MICHIGAN ROSS

Predictive Value of Commercial Trading Activity in Eurodollar Futures Market on US Stock Market Indices From 2000 Through 2019

by

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Abstract

This paper examines the predictive value of commercial Eurodollar futures trading activity on US public equities. The inspiration behind this topic stems from a May 2011 publication by Tom McClellan of *The McClellan Market Report*. In it, McClellan charts the S&P 500 Index and net commercial trading position as a percentage of total open interest in the Eurodollar futures market ("monthly commercial positioning") from January 2007 to May 2011. After shifting the monthly commercial positioning data forward by 52 weeks, McClellan brings viewers' attention to the strong lagged correlation between the 2 time series.

In this study, we reproduce this time delayed interaction for the period 2000 through 2019 and notice a correlation exceeding 0.8 between monthly commercial positioning and a 52-week lagged reproduction of the S&P 500 Index. We then employ a bivariate econometric procedure to explore cointegration and short-run and long-run Granger-causality. Specifically, we separately measure the forecasting power of monthly commercial positioning on 14 US stock market indices (3 broad-based indices and 11 sector-specific indices).

In a majority of our results, monthly commercial positioning is shown not to be a statistically significant indicator of US equity markets.

Contents

Introduction and Statement of Problem

A Eurocurrency is a type of fixed interest rate bank money varying between overnight and 6 months in maturity. Being a term deposit, however, restricts this store of value from being used as legal tender. At an asset level, the Eurocurrency is uncollateralized and denominated in a currency (e.g. US dollars) *noncorresponding* to its country of domicile (e.g. United Kingdom). In this instance, the Eurocurrency would be titled *Eurodollar*. As consequences to being issued outside the United States, this deposit is neither subject to regulatory oversight by the Federal Reserve nor protected by the Federal Deposit Insurance Corporation (FDIC). Moreover, the offshore location of this deposit exposes it to sovereign and credit risk associated with the host country – in this case, the United Kingdom. These 2 characteristics help explain why a Eurocurrency's yield commands a structural premium over its domestic counterpart.

A closer look at the Eurodollar reveals that pricing takes place in 2 forms. The Federal funds rate, or interest rate at which institutions lend uncollateralized reserve balances to one another, guides deposits with overnight to one-week maturities. Separately, longer maturing deposits are priced using the London Interbank Offered Rate (LIBOR) – an interest-rate average at which a consortium of banks will lend short-term loans to each other. Customarily, deposit sizes exceed $100,000, although counterparties will also place lot sizes over $5,000,000, with transactions and maturities taking place overnight and the following business day, respectively. Weekends can extend this window to 4 days, while transactions maturing more than 6 months out are recognized as certificates of deposit (CDs).

Western Europe is credited with the invention of the Eurocurrency during the 1950s. At the time, the (i) installment of the 1948 Marshall Plan and (ii) rise of imports entering the US following World War II led to an influx of US dollars in European financial institutions. During this period, it did not take long for newly minted Eurodollars to be repatriated via foreign banks' investments in US money markets (Carlozzi, 1981). However, with a push towards globalization and displacement of the Pound sterling by the US Dollar as the universal trade currency from 1960 onwards, European banks began lending Eurodollars in short duration loans to a variety of counterparties (e.g., overseas financial institutions and commercial firms) (Carlozzi, 1981). Shortly after, non-USD term deposits also saw an uptick, with London and Paris rapidly becoming hubs for Euroyen and Eurosterling markets, respectively. Before long, Eurocurrencies began scaling internationally as "one of the fastest-growing as well as […] most vital and important capitalist institutions" (Stigum and Crescenzi 2007, p. 209). From 1969-1979, these assets – consisting of both loans made to clients and deposits credited at foreign banks – grew at a CAGR of 27% (Carlozzi, 1981). Astoundingly, even the largest US commercial banks, over the same period, only saw their assets grow 8% annually (Carlozzi, 1981).

With the onset of the "Decade of Greed" came a momentary pause in worldwide Eurocurrency growth. Much of this can be attributed to the arrival of securitization and financial engineering of derivatives (Battilossi, Cassis, and Yago, 2019). For the first time in international money markets, participants were able to decouple risk factors (e.g., currency fluctuations and interest rate hikes), repackage them as short-term liabilities, and speculate with or against them. Among one of the first of these off-balance sheet securities was the Eurodollar futures contract (ED) introduced in December 1981 (Battilossi, Cassis, and Yago, 2019). This cash-settled agreement's underlying unit is a $1mm USD Eurodollar term deposit maturing in 3 months. Put more simply, contract prices are calculated as $100 minus the implied International Monetary Market (IMM) 3-Month LIBOR, reflecting the interest rate anticipated on the contract's settlement date. The examples below demonstrate this and how the instrument is frequently used as a hedging vehicle against interest rate volatility.

Example 1: Eurodollar Futures Contract: Pricing and Proceeds from Short Sale

January (purchase):	IMM 3-Month LIBOR *at time of purchase* is 0.25
	Trader buys March contract for $100 – 0.25 = $99.75
March (settlement):	IMM 3-Month LIBOR *at time of settlement* is 0.19
	Trader settles contract for $100 – 0.19 = $99.81
Basis Point Value (BPV):	$\$1mm * \left(\frac{90}{360}\right) x0.01\% = \$25$
Proceeds:	$\$99.81\ (sale) - \$99.75\ (purchase) = 6\ bps * \$25 = \$150$

Example 2: Using the Eurodollar Futures Contract to Hedge Interest Rate Risk

Bank Loan

Tenor:	Borrow loan on 3/14/20. Repay on 6/13/20.
Rate:	3-Month LIBOR + 1% (3-Month LIBOR set on 3/14/20 for interest payment on 6/13/20)
Notional Value:	$\$1mm$
Basis Point Value:	$\$1mm\ x\ \frac{90\ days}{360\ days}\ x\ 1\ bps = \$24.66$

Eurodollar Futures Contract

Tenor:	ED: 3-Month LIBOR coverage from 3/14/20 + 90 days
Rate:	ED expires on 6/14/20
Notional Value:	$1 *million* per contract per quarter
Basis Point Value:	$25 per Chicago Mercantile Exchange (CME) rulebook

Selling the above ED contract (initiating a short position) will result in the following:

- For every rate increase of 1 bps across the 3-Month forward interval spanned by the loan:
    - profits realized from ED = $25.00
    - loss realized from increase in interest on bank loan = $24.66
        - Net Profit = $0.34
- For every rate decrease of 1 bps across the 3-Month forward interval spanned by the loan:
    - losses realized from ED = $25.00
    - profits realized from decrease in interest on bank loan = $24.66
        - Net Loss = $(0.34)

As a product, the Eurodollar futures contract has benefited considerably from its myriad of uses and heterogeneous market participants. Hedge funds routinely use the derivative to speculate on Federal Reserve policy revisions, while lenders (e.g., banks and BDCs) and borrowers (e.g., governments and corporations) will often take opposite positions to shield against interest rate shocks (Osipovich, 2019). By comparison, Eurodollar futures regularly surpasses the 10-Year Treasury Note futures, E-Mini S&P 500 futures, and crude oil futures in average daily trading volume (Blystone, 2020). In fact, at the end of February 2020, open interest in the Eurodollar futures market was tallied at $10.79 trillion – over 20x the size of the next most traded interest rate futures product (i.e. SOFR futures) (CME Group, n.d.).

For a market that transacts $3 trillion daily, CME's Fred Sturm is accurate in describing Eurodollar futures as "one of the largest liquidity pools on God's green earth" (Osipovich, 2019) and Brecht, 2016). This density offers clear benefits. For example, (Tse and Bandyopadhyay, 2006) noted that the Eurodollar futures market saw bid-ask spreads decline from September 2003 onwards as liquidity levels steadily rose following the CME's inauguration of electronic trading.

Another side effect was the Eurodollar futures market's consistently lower friction costs and quicker assimilation of new information, or "price discovery", compared to its cash (spot) market counterpart (Cheung and Fung, 1997).

Something less discussed, however, is the overlap between trading activity in the Eurodollar futures market and US stock markets. This observation was first noted by Tom McClellan, editor of *The McClellan Market Report*. In an issue published in May 2011, Tom analyzed the US Commodity Futures Trading Commission's (CFTC) Commitments of Traders (COT) reports. These weekly disclosures "provide a breakdown of each Tuesday's open interest for futures […] markets in which 20 or more [commercial or noncommercial] traders hold positions equal to or above the reporting levels established by the CFTC" (CFTC, n.d.). Commercial traders – the focus of this paper – are recognized as "hedgers" or the "smart money" in the market. They typically have a commercial interest in the underlying asset or financial instrument (in this case, the interest rate attached to a Eurodollar term deposit maturing in 3 months) and are focused on hedging exposure. By contrast, non-commercial traders predominantly consist of large speculators (e.g., hedge funds, commodity trading advisors, and money managers) who do not have a commercial interest in the underlying asset or financial instrument. These futures traders are viewed as profit seekers and are not commercially exposed to the underlying asset or financial instrument's supply and demand characteristics (CFTC, n.d.). An analysis of monthly commercial positioning alongside the S&P 500 revealed to Tom McClellan that "the movements of the S&P 500 tend to echo what the commercial Eurodollar [futures] traders were doing previously" (McClellan, 2011). After experimenting with a range of time delays, he further notes that "a one-year lead time gave the best correlation" (McClellan, 2011). Testing this theory for the period 2000 through 2019 reveals a noticeable jump in correlation as displayed numerically in Table 1 and visually in Figure 1 and Figure 2.

Table 1: Correlation between (i) S&P 500 and Monthly Commercial Positioning and (ii) S&P 500 (Lagged by 12 Months) and Monthly Commercial Positioning

Variable 1	Variable 2	R	R^2
S&P 500	Monthly Commercial Positioning	0.594	0.353
S&P 500 (Lagged by 12 Months)	Monthly Commercial Positioning	0.820	0.673

Figure 1: S&P 500 Index Versus Monthly Commercial Positioning

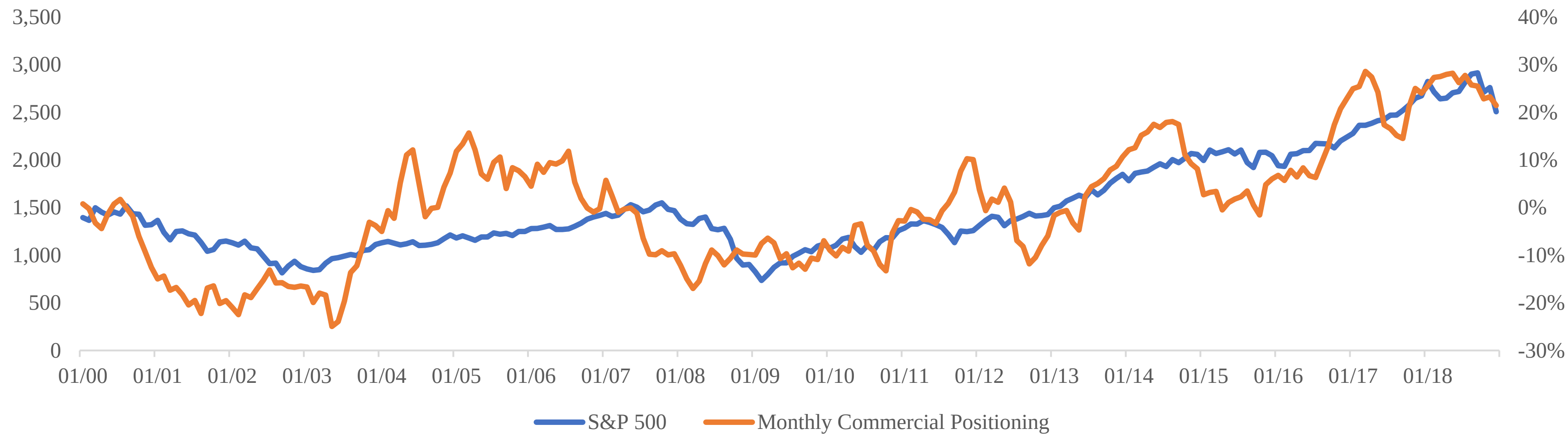
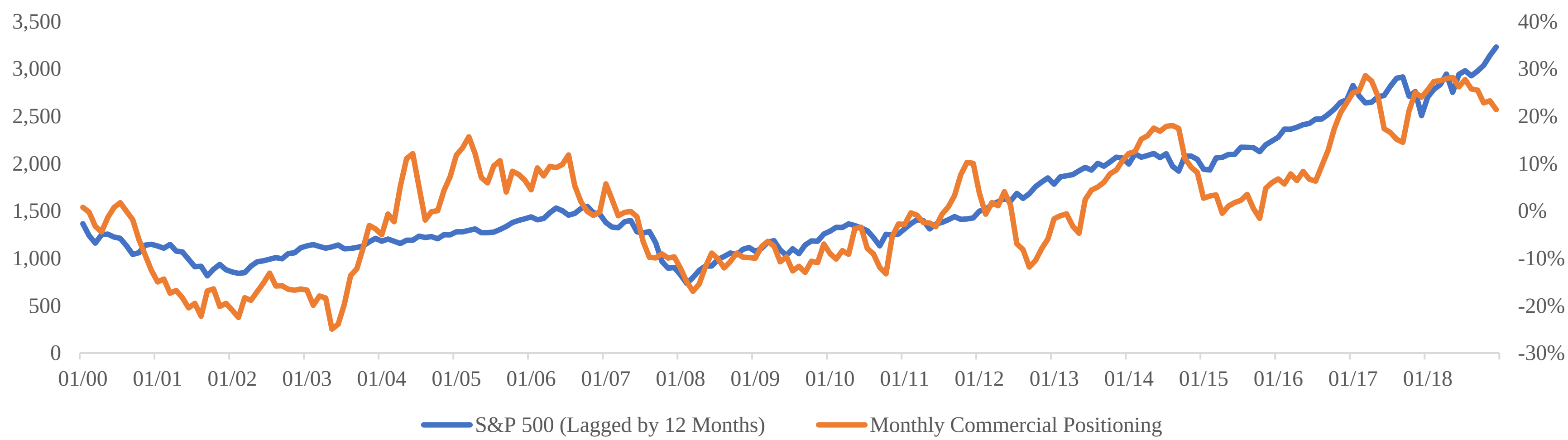


Figure 2: S&P 500 Index (Lagged by 12 Months) Versus Monthly Commercial Positioning



According to Tom and Sherman McClellan, this correlation translates to commercial Eurodollar futures traders responding to “immediate banking liquidity conditions”, which are “revealed first in the banking system” before pulsating through the stock market over the following 52 weeks (McClellan, 2011). Tom McClellan substantiated this theory with the fact that “commercial traders of Eurodollar futures are typically the big banks, who are using these futures contracts to manage their asset and fund flows” and hedge against deposit and loan balances (McClellan, 2011). While (McClellan, 2011) insinuated that this correlation explained liquidity conditions across the entire stock market rather than any one index, it did not report (i) other broad-based indices and sectors across which this comovement was discernable and (ii) whether there were statistically significant unidirectional or bidirectional causal effects running between the 2 variables. Our study attempted to explain these gaps. Through a bivariate econometric approach, we explored the hypothesis of using Monthly Commercial Positioning as a leading indicator of directional movements across US public equity indices from 2000 through 2019. These indices included the S&P 500 Index and a series of other broad-based and sector-specific market indices. Our overall objective was to add more color to Tom McClellan’s initial observation and identify exact causal interactions and long-run equilibrium relationships between pairs of variables.

The period 2000-2019 was selected for examination for several market related reasons. For one, this nearly 2-decade long window includes 3 distinct yet considerable United States led stock market collapses. Moreover, each collapse varied materially in its pace of decline, loss in market value, duration, and speed of recovery. The 2000-2002 Dot-com Bubble, for instance, saw the Nasdaq Composite shed nearly 80% of its 5,000+ point peak over 2.5 years, while during the more recent 2008 Financial Crisis, the Dow gave back over 50% of its pre-recession 14,000+ point peak over 2.25 years (Picardo, 2020) and (Amadeo, 2020). Recovery periods also differed, with the Dow and Nasdaq Composites taking another 6 and 8 years, respectively, to reach fresh highs (Zach, 2019). In sharp contrast, during the May 6, 2010 Flash Crash, over a trillion dollars left and reentered US markets in 36 minutes (Reid, 2020). Each of the 3 domestic market failures was also rooted in different issues. Reckless speculation, cheap and highly accessible venture capital, and a lack of bottom-line corporate profits to support lofty valuations helped inflate and burst the Dot-com Bubble (Hayes, 2019). Years later, record low-interest rates led to frenzied home buying by interest-only (subprime) loan borrowers. This, coupled with institutions attempting to buy and sell risky mortgage debt while housing prices rapidly depreciated, led to the mass defaults, foreclosures, and bank runs that would set the Financial Crisis in motion (Amadeo, 2019). This 19-year period also captures 2 short-lived domestic market declines triggered by geopolitical and worldwide economic uncertainties. The 2011 “Black Monday” selloff saw the Wilshire 5000 drop 7% as markets across Asia, Europe, and the Middle East concomitantly deteriorated (Hargreaves, 2011). This reflected, at least in part, US investors’ worry of the (i) European sovereign debt crisis contaminating markets in Italy and Spain and (ii) possible downgrade of France’s AAA-rated sovereign bonds (Bowley, 2011). In a separate incident, turbulence in Chinese markets (including devaluation of the yuan) and Greece’s inability to make payments on its sovereign debt fueled the 2015 Dow selloff (Driebusch, 2015 and Cheng, 2015). Lastly, the 2000-2019 timeframe contains much of the longest-running bull market in American history. This expansion, being more than 10 years in length, provides a one-off opportunity to study when net commercial positioning might align with and decouples from the broader market. Given that both national (e.g. FOMC announcements and economic releases) and global (e.g., LIBOR rate changes, overseas credit risk, and borrowing demand) components guide pricing and trading in the Eurodollar futures market, 2000-2019 proves to be a desirable period of study given the host of local and foreign factors that have influenced domestic stock returns.

Justification of Problem

Studying the relationship between Monthly Commercial Positioning and US stock market indices from 2000 through 2019 can provide insights widely applicable to academic, government, and commercial settings. Research in this space sheds light on a hedging instrument that has only recently surfaced yet has gained significant traction among sophisticated money managers and global financial institutions. Following its inauguration in the early 1950s, the Eurocurrency market, in its entirety, commanded nearly $7.8tn in notional value by 1995, making it (at the time) larger than the US' M2 money supply (Carlozzi, 1981). In effect, this study may help academics better understand global implications of a market of this size, its effects on smaller, more dependent emerging economies that trade in tandem with the US, and the extent that forward-rate expectations are being priced into both global Eurocurrencies and their respective futures contracts. In addition to this, a more clear understanding of this space offers policymakers the opportunity to recognize how (i) the Federal Reserve's recent installment of Zero Interest-rate Policy (ZIRP) and (ii) LIBOR's expected replacement may affect trading activity and capital allocation. On the other end, buy side traders and investors may find value in using this study to investigate similar correlations in emerging and frontier markets. Since these economies present severe liquidity constraints, long-term macro investing becomes a more attractive way of deploying capital compared to timing the entry and exit of trades. Ultimately, this shift in strategy has multiple implications. For one, capital is effectively allocated to the most at-need regions. And secondly, investors are able to access new, uncovered opportunities and unlock value for limited partners through novel strategies. Although the first may be an unintentional consequence for investment firms seeking high yields above everything else, it could certainly affect future economic development across markets.

Literature Review

(a) Leader-follower Relationships Across Tradeable Assets

A cursory search reveals how extensively researchers have sought out leader-follower connections between seemingly discrete assets, markets, and order flow data. A characteristic example is the series of tests carried out by (Bhattacharya and Mukherjee, 2003) to test for bidirectional causal relationship(s) between the S&P Bombay Stock Exchange (i.e. BSE SENSEX) and several macroeconomic barometers (i.e. exchange rate, foreign exchange reserves, and value of trade balance) for the periods 1990-1991 and 2000-2001. The study complemented past observations on the correlation between such variables in US capital markets (Aggarwal, 1981 and Soenen and Hennigar, 1988). Ultimately, (Bhattacharya and Mukherjee, 2003) concluded that none of the macroeconomic variables under scrutiny could be dependably used as a forecasting mechanism of the BSE SENSEX and vice versa, precluding the two from challenging Fama's Efficient Market Hypothesis (EMH) (Fama, 1970). One-half decade later, (Cong, Wei, Jiao, and Fan, 2008) examined the price histories of Brent Crude Oil and 10 Chinese stock market sector indices from 1996 to 2001 in search of two-way time-delayed linkages. Use of a multivariate vector autoregression (VAR) analysis revealed that oil price shocks and manufacturing index returns shared the one and only statistically significant relationship (Cong, Wei, Jiao, and Fan, 2008). 2 years following concluding remarks, (Arouri and Nguyen, 2010) used past Brent crude oil levels and 12 Dow Jones Stoxx (European) sector indices to uncover similar relationships on a global level. As a baseline, analogous past works detailing connections between oil prices and sectors in Canada and the United Kingdom were referenced (Sadorsky, 2001; Boyer and Filion, 2007; El-Sharif, Brown, Burton, Nixon, Russel, 2005). A multifactor pricing model and Granger causality tests indicated that increases in oil prices negatively affected 3 sectors (i.e. Food and Beverages, Health Care, and Technology), positively affected 5 sectors (i.e. Financials, Oil and Gas, Industrials, Basic Materials, and Consumer Services) and immaterially affected 3 sectors (i.e. Personal and Household Goods, Telecommunications, and Utilities) (Arouri and Nguyen, 2010). More recently, (Dritsaki, 2017) conducted a formal search for long-run relationships between inflation and nominal interest rates (Fisher, 1930) across Germany, United Kingdom, and Switzerland. As an extension to similar studies, namely (Mishkin and Simon, 1995) for Australia and (Weidmann, 1997) for Germany, this investigation relied on an Autoregressive Distributed Lag (ARDL) model to validate existence of cointegration between the 2 variables for all 3 countries. What was more unique at the time was the study's use of the Toda and Yamamoto (1995) no-causality test to establish unidirectional causality (flowing from nominal interest rates to inflation) for United Kingdom and Switzerland and bidirectional causality for Germany (Dritsaki, 2017).

(b) Leader-follower Relationships Between Monthly Commercial Positioning and Futures Prices

Of late, researchers have also taken efforts to diagnose if such relationships exist within futures markets. In doing so, studies have often displayed periods when Monthly Commercial Positioning and futures prices move in tandem given a gap between the two variables. (Irwin, Sanders, and Merrin, 2009), for instance, studied the usefulness of the CFTC's Monthly Commercial Positioning data in prognosticating returns for 10 agricultural futures markets. (Irwin, et al., 2009) noted that past works have often returned mixed results due, in part, to the time period under investigation. For example, while (Wang 2001) concluded that Monthly

Commercial Positioning reliably foreshadowed reversals (i.e. directional changes during a price rally) for 6 futures markets (i.e. corn, soybeans, soymeal, wheat, cotton, and world sugar) from 1993 to 2000, (Gorton, Hayashi, and Rouwenhorst, 2007) remarked that net commercial position data seldom predicted pricing action across 31 agricultural futures markets (including ones analyzed by Wang) between 1971 and 2010. Similar to other studies, (Irwin, et al., 2009) first (i) employed a bivariate Granger-causality framework to detect any lead-lag relationships and then (ii) tested the ordinary least squares (OLS) residuals for autocorrelation, heteroskedasticity, and long-term stability. Findings described Monthly Commercial Positioning as having a limited and inconsistent ability to lead futures prices from 1995 to 2006. In fact, certain traders enhanced their long positions following price increases in the futures market, suggesting the presence of “trend following” instead of “trend setting” behavior (Irwin, et al., 2009). Since this recent examination, an exhaustive set of observations have been made across Monthly Commercial Positioning and corresponding futures markets. (Harris and Buyuksahin, 2011) deemed the use of such trader data insufficient in forecasting price fluctuations in West Texas Intermediate (WTI) Light Sweet Crude Oil Futures for the period 2000 to 2009. By contrast, (STUDY) indicated significant predictive value of X on Y. In yet another instance, (Often and Wisen, 2013) reported mixed results, concluding that Live Cattle futures routinely followed Monthly Commercial Positioning whereas futures markets for Corn, Natural Gas, Copper, and Coffee showed no such connectedness (Often and Wisen, 2013).

(c) Leader-Follower Relationships Between Monthly Commercial Positioning and Spot Prices

Although few and far between, studies measuring the ability of order flow data to forecast spot prices have also made appearances in economic literature. A spot price represents the instantaneous cash price that a financial instrument is purchased or sold at for immediate delivery/settlement (Chen, 2019). In contrast, a futures contract denotes the price of a financial instrument for future delivery/settlement (Chen, 2019). The differential between the 2 prices is known as the basis (Chen, 2019). Studies denoting the lagged comovements between Monthly Commercial Positioning and spot prices have spanned multiple markets. (Mutafoglu, 2010), for example, hypothesized that noncommercial trading activity belonging to currency futures markets could be used to foretell movements of their respective spot exchange rates. The paper notes that previous macroeconomic models – the use of which was standard at the time – have been unsymmetrical in their findings (Mutafoglu, 2010). As such, this study used a microstructure model to investigate the cointegration relation between commercial and non-commercial traders' net positions and spot exchange rates. Results pointed to long run equilibria between noncommercial trading activity and each of the 5 spot exchange rates (i.e. Australian Dollar, British Pound, German Mark, Japanese Yen, and Swiss Franc) (Mutafoglu, 2010). This was followed-up with a sequence of multivariate Granger-causality tests (Mutafoglu, 2010). Unidirectional causality running from noncommercial trading activity in the German Mark and Swiss Franc futures to the spot DEM/USD and CHF/USD rates, respectively, was found (Mutafoglu, 2010). Reverse causality was also identified between the AUD/USD rate and Australian Dollar futures (Mutafoglu, 2010). Moreover, bidirectional causality existed between the British Pound and Yen futures and GBP/USD and JPY/USD rates, respectively (Mutafoglu, 2010). Shortly after Mutafoglu's paper, (Mutafoglu, Tokat, and Tokat, 2012) detailed the results from a similar procedure used to assess gold, silver, and platinum futures markets for the period 1993 to 2009. To recognize the price rally across all three markets till 2008, a structural break in the early 2000s was used to bifurcate the analysis (Mutafoglu, et al., 2012). After fitting a 2-

variable VAR model and Granger-causality tests to the data, results highlighted that (i) only Monthly Commercial Positioning for silver and platinum futures markets had forecasting power on pre-break spot prices and (ii) no causal relationships existed in post-break markets (Mutafoglu, et al., 2012). Similar to observations made in (Irwin, et al., 2009) and (Mutafoglu, et al., 2012), commercial traders were overwhelmingly “trend followers”, with Gold, Silver and Platinum pre-break spot prices and Silver and Platinum post-break spot prices leading Monthly Commercial Positioning (Mutafoglu, et al., 2012). Possibilities of causal links between Monthly Commercial Positioning and deeply traded commodities have also been explored. Among them, (Alquist and Gervais, 2013) outlined relationships between Monthly Commercial Positioning and WTI Crude Oil spot prices. Through a 3-period study spanning17 years of data, (Alquist, et al., 2013) demonstrated that Monthly Commercial Positioning Granger-causes oil prices for only 1 period – 1993 to 2010 – while the inverse is true for all 3 periods – 1993 to 2010, 2003 to 2008, and 2003 to 2010. Adjacent findings, notably (Hamilton, 2009) for the period 1997 to 2008 and (Fattouh, Kilian, and Mahadeva, 2012) for the period 2003 to 2008, have shown connections between speculative (noncommercial) demand in oil futures markets and spot prices.

Recent efforts to uncover linkages between trading behavior, assets, and respective derivative markets have led researchers to an assortment of conclusions. In large part, this is due to the diversity of econometric models used to diagnose relationships, varying time periods under consideration, and numerous interpretations of trends, significance, and causality. Unfortunately, no literature has yet identified if Monthly Commercial Positioning in the Eurodollar futures market can prognosticate any US stock market indices over any time period. Before designing our study, we learned about our data and recorded unique characteristics. Then, we used a curated list of past studies to define an appropriate econometric procedure to follow. Lastly, we aggregated our results and simultaneously noted areas of interest.

Data and Methodology

Data Selection and Scrubbing

The data samples used in this study include historical (i) price levels of US equity markets and (ii) net commercial trading positions as a percentage of total open interest in the Eurodollar futures market. Data sets were compiled in monthly increments ranging from 2000 through 2019[1].

Within category (i), 3 major US stock market indices [i.e. S&P 500, Dow Jones Industrial Average (DJIA), and Nasdaq Composite] and 11 S&P 500 sector indices (i.e. Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Utilities, and Real Estate) are included to proxy equity market performance. Although broad-based in nature, each major market index comprises a unique set of companies that vary in volume, type, and weighting. The S&P 500, for instance, pools together all companies listed on the New York Stock Exchange (NYSE) and NASDAQ Stock Market (NASDAQ), rank orders them by market capitalization, and then selects the largest 500 firms to include. Those included are weighted by equity value, meaning a 1% move in a large stock [e.g. Apple (NASDAQ: AAPL)] would move the index more aggressively than a 1% move in a smaller stock [e.g. SVB Financial Group (NASDAQ: SIVB)] (Reiss, 2017). The Nasdaq Composite follows a similar methodology. By contrast, however, the Nasdaq Composite draws exclusively from approximately 3,300 companies listed on the NASDAQ (Chen, 2019). Moreover, the Nasdaq Composite is much narrower in scope, with nearly 50% of the index

[1] The S&P 500 Real Estate Sector Index was launched in October 2001. Monthly market data is included from that point through 2019.

belonging to technology firms, followed by firms representing consumer services, health care, and financials (Reiss, 2017 and Chen, 2019). Unlike the two indices mentioned, the DJIA is more limited in volume, including only 30 blue-chip companies that represent the economy (Ganti, 2020). The DJIA also price-weights its selection, allowing firms with higher priced shares to disproportionately influence the index (Ganti, 2020). Table 2 below decomposes S&P 500 sectors into the industries they represent. Data on all stock market indices were obtained using FactSet Research Systems.

Table 2: Representation of S&P 500 Sectors by Industries Included in Each

S&P 500 Sector	Industries Included
Communication Services	Diversified Telecommunication Services; Wireless Telecommunication Services; Entertainment; Media; Interactive Media & Services
Consumer Discretionary	Automobile Components; Automobiles; Distributors; Diversified Consumer Services; Hotels; Restaurants & Leisure; Household Durables; Leisure Products; Multiline Retail; Specialty Retail; Textile; Apparel & Luxury Goods; Internet & Direct Marketing
Consumer Staples	Beverages; Food & Staples Retailing; Food Products; Household Products; Personal Products; Tobacco
Energy	Energy Equipment & Services; Oil, Gas & Consumable Foods
Financials	Banking; Capital Markets; Consumer Finance; Diversified Financial Services; Insurance; Mortgage Real Estate Investment Trusts (REITs); Thrifts & Mortgage Finance
Health Care	Biotechnology; Health Care Equipment & Supplies; Health Care Providers & Services; Health Care Technology; Life Sciences Tools & Services; Pharmaceuticals
Industrials	Aerospace & Defense; Air Freight & Logistics; Airlines; Building Products; Commercial Services & Supplies; Construction & Engineering; Electrical Equipment; Industrial Conglomerates; Machinery; Marine; Professional Services; Road & Rail; Trading Companies & Distributors; Transportation Infrastructure
Information Technology	Communications Equipment; Electronic Equipment, Instruments & Components; IT Services; Semiconductors & Semiconductor Equipment; Software; Technology Hardware, Storage & Peripherals
Materials	Chemicals; Construction Materials; Containers & Packaging; Metals & Mining; Paper & Forest Products
Real Estate	Equity Real Estate Investment Trusts; Real Estate Management & Development
Utilities	Electric Utilities; Gas Utilities; Independent Power & Renewable Electricity Producers; Multi-Utilities; Water Utilities

Data contained in category (ii) were extracted from the CFTC's COT reports described earlier. Calculating the monthly average net commercial trading position as a percentage of total open interest in the Eurodollar futures market required first locating open interest, long interest, and short interest in weekly COT reports. Each week's net long position (total long interest minus total short interest) was then divided by that week's open interest, resulting in the net commercial trading position as a percentage of total open interest *for that week* ("Weekly Net %"). This process was then repeated for each week every month. Results were then used to compute Monthly Commercial Positioning by applying a weighted average based on each week's open interest. An example set of calculations is provided in Table 3 below for August 2018.

Table 3: Monthly Commercial Positioning Calculation for August 2018

Week Ending	Open Interest (mm)	Long Interest (mm)	Short Interest (mm)	Net Long (mm)	Weekly Net %	Monthly Commercial Positioning
8/7/18	14.039548	10.004922	6.224883	3.780039[a]	26.92%[b]	25.75%[c]
8/14/18	13.946092	9.806008	6.255742	3.550266	25.46%	
8/21/18	14.046440	9.848666	6.295344	3.553322	25.30%	
8/28/18	14.141665	9.852561	6.269547	3.583014	25.34%	

Notes:

(a) $Long\ Interest\ (mm) - Short\ Interest\ (mm) = 10.004922 - 6.224883 = 3.780039$

(b) $\frac{Net\ Long\ (mm)}{Open\ Interest} = \frac{3.780039}{14.039548} \approx 26.92\%$

(c) Weighted average of Weekly Net % based on average aggregate open interest

Descriptive Statistics

Please view market data in Figure 3 and Figure 4. Preliminary analysis was performed on each time series with results summarized in Table 4.

Figure 3: US Stock Market Indices (Indexed) versus Monthly Commercial Positioning

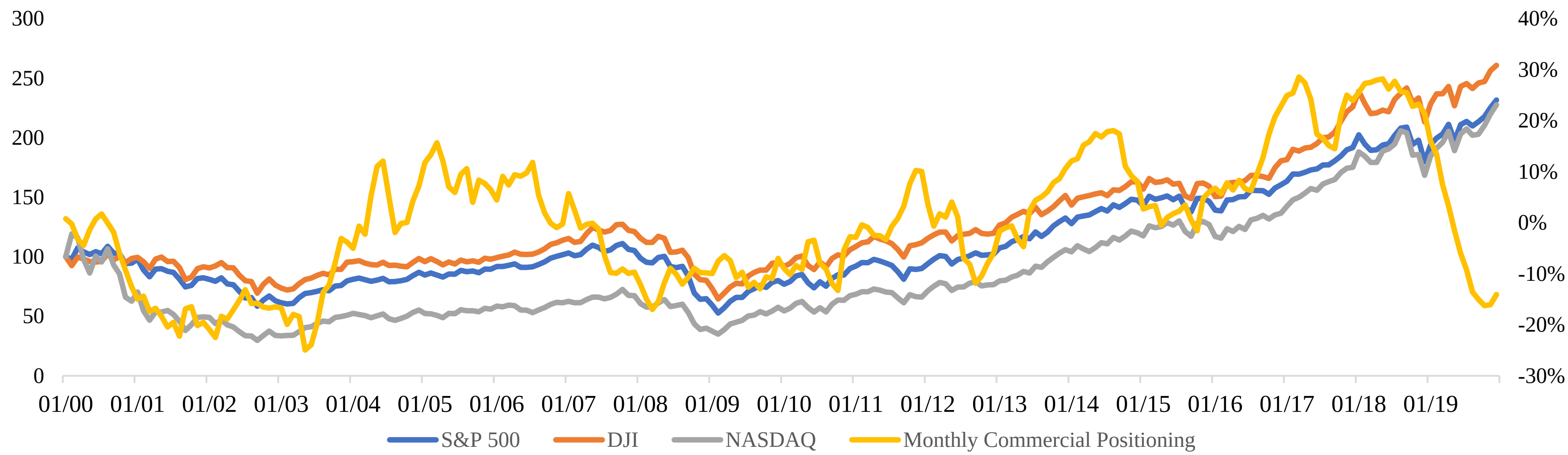


Figure 4: S&P 500 Sector Indices (Indexed) versus Monthly Commercial Positioning

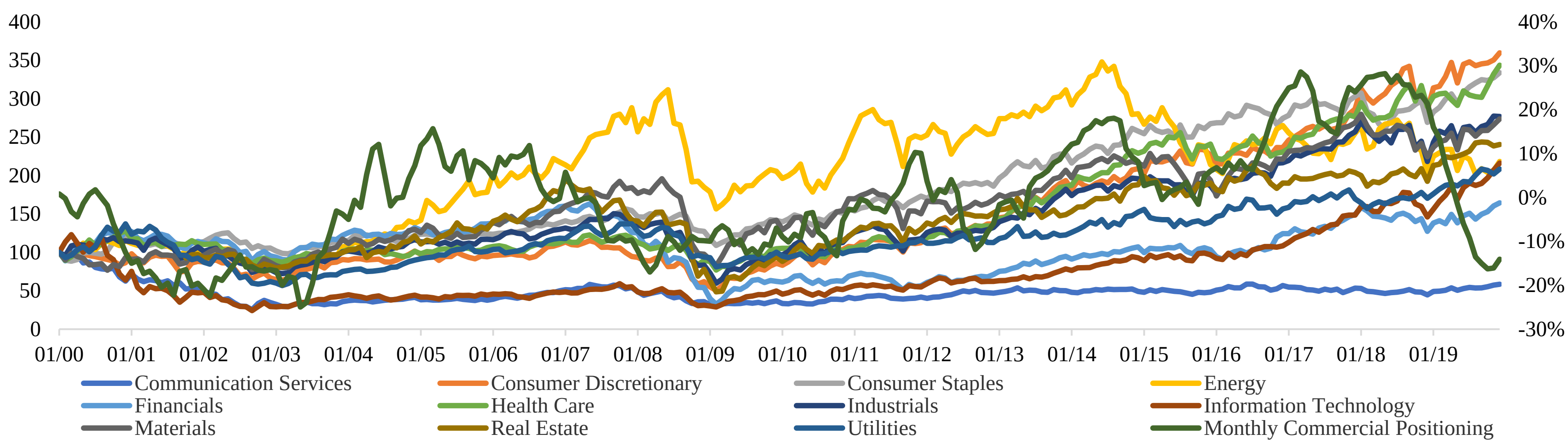


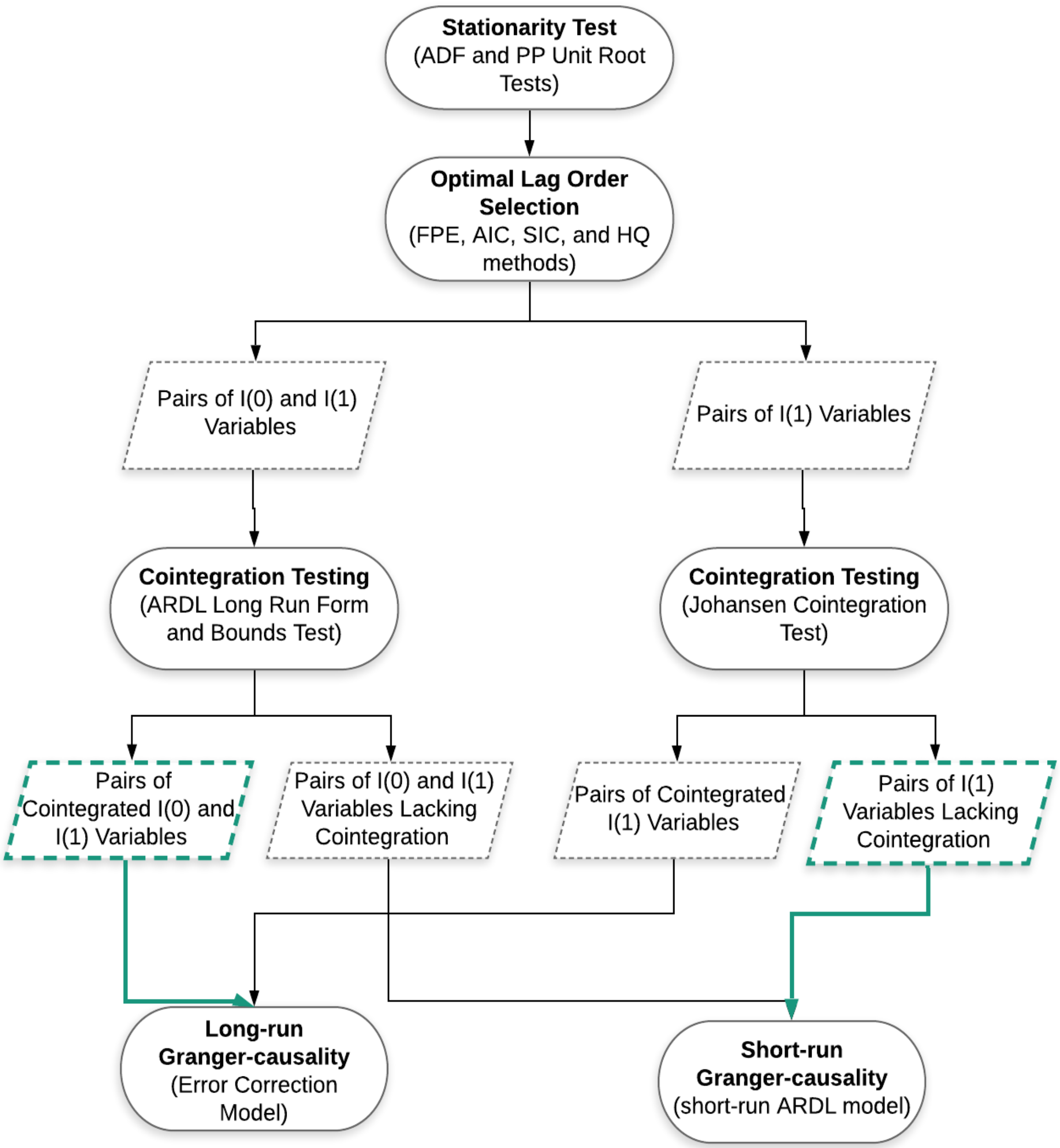
Table 4: Descriptive Statistics of Monthly Commercial Positioning and US Stock Market Indices

	Mean	Median	Std. dev.	Skewness	Kurtosis	Corr. w/ Monthly Comm. Pos.	Corr. w/ S&P 500	Corr. w/ DJIA	Corr. w/ NASDAQ
Monthly Commercial Positioning	0.15%	-0.45%	0.13	0.33	2.40	-	-	-	-
S&P 500	1577.89	1366.22	591.04	0.99	2.95	0.59	-	-	-
DJIA	14065.38	12219.74	5244.60	1.14	3.27	0.58	-	-	-
NASDAQ	3476.45	2636.31	1917.59	1.11	3.16	0.58	-	-	-
Communication Services	147.10	148.91	37.53	1.64	7.59	0.12	0.37	0.28	0.39
Consumer Discretionary	403.41	289.96	224.77	1.08	2.92	0.59	0.99	0.99	0.98
Consumer Staples	347.79	288.20	136.27	0.63	1.89	0.58	0.93	0.94	0.91
Energy	428.91	453.43	143.55	-0.31	2.00	0.49	0.51	0.53	0.45
Financials	333.49	333.94	95.71	-0.24	2.15	0.31	0.49	0.46	0.41
Health Care	533.93	391.14	250.74	0.99	2.48	0.57	0.98	0.97	0.96
Industrials	360.87	312.82	137.10	0.84	2.57	0.63	0.99	0.99	0.96
Information Technology	552.26	411.80	319.90	1.33	3.93	0.50	0.95	0.94	0.98
Materials	228.38	225.57	77.75	0.28	1.96	0.63	0.91	0.93	0.86
Real Estate	146.22	146.36	44.99	0.05	2.10	0.56	0.92	0.90	0.87
Utilities	189.41	184.90	53.14	0.44	2.67	0.50	0.94	0.92	0.90

Methodology

At a high level, this study used time domain analysis to uncover possible lead-lag relationships between net commercial trading activity in the Eurodollar futures market and a collection of US stock market indices. Procedurally, this took the form of a bivariate econometric analysis employed through the framework provided in Figure 5.

Figure 5: Methodology Framework



(Step 1) Checking for Stationarity

Evaluating stationarity of the time series in question was the first step in executing time domain analysis. Over a finite time period, stationary data sets exhibit a constant mean, variance, and covariance (Cryer and Chan, 2008). In other words, the time series' "shape" from t_0 to t_n, where $n > 0$, is identical to any data segment of any length within the series (Cryer, et al., 2008). Since it is rarely possible to evaluate stationarity using visual cues alone, hypothesis testing (in the form of unit root tests) was used as a qualifying step to further analysis. We recognized that presence of a unit root could lead to spurious correlation (i.e. unjustifiably high r-squared values between data sets) and other unpredictable results (e.g. t-ratios that do not obey a t-distribution) (Ducasse, 2016). To avoid this, we used the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to isolate unit roots (Dickey and Fuller, 1979 and Phillips and Perron, 1988) for each time series. We performed these tests *individually* for all data sets (i.e. 3 market indices, 11 sector indices, and Monthly Commercial Positioning). The null hypothesis, H_o, assumed presence of a unit root, while the alternative, H_1, indicated that Y_t was stationary at the given difference.

We used the following ADF test regressions and, on a case by case basis, included deterministic elements [i.e. (1) has a constant alone, (2) has a constant and trend, and (3) has neither (Dickey and Fuller, 1979)]:

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \sum_{r=1}^{s} m_r \, \Delta Y_{t-r} + w_t \tag{1}$$

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \gamma t + \sum_{r=1}^{s} m_r \, \Delta Y_{t-r} + w_t \tag{2}$$

$$\Delta Y_t = \delta Y_{t-1} + \sum_{r=1}^{s} m_r \, \Delta Y_{t-r} + w_t \tag{3}$$

where Y_t is the differential form autoregressive equation being examined; α denotes presence of a constant (i.e. intercept, or "drift"); δ is the coefficient of the current root (i.e. focus of the t-test); γ is the coefficient of the trend parameter; s are the total lags being regressed upon to test for stationarity; and w_t is white noise (i.e. independent and identically distributed random variables).

An OLS estimate of δ was then computed and a modified T-Statistic (Dickey-Fuller statistic) was compared to the corresponding critical value. If it was less than the critical value, the null hypothesis was rejected and stationarity at level was accepted. If not, the time series was reevaluated at its first difference.

To execute the PP test, we used the following regressions and also decided to include deterministic elements if needed [i.e. (1) has a constant alone, (2) has a constant and trend, and (3) has neither (Phillips and Perron, 1988)]. Unlike the ADF regressions above, PP regressions do not rely on lagged values of the first difference, as shown:

$$Y_t = \alpha + \beta Y_{t-1} + w_t \quad (4)$$

$$Y_t = \alpha + \gamma t + \beta Y_{t-1} + w_t \quad (5)$$

$$Y_t = \beta Y_{t-1} + w_t \quad (6)$$

where

Y_t is the time series being examined; α denotes presence of a constant (i.e. intercept, or “drift”); and β is the OLS estimate (for a time series of n samples) of the autocorrelation parameter computed as:

$$\beta = \frac{\sum_{i=1}^{n} Y_{i-1} Y_{i-1}}{\sum_{i=1}^{n} Y_i^2}; \quad (7)$$

and w_t is white noise (i.e. independent and identically distributed random variables).

The PP test statistic is an augmented version of the Dickey-Fuller test statistic and is capable of addressing serial correlation and heteroskedasticity in error terms. If less than the associated critical value, the T-Statistic allowed us to reject the null hypothesis. If not, we had to retest the variable in question at its first difference.

If a pair of time series (X, Y) was each $I(0)$ (integrated of order 0) for the ADF and PP tests at the 5% significance level, we employed a vector autoregressive (VAR) model to test for interactions. If only one time series was $I(0)$, we retested the other at its first difference and confirmed it was $I(1)$. If neither time was $I(0)$, we retested both at their respective first differences to verify they were $I(1)$. In any case, we identified the optimal lag order for each variable upon completion of the stationarity tests. The remaining Methodology sections presume that no 2 variables being jointly evaluated, (X, Y), were individually $I(0)$ and no variables were integrated of an order greater than 1.

(Step 2) Selecting Optimal Lag Order

Following confirmation that all time series were stationary at $I(0)$ or $I(1)$, we determined appropriate lag orders. This estimation process was crucial since it (i) served as a component in future bivariate time series analyses and (ii) directly affected any statistical inferences drawn (Liew, 2004). At a high level, the lag for a certain time series indicates how many “turns” of past values determine the current value of the series. We chose to use 4 standard screens during the selection process – Akaike’s Final Prediction Error (FPE) (Akaike, 1998), Akaike Information Criterion (AIC) (Akaike, 1998), Schwarz Information Criterion (SIC) (Schwarz, 1978), and Hannan-Quinn Information Criterion (HQ) (Hannan and Quinn, 1978). According to (Liew, 2004), the Hannan-Quinn Information Criterion (HQ) performs best with large (at least 120 data points) time series while the “AIC and FPE are found to produce the least probability of under estimation among all criteria […]” Moreover, (Ludden, Beal, and Sheiner, 1994) contended that both AIC and SIC can reliably pinpoint an accurate lag order when forced to select from an extensive number of lags. Accordingly, we computed each of the 4 criteria displayed below and selected the lag order associated with the minimum value for each. The estimators are as follows:

$$FPE = \sigma_n^2 * (S - n)^{-1} * (S + n) \quad (8)$$

$$AIC = -2S[ln(\sigma_n^2)] + 2n \quad (9)$$

$$SIC = ln(\sigma_n^2) + \frac{[n*ln(S)]}{S} \quad (10)$$

$$HQ = ln(\sigma_n^2) + 2S^{-1} * n * ln[ln(S)] \quad (11)$$

where S is the sample size under observation and n is the equation minimizing lag operator. We then compared results and chose the final lag order based on a majority. Following this step, we tested pairs of $I(0)$ and $I(1)$ variables for cointegration (Step 3A) and short-run and long-run causal interactions (Step 4A). Separately, we tested pairs of $I(1)$ variables for cointegration (Step 3B) and short-run causal interactions (Step 4B).

(Step 3A) ARDL Long Run Form and Bounds Test

For several years, researchers have experimented with different methods of establishing linkages between variables. (Park, 1990) introduced a variable addition strategy, which was shortly followed by a procedure that used residuals to test the null hypothesis (H_0), as first demonstrated by (Shin, 1994). Both approaches, however, necessitated that all data sets be $I(1)$. Even (Stock and Watson, 1988) could not circumvent this through a stochastic trends process. In light of this obstacle, (Pesaran and Shinn, 1995) developed the ARDL Long-run Form and Bounds Test to handle a blend of $I(0)$, $I(1)$, or fractionally integrated time series over the short-run and long-run. The regression is expressed as follows:

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i \, \Delta Y_{t-i} + \sum_{i=0}^{q} \delta_i \, \Delta Z_{t-q} + \varphi_1 Y_{t-1} + \varphi_2 Z_{t-1} + w_t \quad (11)$$

where

β_0 is a constant term; Y_t is a time series; Z_t is a time series; p and q are previously selected lag operators; and w_t is white noise (i.e. independent and identically distributed random variables).

Next, the Form and Bounds approach was applied. The following null and alternative hypotheses were used:

$$H_0: \varphi_1 = \varphi_2 = 0 \text{ (no cointegration)} \tag{12}$$

$$H_1: \varphi_1 \neq \varphi_2 \neq 0 \text{ (cointegration)} \tag{13}$$

(Pesaran, et al., 1995) used the F-Statistic (Wald Test) through an ordinary Dickey-Fuller (DF) regression to ascertain the predictive value of lagged variables on the dependent variable of interest. This was done by comparing the F-statistic to the lower and upper bound critical values at different significance levels. The lower bound value represents the $I(0)$ time series, while the upper bound value represents the $I(1)$ time series. If the F-statistic was greater than the upper bound, H_0 was rejected, which indicated existence of cointegration. If the F-statistic was lower than the lower bound, H_0 could not be rejected. Lastly, if the F-statistic was between the critical values, a conclusive inference could not be made.

If cointegration was established, we would move forth with the Error Correction Model (ECM) to identify short-run and long-run causal effects (Step 3B). Otherwise, we proceeded with the short-run ARDL model to test for strictly short-run causal effects (Step 4B).

(Step 3B) Error Correction Model (ECM)

According to (Engle and Granger, 1987), if $I(0)$ and $I(1)$ variables are cointegrated, it is possible to abstract this relationship to an error correction form. This representation expresses movements in the dependent variable as a function of the (i) independent variable and (ii) extent of deviation in the cointegrating relationship, which the Error Correction Term (ECT) captures. This procedure begins with an estimation of the following regression:

$$\Delta \mathrm{Y_t} = \beta_0 + \sum_{i=1}^{p} \beta_i \Delta \mathrm{Y}_{t-k} + \sum_{i=0}^{q} \delta_i \Delta \mathrm{Z}_{t-k} + \varphi \mathrm{ECT}_{t-1} + \mathrm{w_t} \quad (14)$$

where

β_0 is a constant term; Y_t is a time series; Z_t is a time series; p and q are previously selected lag operators; φ is classified as convergence speed, or length of time taken for variable Y_t to revert to equilibrium following a shift in Z_t; ECT_{t-1} is the Error Correction Term equaling the OLS residuals from the cointegrating regression below:

$$Y_t = \beta_0 + \beta_1 Z_{1t} + \beta_2 Z_{2t} + w_t \quad (15)$$

$$ect_{t-1} = \mathrm{y}_{t-1} - \beta_0 - \beta_1 * \mathrm{Y}_{t-1}; \quad (16)$$

and w_t is white noise (i.e. independent and identically distributed random variables)

Next, we determined whether the coefficient of the ECT was significant enough to confirm long-run Granger-causality. This was done by comparing the T-Statistic to the corresponding critical value. Additionally, we checked for short-run Granger-causality by executing the same procedure but for short-run coefficients. Following this, we switched the dependent and explanatory variables to see if short-run and/or long-run Granger-causality could be established in the opposite direction.

(Step 4A) Johansen Cointegration Test

We tested pairs of variables that were integrated of order 1, [$Z_t, Y_t \sim I(1)$], for cointegration to understand if they shared latent equilibrium, or coexisting parameters, over the long-run. More specifically, the objective of this step was to generate a new time series, R_t, that was integrated of an order less than 1, or $(1 - c)$. R_t can be estimated as follows:

$$R_t = Z_t - \beta * Y_t \quad (17)$$

where

β denotes a constant; Z_t is an $I(1)$ variable; and Y_t is an $I(1)$ variable

If successful, Z_t and X_t in the example above are ascertained to be cointegrated,

$[Z_t, Y_t \sim CI(1{,}1-c)]$.

Several techniques help to extract cointegrating equation(s). (Maddala and Kim, 1999) compared these methods for repeatability and precision before recommending the Johansen Cointegration Test. Related studies, such as (Gonzalo, 1994), (Bilgili, 1998), and (Hubrich, Lutkepohl, and Saikkonen, 2007), lend support. (Cheung and Lai, 1993) asserted that the Johansen Cointegration Test, in conjunction with AIC and SIC lag order selections, yield the most robust estimates of long-run relationships between X and Y. Moreover, the Johansen Cointegration Test's Trace Statistic is resilient to variables exhibiting high skewness and kurtosis (Cheung, et al., 1993). Since most variables of our interest (i) have varying degrees of positive and negative skewness and (ii) are slightly leptokurtic or platykurtic, as shown in Table 4, we proceeded with the Johansen Cointegration Test. The first step required estimating the following system:

$$\Delta C_t = \omega + \sum_{i=1}^{n-1} \tau \Delta C_{t-1} + \Pi C_{t-1} + e_t \tag{18}$$

where

ΔC_t is a vector of size $p * 1$ stochastic variables (i.e. Z_t and Y_t); ω denotes a constant; n is the lag length; Π is classified as "rank" and is computed as follows:

$$\Pi = \alpha\beta' \tag{19}$$

where

β is a $p * r$ matrix that holds r cointegrating equations andα is a $p * r$ matrix that holds corresponding adjustment of coefficients;

and e_t is white noise (i.e. independent and identically distributed random variables).

(Johansen, 1988) proposed the joint usage of the Trace and Maximum Eigenvalue test statistics to calculate the number of existing cointegrating vectors.

For the remainder of the methodology section, we will assume both test statistics jointly confirm no cointegration for all $I(1)$ pairs tested. As such, we continued with a short-run ARDL model (Step 4B) to test for strictly short-run causal effects.

(Step 4B) Short-run ARDL Model

To employ the short-run ARDL model, we begin with an OLS estimation of the following regression:

$$\Delta Y_t = \beta_0 + \sum_{k=1}^{p} \beta_i \, \Delta Y_{t-k} + \sum_{k=0}^{q} \delta_i \, \Delta Z_{t-q} + w_t \qquad (20)$$

where

Y_t is a time series; Z_t is a time series; β_0 is a constant term; p and q are previously selected lag operators; and w_t is white noise (i.e. independent and identically distributed random variables)

The short-run ARDL model measures the T-Statistic of each explanatory variable's coefficient at the 5% significance level to deduce if that variable Granger-causes the dependent variable.

Similar to the ARDL Long-run Form and Bounds Test, the model is (i) *autoregressive*, meaning Y_t can be rationalized by its own lagged values, and (ii) includes a *distributed lag* element, which uses preceding values of Z_t to explain Y_t. This makes the ARDL model dynamic and capable of directly approximating short-run characteristics.

As the final step in our study, we compared the T-Statistic to the corresponding critical value for each pair to identify if short-run causal effects were existent.

Empirical Results

This segment of the paper applies the methodology above to the time series introduced earlier to investigate potential lead-lag relationships. Results are reported in the same chronology as the methodology. As such, analysis is performed by first checking all variables for stationarity and determining optimal lag lengths. Next, we attempt to establish cointegration and directionality using either (i) an ARDL Long-run Form and Bounds Test and ECM or (ii) Johansen Cointegration Test and short-run ARDL model. Following the results section is a discussion of the presented results, disclosure of limitations, and research angles for future works.

Findings from the ADF and PP unit root tests are detailed in Table 5 below. All variables were examined at level and again at first difference if necessary. To select if the data has an (i) intercept and trend, (ii) intercept, or (iii) neither when performing these tests, we observed each variable's visual bias(es) and mean. For instance, clear indication of an upward trend coupled with a non-zero mean required use of intercept and trend in both ADF and PP tests.

Table 5: ADF and PP Unit Root Tests Results

	Level		**First Difference**	
	ADF	**PP**	**ADF**	**PP**
Monthly Commercial Positioning	-2.21	-2.02	-11.85*	-11.79*
S&P 500	-1.01	-0.87	-16.63*	-16.66*
DJIA	-0.98	-0.75	-16.96*	-17.08*
NASDAQ	-1.66	-1.43	-16.94*	-17.17*
Communication Services	-2.03*	-2.12*	-	-
Consumer Discretionary	-0.67	-0.56	-18.63*	-19.99*
Consumer Staples	-1.86	-1.60	-16.51*	-17.14*
Energy	-1.82	0.62	-15.99*	-15.98*
Financials	0.50	0.36	-15.17*	-15.30*
Health Care	-0.72	-0.42	-17.64*	-17.77*
Industrials	-1.62	-1.50	-17.49*	-17.47*
Information Technology	-0.92	-0.64	-17.07*	-17.20*
Materials	-3.11	-3.39	-15.89*	-15.88*
Real Estate	-1.93	-2.11	-14.68*	-14.70*
Utilities	-1.58	-1.68	-15.18*	-15.18*

Note: All figures represent the ADF or PP T-Statistic associated with the variable either at level or first difference. " * " indicates that at the 5% significance level, the null hypothesis should be rejected. Hypothesis testing at the first difference was omitted for Communication Services.

Apart from Communication Services, all variables are understood to be nonstationary at level at the 5% significance level. Repeating the ADF and PP tests for all nonstationary variables resulted in stationarity at first difference. Therefore, we concluded that Communication Services is $I(0)$ and all other time series are $I(1)$.

Following completion of a stationarity check, we determined the lag operator for Monthly Commercial Positioning and all market indices. To do so and for precision, we relied on multiple information criteria, namely FPE, AIC, SIC, and HQ. Results from the 4 estimators are detailed in Table 6.

Table 6: Optimal Lag Order Selection Criteria Results

	S&P 500				DJIA				NASDAQ			
Lag	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ
1	3.732	6.993	7.095	7.034	293.492	11.358	11.460	11.399	30.946	9.108	9.211	9.150
2	3.427	6.907	7.078	6.977	269.995	11.274	11.445	11.343	28.421	9.023	9.194	9.092
3	3.563	6.946	7.186	7.043	280.552	11.312	11.552	11.409	29.563	9.062	9.301	9.159

	Communication Services				Consumer Discretionary				Consumer Staples				Energy			
Lag	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ
1	0.036	2.356	2.458	2.397	0.425	4.820	4.923	4.862	0.145	3.742	3.845	3.784	0.739	5.374	5.476	5.415
2	0.034	2.305	2.476	2.374	0.374	4.692	4.863	4.761	0.136	3.684	3.855	3.753	0.676	5.285	5.456	5.354
3	0.035	2.329	2.569	2.426	0.388	4.730	4.969	4.827	0.139	3.706	3.945	3.803	0.689	5.304	5.543	5.401

	Financials				Health Care				Industrials				Information Technology			
Lag	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ
1	0.257	4.316	4.418	4.357	0.524	5.030	5.133	5.072	0.309	4.503	4.605	4.544	0.899	5.569	5.672	5.611
2	0.232	4.215	4.386	4.284	0.484	4.950	5.121	5.019	0.285	4.420	4.591	4.489	0.833	5.493	5.664	5.562
3	0.241	4.252	4.492	4.349	0.501	4.984	5.223	5.081	0.294	4.451	4.690	4.548	0.862	5.528	5.767	5.625

	Materials				Real Estate				Utilities			
Lag	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ	FPE	AIC	SIC	HQ
1	0.151	3.782	3.885	3.824	0.054	2.755	2.866	2.800	0.051	2.703	2.805	2.744
2	0.140	3.709	3.880	3.778	0.051	2.692	2.877	2.767	0.049	2.666	2.837	2.735
3	0.145	3.743	3.982	3.840	0.052	2.724	2.983	2.829	0.051	2.694	2.933	2.790

Note: Lag selection criteria was performed between each variable and Monthly Commercial Positioning. Highlighted figures indicate the minimum score achieved for each test and denote ideal lag operators.

Based on 52 of the 56 estimators displayed above, the lag order was designated as 2 for all variables. From this point onwards, we detail the results from cointegration and Granger-causality testing. We begin with the ARDL Long-run Form and Bounds Test and ECM followed by the Johansen Cointegration Test and short-run ARDL model.

Executing the ARDL Long-run Form and Bounds Test for sets of $I(0)$ and $I(1)$ variables required comparing the F-Statistic to lower and upper bound critical values. Cointegration was only established if the F-Statistic exceeded the upper bound critical value. Results are provided in Table 7.

Table 7: Autoregressive Distributed Lag (ARDL) Long-run Form and Bounds Test Results

Variable 1	Variable 2	F-Statistic	Significance Level	Critical Values	
				Lower Bound	Upper Bound
Monthly Commercial Positioning	Commercial Services	7.744	10%	4.04	4.78
			5%	4.94	5.73
			1%	6.84	7.84

To assess the pair Monthly Commercial Positioning and Commercial Services for long-run, shared parameters, we compared the F-Statistic of 7.744 to the lower bound and upper bound critical values at different significance levels. Based on Table 7, we determined that we could safely reject H_0 and conclude that the 2 variables are cointegrated at the 5% significance level. Next, we used the ECM to deconstruct short-run and long-run Granger-causality between variables. Findings are reported in Table 8.

Table 8: Error Correction Model (ECM) Results

Dependent Variable	Regressor	Coefficient	T-Statistic	Probability
Communication Services	N	9.38354	2.31682	0.02140
	D(CommServices(-1))	-0.13146	-2.20240	0.02860
	D(CommServices(-2))	-0.11572	-1.96257	0.05090
	D(N)	-19.74344	-1.12271	0.26270
	D(N(-1))	-36.52743	-1.99829	0.04690
	D(N(-2))	-4.94055	-0.27371	0.78460
	ECT(-1)	-0.09051	-6.09228	0.00000
Monthly Commercial Positioning	C	-0.00027	-0.14122	0.88780
	D(N(-1))	0.26612	4.03128	0.00010
	D(N(-2))	0.02540	0.38047	0.70400
	D(CommServices)	-0.00006	-0.24224	0.80880
	D(CommServices(-1))	0.00003	0.15192	0.87940
	D(CommServices(-2))	-0.00004	-0.17948	0.85770
	ECT(-1)	-0.03117	-2.02326	0.04420

Note: "N" represents Monthly Commercial Positioning

Beginning with short-run causal effects at the 5% significance level, the computed T-Statistic demonstrated that Monthly Commercial Positioning Granger-causes Communication Services when time delayed by 1 period. Short-term causal effects, however, were absent in the opposite direction. Moreover, the significance of the ECTs in both models signaled long-run bidirectional Granger-causality between Monthly Commercial Positioning and Communication Services. Coefficients for both ECTs indicated that approximately 9.1% and 3.1% of departures from long-run equilibrium were corrected each period, respectively.

As described, use of the Johansen Cointegration Test required determining whether the p-values associated with Trace and Maximum Eigenvalue test statistics were significant at the 5% significance level. This step was repeated for multiple null hypotheses, beginning first with the assertion that there is no cointegrating equation. For this test, if the corresponding Trace Statistic and Max-Eigen Statistic exceeded the 5% critical value, we retested H_0 with the claim that there is at most 1 cointegrating equations, then at most 2, et cetera. For each case, the alternative (H_1) was that H_0 is not true. Summarized results from executing this procedure are in Table 9.

Table 9: Johansen Cointegration Test Results

Variable 1	Variable 2	Trace Statistic	5% Critical Value	Probability	Max-Eigen Statistic	5% Critical Value	Probability
Monthly Commercial Positioning	S&P 500	10.467	15.495	0.247	10.268	14.265	0.195
	DJIA	10.475		0.246	10.261		0.195
	NASDAQ	10.167		0.268	9.744		0.229
	Cons. Disc.	11.131		0.204	10.098		0.206
	Cons. Staples	6.539		0.632	6.218		0.585
	Energy	10.545		0.241	7.070		0.481
	Financials	11.162		0.202	8.481		0.332
	Health Care	9.624		0.311	9.371		0.257
	Industrials	7.687		0.500	7.646		0.416
	Info. Tech.	12.057		0.154	11.917		0.114
	Materials	8.031		0.462	7.173		0.469
	Real Estate	14.670		0.066	11.610		0.126
	Utilities	14.610		0.068	12.338		0.099

Findings from Table 9 indicated that none of the market indices are cointegrated with Monthly Commercial Positioning at the 5% significance level. For instance, when testing whether cointegration exists between S&P 500 and Monthly Commercial Positioning, both the Trace Statistic of 10.467 and Max-Eigen Statistic of 10.268 were lower than their corresponding 5% critical values, 15.495 and 14.265, respectively. We therefore were unable to reject the null hypothesis (H_0) that no cointegration equations exist. By implication, this suggested that none of the market indices examined in Table 9 shared a long-run relationship with Monthly Commercial Positioning.

Lastly, we used the short-run ARDL model to audit Monthly Commercial Positioning and $I(1)$ variables for short-run Granger-causality. Regression outputs are detailed in Table 10 for causal effects running from market index to Monthly Commercial Positioning and Table 11 for causal effects in the opposite direction. Results indicated that, given a 1 period lag, Monthly Commercial Positioning Granger-causes Consumer Discretionary at the 5% significance level. Conversely, S&P 500, Energy, and Materials Granger-cause Monthly Commercial Positioning when lagged 1 period. There are no instances of bidirectional Granger-causality between the variables tested.

Table 10: Short-run Autoregressive Distributed Lag (ARDL) Model Results

Dependent Variable	Regressor	T-Stat	Prob.	Dependent Variable	Variable	T-Stat	Prob.
S&P 500	C	1.795	0.074	Health Care	C	2.498	0.013
	D(S&P500(-1))	-0.706	0.481		D(HealthCare(-1))	-1.609	0.109
	D(S&P500(-2))	0.363	0.717		D(HealthCare(-2))	1.134	0.258
	D(N)	-0.353	0.725		D(N)	-0.462	0.644
	D(N(-1))	-1.271	0.205		D(N(-1))	-1.273	0.204
	D(N(-2))	0.711	0.478		D(N(-2))	0.228	0.820
DJIA	C	2.198	0.029	Industrials	C	1.631	0.104
	D(DJIA(-1))	-1.009	0.314		D(Industrials(-1))	-1.624	0.106
	D(DJIA(-2))	-0.248	0.804		D(Industrials(-2))	1.003	0.317
	D(N)	-0.413	0.680		D(N)	-0.573	0.567
	D(N(-1))	-1.186	0.237		D(N(-1))	-1.049	0.295
	D(N(-2))	0.762	0.447		D(N(-2))	1.418	0.158
NASDAQ	C	1.433	0.153	Information Technology	C	1.208	0.228
	D(NASDAQ(-1))	-0.159	0.874		D(InfoTech(-1))	-0.738	0.461
	D(NASDAQ(-2))	-0.618	0.537		D(InfoTech(-2))	0.092	0.927
	D(N)	0.088	0.930		D(N)	0.196	0.845
	D(N(-1))	-0.390	0.697		D(N(-1))	-0.718	0.473
	D(N(-2))	0.406	0.685		D(N(-2))	0.446	0.656
Consumer Discretionary	C	2.514	0.013	Materials	C	1.277	0.203
	D(ConsDisc(-1))	-2.413	0.017		D(Materials(-1))	-0.396	0.693
	D(ConsDisc(-2))	0.195	0.845		D(Materials(-2))	0.547	0.585
	D(N)	0.141	0.888		D(N)	-0.502	0.616
	D(N(-1))	-1.968	0.050		D(N(-1))	-0.661	0.509
	D(N(-2))	0.559	0.577		D(N(-2))	-0.144	0.885
Consumer Staples	C	2.798	0.006	Real Estate	C	1.389	0.166
	D(ConsStaples(-1))	-1.096	0.274		D(RealEstate(-1))	-0.120	0.904
	D(ConsStaples(-2))	-0.619	0.536		D(RealEstate(-2))	-0.799	0.425
	D(NetMonthly%)	-1.513	0.132		D(N)	-2.235	0.027
	D(NetMonthly% (-1))	-0.787	0.432		D(N(-1))	-0.263	0.793
	D(NetMonthly% (-2))	0.344	0.731		D(N(-2))	-1.261	0.209
Energy	C	0.558	0.578	Utilities	C	1.379	0.169
	D(Energy(-1))	-0.461	0.645		D(Utilities(-1))	0.267	0.789
	D(Energy(-2))	1.795	0.074		D(Utilities(-2))	-0.271	0.787
	D(N)	-0.320	0.750		D(N)	-1.885	0.061
	D(N(-1))	-0.345	0.730		D(N(-1))	0.925	0.356
	D(N(-2))	0.923	0.357		D(N(-2))	-0.605	0.546
Financials	C	0.648	0.517				
	D(Financials(-1))	0.691	0.490				
	D(Financials(-2))	-0.202	0.840				
	D(N)	-0.053	0.958				
	D(N(-1))	-1.420	0.157				
	D(N(-2))	0.565	0.573				

Note: “N” represents Monthly Commercial Positioning

Table 11: Short-run Autoregressive Distributed Lag (ARDL) Model Results

Dependent Variable	Regressor	T-Stat	Prob.	Dependent Variable	Variable	T-Stat	Prob.
Monthly Commercial Positioning	C	-0.29002	0.7721	Monthly Commercial Positioning	C	-0.097	0.923
	D(N(-1))	3.887038	0.0001		D(N(-1))	3.872	0.000
	D(N(-2))	0.119119	0.9053		D(N(-2))	0.007	0.995
	D(S&P500)	-0.35293	0.7245		D(HealthCare)	-0.462	0.644
	D(S&P500(-1))	1.658635	0.0985		D(HealthCare (-1))	0.711	0.478
	D(S&P500(-2))	-0.11469	0.9088		D(HealthCare (-2))	-0.634	0.527
Monthly Commercial Positioning	C	-0.28608	0.7751	Monthly Commercial Positioning	C	-0.230	0.818
	D(N(-1))	3.872021	0.0001		D(N(-1))	3.850	0.000
	D(N(-2))	0.111648	0.9112		D(N(-2))	0.104	0.918
	D(DJIA)	-0.41346	0.6797		D(Industrials)	-0.573	0.567
	D(DJIA(-1))	1.494648	0.1364		D(Industrials(-1))	1.139	0.256
	D(DJIA(-2))	-0.06797	0.9459		D(Industrials(-2))	0.153	0.879
Monthly Commercial Positioning	C	-0.23835	0.8118	Monthly Commercial Positioning	C	-0.249	0.804
	D(N(-1))	3.896352	0.0001		D(N(-1))	3.875	0.000
	D(N(-2))	0.016979	0.9865		D(N(-2))	0.036	0.971
	D(NASDAQ)	0.088388	0.9296		D(InfoTech)	0.196	0.845
	D(NASDAQ(-1))	1.496963	0.1358		D(InfoTech(-1))	1.181	0.239
	D(NASDAQ(-2))	-0.48474	0.6283		D(InfoTech(-2))	-0.104	0.917
Monthly Commercial Positioning	C	-0.317	0.751	Monthly Commercial Positioning	C	-0.249	0.803
	D(N(-1))	3.896	0.000		D(N(-1))	3.929	0.000
	D(N(-2))	0.123	0.902		D(N(-2))	0.051	0.959
	D(ConsDisc)	0.141	0.888		D(Materials)	-0.502	0.616
	D(ConsDisc(-1))	1.378	0.170		D(Materials(-1))	1.832	0.068
	D(ConsDisc(-2))	-0.353	0.725		D(Materials(-2))	-0.213	0.831
Monthly Commercial Positioning	C	0.181	0.856	Monthly Commercial Positioning	C	0.511	0.610
	D(N(-1))	3.829	0.000		D(N(-1))	3.178	0.002
	D(N(-2))	-0.058	0.954		D(N(-2))	-0.763	0.446
	D(ConsStaples)	-1.513	0.132		D(RealEstate)	0.022	0.982
	D(ConsStaples(-1))	0.426	0.670		D(RealEstate(-1))	1.350	0.179
	D(ConsStaples(-2))	-1.008	0.315		D(Realestate(-2))	-0.165	0.869
Monthly Commercial Positioning	C	-0.263	0.793	Monthly Commercial Positioning	C	0.106	0.916
	D(N(-1))	3.872	0.000		D(N(-1))	3.776	0.000
	D(N(-2))	0.004	0.997		D(N(-2))	-0.011	0.991
	D(Energy)	-0.320	0.750		D(Utilities)	-1.885	0.061
	D(Energy(-1))	2.807	0.005		D(Utilities(-1))	-1.048	0.296
	D(Energy(-2))	0.348	0.728		D(Utilities(-2))	0.040	0.968
Monthly Commercial Positioning	C	-0.245	0.807				
	D(N(-1))	3.806	0.000				
	D(N(-2))	0.154	0.878				
	D(Financials)	-0.053	0.958				
	D(Financials(-1))	1.410	0.160				
	D(Financials(-2))	0.472	0.637				

Note: "N" represents Monthly Commercial Positioning

Discussion

Tom McClellan's May 2011 issue in *The McClellan Report* serves as the inspiration behind this study. In it, McClellan lagged the S&P 500 by 52 weeks and performed a cross-correlation analysis between the 2 variables before noting strong synchronous movements for the period January 2007 to May 2011. Interestingly, over an even longer time segment of 2000 through 2019, this correlation exceeds 0.8, making it an exciting one to investigate.

This paper explores the nexus between net commercial trading activity in the Eurodollar futures market and US equity market indices for the period 2000 through 2019. This is examined through the lens of a bivariate econometric analysis. More specifically, we used an ARDL Long-run Form and Bounds Test and the Johansen Cointegration Test to evaluate long-run relationships for sets of $I(0)$ and $I(1)$ variables and strictly $I(1)$ variables, respectively. Pursuant to this, we employed a dynamic ECM and short-run ARDL model to understand long-run and short-run Granger-causality.

The empirical findings here aim to give the relationship discovered by McClellan more depth. First, Communication Services is the only market index that is cointegrated with Monthly Commercial Positioning. Furthermore, over the long-run, both variables Granger-cause each other. However, this bidirectional relationship disappears in the short-run, during which Monthly Commercial Positioning Granger-causes Communication Services given a 1 period lag but not vice versa.

The lack of cointegration between Monthly Commercial Positioning and other market indices prohibited us from exploring long-run Granger-causality. Over the short-run, however, we observed 1 linkage running from Monthly Commercial Positioning to a market index and 2 linkages for Granger-causality in the opposite direction. Regarding the former, net commercial trading position in the Eurodollar futures market was found to only Granger-cause the Consumer Discretionary index. When observing the latter, S&P 500, Energy, and Materials indices all separately Granger-caused the net commercial trading position in the Eurodollar futures market. Interestingly, each of these relationships relied on just 1 lag.

Limitations

This study's scope, both in what markets are observed and data are analyzed, introduces limitations. For one, mutually exclusive categorization of traders as hedgers or speculators is idealistic. Historically, traders who were commercially interested in or exposed to the contract's underlying asset were called hedgers. Those who had no such unit to offset were known to be speculators, commonly hedge funds, multi-asset managers, and the like. In practice, however, this is not clear cut. In certain unanticipated market conditions, commercial traders may have an opinion on futures price levels and speculate accordingly. Separately, they may abandon using derivatives altogether, even with exposure to the underlying asset, which would be considered speculative in nature. Such behavior was apparent in the NYMEX light sweet crude oil futures market for the period 2000 to 2009, as noted in (Buyuksahin and Harris, 2011).

Data limitations also pose a challenge. The CFTC reports trader positions in weekly intervals. This curbs the power of our study's econometric approach since (i) contract maturity months cannot be paired precisely with shifts in Monthly Commercial Positioning and prices and (ii) tracing daily changes in Monthly Commercial Positioning is infeasible. This is particularly relevant during highly volatile one-day trading sessions (e.g. 2010 Flash Crash), whose price swings may not be fully captured.

Another limitation to consider is the effect an unobserved variable may be having on Monthly Commercial Positioning and US stock markets in succession. In one example, this may be the effect noncommercial traders have on commercial ones. As mentioned in (Guttmann, 2016), hedgers sell risk to speculators. (Haigh, Hranaiova, and Overdahl, 2007) found that across US energy futures markets, hedge funds were key liquidity providers to other participants. This made it seamless for hedgers to transact at their convenience, frequently, and in large volumes (Haigh, et al., 2007). In a separate analysis across futures markets for crude oil, natural gas, and corn, hedge funds and swap dealers were perceived as liquidity providers and price discoverers (Brunetti, Buyuksahin, and Harris, 2015). Periods of sharp pullback among noncommercial traders, however, reduced liquidity, inhibited commercial traders from making market entries and exits, and distorted price levels (Brunetti, et al., 2015). If such liquidity shocks also led to disturbances in equity markets, it is entirely possible that noncommercial traders played a role in the movement of both securities. This concept can also be abstracted to any set of variables that a coordinate effect on both Monthly Commercial Positioning and any of the US stock market indices of interest.

Future Studies

Results from this study supplement academic institutions, commercial firms, and the public sector in better understanding how trading behavior can affect asset prices. The results from this study suggest that commercial traders in the Eurodollar futures market have a minimal effect on US stock market activity.

The conclusion reached in this study raises questions about whether noncommercial trading could serve as a more reliable barometer. This class of traders enters positions with a purely financial intention. As such, any lagged comovements with US stock market indices could be an interesting area to study. Testing this hypothesis could be done using the same methodology supplied in this study or an entirely different one guided by past research on noncommercial trading.

Future studies may also consider analyzing whether trading activity in other Eurocurrency futures markets have any lead-lag relationships with equity markets. An example of this would be understanding whether any Granger-causality exists between net commercial interest in Euroyen futures and the Nikkei 225 index. Similar leader-follower features may be inspected for between Euroswiss futures and the Swiss Market Index.

Another area of further inquiry concerns trading behavior across independently traded interest rate derivatives. These studies could span varying lengths of time to see whether relationships strengthen or weaken during distinct market episodes. Interest rate futures could include ones traded on the CME (e.g., 1-Month SOFR Futures and 30-Day Federal Funds Futures) as well as others in overseas markets (e.g. 3-Month Euribor in Europe). Since these securities have unique underlying units, researchers may consider testing causal effects with spot markets or a variety of other liquid assets.

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