# The implied convenience yield of precious metals: Safe haven versus industrial usage

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Current draft 15 January 2011

#### Abstract

During a financial crisis, investors find it convenient to hold gold (Gd) as a safe haven. But during good economic times, manufacturing firms find it convenient to stockpile platinum (Pl), palladium (Pd) and especially silver (Si), for industrial consumption. We have three related objectives. First, we examine the nature of crossmarket interactions among the convenience yields  $(cy_{it})$  of {Gd, Pl, Pd, Si}, which are implied from cost-of-carry relations. Second, we test if the more influential  $cy_{it}$  of certain precious metals are also affecting the return, volatility and/or volume dynamics of other precious metals. Third, we analyze if the  $cy_{it}$  of gold is enhanced (diluted) during (after) the Asian, Dotcom and Global financial crises. We find, consistent with our propositions, that during crisis period, gold's  $cy_{it}$  provides incremental information to the volatility series of {Gd, Pl, Pd, Si}. But during good economic times, it is silver's  $cy_{it}$  that has the most influence on the return series across {Gd, Pl, Pd, Si}. This is not surprising given that Si has the largest proportion of industrial usage among the four metals.

JEL classification: G14, G15.

*Keywords*: Precious metals, convenience yields; cross-market.

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## 1 Introduction

The flow of investment capital into commodity-related sectors have increased more than tenfold in the last decade. In particular, soaring prices and increasing volatility have elevated precious metals to a stand-alone asset class in the investment community. The increasing importance of precious metals in tactical asset allocation is evidenced by the sharp rise in the number of exchange-traded funds linked to precious metals. According to Solt and Swanson (1981), precious metals are widely regarded as alternative investments to equity and bonds. Jaffe (1989), Lucey et al (2004) and Hillier et al (2006) examine the diversification benefits of precious metals in portfolio allocations. Furthermore, precious metals have all along been regarded as an effective hedge against expected inflationary pressures as well as a safe haven during times of financial turmoil. Baur and Lucey (2010) confirms that this is indeed the case for gold. During September 2008, the Wall St meltdown brought on by the US sub-prime crisis sees the collapse of several financial institutions. In that same month, the NYMEX gold futures market recorded its largest one-day price jump of \$70/oz.

The cost-of-carry argument focuses on storage costs, including interest foregone, ware-housing and shrinkage. But many commodities constitute essential inputs that are heavily consumed by relevant industry groups. Whether it is due to supply shocks that affect production level, or a surge in industrial demand, there is a convenience yield  $cy_{it}$  associated with maintaining a physical stockpile of commodity i. The notion of convenience yield in commodity markets is akin to liquidity premium in equity markets. The theory of storage predicts low  $cy_{it}$  when there is an abundance of the commodity, and high  $cy_{it}$  when stockpiles are running low i.e. stock out. These predictions are empirically confirmed by Telser (1958).

We outline the cost-of-carry relation with convenience yield in equation(1). Denote  $S_{it}$  and  $F_{it}$  as the spot and futures prices of commodity i;  $r_f$  and u are the continuously compounded annual risk-free rate and percentage storage cost, both of which are associated with physical ownership.  $cy_{it}$  is the benefit of convenience from physically owning the commodity. If  $r_f+u=cy_{it}$ , then  $F_{it}=S_{it}$ . Since the costs and benefit of physical ownership balance out, the market is generally indifferent between owning commodity i directly, or through a futures contract. Similarly, if  $r_f+u>(<)cy_{it}$ , then  $F_{it}>(<)S_{it}$  since the costs (benefit) of physical ownership outweighs the benefit (costs). Since  $cy_{it}$  is the only unobservable variable, we can extract a

time-series of implied convenience yield from equation(1) using other observable variables.

$$F_{it} = S_{it}e^{(r_f + u - cy_{it})(T - t)}$$

$$cy_{it} = r_f + u - Ln(\frac{F_{it}}{S_{it}})/(T - t)$$
 (1)

Our motivation is to acquire a better understanding of the nature of cross-market interactions among the convenience yields  $(cy_{it})$  of four precious metals: Gold (Gd), Platinum (Pl), Palladium (Pd) and Silver (Si). We analyze  $cy_{it}$ ,  $i = \{Gd, Pl, Pd, Si\}$  that is implied from equation(1) using Tokyo Commodity Exchange (TOCOM) futures prices, London Bullion Market Association (LBMA) Gd and Si price fixings and London Platinum Palladium Market (LPPM) for Pl and Pd price fixings. TOCOM is the only exchange that trades futures contracts on all four precious metals. LBMA and LPPM, which are wholesale trading centers, are widely accepted as centralized spot markets for Gd, Si, and for Pl, Pd respectively.

We have three related objectives. First, we analyze the cross-market time-series dynamics among the  $cy_{it}$  for {Gd, Pl, Pd, Si}. Second, we test if the more influential  $cy_{it}$  of one precious metal also affects the return, volatility and/or volume dynamics of a less influential precious metal. Third and most importantly, we examine if the information content of  $cy_{it}$  varies over time depending on the extent of each precious metal's global industrial consumption. For Gd, industrial usage constitutes only 12% of global consumption. In stark contrast, industrial usage constitutes more than 60% of global consumption for silver<sup>1</sup>. Pl and Pd are somewhat caught in between. Both metals are more precious than Si and they feature more prominently in various investment strategies. However, unlike Gd, around 50% of global Pd and Pl output are consumed by the automobile industry<sup>2</sup>.

It is reasonable to argue that the perceived convenience yield from physical ownership is heavily influenced by the dominant investor clientele. Given the entrenched perception of Gd as a safe haven, it becomes increasingly convenient for investors to hold gold during times of financial turbulence. In contrast, manufacturing firms find it increasingly beneficial and convenient to stockpile Si, Pl and/or Pd during good economic times to ensure that their

<sup>&</sup>lt;sup>1</sup>For example, batteries, electronic circuit boards, brazing and soldering. Source: http://www.silverinstitute.org/silver uses.php

<sup>&</sup>lt;sup>2</sup>This is primarily for making catalyst converters, which control exhaust fumes emissions from passenger vehicle mufflers. It converts up to 90% of harmful gases from auto-exhaust fumes (hydrocarbons, carbon monoxide and nitrogen oxide) into less harmful substances (nitrogen, carbon dioxide and water vapor). Source: http://www.palladiumcoins.com/productionJM.html. Palladium: Metal of the 21st Century.

own production process is not disrupted by supply shocks to an essential input commodity. Fama and French (1988) examine the time-series of  $cy_{it}$  for aluminum, copper, lead, tin, and zinc. They find that, near business cycle peaks, positive demand shocks for these industrial metals reduce inventory levels, thereby generating large  $cy_{it}$ .

The preceding argument implies that the nature of any existing cross-market interactions between  $cy_{it}$  and the trading dynamics of {Gd, Pl, Pd, Si} will vary over time depending on the state of the global economy. Specifically, we expect the cross-market influence exerted by Gd's  $cy_{it}$  to be enhanced (diluted) during (after) a large scale financial crisis, due to its safe haven status. Similarly, we expect the  $cy_{it}$  of Si, which has the largest industrial usage, to exert a greater influence on the other precious metal markets during good economic times. If our argument holds, it would be empirically manifested in the cross-market influence of  $cy_{it}$  oscillating from Gd on one end to Si on the other end, as the global economy enters and exists the Asian Financial Crisis (AFC), the Dotcom Crisis (DCC) and the Global Financial Crisis (GFC). This constitutes both the main proposition and the title of our paper.

Many existing studies on commodity futures are based on NYMEX and/or LME markets. This is despite the fact that TOCOM is ranked sixth globally in terms of commodity futures trading volume in 2006. It is the largest commodity exchange in Japan, handling 83% of all commodity futures trades. Although LME is the world's largest metal exchange, it specializes in non-ferrous metals<sup>3</sup>. In contrast, TOCOM is renowned for trading precious metal derivatives, including gold, platinum, palladium and silver<sup>4</sup>.

Studies on precious metals examine one or more of {Gd, Pl, Pd, Si}. Many earlier studies focus on the cointegrating relation between gold and silver<sup>5</sup>. Ciner (2001) argues that a long-run relationship between gold and silver prices exist since silver is historically being regarded as a substitute for gold as an investment asset. However, the cointegrating relation has weakened over time as Si is increasingly being consumed as an industrial metal. Ciner (2001) confirms that the long-run equilibrium pricing between Gd and Si that is documented in earlier studies does not exist for the sample period 1990 to 1998. Subsequent studies apply more sophisticated analysis to uncover evidence of a more subtle pricing link between Gd and Si. This includes fractional cointegration analysis Liu and Chou (2003) and Escribano

<sup>&</sup>lt;sup>3</sup>For example, copper, aluminum, tin, nickel etc.

<sup>&</sup>lt;sup>4</sup>In addition to the standard futures, TOCOM also trades options and mini-futures contracts on both gold and platinum.

<sup>&</sup>lt;sup>5</sup>See Solt and Swanson (1981), Chan and Mountain (1988) and Frank and Stengos (1989).

and Granger (1998), and time-varying cointegration analysis in Lucey and Tully (2006) and Gerolimetto et al (2006).

The main critique on gold-silver studies stems from the argument that gold is commonly regarded as a storage of value that the central banks in many countries hold as foreign reserves. In stark contrast, the biggest global consumption of silver is driven by various industrial usages<sup>6</sup>. In 2009, industrial applications consume around three times as much silver as investment and jewellery<sup>7</sup>. Our findings confirm that the pricing relationship among precious metals is indeed time-varying. More importantly, we provide a simple economic argument to show that the time-varying nature of the pricing relation between Gd and Si is associated with the state of the global economy i.e. normal versus crisis period. This is due to the contrasting perception of Gd as a safe haven and Si as an industrial metal.

VAR estimation on  $cy_{it}$  reveals significant cross-market interactions among the four precious metals. VAR results show that the  $cy_{it}$  of GD has the most cross-market influence. The lagged  $cy_{it}$  of Si and Pl are also significant in the  $cy_{it}$  of other metals. The  $cy_{it}$  of Pd is not significant beyond its own lag dynamics. Sub-sample analysis confirms that the pecking-order of influence is time-varying and oscillates between Gd and Si as the estimation window progresses across the three financial crises during our sample period.

We separately include the lagged  $cy_{it}$  of Gd, Si and Pl as exogenous variables into three rounds of VAR estimations on returns  $(r_{it})$ , volatility  $(\sigma_{it})$  and trading volume  $(v_{it})$ . We confirm that  $cy_{it}$  provides incremental information to the various measures of trading activity to varying degrees. The significance of  $cy_{it}$  is more evident in the  $r_{it}$  and  $\sigma_{it}$  VARs compared to  $v_{it}$ . Our moving window estimation reveals similar evidence that the relative significance of  $cy_{it}$  shifts between Gd and Si. Specifically, the  $cy_{it}$  of Si is highly significant in the  $r_{it}$  of all four metals during normal economic conditions. The  $cy_{it}$  of Gd affects the short-run dynamics of  $\sigma_{it}$  across all four metals during times of economic crisis. The two findings support our main proposition that the nature of cross-market trading interaction among precious metals is time-varying, and is conditional on the state of the economy in conjunction with the extent of each metal's industrial usage.

Our paper proceeds as follow. The methodology and estimation are outlined in section 2. The results are reported in section 3. Section 4 concludes.

<sup>&</sup>lt;sup>6</sup>For example, batteries, electronic circuit boards, brazing and soldering.

<sup>&</sup>lt;sup>7</sup>Source: http://www.silverinstitute.org/supply demand.php

## 2 Background and methodology

### 2.1 Backing out implied convenience yields

Our daily sample runs from January 1996 to July 2010, or 3,451 daily observations over 14.5 years. We only includes observations when TOCOM, LBMA and LPPM are open for trading. Our sample period straddles notable financial events such as the Asian Financial Crisis (AFC), Dot-Com Crash (DCC) and Global Financial Crisis (GFC). We partition our sub-samples into periods corresponding to normal versus adverse economic conditions.

TOCOM was established on 1<sup>st</sup> Nov 1984 from the merger between the rubber, textile and gold exchanges. Daily data is downloaded directly from the TOCOM website. The files contain open, high, low, closing prices (afternoon session), volume and open interest for all contract cycles. Our futures market sample is constructed using the most heavily traded contract cycle. Unlike US or UK futures markets, trading activity in Japanese commodity futures are clustered on the most deferred contract<sup>8</sup>. We present contractual specifications for the four TOCOM precious metal contracts in Table 1<sup>9</sup> We use open interest data as a proxy to isolate on the range of dates when most traders would roll-over their futures positions. This is indicated by a sudden drop in the open interest of the most deferred contract and a simultaneous increase in the open interest of the next most deferred contract. The switching phenomenon on TOCOM tends to occur around the middle of every odd month, and it is consistent across all four precious metals<sup>10</sup>. We nominate the 15<sup>th</sup> of every odd month as the switch date to piece together a continuous time series of observations.

#### INSERT TABLE 1

For commodities, it is often a challenge to justify or even identify a centralized spot market. The physical trading often occurs over-the-counter, where specific terms are not

 $<sup>^{8}</sup>$ Webb (1995) suggests this is due to Japanese speculators allowing more time for their longer maturity contracts to become profitable.

<sup>&</sup>lt;sup>9</sup>We exclude the sample period 24-Feb-2000 to 31-Mar-2000 due to a trading halt issued by TOCOM on its palladium contracts. The year 2000 witnessed a dramatic spike in the prices of palladium due in part to delivery interruptions from Russia creating a shortfall in supply. Prices were frozen to allow an orderly liquidation of contracts (See Hilliard, 2000). From the Dec 2010 contract onwards, the contract size for Si is reduced from 30kg to 10kg per contract. The tick size is also increased from 0.1 Yen/10g to 0.1 Yen/g from the Dec 2010 contract onwards.

<sup>&</sup>lt;sup>10</sup>For example, trading interest in the Gd contract in early Mar 2006 centers on the Feb 2007 contract. Around mid-Mar 2006, open interest in the Feb 2007 contract started to decline sharply, but this is accompanied by the surge in open interest in the new Apr 2007 contract.

standardized e.g. pricing mechanism, quantity, grade, delivery dates etc. Fortunately for precious metals, global spot prices are heavily influenced by daily price fixings set by the LBMA for Gd and Si, and by the LPPM for Pl and Pd. The LBMA is a London-based trade association that embodies the wholesale over-the-counter market for gold and silver in London. The significant rise in Gd and Si prices in the 1980s, strengthened by the oil price inflation, resulted in extensive foreign interest and global reliance on the LBMA for price discovery. Driven by growth and financial deregulation, the LBMA was formed on 14 December 1987. London platinum quotations was introduced in 1973, with palladium quotation to follow shortly after. The London Platinum and Palladium quotations were upgraded to full fixings in 1989.

The LBMA and LPPM jointly provides a set of transparent and globally recognized benchmark prices for standardized grades of {Gd, Pl, Pd, Si}. The price fixings are set twice a day at 10:30 and again at 15:00 London time by a Fixing Board that is made up of principal members of the association<sup>11</sup>. For  $S_{it}$ , we use the morning price fixings to reduce the time zone differential between  $S_{it}$  in London and  $F_{it}$  in Japan. The price fixing mechanism is similar to a batch-auction system, where interim prices are adjusted until all buy and sell orders are matched, after which all orders are transacted at the fixed market clearing price<sup>12</sup>.

We use the Bank of England official bank rate as our proxy risk free rate  $r_f$ . Since  $p_{it}$  are quoted in British pounds and  $F_{it}$  are in Japanese Yen, we use the GBP/Yen daily exchange rates from OANDA<sup>13</sup> to convert  $F_{it}$  from Yen to GBP. Lastly, for storage cost u, we use the 0 43%pa management fee charged by ETF Securities Ltd on their value-weighted average Physical Precious Metal Basket ETF. Listed on the Australian Securities Exchange, this ETF is backed by physical holdings of all four precious metals that are held by the designated custodians. The legal form of this are redeemable preference shares that constitute property rights to the physical holdings.

<sup>&</sup>lt;sup>11</sup>This includes commercial banks, fabricators, miners refiners, transport companies and brokers etc.

<sup>&</sup>lt;sup>12</sup>For example, the LBMA Gold Fixing Board comprises five fixing members. Orders are placed through the dealing rooms to the Gold Fixing Board members. The orders are netted, prices are adjusted and communicated back to the dealing room representatives. A next round of orders are collected and reviewed. This process continues until a market-clearing price is obtained.

<sup>&</sup>lt;sup>13</sup>OANDA is a large Internet-based foreign exchange trading and currency service firm.

### 2.2 Trading variables and sub-sample analysis

Our key variables are return  $r_{it} = Ln(\frac{p_{it}}{p_{it-1}})$ , volatility  $\sigma_{it} = |r_{it}|$  and Yen-denominated volume  $v_{it}$  i.e. turnover volume. The latter facilitates a comparison between different contract sizes<sup>14</sup> due to differences in contract size<sup>15</sup> For robustness, our volatility analysis incorporates a set of different measures. We focus only on findings that are robust across different measures. In addition to  $\sigma_{it} = |r_{it}|$ , we also consider the range-based measures of Parkinson (1980) and Garman and Klass (1980), which incorporates open  $(O_{it})$ , high  $(H_{it})$  and low  $(L_{it})$  prices. These measures are jointly presented in equation (2).

$$\sigma_{it}^{Park} = \sqrt{Ln(\frac{p_{it}^h}{p_{it}^l})^2/4Ln(2)}$$

$$\sigma_{it}^{GK} = \sqrt{\frac{1}{2}Ln(\frac{p_{it}^h}{p_{it}^l})^2 - (2Ln(2) - 1)Ln(\frac{p_{it}}{p_{it}^o})^2}$$
(2)

Augmented Dickey Fuller tests confirm that all price variables are I(1) stationary while all volume variables are I(0) stationary. The time-series for  $cy_{it}$  across all four metals are also found to be stationary. A time-series plot of Gd and Pl futures prices in Figure 1 shows that the relative price movement between the two precious metals is affected by the DotCom crisis in May 2000, and more substantially, by the GFC in Sep 2008. During both crises, there is a breakdown of price co-movements between the two metals, with the price of Pl surging relative to Gd.

#### INSERT FIGURE 1

Accordingly, a sub-sample analysis that distinguishes between normal versus crisis economic periods constitutes an important aspect of our analysis on cross-market trading interactions among the four precious metals. However, it remains an open question as to how we ascertain the start and end date for each of the three crises: AFC, DCC and GFC. The start of a financial crisis is generally associated with some cataclysmic events e.g. the collapse of the Thai Baht that sparks the AFC; Lehman Brothers collapse and the onset of the GFC. It

<sup>&</sup>lt;sup>14</sup>We consider two volume measures by scaling the daily number of commodity i contracts traded by  $p_{it}$  and the mid-point between high and low prices for day t. As main results are stable across both volume measures, we report results based on volume scaled by  $p_{it}$ .

<sup>&</sup>lt;sup>15</sup>For example, the Gd contract size is 1kg while for the Pl contract, it is 0.5kg.

 $<sup>^{16}\</sup>mathrm{ADF}$  test statistics and details of lag specifications for each variable are available upon request.

is potentially problematic to specify and justify the end date for a financial crisis. In Table 2, we identify major 'headline' events covered by the financial media associated with the each of the three crises.

#### INSERT TABLE 2

We designate 02-Jul-1997, the day when Thailand devalues the Baht, as the start of the AFC. When the Dow Jones Index closes above 10,000 points on 29-Mar-1999, we assume that the global economy has returned to normal trading conditions. We set 01-May-2000 as the start of the DCC, when the NASDAQ fell sharply from its all-time high of around 4,800 points, as shown in Figure 2A. We associate 20-Jan-2002 as the recovery from the DCC, when Amazon announced its first-quarter profits. Lastly, the collapse of Lehman Brothers on 14-Sep-2008 is commonly perceived as the trigger that turned the US sub-prime crisis into a GFC. We can also see from Figure 2B that the Treasury Euro-Dollar spread and US 3-month LIBOR rate became extremely volatility shortly after the collapse of Lehman Brothers. We denote 31-Dec-2009 as the recovery phase, which is associated with increasing trends in the major stock market indices around the round.

#### INSERT FIGURE 2

In Figure 2C, we plot the cumulative return on the S&P 500, Nikkei 225 and FTSE 100 indices using the start of our sample as the base date. The graphs show that our designated sub-samples for the DCC and GFC correspond to overall declines across all three market indices of the major global economies. For the AFC, only the Nikkei 225 exhibited a downward trend. This suggests that the AFC is primarily a regional crisis sparked by hedge fund attacks on South-East Asian currencies, rather than a full-scale global crisis. In addition, the AFC did not exert the same adverse impact on US markets as the DCC and GFC. Indeed, our empirical analysis on various sub-samples confirm that results from the AFC sub-sample is generally similar to the normal trading sub-sample. In addition, both sub-samples provide contrasting results to the other two crisis sub-samples corresponding to the DCC and GFC.

We complement our sub-sample analysis with a series of rolling window VAR estimations to track the t-stats of  $cy_{it}$  over time. In particular, we focus on whether the explanatory power of  $cy_{it}$  for Gd and Si fluctuates in opposite directions as our estimation window enters

and exists each of the three financial crises. The results should offer further insights into the nature of time-varying information content of  $cy_{it}$  for different precious metals during normal versus crisis time periods.

## 2.3 Vector Autogressive (VAR) Estimation

We apply VAR estimation to analyze  $\{r_{it}, \sigma_{it}, v_{it}\}$  interactions among the  $\{Gd, Pl, Pd, Si\}$  futures markets. We focus on futures trading activity since volume data is available. In subsequent work, we shall extend our analysis to the  $\{r_{it} \text{ and } \sigma_{it} \text{ using LBMA and LPPM prices. Our analysis is conducted sequentially over three rounds of VAR estimation for <math>i, j = \{Gd, Pl, Pd, Si\}$ .

First, we estimate a four-equation VAR using  $cy_{it}$  for the four metals in equation (3). This allows us to examine the relative influence that the  $cy_{it}$  of one metal exerts onto another.

$$cy_{it} = \beta_{0i} + \sum_{j} \sum_{s=1}^{S} \beta_{1ijs} cy_{jt-s} + u_{it}$$
(3)

Second, we separately estimate four sets of four-equation VAR that comprises  $\{cy_{it}, r_{it}, \sigma_{it}, v_{it}\}$ , one for each of  $\{Gd,Pl,Pd,Si\}$ . Our aim here is to examine the extend of each metal's  $cy_{it}$  on its own-market trading activity.

$$cy_{t} = \delta_{01} + \sum_{s=1}^{S} (\delta_{1s}cy_{t-s} + \delta_{2s}r_{t-s} + \delta_{3s}\sigma_{t-s} + \delta_{4s}v_{t-s}) + u_{1t}$$

$$r_{t} = \alpha_{02} + \sum_{s=1}^{S} (\alpha_{1s}cy_{t-s} + \alpha_{2s}r_{t-s} + \alpha_{3s}\sigma_{t-s} + \alpha_{4s}v_{t-s}) + u_{2t}$$

$$\sigma_{t} = \beta_{03} + \sum_{s=1}^{S} (\beta_{3s}cy_{t-s} + \beta_{3s}r_{t-s} + \beta_{3s}\sigma_{t-s} + \beta_{2s}v_{t-s}) + u_{3t}$$

$$v_{t} = \gamma_{04} + \sum_{s=1}^{S} (\gamma_{4s}cy_{t-s} + \gamma_{4s}r_{t-s} + \gamma_{4s}\sigma_{t-s} + \gamma_{2s}v_{t-s}) + u_{4t}$$

$$(4)$$

Lastly, we separately estimate three sets of eight-VAR to examines the interactions between the  $cy_{it}$  and each of  $\{r_{it}, \sigma_{it}, v_{it}\}$  across all four metals. Our focus is on whether the lagged  $cy_{it}$  of one precious metal Granger-causes the trading variable of another, especially  $r_{it}$  and/or  $\sigma_{it}$ , and whether such incremental information, if present, varies over time conditional on normal versus crisis economic conditions. Any positive findings we have on  $r_{it}$  or  $\sigma_{it}$  possess practical relevance for trading and hedging applications respectively.

$$cy_{it} = \delta_{0i} + \sum_{j} \sum_{s=1}^{S} (\delta_{1ijs} cy_{jt-s} + \delta_{2ijs} \sigma_{jt-s}) + u_{1it}$$

$$\sigma_{it} = \beta_{0i} + \sum_{j} \sum_{s=1}^{S} (\beta_{1ijs} cy_{jt-s} + \beta_{2ijs} \sigma_{jt-s}) + u_{2it}$$
(5)

We perform the usual diagnostic tests to determine the optimal lag specification (S) for each of the VAR specifications. This is a vital consideration since VAR estimates, which constitute our main results, are sensitive to the specified lag structure. We use the Schwarz Information Criterion (SIC) to identify specific lag structures. From there, we perform both lag-exclusion F-tests and likelihood ratio tests to determine an optimal S for each VAR estimation.

## 3 Empirical Results

### 3.1 Preliminary results

In Figure 3, we present the price plots  $S_{it}$  and  $F_{it}$  for each of the four metals. The pair of prices for each metal show near-synchronous movements over time. It also appears that Gd, Si and Pd share similar price patterns, while Pd only display co-movements with Pl in the last few years of our sample. Lastly, it is also apparent that the four metals are all affected by the GFC.

#### **INSERT FIGURE 3**

We plot the time series of  $cy_{it}$  in Figure 4. Consistent with Figure 3, the graphs show similar fluctuations in the  $cy_{it}$  for Gd, Pl and Si. It is also interesting to note that Pd and Si display negative  $cy_{it}$  more often than Gd and Pl. Since Si and Pd have substantially heavier industrial usage than Gd and Pl, manufacturers sometimes find it inconvenient to hold physical stock e.g. when their industry is experiencing a downturn.

#### INSERT FIGURE 4

We report descriptive statistics for key variables in Table 3. Panel A figures are based on the full sample, while those in Panel are based on the GFC sub-sample. The comparison allows us to ascertain if the GFC has induced a structural break in the data for precious metals.

The summary statistics of  $cy_{it}$  between the two panels confirms that  $cy_{it}$  has experienced a GFC-related structural break. The mean  $cy_{it}$  for all four metals is positive in both Panels A and B. However, the mean  $cy_{it}$  values are lower in the GFC sub-sample, but with noticeable increases in the volatility of  $cy_{it}$ . In Panel A, Pl has a larger mean  $cy_{it}$  than Gd. But in Panel B, it is Gd that has a larger mean  $cy_{it}$  than Pl. This is consistent with our argument that during a credit-constraint financial crisis, manufacturers, especially car-makers, are liquidating their holdings of Pl for cash. Si has a lower mean  $cy_{it}$  than Pl and Pd in Panel, but Si has the highest mean  $cy_{it}$  in Panel B. Since Si has the highest industrial usage and the cheapest among the four precious metals, it remains convenient to hold Si during the GFC relative to Pl and Pd.

#### INSERT TABLE 3

The two panels also reveal a substantial increase in the return volatility of all four metals. Pd has the highest volatility while Gd had the lowest volatility of the four precious metals. This is consistent with the argument of Sari et.al (2010) of a large stockpile of gold available, although mostly held in the vaults of reserve banks. In addition, due to its safe-haven status gold, there is substantial trading liquidity in gold markets. As such, there is a smaller tendency for gold markets to display excessive volatility.

#### **INSERT TABLE 4**

We report correlation coefficients between key variables in Table 4. The  $r_t$  among the various precious metals are all highly correlated. The highest is between Gd and Si at 0.78, while the lowest is between Si and Pd at 0.53. The  $cy_{it}$  for Gd is positively correlated with the  $cy_{it}$  of the other three metals. Interestingly, the  $cy_{it}$  for Gd is negatively correlated with the  $r_t$  of Gd (0.086), Pd (0.095) and Si (0.133).

For unit root tests, we use the Dickey and Fuller (1979) and Phillips and Perron (1988) tests. In addition, we also use the Dickey-Fuller GLS-detrend unit root tests advocated in Sari et al (2010). We include an intercept and time-trend for testing  $r_{it}$ . For  $\sigma_{it}$ , we include only an intercept since there is no reason to believe precious metals are becoming more volatile over time. We include an intercept for  $v_{it}$ . Lastly, for  $cy_{it}$ , we include an intercept in our stationary tests. The descriptive statistics in Table 3 and the  $cy_{it}$  time-series plots in Figure 4 strongly suggests that  $cy_{it}$  for all four metals have zero means. The tests confirm that  $cy_{it}$  is stationary.

### 3.2 Main Results

In this section, we present and discuss the three sets of VAR estimations: i) VAR on  $cy_{it}$ ; ii) VAR on own-market trading variables and iii) VAR on  $cy_{it}$  and each trading variable across all markets.

#### 3.2.1 VAR estimation on $cy_{it}$

Impulse response functions from VAR estimations reveal the adjustment process of each variable to exogenous shocks that enter the system. We examine the impulse response functions from VAR estimations on  $cy_{it}$ , which provides a good indication of the direction and magnitude of one metal's  $cy_{it}$  on another i.e. the relative influence of each metal s  $cy_{t}$  across all four metals. Sari et.al (2010) suggest that the generalized impulse response approach has an advantage over the orthogonalized approach, which is sensitive to the ordering of variables in the VAR equations. However, the interpretation of the generalized impulse response functions is not straightforward due to non-zero covariances between the components. We employ the Cholesky one standard deviation decomposition impulse response functions to transform the innovations as to allow the resulting components to be uncorrelated. We also results of the generalized approach as a robustness check.

#### INSERT FIGURE 5

We present the impulse responses functions in Figure 5, which shows the size of the initial shock and the rate of dissipation by each variable in the VAR estimation. The graphs on the diagonals show that Pl's  $cy_{it}$  is the most efficient, since most of an exogenous shock is

dissipated within 10 lags. For Gd and Si, portion of the initial shocks remain even after 10 lags. The  $cy_{it}$  of Pd appears the least efficient, with shocks persisting even after 10 lags. In the off-diagonals, the  $cy_{it}$  of Gd seems to be the only variable exerting a cross-market influence on the  $cy_{it}$  of Pl and Si. And in both cases, the shock persist even after 10 lags.

To confirm the influence of Gd's  $cy_{it}$  that is suggested by Figure 5, we compute and plot the variance decomposition functions in Figure 6 across four panels. These panels correspond to each of the three crises as well as the normal period in between the DCC and GFC. The forecast error variance decomposition demonstrates the relative importance of the effects of unexpected innovations of the  $cy_{it}$  of Gd on the  $cy_{it}$  of the other three metals.

#### INSERT FIGURE 6

The cross-market influence of Gd's  $cy_{it}$  is clearly shown in both Panel B (DCC) and Panel D (GFC). In stark contrast, Panel C shows that the influence of Gd's cy during normal economic times is comparatively subdued. This finding is consistent with Figure 5 and it also confirms our argument that the convenience of gold is elevated during periods of financial turmoil. The results are not evident for Panel A (AFC). We noted earlier that it is arguable whether the AFC has the same impact on the global economy compared to the DCC and GFC.

We present the VAR(4) estimation results in Table 5 Panel A for the full sample, Panels B and C for the AFC and DCC, Panel D for the normal period, and lastly in Panel E, estimates for the GFC.

#### **INSERT TABLE 5**

The influence of lagged  $cy_{it}$  for Gd on Si and Pl is significant and generally robust across four sub-samples. As supported by the variance decomposition in Figure 6, the t-statistics of Gd's  $cy_{it}$  increases during the DCC and GFC sub-samples. The  $cy_{it}$  of Pl also display some cross-market explanatory power, albeit less substantial than Gd. While this is also true for the  $cy_{it}$  of Si, its influence is not robust across sub-samples. Specifically, its cross-market influence on the other three metals is not evident during the crisis sub-samples. The strongest evidence of the cross-market influence of Si's cy is found in Panel D i.e. during normal

economic times. Pd has the least cross-market influence on the other metals. However, the  $cy_{it}$  of Pd affects the  $cy_{it}$  of Gd and Si, but only during the GFC in Panel E.

In sum, the VAR results on  $cy_{it}$  suggest that Gd is the most influential. This is followed by Pl and Si. The  $cy_{it}$  of Pd has the least cross-market influence.

#### 3.2.2 Own-market VAR estimation

In this section, we examine if the  $cy_{it}$  of a given metal provides any explanatory power over its own-market trading dynamics  $\{r_t, \sigma_t, v_t\}$ . The analysis will reveal whether  $cy_{it}$  is providing incremental information through a market's return, volatility or volume effects. Combined with results from the first set of VAR estimation, we are able to infer possible cross-market influence that the  $cy_{it}$  of one metal exerts onto a specific trading variable of another metal. Our estimation is based on both full and sub-samples to ascertain the time-varying nature of  $cy_{it}$  on own-market trading activity.

#### INSERT TABLE 6

We present VAR estimates in Table 6. Similar to Table 5, the results are presented across five panels corresponding to the full sample and various sub-samples. We also perform similar VAR estimations using the range-measures of Parkinson (1980), Garman-Klass (1980), as well as  $\sigma_{it} = Ln(\frac{H_{it}}{L_{it}})$ . With the exception of the Garman-Klass (1980) measure for the GFC measure, the VAR results we obtained for other volatility measures are consistent with those using  $\sigma_{it} = |r_{it}|^{17}$ . We report only the coefficient estimates for lagged  $cy_{it}$  in the each of the  $r_t$ ,  $\sigma_t$  and  $v_t$  equations, due to space constraint.

For Gd,  $cy_{t-1}$ ,  $cy_{t-2}$  and  $cy_{t-3}$  are all significant in the  $r_t$  equation across Panels A (full-sample), B (AFC) and D (normal). The  $cy_{it}$  of Gd is not significant in its  $r_t$  equation during the DCC and GFC. Instead, the explanatory power of lagged  $cy_{it}$  for Gd shifted from the  $r_t$  to the  $\sigma_t$  equation during the DCC and GFC sub-samples in Panels C and D respectively.

For Pl,  $cy_{t-1}$  is significant in the  $r_t$  equation. The result is robust across all except the GFC sub-sample. For the latter,  $cy_{t-1}$  becomes significant in the  $\sigma_t$  equation. There is also some evidence that lagged  $cy_{it}$  is affecting Pl trading volume, although this is not robust across sub-samples.

<sup>&</sup>lt;sup>17</sup>We excluded them due to space constraint, but they are readily available upon request.

For Si,  $cy_{t-1}$  is significant in the  $r_t$  equation in all except the GFC sub-sample. Interestingly, the coefficient for  $cy_{t-1}$  is positively significant, while the coefficient for  $cy_{t-2}$  is negatively significant. This suggests some inherent return reversal for Si in response to its own  $cy_{it}$ . There is some evidence that  $cy_{t-4}$  is significant in the Si volatility series.

Lastly, for Pd,  $cy_{it}$  provide limited explanatory power to its own-market trading activity. The only robust evidence is the significance of  $cy_{t-1}$  and  $cy_{t-2}$  in the Pd return equation. Our results also reveal that the significance level of  $cy_{t-1}$  and  $cy_{t-2}$  on returns are comparatively lower during the crisis sub-samples compared to the interval sub-sample that corresponds to normal economic times.

### 3.2.3 VAR estimation of $cy_{it}$ on cross-market return, volatility and volume

We utilize the findings from previous VAR estimations to investigate potential interactions between the  $cy_{it}$  of a given metal against the trading dynamics of another metal. The first round of VAR estimations reveal that  $cy_{Gd,t}$  offers substantial explanatory power to both  $cy_{Pl,t}$  and  $cy_{Si,t}$ . Lagged  $cy_{Pl,t}$  is also significant in both the  $cy_{Gd,t}$  and  $cy_{Si,t}$  equations. Lastly, while  $cy_{Si,t}$  also exerts some cross-market influence on  $cy_{Gd,t}$  and  $cy_{Pl,t}$ , this is found only in Table 5 Panels D and E i.e. in the later part of the sample period. The results in Table 6, which are generated from the second round of VAR estimations, show that  $cy_{Gd,t}$  and  $cy_{Si,t}$  both exhibit substantial explanatory power over their own-market trading dynamics.

Taking into consideration both sets of findings, we investigate if there is any potential cross-market interactions between  $cy_{Gd,t}$  or  $cy_{Si,t}$  and the return  $r_{it}$ , volatility  $\sigma_{it}$  and/or volume  $v_{it}$  dynamics across the four metal contracts. The findings from such analysis offer meaningful implications in terms of harnessing the information content of  $cy_{it}$  from related markets to provide the out-of-sample  $r_t$  and/or  $\sigma_t$  forecast for trading and hedging applications. We will also examine if the incremental information provided by  $cy_{Gd,t}$  and  $cy_{Si,t}$  to cross-market trading dynamics varies over time across crisis and normal sub-samples in accordance with the safe haven status of Gd and the industrial usage status of Si.

#### VAR estimation on returns

We report the estimation results in Table 7 across five panels corresponding to full and sub-sample analysis. Due to space constraint, we report only the coefficient estimates for lagged convenience yields. Since it is extracted from cost-of-carry,  $cy_{it}$  is a cointegrating variable of Metal i's spot-futures price differential. If the spot market contributes to price discovery, we expect lagged convenience yields, especially  $cy_{it-1}$ , to be significant in its own return equation. However, Table 7 should not be read as VECM estimation results since the endogenous variables are cross-metal futures returns, rather than spot-futures returns.

#### INSERT TABLE 7

We find that  $cy_{it-1}$  is significant in its own return equation for all metals across all sub-samples. The exceptions are  $cy_{Gd,t-1}$  in the DCC and GFC sub-samples, and  $cy_{Pl,t-1}$  in the GFC sub-sample. This result has two variant interpretations: i) the spot market for Pl (Gd) is not contributing to price discovery during the (DCC and) GFC sub-sample; ii) the cointegrating relation between  $S_{it}$  and  $F_{it}$  for Pl (Gd) breaks down during the (DCC and) GFC. Either interpretation suggests that during a financial crisis, Gd, and to a certain extent, Pl, are affected differently from Pd and Si. In Panels D and E,  $cy_{Gd,t-1}$  is significant in the return equations of the other three metals. In Panel D, the lagged convenience yields of the other precious metals are significant in the  $r_{Gd,t}$  equation. However, all cross-metal convenience yields become insignificant in the GFC sub-sample.  $cy_{Gd,t-1}$  also significant in the  $r_{Pd,t}$  and  $r_{Pl,t}$  equations for the AFC sub-sample.  $cy_{Gd,t-1}$  and  $cy_{Gd,t-3}$  are both significant in the  $r_{Si,t}$  equation for all sub-samples except the AFC.

Panel A shows that the lagged convenience yield of Si is significant in the  $r_{Gd,t}$ ,  $r_{Pl,t}$  and  $r_{Pd,t}$  equations. However, sub-sample analysis shows that this is mainly driven by the interval sub-sample in Panel D. The significance of  $cy_{Si,t-1}$  in cross-metal returns during normal trading period is consistent with our argument that, as the cheapest of the four metals with the heaviest industrial usage,  $cy_{Si,t-1}$  is more informative during normal economic conditions, but becomes less relevant during crisis times.

In sum, Table 7 Panel A shows that there is evident cross-market interactions between lagged convenience yields and futures returns. Specifically, there are bi-directional interactions between Gd and Si, Pl and Si as well as Pd and Si. There is also some interactions between Pd and Pl, with  $cy_{Pl,t-1}$ ,  $cy_{Pl,t-2}$  significant in the  $r_{Pd,t}$  equation, and  $cy_{Pd,t-1}$  significant in the  $r_{Pl,t}$  equation. However, sub-sample analysis reveals that the nature of cross-metal interaction varies substantially over time depending on whether the global economy is experiencing some form of financial crisis. This is especially the case for Gd and Si.

#### INSERT FIGURE 7

While Table 7 provides some insight into the time-varying nature of cross-metal interactions between return and lagged convenience yields, it is not easy to gauge the specific shifts in inherent interactions when we move from one sub-sample to the next. To complement Table 7, we perform a 300-observation window one-step rolling VAR estimation on the full sample<sup>18</sup>. This allows us to generate a daily time-series of t-statistics for  $cy_{Gd,t-1}$  and  $cy_{Si,t-1}$  from each of the four metal's  $r_t$  equation, which we plot in Figures 7A and 7B respectively.

Figure 7A shows that the significance of  $cy_{Gd,t-1}$  trends upwards during the onset of the AFC, DCC and GFC. In stark contrast, Figure 7B shows that the significance of  $cy_{Si,t-1}$  trends downwards during the DCC and GFC sub-sample periods across all four metals. During the interval sub-sample between the DCC and GFC, the t-stats for  $cy_{Si,t-1}$  trend upwards. The two figures support our main proposition that the explanatory power of  $cy_{Gd,t}$  and  $cy_{Si,t}$  fluctuates inversely against each other due to the importance of Gd as a safe haven for the crisis sub-samples, and the heavy industrial usage of Si for the interval sub-sample.

#### VAR estimation on volatility

We repeat the preceding VAR analysis to examine the informational role of lagged convenience yield in cross-metal volatility interactions. The results are presented in Table 8, which follows the same format as Table 7.

Full-sample results in Panel A reveal that the  $cy_{it}$  of Gd, Pl and Si all exert substantial cross-market influence on the volatility of other precious metals. Specifically,  $cy_{Gd,t-2}$  is significant in the  $\sigma_{Pd,t}$  and  $\sigma_{Si,t}$  equations, while  $cy_{Gd,t-3}$  and  $cy_{Gd,t-4}$  are significant in both the  $\sigma_{Pl,t}$  and  $\sigma_{Si,t}$  equations.  $cy_{Si,t-1}$  is significant in the Pl and Pd  $\sigma_{it}$  equations, while  $cy_{Si,t-4}$  is significant in  $\sigma_{it}$  equations of the other three precious metals. In contrast, none of Pd's lagged convenience yields are significant in the other three metals' volatility equations.

#### **INSERT TABLE 8**

Interestingly, Table 8 shows that cross-metal interactions in Panel A are driven primarily by the GFC sub-sample in Panel E. The exception is Gd. While  $\sigma_{Gd,t}$  is affected by the lagged

<sup>&</sup>lt;sup>18</sup>The results are consistent across estimation windows with 250, 300 or 350 observations.

convenience yields of Pl, Pd and Si,  $cy_{Gd,t-4}$  is the only variable that is significant in the  $\sigma_{Pl,t}$  and  $\sigma_{Si,t}$  equations. It appears strange that the preceding findings apply to the GFC, but not the AFC or DCC. However, it is reasonable to assert that, out of the three crises, the GFC probably has the most severe impact on manufacturing firms. If so, our results suggest that during the credit-crunch, manufacturing firms are being forced to liquidate their inventory of {Pl, Pd, Si} in the spot markets for cash. The mass spot liquidation within a short time frame is picked up by the  $cy_{it}$  for {Pl, Pd, Si}, which is reflected by their significance in the  $\sigma_{Gd,t}$  equation.

#### **INSERT FIGURE 8**

We use the same rolling-window approach to plot the daily t-stats for  $cy_{Gd,t-1}$  and  $cy_{Gd,t-4}$  in Figures 8A and 8B respectively. The former shows that  $cy_{Gd,t-1}$  significantly affects the  $\sigma_{it}$  process of all precious metals during the DCC. The huge spikes in the t-stats occurred during the midst of the DCC during 2000. The extent of its influence is short-lived, and the significance of  $cy_{Gd,t-1}$  is diluted in the months that follow.

In contrast, we do not observe similarly evident spikes in t-stats when we move the estimation window over the GFC. This is consistent with our argument that the GFC is dominated by inventory run-downs in  $\{Pl, Pd, Si\}$ , all of which have substantive industrial usage relative to Gd. This is not the case for the DCC, which is caused by over-exuberance in the growth potential of tech-firms. With the onset of the DCC, the response is the flight to quality and safe havens. That would explain why we observe a spike in t-stats for  $cy_{Gf,t}$  during the DCC, but not the GFC. Interestingly, when we plot the t-stats for  $cy_{Gd,t-4}$  Figure 8B, it reveals a spike in t-stats against all four metals in early 2009. We leave the exposition of this phenomenon in a subsequent paper.

#### VAR estimation on turnover volume

For completeness, we present results from cross-market turnover volume VAR estimation in Table 9. Full sample estimation in Panel A and Interval sub-sample estimation in Panel D both suggests that  $cy_{it}$  exerts substantial cross-market influence on one another's turnover volume. Interestingly, the lagged  $cy_{it}$  for Gd exert some cross-market influence on the turnover volume of the other three metals during the AFC and DCC, but not the GFC. In stark

contrast, the lagged  $cy_{it}$  for Pl does not exhibit significant cross-market influence on the turnover volume of other precious metals during the AFC and DCC, but it is influential for the GFC sub-sample in Panel E.

#### INSERT TABLE 9

Compared to  $r_{it}$  and  $\sigma_{it}$  VAR estimations in Tables 7 and 8, the findings in Table 9 may not appear to offer much practical trading or hedging implications. However, the main findings from Table 9 help explain some of our earlier findings. Specifically, not only is there time-varying significance among the various metals'  $cy_{it}$  between normal and crisis times, the nature of the influence from the convenience of holding Gd and the inconvenience of holding other precious metals with industrial usages during a crisis seem to depend on the nature of the crisis itself.

The lead-up to the DCC is described by high volatility and heavy turnover volume in financial markets. When it happened, the DCC affected financial markets, which then spillover to the real economy. This is picked up by the explanatory power of Gd's convenience yield during the DCC. In contrast, the GFC is associated with years of unsustainable growth in the real economy fueled by credit markets. When it happened, the GFC is associated with fundamental problems in the real economy, which then affects financial markets. This is picked up by the explanatory power in the convenience yield for Si, and to a lesser extent, Pd and Pl.

## 4 Concluding remarks

We extract the daily implied convenience yield of gold, platinum, palladium and silver from 1996 to 2009 using the cost-of-carry for commodities. We confirm that there is substantial cross-metal interactions among convenience yields in a VAR framework. There is some evidence of interactions between  $cy_{it}$  and own-market return, volatility and/or volume dynamics. While the extent of the significance of  $cy_{it}$  differs across precious metals and varies over subsamples, the overall findings do suggests that lagged  $cy_{it}$  provide incremental explanatory power to trading variables over their own lagged variables.

In cross-market analysis, we confirm that the more influential  $cy_{it}$  of Gd and Si also affect the return and volatility processes of other precious metals. More importantly, we can

confirm that the relative influence of Gd and Si's  $cy_{it}$  varies over time depending on whether the global economy is in a normal or crisis state. Gd is convenient to hold as a storage of value in times of financial turmoil due to its safe-haven status. In stark contrast, Si is the cheapest of the four precious metals, and since it carries the heaviest industrial usage, Si is convenient to hold during normal economic times. Our finding confirms that the  $cy_{it}$  of Si is the most influential in the return equations of all precious metals during normal economic times. Gd's  $cy_{it}$  is short-run influence on the  $\sigma_{it}$  of other precious metals during crisis periods.

The implication of our finding is threefold. First, our results support the time-varying nature of inherent economic linkages among {Gd, Pl, Pd, Si}, which is relevant for dynamic asset allocation that incorporates precious metals as an asset class. Furthermore, we show that inherent economic linkages among precious metals vary over time depending on whether the global economy is in a normal or crisis state. This is due to the fact that the four precious metals have dissimilar levels of industrial usage.

Second, our findings provide some insight into the literature's mixed empirical findings of a long-run equilibrium relation between Gd and Si. Sub-sample analysis and rolling VAR estimation results throw support to an evident economic linkage between the two metals, but only during normal economic times. Accordingly, it is not per se true that the co-integrating link doesn't exist. Rather, the link between Gd and Si strengthens and weakens with the state of the overall gloabl economy.

Third, our findings suggest that any conditional trading or hedging strategies that attempt to harness potential incremental information from related precious metal markets has the potential to generate incremental profits. The caveat is that, due to the time-varying nature of the inherent economic linkages, the conditional strategies themselves should be examined conditional on the current economic climate i.e. normal or crisis state. For example, incorporating the  $cy_{it}$  of Si into return-based trading strategies for Gd may yield incremental profits, but only during normal economic times. We leave the detailed expositions to a separate paper.

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 Table 1: Contract specification for Gold, Silver Platinum and Palladium futures as traded on TOCOM

	Gold	Silver	Platinum	Palladium
Date of Listing	March 23, 1982	January 26,1984	January 26,1984	August 3, 1992
Standard	Gold of minimum 99.99% fineness	Silver of minimum 99.99% fineness	Platinum of minimum 99.95% fineness	Palladium of minimum 99.95% fineness
Contract Unit	1 kg / contract	30 kg / contract	500 g / contract	500 g / contract
	(approximately 32.15 troy ounces)	(approximately 964.53 troy ounces)(1/5 of standard contract)	(approximately 16.08 troy ounces)	(approximately 16.08 troy ounces)
Delivery Unit	1 kg	30 kg	500 g	3 kg (Delivery Unit = 6 Contract Units)
Minimum Price Fluctuation	JPY 1 per gram	JPY 0.1 per 10 grams	JPY 1 per gram	JPY 1 per gram
	Commercials *1	Commercials *1	Commercials *1	Commercials *1
	and investment funds *2:	and investment funds *2:	and investment funds *2:	and investment funds *2:
	Current contract month	Current contract month	1st contract month in an even month*3:	1st contract month in an even month*3:
	10,000 contracts	3,000 contract	600 contracts	450 contracts
	All contract months combined:	All contract months combined:	1st contract month in an odd month:	1st contract month in an odd month:
	30,000 contracts	30,000 contracts	700 contracts	600 contracts
			2nd contract month: 1,200 contracts	2nd contract month: 1,200 contracts
			All contract months combined:	All contract months combined:
<b>Customer Position Limit</b>			10,000 contract	9,000 contract
(for each long/short position)				
	Other customers	Other customers	Other customers	Other customers
	All contract months combined:	Current contract month: 1500 contracts	1st contract month in an even month*3:	1st contract month in an even month*3:
	5,000 contracts		100 contracts	60 contracts
			1st contract month in an odd month:	1st contract month in an odd month:
			150 contracts	120 contracts
			2nd contract month: 200 contracts	2nd contract month: 240 contracts
			All contract month combined:	All contract month combined:
			3500 contracts	2500 contracts
Contract Months	All even months within a year (on th	e day when a New Contract Month is generated, there will be 6 e		the month which the said day belongs to)
First Trading Day of New Contract Month		Day session on the business day following the Last Trading Day		
Last Trading Day		Day session on the third business day preceding the Delivery D	.'	
Final Settlement Day	N/A	N/A	N/A	N/A
Delivery Day	The last day of each even month *4	The last day of each even month *5	The last day of each even month *5	The last day of each even month *5
Trading Hours		Day session 9:00 - 15:30 (JST) Night session 17:00 - 23	3:00 (JST)	

**Table 2:** Timeline of events to delineate crisis and non crisis subsamples

Sub-sample	Sample period	"Head-Line" Financial Media Events
	Start: 2 <sup>nd</sup> Jul 1997	Start: Bank of Thailand devalues Thai Baht
AFC (1997-1999)	End: 29 <sup>th</sup> Mar 1999	End: The Dow Jones Industrial Average Index closed above 10,000 points
	Start: 1 <sup>st</sup> May 2000	Start: NASDAQ comes off its all time highs; See Figure 2A
DCC (2000 – 2002)	End: Jan 2002	End: Amazon.com announces 1 <sup>st</sup> quarter profit
	Start: 1 <sup>st</sup> Jan 2003	
Interval (2003-2008)	End: 1 <sup>st</sup> Aug 2008	Recovery/Normal Trading Period
	Start: 14 <sup>th</sup> Sep 2008	Start: Lehman Brother Collapse;
GFC (2008-2009)	End: 31 <sup>st</sup> Dec 2009	Overnight freezing of wholesale money markets; See Figure 6 TED spreads
		End: Six months after Ben Bernanke's 60-Minutes interview in mid-March 2009 when he introduced the media term "Green shoots of recovery".

**Table 3:** Summary statistics of key variables. Panel A represents the statistics of the full sample of data and panel B the notable sub sample period of GFC for comparison. The subsample periods corresponding to the AFC and GFC are excluded for brevity and key statistics are shown in Figure 7

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Sum	SumSq. Dev.	Observation
NELA - FUILS	AMPLE											
$cy_{Gd}$	0.054425	0.053361	0.169668	-0.035328	0.024576	-0.25654	4.124394	219.6439	0	187.8201	2.083767	34:
r <sub>Gd</sub>	0.000275	0.00068	0.068677	-0.137146	0.012334	-0.66995	10.50271	8352.276	0	0.947624	0.524821	34:
$\sigma_{Gl}$	0.008706	0.006292	0.137146	0	0.00874	2.933	22.8034	61339.33	0	30.04392	0.263523	34:
$\sigma_{\text{Gd}(GK)}$	9.80E-05	3.21E-05	0.008014	0	0.000263	12.88996	292.9224	12181972	0	0.338299	0.000238	34
$v_{Gd}$	6.82E+10	4.08E+10	5.97E+11	2.67E+09	7.08E+10	2.16E+00	9.60E+00	8954.197	0	2.35E+14	1.73E+25	34:
$\operatorname{Spot} P_{\operatorname{CD}}$	294.7067	225.119	860.0883	152.9455	158.3533	1.70331	5.034691	2264.011	0	1017033	86511369	34:
Future $P_{\mathrm{CD}}$	294.5178	225.023	867.45	157.033	157.1293			2331.245	0		85179138	34:
cy <sub>Pd</sub>	0.076549	0.055359	0.680567	-0.735028	0.095513		13.34132	15656.43	0	264.17		34
r <sub>Pd</sub>	0.000332	0.000682	0.164976	-0.218078		-0.38645	7.83204	3443.235		1.144606		34
$\sigma_{Pd}$	0.016909	0.011405	0.218078	0	0.017191		14.13582	21083.05		58.35194		34
$\sigma_{Pd(GK)}$	0.000183	7.68E-05	0.006803	0		7.038574		1198056	0			34
$\nu_{Pd}$	1.57E+09	2.49E+08	3.88E+10	932000	3.62E+09		27.14612	94481.77		5.43E+12		34
$\operatorname{Spot} P_{\operatorname{Pd}}$	198.838	169.65	747	67.9		2.00477		5134.294		686189.8		34
Future $P_{\rm Pd}$	460.6409	398.5863	1178.64	189.4339	235.0109		3.235179	585.4166		1589672		34
cy <sub>Pl</sub>	0.09874	0.089161	0.390129	-0.041817		0.87866		808.6902		340.7507		34
r <sub>Pl</sub>	0.000347	0.00073	0.108936	-0.114585		-0.46837		3271.956		1.196711		34
$\sigma_{Pl}$	0.011507	0.007893	0.114585	0		2.45579		16977.59		39.70906		34
$\sigma_{Pl(GK)}$	0.00013	5.68E-05	0.005295	0	0.000299	8.599248	102.3524	1461884	0	0.448898	0.000309	34
$\nu_{Pl}$	3.42E+10	2.55E+10	2.58E+11	1.17E+09	2.90E+10	1.76323	7.561839	4780.534	0	1.18E+14	2.89E+24	34
$\operatorname{Spot} P_{\operatorname{Pl}}$	474.9457	425.8	1183	197.5	231.7285		3.304325	577.4351	0	1639038	1.85E+08	34
Future $P_{\rm Pl}$	4.78813	3.381294	13.28305	2.563411	2.538491	1.40241		1248.914	0	16523.84	22231.59	34
cy si	0.061283	0.056526	0.312583	-0.052123	0.033221	0.94974	6.334078	2117.203		211.4887		34
r <sub>Si</sub>	0.00031	0.000605	0.132512	-0.125715	0.018243	-0.26004	8.485039	4364.958	0	1.069855	1.14815	34
$\sigma_{Si}$	0.012951	0.00934	0.132512	0	0.01285	2.65982	16.55076	30472.56	0	44.69389	0.569651	34
$\sigma_{Si(GK)}$	8.27E-05	2.76E-05	0.003293	0	0.00019	7.42874	84.92566	996844.1	0	0.285389	0.000125	3
$\nu_{si}$	1.49E+09	1.00E+09	2.78E+10	12952500	1.71E+09	4.62869	44.52682	260288.2	0	5.14E+12	1.01E+22	34
$\operatorname{Spot} P_{\operatorname{Si}}$	4.808999	3.42979	13.489	2.509	2.506434	1.38338	3.844971	1203.381	0	16595.86	21673.62	34
Future $P_{\mathrm{Si}}$	4.78813	3.381294	13.28305	2.563411	2.538491	1.40241	3.904753	1248.914	0	16523.84	22231.59	34
VEL B - GLOBA												
cy <sub>Gd</sub>	0.016308	0.010943	0.148723	-0.032329		1.617422		290.2576		4.990342		:
r <sub>Gd</sub>	0.000718	0.002066	0.068677	-0.068677		-0.249106		59.38438	0			-
$\sigma_{\mathrm{Gl}}$	0.014283	0.010459	0.068677	0		1.869548	6.76612	359.0972	0	4.37072	0.056145	3
$\sigma_{Gd(GK)}$	0.000335	0.000172	0.008014	0	0.00062	7.560166	83.7041	85957.65	0			3
$\nu_{Gd}$	9.91E+10	9.78E+10	3.69E+11	5.06E+09	7.16E+10	1.041064	4.719819	92.98613	0	3.03E+13	1.57E+24	-
Spot $P_{\times}$	594.1751	598.1065	731.594	435.663	66.22917	-0.355695	2.580959	8.69129	0.012963	181817.6	1337822	:
Future $P_{\mathrm{CD}}$	594.9323	601.9498	741.1868	415.6339	69.12916	-0.426543	2.654642	10.79962	0.004517	182049.3	1457546	
cy <sub>Pd</sub>	0.011661	0.006826	0.128079	-0.053762		1.317766	6.095523	210.7357	0	3.568369		
r <sub>Pd</sub>	0.001027	0.002568	0.125769	-0.125163	0.032634	-0.283918	4.703871	41.12658	0	0.314381	0.324818	
$\sigma_{Pd}$	0.024316	0.018692	0.125769	0	0.021744	1.764538	6.704951	333.8082	0	7.440764	0.144209	-
$\sigma_{Pd(GK)}$	0.000413	0.000267	0.002915	1.24E-05		2.414365		935.8074	0	0.126492	6.54E-05	
$v_{Pd}$	1.08E+08	91721000	4.35E+08	5784000	77938249	1.110702	4.111729	78.67489	0	3.31E+10	1.85E+18	
$\operatorname{Spot} P_{\operatorname{Pd}}$	157.1768	150	246.05	98.75	32.67162	0.786947	2.880376	31.76604	0	48096.1	325567.6	
Future $P_{\rm Pd}$	157.8888	151.6604	246.8114	103.1222	32.49112	0.749072	2.86569	28.84658	0.000001	48313.96	321980.3	:
cy <sub>Pl</sub>	0.017703	0.012132	0.132655	-0.041817	0.026831	1.406087	5.421469	175.5908	0	5.417056	0.219571	
r <sub>Pl</sub>	0.000272	0.002826	0.108936	-0.114585	0.029235	-0.41711	5.298038	76.20553	0	0.083133	0.26068	
$\sigma_{Pl}$	0.020984	0.01516	0.114585	0.000286	0.020323	1.904979	7.18215	408.0786	0	6.420954	0.125969	
$\sigma_{Pl(GK)}$	0.000483	0.000214	0.005295	2.86E-05	0.000767	3.471554	16.4887	2934.436	0	0.147664	0.000179	
$\nu_{Pl}$	1.95E+10	1.85E+10	7.27E+10	1.17E+09	1.33E+10	0.605533	3.326187	20.05675	0.000044	5.97E+12	5.37E+22	:
Spot $P_{\rm Pl}$	721.6342	743.775	921.35	488.7	104.9216	-0.457994	2.358087	15.95134	0.000344	220820.1	3357605	:
Future $P_{\rm Pl}$	721.6674	745.3586	928.9553	461.3339	107.2864	-0.499568	2.401215	17.29939	0.000175	220830.2	3510665	3
cy Si	0.020924	0.015515	0.150555	-0.052123	0.029887	1.465951	6.026451	226.382	0	6.402629	0.272433	3
r <sub>Si</sub>	0.001009	0.002063	0.132512	-0.125715	0.032847	-0.000187	6.12691	124.664	0	0.308814	0.329077	
$\sigma_{Si}$	0.023585	0.01813	0.132512	0	0.022844	2.225288	9.447932	782.6391	0	7.217131	0.15917	
$\sigma_{Si(GK)}$	0.000344	0.000221	0.003148	2.96E-06	0.000409	2.901124	14.01206	1975.376	0	0.105376	5.11E-05	
V <sub>Si</sub>	4.78E+08	3.76E+08	1.92E+09	12952500	3.89E+08	1.195189	4.086458	87.90227	0	1.46E+11	4.62E+19	
Spot $P_{Si}$	8.697723	8.739565	11.496	5.52921	1.50115	-0.200742	2.179802	10.6324	0.004911	2661.503	687.3026	3

**Table 4:** Correlation matrix of key variables across the four precious metals. Correlation coefficients of key variables with corresponding t – test statistics reported on the second line. Shading represents confidence interval of p =0.05.

Correlation																
t-Statistic	cy Gd	r <sub>Gd</sub>	$\sigma_{\mathrm{Gl}}$	$v_{\rm Gd}$	cy <sub>Pd</sub>	r <sub>Pd</sub>	$\sigma_{Pd}$	$\nu_{Pd}$	cy <sub>Pl</sub>	r <sub>Pl</sub>	$\sigma_{Pl}$	$\nu_{Pl}$	$cy_{Si}$	r <sub>Si</sub>	$\sigma_{Si}$	$\nu_{si}$
cy Gi	1															
r <sub>Gd</sub>	-0.198487 -7.388379	1														
$\sigma_{\mathrm{Gl}}$	-0.052631		1													
	-1.922795	-2.7516														
$ u_{\mathrm{Gd}} $	-0.089155 -3.265647		0.371549 14.60037 -	1												
cy <sub>Pd</sub>	0.181838	-0.03187	0.040371	0.020404	1											
	6.746462	-1.16323	1.474053	0.744561												
r <sub>Pd</sub>	-0.129955 -4.781689		-0.066016 -2.413726	0.043665 1.594549	0.049825 1.82											
$\sigma_{ m Pd}$	-0.117013 -4.298509		0.403614 16.09413		-0.00172	-0.0257 -0.93784	1									
V <sub>Pd</sub>	-0.010171		0.124286				0.209278	1								
· ru	-0.37108		4.569737				7.80797									
Cy <sub>Pl</sub>	0.233005 8.741289	-0.08936 -3.27314	-0.043301 -1.581242	-0.093749 -3.435367			0.044825 1.63698		1							
r <sub>Pl</sub>	-0.117841 -4.32933		-0.073102 -2.674114				-0.11126 -4.08436		-0.02972 -1.08483	1						
$\sigma_{ m Pl}$	0.023063		0.45926	0.201121			0.466206		0.107755	-0.08997	1					
	0.841629		18.86194				19.2257			-3.2958						
V <sub>Pl</sub>	-0.053925 -1.970197		0.174449 6.463506				0.107686 3.95169		-0.07694 -2.81536							
су <sub>Si</sub>	0.273651 10.37978		-0.072716 -2.659935				-0.08643 -3.16522									
r <sub>Si</sub>		0.779444	-0.090937				-0.11276							7 1		
	-3.908748		-3.331456	-0.690036								-0.04062				
σ <sub>Si</sub>	-0.045211 -1.651108	-0.08278 -3.0304	0.620078 28.83502	0.229041 8.584285			0.353717 13.7965			-0.09182 -3.36409				-0.09344 -3.42386	1	
V Si	-0.194068 -7.217359		0.105679 3.877187		0.004696 <i>0.17133</i>		0.097649 3.57964		-0.17643 -6.53917					2 0.051374 1.87674		

**Table 5:** VAR estimation of cross-market interactions in terms of convenience yields

Panel A: Full sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	cy <sub>Si,t-4</sub>
$cy_{Gd,t}$	19.003	9.872	1.206	7.723	0.076	0.770	0.002	0.961	2.212	-1.057	1.351	-2.083	0.206	-3.035	2.142	0.668
$cy_{Pd,t}$	0.520	-0.713	0.711	0.742	25.159	4.521	10.243	4.458	0.236	1.736	-1.589	0.186	1.278	-1.210	0.900	0.928
$cy_{Pl,t}$	-4.298 ***	1.467	-0.400	2.606	1.001	1.242	-1.320	-0.417	31.412	6.981	2.496	4.136	0.144	-2.440 ***	1.801	0.616
$cy_{Si,t}$	0.130	2.546	-1.373	-0.745	-0.477	0.809	-0.055	1.202	1.697	-1.343	0.634	-0.663	21.343	5.529	7.043	7.546 ***

Panel B: Asian Financial Crisis (AFC) sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$cy_{Gd,t}$	5.066	4.949	1.219	2.943	-0.646	-0.431	-0.246	1.403	1.833	-1.391	2.161	-2.306 ***	-0.707	0.445	-0.200	0.357
$cy_{Pd,t}$	-0.961	0.441	1.112	-1.014	14.588	1.617	-0.007	0.001	-0.023	0.515	-0.353	0.022	-0.172	-0.072	-1.587	3.359
$cy_{Pl,t}$	-3.195 ***	1.591	2.159	-0.706	-2.218 ***	1.662	-0.266	-0.051	13.267	1.248	0.395	1.058	0.145	-1.103	-0.298	1.820
$cy_{Si,t}$	-2.236 ***	2.238	0.104	-0.983	-1.060	0.422	0.717	-0.750	1.817	-1.241	0.032	-0.149	12.179	1.901	1.014	2.403

Panel C: Dot-Com Crisis (DCC) sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$cy_{Gd,t}$	9.681	3.786	-0.304	1.294	1.399	-1.086	1.066	-0.948	0.824	-1.271	1.752	-1.274	1.072	0.208	-0.372	-0.544
$cy_{Pd,t}$	1.542	1.046	-2.708 ***	0.886	12.878	1.600	3.427	1.882	0.277	-0.565	2.458	-2.087 ***	-0.332	-0.340	0.820	-0.741
$cy_{Pl,t}$	0.243	1.022	-1.394	-0.147	0.137	-1.543	1.988	-0.470	13.896	3.440	1.616	0.218	0.287	-0.694	1.083	-0.197
$cy_{Si,t}$	3.914	-0.677	-1.518	-0.955	0.344	0.799	-0.755	-0.397	-0.274	-1.675 **	1.785	0.091	8.277	3.139	2.590	1.450

## Panel D: Interval sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$cy_{Gd,t}$	9.114	4.390	1.610	6.649	0.131	0.388	-0.207	0.255	0.884	0.635	-0.309	-2.194 ***	-1.319	-3.243	0.453	-1.956 **
$cy_{Pd,t}$	1.110	-1.006	1.047	2.536	9.238	-1.681 **	2.617	-2.670 ***	-0.938	1.910	-1.670 **	-0.974	1.101	-0.963	0.703	-0.180
$cy_{Pl,t}$	-2.323 ***	-1.322	-0.483	2.133	0.518	1.358	-0.729	-0.268	17.009	5.944 ***	3.383	3.553	-1.090	-2.039 ***	0.411	-2.481 ***
$cy_{Si,t}$	-3.669 ***	2.250	-1.675 **	1.611	-0.290	0.427	0.186	0.768	1.117	-0.534	-0.600	-1.644 **	11.934	2.028	2.361	3.926

Panel E: Global Financial Crisis (GFC) sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$cy_{Gd,t}$	2.839	-0.168	-0.740	1.643	-0.954	0.459	-2.541 ***	-0.323	1.410	2.239	0.904	-0.957	-0.844	-2.311 ***	1.818	0.571
$cy_{Pd,t}$	2.915	-0.759	-1.013	1.041	-0.149	0.804	-0.725	1.268	-0.341	1.224	0.305	-1.037	-0.758	-1.405	2.157	0.316
$cy_{Pl,t}$	1.815	-0.266	-1.902 **	1.759	-0.999	0.609	-2.393 ***	-0.182	2.182	1.721	1.591	-0.877	-0.827	-1.461	2.373	0.564
$cy_{Si,t}$	1.593	-0.801	-1.931 **	1.213	-1.706 **	0.078	-1.698 **	-0.230	1.639	1.720	1.588	-1.191	0.513	-0.462	3.111	0.725

Table 6: VAR estimation of own-market interactions between convenience yield and return, volatility and volume trading dynamics

Panel A: Full sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$		$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$
$r_{Gd,t}$	6.810***	-2.497***	-1.045	-2.859***	$r_{Pd,t}$	13.081***	-5.463***	-1.059	-2.577***
$\sigma_{Gd,t}$	1.895**	-2.365***	-3.052***	4.090***	$\sigma_{Pd,t}$	0.162	-0.162	1.410	-1.221
$v_{Gd,t}$	0.970	-1.663**	-0.269	-0.544	$v_{Pd,t}$	1.370	0.544	0.412	0.530
$\sigma^{GK}_{Gd,t}$	3.422***	0.827	0.055	-4.743	$\sigma^{GK}_{Pd,t}$	1.857	0.108	0.259	-0.761
	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$		$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Pl,t}$	8.225***	-4.605***	-1.377	-0.520	$r_{Si,t}$	13.008***	-3.432***	-5.784***	-1.811**
$\sigma_{Pl,t}$	-0.770	0.379	-1.063	1.631	$\sigma_{Si,t}$	-3.643***	0.710	0.177	1.602
$v_{Pl,t}$	3.695***	-3.622***	1.077	-0.947	$v_{{\scriptscriptstyle Si},t}$	1.913**	0.960	-1.788**	0.413
$\sigma^{GK}_{Pl,t}$	-0.704	2.497***	-0.844	-1.695**	$\sigma^{GK}_{Si,t}$	2.561***	0.150	-0.490	-2.943***

Panel B: AFC sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$		$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$
$r_{Gd,t}$	7.565***	-1.385	-2.675***	-1.760	$r_{Pd,t}$	2.961***	-1.546	0.089	-0.290
$\sigma_{Gd,t}$	-0.567	-0.595	0.937	0.141	$\sigma_{Pd,t}$	1.624	-1.697**	1.067	-0.404
$v_{Gd,t}$	-0.386	1.859**	-0.898	-1.699 <sup>**</sup>	$v_{Pd,t}$	0.544	-0.738	0.825	-0.596
$\sigma^{GK}_{Gd,t}$	-0.248	2.595***	-2.015***	-0.498	$\sigma^{GK}_{Pd,t}$	-1.502	0.634	0.064	1.105
	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$		$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Pl,t}$	3.231***	-0.545	-0.244	-1.730**	$r_{Si,t}$	5.706***	-1.159	-2.913	-0.279
$\sigma_{Pl,t}$	0.300	-1.469	1.192	0.522	$\sigma_{Si,t}$	-0.101	0.890	-0.007	-1.341
$v_{Pl,t}$	1.204	-1.060	0.509	-1.166	$v_{Si,t}$	3.634***	1.780**	-0.709	-3.032***
$\sigma^{GK}_{Pl,t}$	0.397	0.017	-0.553	0.204	$\sigma^{GK}_{Si,t}$	2.505***	1.778	-2.627***	-0.885

Panel C: DCC sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$		$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$
$r_{Gd,t}$	0.315	-0.282	0.780	-1.055	$r_{Pd,t}$	11.227***	-4.370***	-1.804**	-1.630
$\sigma_{Gd,t}$	-0.095	1.945**	-2.492***	0.852	$\sigma_{Pd,t}$	-0.758	1.133	0.656	-1.988***
$v_{Gd,t}$	0.443	1.658**	-1.237	-0.697	$v_{Pd,t}$	-3.359***	3.464***	0.022	-0.972
$\sigma^{GK}_{Gd,t}$	1.963***	0.415	-1.011	-0.924	$\sigma^{GK}_{Pd,t}$	-1.430	1.347	-0.360	-0.614
	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$		$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Pl,t}$	4.970***	-3.410***	-0.835	0.767	$r_{Si,t}$	3.057***	-2.216***	0.405	-0.808
$\sigma_{Pl,t}$	-1.596	1.494	-0.753	0.782	$\sigma_{Si,t}$	0.198	-0.428	0.352	0.140
$v_{Pl,t}$	0.626	-0.684	0.403	-0.699	$v_{{\scriptscriptstyle Si},t}$	-1.031	0.220	-0.575	1.866**
$\sigma^{GK}_{Pl,t}$	0.733	0.582	-1.229	0.125	$\sigma^{\mathit{GK}}_{\mathit{Si},t}$	2.254***	-0.568	1.255	-2.427***

Panel D: Interval sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$		$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$
$r_{Gd,t}$	4.767***	1.224	-1.501	-1.567	$r_{Pd,t}$	11.796***	-2.957***	1.079	-0.429
$\sigma_{Gd,t}$	0.880	-1.466	-2.046***	-0.024	$\sigma_{Pd,t}$	-0.343	0.300	0.747	-0.476
$v_{Gd,t}$	-0.231	-1.283	-0.898	-0.021	$v_{Pd,t}$	1.012	-0.995	0.406	-0.366
$\sigma^{GK}_{Gd,t}$	-1.474	-2.068***	-2.016***	1.132	$\sigma^{GK}_{Pd,t}$	4.195***	-0.938	-0.039	-0.539
	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$		$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Pl,t}$	6.181***	-1.847**	-1.489	-1.780**	$r_{Si,t}$	12.159***	-2.542***	-2.665***	-1.437
$\sigma_{Pl,t}$	0.466	0.661	-0.945	0.280	$\sigma_{Si,t}$	-2.628	1.274	1.354	-1.774**
$v_{Pl,t}$	4.872***	-3.712***	-0.204	-0.838	$v_{{\scriptscriptstyle Si,t}}$	1.305	0.178	-1.429	1.613
$\sigma^{GK}_{Pl,t}$	1.480	-0.912	-0.426	-0.084	$\sigma^{GK}_{Si,t}$	0.353	1.864**	0.652	-1.374

Panel E: GFC sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$		$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$
$r_{Gd,t}$	0.828	-0.205	-0.606	-0.368	$r_{Pd,t}$	1.846**	-1.936**	0.016	0.641
$\sigma_{Gd,t}$	3.555***	-0.499	-0.468	3.721***	$\sigma_{Pd,t}$	0.678	-0.972	1.821**	0.856
$v_{Gd,t}$	1.805**	-1.889**	1.113	0.413	$v_{Pd,t}$	1.786**	0.625	0.222	-0.961
$\sigma^{GK}_{Gd,t}$	1.178	0.630	1.199	-1.576	$\sigma^{GK}_{Pd,t}$	0.325	0.928	0.929	0.245
	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$		$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Pl,t}$	-0.078	-1.733	-0.649	1.440	$r_{Si,t}$	1.204	0.302	-2.433***	1.204
$\sigma_{Pl,t}$	2.267***	-1.143	-0.144	1.207	$\sigma_{{\scriptscriptstyle Si},t}$	-0.791	-0.085	1.162	3.238***
$v_{Pl,t}$	1.855**	0.549	-0.357	-0.045	$v_{{\scriptscriptstyle Si},t}$	3.562***	-0.548	0.406	0.274
$\sigma^{GK}_{Pl,t}$	1.785	2.370	-0.043	-1.198	$\sigma^{\mathit{GK}}_{Si,t}$	1.261	-0.237	0.581	-0.536

**Table 7:** VAR estimation of cross-market returns on convenience yields

Panel A: Full sample estimation results

						1 00.0		sumpre co		. 000000						
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Gd,t}$	6.868	-2.114	-0.932	-3.378 ***	1.363	-0.346	-0.243	-1.252	1.776	-0.968	-1.376	0.890	8.821	-2.221 ***	-3.277 ***	-1.998 ***
$r_{Pd,t}$	2.444	-1.002	-0.958	0.027	13.016	-5.178 ***	-1.110	-2.710 ***	4.382	-2.948 ***	-0.506	0.043	5.496 ***	-1.414	-2.055 ***	-0.630
$r_{Pl,t}$	1.529	-0.403	-1.337	-0.440	3.262	-1.239	-0.739	-1.469	8.046	-4.543 ***	-1.594	-0.033	5.479 ***	-1.134	-2.387 ***	-1.566
$r_{Si,t}$	10.811	-1.412	-5.416 ***	-2.773 ***	2.594	-0.182	-1.428	-1.315	6.478 ***	-0.902	-4.535 ***	0.137	17.352	-2.908 ***	-7.217 ***	-4.512 ***
						Panel	B: AFC st	ub-sample	estimatio	on results						
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Gd,t}$	6.702	-1.312	-2.404 ***	-1.659 **	0.718	0.457	-0.586	-0.492	2.981	-0.811	-1.037	-0.367	3.785	-1.722	-0.493	0.239
$r_{Pd,t}$	2.444	-1.002	-0.958	0.027	3.221	-1.531	-0.093	-0.480	2.298	-0.966	1.328	-2.192 ***	0.072	-0.846	1.094	-1.452
$r_{Pl,t}$	2.513	-0.372	-2.469 ***	-0.080	1.128	0.028	-0.380	-0.470	3.050	-0.617	-0.249	-1.377	0.526	0.854	-1.376	-0.775
$r_{Si,t}$	-0.237	0.413	-0.731	1.223	1.172	-0.138	-2.306 ***	1.854	-0.210	0.948	-1.741	1.240	6.034	-0.152	-2.604 ***	0.563
						Panel	C: DCC s	ub-sample	e estimatio	on results						
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Gd,t}$	0.324	0.204	0.097	-0.840	-1.488	2.237	-1.219	0.156	-0.652	0.512	0.206	0.018	0.256	-0.711	0.255	0.149

$r_{Pd,t}$	0.737	-0.630	0.060	0.081	11.713	-4.087	-2.438	-1.425	0.437	-0.255	-1.287	1.934	1.060	-1.405	0.433	0.194
					***	***	***	*			*	**		*		
$r_{Pl.t}$	1.160	-1.114	-0.285	0.295	4.333	-1.528	-2.448	0.570	4.836	-2.807	-1.565	1.234	1.890	-2.208	0.185	0.363
1 0,0					***	*	***		***	***	*		**	***		
$r_{Si,t}$	2.546	-0.156	-1.659	0.104	0.711	1.252	-1.078	-0.055	1.142	1.278	-2.592	1.309	5.580	-2.686	-0.476	-1.158
,-	***		**								***	*	***	***		

## Panel D: Interval sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Gd,t}$	5.367	1.218	-1.443	-1.896 **	2.533	0.005	0.713	0.175	0.977	0.333	-1.645 **	-0.054	8.360	-0.462	-1.713 **	-1.744 **
$r_{Pd,t}$	2.984	-0.201	-1.745 **	0.076	12.162	-3.038 ***	0.592	-0.139	2.296	-1.201	-1.552	0.200	6.502	0.043	-2.232 ***	0.727
$r_{Pl,t}$	2.618	0.850	-1.080	-0.649	2.801	-1.482	-0.151	-1.045	5.626	-2.274 ***	-1.060	-1.284	5.169 ***	0.000	-0.838	-0.902
$r_{Si,t}$	7.189 ***	1.397	-2.637 ***	-2.349 ***	1.698	-0.162	-0.843	0.179	1.594	1.297	-2.243 ***	-0.412	13.674	-1.310	-3.231 ***	-2.482 ***

## Panel E: GFC sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$r_{Gd,t}$	-0.052	0.525	-0.381	-0.341	0.176	0.134	0.234	0.457	0.051	-0.207	-1.056	1.266	0.982	0.939	-1.534	0.172
$r_{Pd,t}$	-1.589 *	1.222	-0.163	-0.162	2.626	-0.642	0.400	0.164	-0.082	-0.936	-0.916	1.275	-0.050	1.586	-1.101	0.126
$r_{Pl,t}$	-1.723 **	0.610	-0.405	0.308	-0.167	-0.961	-0.045	1.214	0.103	-1.359 *	-1.422 *	1.762	-0.051	0.795	-1.147	0.251
$r_{Si,t}$	2.334	0.180	-1.620 *	-0.625	3.212	-0.704	-0.325	-0.531	3.099	-0.694	-2.749 ***	0.776	4.128	0.656	-2.222 ***	-0.609

**Table 8:** VAR estimation of cross-market volatility on convenience yields

Panel A: Full sample estimation results

								1								
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$\sigma_{Gd,t}$	2.999	-2.577 ***	-4.141 ***	3.654	0.003	-0.216	-0.709	-0.063	2.738	-1.844 **	-3.371 ***	2.692	-0.012	0.089	-3.889 ***	4.102
$\sigma_{Pd,t}$	0.501	-2.720 ***	1.018	0.571	-0.221	-0.782	1.830	-0.134	0.958	-2.208 ***	1.214	0.240	-2.795 ***	-0.607	0.622	2.393
$\sigma_{Pl,t}$	-0.703	-1.166	-2.043 ***	3.612	0.421	-1.056	0.025	-0.288	0.095	-0.830	-1.394	2.512	-3.842 ***	-0.320	-1.090	4.670
$\sigma_{Si,t}$	-1.229	-1.964 ***	-1.774 **	3.244	-1.463	-0.324	-0.515	0.155	-0.652	-1.745 **	-2.237 ***	2.880	-4.077 ***	0.453	-0.554	3.166
						Panel	B: AFC s	ub-sample	e estimatio	on results						
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$\sigma_{Gd,t}$	-0.798	-1.408	0.557	0.698	0.048	-1.181	0.580	0.272	0.607	-1.678 **	0.344	0.589	-1.653	0.470	-1.297	2.300
$\sigma_{Pd,t}$	-0.528	0.162	0.796	-0.283	0.008	-0.237	0.345	0.665	0.030	-0.489	0.603	0.344	-3.116	0.777	-0.444	1.732
$\sigma_{Pl,t}$	-1.159	-0.259	0.657	0.674	0.139	-0.096	-0.133	-0.035	0.495	-1.691 **	0.928	0.852	-1.248	-0.533	-0.433	1.277
$\sigma_{Si,t}$	0.123	0.100	0.315	-0.688	-1.318	0.269	0.758	-0.423	-0.146	-0.863	0.348	0.869	-0.547	0.884	0.509	-0.435
						Panel	C: DCC s	ub-sample	e estimati	on results						
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$\sigma_{Gd,t}$	-0.023	1.595	-1.899 **	0.525	0.473	1.703	-0.968	-1.356	2.474	0.469	-2.524 ***	0.351	0.456	0.302	-0.865	0.644

$\sigma_{Pd,t}$	-0.607	0.032	0.666	-0.661	-0.720	-0.665	1.580	-0.778	0.744	-1.247 *	0.350	0.085	0.700	-0.530	0.223	-0.552
$\sigma_{Pl,t}$	-1.737 **	1.434	-0.778	0.926	-1.252	1.266	-1.111	1.114	-1.423	0.600	0.178	0.645	-1.845	1.205	-0.230	0.778
$\sigma_{Si,t}$	-0.848	1.688	-0.738	-0.448	0.555	-0.004	-0.438	-0.939	1.302	-0.473	-1.222	0.295	0.025	-0.126	0.233	0.300
						Panel D	: Interval	sub-samp	ole estima	tion resul	ts					
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$\sigma_{Gd,t}$	1.775	-2.678 ***	-2.309 ***	-1.082	-0.524	0.336	-0.590	0.059	0.409	-0.516	-1.437	0.228	0.576	-0.966	-0.246	-0.078
$\sigma_{Pd,t}$	-1.411	-3.478 ***	0.857	-1.451	-1.184	-0.615	0.806	-0.275	-0.952	-0.448	1.616	-0.225	-2.793 ***	-1.263	1.370	0.878
$\sigma_{Pl,t}$	0.235	-1.958 **	-0.442	0.990	0.402	-1.196	0.311	-1.063	1.327	-0.625	-0.783	0.934	-2.301 ***	-2.024 ***	-0.002	1.515
$\sigma_{\!\scriptscriptstyle Si,t}$	-0.660	-1.780 **	-0.316	0.404	-0.681	0.532	0.087	0.591	-1.996 ***	0.130	-1.150	1.004	-2.423 ***	0.829	1.951	-0.020
						Panel 1	E: GFC s	ub-sample	e estimatio	on results						
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$\sigma_{Gd,t}$	3.618	0.554	-2.054 ***	4.340	2.688	0.479	-1.377	3.475	3.580	0.315	-2.041 ***	3.959	2.154	2.274	-2.233	4.053
$\sigma_{Pd,t}$	1.441	-0.849	1.528	1.482	2.056	-1.186	1.395	1.051	1.743	-1.047	1.708	0.844	0.419	0.089	0.926	2.166
$\sigma_{Pl,t}$	1.478	-0.179	0.625	1.956	1.774	-0.983	-0.136	0.988	2.625	-0.155	-0.360	1.388	0.041	1.386	0.647	2.683
$\sigma_{Si,t}$	0.367	-0.255	-0.303	2.776	0.123	-0.736	-0.701	2.922	1.367	-1.218	-0.590	2.375	-0.811	0.327	-0.418	3.060

**Table 9:** VAR estimation of cross-market turnover volume on convenience yields

Panel A: Full sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$v_{Gd,t}$	0.740	-1.743 **	0.057	-0.731	1.662	-1.900 **	-0.803	-1.018	1.432	-2.198 ***	0.208	-0.314	0.175	-2.092 ***	2.022	-0.793
$v_{Pd,t}$	1.011	-0.570	0.586	0.064	0.990	1.150	0.024	0.919	0.506	-1.462 *	0.411	1.037	-0.343	-0.138	0.425	1.688
$v_{Pl,t}$	0.714	-0.754	-1.168	0.723	2.089	-2.381 ***	0.928	-1.303	3.516	-2.910 ***	0.086	0.021	-1.459 *	-0.652	-0.663	2.873
$v_{Si,t}$	3.129	-1.647 **	-0.388	-0.720	1.672	-1.697 **	-0.180	-0.656	1.708	-2.089 ***	0.039	0.348	1.642	0.747	-1.219	1.342
						Panel .	B: AFC sı	ub-sample	estimatio	on results						
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$v_{Gd,t}$	-0.285	1.178	-1.065	-0.653	0.115	0.639	-1.212	0.038	-0.355	0.810	-0.814	0.217	0.557	0.366	-1.940 **	0.673
$v_{Pd,t}$	-1.055 *	-0.442	-0.013	-1.072	0.177	0.414	-0.103	-0.411	-0.787	-0.767	1.397	-0.931	-1.186	-1.072	1.125	0.830
$v_{Pl,t}$	-0.702	0.379	-0.597	1.653	0.527	0.106	-0.625	-0.068	0.844	-0.856	-0.316	-0.219	-0.702	-0.605	-1.092	2.785
$v_{Si,t}$	1.518	-0.169	-1.578	0.151	-0.065	-0.756	0.735	-0.345	0.635	-0.314	-0.821	0.461	3.162 ***	1.606	-0.688	-2.220 ***
						Panel (	C: DCC s	ub-sample	e estimatio	on results						
	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$v_{Gd,t}$	-0.765	1.977	-1.571 *	0.355	-0.178	0.280	-2.106 ***	1.550	-0.955	0.287	-0.405	0.862	-0.276	0.642	0.002	-0.144

$v_{Pd,t}$	1.413	-1.718	0.378	0.252	-2.596	1.614	0.442	0.176	1.160	-0.589	0.633	-1.551	0.736	-1.573	0.798	0.182
	*	**			***	*								*		
$v_{Pl,t}$	0.334	-0.902	-0.605	0.967	0.033	0.354	-1.664	1.147	0.160	-1.511	1.146	-0.298	-1.286	-0.574	-0.166	1.430
	*						**						*			*
$v_{si,t}$	-0.488	-0.059	-0.234	0.715	0.414	-0.195	-1.987	1.531	-0.366	0.425	-0.776	0.432	-1.146	-0.347	-0.192	2.147
	**						***	*								***

## Panel D: Interval sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$v_{Gd,t}$	-0.508	-2.027 ***	-0.569	-0.003	1.837	-0.784	-0.161	-0.094	1.620	-2.195 ***	-0.584	0.641	0.044	-1.421 *	2.237	0.528
$v_{Pd,t}$	-0.500	0.910	-0.525	-0.834	0.694	0.286	-0.469	-0.182	0.048	-0.012	-0.610	0.911	-0.749	0.362	0.180	0.650
$v_{Pl,t}$	-0.501	-0.361	-1.418 *	0.576	2.037	-1.513 *	0.966	-0.397	4.004 ***	-3.230 ***	-0.741	-0.050	-1.016	-0.554	-0.139	1.540
$v_{si,t}$	2.231	-1.314 *	-0.960	-2.571 ***	1.194	-1.180	-0.456	-0.737	1.788	-2.413 ***	0.047	-0.103	-0.575	-0.017	-1.103	2.571

## Panel E: GFC sub-sample estimation results

	$cy_{Gd,t-1}$	$cy_{Gd,t-2}$	$cy_{Gd,t-3}$	$cy_{Gd,t-4}$	$cy_{Pd,t-1}$	$cy_{Pd,t-2}$	$cy_{Pd,t-3}$	$cy_{Pd,t-4}$	$cy_{Pl,t-1}$	$cy_{Pl,t-2}$	$cy_{Pl,t-3}$	$cy_{Pl,t-4}$	$cy_{Si,t-1}$	$cy_{Si,t-2}$	$cy_{Si,t-3}$	$cy_{Si,t-4}$
$v_{Gd,t}$	0.678	-1.177	1.457	-1.318 *	-0.359	0.017	0.767	-0.403	0.252	-0.357	1.661	-1.577 *	0.706	-1.222	1.491	-1.085
$v_{Pd,t}$	-0.086	0.167	-0.948	-0.542	0.391	0.231	-0.845	-0.504	1.351	-0.265	-1.944 **	-0.065	-0.432	0.335	-1.170	-0.267
$v_{Pl,t}$	-0.213	1.005	-1.075	0.280	-0.740	1.325	-1.142	0.320	0.681	0.962	-1.331 *	0.197	-0.103	0.668	-1.173	0.743
$v_{{\scriptscriptstyle Si,t}}$	2.322	-0.397	-0.109	0.604	1.919	0.313	0.398	0.629	2.389	0.316	-0.493	0.908	2.293	-0.191	0.230	0.533

Figure 1: Gold and Platinum future prices on TOCOM (GBP) for the whole sample period

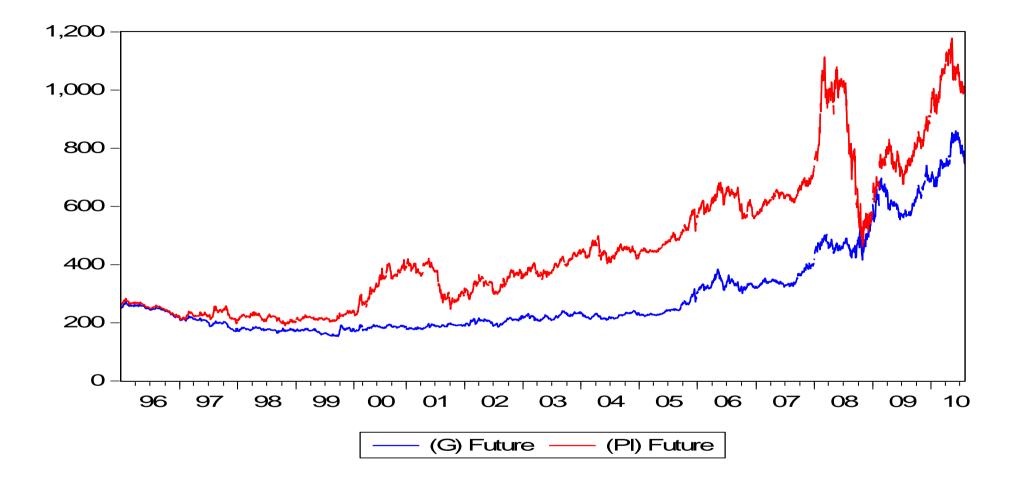


Figure 2A. NASDAQ 100 index for entire sample. Sample representing the DCC is shown as NASDAQ retreats from high in May 2000. (Source: CapitalIq 2010)



**Figure 2B:** TED spread September 2008. Graph demonstrates the overnight wholesale credit market freeze on the collapse of Lehman Brothers as represented by Treasury note euro dollar spread. This date is selected to represent the beginning of the GFC sub sample period. (Source: ChartMechanic)



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Figure 2C. Sub sample of crisis and non-crisis time periods.

The Nikkei 225 Index, Ftse 100 and S&P500 Indices rebased to 0 at start of our data series. Graphic overlay demonstrates the sub sample estimation windows compared to that of the full sample. (Source: CapitalIq)

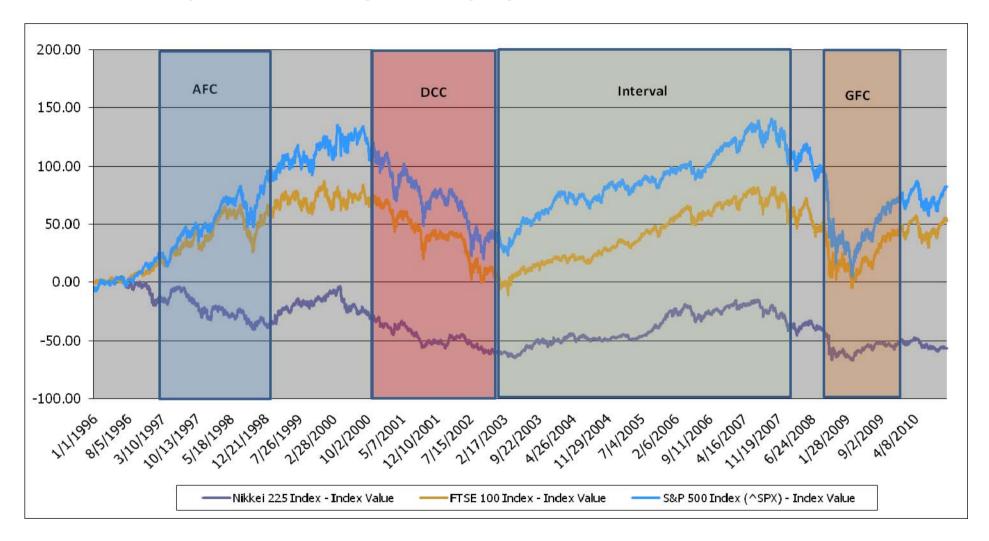


Figure 3: Spot and futures prices for each of the four precious over the full sample period

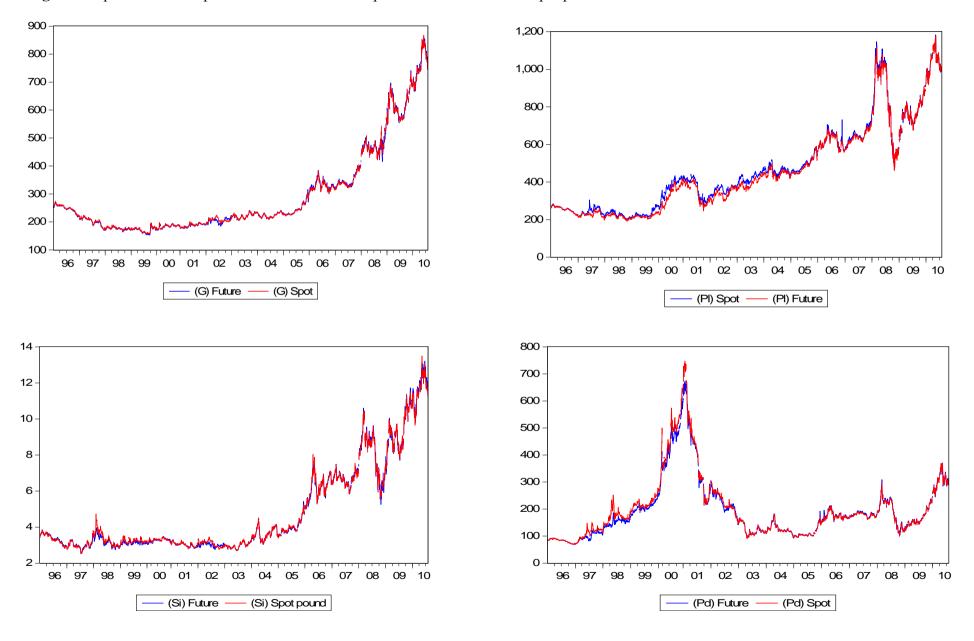


Figure 4: Implied convenience yields for each of the four precious metals for the full sample period.

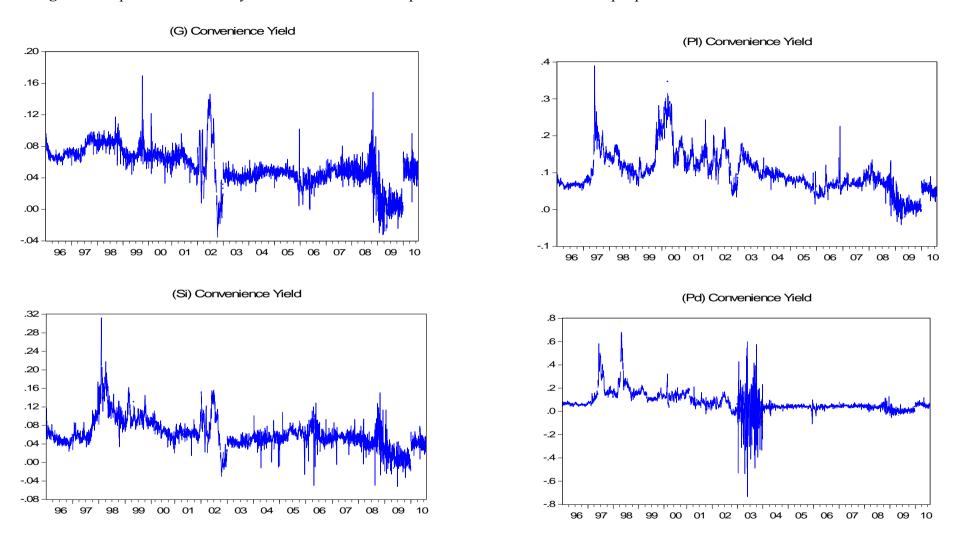
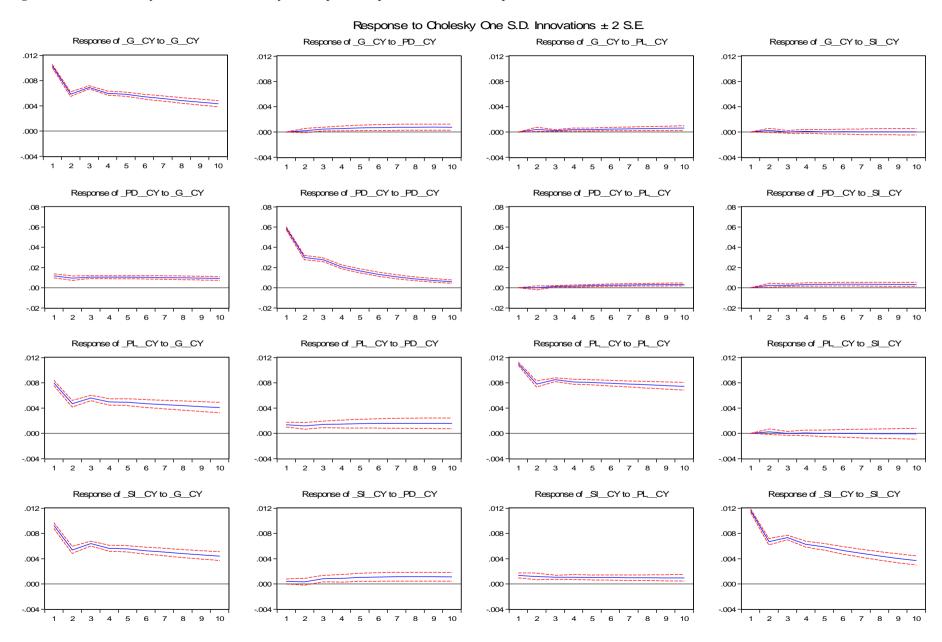
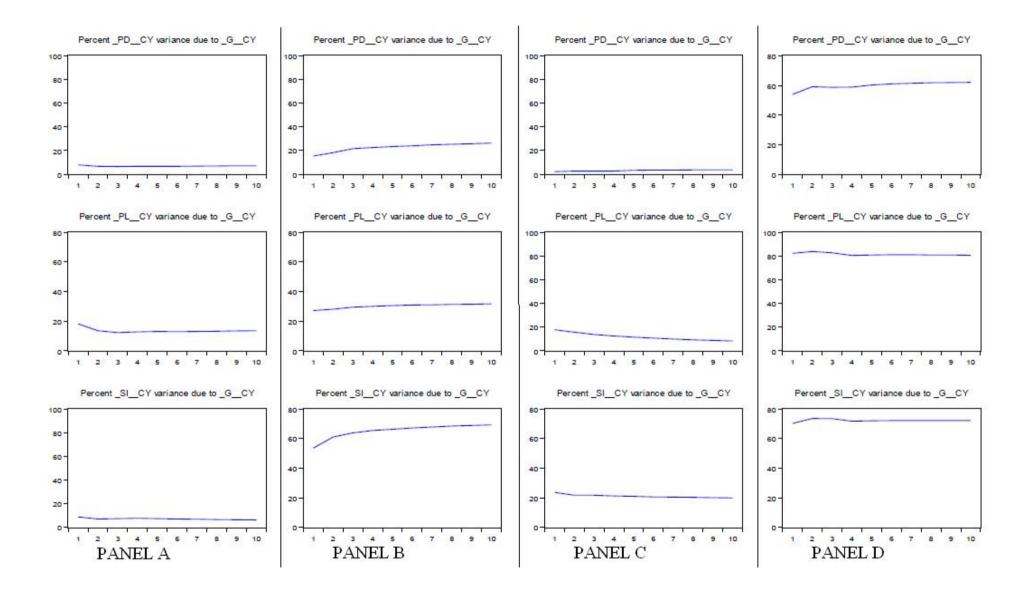


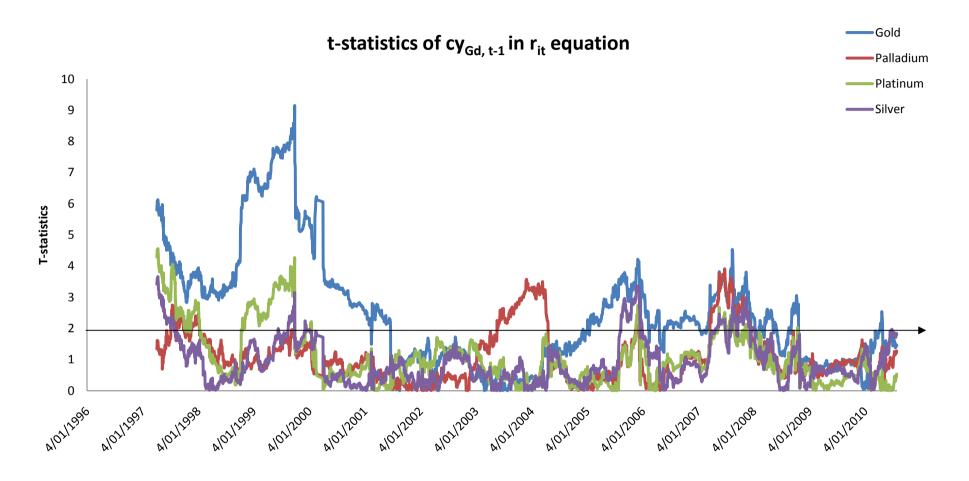
Figure 5: Convenience yield on convenience yield impulse response functions. We present the one standard deviation innovations.



**Figure 6:** Variance decomposition of  $cy_{Gd,t}$  on  $cy_{Pl,t}$ ,  $cy_{Pd,t}$  and  $cy_{Si,t}$  across subsamples.

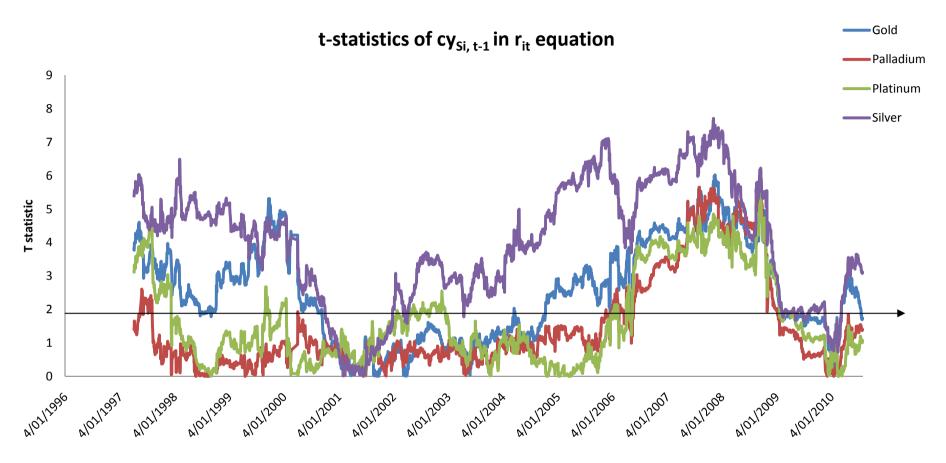


**Figure 7A:** Tracking the t-statistics of cy<sub>Gd,t-1</sub> in precious metal return equations from rolling-window VAR estimations



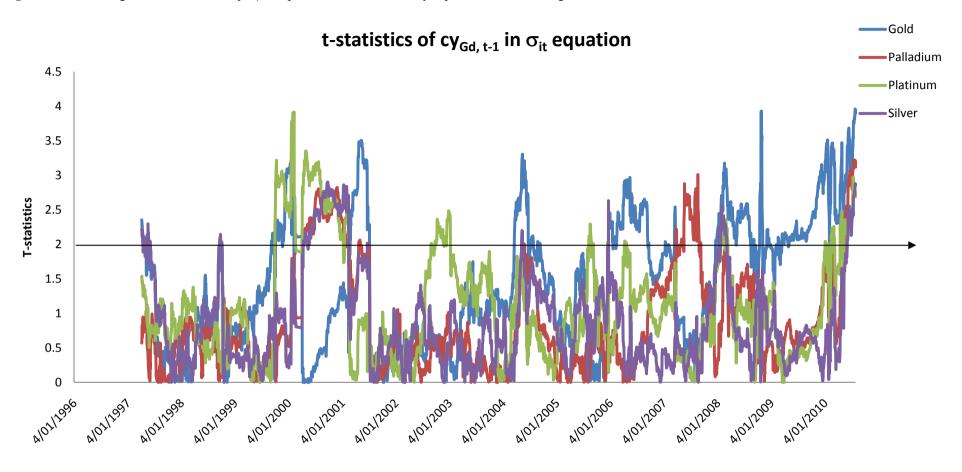
The graphs plot the daily time-series of t-statistics for  $cy_{Gd,t-1}$  in the return equations of the four precious metals. The t-statistics are generated from a series of one-step rolling-window VAR estimation (300 observations) with  $cy_{Gd,t-1}$  to  $cy_{Gd,t-4}$  included as exogenous variables.

**Figure 7B:** Tracking the t-statistics of cy<sub>Si,t-1</sub> in precious metal return equations from rolling-window VAR estimations



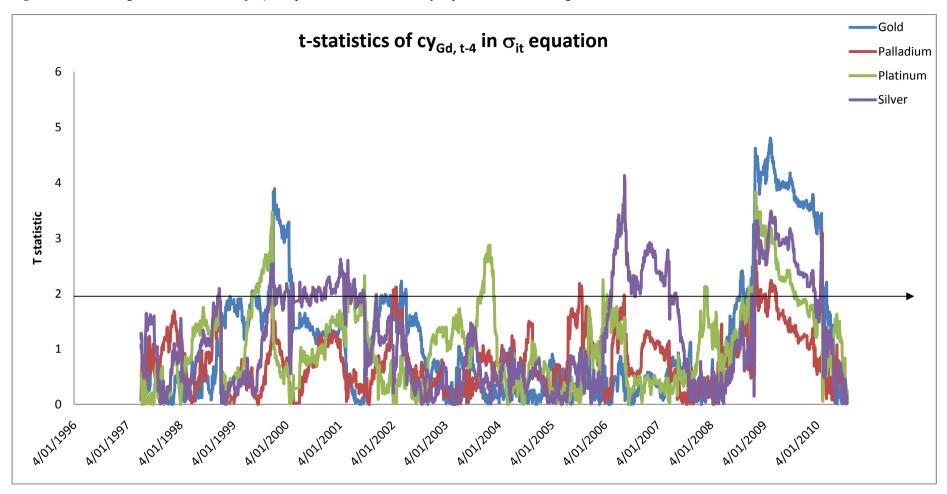
The graphs plot the daily time-series of t-statistics for  $cy_{Si,t-1}$  in the return equations of the four precious metals. The t-statistics are generated from a series of one-step rolling-window VAR estimation (300 observations) with  $cy_{Si,t-1}$  to  $cy_{Si,t-4}$  included as exogenous variables.

**Figure 8A:** Tracking the t-statistics of cy<sub>Gdt-1</sub> in precious metal volatility equations from rolling-window VAR estimations



The graphs plot the daily time-series of t-statistics for  $cy_{Gd,t-1}$  in the volatility equations of the four precious metals. The t-statistics are generated from a series of one-step rolling-window VAR estimation (300 observations) with  $cy_{Gd,t-1}$  to  $cy_{Gd,t-4}$  included as exogenous variables.

Figure 8B: Tracking the t-statistics of cy<sub>Gdt-4</sub> in precious metal volatility equations from rolling-window VAR estimations



The graphs plot the daily time-series of t-statistics for  $cy_{Gd,t-4}$  in the volatility equations of the four precious metals. The t-statistics are generated from a series of one-step rolling-window VAR estimation (300 observations) with  $cy_{Gd,t-1}$  to  $cy_{Gd,t-4}$  included as exogenous variables.