.002 | -0.169 | 0.004 | 0.102 | 0.115 | -0.85 | 1 | | |
| CMA | 0.053 | 0.016 | -0.019 | 0.085 | 0.007 | -0.069 | 0.66 | -0.565 | 1 | |
| MOM | 0.038 | -0.002 | -0.318 | 0.062 | 0.018 | 0.192 | -0.44 | 0.369 | -0.117 | 1 |

Table A.4: **Correlation of variables (monthly)**

This table shows the monthly correlations of risk neutral covariances between equity and corresponding currency returns for Japan with other major variables.

| | RNC (JPN) | FX Ret | Local Equity Ret | VIX | BBD (2016) Economic | BBD (2016) Fiscal | BBD (2016) Monetary | BBD (2016) Trade | BBD (2016) Exchange Rate |
|---|---|---|---|---|---|---|---|---|---|
| RNC (JPN) | 1 | | | | | | | | |
| FX Ret | -0.311 | 1 | | | | | | | |
| Local Ret | -0.422 | 0.613 | 1 | | | | | | |
| VIX | 0.689 | -0.226 | -0.621 | 1 | | | | | |
| BBD(2016) Economic | 0.642 | -0.229 | -0.166 | 0.239 | 1 | | | | |
| BBD(2016) Fiscal | 0.639 | -0.298 | -0.2 | 0.213 | 0.954 | 1 | | | |
| BBD(2016) Monetary | 0.737 | -0.268 | -0.213 | 0.284 | 0.828 | 0.817 | 1 | | |
| BBD(2016) Trade | 0.065 | 0.154 | 0.019 | 0.185 | 0.408 | 0.262 | 0.113 | 1 | |
| BBD(2016) Exc. Rate | 0.623 | -0.211 | -0.32 | 0.249 | 0.714 | 0.78 | 0.635 | 0.103 | 1 |

# Chapter 2

# Beyond Financialization of Commodities: Hedging Demands and Predictability in the Futures Market

## 2.1 Introduction

A while ago, Tang and Xiong (2012) documented that the popularized index investments increased correlations within commodity futures and correlations between commodities and equity. Following their findings, Cheng and Xiong (2013) also documented the second point, and Basak and Pavlova (2015) recently developed a formal model to accommodate this so-called Financialization of Commodities. However, if one tracks what happened in those markets after 2010, at which the periods of many paper's scopes stopped, the correlation between commodities and equity has decreased sharply in 2011, 2014, and 2015.

[Insert Figure 2.1 here.]

Figure 2.1 shows that it is not only commodity-equity correlation, but also correlations between bond and commodity and currency and commodity are highly time-varying. Myriad of previous papers ascribed increased correlation between commodity and equity to the rising popularity of index investment and the participation of the institutional investors, but there is no evidence that such popularity of index investment suddenly dropped in 2011, 2014, and 2015, nor there was a sudden outflow of the institutional money from the futures market. Therefore, I hypothesize there is some other reason that could cause this highly time-varying nature of cross-asset correlations, though the inflow of institutional money played a partial role in heightened correlations between equity and commodities in terms of long-term movements.

This paper consists of two parts. The first part is mainly about commodity returns and the second part is about currency returns. In the first part, this paper empirically tests what drives this time-varying cross-asset correlations and then, exploiting the results, proposes the new measure that signals trading activities and mispricing in the futures market relating them with return predictability. Beyond the financialization of commodities, this first part answers to why return correlations between asset classes, not only commodity and equity, are highly time-varying and experienced the sudden drops after 2012.

In the second part, which is about currency returns, I investigate the role of the limit to arbitrage in the currency market in a relation to return spillovers from the commodity market empirically and theoretically. This paper proposes a model of the limit to arbitrage with my purpose of understanding how different hedging and arbitrage activities would affect asset prices and returns. In my model[1], I introduce the motives to hedge exchange rate risks

[1]It is built upon Hong and Yogo (2012). Their model is of 1 producer and 1 speculator without local currency costs and the FX market. Their model is similar to Acharya et al.

in producers/dealers as well as margin constraints. Further, I introduce currency speculators in analogous to commodity speculators to clear the market. This part empirically investigates if commodity open interests predict currency excess returns.

This paper's main contribution is to document that trading and hedging activities with different asset classes, as opposed to mere fundamentals or index investments, affect return correlations of different asset classes and to propose a new measure to capture this phenomenon. This will complement our understanding of the futures market – especially, the commodity-equity relationship after 2010, which the previous literature cannot fully explain.

For the first part of this paper, I find the following evidences. First, the return correlation between equity and commodity is driven by the correlation of net positions of investors between equity and commodity. From 2 month returns and afterwards, it predicts positively future correlations of equity and commodity returns. The higher contemporaneous correlation of trading positions leads to higher correlations of returns in the future. For the commodity-bond pair involving a less riskier asset, I find that correlations of net positions predict negatively correlations of returns for corresponding pairs around 4 months and 6 months, signaling a reversal. Between FX and commodity, evidences are limited, and there are some predictability to return correlations around 3 months from the contemporaneous correlation of net positions.

Second, this measure, based on trading positions of commodity and bond, predicts strongly commodity future returns of 2 month and afterwards. The higher cross-asset trading activities of investors for the commodity-bond pair, the higher future returns for commodities. In contrast, between commodity and currency, the measure predicts negatively future commodity returns of 2

(2013), but the model of the latter is with an inventory decision.

month and afterwards. For the commodity-equity pair, the evidence is less comprehensive, but for returns of around 1 month and 16 weeks there seems some predictability.

Third, I examine alternative measures based on prices to test predictability. With the measure, using the contemporaneous correlation of returns, the higher the contemporaneous correlation of returns between commodity and bond, the *lower* the future commodity returns of 1 month and afterwards up to 6 months. This seems to capture reversals. For the pair of commodity and currency, the higher the contemporaneous correlation of returns, the higher the future commodity returns of 1 week and afterwards up to 6 months.

Overall, the findings suggest that studying how investors uses futures contracts of different asset classes can shed light on what types of futures are momentarily mispriced, independent of their fundamentals, and how likely they are to revert, which affect future returns depending on risks of paired assets. When paired with bond, which is safer, higher cross-asset trading positions suggest underpricing of commodities and reversals. On the other hand, when paired with currency, which is risky, higher cross-asset trading positions suggest overpricing of commodities and following negative returns. All of the results are obtained after controlling well known predictors in the futures market such as Basis and Hedging Pressure.[2]

For the second part of this paper, I find that theory suggests the currency excess return is decreasing in commodity open interests in a direction of covariance between the corresponding exchange rate and commodity price, if a state of economy in a next period is good. Conversely, the currency excess return is increasing in commodity open interests in a direction of covariance between the corresponding exchange rate and commodity price, if a state of economy

[2] Basis is from Gorton et al. (2013) and Hedging Pressure is from Kang et al. (2017)

in a next period is bad. Furthermore, theory suggests that the impact from hedging demands of commodities on currency excess returns is proportional to the following three factors: the informativeness ratio of the currency and commodity market, mean risk aversion of investors in the currency market, and the covariance between corresponding currency and commodity.

The empirical analysis backs up these theoretical predictions. First, short and long positions of producers predict currency excess returns with negative coefficients. This evidence suggests hedging demands of commodity, in short horizon, predicts *depreciation* of foreign currency and hence lower excess returns. One point increase in short positions of WTI oil futures, the commodity hedging demand, *lowers* currency excess returns of Australian dollar by 0.66 point. Similarly, it *lowers* currency excess returns of Mexican peso by 0.61 point. The contributions of this part are (i) to empirically document the cross-predictability of hedging demands of commodities/fixed income to currency excess returns for a set of currency pairs and (ii) to develop a model of commodity producers that explains a mechanism of why such predictability occurs. In a broader context, this paper also contributes to the long strand of commodity currency literature since Chen and Rogoff (2003) in International Economics, in that I bring the limits of arbitrage perspective and quantify it with weekly data given its literature is typically of much lower frequencies.

The rest of paper goes as follows. Section 2.2 covers a brief literature, Section 2.3 covers the main empirical analysis. I introduce a new measure of mispricing, decompose cross-asset return correlations, and finally examine return predictability with proposed measures of different specifications. Section 2.4 covers currency returns with an empirical analysis and a theoretical work on a role of the limit to the arbitrage in the futures market in a relation to spillovers from the commodity market, and Section 2.5 concludes the paper.

Section 2.3 answers four questions. i) Why did once-heightened return correlations between commodities and equity drop after 2011?, ii) (partially) Why are return correlations between asset classes, not only commodities and equity, highly time-varying?, iii) How can we exploit this relationship between return correlations and net positions to predict future returns?

## 2.2 Literature

On Financialization of Commodities, Tang and Xiong (2012) first documented the direct effect of index investments. It showed a large increase in the price volatility of non-energy commodities around 2008. This became a basis for the following works. Gorton et al. (2013) first formerly examined a role of physical inventories and the convenience yield in the commodity market. They also documented that price measures such as Basis reflect information on inventories and costs of commodity carry and are closely tied to the convenience yield. Their study is between 1971 and 2010. In their paper, they did not find an evidence of the quantity data, i.e. long and short positions of commodity futures, having a predictive power to the risk premiums in the future. Further, Kang et al. (2017) empirically studied how two countervailing forces, long-term hedging demands of commercial hedgers and short-term liquidity demands of impatient speculators, affect variations in the expected returns of commodity futures with opposite signs. On a theoretical side, Basak and Pavlova (2015) developed a formal equilibrium model that shows commodity future prices, volatilities, and correlations among commodities and between commodity and equity increase with the financialization of commodities due to the common factor, with the presence of the institutional investors whose utility is a function of commodity indices. They also showed that the effect is stronger for the indexed commodities than non-indexed commodities.

Other strands of papers study its linkage to the currency market and the limit to arbitrage especially in the futures markets. First, Ready et al. (2017) developed a general equilibrium model that links international trade and currency pricing and showed that commodity-currency exchange rates and risk premia are driven by productivity differentials between two countries and trade frictions. Cheng et al. (2014) studied the responses of commodity future prices and positions to changes in VIX. They found convective risk flows, that is, hedgers reduce their short positions and traders reduce their long positions during the crisis in a response to the market distress. Further, Hong and Yogo (2012) pay attention especially to information open interests have about economic uncertainty. They studied if volumes of futures are informative or not within the same asset class. (e.g commodity futures to commodity returns) They found that the movements in commodity open interests predict movements in corresponding asset prices as well as in the bond and stock markets. They also proposed a simple model in which open interests predict corresponding returns in the same asset class. Similarly, Acharya et al. (2013) studied how the limit on the risk-taking capacity of speculators affects commodity prices via the optimal inventory decisions. They built a similar model as Hong and Yogo (2012) and empirically found that such hedging demands of producers are one of the important sources that affect commodity prices.

## 2.3 Empirical Analysis

### 2.3.1 Data

My main datasets consist of the data from the following: Commodity Research Bureau, Commodity Futures Trading Commission (Henceforth, CFTC), Bloomberg, and Thomson Reuters. All the positions of commodity[3] and currency futures are from Commitment of Traders (COT) report at CFTC, Disaggregated COT report, Financial Futures report. All of the above are of weekly frequency or those converted from daily returns. Data are from 2006 to 2016. I also examine financial futures (bond, fx, equity).

For commodities, I use weekly returns with different horizons. Table 2.1 shows summary statistics of commodity future returns. Many types of commodities exhibit negative returns. Basis and Hedging Pressure are computed following the earlier literature.[4] Three overpricing measures I introduce are: correlation of net positions with other assets, covariance of net positions with other assets, and correlation of returns with other assets. These are computed for each type of commodities and used either quantity data (i.e. long and short positions in open interests[5]) from CFTC[6] or price data from CRB (Commodity Research Bureau). I explain the construction of these measures in detail in Section 2.3.2. Lastly, tenor shows the maximum tenor available in each types of commodity futures contracts. As known, WTI is the most liquid type of commodity instruments.

[Insert Table 1 here.]

[3]Types of commodity futures we examine are such as Wheat, Corn, Soybeans, Soyoil, Soymeal, Hogs, Cocoa, Wheat, Coffee, Cotton, Sugar, WTI, Gasoline, Natural Gas, Gold, Copper

[4]Kang et al. (2017), Gorton et al. (2013)

[5]Types of investors/positions I examine in open interests of futures are: All Open Interests, Producer Long, Producer Short, Swap Dealer Short, Swap Dealer Long,Swap Dealer Spread, Money Manager Short, Money Manager Long, Money Manager Spread, Other Reportables Long, Other Reportables Short, Total Positions Long, Total Positions Short, Non-Report Positions Long, Non-Report Positions Short.

[6]Details are found in CFTC - Disaggregated Explanatory Notes

### 2.3.2 Measure: Mispricing in Asset Classes

I introduce a new measure, using either quantity or price data, to capture how crowded trading activities are and mispricing in each commodity futures contract. The baseline version of the measure is the following. I omitted a time-subscript from all the variables, because it is common to all.

$$Measure_{i,m} = \sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr(HP_i, HP_{j,m}) \tag{2.1}$$

$i = \{wheat, corn, wti, ..., copper\}$

$j = \{AUDUSD, USDJPY, EURUSD, ..., SP500, VIX, ..., TBond, TBondUltra...\}$

$m = \{FX, Equity, Bond\}$

$HP_i = (ShortPosition_i - LongPosition_i)/OpenInterest_i$

For each commodity i and a paired asset class m, I compute rolling pairwise correlations and covariances of Hedging Pressures in commodity futures i and other financial futures j within the paired asset class, m. Hedging Pressure are defined as $HP_i = (ShortPosition_i - LongPosition_i)/OpenInterest_i$ [7] and are time-varying and contract-specific, though they are not specific to tenors. Paired assets are in three classes: bond, equity, and currency. I compute rolling correlation/covariance in each period t for the combination of (**N** of commodity types)$*$(**N** of bond futures types + **N** of equity futures types + **N** of currency futures Types), then aggregate within each asset classes of paired assets (bond, equity, fx). These yield the three measures that capture overpricing: $Measure_{i,Bond} = \sum \frac{OI_{j,Bond}}{\Sigma OI_{j,Bond}} Corr(HP_i, HP_{j,Bond})$, $Measure_{i,Equity}$, and

[7] To compute rolling correlation and covariances of positions held by the same categories of investors, I use the category of Leveraged Fund in financial futures and the category of Money Managers in commodity futures to match. Otherwise there is no corresponding counterpart for "producers" in financial futures quantity data.

$Measure_{i,FX}$. These measures capture mispricing in the futures market, because 1) correlation/covariance between net positions of two futures contracts in different asset classes tells us how much investors are betting on different asset class simultaneously, and the other investors deduce potential mispricing from large coordinated moves across different asset classess, 2) It relates itself to momentum. CTAs (Commodity Trading Advisors) who trade these futures often use momentum strategies with various types of futures contracts, and thus co-movements across futures contracts in different asset classes can indicate their willingness of trading on various asset classes exploiting factors rather than asset class-specific events and supply-demand fundamentals.[8]

I list alternatives to the proposed measure below. The first one is normalized covariance of hedging pressure weighted by open interests. The second is the return-based correlation. Instead of hedging pressure, which is net position for each type of futures contracts, I use 1-week returns of corresponding futures contract. One advantage of this alternative measure is that I can construct for every different tenor for any futures contract, rather than at the level of types of futures contract such as WTI and COCOA. In other words, this alternative is a less coarse measure of trading activities, despite being an indirect one.

Alternatives:

$$Measure_{i,m} = \sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} \frac{Cov(HP_i, HP_{j,m})}{\sigma(Cov(HP_i, HP_{j,m}))} \tag{2.2}$$

$$Measure^k_{i,m} = \sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr(R^k_i, R^k_{j,m}) \tag{2.3}$$

For the second alternative measure, I aggregate over paired futures contracts tenor-by-tenor within each asset class. A superscript k stands for a

[8]If they trade on fundamentals or specific events, effects of such trades should be reflected in fundamental-based covariates.

tenor of the underlying returns. Therefore, this version of the measure is dependent not only on a commodity type and paired asset class, but also on a tenor. Figure 2.2 and 2.3 show the time variations of the measures. Figure 2.2 shows Measure (2.1), and Figure 2.3 shows a version of Measure (2.3) for each paired asset class, aggregated over a type of commodity futures, i. First, the correlation of commodity with currency is very high on average in both specifications, though the former is more volatile than the return-based measure.

[Insert Figure 2.2 here.]

[Insert Figure 2.3 here.]

This is because of the tight connection between currency and commodity - that is, many commodity derivative instruments are dollar-denominated and hence the natural hedge or the risk-amplifying effect for foreign commodity investors through a channel of exchange rate fluctuation and the associated demands of trading currency futures. I will examine this tight relationship in detail in Section 2.4 empirically and theoretically.

Second, the correlation between commodity and equity confirms the findings from the earlier literature – that is, the correlation between the GSCI and the S&P500 stock Index has spiked from the end of 2008, throughout 2000, and towards the end of 2009. Since then, the average level of equity-commodity correlation stay high relative to before.

Third, the correlation between commodity and bond shows an opposite pattern – that is, their correlation dips while the correlation between equity and bond went high (see Figure 2.1). This is not surprising, as bond is safer asset than equity and commodity and the financial crisis triggered investors to fly to safer assets.

### 2.3.3 Decomposing Cross-asset Return Correlation

Many papers[9] ascribed increased return correlations between equity and commodity to the increased popularity of indexing and the inflow of institutional money into the commodity market. If it is solely driven by them, the following should also be true: If there are no high correlation between equity and commodity, then there should not be the gained popularity of indexing and the inflow of institutional money into the commodity market. However, this is not true.

[Insert Figure 2.4 here.]

Figure 2.4 shows cross-asset correlations of returns for three pairs of asset classes (commodity v.s. bond/equity/fx respectively) by tenor. In any tenor, it shows that commodity-equity correlations have dropped around 2014, despite the initial surge after the financial crisis. Given that there is no evidence that the popularity of indexing has suddenly dropped around that time, it is hard to ascribe the increased correlation between equity and commodity solely to the increased popularity of indexing and the inflow of institutional money into the futures market.

I document excess correlations driven by leveraged money along the baseline correlation across asset classes in the market. I calculate an excess correlation of futures returns across different asset classes in the following manner.

$$\begin{aligned} &ExcessCorrelation_{m,t} \\ &= \sum^{N} \frac{1}{N} \sum^{K} \frac{1}{K} \Big( \sum \frac{OI_{j,m}}{\Sigma^{J} OI_{j,m}} Corr_t(R_i^k, R_{j,m}^k) - \sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr_t(R_i^{k=1}, R_{j,m}^{k=1}) \Big) \end{aligned}$$

[9] Tang and Xiong (2012), Cheng and Xiong (2013), and Basak and Pavlova (2015)

This construction results in three aggregate variables: *Excess Correlation*$_{Bond}$, *Excess Correlation*$_{Equity}$, and *Excess Correlation*$_{FX}$. Using these, I plot an aggregated excess correlation against an aggregated fundamental correlation, $FundamentalCorrelation_{m,t} = \sum^{N} \frac{1}{N} \sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr_t(R_i^{k=1}, R_{j,m}^{k=1})$. The reason I construct this way is due to the market structure of the futures market. Institutional investors who manage index products and hedge funds do not trade front-end contracts in general[10](i.e. contracts with tenor less than 1 month) due to the fact that they do not possess delivery capacities for underlying commodity products.[11] Even though it is not observable in the CFTC data, but the customary is that it is mainly players with real demands, e.g. commodity producers and airlines, who trade actively the front-month contracts to meet their short-term demand and supply mismatches.[12] Taken together, the effect of institutional investors should appear more strongly in the non-front end contracts. Hence, the difference of the aggregated cross-asset correlations with tenors longer than 1 and the aggregated cross-asset correlations only with tenor being 1.

Figure 2.1 shows the excess cross-asset correlations of commodities with paired assets of bond, equity and currency in blue, and the fundamental components of which in gray. In the middle panel of the equity-commodity correlation, it shows that excess and fundamental correlations tend to move together following the similar trends, but variations of the sizes in each correlation do

[10]Typically, who is active in front-end is those with physical demands and with delivery capabilities such as commodity producers such as exploration companies and refiners, mining companies, airline companies. Exception was when Goldman Sachs bought inventories company, which was registered with COMEX-CME, trying to profit from real commodity trading activities. Also, it was recently reported that Citadel acquired some delivery capabilities in physical commodity market.

[11]The CFTC regulation states that investors without physical delivery capabilities need to close out front-month positions by buying offsetting positions to match excess short/long positions by the end of the day.

[12]Documented in Kang et al. (2017)

not necessarily go to the same direction at each point of time (i.e. the fundamental correlation can be increasing or positive, while the excess counterpart is decreasing or even being negative).

To understand why return correlations between different asset classes are highly time-varying, I test if large co-movements of investors' net positions across asset classes affect the correlations of corresponding asset classes. I use the following specifications:

$$
\begin{aligned}
Corr_{t+q}(R_i^k, R_{j,m}^k) = {} & \alpha_{i,m,q}^k \\
& + \beta_{m,q} Corr_t\Bigg(\frac{(Short_i - Long_i)}{OI_i}, \frac{(Short_{j,m} - Long_{j,m})}{OI_{j,m}}\Bigg) + \epsilon_{i,j*m,t+q}^k
\end{aligned}
$$

The above model can be seen as the counterpart of cross-sectional regression in Fama-Macbeth regression with $\beta_{m,q}$. I estimate rolling-correlations in time-series first and run cross-sectional regressions of the correlation of returns on the correlation of net positions for different time horizons $q$ and each asset class $m$. This model uses *raw* rolling correlations so as to test the relationship in a clear fashion.

[Insert Table 2.3 here.]

Table 2.3 shows that the return correlation between equity and commodity is strongly driven by the correlation between net positions between equity and commodity especially after 8 weeks and afterwards in the horizons. This finding gives more comprehensive view on the drivers of the time-varying correlation between equity and commodity. The earlier literature documented the increased correlation between equity and commodity after the financial crisis and ascribed it to the inflow of institutional money due to the rise of index investing, which cannot explain the decreased time-varying return correlation after 2013. This measure used on the right hand side explains this highly time-varying correlation and its sudden drops after the financial crisis spanning the whole period, not only up to 2010.

### 2.3.4 Return Predictability of Cross-asset Net Position-based and Return-based Measures

In this section, I assess the predictability of the proposed measures. The other covariates are based on the earlier literature. HP(Hedging Pressure) is originated from Kang et al. (2017), and Basis is from Gorton et al. (2013).[13]

#### Model based on Net Position-based Measures

$$
\begin{aligned}
R^k_{i,t+1} = \alpha^k_{i,t+1} &+ \beta_{Bond}\Big(\sum \frac{OI_{j,Bond}}{\Sigma OI_{j,Bond}} Corr_t(HP^k_i, HP^k_{j,Bond})\Big) \\
&+ \beta_{Equity}\Big(\sum \frac{OI_{j,Equity}}{\Sigma OI_{j,Equity}} Corr_t(HP^k_i, HP^k_{j,Equity})\Big) \\
&+ \beta_{FX}\Big(\sum \frac{OI_{j,FX}}{\Sigma OI_{j,FX}} Corr_t(HP^k_i, HP^k_{j,FX})\Big) \\
&+ \beta_{HP} HP_t + \beta_{Basis} Basis_t + \beta_{CONTROL} CONTROL_t + \epsilon^k_{i,t+1}
\end{aligned}
$$

Table 2.4 shows that the proposed measures predict returns especially after 8 weeks horizon and afterwards. The measure of bond-commodity net position correlation predicts positively commodity returns in the future, while the measure of equity-commodity/fx-commodity net position correlation predicts negatively commodity returns in the future. As premise, the baseline correlation between commodity and bond is typically negative, while those with equity and with currency respectively are both positive. Then, the higher co-

[13] Basis is essentially commodity version of currency carry, which is a forward discount. Recently Koijen et al. (2018) summarizes forward discounts of different asset classes (fx, commodity, equity, and bond) and proposes a more unified view of this factor.

movement of the short positions with low-risk assets leads to the higher return of commodity in the future. In contrast, the higher co-movement of the short positions with high-risk assets leads to the lower return of commodity in the future. This suggests that underpricing is taking place for a pair of asset classes with low-risk assets, while overpricing is taking place for a pair of asset classes with high-risk assets. Further, findings on other variables are consistent with the literature. For instance, the coefficients of hedging pressure being negative reflect the counterveiling two forces documented in Kang et al. (2017), and controlling further short-term trading makes the positive relationship between hedging pressure and expected futures risk premium reemerge.

[Insert Table 2.4 here.]

With the result from Table 2.3 that the higher bond-commodity net position correlation leads to lower return correlations, I find that, from Table 2.4, the higher net position correlation leading to higher returns in the future is due to a potential reversal after commodities being traded more similarly to bonds than otherwise. This suggests either temporal underpricing on commodities or heighten riskiness reflecting a higher volatility. Also, a natural conjecture could be that higher bond-commodity return correlations lead to lower return in the future. The result from Table 2.5 confirms this triangular relationship between net position correlation, return correlation, and future returns.

### Model based on Return-based Measures

$$
\begin{aligned}
R^k_{i,t+1} = \alpha^k_{i,t+1} &+ \beta_{Bond}\Big(\sum \frac{OI_{j,Bond}}{\Sigma OI_{j,Bond}} Corr(R^k_i, R^k_{j,Bond})\Big) \\
&+ \beta_{Equity}\Big(\sum \frac{OI_{j,Equity}}{\Sigma OI_{j,Equity}} Corr(R^k_i, R^k_{j,Equity})\Big) \\
&+ \beta_{FX}\Big(\sum \frac{OI_{j,FX}}{\Sigma OI_{j,FX}} Corr(R^k_i, R^k_{j,FX})\Big) \\
&+ \beta_{HP} HP_t + \beta_{Basis} Basis_t + \beta_{CONTROL} CONTROL_t + \epsilon^k_{i,t+1}
\end{aligned}
$$

[Insert Table 2.5 here.]

In a similar manner, for currency-commodity pair, Table 2.4 suggests that higher currency-commodity net position correlation leads to lower future returns, and Table 2.5 suggests that higher currency-commodity return correlation leads to higher future returns. The fact that the signs of coefficients flip when the baseline independent variable, the net position-based measure, is swapped by the return-based measure reflects that the return-based measure captures reversals, while the net position-based measure involving open interests is more forward-looking. A natural conjecture would be the case that higher currency-commodity net position correlation leads to *lower* currency-commodity return correlations by triangular relationship. However, Table 2.3 does not provide significant support for this relationship, but the direction of sign seems correct. Figure 2.5 visually describe these relationships.

**Model based on Alternative Net Position Measures**

$$
\begin{aligned}
R^k_{i,t+1} = \alpha^k_{i,t+1} &+ \beta_{Bond}\Big(\sum \frac{OI_{j,Bond}}{\Sigma OI_{j,Bond}} \frac{Cov_t(HP_i, HP_{j,Bond})}{\sigma(Cov_t(HP_i, HP_{j,Bond}))}\Big) \\
&+ \beta_{Equity}\Big(\sum \frac{OI_{j,Equity}}{\Sigma OI_{j,Equity}} \frac{Cov_t(HP_i, HP_{j,Equity})}{\sigma(Cov_t(HP_i, HP_{j,Equity}))}\Big) \\
&+ \beta_{FX}\Big(\sum \frac{OI_{j,FX}}{\Sigma OI_{j,FX}} \frac{Cov_t(HP_i, HP_{j,FX})}{\sigma(Cov_t(HP_i, HP_{j,FX}))}\Big) \\
&+ \beta_{HP} HP_t + \beta_{Basis} Basis_t + \beta_{CONTROL} CONTROL_t + \epsilon^k_{i,t+1}
\end{aligned}
$$

The last alternative specification is to use the covariance of net positions between asset classes. It is normalized by the volatilities of each types of paired assets. I did not find an evidence for bond-commodity and FX-commodity pair. This echos the view that Pollet and Wilson (2010) argue for the stock market in that higher aggregate risk can be revealed by higher correlation between futures in this setting.

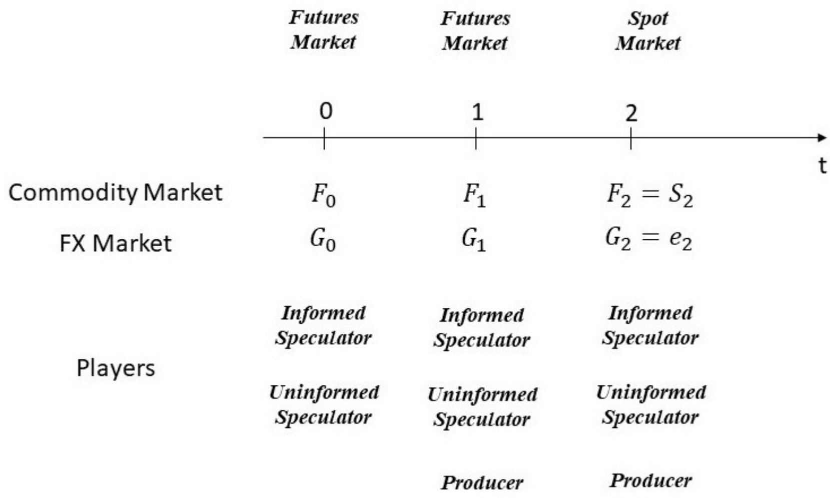
[Insert Table 2.6 here.]

## 2.4 Currency Returns: Predictability of Open Interests

### 2.4.1 Theory

My motivation in this section is based on several facts regarding the commodity market. First, commodity production is around the world. Second, many of commodity financial products are quoted in dollars and transacted in dollars. Therefore, non-US commodity producers inherently bear currency risk on top of commodity price risk as long as there are local currency costs that they need to pay. Further, the covariance of the prices between these two assets are non-

**Environment**




zero. That means having position in one of these two assets gives producers "natural hedge" against the other risk or amplifies the risk they are facing.

I present a simple model where a commodity producer faces both foreign exchange rate risk and commodity price fluctuation risk, which they need to hedge away.[14] There are the commodity futures/spot market and currency futures/spot market. Speculators in each market consist of an informed speculator and uninformed speculator, of which populations are denoted by $\lambda$ and $1-\lambda$ respectively. They trade with a commodity producer. Depending on a state of the economy, who takes which side of the trades changes. An environment is the above. There are 3 periods, $t = 0, 1, 2$. In $t = 0$, only speculators trade those 2-period ahead futures, $F_0$, that expire in $t = 2$ each other in each market. In $t = 1$, a producer enters markets too, and all trade 1-period ahead futures, $F_1$, that mature in $t = 2$ with each other. Y is the quantity that a commodity producer *commits* to sell[15], C is the cost needs to be paid in a local

[14] As compared to Hong and Yogo (2012) and Acharya et al. (2013), our model includes a local currency cost, C, and a position for currency futures, $D^{Producer,FX}$ as well as a margin constraint

[15] as it is only a commitment, it can also be negative – in that case we interpret that a producer is buying contracts to meet an insufficient supply for a specific grade of commodity products

currency. $S_2$ is the spot price of commodity in $t = 2$, $e_2$ is spot exchange rate in $t = 2$, $F_1$ is commodity futures price $t = 1$, and $G_1$ is currency futures price $t = 1$. In $t = 2$, there are two states $Y = Y^H$ and $Y^L$ and an informed investor knows that in $t = 1$, but still faces uncertainty $\sigma_S^2$ and $\sigma_e^2$ respectively in both asset markets. I assume $|Y^H| > |Y^L|$ and $Y_L = 0$ for brevity.

A producer minimizes the variance of profits from commodity producing operations and the variance of profits from trading futures.

$$\min_{D_1^{P,COM}, D_1^{P,FX}} Var_1(S_2Y - (e_2 - \bar{e})C + (S_2 - F_1)D_1^{P,COM} + (e_2 - G_1)D_1^{P,FX}) \quad (2.4)$$

subject to

$$|D_1^{P,COM}|mS_1 \leq YS_2$$

One of the key features of the model is that he needs to pay local currency costs, C, not in dollar. This is true to the reality, as many commodity transactions and assets are dollar-denominated, and he faces local currency costs if he runs producing or refining operations in foreign countries other than US. C is fixed in the short run, which is reasonable as we are going to use *weekly* data, and it requires huge upfront fixed costs to operate businesses. It can be human resources, local capital inputs, and such.

The other key feature of the model is the margin constraint, $|D_1^{P,COM}|mS_1 \leq YS_2$. In a spirit of Garleanu and Pedersen (2011) , a producer faces this margin constraint with a multiplier $\Psi^P$.[16]

In the commodity market, the spot price $t = 2$ follows $S_2 \sim \mathcal{N}(S^H, \sigma_S^2)$ in a high state and $S_2 \sim \mathcal{N}(S^L, \sigma_S^2)$ in a low state. I assume $S^H > S^L$.

[16] In contrast to Garleanu and Pedersen (2011), a producer pledges future revenues from selling commodity outputs, $YS_2$, using short term loans. I assume a competitive credit market and normalizes a risk-free rate to 1.

There are two classes of investors, one is an informed investor, and it is a mass $\lambda \in (0,1)$ in the population of all investors. Another is an uninformed investor, a mass $(1-\lambda) \in (0,1)$ in the population of all investors. The difference is that an informed investor knows the distribution of S and e, though he still faces uncertainty. Specifically, their expectation formations are different in the following way. $I$ stands for "informed", and $U$ stands for "uninformed".

For an informed investor:

$$\mathbb{E}_0^I[S_2] = \overline{S}$$

$$\mathbb{E}_1^I[S_2] = \{S_H, S_L\}$$

$$Var_0^I[S_2] = Var_0^U[S_2] \neq \sigma_S^2$$

$$Var_1^I[S_2] = \sigma_S^2$$

For an uninformed investor:

$$\mathbb{E}_0^U[S_2] = \overline{S}$$

$$\mathbb{E}_1^U[S_2] = \overline{S}$$

$$Var_0^U[S_2] = Var_1^U[S_2] = Var_0^I[S_2]$$

His objective function is a standard mean-variance utility. $i = \{I, U\}$.

$$\max_{D_t^{i,COM}} \mathbb{E}_t^i[(F_{t+1} - F_t)]D_t^{i,COM} - \frac{\gamma_c}{2} Var_t^I[D_t^{i,COM}(F_{t+1} - F_t)] \tag{2.5}$$

subject to

$$|D_t^{I,COM}|mS_t \leq |D_t^{I,COM}(F_{t+1} - F_t)|$$

An informed investor chooses optimal positions in $t = 0, 1$. In this setting, I assume $R_f = 1$ , hence $M_{t+1} = 1$ for simplicity. I still can get a main economic mechanism with a constant SDF. On the other hand, an uninformed investor does not know the distribution of S and e and cannot form an expectation properly, so he keeps the prior $(0.5, 0.5)$ for each state. As a result, he uses a simple mean with the prior, $\overline{S} = S^H * 0.5 + S^L * 0.5$, regardless of time periods.

In the currency market, a formulation of investors are analogous to the one in the commodity market as follows. An informed investor and uninformed investor's optimal demands are:

$$\max_{D_t^{I,FX}} E[(G_{t+1} - G_t)]D_t^{I,FX} - \frac{\gamma_{FX}}{2} Var[D_t^{I,FX}(G_{t+1} - G_t)] \tag{2.6}$$

$$D_t^{I,FX} = \frac{E_t[(G_{t+1} - G_t)]}{\gamma_{FX} Var_t[G_{t+1} - G_t]} \tag{2.7}$$

$$D_t^{U,FX} = \frac{\overline{e} - G_t}{\gamma_{FX} Var_0[e_2]} \tag{2.8}$$

To solve for the equilibrium futures prices and returns, we need to solve backwards from period $t = 1$. Market clearing conditions are the following. In $t = 1$, $\lambda D_1^{I,COM} + (1-\lambda) D_1^{U,COM} + D_1^{P,COM} = 0$ for commodity and $\lambda D_1^{I,FX} + (1 - \lambda) D_1^{U,FX} + D_1^{P,FX} = 0$ for currency. In $t = 0$, $\lambda D_0^{I,COM} + (1 - \lambda) D_0^{U,COM} = 0$ for commodity and $\lambda D_0^{I,FX} + (1 - \lambda) D_0^{U,FX} = 0$ for currency.

With optimal demands and the market clearing conditions in both markets, futures prices at $t = 1$, $F_1^*$ and $G_1^*$, can be solved.[17] In a similar manner, using the market clearing condition in $t = 0$, I can solve out futures prices $F_0$ and $G_0$. Further, expressions for open interests can be found with

[17] See Section 2.7 Appendix.

the optimal future prices and optimal demands of speculators above. Open interest is the amount of futures contract outstanding, a count on one side of trades. It depends on the realization of a state of the economy in $t = 2$. For instance, $\mathbf{O}_1^{COM,H} = |-Y - \frac{\Psi^P m S_1}{2\sigma_S^2(1-\rho^2)}|$, when only producers short.

With the equilibrium futures price $G_1^*$, one can find an expression for the currency excess return, $R_2^{FX} = e_2 - G_1^*$, which is a return on buying futures in $t = 1$ and sell it in the spot market in $t = 2$. Given the currency excess return, $\mathbb{E}_t[R_{t+1}^{FX}]$, and the open interests

**Proposition 1.** *The currency excess return is decreasing/increasing in the commodity open interests,* $\mathbf{O}_t^{COM}$*, with a direction of covariance between the corresponding exchange rate and commodity price when the state of economy is high in the next period:*

$$\frac{d}{d\mathbf{O}_t^{COM,H}}\mathbb{E}_t[R_{t+1}^{FX}] = -\frac{\alpha_t \gamma_{FX}}{\lambda} Cov(e, S) \tag{2.9}$$

### 2.4.2 Empirical Analysis

In this section, I examine the main regression, which tests whether open interests of futures in the commodity market predict excess returns in the currency market. The specification is the following. The dependent variable is an excess return of holding foreign interest-bearing deposits for a home investor. $e_{t+1}$ and $e_t$ are denominated in a home currency (USD, EUR, GBP, JPY respectively) I always think a home investor as US investor, who is funded in dollars, to compute this excess return of a foreign currency. For the currency pairs that do not include USD, a home investor is either an Euro investor, a Sterling investor, or an Yen investor. Therefore, the interpretation of coefficients is the following. An independent variable predicts appreciation of foreign currency if a coefficient is positive and depreciation of foreign currency if a coefficient is negative.[18]

$$
\begin{aligned}
R^i_{t+1} = \alpha^{COM} &+ \beta_1(OpenInterests^{COM}_t) \\
&+ \beta_2(ProducerLong^{COM}_t) + \beta_3(ProducerShort^{COM}_t) \\
&+ \beta_4(SwapDealerLong^{COM}_t) + \beta_5(SwapDealerShort^{COM}_t) \\
&+ \beta_6(MoneyManagerLong^{COM}_t) + \beta_7(MoneyManagerShort^{COM}_t) \\
&+ \beta_8(CONTROLS^{i,COM}_t) + \epsilon^{i,COM}_{t+1}
\end{aligned}
$$

where $COM = \{WHEAT, CORN, WTI, ..., COPPER\}$,

$i = \{AUDNZD, AUDJPY, ..., GBPEUR, ..., USDAUD, ..., USDSGD, USDZAR\}$, and $R^i_{t+1} = e_{t+1} - G_t \simeq \Delta e_{t+1} + \tilde{r}_t - r_t$

[Insert Table 2.7 here.]

The main result is in Table 2.7, in a case of commodity futures positions for WTI. I find that short positions of producers and long positions of money managers have strongly statistically significant negative coefficients. For instance, taking example of AUDUSD, 1 unit increase (100,000 contracts) in producers' short position will *lower* the excess return of investing in Australian dollar interest-bearing assets by 0.66 points. This means 1 unit increase in short positions lead to 0.66 point *depreciation* of Australian dollar. This confirms two points raised before in the model. First, predictability from the commodity futures market to the currency market arises due to trading between commodity

[18] Controls include OTC trading volumes of Spot, Swap, and Forwards contracts as well as past price $e_{t+1}$.Those volume variables are converted into the growth terms.

producers and arbitragers and associated changes in dollar demands.[19] Second, the currency pairs, of which excess returns are responding strongly, are so-called commodity currencies. For instance, Australian dollar, New Zealand dollar, Canadian dollar, Danish Krone, Mexican Peso, Norwegian Krone, and South Africa respond well. In contrast, Japanese Yen, Islaeli Shekel, Swedish Krone, and Swiss Franc do not respond.

What does the quantity of the coefficients tell us? Let us go back to Proposition 1. The model says the coefficient on commodity open interests measures $\frac{\alpha_t \gamma_{FX}}{\lambda} Cov(e, S)$. Hence, the difference in sizes reflects either one fo these variables. First, $\alpha_t = \frac{\lambda Var_0(e_2)}{\lambda Var_0(e_2) + (1-\lambda)\sigma_e^2}$ is positive and bounded between $[0, 1]$. Rewriting $\alpha_t$ by $\alpha_t = \frac{\frac{\lambda}{\sigma_e^2}}{\frac{\lambda}{\sigma_e^2} + \frac{(1-\lambda)}{Var_0(e_2)}}$, it captures how informative the currency market is. Hence, the higher informativeness, the elasticity of currency excess returns to commodity hedging demands will be larger. The second quantity, $\frac{\gamma_{FX}}{\lambda}$, represents average risk aversion among informed investors, assuming risk aversion varies across investors. Therefore, the high coefficient means either high informativeness, high average risk aversion among informed investors, or high covariance between currency and commodity.

Let us interpret the sign in front of coefficients. With the sign in front of $\frac{\alpha_t \gamma_{FX}}{\lambda} Cov(e, S)$, which is *negative* if agents expect the state of economy is high in the next period, it means the following. If agents expect the next period going to be a high state, commodity hedging demands predict a sharper decrease in currency excess returns. The effect will be larger if the average risk aversion among informed agents is higher.

All open interests, producer's long and short interests, and money man-

[19]To be precise, "Producer" category includes refineries and such more upstream companies in the oil market, but overall it is been said that the main player whose positions are counted in this category is a producer. You can also recall Keynes-Hicks theory of Normal Backwardation(1930, 1946) - which states end-producers of commodity face far greater risks than end-consumers. Hence, the short positions by end-producers exceed the long position of end-consumers and it is net-short in futures curve.

agers' short interests strongly predict excess returns. Especially, the coefficients on short interests of producers are negative for currency pairs that involves USD. For instance, in case of AUDUSD, 1 point increase in producer short open interests leads to 0.66 point *decrease* in the excess return of AUDUSD. That means, the higher hedging demands from producers will lead to depreciation of a foreign currency against dollar. This result is aligned with the predictions of the model. The model shows why such depreciation can be induced. For currency pairs that involve dollar, a producer gets "natural hedge" for the exchange rate risk that he faces for his local costs when he hedges oil price fluctuations by shorting oil futures, as long as covariance between corresponding exchange rate and commodity price is negative. Then, he does not necessarily need to hedge all the exchange rate risk and thus hedging (long) demands for local currency (and hence short demand for dollar) become smaller than otherwise. In contrast, producers will get "natural risk amplification" if covariance between two assets are positive. In this case, the amount he optimally hedges is bigger than the fundamental demand of commodity futures. The same logic applies when he mainly hedges exchange rate risk via currency futures.

## 2.5 Conclusion

For commodity returns, I first show that the return correlations between different asset classes are driven by the net positions of investors. My mispricing measures exploiting this effect exhibit predictability for future commodity returns. This not only offers an updated and complementary view of equity-commodity linkages beyond the financialization of commodities, but also gives us a possibility of explaining time-varying return correlations for non-commodity pairs of asset classes, i.e. equity and bond, equity and currency, and bond and currency.

For currency returns, I motivate it with a simple model of arbitragers and hedgers and document the cross predictability of commodities hedging demands to currency excess returns, the prediction that commodity hedging demands predict decrease/increase in currency excess returns depending on the state of the economy in the future. In more general context, these findings do not limit themselves to the linkage between commodity and currency. The model is applicable to financial intermediaries instead of producers who hedge commodity and currency risks. Finally, these findings imply that prices are not fully reflecting past information, and therefore the volumes, both trading volumes of currencies and commodity open interests, are important sources to predict future returns to the extent of the limits to arbitrage being present.

## 2.6 Figures and Tables

Figure 2.1: **Cross-asset Fundamental Correlation of Returns**

This shows the cross-asset correlations of commodities with paired assets of bond, equity and currencies. The shaded lines by gray correspond to the fundamental components, while the blue parts corresponds to the excess components. The fundamental correlation is computed as $FundamentalCorrelation_{m,t} = \sum^{N} \frac{1}{N} \sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr_t(R_i^{k=1}, R_{j,m}^{k=1})$, where $m$ is a type of asset class paird with. $i$ and $j$ are each product within commodities and paired assert classes respectively (e.g. i=Oil, j=SP500, m=equity). In contrast, $ExcessCorrelation_{m,t} = \sum^{N} \frac{1}{N} \sum^{K} \frac{1}{K} \big( \sum \frac{OI_{j,m}}{\Sigma^{J} OI_{j,m}} Corr_t(R_i^{k}, R_{j,m}^{k}) - \sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr_t(R_i^{k=1}, R_{j,m}^{k=1}) \big)$.

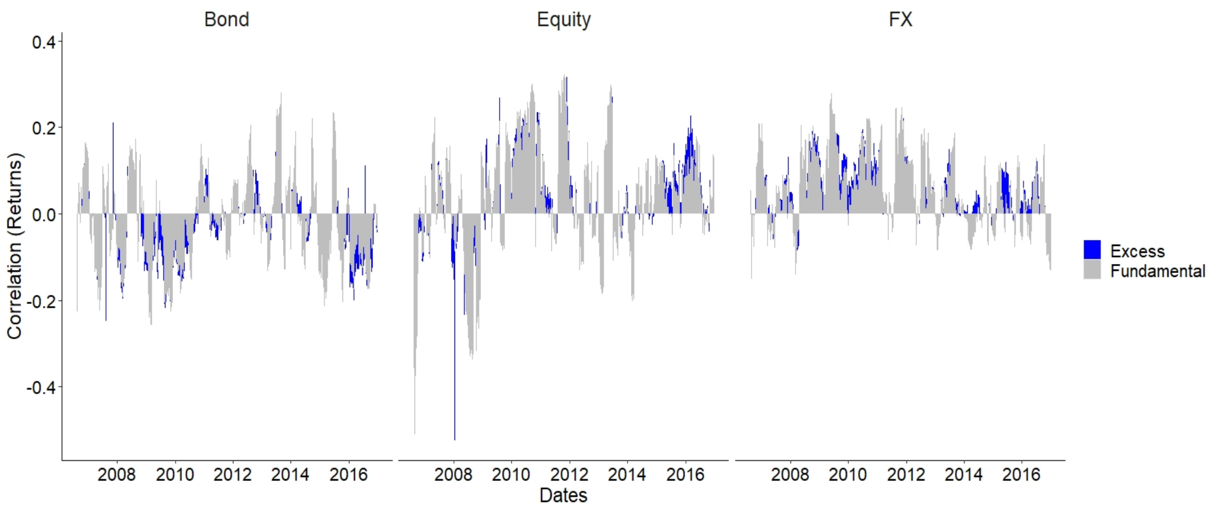


Figure 2.2: **Cross-asset Fundamental Correlation of Net Positions**

This shows rolling pairwise correlations of hedging pressure in the commodity futures with a paired asset j, aggregated by the asset classes, $\sum^{N} \frac{1}{N} \sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr(HP_i, HP_{j,m})$, where $i = \{wheat, ..., copper\}$, $j = \{AUDUSD, ..., SP500, ..., TBond, ...\}$, $m = \{FX, Bond, Equity\}$, and $HP_i = (ShortPosition_i - LongPosition_i)/OI_i$. $HP$ stands for Hedging Pressure, and $OI$ stands for Open Interests.

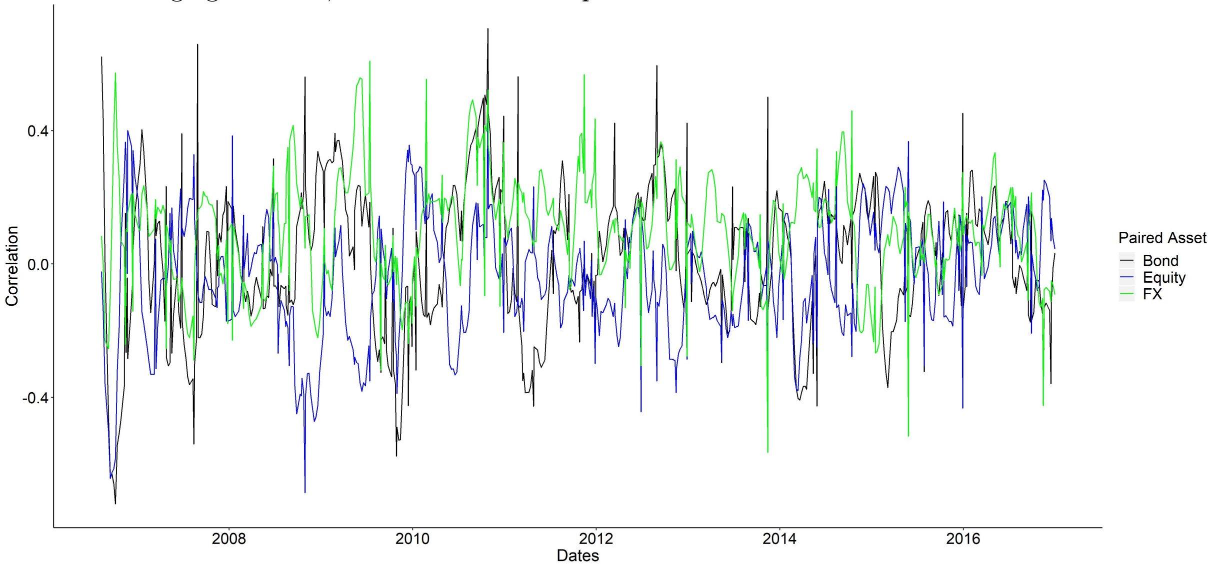



Figure 2.3: **Cross-asset Correlation of Returns**

This shows rolling pairwise correlations of returns for each tenor in the commodity futures with a paired asset j, aggregated by the asset classes, $\sum^{N} \frac{1}{N} \sum^{K} \frac{1}{K} \sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr(R_i^k, R_{j,m}^k)$, where $i = \{wheat, ..., copper\}$, $j = \{AUDUSD, ..., SP500, ..., TBond, ...\}$, $m = \{FX, Bond, Equity\}$, and $HP_i = (ShortPosition_i - LongPosition_i)/OI_i$. $OI$ stands for Open Interests.

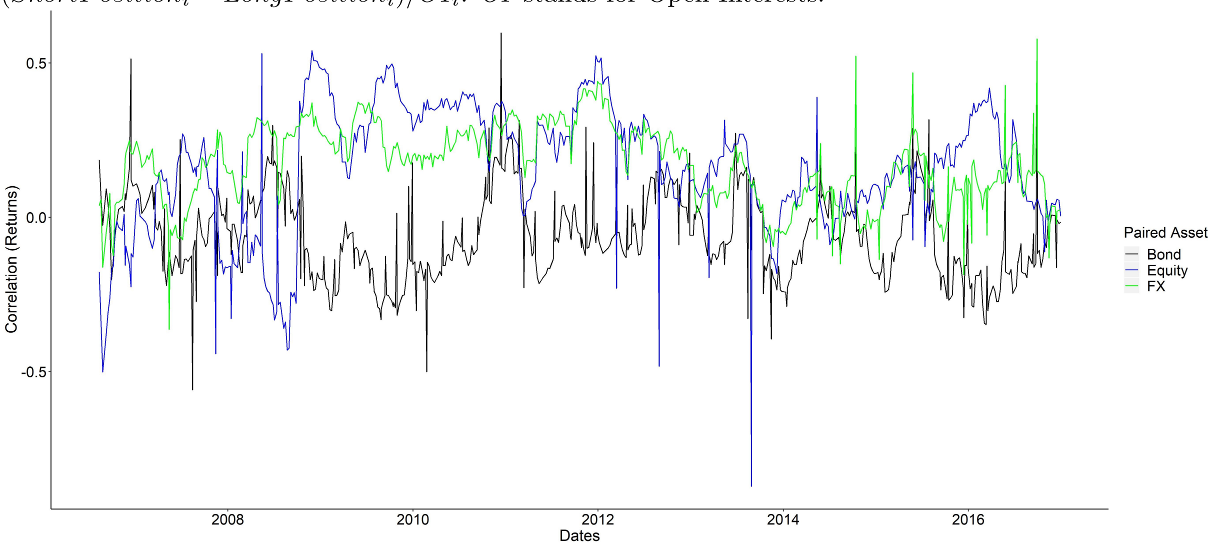


Figure 2.4: **Cross-asset Correlation of Returns by Tenor**

This shows rolling pairwise correlations of returns for each tenor in the commodity futures with a paired asset j, aggregated by the asset classes, $\sum^{N} \frac{1}{N} \sum \frac{OI_{j,m}}{\Sigma^{J} OI_{j,m}} Corr(R_i^k, R_{j,m}^k)$, where $i = \{wheat, ..., copper\}$, $j = \{AUDUSD, ..., SP500, ..., TBond, ...\}$, $m = \{FX, Bond, Equity\}$, and $HP_i = (ShortPosition_i - LongPosition_i)/OI_i$. $OI$ stands for Open Interests.

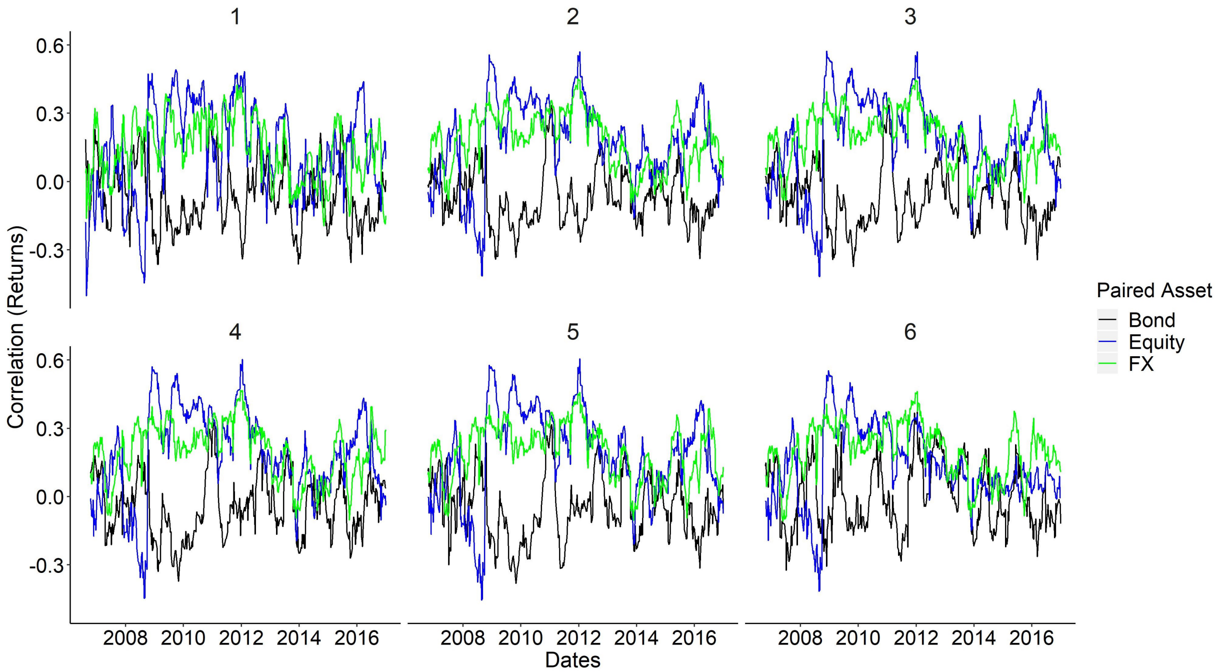


Figure 2.5: **Relationship between Net Positions and Returns**

A. Commodity paired with a less risky asset class: Bond

$$\begin{tikzcd} & \rho(NetPositions) \arrow[dl, "-"'] \arrow[dr, "+"] & \\ \rho(Returns) \arrow[rr, Rightarrow, "-"'] & & FutureReturns \end{tikzcd}$$

B. Commodity paired with a risky asset class: FX

$$\begin{tikzcd} & \rho(NetPositions) \arrow[dl, "-"'] \arrow[dr, "-"] & \\ \rho(Returns) \arrow[rr, Rightarrow, "+"'] & & FutureReturns \end{tikzcd}$$

# Tables

Table 2.1: **Summary Statistics**

The table shows the summary statistics of variables used in the paper. Returns are annualized and holding returns. Correlation/covariance are raw values, not the aggregated versions. Correlation of returns, $Corr_t(R_i^k, R_{j,m}^k)$, are measured by matching tenors of instruments, and correlation of net positions, $Corr_t\left(\frac{(Short_i - Long_i)}{OI_i}, \frac{(Short_{j,m} - Long_{j,m})}{OI_{j,m}}\right)$, are measured without information on tenors. Hedging Pressure and Basis are defined as $\frac{(Short_{i,t} - Long_{i,t})}{OI_{i,t}}$ and $\frac{ln(F_{i,t}^{k_2}) - ln(F_{i,t}^{k_1})}{k_2 - k_1}$. Data are from 2006 to 2016 and matched with the commodity database, CRB Futures.

| | Return 1w (%) | | Return 16w (%) | | Basis | | Hedging Pressure | | Correlation of Net Positions with Other Assets | | Covariance of Net Positions with Other Assets | | Correlation of Returns with Other Assets | | Tenors |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | s.d. | Mean | s.d. | Mean | s.d. | Mean | s.d. | Mean | s.d. | Mean | s.d. | Mean | s.d. | |
| COCOA | 2.81 | 26.93 | -0.66 | 23.88 | 0.002 | 0.01 | 118.10 | 44.45 | 0.02 | 0.47 | 3.71 | 90.22 | 0.16 | 0.28 | 9 |
| COFFEE | -1.15 | 28.27 | -1.32 | 26.45 | 0.013 | 0.01 | 20.88 | 29.70 | -0.02 | 0.49 | -16.25 | 209.33 | 0.10 | 0.30 | 14 |
| COTTON | -2.32 | 25.97 | -1.94 | 29.23 | 0.003 | 0.03 | 39.62 | 12.58 | 0.08 | 0.48 | 10.35 | 60.14 | 0.10 | 0.30 | 14 |
| SILVER | -16.02 | 25.07 | -7.61 | 22.37 | 0.003 | 0.00 | 42.66 | 44.40 | -0.03 | 0.47 | -8.79 | 147.77 | 0.20 | 0.30 | 22 |
| GOLD | 7.29 | 21.53 | 8.76 | 18.92 | 0.003 | 0.00 | 46.56 | 21.16 | 0.03 | 0.50 | 7.62 | 61.10 | 0.17 | 0.34 | 33 |
| COPPER | -3.54 | 27.07 | -2.85 | 26.26 | 0.000 | 0.00 | -11.04 | 9.60 | -0.04 | 0.44 | -0.76 | 14.01 | 0.16 | 0.37 | 24 |
| HOGS | -5.46 | 28.18 | -3.54 | 28.53 | 0.009 | 0.06 | 88.99 | 30.95 | 0.03 | 0.49 | 3.54 | 80.14 | 0.02 | 0.25 | 12 |
| SOYBEANS | -1.93 | 23.96 | -0.93 | 26.36 | -0.005 | 0.02 | 334.77 | 155.60 | 0.01 | 0.50 | 21.96 | 421.73 | 0.10 | 0.30 | 26 |
| SOYMEAL | -2.94 | 26.95 | 0.09 | 26.14 | -0.009 | 0.02 | 1.28 | 3.10 | 0.04 | 0.49 | 1.00 | 16.14 | 0.06 | 0.27 | 31 |
| SOYOIL | -8.73 | 22.97 | -8.56 | 26.77 | 0.004 | 0.00 | 96.80 | 38.33 | 0.07 | 0.47 | 8.05 | 79.35 | 0.11 | 0.31 | 31 |
| SUGAR | 2.29 | 27.04 | 0.20 | 27.69 | 0.002 | 0.03 | 80.95 | 41.91 | 0.01 | 0.49 | 4.87 | 112.62 | 0.09 | 0.28 | 11 |
| WHEAT | -5.31 | 30.67 | -5.12 | 28.87 | 0.013 | 0.03 | 94.55 | 54.62 | 0.05 | 0.47 | 13.74 | 137.87 | 0.09 | 0.29 | 15 |
| CORN | -6.07 | 29.22 | -4.64 | 31.56 | 0.005 | 0.03 | 31.20 | 19.84 | 0.09 | 0.49 | 12.61 | 73.05 | 0.10 | 0.28 | 19 |
| WTI | -3.69 | 28.33 | -5.52 | 33.08 | 0.004 | 0.01 | 104.20 | 55.15 | 0.05 | 0.53 | 11.39 | 76.75 | 0.09 | 0.34 | 36 |
| GASOLINE | -4.51 | 31.84 | -4.56 | 35.40 | 0.000 | 0.03 | 152.93 | 91.39 | 0.03 | 0.49 | 26.18 | 257.73 | 0.09 | 0.35 | 36 |
| NATURALGAS | -7.36 | 37.27 | -14.39 | 40.47 | 0.019 | 0.04 | 118.75 | 40.54 | 0.06 | 0.47 | 16.35 | 120.15 | 0.02 | 0.26 | 36 |

Table 2.2: **Correlation of Measures**

| | **Basis** | **HP** | **Bond** | **FX** | **Equity** | **MKT** | **SMB** | **HML** | **RMW** | **CMA** | **MOM** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Basis** | 1 | 0.46 | 0.15 | 0.03 | -0.1 | -0.03 | 0.01 | 0.11 | -0.07 | 0.03 | -0.1 |
| **HP** | | 1 | 0.07 | -0.14 | -0.05 | 0.05 | 0.04 | 0.06 | -0.12 | 0 | -0.05 |
| **Bond** | | | 1 | 0.13 | -0.14 | 0.08 | 0.09 | -0.03 | -0.1 | -0.02 | 0.06 |
| **FX** | | | | 1 | -0.21 | 0.05 | 0 | 0.06 | -0.02 | 0.11 | 0 |
| **Equity** | | | | | 1 | -0.07 | -0.02 | -0.13 | 0.04 | -0.03 | 0.13 |
| **MKT** | | | | | | 1 | 0.25 | 0.29 | -0.31 | -0.07 | -0.29 |
| **SMB** | | | | | | | 1 | 0.13 | -0.28 | -0.07 | -0.12 |
| **HML** | | | | | | | | 1 | -0.44 | 0.23 | -0.52 |
| **RMW** | | | | | | | | | 1 | 0.1 | 0.21 |
| **CMA** | | | | | | | | | | 1 | 0.05 |
| **MOM** | | | | | | | | | | | 1 |

Table 2.3:
**Fama-Macbeth Regression of Returns Correlation on Net Positions Correlation**

The table shows the results of weekly Fama-MacBeth regressions. It shows time-series averages of the slopes, $\frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_{t+q}$, from weekly Fama-MacBeth regressions of the cross-section of futures contract return correlation, $Corr_{t+q}(R_i^k, R_{j,m}^k)$, on $Corr_t\big(\frac{(Short_i - Long_i)}{OI_i}, \frac{(Short_{j,m} - Long_{j,m})}{OI_{j,m}}\big)$, raw net position correlations, and the controls including lagged return correlations of futures contracts. The time horizons, q, were chosen 1, 4, 8, 12, 16, 20, and 24 weeks. The regressions were run respectively for each paired asset class, m = bond, equity, and currency. Both $Corr_{t+q}(R_i^k, R_{j,m}^k)$ and $Corr_t\big(\frac{(Short_i - Long_i)}{OI_i}, \frac{(Short_{j,m} - Long_{j,m})}{OI_{j,m}}\big)$ are first estimated with a rolling 16 weeks window. T-statistics are reported in parentheses. Data are from Bloomberg, CFTC, and CRB Futures.

| | 1w | 4w | 8w | 12w | 16w | 20w | 24w |
|---|---|---|---|---|---|---|---|
| $\hat{\beta}_{Bond}$ | 0.164 | 0.187 | 0.08 | -0.061 | -0.159 | -0.1 | -0.201 |
| | (1.28) | (1.41) | (0.59) | (-0.69) | (-1.96) | (-1.17) | (-2.26) |
| $\hat{\beta}_{Equity}$ | 0.005 | 0.021 | 0.068 | 0.126 | 0.157 | 0.166 | 0.181 |
| | (0.17) | (0.70) | (2.15) | (3.84) | (4.78) | (4.91) | (5.23) |
| $\hat{\beta}_{FX}$ | -0.07 | -0.162 | -0.095 | 0.731 | -0.066 | 0.041 | -0.323 |
| | (-0.17) | (-0.42) | (-0.30) | (1.68) | (-0.26) | (0.18) | (-0.86) |
| Adj.$R^2$ | 0.277 | 0.268 | 0.259 | 0.246 | 0.227 | 0.215 | 0.196 |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 577 | 577 | 577 | 577 | 577 | 577 | 577 |

Table 2.4:
**Fama-Macbeth Regression of Commodity Returns on the Measure: Net Positions Correlation**

The table shows the results of weekly Fama-MacBeth regressions. It shows time-series averages of the slopes, $\frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_{t+q}$, from weekly Fama-MacBeth regressions of the commodity futures returns, $R^k_{i,t+q}$, on $\sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr_t(HP^k_i, HP^k_{j,m})$, constructed measures, and the controls: log basis, hedging pressure, and lagged futures returns. The time horizons, q, were chosen 1, 4, 8, 12, 16, 20, and 24 weeks. The RHS variable, $\sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr_t(HP^k_i, HP^k_{j,m})$, are first estimated with a rolling 16 weeks window. $HP_{i,t}$ and $Basis_{i,t}$ are defined as $\frac{(Short_{i,t}-Long_{i,t})}{OI_{i,t}}$ and $\frac{ln(F^{k_2}_{i,t})-ln(F^{k_1}_{i,t})}{k_2-k_1}$ respectively. T-statistics are reported in parentheses. Data are from Bloomberg, CFTC, and CRB Futures.

| | 1w | 4w | 8w | 12w | 16w | 20w | 24w |
|---|---|---|---|---|---|---|---|
| Bond | 0.041 | 0.094 | 0.185 | 0.306 | 0.442 | 0.577 | 0.611 |
| | (1.09) | (1.21) | (1.77) | (2.24) | (2.97) | (3.23) | (3.19) |
| Equity | -1.829 | -5.844 | -0.201 | -0.311 | -0.607 | -0.103 | 0.414 |
| | (-0.75) | (-1.65) | (-0.76) | (-0.95) | (-1.62) | (-0.34) | (0.50) |
| FX | -0.503 | -5.053 | -0.467 | -0.514 | -0.79 | -0.562 | -0.49 |
| | (-0.14) | (-1.49) | (-2.30) | (-1.98) | (-2.44) | (-1.54) | (-0.93) |
| HP | -0.007 | 0.016 | -0.003 | -0.002 | (-0.00) | -0.004 | -0.006 |
| | (-0.63) | (1.34) | (-1.37) | (-2.37) | (-2.52) | (-3.65) | (-2.53) |
| Basis | 6.878 | 18.393 | 24.553 | 11.847 | 7.569 | 9.817 | -0.769 |
| | (3.28) | (1.23) | (2.07) | (2.49) | (2.20) | (2.42) | (-0.03) |
| Adj. $R^2$ | 0.355 | 0.4 | 0.383 | 0.393 | 0.38 | 0.356 | 0.344 |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 542 | 542 | 542 | 542 | 542 | 542 | 542 |

Table 2.5:
**Fama-Macbeth Regression of Commodity Returns on the Measure: Returns Correlation**

The table shows the results of weekly Fama-MacBeth regressions. It shows time-series averages of the slopes, $\frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_{t+q}$, from weekly Fama-MacBeth regressions of the commodity futures returns, $R^k_{i,t+q}$, on $\sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr_t(R^k_i, R^k_{j,m})$, constructed measures, and the controls: log basis, hedging pressure, and lagged futures returns. The time horizons, q, were chosen 1, 4, 8, 12, 16, 20, and 24 weeks. The RHS variable, $\sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} Corr_t(R^k_i, R^k_{j,m})$, are first estimated with a rolling 16 weeks window. $HP_{i,t}$ and $Basis_{i,t}$ are defined as $\frac{(Short_{i,t}-Long_{i,t})}{OI_{i,t}}$ and $\frac{ln(F^{k_2}_{i,t})-ln(F^{k_1}_{i,t})}{k_2-k_1}$ respectively. T-statistics are reported in parentheses. Data are from Bloomberg, CFTC, and CRB Futures.

| | 1w | 4w | 8w | 12w | 16w | 20w | 24w |
|---|---|---|---|---|---|---|---|
| Bond | -0.031 | -0.141 | -0.414 | -0.55 | -0.582 | -0.843 | -1.078 |
| | (-0.68) | (-1.65) | (-3.11) | (-3.36) | (-3.24) | (-4.34) | (-5.03) |
| Equity | -0.004 | -0.035 | -0.062 | -0.08 | -0.087 | -0.182 | -0.079 |
| | (-0.12) | (-0.52) | (-0.57) | (-0.56) | (-0.56) | (-1.11) | (-0.46) |
| FX | 0.099 | 0.344 | 0.542 | 0.798 | 1.000 | 1.168 | 1.094 |
| | (1.76) | (3.54) | (3.68) | (4.47) | (4.80) | (5.49) | (4.99) |
| HP | 0 | -0.001 | -0.001 | -0.001 | (-0.00) | -0.002 | -0.002 |
| | (-1.03) | (-3.90) | (-3.60) | (-4.67) | (-4.86) | (-5.46) | (-5.62) |
| Basis | 1.556 | 5.548 | 8.679 | 10.321 | 10.95 | 10.478 | 8.934 |
| | (12.00) | (25.79) | (37.87) | (39.30) | (31.46) | (28.14) | (20.58) |
| Adj. $R^2$ | 0.373 | 0.398 | 0.412 | 0.409 | 0.399 | 0.381 | 0.355 |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 470 | 470 | 470 | 470 | 470 | 470 | 470 |

Table 2.6:
**Fama-Macbeth Regression of Commodity Returns on the Measure: Net Positions Covariance**

The table shows the results of weekly Fama-MacBeth regressions. It shows time-series averages of the slopes, $\frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_{t+q}$, from weekly Fama-MacBeth regressions of the commodity futures returns, $R^k_{i,t+q}$, on $\sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} \frac{Cov_t(HP_i,HP_{j,m})}{\sigma(Cov_t(HP_i,HP_{j,m}))}$, constructed measures, and the controls: log basis, hedging pressure, and lagged futures returns. The time horizons, q, were chosen 1, 4, 8, 12, 16, 20, and 24 weeks. The RHS variable, $\sum \frac{OI_{j,m}}{\Sigma OI_{j,m}} \frac{Cov_t(HP_i,HP_{j,m})}{\sigma(Cov_t(HP_i,HP_{j,m}))}$, are first estimated with a rolling 16 weeks window. $HP_{i,t}$ and $Basis_{i,t}$ are defined as $\frac{(Short_{i,t}-Long_{i,t})}{OI_{i,t}}$ and $\frac{ln(F^{k_2}_{i,t})-ln(F^{k_1}_{i,t})}{k_2-k_1}$ respectively. T-statistics are reported in parentheses. Data are from Bloomberg, CFTC, and CRB Futures.

| | 1w | 4w | 8w | 12w | 16w | 20w | 24w |
|---|---|---|---|---|---|---|---|
| Bond | -0.048 | 0.202 | -0.125 | -0.475 | -0.739 | -0.123 | 0.628 |
| | (-0.20) | (0.64) | (-0.36) | (-1.06) | (-1.05) | (-0.16) | (0.79) |
| Equity | -0.696 | 3.499 | 2.61 | 0.456 | 2.011 | 1.197 | 4.882 |
| | (-0.80) | (1.19) | (2.77) | (1.06) | (1.13) | (1.30) | (1.14) |
| FX | 0.003 | 4.649 | 1.915 | -0.081 | -0.273 | -0.249 | 0.162 |
| | (0.01) | (0.97) | (1.21) | (-0.20) | (-0.53) | (-0.50) | (0.21) |
| HP | 0 | -0.02 | -0.008 | -0.002 | (-0.00) | -0.002 | 0.001 |
| | (0.00) | (-1.31) | (-1.59) | (-2.90) | (-1.37) | (-3.54) | (0.26) |
| Basis | 3.597 | 16.503 | 22.224 | 8.589 | 5.811 | 9.03 | -4.567 |
| | (2.07) | (1.10) | (1.85) | (1.93) | (1.67) | (2.16) | (-0.15) |
| Adj. $R^2$ | 0.354 | 0.402 | 0.404 | 0.402 | 0.391 | 0.365 | 0.353 |
| Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 542 | 542 | 542 | 542 | 542 | 542 | 542 |

Table 2.7: **Predictability of Commodity Hedging Demands to Currency Returns**

The table shows the regressions of currency returns on commodity hedging demands, proxied by the open interests of futures contracts. In this example, the commodity is WTI oil futures. Controls are dollar amount trading volumes and lagged returns. Robust standard errors are reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Data are from Bloomberg, CFTC, and CRB Futures.

| Type of Institution | Position | GBP | AUD | EUR | NZD | CAD | CHF | DKK | HKD |
|---|---|---|---|---|---|---|---|---|---|
| All Open Interests | | 2.15* | 0.03 | -5.62 | 1.72 | -0.34 | 3.21 | -0.27 | 0.21 |
| | | (1.17) | (1.01) | (5.9) | (1.12) | (0.86) | (4.19) | (1.35) | (0.8) |
| Producer | Long | 0.07 | -0.17 | -1.67** | -0.06 | -0.13 | -5.64** | -2.74*** | -0.38* |
| | | (0.14) | (0.15) | (0.81) | (0.17) | (0.15) | (1.76) | (0.73) | (0.19) |
| | Short | -0.55** | -0.66*** | 2.19** | -1.15*** | -1.06*** | 6.01** | 0.12 | -1.69*** |
| | | (0.27) | (0.2) | (0.89) | (0.24) | (0.24) | (1.51) | (1.32) | (0.3) |
| Swap Dealer | Long | 0.58** | 0.68** | 3.54*** | 0.88*** | 0.68** | 4.47 | 4.2*** | 1.4*** |
| | | (0.3) | (0.3) | (1.43) | (0.34) | (0.29) | (2.75) | (1.78) | (0.33) |
| | Short | -4.04*** | -3.76*** | -1.42 | -4.68*** | -5.15*** | 3.36 | 3.92*** | -2.86*** |
| | | (0.29) | (0.29) | (0.95) | (0.25) | (0.28) | (2.54) | (1.08) | (0.31) |
| Money Manager | Long | -11.25*** | -5.94** | 24.49*** | -10.93*** | -8.36*** | -1.73 | -26.93*** | -1.47 |
| | | (2.65) | (1.95) | (6.88) | (1.94) | (2.12) | (22.03) | (8.96) | (2.94) |
| | Short | 0.57 | -0.13 | -0.26 | -0.43 | 0.31 | 5.16 | -3.23 | -0.77 |
| | | (0.38) | (0.33) | (1.64) | (0.39) | (0.37) | (2.17) | (3.17) | (0.42) |
| Adj, $R^2$ | | 0.72 | 0.56 | 0.48 | 0.64 | 0.72 | 0.35 | 0.6 | 0.32 |
| N | | 267 | 269 | 149 | 269 | 269 | 36 | 76 | 269 |
| Type of Institution | Position | ILS | JPY | KRW | MXN | NOK | SEK | SGD | ZAR |
| All Open Interests | | 0.9 | -4.46** | 0.66* | -0.47 | -0.81 | -0.1 | 1.12 | 1.37 |
| | | (0.57) | (2.32) | (0.29) | (0.44) | (0.6) | (1.53) | (0.85) | (0.98) |
| Producer | Long | 0.0 | -0.43* | 0.26 | -0.08 | -0.08 | -0.16 | -0.06 | -0.14 |
| | | (0.2) | (0.26) | (0.22) | (0.12) | (0.14) | (0.31) | (0.14) | (0.14) |
| | Short | -0.51* | -0.41 | -1.32*** | -0.61*** | -0.84*** | 0.1 | -0.89*** | -0.92*** |
| | | (0.23) | (0.38) | (0.35) | (0.16) | (0.2) | (0.38) | (0.2) | (0.2) |
| Swap Dealer | Long | -0.15 | -0.06 | -0.19 | 0.28 | 0.55** | -0.06 | 0.61** | 0.58** |
| | | (0.36) | (0.52) | (0.44) | (0.22) | (0.28) | (0.55) | (0.26) | (0.27) |
| | Short | -2.34*** | -0.92 | -4.96*** | -2.52*** | -3.87*** | -1.19 | -4.12*** | -4.03*** |
| | | (0.35) | (0.64) | (0.45) | (0.22) | (0.23) | (0.75) | (0.22) | (0.28) |
| Money Manager | Long | -5.24* | -2.43 | -7.57** | -4.34** | -6.38*** | 1.57 | -6.64*** | -6.29*** |
| | | (3.07) | (3.69) | (3.37) | (1.66) | (1.69) | (4.86) | (1.9) | (1.89) |
| | Short | -0.55 | -0.64 | -0.2 | 0.57* | 0.01 | 0.49 | 0.22 | 0.28 |
| | | (0.45) | (0.59) | (0.54) | (0.25) | (0.31) | (0.63) | (0.31) | (0.32) |
| Adj. $R^2$ | | 0.57 | 0.52 | 0.61 | 0.57 | 0.6 | 0.19 | 0.63 | 0.63 |
| N | | 268 | 269 | 249 | 269 | 268 | 110 | 269 | 268 |

## 2.7 Appendix

## A. Derivations: Forward Premium and Open Interests

Producers' optimal demands are

$$D_1^{*P,COM} = \begin{cases} -Y + \frac{\Psi_t^P m S_t}{2\sigma_S^2(1-\rho^2)}, & \text{if} \quad D_t^{P,COM} > 0 \\ -Y - \frac{\Psi_t^P m S_t}{2\sigma_S^2(1-\rho^2)}, & \text{if} \quad D_t^{P,COM} < 0 \end{cases}$$

$$D_1^{*P,FX} = \begin{cases} C - \frac{\rho}{\sigma_e \sigma_S} \frac{\Psi_t^P m S_t}{2(1-\rho^2)}, & \text{if} \quad D_t^{P,COM} > 0 \\ C + \frac{\rho}{\sigma_e \sigma_S} \frac{\Psi_t^P m S_t}{2(1-\rho^2)}, & \text{if} \quad D_t^{P,COM} < 0 \end{cases}$$

Investors' optimal demands are

$$D_t^{*I,COM} = \begin{cases} \frac{\mathbb{E}_t^I[(F_{t+1}-F_t)] + \Psi_t^S (S_{t+1}-F_t-S_t m)}{\gamma_c Var_t^I[F_{t+1}-F_t]}, & \text{if} \quad D_t^{I,COM} > 0 \\ \frac{\mathbb{E}_t^I[(F_{t+1}-F_t)] - \Psi_t^S (S_{t+1}-F_t-S_t m)}{\gamma_c Var_t^I[F_{t+1}-F_t]}, & \text{if} \quad D_t^{I,COM} < 0 \end{cases}$$

$$D_t^{*U,COM} = \begin{cases} \frac{\overline{S} - F_1 + \Psi_t^S (S_{t+1}-F_t-S_t m)}{\gamma_c Var_0^U[F_{t+1}-F_t]}, & \text{if} \quad D_t^{U,COM} > 0 \\ \frac{\overline{S} - F_1 - \Psi_t^S (S_{t+1}-F_t-S_t m)}{\gamma_c Var_0^U[F_{t+1}-F_t]}, & \text{if} \quad D_t^{U,COM} < 0 \end{cases}$$

In terms of equilibrium futures prices, when $\quad \mathrm{D}_t^{P,COM} < 0, \quad D_t^{I,COM} > 0, \quad and \quad D_t^{U,COM} > 0,$

$$F_1^* = \frac{1}{1+\Psi_1^S}\Big( -\frac{\omega_1 \gamma_{COM}\sigma_S^2}{\lambda}Y + \omega_1 \mathbb{E}_1^I[S_2] + (1-\omega_1)\overline{S} + \Psi_1^S(S_2 - S_1 m) - \Psi_1^P\left(\tfrac{\omega_1\gamma_{COM} m S_1}{2\lambda(1-\rho^2)}\right)\Big)$$

where $\omega_1 = \frac{\lambda Var_0(S_2)}{\lambda Var_0(S_2)+(1-\lambda)\sigma_s^2}$

$$G_1^* = \alpha_1 \mathbb{E}_1^I[e_2] + (1-\alpha_1)\overline{e} + \frac{\alpha_1\sigma_e^2\gamma_{FX}}{\lambda}\left(C + \frac{\rho}{\sigma_e\sigma_S}\frac{\Psi_1^P m S_1}{2(1-\rho^2)}\right)$$

where $\alpha_1 = \frac{\lambda Var_0(e_2)}{\lambda Var_0(e_2)+(1-\lambda)\sigma_e^2}$

Withe these, the currency excess return becomes

$$\mathbb{E}_1[R_2^{FX}] = (1-\alpha_1)(\mathbb{E}_1^I[e_2] - \overline{e_2}) - \frac{\alpha_1\gamma_{FX}\sigma_e^2}{\lambda}C + \frac{\alpha_1\gamma_{FX}Cov(e,S)}{\lambda}Y - \frac{\alpha_1\gamma_{FX}Cov(e,S)}{\lambda}\mathbf{O}_1^{COM,H}$$

# Chapter 3

# Real Integration and Asset Return Comovement

## 3.1 Introduction

A perennial issue in international finance is to understand how the forces of globalization shape the international comovement of asset returns - in particular that of stock markets. In this literature, there has been surprisingly little empirical evidence that the comovement of asset returns can be traced to real interlinkages, ie trade in goods and services. By contrast, the literature seems to have converged to a view that asset price comovement largely owes to financial integration. This perspective, widely known for instance by the work of

The finding that, in the aggregate, real integration does not affect the comovement of asset returns is striking against the backdrop of the magnitude of international trade, as well as event-study evidence documenting a pronounced stock return reaction to shocks affecting firms' export prospects or threats to import competition.[1] During the last decade, global trade in goods typically accounted for just shy of 30% of world GDP.[2] Given these numbers, one would expect that real interlinkages should play a non-negligible role in driving international equity market developments. But, past empirical research that has related stock market comovement and real integration—focusing on the relationship between overall trade integration (i.e. (exports+imports)/GDP) and the comovement of national stock market indices —has to date failed to provide evidence that the real side would matter. Recent work by Bekaert et al. (2016) for instance demonstrates that, once a time trend is included, there is no relation between standard measures of openness (aggregate imports and exports) and measures of equity market comovement. In a similar vein, Baele and Soriano (2010) conclude that the increase in equity market comovement mainly arises from financial rather than economic integration.

This paper revisits the role of real integration as a potentially important driver of international asset return comovement and overturns some of the previous dismal findings in this literature regarding the role of trade. One novel angle that we bring to the literature is to study real interconnectedness via bilateral measures of trade in final and intermediate goods and services, as opposed to aggregated measures of trade interlinkages examined in prior work. To make progress in the understanding of the role of trade, we assemble a data set on global value chain (GVCs), which we combine with data on bilateral stock market correlations. Another new feature is that we show how such trade data should be aggregated to construct measures of final goods

[1]For recent event study evidence showing that the stock prices of internationally-oriented firms are significantly affected by changes in (expected) trade policies as well as global supply chain disruptions see e.g., Desai and Hines (2008), Wagner et al. (2018), Huang et al. (2019), and Ramelli and Wagner (2020).

[2]For example, in 2018, global merchandise exports amounted to USD 19,450 billion, global service exports to USD 5850 billion , while global nominal GDP equalled USD 85,304 (UNCTAD, 2019)

and intermediate goods trade openness that are relevant to the international comovement of profits and hence equity prices.

We then show that intermediate and final good trade linkages are important drivers of global asset return comovement – both bilaterally between countries, and of single countries' stock markets with the world market portfolio. In contrast to the prior literature, we find a strong link between real integration and equity market comovement – a relation that remains significant also when controlling for trends or aggregate fluctuations, country characteristics, socioeconomic ties, and financial integration.

While the channels through which financial integration affects asset return comovement have received a fair amount of attention in the literature, less emphasis has been paid regarding the mechanisms through which real interlinkages affect comovement. We hypothesize that, as a starting point, real integration via GVCs should matter for asset comovements primarily via the impact of trade on profits of firms in different countries via sales in export markets as well as through cost (input-output, or GVC) linkages. This in turn will affect asset price comovement through (i) comovement in profits and expected cash flows to investors, and (ii) via greater synchronicity in macroeconomic quantities (e.g. output and inflation) which in turn will lead discount rates to comove. Trade interlinkages are likely to contribute to stock return comovement via a combination of these two channels.

We present a simple model of international trade guiding us how to construct two empirical measures of intermediate goods and final goods trade intensity (**ITI** and **FTI**, respectively) that matter for stock market comovement. The main mechanism operates via sales in export markets as well as cost linkages, and is quite intuitive: if a firm is based in country A and exports to country B, a negative demand shock in country B that in a closed economy would only lead to a decline profits and stock market returns of firms in country B will also affect export sales of firms based in A. This in turn will also depress profits and stock prices in country A, and ultimately induce a higher co-movement in the two country's stock markets. A second link arises from the input-cost channel: if a firm in country A sources inputs from B, a negative productivity shock in B will slow production down also in A, thus again leading to co-moving stock market returns. And, in a network of global input-output trade, third-country effects exist as well.[3]

The model-implied indices of real integration we derive allow us to resurrect international trade as an important driver of equity market comovement, besides financial integration. In our empirical analysis, we merge several datasets of bilateral final and intermediate goods trade linkages that have hitherto not been used in the literature on asset market comovement. These data—-a novel combination of the various vintages of the World Input-Output database from the latest ADB MRIO Input-Output Table and OECD Input-Output Database and IDE-JETRO Asian Input-Output tables used in Johnson and Noguera (2017)—cover up to 30 sectors, 41 countries (both developed and emerging ones) during the period 1980 to 2017.

We obtain thee main results. *First*, as a preliminary analysis, we show there are substantial differences between **ITI** and **FTI** on the one hand and traditional openness measures, such as (exports+imports)/GDP, on the other hand. In particular, **ITI** is very distinct from the traditional measures in large countries such as the US or Germany. *Second*, we find that bilateral stock market co-movement to be related to trade integration measured by granular input-output linkages and value added of trade (whereas the traditional trade measures also fail to explain stock market correlations in our sample). A one

[3]For simplicity, the model abstracts from financial factors, and only focuses on trade linkages in affecting bilateral stock market co-movement.

standard deviation in bilateral intermediate goods trade intensity is associated with a 24% of a standard deviation increase in bilateral stock market correlations, a sizable effect. *Third*, real integration remains a robust determinant of equity market correlation even when controlling for time trends, country characteristics, socioeconomic ties, and measures of financial integration. Even in the most complete specification including country-pair fixed effects and time trends, the effect remains economically and statistically strong.

Our approach thus allows us to resolve the failure of traditional measures of real integration in explaining international asset comovement. Tracing stock market comovement to cross-country linkages in final and intermediate goods trade is intuitive in light of the developments in trade over the past few decades. In today's trading system, the same good crosses borders multiple times differently depending on sectors as inputs in different countries. The aggregate volume of trade between countries, as often relied upon in past research, is therefore a highly inaccurate measure of true economic linkages. In contrast, our proposed measures take account of input-output linkages and value chain structure in trade flows. This in turn results in a more accurate representation of how much an economy depends on production inputs from its trading partner.

Overall, our findings suggest that international trade is indeed an economic force that matters for equity market comovement. This implies that investors seeking international diversification should pay attention to ongoing developments in international trade, and that policy-makers need to take into account both financial flows and real integration. The question of the impact of global trade on asset market developments is particularly relevant in light of recent geopolitical evens (not least, Brexit or the US-China trade war), as well as the ongoing disruption of supply chains due to the COVID-19 pandemic. These events underline the importance of examining how real integration via GVCs shapes international stock market comovement.

**Related literature.** Our paper contributes to three main strands of literature. First, it contributes to the literature on asset market comovement and international asset pricing.[4] Classical papers in this literature, e.g. Karolyi and Stulz (1996), Ang and Bekaert (1999), and Longin and Solnik (2001) typically focused on the measurement of comovement and questions around international diversification. Several papers also sought to connect international asset return comovement with the process of globalisation. For instance, Bekaert et al. (2009) study stock return comovements but did not find evidence for an upward trend in return correlations, except for European stock markets. Pukthuanthong and Roll (2009) propose a novel measure based on the regression $R^2$ of a global factor model and interpret their evidence as suggesting a rise in market integration over time.

Some work in international asset pricing has also tried to go a step further, linking comovement in returns with observable proxies for real and financial integration.[5] In early work, drawing on aggregate measures, Karolyi (2003) only finds very weak evidence of trade integration as a driver of asset comovements.

[4]See Lewis (2011) for a literature review.

[5]Some papers have approached this question indirectly from the standpoint of the Campbell and Shiller (1988) VAR framework. In particular, Ammer and Mei (1996) study the integration of stock markets between the United Sates and the United Kingdom and find that common news about future risk premiums accounts for the bulk of stock return comovements between the two countries, while the dividend growth components of the two returns are also highly correlated. Baele and Soriano (2010), also drawing on a Campbell-Shiller framework, document a rise in European stock market comovement, which they trace to greater comovement in discount rates, rather than cash flows. In another indirect approach, Petzev et al. (2016) observe that will a global factor model has increasing explanatory power (R-squared), there is no conclusive evidence for a global factor model catch-up in terms of pricing errors (alpha) or a convergence in country-specific factor premia. They argue that progressing real integration in the presence of remaining barriers to fully integrated pricing can explain this pattern. Caselli et al. (2019) also argue that international trade is a more relevant source of comovement than financial integration for most countries.

Lane and Milesi-Ferretti (2002) studies the impact of cross-country portfolio holdings via IMF CPIS data. Our paper relates closely to Bekaert et al. (2016) who provide a very thorough analysis of the drivers of international comovement in asset returns, including proxies of financial and real integration. While measures of financial integration perform quite well as explanatory variables, they show that trade flow fails to explain asset comovements once taking account of time trends. We advance this literature by showing that, properly measured, international trade powerfully helps explain international equity co-movement.[6]

Second, our paper contributes to a growing literature that employs the richness of economic networks to study asset pricing phenomena. A few papers have exploited trade networks. For instance, Du et al. (2018) study the predictability in CDS premia based on trade networks. Richmond (2019) documents that trade centrality plays a key role as a driver of risk premia in currency markets. Ready et al. (2017) link carry trade returns to commodity-trading patterns across countries. In addition, some recent papers argue that network structures themselves play an important role in the moments of asset prices. For instance, Herskovic et al. (2013) use customer-supplier network to analyze how shocks propagate through the network, thereby leading to an amplification that increases the volatility of returns. Gofman et al. (2020) focus on the vertical position in production networks and study implications for the predictability stock returns.

Last, but not least, our paper extends the growing literature on global value chains, which has hitherto largely focused on the real economy, by showing

[6]Some earlier studies suggest a link between trade and comovement, e.g. Chen and Zhang (1997) and Forbes and Chinn (2004). The robustness of those results is questionable, however. For instance, the earlier literature typically did not incorporate fixed effects nor socio-economic and financial variables studied in the international trade/finance literature, as pointed out also by Bekaert et al. (2016). As such, we regard our study to be the first one to document this relationship in robust fashion.

its power to explain phenomena in financial markets. Johnson and Noguera (2012) and Johnson and Noguera (2017) highlight the importance of GVCs and document that trade flows are most accurately captured through value added terms (see also Timmer et al. (2016)). Several papers try to establish a link with international business cycles and output synchronization. Auer et al. (2017) study the impact on domestic CPI inflation, while Auer et al. (2019) document that input-output linkages account for half of the synchronization in producer prices across countries. di Giovanni et al. (2018) document the evidence of transmission of business cycle shocks through direct trade and multinational ownership linkages at the firm level.[7] Some more recent work addresses the disruption of supply chains due to COVID-19; see, for example, Bonadio et al. (2020), who use the Huo et al. (2020) framework, and Eppinger et al. (2020).

Some authors have recently begun to link elements of trade activities to developments in financial markets. Gopinath and Stein (2018) argue that when a larger share of a country's imports are invoiced in U.S. dollar, its citizens have a greater demand for dollar-denominated safe claims. Bruno et al. (2018) argue that a dollar strength is a determinant of global trade activity, as a stronger dollar tightens of dollar credit conditions. Our paper extends this emerging literature on the relationship between GVCs and financial markets by providing the first evidence of the linkage between granular trade flows and equity comovement. In a related study, Di Giovanni and Hale (2021) study how US monetary policy shocks exhibit ripple effects throughout the world by way of global value chains. Our focus, by contrast, is not on the spillovers of monetary policy shocks but on the determinants of stock market comovement via trade channels (also between countries other than the US).

[7]Kalemli-Ozcan et al. (2009) show how banking sector integration affects GDP synchronization.

## 3.2 Measuring Real Integration and Its Effect on Profit Comovement

In this section, we use a theoretical model to examine how real linkages give rise to international comovement in profits and share prices. We show that the impact of bilateral trade linkages can be subsumed into two indices, one measuring final goods trade intensity (FTI) and another one measuring intermediate goods trade intensity (ITI).[8] We then construct these two indices of real integration using relevant International Trade Input-Output Tables in the subsequent section.

We want to model how firm profits, and consequently stock market valuations, comove in the presence of trade in final consumption goods, as well as reciprocal input-output linkages. As we will show, such linkages give rise to cross-border spillovers of national demand and supply shocks. We start from the perspective of an individual firm that sells its final good both domestically and on foreign export markets, and that sources its production inputs both domestically and internationally. We then aggregate firm-specific profit comovement to the national level, to examine how overall profits co-move depending on aggregate bilateral trade flows.

The notation we adopt is the following. $f \epsilon F$ indexes final goods producers. Each firm has one location of production, $c \epsilon C$. The set of firms that is located in country $c$ is $F_C$. A firm $f$ located in c sells to many export markets. For expositional clarity, when summing over exports to various markets, we index export markets by $e \epsilon C$. A firm $f$ located in c uses imports from potentially many source countries. For expositional clarity, when summing over imported

[8]In the empirical section, we take into consideration international trade in both goods and services. For sake of brevity, we refer only to "goods" in this theoretical section.

inputs from various sources, we index source countries by $s\epsilon C$.

The structure of the economy is as follows. In each country, a competitive input production sector transforms local labor into intermediate goods. Intermediate goods are used by monopolistic final producers. The output of these final goods producers is consumed by households. Both final and intermediate goods are internationally tradeable.

**Consumer demand, pricing, and profits.** Suppose that in each export market $e\epsilon C$, demand for each firm's consumption variety $f$ is isoelastic in its price, and sales are further affected by country-specific demand shocks $d_{e,t}$. At each point in time $t$, the representative household in $e$ obtains utility

$$u_{e,t} = d_{e,t} \sum_{f\epsilon F} (q_{f,e,t})^{\frac{\sigma-1}{\sigma}} + O_{e,t}, \tag{3.1}$$

where $O_{e,t}$ is the quantity of the outside O good that is available at a price normalized to 1. $d_{e,t}$ is a time-varying demand shifter for differentiated goods. $\sigma$ is the elasticity of substitution. The household's maximization of (3.1) implies that demand for variety $f$ on market $e$ is $q_{f,e,t} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} (p_{f,e,t} / d_{e,t})^{-\sigma}$.[9] If we denote the constant marginal cost of production of firm $f$ by $mc_{f,t}$ and the iceberg trade cost to ship from $f$'s home market $c$ to $e$ by $\tau_{c,e}$, the firm charges a price of $p_{f,e,t} = \frac{\sigma}{\sigma-1}\tau_{c,e} mc_{f,t}$. $f$'s profits on market $e$ are thus

$$\pi_{f,e,t} = (p_{f,e,t} - \tau_{c,e} mc_{f,t}) d_{e,t} = \frac{(d_{e,t})^{\sigma}}{(\tau_{c,e} mc_{f,t})^{(\sigma-1)}} (\sigma-1)^{-1} \tag{3.2}$$

Equation (3.2) also holds for domestic firms, i.e. the firms that are producing in market $e$. For the latter set of firms, $\tau_{e,e} = 1$, whereas $\tau_{c,e} > 1$ for all other firms.

[9] Throughout the analysis, we assume that income in $c$ is larger than $\left(\frac{\sigma-1}{\sigma}\right)^{\sigma} (d_{c,t})^{\sigma} \sum_{f\epsilon F} p_{f,c,t}^{1-\sigma}$, such that consumption of the O good is nonnegative.

**Production technologies & costs.** In each country $c$, final goods producers $f$ combine intermediate inputs to produce. Final good producers can use both domestic and imported input varieties. The production function features a constant elasticity of demand $\rho$ over each input good. Denoting firm $f$'s total production by $q_{f,t}$ and the amount of inputs that firm $f$ uses from supplying country $s$ by $q_{f,s,t}$, we have

$$q_{f,t} = \varphi_{f,t} \left( \sum_{s \epsilon C} \left(q_{f,s,t}\right)^{(\rho-1)/\rho} \right)^{\rho/(\rho-1)}. \tag{3.3}$$

Here, $\varphi_{f,t}$ is a firm-specific productivity shifter. Minimizing total costs $\sum_{s \epsilon C} p_{f,s,t} q_{f,s,t}$ for a given level of production implies that the marginal cost of production $mc_{f,t}$ is equal to

$$mc_{f,t} = \varphi_{f,t}^{-1} \left( \sum_{s \epsilon C} \left(p^I_{f,s,t}\right)^{-(\rho-1)} \right)^{-1/(\rho-1)} \tag{3.4}$$

Production of input goods is perfectly competitive. Each input good takes one unit of local labor to produce and can thus be produced at the wage of the supplying country $w_{s,t}$. It can be shipped from $s$ to the market where $f$ is located at iceberg trade costs $\tau^I_{s,c}$. It thus holds that $p^I_{f,s,t} = w_{s,t} \tau^I_{s,c}$.[10]

**The outside good and market equilibrium**. The production of the outside good is done in a competitive sector according to $y^O_{c,t} = \varphi^O_{c,t} L^O_{c,t}$. The outside good can be freely traded, which, together with the normalization of its price to 1 pins down the wage in each country: $w_{c,t} = \varphi^O_{c,t}$. Denoting labor supply in $c$ by $L_{c,t}$, market clearing requires that the amount of inputs used by firm f adjusted for the iceberg trade cost from c to f, $\tau^I_{c,f}$, plus the amount of labor that is used for the production of the outside good do not exceed the

[10] Iceberg shipping costs are $\tau^I_{c,c} = 1$. whereas $\tau^I_{s,c} > 1$ whenever $s \neq c$.

supply of labor: $\sum_{f\epsilon F}\tau^I_{c,f}q_{f,c,t} + L^O_{c,t} = L_{c,t}$.[11]

**Aggregation, shocks, and observables.** Above, we have laid out a firm-specific theory. However, we empirically observe trade linkages only at an aggregate level, that is, between countries. We therefore aggregate across firms and then show how shocks are propagated. Importantly, as we show in the appendix, the extent to which shocks at home and abroad affect the profitability of the domestic industry can be expressed in terms of sectoral aggregates that we observe in international input-output data sets. In what follows below, a $\widehat{}$ denotes a percentage change in a variable.

**Proposition 1** (Shocks and observables). *$\widehat{\pi}_{c,t}$, the change in total profits of c's industry is equal to*

$$\widehat{\pi}_{c,t} = -\left(\sigma - 1\right)\sum_{s\epsilon C}\gamma_{c,s,t}\widehat{w}_{s,t} + \sigma\sum_{e\epsilon C}s_{e,c,t}\widehat{d}_e + \widehat{\varepsilon}_{c,t}$$

*where $s_{e,c,t}$ is the share of sales that firms producing in c make in market e ($\sum_{e\epsilon C}s_{e,c,t} = 1$), $\gamma_{c,s,t}$ is the aggregate cost share of inputs from s in the production of final goods in c ($\sum_{s\epsilon C}\gamma_{c,s,t} = 1$), and $\widehat{\varepsilon}_{c,t}$ is equal to $(\sigma - 1)\,\widehat{\varphi}_{c,t}$.*

*Proof.* See appendix □

**Interpretation and derivation of bilateral real integration indices.** Proposition 1 provides a general result mapping profit comovement in a multi-country world. To see the intuition for this result, we next illustrate profit comovement in a two-country case, corresponding to an analysis of a given country vis-a-vis the rest of the world.[12] Indexing the two countries by 1 and

[11] If each national stock market is fully owned by local households and profits are fully disbursed, income in each market is equal to $w_{c,t}L_{c,t} + \sum_{f\epsilon F_c}\sum_{e\epsilon C}\pi_{f,e,t}$, where $F_c$ is the set of firms that is owned by households in $c$ and $e$ indexes export markets.

[12] We present a measure of value added trade that also accounts for third-country effects in the next section

2, Proposition 1 implies that the evolution of profits in country 1 is equal to[13]

$$\widehat{\pi}_1 = \sigma \left(\underbrace{s_{1,1}\widehat{d}_1}_{\substack{\text{home share}\\ \text{scaled by home}\\ \text{demand shock}}} + \underbrace{s_{1,2}\widehat{d}_2}_{\substack{\text{foreign sales}\\ \text{scaled by foreign}\\ \text{demand shock}}}\right) - (1-\sigma) \left(\underbrace{\gamma_{1,1}\widehat{w}_1}_{\substack{\text{intermed goods}\\ \text{home share scaled by}\\ \text{home supply shock}}} + \underbrace{\gamma_{1,2}\widehat{w}_2}_{\substack{\text{intermed goods}\\ \text{foreign sales scaled by}\\ \text{foreign scaled by supply shock}}}\right) + \widehat{\varepsilon}_1 \tag{3.5}$$

where $\widehat{d}$ and $\widehat{w}$ are the demand and supply shocks respectively for each country. A symmetric equation holds for country 2.[14]

Final good linkages create comovement because firms that sell final goods on the same markets are commonly affected by fluctuations in demand in this market. Assume that within a country, demand and supply shocks are independent and that the standard deviation of shocks within countries are identical.[15] Then, comovement can be captured by an index we call **FTI**, given by:[16]

$$Final\ Trade\ Intensity_{i,j} = \mathbf{FTI}_{i,j} = \underbrace{s_{j,i}}_{\substack{import\\ j\to i}} \underbrace{s_{i,i}}_{\substack{home\\ share\ i}} + \underbrace{s_{i,j}}_{\substack{export\\ i\to j}} \underbrace{s_{j,j}}_{\substack{home\\ share\ j}} \tag{3.6}$$

In turn, intermediate good linkages generate comovement as they propagate cost shocks. The strength of these effects can be aggregated into **ITI** as:

$$Intermediate\ Trade\ Intensity_{i,j} = \mathbf{ITI}_{i,j} = \underbrace{\gamma_{j,i}}_{\substack{import\\ j\to i}} \underbrace{\gamma_{i,i}}_{\substack{home\\ share\ i}} + \underbrace{\gamma_{i,j}}_{\substack{export\\ i\to j}} \underbrace{\gamma_{j,j}}_{\substack{home\\ share\ j}} \tag{3.7}$$

[13]All variables are indexed by $x_{exporter,importer}$.

[14]ie $\widehat{\pi}_2 = \sigma\left(s_{2,1}\widehat{d}_1 + s_{2,2}\widehat{d}_2\right) - (1-\sigma)\left(\gamma_{2,1}\widehat{w}_1 + \gamma_{2,2}\widehat{w}_2\right) + \widehat{\varepsilon}_2$

[15]That is, $var\left(\widehat{d}_1\right) = var\left(\widehat{d}_2\right) = \Omega_d^2$, while $var\left(\widehat{w}_1\right) = var\left(\widehat{w}_1\right) = \Omega_w^2$; and $cov\left(\widehat{d}_1, \widehat{d}_2\right) = cov\left(\widehat{w}_1, \widehat{w}_2\right) = 0$

[16]Note that $s_{1,1}$ are home shares in 1, ie $s_{1,1} = 1 - s_{2,1}$ and $s_{2,2} = 1 - s_{1,2}$.

Overall, intuitively, in this very simple model which abstracts from financial forces (and in particular the role of risk premia), trade linkages affect bilateral stock market co-movement through a profit channel that operates via sales in export markets and via cost linkages. First, if a firm is based in country A and exports to B, a negative demand shock in country B that in a closed economy would only lead to a decline of B's profits and hence stock prices will also affect export sales of firms based in A, thus depressing its stock price and ultimately leading to co-movement. A second link is via the input-cost channel: if a firm in country A sources inputs from B, a negative productivity shock in B will slow production down also in A, thus again leading to co-moving stock market returns. Third, in a network of global input-output trade, also higher-order effects matter, as for example a shock in country 1 affects prices in country 2, which in turn affects prices in country 1. Overall, the correlation of profits in two countries is given by:

$$\text{Corr}\left(\widehat{\pi}_1, \widehat{\pi}_2\right) = \underbrace{\frac{\sigma^2 \mathit{\Omega}_d^2}{\sigma_{\pi_1}\sigma_{\pi_2}}}_{\text{Demand shock } \beta} FTI_{1,2} + \underbrace{\frac{(1-\sigma)^2 \mathit{\Omega}_w^2}{\sigma_{\pi_1}\sigma_{\pi_2}}}_{\text{Supply shock } \beta} ITI_{1,2} \tag{3.8}$$

Here, $\mathit{\Omega}_d$ and $\mathit{\Omega}_w$ denote variance for demand shock and supply shock respectively. Intuitively, comovement of profits between two countries derives from a demand shock-driven component and supply shock-driven component. Empirically, since we do not know the elasticity of substitution $\mathit{\Omega}_d$ nor the variance of demand and supply shocks $\mathit{\Omega}_d$ and $\mathit{\Omega}_w$, we estimate those in a regression of the form

$$cov(\widehat{\pi}_1, \widehat{\pi}_2) = \widehat{\beta}_d FTI_{1,2} + \widehat{\beta}_w ITI_{1,2} \tag{3.9}$$

.

## 3.3 Measuring Integration and Equity Comovement: Data Sources

An overview of the definitions of all variables of interest is contained in Table A.1 in the Appendix. We present summary statistics in Table 1.1, which we discuss in the subsequent subsections. Correlations are in Table A.2 in the Appendix.

[Insert Table 3.1 here.]

### 3.3.1 Measuring Stock Market Comovement

Our dependent variable is equity index comovement of country $i$ and $j$ in year $t$. We follow Pukthuanthong and Roll, 2009) in employing equity indices from Thomson Datastream. Taking into account the data availability of international trade (see below), our sample consists of 40 countries from 1980 to 2017.

We use a popular form of static sample correlation that has been used both in and outside the comovements literature and we are able to show a strong evidence of real integration driving comovements, which the earlier literature found limited evidences with limited robustness and tried to resolve by looking at different measurements. Static sample correlation is a relevant measure for us to use, as opposed to rolling correlation.

We estimate annual realized correlations drawing on sums of cross-products of daily stock returns as follows

$$\hat{\rho}_{i,j,t} = \frac{\frac{1}{N(t)}\sum_{k=1}^{N(t)}(r_{i,k}-\overline{r_i})(r_{j,k}-\overline{r_j})}{\sqrt{\frac{1}{N(t)}\sum_{k=1}^{N(t)}(r_{i,k}-\overline{r_i})^2}\sqrt{\frac{1}{N(t)}\sum_{k=1}^{N(t)}(r_{j,k}-\overline{r_j})^2}}. \quad (3.10)$$

The methodological underpinning for this approach is provided by Barndorff-Nielsen and Shephard (2004) who study the asymptotic properties of realized variances and covariation based on the statistical theory of Quadratic Variation. Further, beyond the financial econometrics and stock comovement literature, realized correlations are widely used in other applications (see, e.g., Pollet and Wilson, 2010 or Cieslak and Schrimpf, 2019). We prefer this realized correlation measure over possible alternatives such as rolling correlations.

Table 1.1 presents summary statistics. The average equity market correlation is 0.32, but there is wide variation, with the interquartile range going from 0.12 to 0.49.

[Insert Figure 3.2 here.]

Figure 3.2 illustrates how the measure of comovement fluctuates over time, an in particular asks the questions if there are any discernible time trends. It provides a disaggregated look for advanced economies, emerging markets as well as frontier countries. As the graph shows, equity market comovement has generally picked up since the 1980s. Recently however, comovement has receded somewhat.

Correlation coefficients are not normally distributed, as they can take only values between -1 and 1. In most of our regression analysis, we, therefore, normalize our realized correlation measures and define:

$$\mathbf{RCORR}_{i,j,t} \equiv Inverse\ Normal(0.5 + 0.5 * \hat{\rho}_{i,j,t}) \quad (3.11)$$

With this transformation, our comovement measures become normally distributed with infinite support. Our results are robust to not employing this transformation.

### 3.3.2 Constructing ITI and FTI

We next construct the above-introduced measures of trade integration, **ITI** and **FTI**. For this part of the analysis, we combine two different data sets on global trade in final and input goods and services. For one, we rely on the data from Johnson and Noguera (2017) (henceforth, JN), which maps final and input-output trade for the period 1980-2009 in 42 advanced and emerging market economies.[17] Second, we use the Asian Development Bank's Multi-Region Input-Output Database (MRIO), which covers 41 countries and the years from 2008 to 2017.[18]

We chain these two data sets to result in an unbalanced panel of bilateral real integration from 1980 to 2017 for 40 countries. We include the union of the countries covered in JN and MRIO. Of the resulting 47 countries, 40 have a time series of daily stock markets returns reaching back to 1980.[19]

There are breaks between the JN and MRIO data. The reason is that the two sources are constructed using different methodologies - in particular originating when it comes to the employed input-output tables. We therefore chain the data sets as follows. The data from JN is used from 1980 to 2007 and the one from MRIO from 2008 onward. All pre-2008 data is chained backwards, ie. starting from the level in 2008 in MRIO and then using changes within the

[17] JN also covers the period 1970-1980, but we do not use this part of the analysis due to the lack of reliable stock market indices for a large number of markets

[18] See Mariasingham (2015) for a description of the methodology underlying the MRIO. Note that MRIO relies on the World Input Output Database (WIOD) developed in Timmer et al. (2015), which maps global input-output linkages from 1995 to 2011.

[19] The full list of countries in each dataset is in Table A.3. Of the 42 countries included in JN, ARG, CHL, IDN, ISR, NZL, ZAF are not included in MRIO. Of the 41 countries included in MRIO, BGR, CYP, HRV, LTU, and MLT are not included in JN.

JN data for every value before 2007. For example, the 2007 value is based on the 2008 MRIO data adjusted for the 2007-2008 change in JN. All chaining is done at the bilateral level (and for intermediate goods and bilateral final goods separately, as well as for imports and exports separately). For those countries included only in one of the two data sets, we use the full available data. [20]

The sample we cover has seen a dramatic rise in input-output trade, particular during the late 90s and the early 2000s. Figure 3.1 illustrates bilateral trade flows of intermediate goods in 1990 and 2006, respectively. Their comparison shows a change in the network structure of trade. Between 1990 and 2006, China have emerged as a hub and frontier countries such as Estonia, Slovenia, and Slovak Republic become embedded in GVCs.

As Table 1.1 indicates, the average level of **ITI** is only 0.006. However, the standard deviation is large, at 0.012. As an example of the drivers of **ITI**, take bilateral trade between Belgium (country $i$) and Russia (country $j$). On average for the years in our panel, for this country pair, the sample mean of $\gamma_{j,i}$ is 0.007, while the sample mean of $\gamma_{i,j}$ is 0.001. $\gamma_{i,i}$ and $\gamma_{j,j}$ are, respectively, 0.53 and 0.94 on average. With a relatively low home share in Belgium, the first component of ITI will have little weight because Russia as a trade partner is less prone to be affected by a local supply shock in Belgium.

As another example, take trade between France ($i$) and the US ($j$). Here, the sample mean of $\gamma_{j,i}$ is 0.011, while the sample mean of $\gamma_{i,j}$ is 0.001. Home share variables, $\gamma_{i,i}$ and $\gamma_{j,j}$, are, respectively, 0.88 and 0.95. With high home shares, trade flows between two countries will carry more weight because both countries are prone to supply shocks in each local market to pursue economic activity using intermediate goods. With a low home share in Belgium, a similar

[20]We note that since we employ a strategy to chain backwards using absolute changes, it is possible that negative trade flows results. This indeed happens in 604 observations. Whenever it does, we replace the respective data point by the value form the preceding year.

intermediate goods import would not necessarily lead to high trade intensity. Overall, in these two examples, $ITI_{FRA,USA} = 0.011$, while $ITI_{BEL,RUS} = 0.005$. In other words, the resulting intermediate goods trade intensity between France and the US is twice as high as trade intensity between Belgium and Russia.

3.2 Figure 3.3 compares **ITI** with the standard measure of openness, the ratio of exports and imports to GDP. While there is a positive correlation of openness and each of the proposed granular measures, the figure highlights that there are some substantial differences. The bottom-up trade index is in some cases very comparable to the simple trade measure (see, for example, Slovakia, Estonia on the open side and Argentina or Spain on the closed side), but very different in others, most importantly for the US and Germany. Intuitively, although, for example, the rest of the world is not very important to the US in terms of trade, the US is in many aspects very important to the rest of the world. It essentially serves as an important node in the GVC network.

[Insert Figure 3.3 here.]

### 3.3.3 Further Controls: Financial Integration, Historical Ties, and Third-Country Effects

In our regressions we control for factors that can affect stock return comovement other than real integration. A first candidate for this is international financial holdings which are commonly used to proxy for financial integration. The data used to construct variables of bilateral financial integration comes from CPIS (Coordinated Portfolio Investment Survey), IMF. It consists of 37 countries and spans 2001 through 2017. We define equity holdings, debt holdings, and total asset holdings by using total holdings of the institutions across all the sectors in both exporter and importer countries respectively.

We include other relevant variables commonly used in the literature as follows.[21] For bilateral institutional and socioeconomic backgrounds, we control for contiguity, shared languages, geographic distance, and common colonial histories. We obtain these data from the CEPII - GeoDist database.

We also control for a measure of the macroeconomic output cycle, following Bekaert et al. (2016). Output cycle is $Cycle_{i,t} = \frac{gdp_t}{gdp_{t-1}} - \frac{1}{5}\sum_{k=0}^{4} \frac{gdp_{t-k}}{gdp_{t-k-1}}$ using World Bank data.

In the literature, such as Bekaert et al. (2009), it is understood that the correlation between country return and the global factor increases as the volatility of factor increases, $\rho_{i,f} = \beta_i \frac{\sigma_f}{\sigma_i}$, and hence there is a need to control for the volatility of the global equity market. Because we study bilateral correlations, we instead use the volatilities of stock returns for each country pair (that is, the volatility of the importer and of the exporter) to control for effects from each underlying volatilities keeping covariance between two countries constant, and to control for possible volatility spillovers. Realized variance is constructed from Datastream data as $RV_{i,t} = \sum_{d=1}^{N_{days}(t)} [log(R_{t,d-1,d})]^2 \frac{22}{N_{days}(t)}$. Figure A-1 plots volatility over time.

Above, we have laid out how profits comove in a two country setting. However, in a multicountry setting, also third-country effects matter. One key channel is that trade flows also through indirect networks between countries. For example, two countries might be linked economically not because they trade with each other directly, as trade might flow via a third country.

Specifically, we follow Johnson and Noguera (2012) and define value added as

[21] See, e.g., Bekaert et al. (2016).

$$VA_{ij} \equiv \underbrace{\overbrace{f_{ij} + A_{ij}f_{jj}}^{\text{absorption}} + A_{ii}f_{ij} - \overbrace{[\iota[A_{ii} + A_{Ii}]\,\mathrm{diag}(f_{ij})]'}^{\text{total intermediate use}}}_{\text{net absorption}} + \underbrace{\sum_{k \neq i,j} A_{ik}f_{kj}}_{\text{indirect exports}} \tag{3.12}$$

$$\textbf{Value Added}_{i,j} = \frac{VA_{i,j}}{GDP_i} \tag{3.13}$$

where $f_{ij}$ is final goods absorbed in country j from sectors in country i, $A_{ij}$ is ij element of the global I-O matrix A. $A_{Ii} = \sum_{k \neq i} A_{ki}$ is the overall imported input use matrix for country i.

## 3.4 Results

Figure 3.4 gives a preview of our central result. The left panel summarizes the glaring lack of link between a country's openness to trade and that country's equity market comovement with the world market, when defining openness as is standard, namely, as the ratio of the sum exports and imports relative to GDP. Similar negative findings with standard measures of trade have been well documented in the literature (Baele and Soriano, 2010; Bekaert et al., 2016).

[Insert Figure 3.4 here.]

The right panel instead considers the average **ITI** of a country in a given year, plotting it against comovement of the country with the global equity markets. A strongly positive association emerges, suggesting that this measure of real integration may help in explaining equity comovement.

To develop this finding more formally and on the bilateral level, we estimate variations of the following panel regression models:

$$RCORR_{i,j,t} = \alpha_{i,j} + \alpha_t + \beta^{ITI} \cdot ITI_{i,j,t} + \beta^{FTI} \cdot FTI_{i,j,t} + \sum^{k} CONTROLS^{k}_{i,t} + \varepsilon_{i,j,t} \tag{3.14}$$

### 3.4.1 Baseline Results

Table 3.2 presents the baseline results. Column (1) shows that bilateral equity-market correlations are strongly positively associated with intermediate good trade intensity, **ITI**. A one standard deviation increase in **ITI** (0.012) is associated with 4.558*0.012/0.244 = 22% of a standard deviation increase in the raw correlation, as sizable effect.

[Insert Table 3.2 here.]

Column (2) instead uses the transformed correlation, and finds the same, both qualitatively and quantitatively. A one standard deviation increase in **ITI** is associated with a 7.712*0.012/0.383 = 24% of a standard deviation increase in RCORR. Similarly, column (3) shows that final good trade intensity also correlates strongly with equity comovement. Regressions further below include other control variables, which allow us to compare this effect with other known determinants of international comovement.

**ITI** and **FTI** are highly correlated (with a correlation coefficient of about 0.9). Therefore, to include both, we orthogonalize them.[22] Moreover, we

[22] We use orthogonalization employing the modified Gram-Schmidt Procedure. The procedure computes Q of the QR decomposition, $A = QR$, where the columns of Q are the

standardize the two measures to have mean zero and standard deviation of unity. Column (4) then includes both measures and finds that both explain equity comovement. Interestingly, the importance of **ITI** surpasses that of **FTI**. A one standard deviation increase in **ITI** (**FTI**) is associated with a 24% (8%) of a standard deviation increase in RCORR.

Next, column (5) includes time fixed effects. This is an important check because in the existing literature, the relevance of the standard measure of openness (exports plus imports over GDP) for equity comovement, if any, has been found to vanish once common time trends of equity comovement and trade are considered (Bekaert et al., 2016). By contrast, column (5) shows that both measures of trade remain economically and statistically significant even after controlling for time fixed effects. (Table 3.9 shows that the results also hold when including a deterministic time trend instead.)

Finally, columns (6) and (7) include our complementary GVC-based measure, **VA** (Value Added). $VA^{exp}_{i,j,t}$ and $VA^{imp}_{i,j,t}$ differ in that the former is denominated by exporter GDP, whereas the latter is denominated by importer GDP. This measure accounts for indirect trade flows as well. (The two measures actually do not correlate strongly, which is why we can include both in the regressions.) We find that **VA** is also associated with equity comovement, and the quantitative impact is similar to that of **ITI**. In what follows, we first present our results using **ITI** and **FTI**, and then provide robustness checks using VA.

orthonormal bases. In our case, we simply have two variables **ITI** and **FTI** and therefore we compute $Proj_{ITI}(FTI)$, projecting the **ITI** vector orthogonally onto the line spanned by the **FTI** vector, to construct an orthogonal vector, $u_2 \equiv Vec_{FTI} - Proj_{ITI}(FTI)$, with normalization, $\tilde{u_2} \equiv \frac{u_2}{\|u_2\|}$. Our results are robust to reversing the order of orthogonalization.

### 3.4.2 Extended Results

While the results so far establish a link between equity comovement and our measures of real integration that does not exist for the standard variables of trade used in the literature so far, it is still possible that the relation would be subsumed by other factors driving both trade and equity comovement. To probe for this possibility, we next control for relevant socioeconomic variables. These controls include the geographical distance between two countries, contiguity between countries, and variables related to their colonial relationships in the past. Alternatively, we proxy for these pair-dependent socioeconomic relationships by country pair fixed effects, $c_{ij}$.

[Insert Table 3.3 here.]

Table 3.3 presents the results. For comparison, Column (1) repeats the baseline regression from Table 3.2. Column (2) shows that higher equity comovement occurs when there is shorter geographical distance.[23] Additionally, as seen in column (3), when a country pair has the same official language, equity comovement is higher. Column (4) adds country fixed effects and column (5) replaces socioeconomic proxies by country pair fixed effects.[24] In all specifications, our main measure, **ITI**, remains statistically significant. The economic significance of the effects is also quite stable across specifications. A one standard deviation higher intermediate goods trade linkage is associated with a 9% to 13% of a standard deviation higher correlation of equity mar-

[23] This finding of a gravity effect in comovement is in line with prior literature that did not control for bilateral trade, such as Flavin et al. (2002). Distance is a main determinant of cross-border capital flows; see, e.g., Bottazi et al. (2005) and Lane and Milesi-Ferretti (2002).

[24] Lucey and Zhang (2010) find more comovement between countries with smaller cultural distance. Aggarwal et al. (2012) and Bottazi et al. (2016) find that cultural distance and trust among nations, respectively, matter for international financial investment decisions. Country-pair fixed effects can control for these factors.

kets. This is about one fourth to one third of the effect of distance between countries, a sizable effect.

Next, in Table 3.4, we test the explanatory power of real integration against variables that represent financial integration, Total Asset Holdings, Total Equity Holdings, and Total Debt Holdings. We standardize these variables to mean zero and standard deviation of unity to facilitate comparison of the effect sizes. As these three variables are highly correlated ($\rho = 0.6 - 0.8$), we separately include them in specifications from column (2) to (4).

The main finding is that our **ITI** measure consistently relates positively to equity comovement. Financial integration is also positively associated with equity comovement. Importantly, however, the economic significance of the real-integration measure is consistently stronger than variables of financial holdings by a factor of 2 to 3. This suggests that real integration is an important force behind global asset comovements. This force has remained veiled in the existing literature because prior work has used only final goods trade and has not considered the importance of the modern world's global value chains.

Column (6) adds Cycle as a control. It is not obvious ex ante what sign to expect for this variable. On the one hand, the coefficient on this variable might be negative, if in recessions assets tend to move together and if linked countries enter recessions together. On the other hand, a country that grows faster than in the past few years may be more tightly linked to the world markets more generally. We find the coefficients of Cycle for both exporter and importer countries positive, though only the former is significant, and even that significance vanishes once controlling for realized volatility.

Next, we take into account that correlation between two countries could be driven by crisis periods in one of the two countries and could also mechanically depend on (the ratio of) volatilities. Therefore, in column (6), we add the two realized volatility (RV) measures. (We use the convention to call country $i$ the exporter and country $j$ the importer.) Even after controlling for possible volatility spillovers across countries, **ITI** remains a significant determinant of bilateral equity correlations.

Finally, column (7) includes all control variables introduced in this table. The coefficient on the real integration measure **ITI** remains highly significant and of similar size.

[Insert Table 3.4 here.]

Next, we consider the role of trade intensity in subsamples among countries and across time. For these tests, we use the fixed effects specification to maximize the sample size, but inferences are similar when using country characteristics, including financial integration measures, for which we have fewer observations.

In Table 3.5 we find that higher trade intensity positively is associated with higher equity comovement most consistently for Advanced Economy (AE) country pairs. By contrast, both among emerging market economy (EME) countries (column (1) and between AE and EME countries (column 3), the effects are weaker. This is reasonable given the fact that EMEs have started playing larger role in global supply chain only in recent years. Further, we eliminate some concerns that our results are driven by large countries such as the US by Column (4) and the concern that our results are driven by intra-trade within trade unions such as the EU by Column (5). Column (6) shows results for the sample of only European countries.

[Insert Table 3.5 here.]

Finally, we test the stability of the main results in subsamples split by time periods. In Table 3.6 we find that higher trade intensity positively is associated with higher equity comovement consistently in every subsample. The economic significance is stronger in the latter samples, which is consistent with the fact that equity comovement shows higher variation in the latter periods (recall Figure 3.2).

[Insert Table 3.6 here.]

## 3.5 Additional Results and Robustness Checks

In this section, we present a variety of additional results and robustness checks.

First, we present the same regression models but use **VA** as the trade intensity measure to see if taking account of indirect trade flows between countries would change the results. Results reported in Table 3.7 indicate that the Value Added variable also enters statistically significantly in all specifications.

[Insert Table 3.7 here.]

Second, we estimate Fama-MacBeth regressions to test the explanatory power of the GVC measures in a cross-sectional setting. Table 3.8 shows the results. Columns (1) and (2) use **ITI** as the explanatory variable, whereas (3) and (4) use **VA** (Value Added). Columns (2) and (4) replace the dependent variable by the one period ahead equity correlation. Throughout the specifications, our GVC-based measures remain statistically significant. This suggests cross-sectional variation in trade intensity across pairs of countries matters for cross-sectional variation in asset comovements. Further, it means that, not just contemporaneously, rather higher trade intensity this year leads to higher asset comovements in the next year.

[Insert Table 3.8 here.]

Finally, we replace time fixed effects with a time trend, see Table 3.9. Throughout all specifications, **ITI** remains statistically significant, while Total Asset Holdings shows slightly weaker statistical significance in comparison with Table 3.4 with time fixed effects.

[Insert Table 3.9 here.]

## 3.6 Conclusion

In this paper, we show that final good linkages and input-output linkages between play an important role in explaining global stock comovement. Based on a parsimonious model of firms, we develop a measure of international trade flows, "trade intensity". We find that higher trade intensity predicts higher equity comovement. This result is robust to financial integration measures and stronger than conventional trade-based measures of openness.

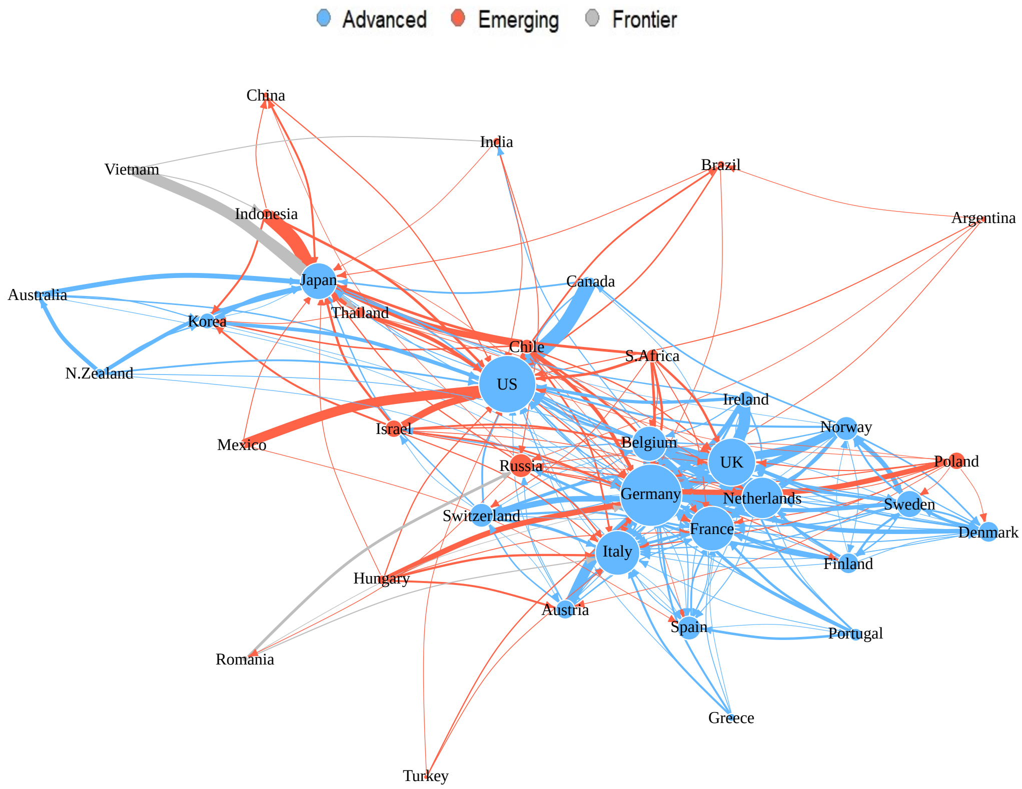
Our contribution, thus, is to bring insights on global value chains to bear on international asset pricing. Our key finding, the importance of intermediate trade intensity in linking stock returns and trades, is in line with higher global substitutability of factor inputs/outputs and higher international competition on interim stages of production.

Our findings also have important implications for portfolio management. For better global asset allocation, investors gain from taking account of developments and disruptions in global supply chains such as Brexit, the US-China trade war, the Japan-Korea trade battle, and the ongoing new Coronavirus (COVID-19) outbreak. While such events are typically analyzed from the perspective of their impact on the stock prices of affected stocks, our analysis highlights that global diversification strategies can be heavily affected by them.

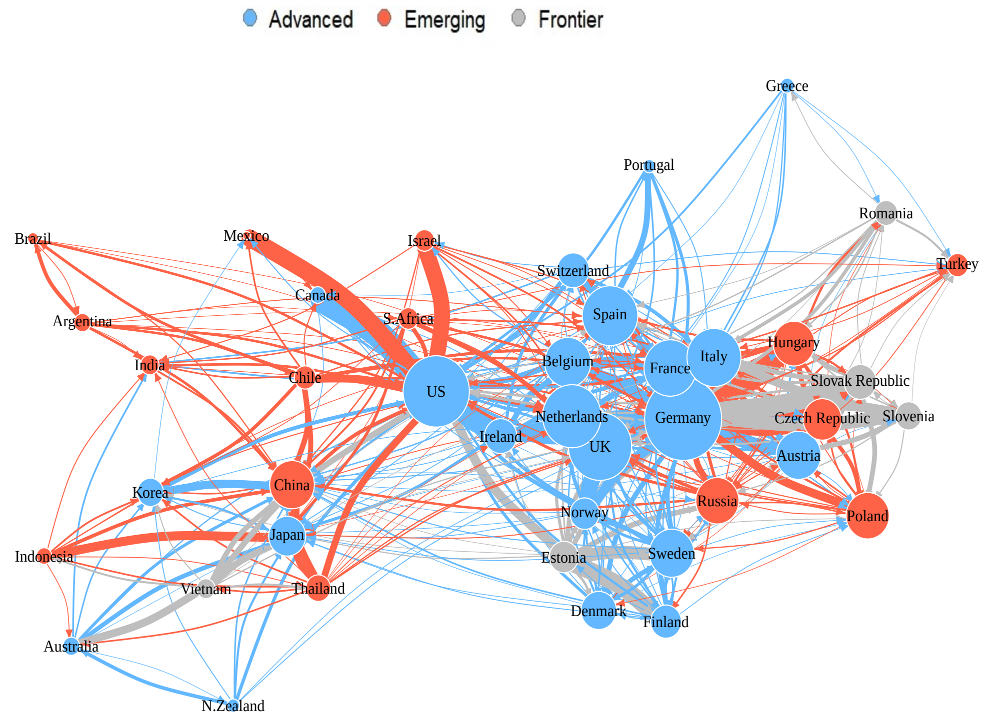
## 3.7 Figures and Tables

Figure 3.1: **Network in GVCs - Intermediate Goods Exports**

This figure visualizes the network of global value chains using intermediate goods exports in 1990 and in 2006. Both are denominated by exporter GDP. The edges are colored based on the country group of exporter country. Arrows indicate the direction of exports. The size of nodes is determined by its degree. The graphical position of nodes are drawn with Fruchterman-Reingold layout algorithm.




**Panel A: Advanced Countries as Center of Trade in 1990**




**Panel B: Emerging and Frontier Countries became intertwined in 2006**

Figure 3.2: **Time Variation in Stock Return Comovements**

This figure shows time variation in stock return comovements, measured by yearly correlation between stock market indices of two countries using daily returns. The computation of correlations is detailed in Section 3.3. Each box is colored based on the country group of country i. Before 1992, stock indices are not available for frontier countries.

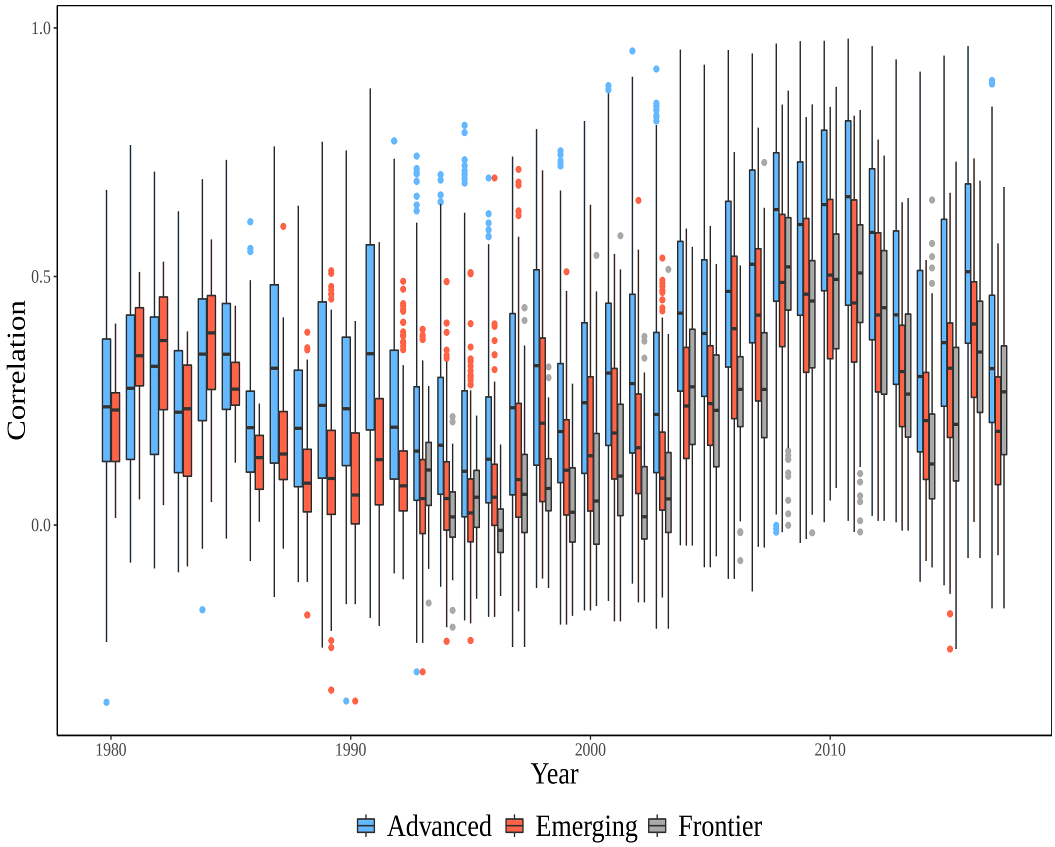


Figure 3.3: **ITI vs Trade Openess**

This figure shows the relation between aggregated intermediate trade intensity, which we summed over country j, and traditional trade openness. That is, the vertical axis shows $ITI_i = \sum_j \sum_t ITI_{i,j,t}$ for each country. The horizontal axies shows $\frac{Export_i + Import_i}{GDP_i} = \sum_t \frac{Export_{i,t} + Import_{i,t}}{GDP_{i,t}}$. All variables are exporter-denominated.

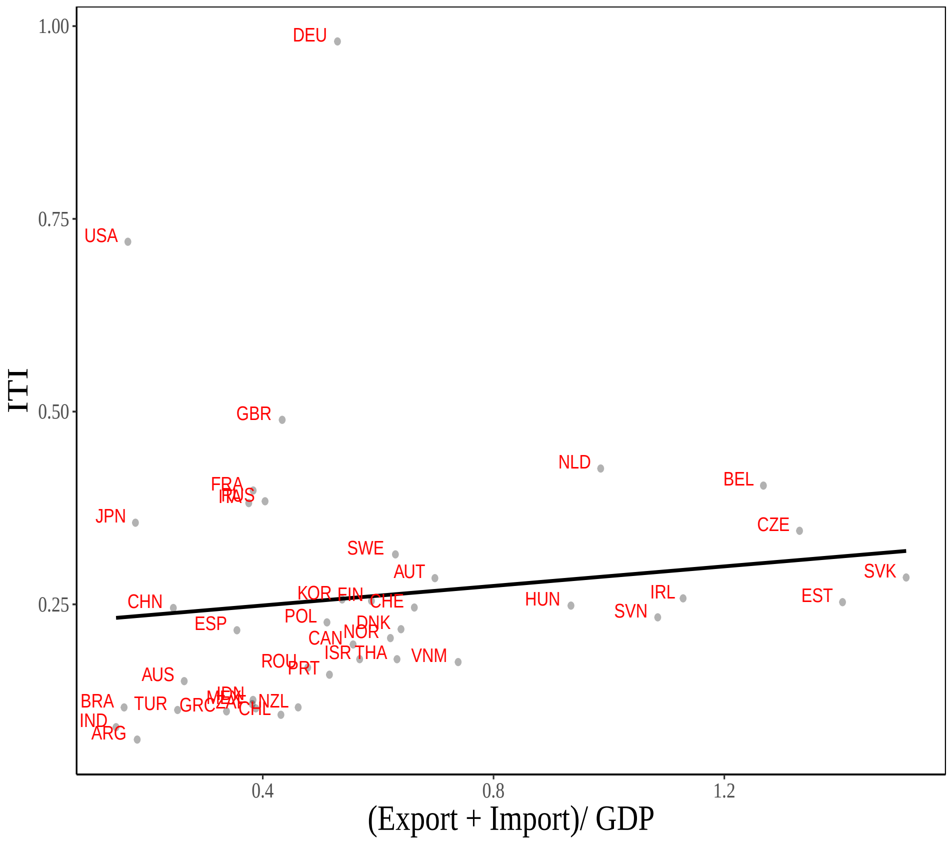


Figure 3.4: **Traditional Trade Measure v.s. GVC Measure**

This figure shows two scatter plots. The left panel reconfirms the failure of the traditional trade measure (on the x-axis) in explaining variation in equity comovements (on the y-axis). The correlation is between the stock index of country i and the world stock index and rescaled as Inverse Normal(0.5 + 0.5* $\hat{\rho}_{i,j,t}$). Traditional trade openness measure is $\frac{Export_{i,t}+Import_{i,t}}{GDP_{i,t}}$ and is shown as the natural logarithm. In the right panel, Intermediate Trade Intensity is averaged over country j, $ITI_{i,t} = \sum_j ITI_{i,j,t}$ and is also shown as the natural logarithm. Correlation is rescaled as Inverse Normal(0.5 + 0.5* $\hat{\rho}_{i,j,t}$) and averaged over country j.

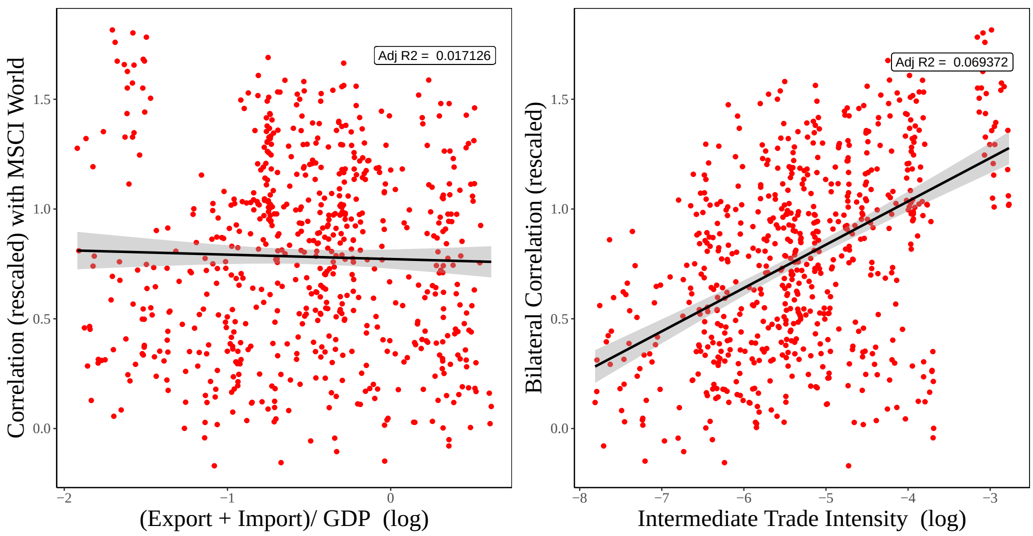


Table 3.1: **Summary Statistics**

This table shows summary statistics of the main variables employed in the analysis. RCORR is time-varying pairwise correlations of two countries i and j, rescaled so as to have infinite support. **ITI** (orthogonalized) and **FTI** (orthogonalized) are orthogonalized in that order. Trade Openess is a commonly used trade measure, defined as $\frac{Export_{i,t}+Import_{i,t}}{GDP_{i,t}}$. (z) refers to the variables that are standardized. (exporter) and (importer) refer to variables being denominated by exporter GDP and importer GDP respectively. RV and Cycle are controls for realized variance and gdp cycle. Details are found in Table A-1. Correlations of those variables are found in Table A-2

| Variable | Obs | Mean | Std. Dev. | Min | Max | P1 | P25 | P50 | P75 | P99 |
|---|---|---|---|---|---|---|---|---|---|---|
| Correlation | 44132 | .317 | .244 | -.357 | .978 | -.099 | .121 | .288 | .486 | .89 |
| RCORR | 44132 | .444 | .383 | -.463 | 2.298 | -.124 | .152 | .369 | .652 | 1.6 |
| ITI | 70054 | .006 | .012 | 0 | .175 | 0 | .001 | .002 | .007 | .061 |
| FTI | 70002 | .005 | .009 | 0 | .12 | 0 | 0 | .002 | .005 | .044 |
| ITI (orthogonalized, z) | 69992 | 0 | 1 | -.538 | 13.959 | -.538 | -.475 | -.348 | .005 | 4.534 |
| FTI (orthogonalized, z) | 69992 | 0 | 1 | -21.65 | 9.567 | -3.194 | -.22 | -.105 | .179 | 3.31 |
| Value Added (exporter) | 68068 | .005 | .012 | 0 | .219 | 0 | 0 | .001 | .004 | .056 |
| Value Added (importer) | 68068 | .005 | .011 | 0 | .193 | 0 | 0 | .001 | .004 | .054 |
| Distance (z) | 71546 | 0 | 1 | -1.47 | 2.991 | -1.391 | -.975 | .105 | .652 | 2.356 |
| Total Asset Holding (z) | 19998 | 0 | 1 | -.274 | 16.55 | -.273 | -.259 | -.244 | -.167 | 4.101 |
| Total Equity Holding (z) | 18108 | 0 | 1 | -.678 | 19.423 | -.229 | -.217 | -.207 | -.154 | 4.557 |
| Total Debt Holding (z) | 17767 | 0 | 1 | -.314 | 21.207 | -.295 | -.275 | -.257 | -.168 | 4.224 |
| RV (z) | 58946 | 0 | 1 | -1.647 | 6.838 | -1.132 | -.443 | -.226 | .042 | 4.676 |
| Cycle (z) | 45786 | 0 | 1 | -3.884 | 4.631 | -2.878 | -.502 | -.015 | .508 | 2.811 |
| Bilateral Aggregate Trade | 60132 | .013 | .034 | 0 | .654 | 0 | .001 | .003 | .01 | .164 |
| Trade Openess | 2036 | .378 | .349 | 0 | 1.707 | 0 | .084 | .335 | .529 | 1.479 |

Table 3.2: **Baseline Results**

This table shows the results of regression **(3.14)**. It presents the coefficients from panel regressions of stock return comovements, measured by $RCORR_{ijt}$, on raw trade intensity measures, $ITI_{ijt}$ and $FTI_{ijt}$, (the first and the second rows), on orthogonalized trade intensity measures (the third and forth rows), and on its corresponding value-added components (the fifth and the sixth rows). This panel regression uses yearly bilateral data from 1980 to 2017. Details on the construction of the variables are described in Section 3.3. Variables are defined in Table A-1. R2 is adjusted for degrees of freedom. The t-stats, shown in parentheses, are based on standard errors clustered by symmetric country pair. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The sample is yearly bilateral data from 1980 to 2017.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent variable: | Correlation | | | RCORR | | | |
| ITI | 4.558*** | 7.712*** | | | | | |
| | (7.79) | (7.29) | | | | | |
| FTI | | | 11.117*** | | | | |
| | | | (7.71) | | | | |
| ITI (orthogonalized, z) | | | | 0.091*** | 0.085*** | | |
| | | | | (7.37) | (7.21) | | |
| FTI (orthogonalized, z) | | | | 0.030*** | 0.025** | | |
| | | | | (3.11) | (2.55) | | |
| Value Added (exporter) | | | | | | 4.992*** | 4.736*** |
| | | | | | | (6.10) | (5.87) |
| Value Added (importer) | | | | | | 5.188*** | 4.869*** |
| | | | | | | (6.59) | (6.21) |
| Constant | 0.279*** | 0.381*** | 0.375*** | 0.428*** | 0.429*** | 0.373*** | 0.376*** |
| | (45.15) | (38.81) | (38.10) | (48.52) | (48.44) | (37.92) | (38.75) |
| Observations | 39,398 | 39,398 | 39,392 | 39,392 | 39,392 | 37,904 | 37,904 |
| N of Country Pair | 1560 | 1560 | 1560 | 1560 | 1560 | 1560 | 1560 |
| Country FE | NO | NO | NO | NO | NO | NO | NO |
| Country Pair FE | NO | NO | NO | NO | NO | NO | NO |
| Time FE | NO | NO | NO | NO | YES | NO | YES |
| Adj. R-squared | 0.061 | 0.070 | 0.077 | 0.077 | 0.387 | 0.061 | 0.37 |

Table 3.3: **Controlling for Socio-economic Ties and Country Fixed Effects**

This table summarizes panel regressions of stock return comovement on trade intensity measures and socioeconomic variables and fixed effects. Contiguity is whether or not the countries are neighburs. Common Official Language is 1 if primary common language is the same. (z) indicates when a variable is standardized. Columns (4) and (5), respectively, include country fixed effects and country-pair fixed effects. Details on the construction of the variables are described in Section 3.3. Variables are defined in Table A-1. R2 is adjusted for degrees of freedom. The t-stats, shown in parentheses, are based on standard errors clustered by symmetric country pair. *p<0.1; **p<0.05; ***p<0.01. The sample is yearly bilateral data from 1980 to 2017.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable: | | | RCORR | | | |
| ITI (orthogonalized, z) | 0.085*** | 0.048*** | 0.032*** | 0.036*** | 0.037** | 0.060*** |
| | (7.21) | (4.66) | (2.63) | (6.01) | (2.49) | (8.76) |
| FTI (orthogonalized, z) | 0.025** | 0.021** | 0.014 | 0.013*** | 0.010 | 0.015*** |
| | (2.55) | (2.27) | (1.57) | (2.83) | (1.34) | (2.65) |
| Distance (z) | | -0.112*** | -0.116*** | -0.093*** | | |
| | | (-11.72) | (-11.96) | (-12.29) | | |
| Contiguity | | | 0.075 | | | |
| | | | (1.12) | | | |
| Common Official Language | | | 0.130*** | | | |
| | | | (4.37) | | | |
| Common Colonizer | | | -0.353*** | | | |
| | | | (-10.91) | | | |
| Colony (post 1945) | | | -0.255*** | | | |
| | | | (-5.46) | | | |
| Observations | 39,392 | 37,894 | 37,894 | 37,894 | 39,392 | 39,392 |
| N of Country Pair | 1560 | 1560 | 1482 | 1482 | 1560 | 1560 |
| Country FE | NO | NO | NO | YES | NO | YES |
| Country Pair FE | NO | NO | NO | NO | YES | NO |
| Time FE | YES | YES | YES | YES | YES | YES |
| Adj. R-squared | 0.387 | 0.454 | 0.467 | 0.724 | 0.788 | 0.706 |

Table 3.4: **Controlling for Financial Linkages**

This table summarizes panel regressions of stock return comovement on trade intensity measures, controlling for measures of financial integration and other economic variables. $ITI_{ijt}$ and $FTI_{ijt}$ are orthogonalized. (z) indicates when a variable is standardized. $Cycle_{i,t}$ captures the current state of the macroeconomic cycle based on GDP. $RV_{i,t}$ is realized volatility. (importer) stands for the variable corresponding to the importer's $Cycle_{j,t}$ and $RV_{j,t}$ (instead of the exporter's). Details on the construction of the variables are described in Section 3.3. Variables are defined in Table A-1. R2 is adjusted for degrees of freedom. The t-stats, shown in parentheses, are based on standard errors clustered by symmetric country pair. *p<0.1; **p<0.05; ***p<0.01. The sample is yearly bilateral data from 1980 to 2017.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent variable: | | | | RCORR | | | |
| | no NA in Total Asset | | | | | | |
| ITI (orthogonalized, z) | 0.064*** | 0.061*** | 0.062*** | 0.063*** | 0.052*** | 0.059*** | 0.048*** |
| | (7.84) | (7.47) | (7.63) | (7.82) | (6.13) | (7.24) | (6.35) |
| FTI (orthogonalized, z) | 0.008 | 0.008 | 0.008 | 0.011* | -0.002 | 0.006 | -0.002 |
| | (1.34) | (1.31) | (1.37) | (1.81) | (-0.33) | (1.04) | (-0.37) |
| Total Asset Holding (z) | | 0.026*** | | | 0.025** | 0.054*** | 0.052*** |
| | | (2.75) | | | (2.26) | (4.48) | (4.00) |
| Total Equity Holding (z) | | | 0.011* | | | | |
| | | | (1.72) | | | | |
| Total Debt Holding (z) | | | | 0.029*** | | | |
| | | | | (3.38) | | | |
| Cycle (z) | | | | | 0.004** | | 0.002 |
| | | | | | (2.41) | | (1.30) |
| Cycle (z, importer) | | | | | 0.002 | | -0.002 |
| | | | | | (1.28) | | (-1.00) |
| RV (z) | | | | | | -0.012*** | -0.019*** |
| | | | | | | (-3.54) | (-5.05) |
| RV (z, importer) | | | | | | -0.012*** | -0.017*** |
| | | | | | | (-3.79) | (-4.97) |
| Constant | 0.182*** | -0.009 | -0.028 | -0.001 | -0.060 | 0.008 | -0.038 |
| | (3.26) | (-0.16) | (-0.44) | (-0.02) | (-0.94) | (0.16) | (-0.63) |
| Observations | 16,059 | 16,059 | 14,974 | 14,447 | 12,622 | 14,381 | 11,157 |
| N of Country Pair | 1,308 | 1,308 | 1,270 | 1,228 | 1,044 | 1,174 | 923 |
| Country FE | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES |
| Adj. R-squared | 0.757 | 0.759 | 0.761 | 0.766 | 0.776 | 0.768 | 0.788 |

Table 3.5: **Subsamples: Countries**

This table summarizes panel regressions of stock return comovement on trade intensity measures, for subsamples split by composition of countries. Details on the construction of the variables are described in Section 3.3. Variables are defined in Table A-1. R2 is adjusted for degrees of freedom. The t-stats, shown in parentheses, are based on standard errors clustered by symmetric country pair. *p<0.1; **p<0.05; ***p<0.01. The sample is yearly bilateral data from 1980 to 2017.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable: | RCORR | | | | | |
| Sample: | EME-EME | AE-AE | AE-EME | w/o US | w/o Europe | Only Europe |
| ITI (orthogonalized, z) | -0.006 | 0.088*** | 0.022* | 0.043*** | 0.030*** | 0.044*** |
| | (-0.19) | (5.16) | (1.86) | (4.41) | (2.64) | (3.84) |
| FTI (orthogonalized, z) | -0.026* | 0.041*** | -0.019** | 0.013* | -0.020*** | 0.027*** |
| | (-1.95) | (3.97) | (-2.45) | (1.86) | (-2.99) | (3.63) |
| Observations | 4,014 | 14,394 | 7,554 | 37,332 | 23,416 | 15,976 |
| N of Country Pair | 182 | 462 | 308 | 1,482 | 960 | 600 |
| Country FE | YES | YES | YES | YES | YES | YES |
| Control | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Adj. R-squared | 0.664 | 0.731 | 0.719 | 0.705 | 0.669 | 0.726 |

Table 3.6: **Subsamples: Time**

This table summarizes panel regressions of stock return comovement on trade intensity measures, for temporal subsamples. Details on the construction of the variables are described in Section 3.3. Variables are defined in Table A-1. R2 is adjusted for degrees of freedom. The t-stats, shown in parentheses, are based on standard errors clustered by symmetric country pair. *p<0.1; **p<0.05; ***p<0.01.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent variable: | RCORR | | | | |
| Sample: | before 1990 | 1995 - 2008 | after 2010 | after 2014 | before 2008 |
| ITI (orthogonalized, z) | 0.040*** | 0.048*** | 0.065*** | 0.064*** | 0.052*** |
| | (3.13) | (5.54) | (9.26) | (7.94) | (5.96) |
| FTI (orthogonalized, z) | 0.017* | 0.006 | 0.024*** | 0.015** | 0.022*** |
| | (1.69) | (0.92) | (4.67) | (2.28) | (3.84) |
| Observations | 4,062 | 18,596 | 8,514 | 4,224 | 27,758 |
| N of Country Pair | 756 | 1,560 | 1,122 | 1,056 | 1,560 |
| Country FE | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES |
| Control | YES | YES | YES | YES | YES |
| Adj. R-squared | 0.563 | 0.648 | 0.793 | 0.754 | 0.621 |

Table 3.7: **Value Added as an Alternative Measure of Trade Intensity**

This table summarizes panel regressions of stock return comovement on an alternative trade intensity measure, $ValueAdded_{ijt}$. It uses the same controls introduced in prior tables. All variables are in annual frequencies. Details on the construction of the variables are described in Section 3.3. Variables are defined in Table A-1. R2 is adjusted for degrees of freedom. The t-stats, shown in parentheses, are based on standard errors clustered by symmetric country pair. *p<0.1; **p<0.05; ***p<0.01. The sample is yearly bilateral data from 1980 to 2017.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent variable: | | | | RCORR | | | |
| | no NA in Total Asset | | | | | | |
| Value Added (z, exporter) | 0.042*** | 0.041*** | 0.042*** | 0.043*** | 0.030*** | 0.057*** | 0.036*** |
| | (6.44) | (6.15) | (6.24) | (6.72) | (4.13) | (4.43) | (2.87) |
| Total Asset Holding (z) | | 0.030*** | | | 0.031*** | 0.059*** | 0.060*** |
| | | (3.10) | | | (2.64) | (5.37) | (5.36) |
| Total Equity Holding (z) | | | 0.014** | | | | |
| | | | (2.08) | | | | |
| Total Debt Holding (z) | | | | 0.033*** | | | |
| | | | | (3.68) | | | |
| Cycle (z) | | | | | 0.005*** | | 0.003* |
| | | | | | (2.99) | | (1.78) |
| Cycle (z, importer) | | | | | 0.003* | | -0.001 |
| | | | | | (1.65) | | (-0.86) |
| RV (z) | | | | | | -0.015*** | -0.022*** |
| | | | | | | (-4.09) | (-5.74) |
| RV (z, importer) | | | | | | -0.015*** | -0.020*** |
| | | | | | | (-4.41) | (-5.83) |
| Constant | 0.538*** | -0.027 | -0.046 | -0.019 | -0.076 | 0.003 | -0.043 |
| | (8.57) | (-0.43) | (-0.66) | (-0.27) | (-1.10) | (0.05) | (-0.65) |
| Observations | 14,766 | 14,766 | 13,771 | 13,256 | 11,531 | 13,156 | 10,129 |
| Number of panelvar | 1,301 | 1,301 | 1,255 | 1,217 | 1,037 | 1,167 | 916 |
| Country FE | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES |
| Adj. R-squared | 0.741 | 0.747 | 0.745 | 0.753 | 0.768 | 0.761 | 0.785 |

Table 3.8: **Fama-MacBeth Regressions**

This table summarizes the results of Fama-MacBeth regressions of contemporaneous and future stock comovements on our trade intensity measures and other characteristics. Coefficients are presented as time-series averages of cross-sectional regressions. Column (1) and (3) use $RCORR_t$ as the dependent variable, whereas Column (2) and (4) have $RCORR_{t+1}$ as dependent variable. Value Added is exporter based, that is denominated by exporter GDP. Details on the construction of the variables are described in Section 3.3. Variables are defined in Table A-1. R2 is adjusted for degrees of freedom. t-stats in parentheses, $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The sample is yearly bilateral data from 1980 to 2017.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable: | RCORR | | | |
| | t | t+1 | t | t+1 |
| ITI (orthogonalized, z) | 0.034 *** | 0.034 *** | | |
| | (11.38) | (11.22) | | |
| FTI (orthogonalized, z) | 0.018 *** | 0.017 *** | | |
| | (3.71) | (3.57) | | |
| Value Added (exporter, z) | | | 0.029 *** | 0.030 *** |
| | | | (12.55) | (13.31) |
| Distance | -0.103 *** | -0.107 *** | -0.104 *** | -0.109 *** |
| | (-8.06) | (-8.78) | (-8.27) | (-8.85) |
| Realized Variance | -0.216 | -0.173 * | -0.228 | -0.187 |
| | (-1.55) | (-1.88) | (-1.56) | (-1.88) |
| Cycle | -0.001 | -0.039 | -0.003 | -0.041 |
| | (-0.12) | (-1.56) | (-0.23) | (-1.61) |
| Contiguity | 0.080 *** | 0.087 *** | 0.127 *** | 0.134 *** |
| | (8.92) | (6.33) | (13.) | (9.84) |
| Common Language | 0.213 *** | 0.209 *** | 0.208 *** | 0.204 *** |
| | (11.28) | (10.06) | (11.62) | (10.43) |
| Avr. N | 655 | 655 | 635 | 635 |
| Adj. R-squared | 0.291 | 0.288 | 0.284 | 0.280 |

Table 3.9: **Deterministic Trend**

This table summarizes panel regressions of stock return comovement on trade intensity measures, but replaces time fixed effects by time trends. It uses the same controls introduced in prior tables. All variables are in annual frequencies. Details on the construction of the variables are described in Section 3.3. Variables are defined in Table A-1. R2 is adjusted for degrees of freedom. Standard errors clustered by symmetric country pair. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. The sample is yearly bilateral data from 1980 to 2017.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent variable: | RCORR | | | | | | |
| | no NA in Total Asset | | | | | | |
| ITI (orthogonalized, z) | 0.071*** | 0.064*** | 0.068*** | 0.062*** | 0.057*** | 0.056*** | 0.059*** |
| | (7.84) | (6.68) | (7.25) | (6.78) | (7.31) | (7.16) | (5.83) |
| FTI (orthogonalized, z) | 0.014** | 0.014** | 0.013* | 0.015** | 0.012** | 0.002 | 0.012* |
| | (2.04) | (1.98) | (1.94) | (2.15) | (2.06) | (0.28) | (1.67) |
| Total Asset Holding (z) | | 0.041** | | | | | 0.049** |
| | | (2.57) | | | | | (2.57) |
| Total Equity Holding (z) | | | 0.020** | | | | |
| | | | (2.27) | | | | |
| Total Debt Holding (z) | | | | 0.046*** | | | |
| | | | | (2.83) | | | |
| RV(z) | | | | | -0.007** | | -0.015** |
| | | | | | (-2.27) | | (-2.25) |
| Cycle(z) | | | | | | 0.008*** | 0.012*** |
| | | | | | | (4.69) | (3.96) |
| Observations | 16,059 | 16,059 | 14,974 | 14,447 | 39,392 | 28,776 | 14,309 |
| N of Country Pair | 1,308 | 1,308 | 1,270 | 1,228 | 1,560 | 1,326 | 1,176 |
| Country FE | YES | YES | YES | YES | YES | YES | YES |
| Time Trend | YES | YES | YES | YES | YES | YES | YES |
| Adj. R-squared | 0.544 | 0.546 | 0.549 | 0.553 | 0.561 | 0.586 | 0.550 |

Internet Appendix for

# Real Integration and Asset Return Comovement

## A. Additional Figures and Tables

Figure A.1: **Realized Volatility**

This figure shows volatilities of stock returns since 1980. The left panel shows volatilities for three country groups. The right panel shows volatility for the world stock index. Volatility is measured monthly based on daily data and averaged for each year.

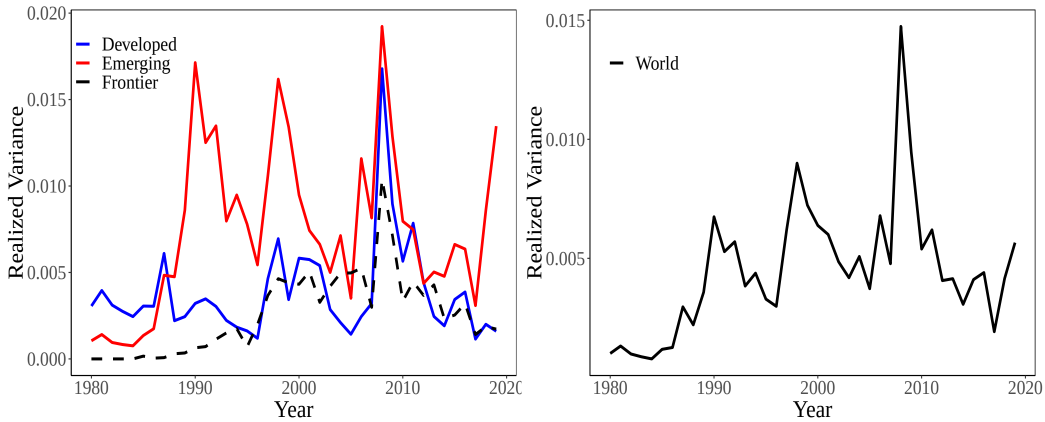


Figure A.2: **Time-variation in Coefficients**

This figure shows the coefficients from Fama-MacBeth regressions since 1980. $RCORR_{t+1}$ is the dependent variable. Cycle, Distance, Contiguity, Common Official Language, and Common Colonizer are included as control variables. Variable definitions are in Table A-1.

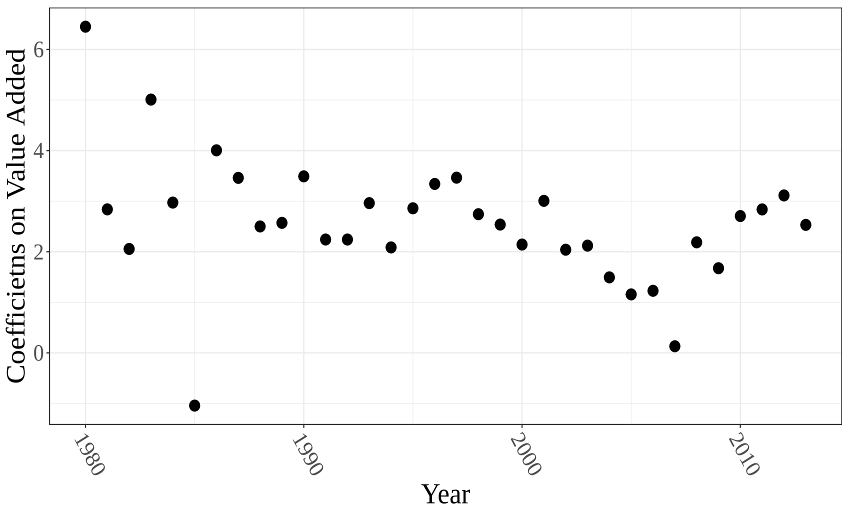


Table A.1: **Definitions**

| Variable | Definition |
|---|---|
| Correlation | $\hat{\rho}_{i,j,t} = \frac{\frac{1}{N(t)}\sum_{k=1}^{N(t)}(r_{i,k}-\overline{r_i})(r_{j,k}-\overline{r_j})}{\sqrt{\frac{1}{N(t)}\sum_{k=1}^{N(t)}(r_{i,k}-\overline{r_i})^2}\sqrt{\frac{1}{N(t)}\sum_{k=1}^{N(t)}(r_{j,k}-\overline{r_j})^2}}$. Using daily data to compute correlations for each year. |
| RCORR | $RCORR_{i,j,t} \equiv Inverse\ Normal(0.5 + 0.5 * \hat{\rho}_{i,j,t})$ |
| FTI | $FTI_{i,j} = s_{j,i}s_{i,i} + s_{i,j}s_{j,j}$, where $s_{i,i}$ is home share of sales and $s_{i,j} = \frac{FinalExports_{i,j}}{GDP_i}$. |
| ITI | $ITI_{i,j} = \gamma_{j,i}\gamma_{i,i} + \gamma_{i,j}\gamma_{j,j}$, where $\gamma_{i,i}$ is home share of costs and $\gamma_{i,j} = \frac{IntermediateExports_{i,j}}{GDP_i}$. |
| Value Added | $\frac{VA_{i,j}}{GDP_i}$. $VA_{i,j}$ is value added exports that take account of indirect export via a third country, following Johnson and Noguera (2012). Value Added (exporter) is denominated by exporter GDP, whereas Value Added (importer) is denominated by importer GDP. |
| Bilateral Aggregate Trade | $\frac{AggregateExport_{i,j}+AggregateImport_{i,j}}{GDP_i}$ |
| Distance | from CEPII, the GeoDist Database. |
| Contiguity | a dummy variable indicating whether the two countries are contiguous. |
| Common Official Language | a dummy variable indicating whether the two countries share a common official language. |
| Common Language (used) | a dummy variable indicating whether the two countries share a commonly used language. |
| Common Colonizer | a dummy variable indicating whether the two countries have had a common colonizer after 1945. |
| Colony (post 1945) | a dummy variable indicating whether the two countries have had a colonial relationship after 1945. |
| Total Asset Holdings | $\frac{TotalAssetHolding_{i,j}}{GDP_i}$ |
| Total Equity Holdings | $\frac{TotalEquityHolding_{i,j}}{GDP_i}$ |
| Total Debt Holdings | $\frac{TotalDebtHolding_{i,j}}{GDP_i}$ |
| RV | Monthly Realized Variance. $RV_{i,t} = \sum_{d=1}^{N_{days}(t)}[log(R_{t,d-1,d})]^2\frac{22}{N_{days}(t)}$, averaged yearly. Ndays(t) is the number of trading days in a month t. |
| Cycle | Output Cycle. $Cycle_{i,t} = \frac{gdp_t}{gdp_{t-1}} - \frac{1}{5}\sum_{k=0}^{4}\frac{gdp_{t-k}}{gdp_{t-k-1}}$ |

Table A.2: **Correlation of Variables**

| | RCORR | FTI | ITI | Value Added (exp) | Value Added (imp) | Asset Holding | Equity Holding | Debt Holding | RV | Cycle |
|---|---|---|---|---|---|---|---|---|---|---|
| RCORR | | 0.277 | 0.265 | 0.181 | 0.179 | 0.131 | 0.079 | 0.143 | -0.074 | -0.089 |
| FTI | | | 0.934 | 0.65 | 0.684 | 0.242 | 0.21 | 0.235 | -0.034 | 0.004 |
| ITI | | | | 0.645 | 0.693 | 0.282 | 0.249 | 0.275 | -0.025 | 0.009 |
| Value Added (exporter based) | | | | | 0.07 | 0.403 | 0.393 | 0.379 | -0.003 | 0.009 |
| Value Added (importer based) | | | | | | 0.008 | -0.004 | 0.004 | -0.033 | 0.006 |
| Asset Holding | | | | | | | 0.88 | 0.965 | -0.02 | 0.018 |
| Equity Holding | | | | | | | | 0.73 | -0.029 | 0.034 |
| Debt Holding | | | | | | | | | -0.012 | 0.01 |
| RV | | | | | | | | | | -0.174 |
| Cycle | | | | | | | | | | |

Table A.3: **Countries in the Sample**

| JN 42 countries |
|---|
| ARG, AUS, AUT, BEL, BRA, CAN, CHE, CHL, CHN, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HUN, IDN, IND, IRL, ISR, ITA, JPN, KOR, MEX, NLD, NOR, NZL, POL, PRT, ROU, RUS, SVK, SVN, SWE, THA, TUR, USA, VNM, ZAF |
| MRIO 41 countries |
| AUS, AUT, BEL, BGR, BRA, CAN, CHE, CHN, CYP, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IND, IRL, ITA, JPN, KOR, LTU, MEX, MLT, NLD, NOR, POL, PRT, ROU, RUS, SVK, SVN, SWE, THA, TUR, USA, VNM |

## B. Solutions

*Proof.* of Proposition 1.

Intuitively, every firm sells on all export markets $e$, and the total profits of all firms located in country $c$ is equal to the sum over the profits of all the firms that produce in this market. export market $e$, it holds that total profits $\pi_{c,t}$ of all firms located in $c$ are equal to

$$\pi_{c,t} = (\sigma-1)^{-1}\,\varphi_{c,t}^{(\sigma-1)}\left(\sum_{s\epsilon C}\left(w_{s,t}\tau_{s,c}^{I}\right)^{-(\rho-1)}\right)^{(\sigma-1)/(\rho-1)}\sum_{e\epsilon C}\left(d_{e,t}\right)^{\sigma}\tau_{c,e}^{-(\sigma-1)} \tag{A..1}$$

where $\varphi_{c,t} \equiv \left(\sum_{f\epsilon F_C}\varphi_{f,t}^{(\sigma-1)}\right)^{1/(\sigma-1)}$ is the productivity aggregator in $c$.

The change in profits is equal to

$$\widehat{\pi}_{c,t} = \frac{\dot{\pi}_{s,t}}{\pi_{c,t}} = \sum_{s\epsilon C}\frac{\partial \pi_{c,t}}{\partial w_{s,t}}\frac{\dot{w}_{s,t}}{\pi_{c,t}} + \sum_{e\epsilon C}\frac{\partial \pi_{c,t}}{\partial d_{e,t}}\frac{\dot{d}_{e,t}}{\pi_{c,t}} + \frac{\partial \pi_{c,t}}{\partial \varphi_{c,t}}\frac{\dot{\varphi}_{c,t}}{\pi_{c,t}}.$$

Each of the sub-terms in the first summation solves to

$$\frac{\partial \left( \sum_{s \epsilon C} \left( w_{s,t} \tau^I_{s,c} \right)^{-(\rho-1)} \right)^{(\sigma-1)/(\rho-1)}}{\partial w_{s,t}} \frac{\dot{w}_{s,t}}{\pi_{c,t}} = -(\sigma-1)\, \gamma_{c,s,t} \widehat{w}_{s,t},$$

where by (3.3), $\frac{\left( w_{s,t} \tau^I_{s,c} \right)^{-(\rho-1)}}{\sum_{s \epsilon C} \left( w_{s,t} \tau^I_{s,c} \right)^{-(\rho-1)}} \equiv \gamma_{c,s,t}$ is the cost share of input goods from $s$ in the production of goods from $c$. Each of the sub-terms in the second summation solves to

$$\frac{\partial \pi_{c,t}}{\partial d_{e,t}} \frac{\dot{d}_{e,t}}{\pi_{c,t}} = \sigma \frac{\left( d_{e,t} \right)^{\sigma} \tau_{c,e}^{-(\sigma-1)}}{\sum_{e \epsilon C} \left( d_{e,t} \right)^{\sigma} \tau_{c,e}^{-(\sigma-1)}} \widehat{d}_{e,t},$$

where by (3.1), $\frac{(d_{e,t})^{\sigma} \tau_{c,e}^{-(\sigma-1)}}{\sum_{e \epsilon C} (d_{e,t})^{\sigma} \tau_{c,e}^{-(\sigma-1)}} \equiv s_{e,c,t}$ is the share of all sales by firms from $c$ that accrues on market $e$. The last term is trivially equal to $(\sigma-1)\, \widehat{\varphi}_{c,t}$. □

**Shocks, linkages, and the comovement of profits**

We next illustrate profit comovement in a two-by-two case featuring country 1 and 2. All variables are indexed by $x_{\exp orter, importer}$. For any shock, it holds that

$$\begin{aligned} \widehat{\pi}_1 &= \sigma \left( s_{1,1} \widehat{d}_1 + s_{1,2} \widehat{d}_2 \right) - (1-\sigma) \left( \gamma_{1,1} \widehat{w}_1 + \gamma_{1,2} \widehat{w}_2 \right) + \widehat{\varepsilon}_1 \\ \widehat{\pi}_2 &= \sigma \left( s_{2,1} \widehat{d}_1 + s_{2,2} \widehat{d}_2 \right) - (1-\sigma) \left( \gamma_{2,1} \widehat{w}_1 + \gamma_{2,2} \widehat{w}_2 \right) + \widehat{\varepsilon}_2 \end{aligned}$$

Final good linkages create comovement because firms that sell final goods on the same markets are commonly affected by fluctuations in demand in this market. For simplicity, assume $\widehat{\varepsilon}_1 = \widehat{\varepsilon}_2 = 0$ and $\widehat{w}_1 = \widehat{w}_2 = 0$ thus eliminating the idiosyncratic element and the impact of input linkages. It holds that

$$\begin{aligned} cov(\widehat{\pi}_1, \widehat{\pi}_2) &= cov(\left(\sigma s_{1,1}\widehat{d}_1 + \sigma s_{1,2}\widehat{d}_2\right), \left(\sigma s_{2,1}\widehat{d}_1 + \sigma s_{2,2}\widehat{d}_2\right)) \qquad \text{(A..2)} \\ &= \sigma^2 \left(s_{1,1}s_{2,1}var\left(\widehat{d}_1\right) + s_{1,2}s_{2,2}var\left(\widehat{d}_2\right) + \left(s_{1,1}s_{2,2} + s_{1,2}s_{2,1}\right) cov\left(\widehat{d}_1, \widehat{d}_2\right)\right) \end{aligned}$$

If, on the other side, $\widehat{d}_1 = \widehat{d}_2 = 0$, it holds that

$$\begin{aligned} cov(\widehat{\pi}_1, \widehat{\pi}_2) &= cov(-\left(1-\sigma\right)\left(\gamma_{1,1}\widehat{w}_1 + \gamma_{1,2}\widehat{w}_2\right), -\left(1-\sigma\right)\left(\gamma_{2,1}\widehat{w}_1 + \gamma_{2,2}\widehat{w}_2\right)) \qquad \text{(A..3)} \\ &= \left(1-\sigma\right)^2 \left(\gamma_{1,1\gamma 2,1}var\left(\widehat{w}_1\right) + \gamma_{1,2}\gamma_{2,2}var\left(\widehat{w}_2\right) + \left(\gamma_{1,1\gamma 2,2} + \gamma_{1,2\gamma 2,1}\right) cov\left(\widehat{w}_1, \widehat{w}_2\right)\right) \end{aligned}$$

In both cases, comovement is increasing in real integration as long as transportation costs are positive and consumption and production are home-biased. In the full case (still assuming $\widehat{\varepsilon}_1 = \widehat{\varepsilon}_2 = 0$),

$$\widehat{\pi}_1 = \sigma s_{1,1}\widehat{d}_1 + \sigma s_{1,2}\widehat{d}_2 - \left(1-\sigma\right)\gamma_{1,1}\widehat{w}_1 - \left(1-\sigma\right)\gamma_{1,2}\widehat{w}_2$$

$$\widehat{\pi}_2 = \sigma s_{2,1}\widehat{d}_1 + \sigma s_{2,2}\widehat{d}_2 - \left(1-\sigma\right)\gamma_{2,1}\widehat{w}_1 - \left(1-\sigma\right)\gamma_{2,2}\widehat{w}_2$$

$$\begin{aligned} cov(\widehat{\pi}_1, \widehat{\pi}_2) = \; & \sigma^2 s_{2,1}s_{1,1}var\left(\widehat{d}_1\right) + \sigma^2 s_{1,1}s_{2,2}cov\left(\widehat{d}_1, \widehat{d}_2\right) \\ & -\left(1-\sigma\right)\gamma_{2,1}\sigma s_{1,1}cov\left(\widehat{d}_1, \widehat{w}_1\right) - \left(1-\sigma\right)\gamma_{2,2}\sigma s_{1,1}cov\left(\widehat{d}_1, \widehat{w}_2\right) \\ & \sigma^2 s_{1,2}s_{2,1}cov\left(\widehat{d}_2, \widehat{d}_1\right) + \sigma^2 s_{1,2}\sigma s_{2,2}var\left(\widehat{d}_2\right) \\ & -\left(1-\sigma\right)\gamma_{2,1}\sigma s_{1,2}cov\left(\widehat{d}_2, \widehat{w}_1\right) - \left(1-\sigma\right)\gamma_{2,2}\sigma s_{1,2}cov\left(\widehat{d}_2, \widehat{w}_2\right) \\ & -\left(1-\sigma\right)\gamma_{1,1}\sigma s_{2,1}cov\left(\widehat{w}_1, \widehat{d}_1\right) - \left(1-\sigma\right)\gamma_{1,1}\sigma s_{2,2}cov\left(\widehat{w}_1, \widehat{d}_2\right) \\ & +\left(1-\sigma\right)^2\gamma_{1,1}\gamma_{2,1}var\left(\widehat{w}_1\right) + \left(1-\sigma\right)^2\gamma_{1,1}\gamma_{2,2}cov\left(\widehat{w}_1, \widehat{w}_2\right) \\ & -\left(1-\sigma\right)\gamma_{1,2}\sigma s_{2,1}cov\left(\widehat{w}_2, \widehat{d}_1\right) - \left(1-\sigma\right)\sigma s_{2,2}\gamma_{1,2}cov\left(\widehat{w}_2, \widehat{d}_2\right) \\ & +\left(1-\sigma\right)^2\gamma_{1,2}\gamma_{2,1}cov\left(\widehat{w}_2, \widehat{w}_1\right) + \left(1-\sigma\right)^2\gamma_{1,2}\gamma_{2,2}var\left(\widehat{w}_2\right) \end{aligned}$$

Further,

$$\begin{aligned}
cov(\widehat{\pi}_1, \widehat{\pi}_2) &= \sigma^2 s_{2,1} s_{1,1} var\left(\widehat{d}_1\right) + \sigma^2 s_{1,2} \sigma s_{2,2} var\left(\widehat{d}_2\right) \\
&+ (1-\sigma)^2 \gamma_{1,1}\gamma_{2,1} var\left(\widehat{w}_1\right) + (1-\sigma)^2 \gamma_{1,2}\gamma_{2,2} var\left(\widehat{w}_2\right) \\
&+\sigma^2 \left(s_{1,1}s_{2,2} + s_{1,2}s_{2,1}\right) cov\left(\widehat{d}_1, \widehat{d}_2\right) + (1-\sigma)^2 \left(\gamma_{1,1}\gamma_{2,2} + \gamma_{1,2}\gamma_{2,1}\right) cov\left(\widehat{w}_1, \widehat{w}_2\right) \\
&- (1-\sigma)\sigma\left(\gamma_{2,1}s_{1,1} + \gamma_{1,1}s_{2,1}\right) cov\left(\widehat{d}_1, \widehat{w}_1\right) \\
&- (1-\sigma)\sigma\left(\gamma_{2,1}s_{1,2} + \gamma_{1,1}s_{2,2}\right) cov\left(\widehat{d}_2, \widehat{w}_1\right) \\
&- (1-\sigma)\sigma\left(\gamma_{2,2}s_{1,1} + \gamma_{1,2}s_{2,1}\right) cov\left(\widehat{d}_1, \widehat{w}_2\right) \\
&- (1-\sigma)\sigma\left(\gamma_{2,2}s_{1,2} + \gamma_{1,2}s_{2,2}\right) cov\left(\widehat{d}_2, \widehat{w}_2\right)
\end{aligned}$$

2. Case allowing for correlated shocks: $cov\left(\widehat{d}_1, \widehat{d}_2\right) = \Omega_d^2 \rho_d$ , $cov\left(\widehat{w}_1, \widehat{w}_2\right) = \Omega_w^2 \rho_w$

$$\left(s_{1,1}s_{2,2} + s_{1,2}s_{2,1}\right)\sigma^2 \Omega_d^2 \rho_d + \left(\gamma_{1,1}\gamma_{2,2} + \gamma_{1,2}\gamma_{2,1}\right)(1-\sigma)^2 \Omega_w^2 \rho_w$$

define two endogeneity indices: Demand Correlation $DC_{1,2}$ and supply correlation $SC_{1,2}$

$$\begin{aligned}
DC_{1,2} &= \left(s_{1,1}s_{2,2} + s_{1,2}s_{2,1}\right) \\
SC_{1,2} &= \left(\gamma_{1,1}\gamma_{2,2} + \gamma_{1,2}\gamma_{2,1}\right)
\end{aligned}$$

A regression would thus yield

$$cov(\widehat{\pi}_1, \widehat{\pi}_2) = \widehat{\beta}_d FTI_{1,2} + \widehat{\beta}_w ITI_{1,2} + \widehat{\beta}_{dc} DC_{1,2} + \widehat{\beta}_{sc} SC_{1,2} \tag{A..4}$$

where the estimated coefficients would be:

$$\begin{aligned}\widehat{\beta}_d &= \sigma^2 \Omega_d^2 \text{ and } \widehat{\beta}_w = (1-\sigma)^2 \, \Omega_w^2 \\ \widehat{\beta}_{dc} &= \sigma^2 \Omega_d^2 \rho_d \text{ and } \widehat{\beta}_{sc} = (1-\sigma)^2 \, \Omega_w^2 \rho_w\end{aligned}$$

Note that $DC_{1,2}$ and $FTI_{1,2}$, as well as $SC_{1,2}$ and $ITI_{1,2}$ would be correlated by construction.

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