# Economic Uncertainty and Commodity Futures Volatility

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## Abstract

This paper investigates the dynamics of commodity futures volatility. I derive the variance decomposition for the futures basis to show how unexpected excess returns result from new information about expected future interest rates, convenience yields, and risk premia. This motivates my empirical analysis of the volatility impact of economic and inflation regimes and commodity supply-demand shocks. Using data on major commodity futures markets and global bilateral commodity trade, I analyze the extent to which commodity volatility is related to fundamental uncertainty arising from increased emerging market demand and macroeconomic uncertainty, and control for the potential impact of financial frictions introduced by changing market structure and index trading. I find that a higher concentration in the emerging market importers of a commodity is associated with higher futures volatility. Commodity futures volatility is significantly predictable using variables capturing macroeconomic uncertainty. I examine the conditional variation in the asymmetric relationship between returns and volatility, and how this relates to the futures basis and sensitivity to consumer and producer shocks.

# 1. Introduction

This paper investigates the time-variation in commodity futures volatility and the factors explaining its dynamics. I analyze the impact of concentration and increased emerging market demand on commodity markets. This research builds on Bloom (2014), who presents evidence that emerging markets and recessionary periods are strongly associated with economic uncertainty, and Gabaix (2011), who shows the impact on aggregate volatility from power laws in size distributions. This paper adds to the literature on what explains fluctuations in volatility (see, for example, Roll (1984); Schwert (1989); Engle and Rangel (2008); Gabaix (2011); Bloom (2014)), while also contributing to the current debate on commodity price dynamics and potential distortions arising from market frictions.[1] In particular, I examine how supply-demand shocks, macroeconomic uncertainty, and financial frictions are related to realized volatility in commodity futures markets.

Volatility dynamics are a key consideration in strategy formation for hedging, derivatives trading, and portfolio optimization. Moreover, producers and consumers benefit from understanding the factors explaining price fluctuations when evaluating real options embedded in investment choices (Schwartz, 1997). Distortions can lead to under- or overinvestment, and even transitory deviations from fundamentals can lead to the long-term misallocation of resources (see, for example, Bernanke (1983); Bloom, Bond, and Reenen (2007)). This is especially important when there are non-convex production functions and large fixed costs to entry and expansion (e.g., a copper producer considering the development of a new mine or a manufacturer considering the opening of a new factory that uses raw commodities as inputs). Uncertainty also increases the difficulty for both producers and consumers when formulating optimal hedging strategies, potentially leading to higher volatility in their cash flows. This can cause higher borrowing costs and lower debt in the presence of non-zero costs to bankruptcy and default, which can in turn lead to lower firm values. Consequently, understanding the relationship between volatility and economic factors is a first-order consideration. For commodities with derivative markets that are illiquid, opaque, or have little market depth or limited expirations, the findings in this paper can provide a useful aid to price discovery, real option evaluation, and

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[1] For recent studies on factors affecting commodity markets, see, *inter alia*, US Senate Permanent Subcommittee on Investigations (2009, 2014); Tang and Xiong (2012); Singleton (2014); Basak and Pavlova (2013a,b), on commodity index and ETF trading and the involvement of banks in commodity markets, Etula (2013); Acharya, Lochstoer, and Ramadorai (2013) on broker-dealer capacity for risk taking, Kilian (2009); Chen, Rogoff, and Rossi (2010) on producer and consumer shocks, Roberts and Schlenker (2013) on changes to regulation.

risk management for end-users as well as financial investors. A better understanding of these futures return dynamics also enables policy-makers to consider the impact of possible market intervention and evaluate regulatory options aimed at achieving a desired welfare objective.[2]

Using a reduced form model of a commodity market with power-law distributed consumers and producers, I present several hypotheses on how concentration and emerging market demand impacts commodity volatility, and test these in the data. When commodity supply and demand are dominated by a handful of countries, their shocks affect global commodity markets. Even in the case where trading partners face homogeneous shocks, the market concentration itself can have an impact on volatility. Heterogeneous consumers and producers may face supply-demand shocks with different variance. When the larger consumers are also riskier and more volatile (experience higher variance shocks), their impact on market volatility is amplified through concentration. This is important when considering the impact of growing emerging market demand on commodity prices. Many of these markets are volatile, segmented, and pose non-diversifiable risks to hedgers and international investors (Bekaert and Harvey, 1997; Bloom, 2014).

I collate data on 22 major commodity futures markets and the global bilateral trade in the underlying commodities and analyze the extent to which commodity volatility is related to increased emerging market demand and other fundamentals such as inflation uncertainty, while controlling for financial frictions introduced by changing market structure and commodity index trading. A higher concentration in the emerging market importers of a commodity is associated with higher futures volatility. The results imply that a 1.00% gain in market concentration by developing country consumers is associated with a 1.19% increase in commodity futures volatility. I find predictability in commodity futures volatility using variables capturing macroeconomic uncertainty, with adjusted R-squared gains of over 10% over the baseline specification. Moreover, controlling for recession periods further increases the explanatory power of the main predictive regressions by over 13%. These reflect economically significant gains for an investor, particularly those engaged in hedging, in evaluating real options embedded in investment choices, or in trading portfolios of derivatives.

I derive the variance decomposition for futures, building on Working (1949); Campbell and Shiller (1988) and Campbell (1991), to show how unexpected changes to the excess basis

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[2]Amartya Sen (*Poverty and Famines* (Oxford University Press, 1983)) and others, highlight the direct and potentially catastrophic consequences of commodity price dynamics.

return of a commodity future are driven by changes to the expectation of future interest rates, convenience yield (the net benefit of holding the underlying physical commodity) and risk premia. These expectations are updated in response to new information about the future state of the economy (e.g., news on inflation and other variables related to the business cycle) and future commodity supply and demand (e.g., news about the economic health of commodity consumers and frictions to producer hedging). Similar to the analysis of stock market volatility by Engle and Rangel (2008), using this decomposition as the theoretical motivation, I examine the time-variation in the relationship between commodity volatility and shocks to relevant factors.

I find that there are significant fluctuations in both the realized volatility and the realized correlations of futures returns for the commodities analyzed in this study (e.g., figures 1, 5, and 6). This is true at different horizons corresponding to different holding periods, and throughout the entire trading history of a contract (e.g., beginning in the 1960s for most grain commodities, April 1983 for crude oil, etc.). Large fluctuations in price and volatility occurred for the commodities in the sample even before the popularization of commodity index and exchange-traded fund (ETF) trading.[3] I analyze the determinants of this variation in volatility, selecting variables that capture the variation in global macroeconomic conditions, commodity supply-demand, and market frictions based on theory and past empirical studies on commodity risk premia (see, for example, Chen, Rogoff, and Rossi (2010); Hong and Yogo (2012) and Acharya, Lochstoer, and Ramadorai (2013)). I add to this from the literature on analyzing the determinants of the realized volatility of financial assets (see, for example, Roll (1984) for an early study on the volatility dynamics of a commodity derivative, Schwert (1989) on understanding the time-variation in equity volatility, Engle and Rangel (2008) on relating low-frequency macroeconomic factors to realized volatility in global equity market indices, Gabaix (2011); Kelly, Lustig, and Nieuwerburgh (2013) on the granular origins of volatility, and Bloom, Bond, and Reenen (2007); Bloom (2009, 2014); Jurado, Ludvigson, and Ng (2014) on uncertainty and its relationship to volatility).

Global commodity markets have undergone major transformations in real economic demand and supply stemming from a sharp increase in demand from emerging market economies over the last two decades (see, for example, figures 2 and 3). The speed and extent of this increase

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[3]The "index financialization" period is commonly identified in the literature as beginning in January 2004 (Tang and Xiong, 2012; Hamilton and Wu, 2012; Singleton, 2014; Basak and Pavlova, 2013b).

is larger compared to similar episodes of major global market transformation in recent history.[4] Emerging market economies have become increasingly significant players in many commodity markets. On the supply side, this has been the case for several decades for certain commodities. More recently, global demand has undergone significant changes. As can be seen from the data from UN Comtrade, countries that are not members of the OECD[5] or G7[6] are now among the largest buyers in many key commodity markets. Developing and emerging market countries have more volatile economies and pose higher levels of legal, political, and economic policy uncertainty (Bekaert and Harvey, 1995, 1997, 2000; Bloom, 2014). Bernanke (1983); Bloom, Bond, and Reenen (2007); Bloom (2009) and others find that such uncertainty can lead to higher risk premia, lower investment levels, higher volatility, higher correlation levels, and deeper market distortions which last longer. Pastor and Veronesi (2011, 2013) show that such political uncertainty can lead to higher return volatility and correlation levels.[7]

Part of the recent debate on commodity price fluctuations attempts to distinguish between the impact on commodity futures markets from changing market structure and investor composition as opposed to changing macroeconomic fundamentals and supply-demand dynamics.[8] Several recent studies find in favor of the "financialization" or trader activity argument, citing, among other evidence, high commodity volatility and correlation (between crude oil prices and other financial markets) in the past decade (especially, after January 2004), when commodity index trading volumes increased substantially. However, I find that the commodity futures volatility observed during the past decade may in fact be largely in line with the high levels of futures volatility observed during past periods of financial crisis and geopolitical uncertainty. Similarly, correlation levels show significant time-variation over the full trading history of commodity futures (e.g., Figure 6).

The remainder of this paper is organized as follows. The next section presents the research framework, including the theoretical motivation and empirical methodology underpinning this research. Section 3 describes the data and variables employed in the analyses. Section 4 presents

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[4]For instance, Japan's emergence as a global financial power post-World War II (1960-1970) was accompanied by slower, smaller market share changes in commodity markets compared with the change in China's share of the major commodity markets since 1990.

[5]Organization of Economics Co-operation and Development.

[6]The Group of Seven.

[7]Raghuram G. Rajan (*Fault Lines: How Hidden Fractures Still Threaten the World Economy* (Princeton University Press, 2010)) discusses the risks associated with different political, legal, and financial systems coming into contact with each other, and how this can generate uncertainty and increase the likelihood of financial market crises.

[8]See footnote 1.

the results from the main empirical analysis. The final section concludes.

## 2.   Research Framework

### 2.1.   Commodity futures volatility

To understand the sources of variation in commodity futures returns, I build on present value models that show how changes in the current price of financial assets react to future changes to the underlying fundamentals. The stock variance decomposition presented in Campbell and Shiller (1988) and Campbell (1991) is widely used to identify the sources of financial asset volatility. This decomposition relates unexpected equity returns to news events that change expectations of future cash flows (stock dividends) and discount rates. Campbell and Ammer (1993) present the equivalent result for bond yields. A similar decomposition can be derived for commodity futures in terms of its basis. In order to understand this correspondence for a future on a storable commodity, begin with the no-arbitrage pricing formula for its futures price (Working, 1933, 1949; Kaldor, 1939; Brennan, 1958; Schwartz, 1997), $F_{t,T} = S_t e^{(r-y)(T-t)}$, where $F_{t,T}$ is the futures price at time $t$ of a unit of the commodity delivered at time $T$, $S_t$ is the spot price, $r$ is the risk-free rate, and $y$ is the convenience yield. Further, $y$ can be decomposed into the "benefit" from holding the physical commodity, $b$, net of the storage (or carry) cost rate $m$, $y = b - m$; $r = \pi + \psi$, where $\pi$ is the inflation rate and $\psi$ the real interest rate. This decomposition and analysis that follow are applicable to any type of future, with the interpretation of $y$ differing depending on the net benefit to holding the underlying asset, e.g., replace $y$ with dividend yield $d$ for stock futures or with the foreign currency interest rate $r^f$ for currency futures.[9, 10]

Consider the discrete-time version of this formula, now with time-dependent $r$ and $y$: the

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[9]This decomposition is exact for the forward price. Due to the mark-to-market gains and losses of the corresponding futures contract, differences can occur between the forward and future prices unless interest rates are deterministic.

[10]Several studies investigate the commodity convenience yield. Casassus and Collin-Dufresne (2005) nest several other models (including Gibson and Schwartz (1990) and Schwartz (1997)), concluding that convenience yield is increasing in the spot price, interest rates, and the extent to which the underlying commodity is used for production purposes.
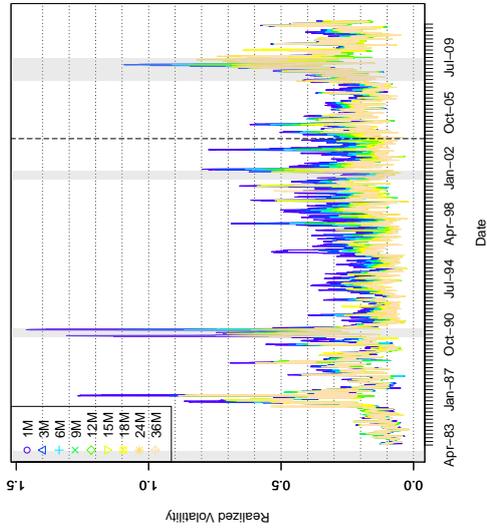
(a) Crude Oil - short-term volatility
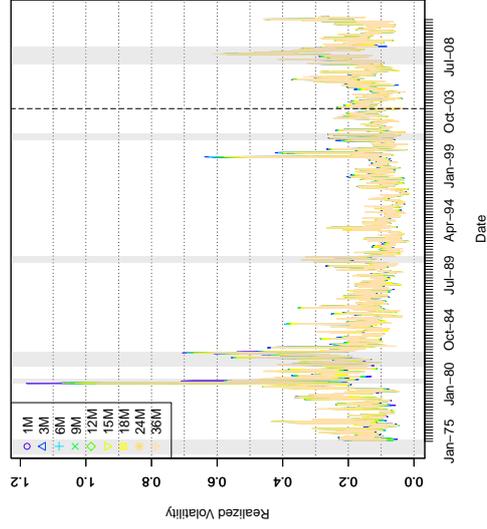
(b) Gold - short-term volatility
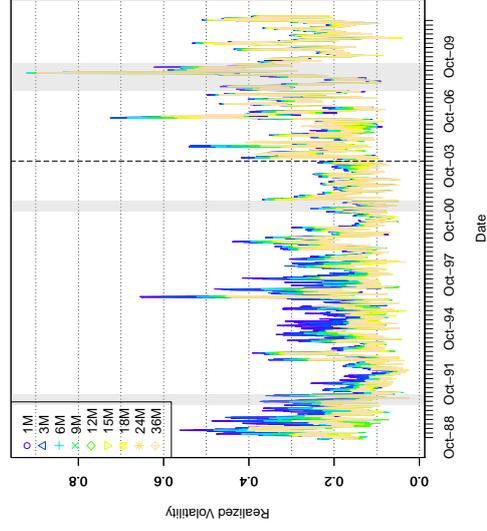
(c) Copper (HG) - short-term volatility
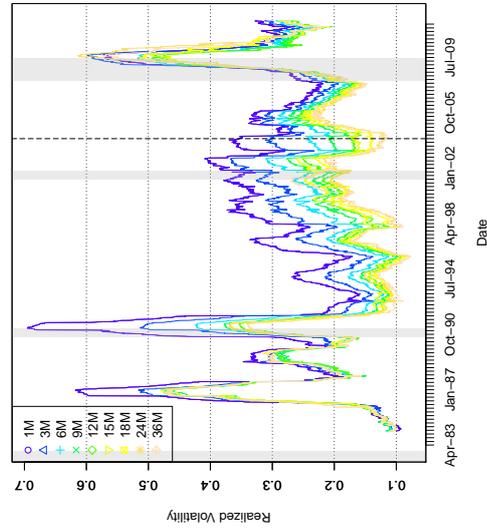
(d) Crude Oil - long-term volatility
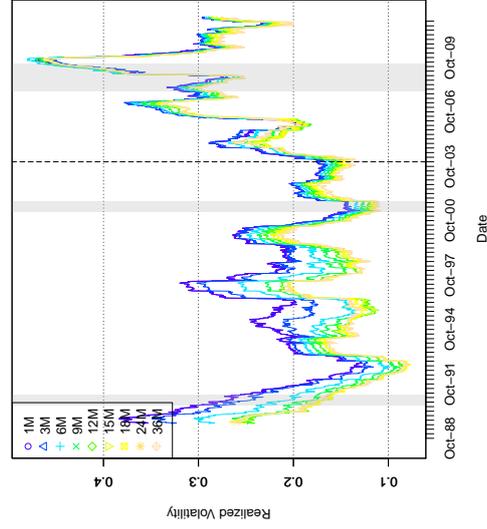
(e) Copper (HG) - long-term volatility
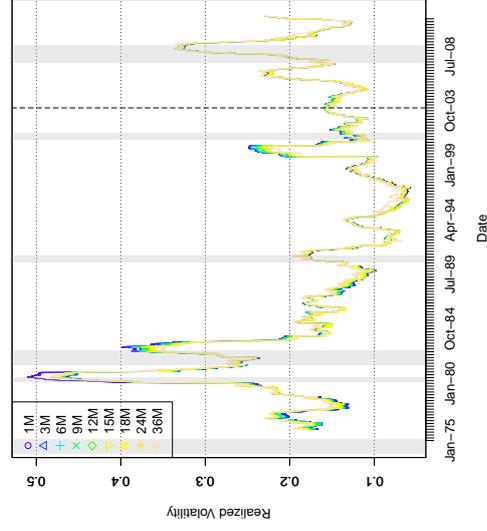
(f) Gold - long-term volatility

Fig. 1. Time series of annualized rolling realized volatility at different horizons crude oil, natural gas, and gold.

Time series of annualized rolling realized volatility at different horizons for 1M, 3M, ..., 36M futures using 3-day returns. Here, short-term volatility refers to the standard deviation for the previous month, while long-term volatility refers to the standard deviation for the previous 12 months. The shaded areas highlight the NBER recession periods. The dotted line marks January 2004. *Source: Author's analysis, Pinnacle Data.*
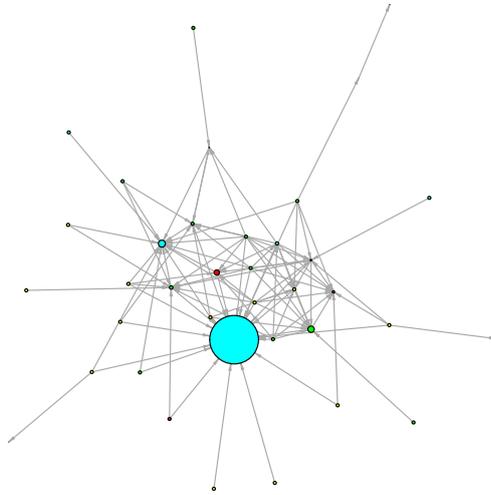
(a) 1990 Imports
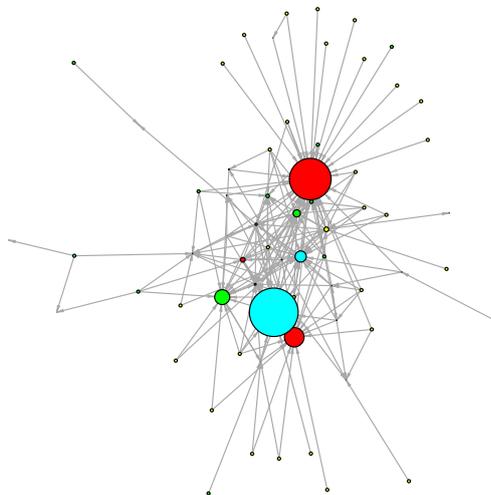


(b) 2007 Imports

Fig. 2. Global copper imports network.

The vertex colors identify the country group: BRIC (red), non-OECD excluding BRIC (yellow), OECD excluding G7 (green), and G7 (blue). The relative size of a country vertex captures its total import value. *Source: Author's analysis, UN Comtrade data.*

price at time $t$ of a future expiring in $n$ periods,

$$F_{n,t} = S_t \frac{(1 + R_{n,t})^n}{(1 + Y_{n,t})^n},$$ (1)

$$(1 + Y_{n,t}) = \left( \frac{1 + B_{n,t}}{1 + M_{n,t}} \right).$$ (2)

Denote the log price at time $t$ of a future expiring in $n$ periods as $f_{n,t}$ and the corresponding log spot price as $s_t$. Accordingly, the log price of the same future at time $t+1$ is $f_{n-1,t+1}$, now with $n-1$ periods to expiry, with an associated log spot price $s_{t+1}$. Define, $r_{n,t} \equiv \ln(1 + R_{n,t}) = \pi_{n,t} + \psi_{n,t}$ and $y_{n,t} \equiv \ln(1 + Y_{n,t}) = b_{n,t} - m_{n,t}$. Note that $r_{n,t}$ and $y_{n,t}$ are *per period* rates at time $t$, corresponding to the interest and convenience yield for the next $n$ periods. Using this notation, I can define the basis, $p_{n,t}$,

$$f_{n,t} = s_t + n(r_{n,t} - y_{n,t})$$ (3)

$$p_{n,t} \equiv f_{n,t} - s_t$$

$$= n(r_{n,t} - y_{n,t}),$$ (4)

We can define the change in basis from $t$ to $t+1$, $\delta_{n,t+1}$, and the return in excess of the cost-of-carry, $x_{n,t+1}$,[11]

$$\delta_{n,t+1} \equiv p_{n-1,t+1} - p_{n,t},$$ (5)

$$= (n-1)(r_{n-1,t+1} - y_{n-1,t+1}) - n(r_{n,t} - y_{n,t}),$$

$$x_{n,t+1} \equiv \delta_{n,t+1} + (r_{1,t} - y_{1,t}),$$ (6)

Given that $p_{0,t} = 0$ for all $t$, solving (5) forward (for $p_{n,t}$, $p_{n-1,t+1}$, $p_{n-2,t+2}$, ..., $p_{1,t+n-1}$) until the maturity date $t+n$, and taking expectations at time $t$ yields,

$$p_{n,t} = - \left[ \delta_{n,t+1} + \delta_{n-1,t+2} + \ldots + \delta_{1,t+n} \right]$$ (7)

$$= - E_t \sum_{i=0}^{n-1} \delta_{n-i,t+i+1}.$$ (8)

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[11] As discussed further in section 2.3, there can be deviations from the no-arbitrage condition due to non-diversifiable risks or market frictions such as producer hedging pressure and borrowing constraints (see, for example, (Keynes, 1930; Cootner, 1960; Hirshleifer, 1988, 1990; Roon, Nijman, Chris, and Veld, 2000; Acharya, Lochstoer, and Ramadorai, 2013)). $x_{n,t+1}$ also captures the part of the futures risk premia due to deviations from the expectations hypothesis in the interest rate term structure, as shown in Appendix 6.1, Eq. (38).

Eq. (7) must hold ex post and ex ante, so taking its expectation yields Eq. (8). Substituting (8) back into (5) gives the decomposition,

$$\delta_{n,t+1} - E_t\delta_{n,t+1} = -(E_{t+1} - E_t)\sum_{i=1}^{n-1}\delta_{n-i,t+i+1}. \tag{9}$$

Eq. (6) can be substituted into (9) to obtain its unexpected change,

$$x_{n,t+1} - E_t x_{n,t+1} = (E_{t+1} - E_t)\left\{\sum_{i=1}^{n-1}r_{1,t+i} - \sum_{i=1}^{n-1}y_{1,t+i} - \sum_{i=1}^{n-1}x_{n-i,t+i+1}\right\}. \tag{10}$$

Eq. (10) means that, if there is an unexpected increase in the excess basis return, either expected future interest rates are higher, expected future convenience yields are lower, or future risk premia are lower. When the assumption that both the expectations hypothesis for the term structure of interest rates and the theory of storage hold exactly, $E[\delta_{n,t+1}] = y_{1,t} - r_{1,t}$ for all $n > 0$, the third summation (of expected future excess basis returns) in (10) is zero. When this assumption is relaxed, the decomposition captures the risk premia reflecting the maturity and spot risk in interest rates and convenience yields. If we further decompose the excess basis return, $x_{n,t+1}$, to separate out the excess return due to the interest rate term structure (i.e., due to deviations from the expectations hypothesis), we can characterize the excess return purely due to the convenience yield and commodity risk premia (see Eq. (39 and (40)) in Appendix 6.1.

The decomposition can be rewritten explicitly in terms of news events relating to convenience yield, the risk-free rate, and risk premia,

$$x_{n,t+1} - E_t x_{n,t+1} = \eta_{t+1}^r - \eta_{t+1}^y - \eta_{t+1}^x. \tag{11}$$

Eq. (11) shows that unexpected changes to the futures risk premium are due to innovations in the future expected convenience yields, interest rates, and excess basis returns. These expectations are updated in response to new information about the future state of the economy (e.g., the level and volatility of inflation and real interest rates) and commodity supply-demand (e.g., inventory levels and the economic health of consumers). A positive shock to future convenience yields (the net benefit from holding the underlying spot commodity) or risk premia has a negative effect on the futures risk premium. The volatility of the excess basis return is driven by unexpected news affecting interest rates, convenience yield, and risk premia. More explicitly,

with correlated components,

$$Var(x_{n,t+1}) = Var(\eta_t^r) + Var(\eta_t^y) + Var(\eta_t^x)$$
$$-2Cov(\eta_t^r, \eta_t^y) - 2Cov(\eta_t^r, \eta_t^x) + 2Cov(\eta_t^y, \eta_t^x) \quad (12)$$

Engle and Rangel (2008) show that it is straightforward to model the unexpected return of a financial asset decomposed in this manner in terms of its stochastic volatility as,

$$x_{n,t+1} - E_t x_{n,t+1} = \sigma_t \epsilon_t, \text{ where } \epsilon_t | \Omega_{t-1} \sim N(0,1). \quad (13)$$

Given (11) and (13), we see that the stochastic volatility, $\sigma_t$, is driven by news on the future state of the economy and commodity supply-demand that directly impact convenience yield and interest rates. Models commonly used to estimate $\sigma_t$ for financial assets and their implementation for commodity futures in this study are discussed in section 3.2. Many studies attempting to understand equity risk premium dynamics decompose unexpected returns into $K$ observable news sources or risk factors which affect expectations of future discount rates and cash flows to equity, i.e., for the unexpected excess equity return, $e_t - E_{t-1}e_t = \eta_t^d - \eta_t^r - \eta_t^e = \sum_{k=1}^{K} \beta_k \lambda_{k,t}$. The equivalent for commodities should use the appropriate information set given the decomposition in (11).

## 2.2. Producer and consumer impact on commodity market volatility

In this section, I illustrate how producer and consumer risks and concentrations can impact commodity market volatility, motivating my empirical approach to analyzing the effect of rapidly growing emerging market demand.

Consider a model where there are $p = 1, \ldots, P$ producers and $c = 1, \ldots, C$ consumers of a commodity. A producer $p$ has market weight $w_{p,t}$ and a consumer has market weight $w_{c,t}$ with $\sum_{p=1}^{P} w_{p,t} = 1$ and $\sum_{c=1}^{C} w_{c,t} = 1$. The distribution of weights is power-law distributed, with a handful of consumers (producers) dominating the demand (supply) side. In this case, the idiosyncratic shocks to the trading parties matter in explaining market dynamics.[12] Similar to formulations in Acharya, Lochstoer, and Ramadorai (2013) and Ready, Roussanov, and Ward (2013), consumers have a downward-sloping demand curve for the commodity with price

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[12]See, for example, Gabaix (2011) for an exposition of this principle applied to firm sizes and aggregate volatility.

elasticity of demand $\epsilon$, and face an idiosyncratic demand shock $A_{c,t}$ such that,

$$S_t = A_{c,t} \left( Q_{c,t} \right)^{-\frac{1}{\epsilon}}. \tag{14}$$

In the near-term, producers have a price-inelastic supply and face an idiosyncratic supply shock $B_{p,t}$, such that $Q_{p,t} = B_{p,t}$. Denote the log quantities and prices in lowercase, with $a_{c,t} \sim N(0, \sigma_{a_c})$ and $b_{p,t} \sim N(0, \sigma_{b_p})$. Given market clearing for the total change in supply and demand in this setting, $\sum_{p=1}^{P} w_{p,t} q_{p,t} = \sum_{c=1}^{C} w_{c,t} q_{c,t}$, I can derive the impact of consumer and producer concentration on the variance of the commodity, $\sigma_{s,t}^2$,

$$\sigma_{s,t}^2 = \beta_c \sum_{c=1}^{C} w_{c,t}^2 \sigma_{a_c}^2 + \beta_p \sum_{p=1}^{P} w_{p,t}^2 \sigma_{b_p}^2 + \eta_t. \tag{15}$$

Consider the case where all consumers and producers have the same distribution in their demand shocks, $a_{c,t} \sim N(0, \sigma_a)$ and supply shocks, $b_{p,t} \sim N(0, \sigma_b)$, respectively. Then, defining consumer and producer Herfindahls as $H_{c,t} = \sum_{c=1}^{C} w_{c,t}^2$ and $H_{p,t} = \sum_{p=1}^{P} w_{p,t}^2$, respectively, yields,

$$\sigma_{s,t}^2 = \beta_c \sigma_a^2 H_{c,t} + \beta_p \sigma_b^2 H_{p,t} + \eta_t. \tag{16}$$

Eq. (16) shows that even with homogeneous shocks to demand and supply, consumer and producer market concentrations can have an impact on market volatility.[13]

Heterogeneous consumers and producers may face supply-demand shocks with different variance. When the larger consumers or producers are also riskier and more volatile (experience higher variance shocks), their impact on market volatility is amplified through concentration. This is important when considering the impact of growing emerging market trade on commodity prices.

Developing and emerging market countries have more volatile economies and greater uncertainty (Bekaert and Harvey, 1995, 2000; Bloom, 2014). We can consider consumers from emerging market, non-OECD countries as having demand shocks, $a_{c_{EM},t} \sim N(0, \sigma_{a_{EM}})$, while all others have demand shocks, $a_{c,t} \sim N(0, \sigma_a)$, with $\sigma_{a_{EM}} > \sigma_a$. All idiosyncratic supply shocks

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[13]This analysis is similar to those on the granular origins of aggregate volatility (see, for example, Gabaix (2011) on the impact of power-law distributed firm sizes on aggregate volatility and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012); Kelly, Lustig, and Nieuwerburgh (2013) on the supplier-customer network and size effects on volatility).

remain uniform, $b_{p,t} \sim N(0, \sigma_b)$. Starting with Eq. (15), with $H_{c,t}^{EM} = \sum\limits_{c \in EM} w_{c,t}^2$,

$$\sigma_{s,t}^2 = \beta_c \sum_{c=1}^{C} w_{c,t}^2 \sigma_{a_c}^2 + \beta_p \sum_{p=1}^{P} w_{p,t}^2 \sigma_{b_p}^2 + \eta_t,$$

$$= \beta_p \sigma_b^2 H_{p,t}$$

$$+ \beta_c \sigma_a^2 H_{c,t} + \beta_c \left(\sigma_{a_{EM}} - \sigma_a\right)^2 H_{c,t}^{EM} + \eta_t. \qquad (17)$$

In the near-term, producers are price-inelastic, with an essentially fixed supply and no unanticipated shocks ($\sigma_{b_p} = 0$). Under these conditions, the second term in Eq. (15) drops out, and producer concentration has no effect on commodity market volatility.

$$\sigma_{s,t}^2 = \beta_c \sum_{c=1}^{C} w_{c,t}^2 \sigma_{a_c}^2 + \beta_p \sum_{p=1}^{P} w_{p,t}^2 \sigma_{b_p}^2 + \eta_t,$$

$$\sigma_{s,t}^2 = \beta_c \sum_{c=1}^{C} w_{c,t}^2 \sigma_{a_c}^2 + \eta_t, \qquad (18)$$

$$= \beta_c \sigma_a^2 H_{c,t} + \beta_c \left(\sigma_{a_{EM}} - \sigma_a\right)^2 H_{c,t}^{EM} + \eta_t. \qquad (19)$$

These hypotheses capture the impact of the concentration and risks of producers and consumers on commodity markets. I empirically test several of the hypotheses related to consumer and producer impact on commodity volatility.

Denote the trade weights in commodity $i$ of country $j$ as,

$$w_{i,j,t}^I = \frac{ImportValue_{i,j,t}}{\sum\limits_{j=1}^{N} ImportValue_{i,j,t}}, \qquad (20)$$

$$w_{i,j,t}^E = \frac{ExportValue_{i,j,t}}{\sum\limits_{j=1}^{N} ExportValue_{i,j,t}} \qquad (21)$$

for imports and exports, respectively. Then, the measures of consumer concentration (of all countries and emerging market countries) are captured through Herfindahl indices and defined

as,

$$H_{i,t}^C = \left[ \sum_{j=1}^N \left( w_{i,j,t}^I \right)^2 \right]^{\frac{1}{2}}, \tag{22}$$

$$H_{i,t}^{C\_EM} = \left[ \sum_{j \in EM} \left( w_{i,j,t}^I \right)^2 \right]^{\frac{1}{2}}, \tag{23}$$

respectively. The corresponding Herfindahl indices for producers, $H_{i,t}^P$ and $H_{i,t}^{P\_EM}$, are similarly defined using export weights. For notational simplicity, define $\lambda_{i,j,t}^E = \left( w_{i,j,t}^E \right)^2$ and $\lambda_{i,j,t}^I = \left( w_{i,j,t}^I \right)^2$.

**Hypothesis 2.1.** Concentration in the importing countries of commodity $i$ impacts its futures volatility, $Vol_{i,t}$,

$$Vol_{i,t} = \mu_i + \beta_1 H_{i,t}^P + \beta_2 H_{i,t}^C + \mathbf{z}_t' \boldsymbol{\theta} + \eta_{i,t}, \tag{24}$$

where, $\mathbf{z}_t$ is a state vector of the relevant controls and $\boldsymbol{\theta}$ a vector of the coefficients. $\beta_2 > 0$ in the specification in Eq. (24).

**Hypothesis 2.2.** Shocks to the major importers of commodity $i$ impact its futures volatility, $Vol_{i,t}$,

$$Vol_{i,t} = \mu_i + \beta_1 \sum_{j=1}^N w_{i,j,t}^E \sigma_{j,t} + \beta_2 \sum_{j=1}^N w_{i,j,t}^I \sigma_{j,t} + \mathbf{z}_t' \boldsymbol{\theta} + \eta_{i,t}, \tag{25}$$

$\beta_2 > 0$ in the specification in Eq. (25).

Greater uncertainty and lower financial market development reduce the ability of commodity market participants (producers, consumers, and other investors) to insure against the risks of developing and emerging market countries (Bekaert and Harvey, 1995, 2000; di Giovanni and Levchenko, 2009; Pastor and Veronesi, 2011, 2013; Bloom, 2014).

**Hypothesis 2.3.** The relationship in hypotheses 2.1 and 2.2 is more significant for imports from countries that have higher policy uncertainty and lower financial openness (denoted EM

countries).

$$Vol_{i,t} = \mu_i + \beta_1 H_{i,t}^P + \beta_2 H_{i,t}^C + \beta_3 H_{i,t}^{P\_EM} + \beta_4 H_{i,t}^{C\_EM} + \mathbf{z}_t{}'\boldsymbol{\theta} + \eta_{i,t}, \tag{26}$$

$$Vol_{i,t} = \mu_i + \beta_1 \sum_{j=1}^{N} w_{i,j,t}^E \sigma_{j,t} + \beta_2 \sum_{j=1}^{N} w_{i,j,t}^I \sigma_{j,t}$$

$$+ \beta_3 \sum_{j=1}^{N} I_{[j \in EM]} w_{i,j,t}^E \sigma_{j,t} + \beta_4 \sum_{j=1}^{N} I_{[j \in EM]} w_{i,j,t}^I \sigma_{j,t} + \mathbf{z}_t{}'\boldsymbol{\theta} + \eta_{i,t}, \tag{27}$$

$\beta_4 > 0$ in the specification in Eq. (26) and (27).

**Hypothesis 2.4.** In the short-term, producers hedge, have a fixed supply, and have no unanticipated supply shocks affecting commodity markets.

$\beta_1 = 0$ in the specifications in Eq. (24) and (25). $\beta_3 = 0$ in the specifications in Eq. (26) and (27).

The sensitivity of commodity futures to consumer and producer shocks will be highest when there is a scarcity or glut in the underlying commodity. Such periods would be captured by periods of high absolute values of the futures basis ($HIGH\_BASIS$). Additionally, information about demand-side or supply-side pressure should be captured by the $\gamma$ coefficient of a GJR-GARCH(1,1) fit of commodity futures daily returns (see Eq. 45 and related discussion in Appendix 6.2).

**Hypothesis 2.5.** The impact of shocks to the major importers of commodity $i$ on its futures volatility, $Vol_{i,t}$, should be highest when the futures term structure exhibits a high basis.

$$Vol_{i,t} = \mu_i + \beta_1 \sum_{j=1}^{N} w_{i,j,t}^E \sigma_{j,t} + \beta_2 \sum_{j=1}^{N} w_{i,j,t}^I \sigma_{j,t} + \mathbf{z}_t{}'\boldsymbol{\theta} + \beta_3 I_{[t-1 \in HIGH\_BASIS]}$$

$$+ \beta_4 I_{[t-1 \in HIGH\_BASIS]} \sum_{j=1}^{N} w_{i,j,t}^E \sigma_{j,t} + \beta_5 I_{[t-1 \in HIGH\_BASIS]} \sum_{j=1}^{N} w_{i,j,t}^I \sigma_{j,t} + \eta_{i,t}, \tag{28}$$

where, $HIGH\_BASIS = 1$ during periods when the absolute value of the futures basis is highest (i.e., when the basis is in the top or bottom quintile), and 0 otherwise.

$\beta_4 > 0$ and $\beta_5 > 0$ in the specification in Eq. (28).

**Hypothesis 2.6.** The impact of shocks to the major importers of commodity $i$ on its futures volatility, $Vol_{i,t}$, should be highest when the asymmetric relationship between commodity

volatility and returns is highest.

$$Vol_{i,t} = \mu_i + \beta_1 \sum_{j=1}^{N} w_{i,j,t}^E \sigma_{j,t} + \beta_2 \sum_{j=1}^{N} w_{i,j,t}^I \sigma_{j,t} + \mathbf{z}_t'\boldsymbol{\theta} + \beta_3 I_{[t-1 \in HIGH\_GAMMA]}$$

$$+ \beta_4 I_{[t-1 \in HIGH\_GAMMA]} \sum_{j=1}^{N} w_{i,j,t}^E \sigma_{j,t} + \beta_5 I_{[t-1 \in HIGH\_GAMMA]} \sum_{j=1}^{N} w_{i,j,t}^I \sigma_{j,t} + \eta_{i,t}, \quad (29)$$

where, $HIGH\_GAMMA = 1$ during periods when the absolute value of the $\gamma$ coefficient of conditional GJR-GARCH(1,1) fits of the commodity futures returns is highest (i.e., when $\gamma$ is in the top or bottom quintile), and 0 otherwise.
$\beta_4 > 0$ and $\beta_5 > 0$ in the specification in Eq. (29).

I further examine the impact of demand and supply shocks on the conditional variation in the asymmetric relationship between commodity volatility and returns.

**Hypothesis 2.7.**

$$Vol_{i,t} = \mu + \alpha |r_{i,t-1}| + \beta Vol_{i,t-1} + \gamma_{i,t-1} I_{i,t-1}^{(+)} |r_{i,t-1}| + \mathbf{z}_{i,t-1}'\boldsymbol{\theta} + \eta_{i,t},$$

$$\gamma_{i,t-1} = \kappa_1 + \kappa_2 a_{i,t-1} + \kappa_3 b_{i,t-1}, \quad (30)$$

where, $I_{i,t-1}^{(+)} = 1$ when $r_{i,t-1} > 0$, and 0 otherwise. $a_{i,t-1}$ and $b_{i,t-1}$ are demand and supply shocks, respectively. $\boldsymbol{\kappa} = [\kappa_1 \ \kappa_2 \ \kappa_3]$ denote regression coefficients.
$\kappa_2 > 0$ and $\kappa_3 > 0$ in the specification in Eq. (30).

## 2.3. Impact of market frictions and limits to arbitrage

Deviations from the decomposition derived from no-arbitrage pricing conditions can occur for a variety of reasons in imperfect markets with frictions (e.g., information asymmetry or disagreement, limits to arbitrage via capital constraints) or due to the natural scarcity of the underlying asset, which is especially important for commodities, an asset class that has historically shown many episodes of market cornering and manipulation.[14] Such conditions can cause Eq. (1) to no longer hold exactly for all investors in the market. In Eq. (10), these deviations are captured in the third term.

The limits to arbitrage and its related literature look at standard theoretical asset pricing models with strong assumptions on the existence of perfect frictionless markets relaxed. Shleifer

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[14]E.g., Haase and Zimmermann (2011) on the scarcity premium in commodity futures prices and Jovanovic (2013) on the possibility of bubbles in the prices of exhaustible commodities.

and Vishny (1997) show that since arbitrage in practice requires capital and is inherently risky, asset prices will diverge from fundamental values under a variety of possible conditions when informed arbitrageurs in the market are constrained from eliminating them. Gromb and Vayanos (2002) find that capital-constrained arbitrageurs may take more or less risk than in a situation where they face perfect capital markets, leading to equilibrium outcomes that are not Pareto optimal. Yuan (2005) uses a modified Grossman and Stiglitz (1980) framework where a fraction of informed investors face a borrowing constraint, which is a function of the risky asset price (the lower the price, the more constrained the investor), and shows that this can result in asymmetric price movements.

Garleanu, Pedersen, and Poteshman (2009) apply this reasoning to options markets, and consider the case where it is not possible to hedge equity option positions perfectly, leading to demand pressure having an impact on option prices. They show empirically with equity index and single stock data that this helps to explain asset pricing puzzles such as option volatility skewness and relative expensiveness, which are anomalies under the assumptions of the Black-Scholes-Merton model (Black and Scholes (1973), Merton (1973)).

Basak and Pavlova (2013a) model the impact on a stock market from institutional investors whose performance is measured against a benchmark equity index. As this results in institutional investors holding more index stocks than is otherwise optimal, there is demand pressure that boosts index stock prices (and not off-index stock prices). This amplifies the volatility of on-index stock prices and the correlations between them, as well as increasing overall market volatility.

The term financialization, in the context of commodities trading, is generally used to describe the increased noise and uninformed speculative trading (usually with no direct exposure to the underlying commodity) through a range of trading activities including index investment and financial portfolio hedging and rebalancing. Given market frictions, such trading can result in price volatility and correlation between markets to an extent that does not reflect underlying fundamentals (Pavlova and Rigobon, 2008; Basak and Pavlova, 2013a). Implicit in the financialization argument is the assumption that there are binding constraints on investors or other significant frictions such as information asymmetries that lead to the persistence of market inefficiencies despite the existence of some informed players in that market. Such frictions render markets incomplete. Under such conditions, financial innovation or the introduction of even redundant assets can change equilibrium allocations and market volatility and efficiency could

increase or decrease. Equilibrium outcomes in markets where arbitrageurs are constrained can be inefficient or indeterminate under a range of common market conditions.[15]

Several recent studies examine the predictive relationships between commodities and other markets, and investigate the possible impact of financialization and investor characteristics on commodity markets. Tang and Xiong (2012) find that non-energy commodities have become increasingly correlated with oil prices, and that this relationship is stronger for constituent commodities of the SP-GSCI and DJ-UBS indices. They link this trend to increased financialization, (mainly via the increased investment in popular commodity indices since the early 2000s), and conclude that the underlying mechanism driving this phenomenon differs from other episodes of commodity price shocks and increased correlation, such as the crisis periods during the 1970s. Singleton (2014) surveys the recent literature in an attempt to explain the impact of trader activity on the behavior of energy markets, particularly crude oil futures prices, and finds futures open interest has important predictive power for crude oil prices, confirming the finding in Hong and Yogo (2012).

Acharya, Lochstoer, and Ramadorai (2013) consider the effect of capital-constrained speculators in a commodity futures market, where producers trade due to hedging needs and link producer default risk to inventories and prices in energy markets. They find that when speculator activity is constrained or reduced, the impact of hedging demand increases, i.e., unconstrained speculator activity will assist the absorption of producer demand shocks. Etula (2013) also finds that the risk-bearing capacity of broker-dealers is predictive of commodity risk premia.

Based on the discussion above, I empirically test several hypotheses related to limits to arbitrage and the impact of trading activity on commodity markets. These test if the effects of "financialization" during the period from January 2004 had a discernible impact on market volatility. This requires that other (possibly more informed) market participants were constrained in their capacity to step in and engage in arbitrage trading to correct any mispricing. Any alternate explanation is that increased participation makes commodity markets more efficient and liquid, correcting any mispricings that may have existed previously due to limited participation and illiquidity.

If financialization increased access to commodity futures markets by participants such as hedge funds, the comovement between futures returns and large-scale trading activity and port-

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[15]See, for example, Cass (1992); Bhamra and Uppal (2006); Basak, Cass, Licari, and Pavlova (2008); Gromb and Vayanos (2010).

folio shocks of hedge funds may have increased to such an extent that cannot be absorbed by other market participants due to borrowing constraints, illiquidity, or other market friction that introduces limits to arbitrage.

**Hypothesis 2.8.** Shocks to hedge funds during the financialization period are associated with higher commodity futures volatility.

$$Vol_{i,t} = \mu_i + \beta_1 HF\_RISK_{t-1} + \mathbf{z}_{t-1}'\boldsymbol{\theta} + \beta_2 I_{[t-1 \in IndexPeriod]}$$
$$+ I_{[t-1 \in IndexPeriod]} * \mathbf{z}_{t-1}'\boldsymbol{\theta}^{INDEX} + \beta_3 I_{[t-1 \in IndexPeriod]} HF\_RISK_{t-1} + \eta_{i,t}, \quad (31)$$

where $HF\_RISK_t$ denotes a proxy capturing hedge fund return activity. $\beta_3 > 0$ in the specification in (31).

## 3. Data and Variable Definitions

In this section, I describe the data used in the empirical analysis. I include a variety of factors that are potentially relevant for commodity prices based on theory and past empirical studies (see, among others, Hong and Yogo, 2012; Engle and Rangel, 2008; Bali, Brown, and Caglayan, 2014). Along the lines of the empirical analysis in Roll (1984) and Engle and Rangel (2008), I model the unexpected shocks to economic and financial variables that are potentially related to commodity prices and test the relationship between these variables and commodity futures volatility.

### 3.1. Price, returns and volatility

I use daily closing prices for commodity options and futures obtained from Barchart.com Inc. These commodities are categorized into four groupings (energy, grain, metal, and softs), traded on NYMEX (energy), COMEX (metal), CBOT (grain), CME, CSCE, and NYCE (softs) as shown in Table 1. Options price data, where available, begin on January 2, 2006. I extend futures data history before January 3, 2005 with data from Pinnacle Data Corp. Futures data go back further for most commodities, with the earliest being July 1959 for cotton, cocoa, and all commodities except rough rice in the grain grouping. To obtain the longest time period within a balanced panel without stale prices, the main regressions exclude natural gas, propane, rough rice, soybean oil, and orange juice futures.

Table 1: Commodity Derivative Contract and Trade Classification Information

This table shows the 22 underlying commodities in the dataset, categorized into four market groupings (energy, metal, grain, and soft). The naming convention for a futures contract is [Contract code][Expiry month code][Last digit of expiry year], e.g., on 5 January 2005, the WTI Crude Oil futures contract expiring in December 2008 is 'CLZ8'.[16]

| Contract Code | Exchange Code | Traded Contract Months | Commodity Name | Futures Data Start |
|---|---|---|---|---|
| Energy | | | | |
| CL | NYMEX | All months | Crude Oil | 03/30/1983 |
| HO | NYMEX | All months | Heating Oil | 11/14/1978 |
| NG | NYMEX | All months | Natural Gas | 04/04/1990 |
| PN | NYMEX | All months | Propane | 01/03/2005 |
| Metal | | | | |
| GC | COMEX | G \| J \| M \| Q \| V \| Z | Gold | 12/31/1974 |
| SI | COMEX | H \| K \| N \| U \| Z | Silver | 06/12/1963 |
| HG | COMEX | H \| K \| N \| U \| Z | Copper | 01/03/1989 |
| PA | NYMEX | H \| M \| U \| Z | Palladium | 01/03/1977 |
| PL | NYMEX | F \| J \| N \| V | Platinum | 03/04/1968 |
| Grain | | | | |
| W | CBOT | H \| K \| N \| U \| Z | Wheat | 07/01/1959 |
| C | CBOT | H \| K \| N \| U \| Z | Corn | 07/01/1959 |
| O | CBOT | H \| K \| N \| U \| Z | Oats | 07/01/1959 |
| S | CBOT | F \| H \| K \| N \| Q \| U \| X | Soybeans | 07/01/1959 |
| SM | CBOT | F \| H \| K \| N \| Q \| U \| V \| Z | Soybean Meal | 07/01/1959 |
| BO | CBOT | F \| H \| K \| N \| Q \| U \| V \| Z | Soybean Oil | 07/01/1959 |
| RR | CBOT | F \| H \| K \| N \| U \| X | Rough Rice | 08/20/1986 |
| Soft | | | | |
| CT | NYCE | H \| K \| N \| V \| Z | Cotton | 07/01/1959 |
| OJ | NYCE | F \| H \| K \| N \| U \| X | Orange Juice | 02/01/1967 |
| KC | CSCE | H \| K \| N \| U \| Z | Coffee | 08/16/1972 |
| SB | CSCE | H \| K \| N \| V | Sugar | 01/04/1961 |
| CC | CSCE | H \| K \| N \| U \| Z | Cocoa | 07/01/1959 |
| LB | CME | F \| H \| K \| N \| U \| X | Lumber | 10/01/1969 |

I calculate commodity futures returns (from holding and rolling futures) at a fixed maturity point in the term structure (1, 3, 6, 9, 12, 15, 18, 24, and 36 months) using the methodology described in Singleton (2014), and generate realized volatility time series for 1, 3, 6, and 12-month horizons using these fixed-term daily returns.

## 3.2. Volatility estimation

Several recent papers have studied the observed behavior of market implied and realized volatilities, and the variation in the volatility risk premium in equity and currency markets. Of these, Engle and Rangel (2008) and Engle, Ghysels, and Sohn (2013) analyze directly the impact of macroeconomic shocks on equity volatility within GARCH-type models that decompose volatility into short-term and long-term components, and identify several macroeconomic variables with significant impact on low and high-frequency equity volatility. Ang, Hodrick, Xing, and Zhang (2006, 2009) study the cross-sectional variation in risk premia and idiosyncratic volatility and find a significant positive relationship between the two. Campbell, Giglio, Polk, and Turley (2012) include stochastic volatility in an intertemporal CAPM framework and conclude that volatility risk is priced in US stocks and may explain stock return anomalies such as the value premium. Previous empirical studies on market volatility have mainly concentrated on the S&P500 index, individual US stocks, and currency markets for a variety of reasons including easy access to the relevant data, long time periods, liquidity, coverage in time-strike space (for implied volatility), etc. A similar systematic analysis of commodity volatility remains a potentially rich area for furthering our understanding of these markets.

A flexible, first-pass estimate for the volatility of an asset over a certain period is its realized volatility over that horizon. Similar to the convention for returns in Singleton (2014), I denote the $d$-day rolling return of the (fixed-term) $f$-month future of commodity $i$ as $R_{i,t}^{fFdD}$. For example, the 5-day rolling return of the (fixed-term) 3-month commodity future at time $t$ is denoted $R_{i,t}^{3F5D}$. Consequently, the realized volatility of $d$-day returns of the $f$-month commodity future at time $t$, over a horizon of $m$ months, is defined as the annualized standard deviation over that period, $\sigma_{i,t} \approx Vol_{i,t}^{fFdDmM}$, where $d \in \{1, 3, 5, 21\}$ is the frequency in days of the return series used to construct the volatility series and the volatility horizon in months, $m \in \{1, 3, 6, 9, 12, 15, 18, 24, 36\}$, with a week, month, and year, defined as 5, 21, and 252 trading

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[16]Month codes: F - Jan | G - Feb | H - Mar | J - Apr | K - May | M - Jun | N - Jul | Q - Aug | U - Sep | V - Oct | X - Nov | Z - Dec |

days, respectively.[17] The baseline panel regressions use the (non-overlapping) end-of-month (EOM) volatility of daily returns of the 1-month future, $Vol_{i,t} = Vol_{i,t}^{1F1DEOM}$ as the dependent variable, except where I explicitly state otherwise. The augmented Dickey-Fuller test (ADF) rejects the existence of a unit root in $Vol_{i,t}$ for all commodities in the sample (Table A3 in the Appendix). The baseline predictive regressions take the form,

$$Vol_{i,t} = \mu + \alpha |r_{i,t-1}| + \beta Vol_{i,t-1} + \mathbf{z}_{i,t-1}'\boldsymbol{\theta} + \eta_{i,t}, \tag{34}$$

where $r_{i,t} = R_{i,t}^{1F21D}$, $\mathbf{z}_{i,t}$ is a vector of $K$ (non-negative) explanatory variables, $\alpha$, $\beta$, and the vector $\boldsymbol{\theta}$ denote regression coefficients. In Appendix 6.2, I discuss the related volatility models and empirical work that attempt to explain realized volatility with economic variables, which inform the framework of my analysis and its future extensions.

Table 2 shows summary statistics for the realized volatility of the commodity futures in this study. Panel A shows the mean and standard deviation of 1-month ("short-term") and 12-month ("long-term") realized volatility for the three maturity points on the futures curve (1M, 3M, and 12M). Plots of short-term and long-term realized volatility for the entire term structure are shown in figures 1 and 5 for crude oil, copper, gold, natural gas, wheat, and lumber.

Relative to commodities in energy, grain and softs, precious metals broadly show little variation in average volatility by contract month. This is also evident in the figures plotting realized volatility for the futures terms structures over time (figures in 1 and 5). This is indicative of parallel shifts to the forward curve being more common for metals than for commodities in other groups. For crude oil, natural gas, wheat, orange juice, and lumber, etc., the contracts in the nearer term are more volatile than longer-dated contracts. This difference is potentially a risk characteristic driven by underlying fundamentals - inventory, storability and the nature of the demand for a particular commodity. Relative to other commodity groups, metals are highly storable (dense and durable), easy to transport, and less exposed to supply-demand uncertainty

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[17]By this definition,

$$Vol_{i,t}^{fFdDmM} = \sqrt{\frac{252}{d} \left[ \frac{1}{N}\sum_{p=1}^{N} \left( R_{i,t-N+p}^{fFdD} \right)^2 - \left( \frac{1}{N}\sum_{p=1}^{N} R_{i,t-N+p}^{fFdD} \right)^2 \right]^{\frac{1}{2}}}, \tag{32}$$

$$Vol_{i,t}^{1F1D1M} = \sqrt{\frac{252}{1} \left[ \frac{1}{21}\sum_{p=1}^{21} \left( R_{i,t-21+p}^{1F1D} \right)^2 - \left( \frac{1}{21}\sum_{p=1}^{21} R_{i,t-21+p}^{1F1D} \right)^2 \right]^{\frac{1}{2}}}, \tag{33}$$

where $N = m * \frac{21}{d}$ is the number of $d$-day return periods in $m$ months. The factor $\frac{252}{d}$ annualizes the volatility.

Table 2: Commodity Futures Volatility Summary Statistics

This table shows the summary statistics of volatility of daily returns for each commodity future at 1-month (1M), 3-month (3M) and 12-month (12M) maturities. This includes the mean and standard deviation of short-term (1-month) and long-term (12-month) realized volatility for the full trading history of each commodity until December 31, 2011 (see Table 1 for futures data start dates by commodity). The standard deviation is a measure of the volatility of volatility. In the Appendix, I show the same summary statistics by decade.

| | Mean | | | Standard Deviation | | |
|---|---|---|---|---|---|---|
| | 1M | 3M | 12M | 1M | 3M | 12M |
| Crude | 30.054 | 26.531 | 22.033 | 16.249 | 13.670 | 11.775 |
| Heating Oil | 29.102 | 25.800 | 21.814 | 14.103 | 11.846 | 10.270 |
| Natural Gas | 44.508 | 34.208 | 20.631 | 19.003 | 13.614 | 10.150 |
| Gold | 16.966 | 16.846 | 16.617 | 9.991 | 9.460 | 9.095 |
| Silver | 28.114 | 26.830 | 26.122 | 15.884 | 12.785 | 12.449 |
| Palladium | 28.896 | 28.258 | 28.305 | 14.481 | 13.604 | 13.305 |
| Platinum | 24.005 | 23.520 | 23.049 | 13.261 | 11.432 | 10.760 |
| Copper | 25.295 | 24.794 | 21.629 | 11.214 | 11.228 | 11.06 |
| Wheat | 23.868 | 22.889 | 19.641 | 10.571 | 10.453 | 10.335 |
| Corn | 20.269 | 19.881 | 17.761 | 10.411 | 10.069 | 9.321 |
| Oat | 27.939 | 26.060 | 20.689 | 10.978 | 9.776 | 9.517 |
| Soybeans | 21.065 | 20.519 | 18.227 | 11.248 | 10.022 | 9.920 |
| Soybean Meal | 23.704 | 22.763 | 20.010 | 13.211 | 12.253 | 12.205 |
| Soybean Oil | 24.322 | 23.790 | 20.921 | 10.269 | 9.919 | 10.170 |
| Cotton | 23.584 | 21.767 | 16.582 | 10.118 | 8.684 | 8.764 |
| Coffee | 32.138 | 30.115 | 25.745 | 15.885 | 14.351 | 11.438 |
| Sugar | 38.880 | 35.493 | 27.793 | 18.477 | 13.884 | 13.416 |
| Cocoa | 29.285 | 27.959 | 24.283 | 9.565 | 9.126 | 8.186 |
| Lumber | 27.263 | 24.579 | 18.635 | 8.586 | 7.703 | 7.426 |

due to weather or geopolitics. Casassus and Collin-Dufresne (2005), in addressing the disparities between the dynamics of convenience yields and futures term structure of crude oil and copper versus gold and silver, hypothesize that oil and copper have a primary function as inputs to production, while the latter two commodities are primarily stores of value. In this case, demand shocks driven by the prevailing economic conditions would drive price fluctuations in production commodities to a greater extent, and create greater variation along the term structure.

Table 3 shows that commodities generally exhibit volatility asymmetry in the opposite direction to equities, with significant gamma coefficients all negative. As documented by Bekaert and Wu (2000); Bollerslev and Todorov (2011) and others, equity indices tend to become more volatile as the price drops, to a greater extent than with index price increases, giving rise to positive gamma coefficients in GJR-GARCH(1,1) specifications. The causes commonly cited for this phenomenon in equities include financial and operating leverage effects, time-varying risk premia, and volatility feedback mechanisms. For commodities, volatility increases are generally larger with large price increases, and this effect merits further study. It appears likely that this effect is greater for commodities with increased inventory risk. In that case, such commodities would also show greater variation in the term structure of volatility.

### Table 3: GARCH(1,1) and GJR-GARCH(1,1) Fits

This table shows the parameter and fit estimates of GARCH(1,1) and GJR-GARCH(1,1) models of commodity futures volatility, and for comparison, other financial data series. The first three rows show results from fitting daily log returns of the S&P 500 index, the FTSE 100 index, and the US-GBP exchange rate. Energy, Grain, Metal, Soft and 'All' correspond to equal-weighted indices of the constituent commodity futures as shown in the grouping in Table 1. The LRT column shows the likelihood ratio test statistic (K - K'=1, critical value (at $\alpha = 0.05$) is 3.841). The series cover the period from September 1988 to December 2011, yielding 5,636 observations of daily log returns.

| | GARCH (1,1) | | | | GJR-GARCH(1,1) | | | | | LRT |
|---|---|---|---|---|---|---|---|---|---|---|
| | Omega | Alpha | Beta | LL | Omega | Alpha | Beta | Gamma | LL | |
| S&P 500 | 0.010 | 0.068 | 0.925 | -7,692.3 | 0.017 | 0.010 | 0.918 | 0.117 | -7,618.7 | 147.2 |
| FTSE 100 | 0.018 | 0.086 | 0.904 | -8,474.5 | 0.022 | 0.028 | 0.913 | 0.090 | -8,434.9 | 79.2 |
| USD-GBP | 0.003 | 0.038 | 0.954 | -4,890.1 | 0.003 | 0.032 | 0.953 | 0.011 | -4,888.5 | 3.2 |
| All Commodities | 0.003 | 0.039 | 0.957 | -6,339.4 | 0.002 | 0.045 | 0.959 | -0.012 | -6,337.4 | 4.0 |
| Grain | 0.017 | 0.069 | 0.923 | -9,056.4 | 0.014 | 0.081 | 0.929 | -0.032 | -9,048.8 | 15.2 |
| Metal | 0.011 | 0.055 | 0.937 | -8,107.8 | 0.010 | 0.062 | 0.938 | -0.014 | -8,106.1 | 3.4 |
| Energy | 0.052 | 0.073 | 0.917 | -11678.0 | 0.051 | 0.076 | 0.919 | -0.009 | -11,677.0 | 2.0 |
| Softs | 0.035 | 0.057 | 0.913 | -8,177.7 | 0.035 | 0.059 | 0.912 | -0.003 | -8,177.7 | 0.0 |

### 3.3. Commodity supply-demand

The main source of data used for global commodity trade flows is UN Comtrade. I match each of the commodity futures contracts in the study to a particular commodity code in UN Comtrade, determined as being most closely related to the underlying commodity. The commodity product classification used is the Standard International Trade Classification (SITC) Revision 2, in order to obtain the longest possible time series (see Appendix Table A1). The global bilateral trade flow information for the matched commodity is the proxy used for the aggregate supply and demand for the commodity underlying the futures contracts. I document the changes to global commodity supply and demand since 1973 for these matched commodities.

Figure 3 illustrates corresponding trends in trade by emerging countries in several commodities markets using annual UN Comtrade from 1978 to 2010. The figures show the trade value as a percentage of total world trade for BRIC[18], non-OECD excluding BRIC, OECD excluding G7, and G7 countries, for wheat, lumber, cotton, crude oil, copper, and aluminum. For most commodities in the dataset, the percentage of total world trade value for both imports and exports increased for BRIC countries and decreased for G7 countries during the past decade.

I construct measures of concentration and economic uncertainty for commodity consumers and producers for each commodity as defined in Eq. (22) and Eq (23). It is common that both the supply and demand side of global trade in a commodity are dominated by a handful of countries. As a result, it is possible to take the set of largest exporters and largest importers for each year to characterize the global supply and demand dynamics for each commodity. In constructing trade-weighted indices for producers (consumers) for a particular commodity as in (23) and (35), I take the set of (minimum five) countries that constitute at least 50% of the total global exports (imports) of that commodity when constructing the producer (consumer) index. In this case, $C\_HHI_{i,t} \approx H_{i,t}^{C}$, $C\_HHI\_EM_{i,t} \approx H_{i,t}^{C\text{-}EM}$, $P\_HHI_{i,t} \approx H_{i,t}^{P}$, and $P\_HHI\_EM_{i,t} \approx H_{i,t}^{P\text{-}EM}$. The empirical results are robust to the choice of these levels.

I obtain seasonally-adjusted quarterly gross domestic product (GDP) growth rate series using raw data from International Financial Statistics (IFS) of the International Monetary Fund (IMF). I discard any country without at least nine quarterly GDP observations and obtain a dataset of 81 countries. The GDP volatility for producers ($P\_VOL_{i,t}$) and consumers ($C\_VOL_{i,t}$) for commodity $i$ at time $t$ is constructed by averaging over the squared absolute value of the innovations from an AR(1) fit of all exporters and importers, respectively. For a
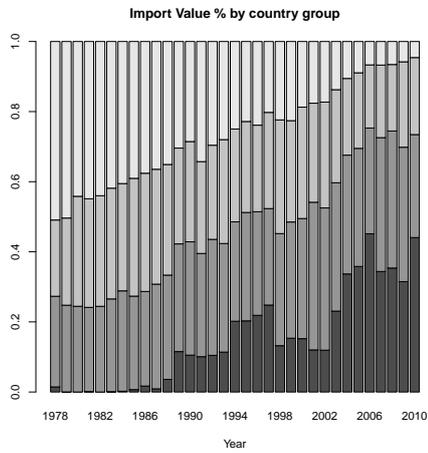
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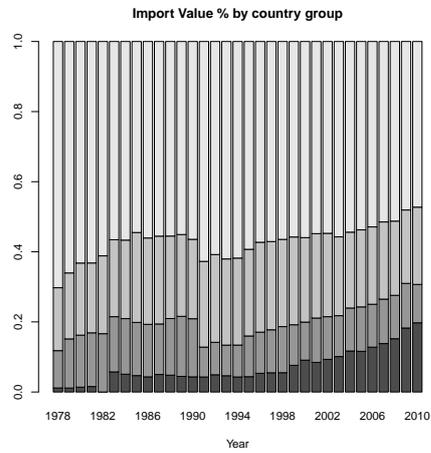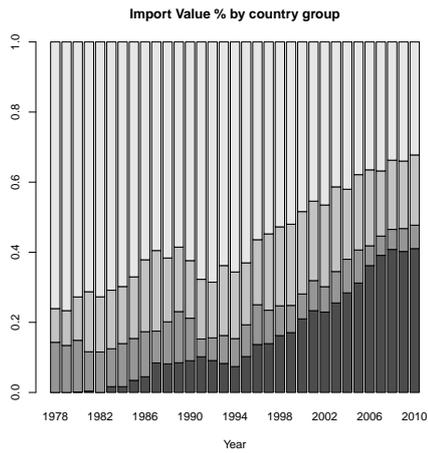[18]Brazil, Russia, India, and China.
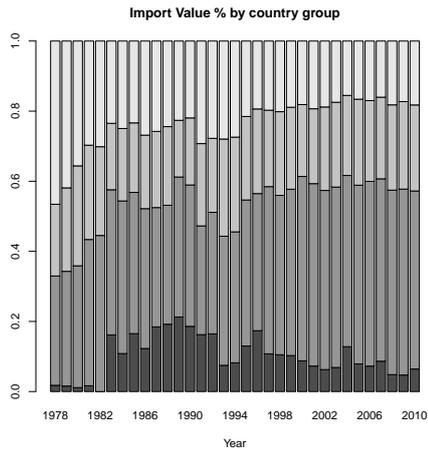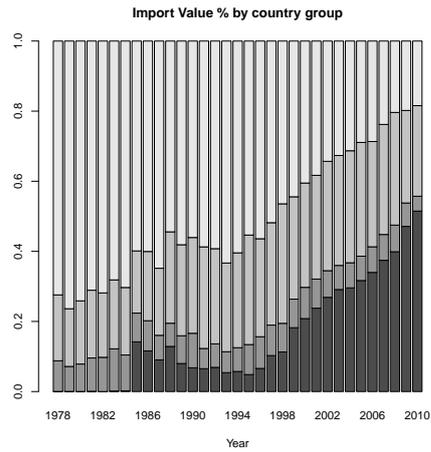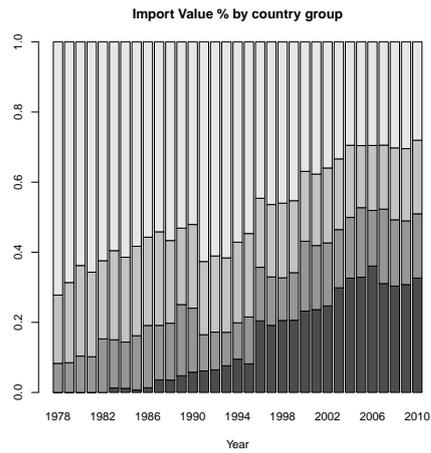
**Fig. 3.** Time series of import value as a percentage of total world imports broken down by country group.

The four groups shown are, from the bottom (darkest to lightest shading): BRIC, non-OECD excluding BRIC, OECD excluding G7, and G7 countries, respectively. *Source: Author's analysis, UN Comtrade data.*

country $j$, the trade weights are as defined in Eqs. (20) and (21).

$$\Delta log(GDP)_{j,t} = \mu_j + \rho_j \Delta log(GDP)_{j,t-1} + \epsilon_{j,t},$$

$$\sigma_{j,t}^2 = \frac{1}{4} \sum_{k=t-3}^{t} |\epsilon_{j,t}|^2,$$

$$C\_VOL_{i,t} = \left[ \sum_{j=1}^{N} \left( w_{i,j,t}^I \right)^2 \sigma_{j,t}^2 \right]^{\frac{1}{2}}. \tag{35}$$

Building on findings that link commodity currency returns to commodity futures returns,[19] I construct producer and consumer FX volatility series as an explanatory variable: $P\_FX_{i,t} = \left[ \sum_{j=1}^{N} \left( w_{i,j,t}^E \right)^2 x_{j,t}^2 \right]^{\frac{1}{2}}$, and the corresponding series for $C\_FX_{i,t}$ for importers, where $x_{j,t}$ is the return at time $t$ of the US dollar exchange rate of the country $j$ currency. All exchange rate data are collated from Datastream and the Federal Reserve Board to obtain the longest available time series.

### 3.4. Market activity

I obtain information on the evolution of different types of traders (classified as commercial (hedger), non-commerical, spread, or non-reporting (small) traders) and their activity in commodity markets from the Commitment of Traders (COT) reports made available by the US Commodity Futures Trading Commission (CFTC). Figure 4 shows the variation in the type of traders holding outstanding long and short positions in commodities, from January 1986 or December 2011. While the fraction of commercial traders' (hedgers') positions has not changed markedly, the fraction of outstanding spread positions (which trade the basis) has increased substantially. Moreover, the imbalance in commercial positions generally appears to be the opposite of the imbalance in non-commercial positions.

The set of variables identified from previous work that examines the impact of speculator activity on commodity futures returns (Hong and Yogo, 2012; Acharya, Lochstoer, and Ramadorai, 2013) used as explanatory variables in $\mathbf{z}_{i,t}$ include changes to open interest and demand imbalance, e.g., using commercial ("hedger") position values collated by the CFTC,

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[19]Chen, Rogoff, and Rossi (2010) find that the exchange rates of countries which are the major exporters of commodities strongly predict world commodity prices, while the reverse relationship is weaker. They find some evidence that "commodity currency" returns Granger-cause global commodity futures returns. This has implications in terms of commodity price hedging, especially for commodities whose forward markets have reduced horizon and depth.
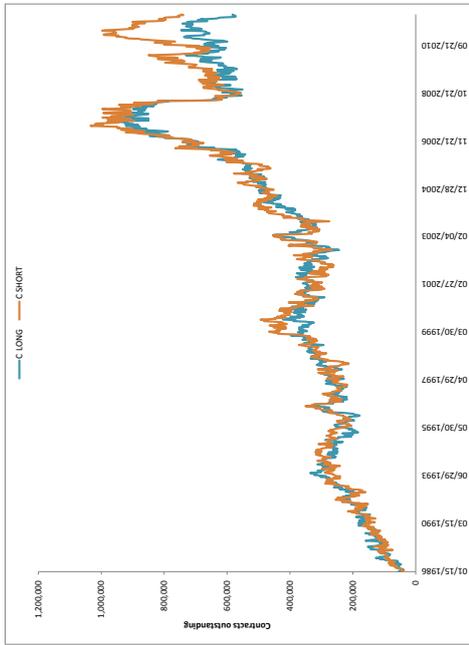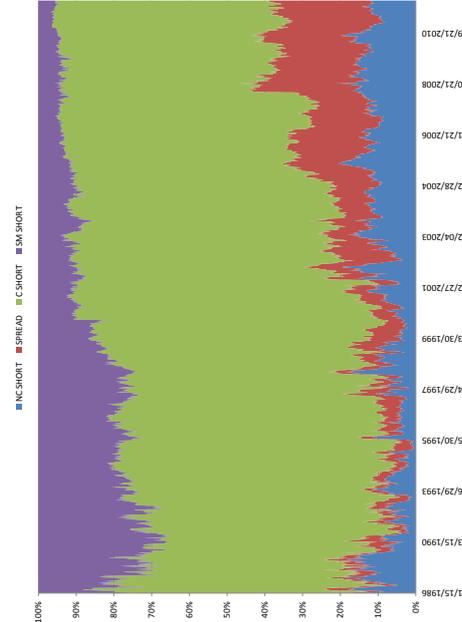
(a) Commercial (hedger) contracts
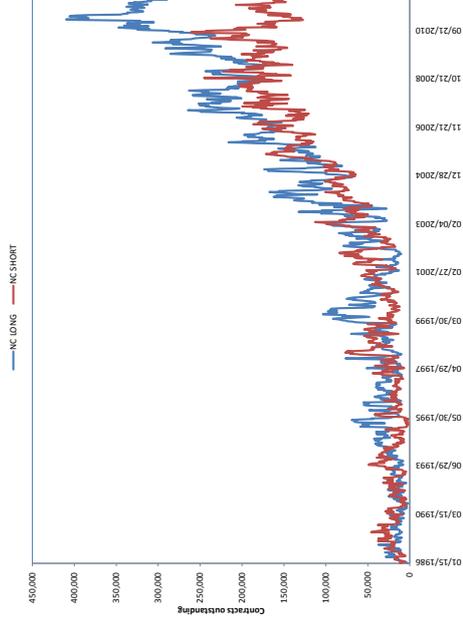


(b) Non-commercial contracts
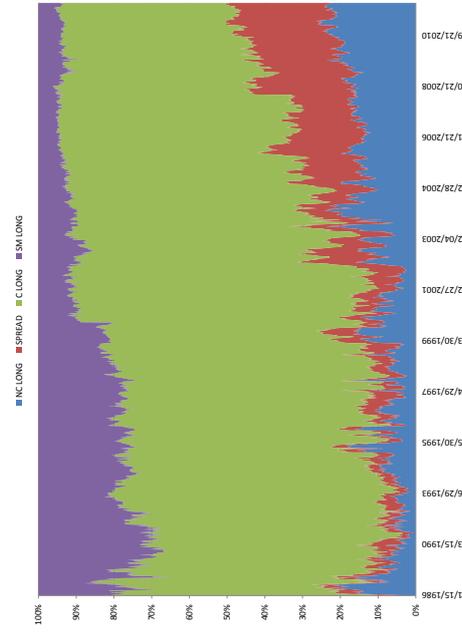


(c) Breakdown by trader type - long positions



(d) Breakdown by trader type - short positions

Fig. 4. The evolution of contract positions for crude oil futures broken down by trader type.

*Source: CFTC Commitment of Traders reports.*

$$HEDGER\_IMB_{i,t} = \frac{ShortOI_{i,t} - LongOI_{i,t}}{ShortOI_{i,t} + LongOI_{i,t}}.[20]$$

I use an indicator for the period beginning January 2004, commonly cited in previous work as the period showing index "financialization" (see, for example, Tang and Xiong, 2012; Singleton, 2014), as $IndexPeriod_t$, when testing for changes in the dynamics of volatility due to commodity index trading.

Finally, the state of the hedge funds industry is captured using the absolute value of the mean of monthly hedge funds returns ($HF\_RET_t$) using hedge fund data collated from the Lipper-TASS, BarclayHedge, Morningstar, HFR and CISDM databases.

### 3.5. Macroeconomic uncertainty indicators

I use the IMF World Economic Outlook Database for aggregate economic variables, and the IMF Direction of Trade Statistics for country-to-country aggregate import-export data. Both of these sources provide data at annual frequency. All interest rates and exchange rates are from the Global Financial Database (GFD) and Datastream. Wherever necessary, World Bank classifications are used to group world economies.[21] The US GDP and CPI (quarterly) forecast statistics are from the Philadelphia Federal Reserve Bank's Survey of Professional Forecasters. Economic forecasts for other countries are from analyst forecasts collated in Bloomberg. US recession period data are from the National Burea of Economic Research (NBER).

The choice of variables used in constructing the macroeconomic uncertainty series is motivated by previous studies (Campbell and Shiller, 1988; Campbell, Giglio, Polk, and Turley, 2012; Bali, Brown, and Caglayan, 2014; Bloom, 2014). $INF\_U$ - US inflation from change in consumer price index. $INFFC\_A$ - Survey of Professional Forecasters, dispersion in next quarter CPI forecasts. $TERM\_U$ - Spread between 10-year and 3-month Treasury yields. $RREL\_U$ - Difference between 3-month Treasury yield and its 12-month geometric mean. $DEF\_U$ - Baa-Aaa (Moody's) rated corporate bond yield spread. $TED\_U$ - 1M LIBOR - 1M-T-Bill rates. $UNEMP\_U$ - US unemployment rate. $GDP\_U$ - US real GDP growth rate per capita. $CFNAI\_U$ - Chicago Fed Economic Activity Index. $RDIV\_U$ - Aggregate real dividend yield on S&P 500. $MKT\_U$ - S&P 500 index excess return. $VXO\_A$ - S&P 100 implied volatility index level.

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[20]Hong and Yogo (2012) investigate the power of futures open interest to predict commodity, currency, stock, and bond prices, and find open interest growth is more informative than other common alternatives as it is reflective of future economic activity.

[21]WB Country and Lending Groups Page (http://data.worldbank.org/about/country-classifications/country-and-lending-groups).

These variables are available from January 1960 to the end of the sample period, except for CFNAI (from May 1967), TED (from January 1971) and VXO (from January 1986). $X\_U_t$ denotes the one period-ahead GARCH(1,1) volatility prediction of variable $X$ made using all available observations up to time $t-1$ and $X\_A_t$ denotes the AR(1) forecast made using all available observations up to time $t-1$.

# 4. Empirical Results

## 4.1. Consumer and producer impact

Table 4 shows the results of regressions using as explanatory variables consumer and producer trade-weighted indices that capture supply-demand uncertainty and vulnerability to shocks. Panel A shows the results with year-over-year changes of the Herfindahl indices. Panel B shows results with trade-weighted volatility indices of consumer and producer shocks. In Panel A, columns 1 to 3 show results from regressions including the change in the Herfindahl index of all major trading countries (HHI_ALL), without separating out non-OECD countries. Under all three regression specifications, only the consumer Herfindahl index has a positive significant coefficient with a $t$-statistic of 3.57, while the coefficient for producer concentration is not significant. This is in line with the predictions set forth in section 2.2. There is a significant impact on futures volatility from consumer concentration. Next, I consider the heterogeneity in shocks between the two groups, OECD and non-OECD.

Columns 4 to 6 in Table 4 show the same regressions with only non-OECD countries (HHI_EM), with the weights of OECD countries replaced with zero in the index. Again, the coefficient on the non-OECD consumer concentration index (CONS_HHI_EM) is the only one that is positive and significant, with a $t$-statistic of 6.38. The final three columns show the results when all four indices are included. The coefficient for CONS_HHI_EM remains essentially unchanged, with a $t$-statistic of 4.71. These results imply that a 1% gain in market concentration by developing country consumers is associated with a 1.19% gain in commodity futures volatility in this period. Regardless of the idiosyncratic variation within the two groups of consumers, controlling for the heterogeneity across the two groups allows us to capture the differential impact of emerging market countries on commodity volatility. These findings are in agreement with previous work that finds emerging markets pose greater uncertainty (Bloom, 2014). These results show how this uncertainty may affect commodity futures. These results

## Table 4: Commodity Futures Volatility - Producer and Consumer Uncertainty

This table shows results for the balanced panel regressions of 1-month volatility of the front-month futures return, Vol(t), as the dependent variable in regressions 1 through 9 in Panels A and B. The regressions shown in Panel A include year-over year changes to producer (exporter) and consumer (importer) concentration indices as the independent variables. The possible values of the HHI concentration indices range from 0 to 1, so that the change in the concentration index is between -1 and 1. Panel B regressions include the trade-weighted volatility indices for producer and consumer country shocks (to quarterly GDP). The results reported here are for all commodities over the entire period of the sample (262 months) for 4,454 commodity-month observations. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. $t$-statistics clustered by month are shown in parenthesis below each coefficient estimate.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Changes to producer and consumer concentrations in global trade** | | | | | | | | | |
| $\Delta PROD\_HHI\_ALL_{(t)}$ | -0.138 | | -0.129 | | | | -0.235** | | -0.228* |
| | (-1.415) | | (-1.303) | | | | (-2.032) | | (-1.949) |
| $\Delta PROD\_HHI\_EM_{(t)}$ | | | | 0.045 | | 0.050 | 0.252 | | 0.251 |
| | | | | (0.336) | | (0.369) | (1.617) | | (1.605) |
| $\Delta CONS\_HHI\_ALL_{(t)}$ | | 0.365*** | 0.360*** | | | | | 0.009 | -0.004 |
| | | (3.571) | (3.496) | | | | | (0.067) | (-0.032) |
| $\Delta CONS\_HHI\_EM_{(t)}$ | | | | | 1.192*** | 1.192*** | | 1.183*** | 1.192*** |
| | | | | | (6.383) | (6.391) | | (4.653) | (4.709) |
| Adjusted R-squared | 0.162 | 0.164 | 0.164 | 0.161 | 0.170 | 0.170 | 0.162 | 0.170 | 0.170 |
| BIC | 34,943.1 | 34,932.2 | 34,938.3 | 34,945.6 | 34,899.7 | 34,908.0 | 34,949.0 | 34,908.1 | 34,920.1 |
| **Panel B: Trade-weighted volatility indices of producer and consumer shocks** | | | | | | | | | |
| $PROD\_VOL\_ALL_{(t)}$ | 0.094* | | 0.072 | | | | 0.023 | | 0.028 |
| | (1.750) | | (1.417) | | | | (0.291) | | (0.365) |
| $PROD\_VOL\_EM_{(t)}$ | | | | 0.099** | | 0.082** | 0.083 | | 0.054 |
| | | | | (2.518) | | (2.215) | (1.410) | | (0.929) |
| $CONS\_VOL\_ALL_{(t)}$ | | 0.165*** | 0.158*** | | | | | 0.113** | 0.105** |
| | | (3.589) | (3.614) | | | | | (2.567) | (2.495) |
| $CONS\_VOL\_EM_{(t)}$ | | | | 0.462*** | 0.451*** | | | 0.405*** | 0.401*** |
| | | | | (6.327) | (6.375) | | | (6.190) | (6.150) |
| Adjusted R-squared | 0.163 | 0.167 | 0.168 | 0.163 | 0.173 | 0.175 | 0.163 | 0.176 | 0.177 |
| BIC | 34,938.2 | 34,913.5 | 34,917.6 | 34,935.0 | 34,880.9 | 34,881.9 | 34,943.2 | 34,875.0 | 34,885.8 |

showing the significance of non-OECD consumers are robust to using the level or change in HHI indices and the inclusion of year fixed effects.

Next, using conditional GJR-GARCH fits of commodity futures returns, I examine the time-variation in the asymmetric relationship between returns and volatility, and analyze how this relates to the commodity basis and sensitivity to consumer and producer shocks (hypothesis 2.6).

### 4.2. Macroeconomic uncertainty

Tables 5 to 8 show the results from balanced panel regressions of the (time, $t$) 1-month realized volatility of the front-month futures return over lagged (time, $t-1$) explanatory variables, as specified in Eq. (34). The volatility series are at a non-overlapping monthly frequency. The results shown are for the commodity groups: energy, metal, grain, soft, and all (of the 17 commodities in the sample, see section 3.1). The panel regressions all include commodity and seasonal (month-of-year) fixed effects, and $t$-statistics clustered by month are shown in parenthesis below each coefficient estimate. All regressions for a particular dependent variable include observations on the same dates, allowing for the comparison of information criterion.[22]

In Table 5, Panel A shows the baseline regressions with only lagged (time, $t-1$) volatility and lagged (absolute) return as explanatory variables ($Vol$ and $Return$). This is similar in concept to a GARCH(1,1) formulation, broadly capturing the same information set at time $t-1$. The coefficients are positive and highly significant. This is similar to empirical observations of equity, bond and other financial markets. In Panel B, I include the variable $PositiveReturn$, which is the return series with negative values replaced with zero. This formulation is similar to a GJR-GARCH(1,1) specification (see Eq. (45)) and allows for the capture of any asymmetric affect on volatility from the direction of the lagged return. Similar to the model fits in Table 3, these results also show that, unlike in the case of equities (Bekaert and Wu, 2000), there is no unconditional directional bias in the relationship between lagged return and volatility for commodity futures. Given the information contained in this asymmetric effect on the concentration and direction of risk and investor demand (Bekaert and Wu, 2000; Bollerslev and Todorov, 2011;

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[22] In the discussion of regression results that follow, model fit is considered using likelihood ratio tests, denoted LRT (Neyman and Pearson, 1933; Wilks, 1938; Engle, 1984), and Schwarz Bayesian information criteria (also known as the Bayesian information criterion), denoted BIC (Schwarz, 1978). LRT can be used to compare two nested models. More generally, a comparison using BIC is possible when the LHS dependent variable is exactly the same, even when two models do not nest. The standard errors shown in the panel regression results are clustered by month (Petersen, 2009).

Garleanu, Pedersen, and Poteshman, 2009), the conditional variation in this relationship bears further study in the commodities space. In later analysis, I examine the impact of demand and supply shocks on the conditional variation in this relationship using the specification in Eq. (30).

Table 5: Commodity Futures Volatility - Panel Regression Results

This table shows the results for balanced panel regressions of (time, $t$) 1-month volatility of the front-month futures return, $Vol_{(t)}$, over lagged (time, $t-1$) volatility and (absolute) return. $PostiveReturn$ is the absolute return series of the front month future with the negative return months set to 0. The results reported here are for the groups energy, metal, grain, soft, and all commodities. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. $t$-statistics clustered by month are shown in parenthesis below each coefficient estimate.

|  | Energy | Metal | Grain | Soft | All |
|---|---|---|---|---|---|
| **Panel A: Baseline panel regression** | | | | | |
| $(Intercept)$ | 20.671 | 6.765 | 10.213 | 16.249 | 11.335 |
|  | (4.571) | (5.084) | (7.897) | (8.419) | (10.582) |
| $|Return_{(t-1)}|$ | 0.617 | 0.416 | 0.227 | 0.371 | 0.391 |
|  | (4.074) | (3.321) | (3.137) | (4.119) | (6.781) |
| $Vol_{(t-1)}$ | 0.412 | 0.478 | 0.520 | 0.336 | 0.428 |
|  | (4.872) | (8.795) | (12.203) | (5.458) | (10.647) |
| Adjusted R-squared | 0.343 | 0.437 | 0.419 | 0.252 | 0.395 |
| Number of commodity-months | 524 | 1,310 | 1,310 | 1,310 | 4,454 |
| **Panel B: Baseline panel regression allowing for asymmetric return effect** | | | | | |
| $(Intercept)$ | 20.739 | 6.768 | 10.227 | 16.260 | 11.349 |
|  | (4.606) | (5.087) | (7.892) | (8.567) | (10.546) |
| $|Return_{(t-1)}|$ | 0.721 | 0.399 | 0.208 | 0.297 | 0.362 |
|  | (4.125) | (3.040) | (2.409) | (2.329) | (4.490) |
| $I_{[Return_{(t-1)}>0]} * |Return_{(t-1)}|$ | -0.141 | 0.025 | 0.031 | 0.118 | 0.044 |
|  | (-0.733) | (0.145) | (0.313) | (1.094) | (0.525) |
| $Vol_{(t-1)}$ | 0.400 | 0.479 | 0.520 | 0.338 | 0.429 |
|  | (4.851) | (8.628) | (12.159) | (5.629) | (10.833) |
| Adjusted R-squared | 0.343 | 0.436 | 0.419 | 0.253 | 0.395 |
| Number of commodity-months | 524 | 1,310 | 1,310 | 1,310 | 4,454 |
| LRT statistic | 1.60 | 0.20 | 0.20 | 3.20 | 1.40 |
| $c[(K - K' = 1), (\alpha = 0.05)] = 3.841$ | | | | | |

In Table 6, I add the variables capturing macroeconomic uncertainty. This results in an adjusted R-squared gain of over 10% (for the energy group) from the baseline specification in Table 5, Panel A. Other comparisons of model fit such as BIC and LRT also show a clear improvement for the commodities in the energy, metal, grain, and all groups. The softs group

has the smallest gain in proportion of explained variation. The inclusion of economic controls consistently improves the adjusted R-squared and information criterion measures of model fit. $INFFC\_A$, $CFNAI\_U$ and $RDIV\_U$ have positive and significant coefficients in the regression including all commodities.[23] These results are in agreement with the implications of the derivation in section 2.1, which show that variation in commodity futures volatility arise due to changes to the expectations of future interest rates, convenience yield and risk premia. The inflation variables capture information about future interest rates and is informative of future economic and inflation regimes (David and Veronesi, 2013). Economic activity is related to the convenience yield (Casassus and Collin-Dufresne, 2005). The results including controls for recession periods (section 4.4) also capture the variation in risk premia associated with the business cycle. Moreover, these findings broadly confirm observations on the effects of uncertainty in other markets (Bloom (2014)).

Table 6: Commodity Futures Volatility and Macroeconomic Uncertainty

This table shows the results for balanced panel regressions of (time, $t$) 1-month volatility of the front-month futures return, $Vol_{(t)}$, over lagged (time, $t-1$) explanatory variables that capture macroeconomic uncertainty. These variables are the first four principal components of 11 lagged macroeconomic uncertainty series (Table A4 and A5 in the Appendix contain details of this PCA). The results reported here are for the groups energy, metal, grain, soft, and all commodities. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. $t$-statistics clustered by month are shown in parenthesis below each coefficient estimate. The LRT row shows the likelihood ratio test statistic comparing the fit shown in Table 5.A to the current results.

|  | Energy | Metal | Grain | Softs | All |
|---|---|---|---|---|---|
| $PC1_{(t-1)}$ | -2.166*** | -1.030*** | -0.890*** | -0.630*** | -0.952*** |
|  | (-4.975) | (-4.723) | (-4.991) | (-4.552) | (-6.934) |
| $PC2_{(t-1)}$ | -1.356** | -0.417 | 0.037 | 0.380 | -0.155 |
|  | (-2.139) | (-1.473) | (0.123) | (1.468) | (-0.759) |
| $PC3_{(t-1)}$ | 2.261*** | 0.538* | 0.291 | 0.426* | 0.586*** |
|  | (4.616) | (1.903) | (1.114) | (1.749) | (3.968) |
| $PC4_{(t-1)}$ | 1.188** | 1.690*** | 1.513*** | -0.320 | 0.977*** |
|  | (2.005) | (5.011) | (3.981) | (-0.997) | (4.489) |
| All predictors in Table 5 | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.442 | 0.474 | 0.459 | 0.263 | 0.423 |
| Number of commodity-months | 524 | 1,310 | 1,310 | 1,310 | 4,454 |
| LRT statistic | 90.0 | 93.2 | 97.4 | 24.2 | 217.2 |
| $c[(K-K'=4),(\alpha=0.05)] = 9.488$ | | | | | |

It is difficult to contemporaneously explain, let alone predict, financial asset volatility using economic factors (see, for example, Roll (1984); Schwert (1989); Engle and Rangel (2008); Engle,

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[23]See Table A7 of the Appendix for the results of Granger causality tests, which show that the direction of predictive causality is from the economic uncertainty variables included here to commodity futures volatility, rather than vice versa.

Ghysels, and Sohn (2013)), even when model results and economic intuition posit a relationship between economic conditions and volatility. Consequently, the results in Table 6 constitute a step forward in our understanding of the factors that drive volatility.

Moreover, such predictive power is economically significant for a mean-variance investor (see, for example, Campbell and Thompson (2008); Inoue and Kilian (2004) and Moskowitz, Ooi, and Pedersen (2012) for further discussion on the value of time series predictability). An adjusted R-squared gain over the baseline model is useful for investors who have a non-zero "vega" exposure in their portfolio ($\frac{\delta V}{\delta \sigma} \neq 0$ in a portfolio with value $V$ and volatility $\sigma$) as, in that case, predicting volatility allows for the prediction of portfolio and position values. This is important for any hedger or derivatives trader as the value of their portfolios and trading strategies is directly tied to the volatility of the traded assets.

For tractability, in the regressions that follow, I use the first four principal components to capture the variation of the 11 economic uncertainty series in the main regressions. Table A4 of the Appendix presents the details of the principal component analysis. The panels in Table A5 show the regressions results with varying numbers of principal components included.[24] In future work, I include uncertainty proxies directly based on work by Jurado, Ludvigson, and Ng (2014).

### 4.3. Hedging and trading activity

Table 7 shows the results once the variables capturing momentum and hedging activity (Hong and Yogo, 2012; Acharya, Lochstoer, and Ramadorai, 2013) are added to the specification in Table 6, which include the macroeconomic controls. While there is some improvement, there is no consistent gain in predictive power. Table A6 of the Appendix shows the results without the inclusion of the macroeconomic controls. The regressions adding only economic uncertainty variables to the baseline specification as in Table 6 perform better on the dimensions of adjusted R-squared and information criterion measures of model fit.

Table 8 controls for hedge fund activity by including lagged hedge fund (absolute) return as an explanatory variable. $HF\_RET$ has a positive and significant coefficient of 0.421 with a $t$-statistic of 1.798, even after the inclusion of all proxies for economic uncertainty and hedging activity included in Table 7. The coefficient for grain commodities is the most significant, and this potentially links to the consequences of market changes related to the US Ethanol Mandate

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[24]See Bai and Ng (2002); Stock and Watson (2002) on selecting the appropriate number of factors.

## Table 7: Commodity Futures Volatility and Commodity Market Risk Factors

This table shows the results for balanced panel regressions of (time, $t$) 1-month volatility of the front-month futures return, $Vol_{(t)}$, over lagged (time, $t-1$) commodity market variables in addition to the macroeconomic uncertainty factors included in Table 6. The results reported here are for the groups energy, metal, grain, soft, and all commodities. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. $t$-statistics clustered by month are shown in parenthesis below each coefficient estimate. The LRT row shows the likelihood ratio test statistic comparing the fit shown in Table 6 to the current results.

|  | Energy | Metal | Grain | Softs | All |
|---|---|---|---|---|---|
| $CMOM_{(t-1)}$ | 0.804 | 4.009*** | 0.503 | -0.615 | 1.767*** |
|  | (0.681) | (3.538) | (0.561) | (-0.665) | (2.882) |
| $HEDGER\_OIG_{(t-1)}$ | 1.235 | -0.177 | 0.282 | 0.774 | 0.320 |
|  | (1.245) | (-0.388) | (0.863) | (1.201) | (1.149) |
| $HEDGER\_IMB_{(t-1)}$ | -0.153 | -0.021 | -0.069 | -0.114 | -0.089** |
|  | (-0.806) | (-0.472) | (-0.786) | (-1.338) | (-2.328) |
| All predictors in Table 6 | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.449 | 0.483 | 0.46 | 0.264 | 0.428 |
| Number of commodity-months | 524 | 1,310 | 1,310 | 1,310 | 4,454 |
| LRT statistic | 9.6 | 27.2 | 5.0 | 4.4 | 41.2 |
| $c[(K-K'=3),(\alpha=0.05)]=7.815$ | | | | | |

(Roberts and Schlenker, 2013). After interacting for the indicator for the "index period", I find that this positive relationship is limited to this period, when the coefficient is 1.085 with a $t$-statistic of 2.627. However, given that this period overlaps significantly with a major recession, this identification in a smaller sample (starting in January 1995) is weak.

### 4.4. Time-variation

Table 9 shows the comparison of model fits, in addition to results with interactions for different time periods added to the specification in Table 7. In column 5, I interact for the NBER recession periods as in regression specification (36), and in column 6, I show the results from interacting with $IndexPeriod$ as in regression specification (37).

$$Vol_t = \mu_i + NBER\_Recession + \mathbf{z}_{t-1}'\boldsymbol{\theta} + NBER\_Recession * \mathbf{z}_{t-1}'\boldsymbol{\theta}^{REC} + \eta_t, \qquad (36)$$

$$Vol_t = \mu_i + IndexPeriod + \mathbf{z}_{t-1}'\boldsymbol{\theta} + IndexPeriod * \mathbf{z}_{t-1}'\boldsymbol{\theta}^{INDEX} + \eta_t, \qquad (37)$$

Interacting for $NBER\_Recession$ increases the model fit for all groups relative to the specification without the interaction with up to a 13.6% adjusted R-squared gain for energy commodities. Commodities in the grain and softs groups show a better fit under $IndexPeriod$

Table 8: Commodity Futures Volatility and Hedge Fund Activity

This table shows the results for balanced panel regressions of (time, $t$) 1-month volatility of the front-month futures return, $Vol_{(t)}$, over lagged (time, $t-1$) absolute value of the hedge fund industry mean return, in addition to all explanatory variables included in Table 7. The results reported here are for the groups energy, metal, grain, soft, and all commodities, from January 1995 to December 2010. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. $t$-statistics clustered by month are shown in parenthesis below each coefficient estimate.

| | Energy | Metal | Grain | Softs | All | | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| | | | | | 1 | 2 | 3 |
| $HF\_RET_{(t-1)}$ | 0.684 | 0.220 | 0.864*** | 0.106 | 0.421* | -0.223 | 0.120 |
| | (1.435) | (0.611) | (2.585) | (0.428) | (1.798) | (-1.125) | (0.702) |
| $IndexPeriod_{(t)} * HF\_RET_{(t-1)}$ | | | | | | 1.085*** | |
| | | | | | | (2.627) | |
| $Recession_{(t)} * HF\_RET_{(t-1)}$ | | | | | | | 1.615** |
| | | | | | | | (1.983) |
| | | | | | | | |
| All predictors in Table 7 | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.451 | 0.473 | 0.440 | 0.250 | 0.416 | 0.422 | 0.427 |
| Number of commodity-months | 376 | 940 | 940 | 940 | 3,196 | 3,196 | 3,196 |

interactions. Metal commodities show no significant difference between the two specifications, while energy commodities have less explanatory power under the interaction with $IndexPeriod$. Next, I analyze the coefficients from rolling regressions in order to investigate the time-variation in commodity futures volatility.

## 5. Conclusions

This paper conducts a systematic analysis in order to understand the dynamics of commodity futures volatility. I derive the variance decomposition for commodity futures to show how unexpected changes to the excess basis return are driven by changes to the expectation of future interest rates, convenience yield, and risk premia. These expectations are updated in response to news about the future state of the economy and future commodity supply and demand. I model time-varying commodity futures volatility and study the impact of variables that proxy for such economic uncertainty, while controlling for the impact of any frictions due to trading activity.

Using data for major commodity futures markets and global bilateral commodity trade, I analyze the extent to which commodity volatility is related to fundamentals that impact convenience yield and interest rates such as increased emerging market demand and inflation uncertainty, as well as financial frictions introduced by changing market structure and commodity index trading. A higher concentration in emerging market importers of a commodity is

## Table 9: Commodity Futures Volatility during Different Time Periods

This table shows model fit measures for the balanced panel regressions of (time, t) 1-month volatility of the front-month futures return over lagged (time, t-1) explanatory variables under different specifications. Panel A shows the adjusted R-squareds, Panel B shows the Bayesian information criterion values, and Panel C shows the likelihood ratio statistic of the different models. Column 1 shows the fit measures from the regression specification in Table 5.A ("Baseline"), column 2 shows those from including all 11 macroeconomic uncertainty series on the RHS, column 3 shows those from Table 6 ("EU_PC 1-4"), and column 4 shows those from Table 7 ("Commodity market"'). Column 5 shows the results with all explanatory variables in Table 7 included, together with interactions for NBER recession periods; the last column shows the results with all explanatory variables in Table 7 included, together with interactions with $IndexPeriod$ (the indicator for the period after January 2004). The results reported here are for the groups energy, metal, grain, soft, and all commodities. All regressions include commodity and season (month) fixed effects.

| | Baseline | Macro uncertainty | EU_PC 1-4 | Commodity market | Interaction for recession periods | Interaction for $IndexPeriod$ |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |

**Panel A: Adjusted R-squared**

| | | | | | | |
|---|---|---|---|---|---|---|
| Energy | 34.3 | 48.9 | 44.2 | 44.9 | 58.5 | 51.1 |
| Metal | 43.7 | 47.3 | 47.4 | 48.3 | 49.2 | 49.3 |
| Grain | 41.9 | 47.8 | 45.9 | 46.0 | 48.6 | 49.1 |
| Softs | 25.2 | 26.3 | 26.3 | 26.4 | 26.2 | 26.7 |
| All | 39.5 | 42.4 | 42.3 | 42.8 | 43.9 | 43.1 |

**Panel B: Bayesian information criterion (BIC)**

| | | | | | | |
|---|---|---|---|---|---|---|
| Energy | 4,136.6 | 4,057.1 | 4,071.6 | 4,080.8 | 3,983.6 | 4,069.7 |
| Metal | 9,760.8 | 9,733.7 | 9,696.2 | 9,690.7 | 9,728.9 | 9,727.6 |
| Grain | 9,306.6 | 9,256.4 | 9,237.8 | 9,254.3 | 9,252.7 | 9,239.6 |
| Softs | 10,210.0 | 10,251.1 | 10,214.4 | 10,231.6 | 10,295.9 | 10,287.9 |
| All | 33,500.9 | 33,351.5 | 33,317.3 | 33,301.3 | 33,285.9 | 33,353.4 |

**Panel C: Likelihood ratio comparison (LRT)**

| $K - K'$ | $K_2 - K_1 = 10$ | $K_3 - K_1 = 4$ | $K_4 - K_2 = 3$ | $K_5 - K_4 = 10$ | $K_6 - K_4 = 10$ |
|---|---|---|---|---|---|
| Critical value ($\alpha = 0.05$) | 18.307 | 9.488 | 7.815 | 18.307 | 18.307 |
| Energy | 142.2 | 90.0 | 9.6 | 159.8 | 73.6 |
| Metal | 98.8 | 93.2 | 27.2 | 33.6 | 34.8 |
| Grain | 122.0 | 97.4 | 5.0 | 73.6 | 86.6 |
| Softs | 30.6 | 24.2 | 4.4 | 7.4 | 15.4 |
| All | 233.4 | 217.2 | 41.2 | 99.4 | 31.8 |

associated with higher futures volatility. I find significant predictability in commodity futures volatility using variables capturing macroeconomic uncertainty.

Such explanatory power can be economically significant for market participants (Campbell and Thompson, 2008; Inoue and Kilian, 2004). Investors who have volatility-sensitivity (a non-zero "vega" exposure) in their portfolios would especially benefit as in that case, predicting volatility allows for the prediction of portfolio and position values. This is important for any hedger or derivatives trader, as the value of their portfolios and trading strategies is directly tied to the volatility of the traded assets. Investors and end-users (commodity producers and consumers) in commodity markets benefit from understanding how the observed price behavior relates to the prevailing economic conditions. Uncertainty can lead to the long-term misallocation of resources as end-users evaluate real options in their investment decisions. Moreover, for many commodities with illiquid or short-dated derivatives markets of little depth, these findings can be a useful aid to price discovery and risk management.

This work builds on results discussed in Bloom (2014) that show emerging markets and recessionary periods are strongly associated with economic uncertainty. This work also adapts studies on the granular origins of volatility (Gabaix, 2011) and shows how the same principle can affect volatility in global markets. It is difficult to contemporaneously explain, let alone predict, financial asset volatility using factors reflecting economic conditions (Roll, 1984; Schwert, 1989; Engle and Rangel, 2008), even when model results and economic intuition posit such a relationship. Consequently, the results in this paper constitute a step forward in our understanding of the factors that drive volatility. As global markets become increasingly interlinked, it is imperative to understand the impact of increased concentration and emerging market participation in commodities trade, and the manner and extent to which shocks propagate between markets.

# 6. Appendix

## 6.1. *Components of the excess basis return*

We can further decompose the excess basis return, $x_{n,t+1}$, in Eq. (10) to separate out the excess return due to the interest rate term structure and characterize the excess return purely due to convenience yield and commodity risk premia:

$$x_{n,t+1} \equiv x^y_{n,t+1} - x^r_{n,t+1}, \tag{38}$$

$$x^y_{n,t+1} - E_t x^y_{n,t+1} = (E_{t+1} - E_t)\left\{ -\sum_{i=1}^{n-1} y_{1,t+i} - \sum_{i=1}^{n-1} x^y_{n-i,t+i+1} \right\}, \tag{39}$$

$$x^r_{n,t+1} - E_t x^r_{n,t+1} = (E_{t+1} - E_t)\left\{ -\sum_{i=1}^{n-1} \pi_{1,t+i} - \sum_{i=1}^{n-1} \psi_{1,t+i} - \sum_{i=1}^{n-1} x^r_{n-i,t+i+1} \right\}, \tag{40}$$

where, $\pi_{1,t}$ is the 1-period inflation rate and $\psi_{1,t}$ is the 1-period real interest rate at time $t$. The derivation of (40) is discussed in Campbell and Ammer (1993).

## 6.2. Volatility models and extensions

In this appendix, I describe the realized volatility models that form the basis of the empirical analysis.

### 6.2.1. GARCH-type models

Drawing on previous work on equity market volatility (Engle and Lee, 1999; Engle and Gallo, 2008; Engle and Rangel, 2008), I use a GARCH-type model of volatility to check the robustness of the baseline regression analysis. A standard GARCH(1,1) process (Engle, 1982; Bollerslev, 1986) for a particular asset is defined as,

$$r_t = \mu_t + \sigma_t \varepsilon_t, \text{ where } \varepsilon_t | \Omega_{t-1} \sim N(0,1), \tag{41}$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{42}$$

$$\sigma_t = \sqrt{h_t}. \tag{43}$$

It follows that the unconditional variance in the model will be $E\left[(r_t - E_{t-1}r_t)^2\right] = E\left[(r_t - \mu_t)^2\right] = \frac{\omega}{1-\alpha-\beta}$. In its simplest form, extensions to the standard GARCH(1,1) process that include $K$ (weakly) exogenous lagged explanatory variables in $\mathbf{z_t}$, with $\boldsymbol{\xi}_t = \frac{\mathbf{z_t}}{E[\mathbf{z_t}]}$, take the form of GARCH-X(1,1),

$$g_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta g_{t-1} + \boldsymbol{\xi}_t' \boldsymbol{\theta},$$

$$\sigma_t = \sqrt{g_t}. \tag{44}$$

Then the unconditional variance, $E\left[(r_t - E_{t-1}r_t)^2\right] = \frac{\omega + \gamma_1 + ... + \gamma_K}{1-\alpha-\beta}$.

Note that, unlike with equity (Bekaert and Wu, 2000; Bollerslev and Todorov, 2011), there is no direct equivalent to the firm leverage effect for commodities and risk can be concentrated in either direction depending on the shock to supply or demand. A model capturing asymmetry in a manner such as the GJR-GARCH model[25] may be useful for learning about the conditional demand- or supply-side pressures in a commodity market. As seen in Tables 3 and 5.B, for commodity futures, there is no unconditional asymmetric volatility effect when controlling solely

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[25]From Glosten, Jagannathan, and Runkle (1993), a GJR-GARCH(1,1) process allows for an asymmetric return effect, and differs from the specification of GARCH(1,1) in (42) by the specification of $h_t$,

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma I_{t-1}^{(-)} \varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{45}$$

where, $I_{t-1}^{(-)}$ is 1 when $\varepsilon_{t-1} < 0$, and 0 otherwise.

for the sign of lagged returns.

### 6.2.2. Long-run and short-run volatility components

Consider the short-term and long-term components of the data-generating process within a framework similar to the models of equity volatility presented in Engle and Rangel (2008) and Engle, Ghysels, and Sohn (2013), differing only in terms of the definition of the slow-moving component of volatility.

$$
\begin{aligned}
r_t &= \mu_t + \sigma_t \varepsilon_t, \\
h_t &= (1 - \alpha - \beta) + \alpha \frac{\varepsilon_{t-1}^2}{\tau_{t-1}} + \beta h_{t-1}, \\
\sigma_t &= \sqrt{\tau_t h_t},
\end{aligned}
\tag{46}
$$

where $\tau_t$ represents the long-term volatility component and, for a set of $K$ lagged explanatory variables in $\mathbf{z_t}$, is defined,

$$
\log \tau_t = m + \mathbf{z}_t{}' \boldsymbol{\theta},
\tag{47}
$$

The size of the set of estimated parameters in the model, $\Theta = \{\mu, \alpha, \beta, m, \gamma_1, \ldots, \gamma_K\}$, is on the same order as the GARCH-X model presented in the previous section. In this model, the unconditional variance corresponds exactly to the low-frequency component as $E\left[(r_t - E_{t-1}r_t)^2\right] = \tau_t E[h_t] = \tau_t$.

Engle, Ghysels, and Sohn (2013), in their analysis of the macroeconomic determinants of equity market volatility, separately consider the impact of the level and volatility of two variables: inflation and industrial production growth. They find a significant impact from these macroeconomic variables even on daily volatility. Their model differs in the definition of $\tau$ in (47) by including multiple lags of each explanatory variable with an imposed weighting function. This limits the number of factors that can be included together as each adds three parameters to $\Theta$.

In contrast, Engle and Rangel (2008), in their spline-GARCH specification (also differing solely in their definition of (47)), estimate $\tau$ nonparametrically using an exponential quadratic

spline.

$$\tau_t = c \exp\left(w_0 t + \sum_{i=1}^{k} w_i((t - t_{i-1})_+)^2\right), \tag{48}$$

where $(t - t_i)_+ = \{t - t_i$ if $t > t_i$, otherwise $0\}$ and $k$ is the optimal number of equally-spaced knots, selected using information criteria (AIC and BIC). This partitions the time series into $k$ equally-spaced intervals, demarked by $\{t_0 = 0, t_1, \ldots, t_k = T\}$. The estimated time series of the slow-moving component ($\tau$) is subsequently used as the dependent variable in an independent regression, with up to eleven explanatory variables in their model: economic development level, market capitalization, inflation level, GDP level and growth, market size (number of listed companies), and volatilities of the short term interest rate, exchange rate, GDP and inflation.

Correspondingly, I include a number of variables in my analysis that are potentially relevant for commodity markets in $\mathbf{z}$ that can capture the impact of macroeconomic uncertainty, supply-demand shocks, and trading activity.

### 6.3. Commodity Market Variation through Time

This section presents evidence of significant time-variation in volatility, correlations, and trends in emerging market commodities trade throughout the history of futures trading since the 1950s, which motivates the analysis presented in the rest of this paper. There are extreme price movements over the entire term structure during the Global Financial Crisis, leading to sharp increases in the volatility exhibited during that period. From late 2001 to early 2007, there is a steady increase in cumulative return across all maturities. figures 1 and 5 illustrate the difference in the estimated time-varying volatility depending on the term structure and holding period. The figures show the rolling 1-month and 12-month realized volatility for 1M, 3M, ..., 36M futures (3-day) returns for crude oil, natural gas, gold, copper, wheat, and lumber.

Table A2 shows the mean and standard deviation of long-term (12-month) realized volatility of daily commodity futures returns over the the three decades: 1980-1989, 1990-1999, and 2000-2009.

Figure 7 shows Chilean exports of copper for the period covered by the OECD STAN Bilateral Trade database. From the early 2000s, there is a sharp upturn in the percentage of exports to China, while the fraction of exports to G7 countries declines over the same period. Starting from near-zero, within less than two decades, the fraction of exports to China rises to 35.64% at the end of 2009, surpassing exports to all G7 countries combined.
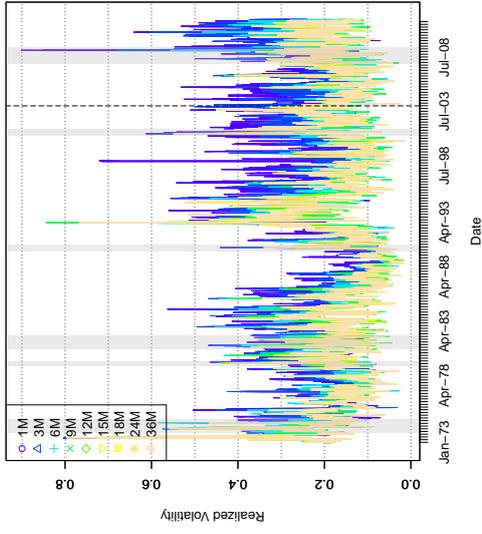
(a) Natural Gas - short-term volatility
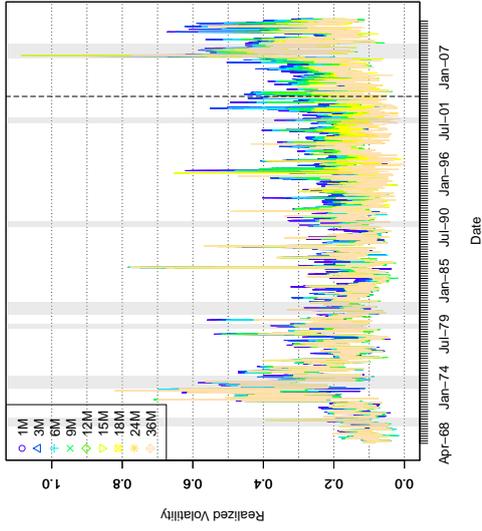
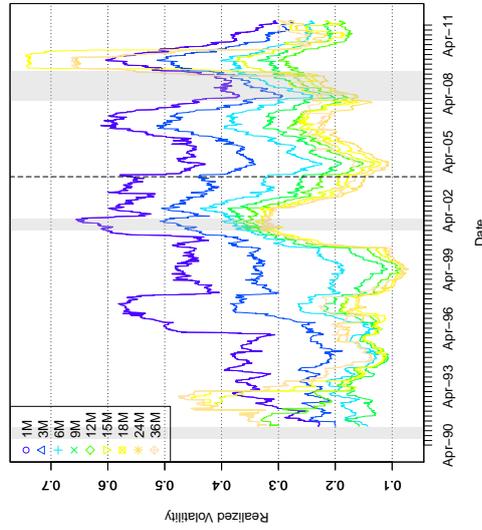(b) Wheat - short-term volatility
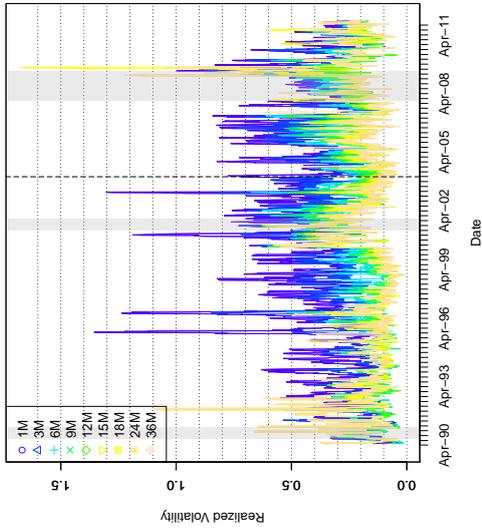
(c) Lumber - short-term volatility
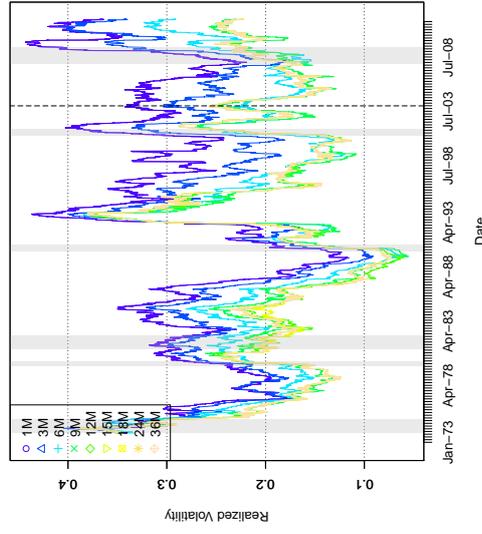
(d) Natural Gas - long-term volatility
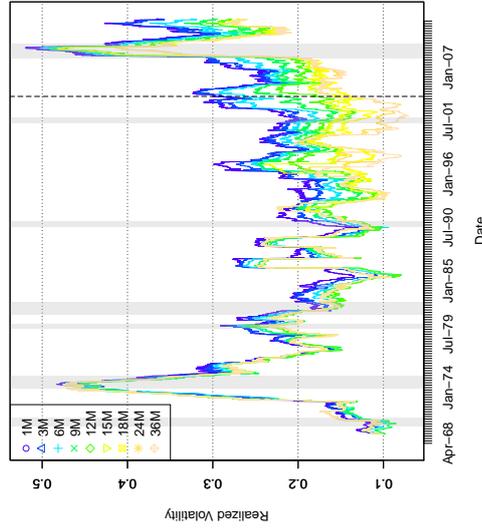
(e) Wheat - long-term volatility

(f) Lumber - long-term volatility

Fig. 5. Time series of annualized rolling realized volatility at different horizons for copper, wheat, and lumber.

Time series of annualized rolling realized volatility at different horizons for 1M, 3M, ..., 36M futures using three-day returns. Here, short-term volatility refers to the standard deviation for the previous month, while long-term volatility refers to the standard deviation for the previous 12 months. The shaded areas highlight the NBER recession periods. The dotted line marks January 2004. *Source: Author's analysis, Pinnacle Data.*
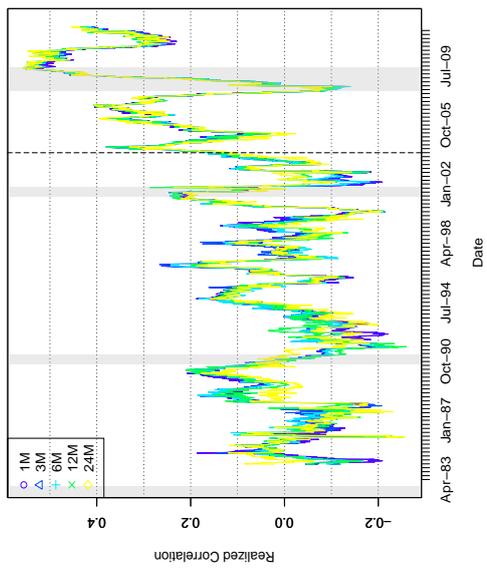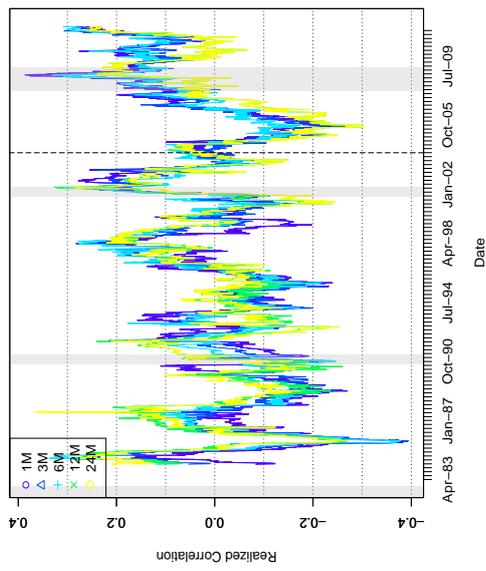
(a) Correlation (crude oil, gold)
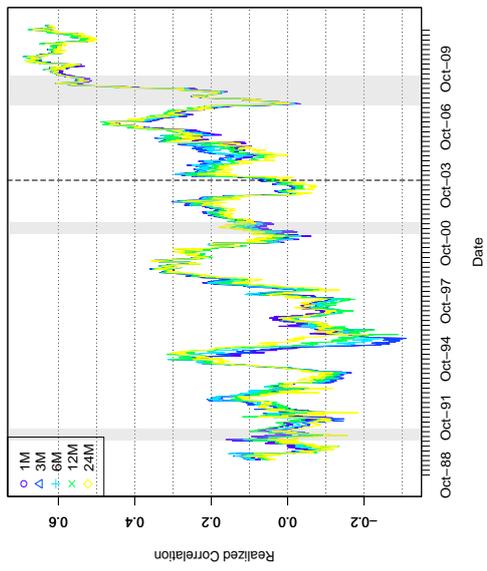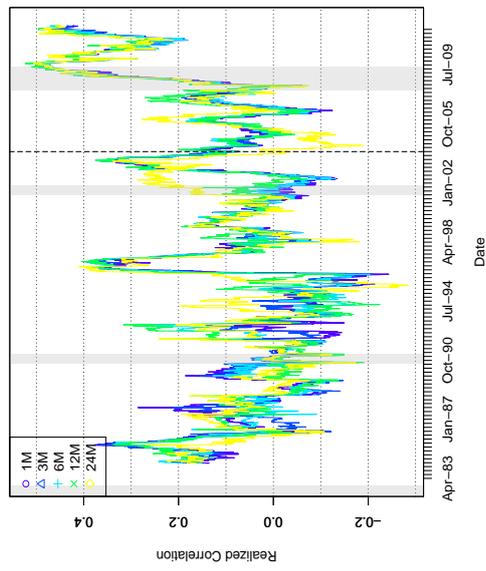
(b) Correlation (crude oil, copper)
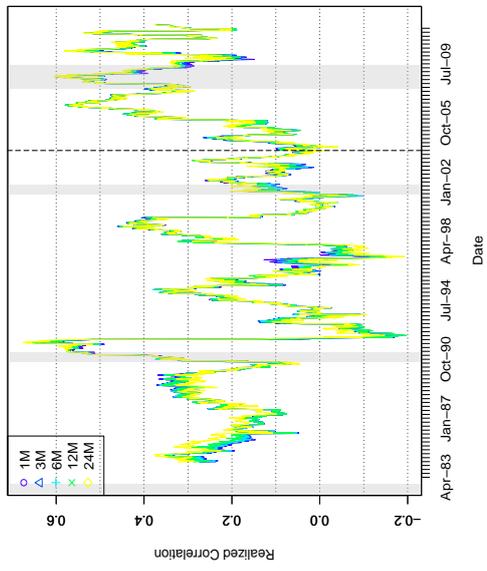
(c) Correlation (crude oil, coffee)
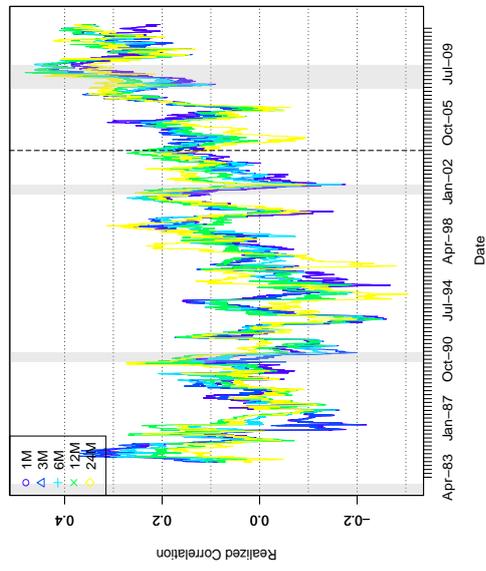
(d) Correlation (crude oil, cotton)

(e) Correlation (crude oil, wheat)

(f) Correlation (crude oil, lumber)

Fig. 6. Time series of the rolling 12-month pairwise correlation between returns of the crude oil 3-month future and gold, copper, coffee, cotton, wheat, and lumber futures returns.

Each date shows the corresponding correlation for the previous 12-month period calculated on 3-day returns. The shaded areas highlight NBER recession periods. The dotted line marks January 2004. *Source: Author's analysis, Pinnacle Data.*
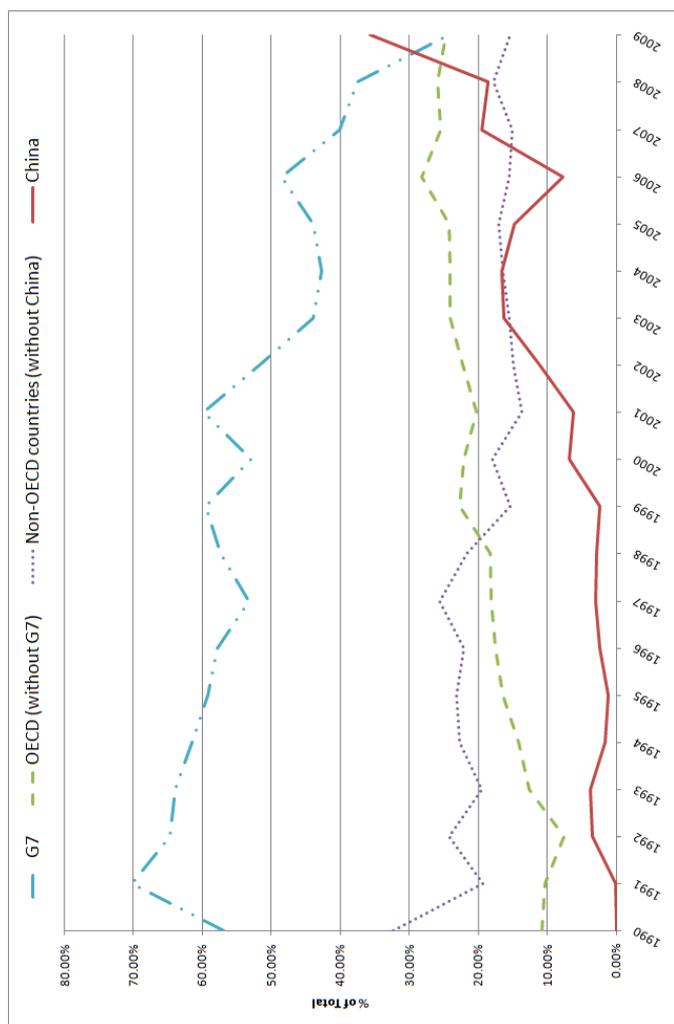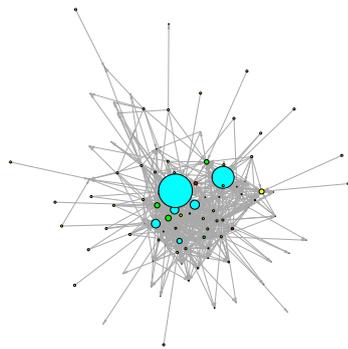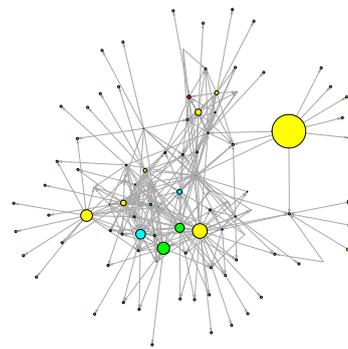
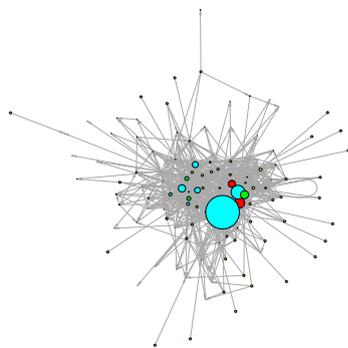Fig. 7. Breakdown of importers of Basic Metals from Chile from 1990 to 2009.

Chile exports close to a third of the world's copper, a key raw material in manufacturing. The four series displayed add up to 100% of Chilean exports of Basic Metals in a given year. *Source: Author's analysis, OECD STAN Bilateral Trade database.*
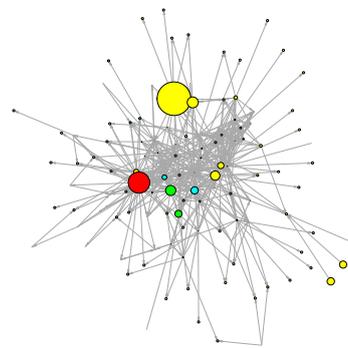
(a) 1990 Imports

(b) 1990 Exports

(c) 2007 Imports

(d) 2007 Exports

Fig. 8. Global crude oil trade network.

The vertex colors identify the country group: BRIC (red), non-OECD excluding BRIC (yellow), OECD excluding G7 (green), and G7 (blue). The relative size of a country vertex captures its total import value. *Source: Author's analysis, UN Comtrade data.*

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