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THE EFFECT OF TECHNOLOGICAL ADVANCEMENTS ON INTERACTIONS IN THE AGRICULTURAL COMMODITIES MARKET

by

SAVANNAH ARMAS

A thesis submitted in partial fulfillment of the requirements
for the Honors in the Major Program in Economics
in the College of Business Administration
and in The Burnett Honors College
at the University of Central Florida
Orlando, Florida

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ABSTRACT

The objective of this research is to find, if and how, real and financial technological advancements influence interactions in the agricultural commodities market. Statistical testing was conducted to identify potential correlation and any positive linear relationships in the price data between agricultural commodities and their complementary agricultural chemical producers. Testing if higher trade volumes in this industry result from higher technology usage were initiated by identifying shared linear growth between general index volumes and agricultural commodities, alongside their chemical complement stock volumes. The scientific development of chemical engineering mirrors financial technologies influencing trader behavior as a significant contributor to agricultural chemical developments. Multiple tests conducted used a variety of dependent variables as included in those specified combinations that may suggest a significant influence on potential volatility and correlation amongst these sectors.

The general result of this research showed evidence of a shared relationship among price and volume for ag-tech related stocks with respect to a generalized index (S&P500). The shared relationship between sample price averages generated from the S&P500 and the S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT) price suggests the growing involvement of traders in the agricultural commodities market and related speculative effects. Heteroscedasticity was indicated among the S&P500 sample volume averages and “Big Four” ag-tech stocks, supporting that more traders are entering markets because of technological advancements relative to trade platform accessibility. Lastly, agricultural chemical production and agricultural commodity returns demonstrate a common positive trend, suggesting that the

agricultural commodity market and trade are gaining moment as a result of technological advancements.

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INTRODUCTION

When distinguishing the 'technologies' referred to in this study, two categories can be used to elaborate on these criteria: real technology and financial technology. Real technology reflects the resource used by farmers to improve the accuracy and efficiency of harvesting yields. In this study, this is encapsulated by the agricultural chemicals used in products, including fertilizers, pesticides, and bio-tech compounds. Financial technologies are those innovations that make up the foundation of trading agricultural commodities, such as software, applications, and data granted to speculative traders. Real technology used by farmers (producers) makes for greater stability in supply, whereas financial technology used by traders allows could generate instability. The risk-sharing aspect of commodities futures is challenged with big data amplifying technical & fundamental analysis and reduced barriers to entry in trade markets, thus resulting in higher volumes.

Statistical analysis found that the general market index shares a positive linear relationship between the agricultural commodity stock index and the complementary agricultural chemical technology index prices. These results support the hypothesis that real technology transfers are imposed on the agricultural commodities market. An additional series of statistical testing found a positive relationship among ag-tech index price, ag-tech production, and agricultural commodity production. These findings are in support of financial technology changes affecting the actual market industry dynamics relative to prices.

Additionally, price-earnings and price-to-book ratios support the indication of strong overvaluation of the agricultural technology index. These inferences are further elaborated on by technological advancements causing more trade relative to the ag-tech industry. This is to be considered alongside the awareness that lack of high frequency/bid-ask spreads data for explicit empirical evidence in favor of the hypothesis surrounding financial technology is not possible. Limitations posed by the lack of sufficient collected data were countered by conducting testing as appropriately as possible and making inferences based on the intermediate results found. As specified in this thesis topic, the role of financial technology advancements was supported by qualifying the results found, given the circumstances.

While the law of supply and demand is definite, as markets gain momentum the environment that houses the law of supply and demand is shifting. That is, the implementation of economic theory can only be most accurately explained while understanding the change in market environments because of technological innovations. The role commodity futures play in hedging risk for farmers can be more dynamically distinguished from its in potential reward for traders.

My results show that there is a positive linear relationship between the general market index and the ag-tech related market. Similarly, findings showed a positive linear relationship between ag-tech stock price and agricultural commodity returns. In summary, the consensus of the statistical analysis in this thesis supports that the agricultural commodities market and their ag-tech complements are gaining moment as a result of technological advancements.

LITERATURE REVIEW

The commodities market emerged with great force, providing hedgers with financial safeguards and traders with risk-reward potential. As for farmers hoping to mitigate risks and maximize profits, technological advancements offer the opportunity for assurance in otherwise uncontrollable forces such as destructive weather conditions, crop disease, diminishing resources, and general cultivation impoverishment. The United States Department of Agriculture released pending projects in research and development initiatives offering promising aids to harvesting uncertainty. As of February 2017, the use of freight containers as hydroponic greenhouses began testing.

While resources for farming, such as land, product for production, and preservation, place stress on producers, Ag-tech is evolving at increasing speeds helping to present innovation incentives. Ag-tech, short for agricultural technology, expands into many criteria of development, including nanotechnology and machinery. As nanotechnology touches base on the efforts of engineering on an atomic scale, increased success, and availability of genetic and chemical engineering presents itself. The United States Department of Agriculture publicly reports that as of 2012, "88 percent of the corn, 94 percent of the cotton, and 93 percent of the soybeans planted in the U.S. were varieties produced through genetic engineering." Looking at data from 2000 to 2020, the percentage of corn produced across the United States incorporating Genetically Engineered processing involving insect-resistant, herbicide-tolerant, and stacked gene varieties jumped from 25 percent in 2000 to 92 percent in 2020. In correspondence, corn yield in the united stated was roughly 136.9 bushels per acre in 2000 and jumped to 177.0 bushels per acre in 2020. Steady growth in the success of agricultural production also leaves room for consideration of the role of land space in the farming industry. In 2012, Acres of corn planted in the united stated dropped from the initial 97.3 million acres to 93.3 million acres in 2021. It can be stated simply that the agricultural industry is evolving.

The biological and genetic engineering timeline continues to demonstrate promising integration into agricultural production as a field study in research and development initiatives. Trade-offs between limited testing and policy concerns relative to the approval process and growing accessibility of pesticides for commercial use are noteworthy observations (Osteen and Fernandez-Cornejo 2013). Pesticide estimates from 1964 to 2010 conducted by the USDA help introduce the price dynamic of agricultural treatments faced by farmers. The report continues to support the basis that declining quantities of insecticides following 1976 result from new compounds being used for treatment. The per-acre application was reduced because of improved formulas, demonstrated by the inverse relationship between the declined quantity of insecticides and increased corn and cotton acreage treated (Osteen and Fernandez-Cornejo 2013.) While concerns over health risks posed by the consumption of chemically treated field crops provide a counterargument to the success of Biotech, The Food Quality Protection Act (FQPA) of 1996 emerged, helping to alleviate some hesitancy. The analysis concluded that increased pesticide use is justified by farming financial returns and encouraged by federal subsidies and biofuel policy. This research was examined while providing strong support for the possibility of environmental sustainability. Additionally, government intervention to provide safeguards for these newly introduced methodologies was included in the study's supporting perspective. However, touching base on economic efficiency, concerns of discouraged pesticide use resulting from crop insurance are addressed. (Osteen and Fernandez-Cornejo 2013.)

While the report was published in 2013, the quantitative analysis only extended back to 2010. Mixed empirical evidence and possible data distortion from the major drought stifling field crop harvest back in 2008 are just a couple examples of those variables not included in this analysis, and thus possible discrepancies. Data collection for the following thesis observing real and financial technological advancements influencing interactions in the agricultural commodities market will incorporate historic price data from 2007 to 2022. The inclusion of comprehensive historical price data reduces omitted variable bias. That is, a longer period will reflect any indication of momentum in markets over a more representative timespan.

A similar report touched base on bioreactors' downstream processing (DSP) to recover fossil fuels and commodity chemicals. Improved efficiency of filtering bioreactors for purer biological properties used in chemical production allows for greater advancement in the biochemical design and production. In this case, biochemicals are intermediate inputs for agricultural chemicals and fertilizers production. The report studies downstream processing (DSP) development by elaborating on the prior scientific contributions that resulted in the separating principles used in DSP.

This is elaborated on with the discussion of plausible trends for the future of chemical engineering, introducing challenges proposed to bioreactor development (Cuellar and Straathof 2020). The significance of building on prior developments is challenged by the role and potential of Artificial Intelligence (AI) and the Internet of Things (IoT) in this industry. Big data and digital manufacturing are strongly supported by elaboration on modeling software, plant automation and control systems, and advanced industrial analytics for historical performance data. These topics of focus are summarized by the conclusion that the possibilities for DSP development and opportunities are more closely related to better hardware and software rather than improved separation methods. This research further implies, but does not directly prove, the impact of technological advancements as an indicator of prospective agricultural production and its role in the markets. This concept, in essence, is the foundation of the thesis question that will be addressed.

The desire for technological advancements, including biotech and access to big data to improve the accuracy and efficiency of agricultural production is greatly motivated by the financial prosperity suggested to farmers. However, research and development initiatives fueled by government financial support is incentivized in efforts to provide solutions to more global concerns. Issues of food security, the depletion of environmental resource access, and long-term environmental extraction trade-offs press agricultural production capacity.

A review constructed on food scarcity amplifies the importance and framework of a "Greener Revolution." This contract entails the contributions that, if made by science and technology, could eliminate the time-dependent concerns surrounding population growth, food security, and climate change (Beddington 2010.) From a short-term perspective, factors supporting this argument were assigned to one of three distinguished categories: Supply and demand, Policies, and Markets and Investment. The perspective then transitions to analysis under the long-term effects, again breaking down supporting information into five categories: 1) Population increase and urbanization, 2) economic changes leading to changes in demand for food, 3) rising demand for energy, water, and land, 4) climate change, and 5) other environmental factors. These two perspectives converge by addressing predictions that increasing population growth threatens limited natural resources, extends over-extraction, and amplifies greenhouse gas emissions.

Asia is periodically referenced in comparison to these topics, given the distinguished population size and nature of food scarcity. The emergence of 'Mega Cities' in Asia and the need to provide these massive populations with appropriate levels of food, water, and energy, in already concentrated regions is suggested as a prospective concern globally for future generations. However, agricultural arrangements in Asia are demonstrating evolutionary stabilization to supply following these large pushes in demand. Statistical data mentioned included "While cereal production in Asia doubled between 1970 and 1995, the total land area cultivated with cereals increased by only 4 percent (IFPRI 2002)."

Prospective contributions by science and technology in support of the "Greener Revolution" are specified by research and development focuses, first categorized by crop improvement. This is achieved by crop varieties developed with the purpose of genetic resistance to pests, diseases, and environmental pressures (i.e., drought-resistant). Next, crop protection is requested by suggesting improved treatment for use on planted acres. These protective measures include chemical treatments that defend against insects destroying crops and insufficient packaging and storage spoiling harvested products. Mechanization and engineering involve the use of technology to collect information, and then monitor conditions and widespread 'Micro-dosing' of fertilizers. These practices prompt a balance between extraction and over-extraction. Finally, nanotechnology offers the opportunity for new diagnostic tools for the prevention and early onset treatment of crop disease (Beddington 2010.) Ultimately, as food security concerns arise, the use of constantly advancing technology amplifies the rate and precision of solution methods.

As more technology is developed, evolved, and integrated into the basic functioning of everyday lives, living as we know it has changed robustly. Minna Lammi and Mika Pantzar focused directly on the impact of technology on the role of the citizen-consumer. This role is further explained by the vicious cycle of the continuous collection and manipulation of consumer data and consumer behavior adjusting to these data-based generated algorithms. The generalization of this theory occurs under the basis of the data economy. This is described by correlating the constant data collection of everyone and data circulating faster than ever to a newly developed digital economy (Lammi and Pantzar 2019). The premise of a data economy explains how industries have become increasingly connected; individual opinions are formed on the basis of information accessed digitally, digital feedback provides a degree of consumer data never seen before, and the cycle of data collection, presentation, and consumer reaction occurs in real-time. For reference, the report states, "Because of its sheer volume, diversity, and rate of accumulation, the body of data traveling at ever increasing speeds within networks" is the framework used to identify big data.

Additionally, data is generated and presented to the citizen-consumer through an individualized algorithm. The efficiency of this algorithm is maximized by using posts, likes, search results, and screen times to engage increased durations and interactions of citizens. While this research does not account for how geographical location, income, government, and demographic impact the premise of the data economy, it is explicitly defined and analyzes how financial markets are adapting to technological advancements.

Big data quickly, and unsurprisingly, assimilated into the financial industry serving as a powerful source of information collection for investment decision making. (Comtois 2013) Discusses the role technological advancement has on improved efficiency and money management. When analyzing the role of the internet and smartphones for traders, he states that these technologies “made easily available to client’s information that was previously only available to money managers.” The discussion proceeds by addressing the evolution of trading culture involving greater sophistication and revolutionization, as well as the “steady incremental specialization” mentioned by Kenny L. Fisher in the article (Comtois 2013). In brief, the article strongly supported the significance of technological advances in trade culture and money management. The claims made by Comtois being relative to the thesis question being statistically tested.

The role of advancing financial technology continues to press the decision-making process of traders. The concept of Information Asymmetry introduced by Akerlof’s Market for Lemons (Akerlof 1970) was drawn as a parallel to smartphone information accessibility in the publication by Fulgence Waryoba (Waryoba 2018). Information asymmetry is used to describe a decision-making event involving two groups/individuals in which one person has more information pretraining to the current situation than the other. Relative to the paper’s conclusion of information asymmetry diminishing with technology, the win-win “Pareto efficient” situation results from these smartphones provides information accessibility. Moreover, the issue of adverse selection that makes decision-makers (traders) less informed when making decisions (placing trades) as a result of information asymmetry is reduced given that “smartphone trading enhances more signals” (Waryoba 2018).

Expanding on consumer rationality and information accuracy resulting from the information presented to individuals digitally, big data and smartphone use influence markets both directly and indirectly. On one side of the spectrum, transaction volumes and speeds are increasing, given the ease of doing so online. On the other side, online trade platforms and smartphone investment apps have barriers to entry at an all-time low.

A research report published in September 2020 defines these relationships in the work “Mobile Devices and Investment News Apps” (Clor-Proell, Guggenmos, and Rennekamp 2020). This study is expanding on the criteria of the traditional Fear of Missing Out (FoMO) individuals’ experience from not participating in social settings to the specified Investor Fear of Missing Out (I-FoMO). This is further elaborated on as the anxiety experienced by investors to receive and act immediately on real-time news releases in effort to profit from ‘breaking news’. On a larger scale, the report suggests this technological integration reduces information asymmetry and cash flow mispricing while improving market pricing efficiency. This study was conducted by validating the scale of I-FoMO and its correlation to the manner in which information notifications are presented. The experiment examined respective levels of I-FoMO by providing the sample of nonprofessional investors with a fake phone designed to mimic an actual smartphone granting access to investment news apps and providing news releases related to firms. Holding the total amount of information constant between two groups, one sample experienced ungrouped news releases occurring over six notifications, the other experiencing grouped news releases occurring over two notifications. The findings showed that ungrouped content and push notifications demonstrate a greater influence on individuals with a higher level of I-FoMO. Additionally, those individuals with a higher level of I-FoMO demonstrated a larger screen time and checked the home screen more frequently.

While the concept of I-FoMo remains specific to the prior research reviewed, concerns surrounding rational decision making by traders with modern trade culture is again discussed. On behalf of the National Bureau of Economic Research, faulty trade behavior is observed with the use of smartphone investing. Research conducted compared portfolio efficiency and performance across different platforms by the same trader over a month. Observations from the smartphone-based trade platform showed that specific investment decisions were limited to trades placed on mobile devices, without duplicating these transactions on other platforms. Additionally, smartphone specific trades were described as "riskier, lottery-type, and hot investments" (Kalda et al., 2021).

The theory surrounding the psychology of trader behavior and impulsive decision making can somewhat be related to economic theory presented early on by John Keynes. Keynes concluded similarities shared between the stock exchange and casinos when stating that "casinos should, in the public interest, be inaccessible and expensive. And perhaps the same if true of Stock Exchanges" (Keynes 1935). While a distinction can be made between options and futures, as options are non-binding transactions while futures are obligatory based on the contract specified, the risk-reward foundation of trading remains likewise. The general concept presented by Keynes' casino theory, in that respect, remains somewhat applicable to any trading environment.

Relaying back to the proposed reaction of impulsive decision making by anxious traders, as demonstrated by the previously defined "I-FoMo" (Clor-Proell, Guggenmos and Rennekamp 2020), technology is the foundation of these increasingly frequent impulses. Alice Ross concluded similar supporting evidence showing PureDeal, a mobile trade smartphone application created by the parent company and online trade platform IG Index, was responsible for roughly ten percent of total trades placed at IG Index after only one month of being released. This research was later followed by statements elaborating on warnings being made to mobile platform traders regarding deviation from "their normal rigorous decision-making process" if acting too fast when placing trades (Ross 2010).

Further elaborating on the increased contributions of naïve traders given smartphone investment simplicity, accessibility, and financial flexibility, these market interactions emphasize false market signals. Noise trading is characterized as speculation influenced by rumors or technical analysis, both of which are considered non-fundamental information (Wang 2009). This interpretation originates from Fischer Black's original Publication, concluding, "The more noise trading there is, the more liquid the markets will be" (Black 1986). Given the nature of noise trading and a modern account of this dynamic with digital trades, this theory is a notable interpretation of speculative effects on possible price inefficiencies.

A more recent journal published in 2014 separates traders based on speculative behavior and examines respective price correlations (Fishe, Janzen, Smith 2014). Market populations are shared between informed traders demonstrating rational expectations (RE) and more naïve participants trading on the basis of difference of opinion (DO). Statistical results gathered from regression analysis of position change on price change show that while traders believe and act on personal signals, producers and others who believe otherwise lead to slow price adjustment. These empirical results find that those price inefficiencies and errors are unlikely to be significant, given that they do not create discrepancies in pricing fundamentals (Fishe, Janzen, Smith 2014).

Prior studies offer analysis evaluating these claims when considering pre-existing occurrences of volatility spillover and price co-movement among agricultural commodities. Empirical evidence collected on corn, wheat, soybean, and soybean oil returns demonstrated significant bidirectional volatility spillover among these commodities. (Bassil, Hamadi, Nehme 2017.). Further analysis of these variables relative to macroeconomic news releases and volatility effects was employed using GARCH analysis. Results conclusive of the basis that news reports had a significant impact on the volatility of these agricultural commodities. However, a significant volatility correlation was found under the premise that these shocks were absorbed quickly (Bassil, Hamadi, Nehme 2017.) Given that volatility clusters motivated by news releases are evident, the stabilization following these trends reflects market efficiency and structural price integrity.

Agricultural commodities demonstrate both substitute and complement good tendencies, and their underlying relationship proves significant under supply-side analysis. Research analyzing the effect and impact of technology on cereal and oilseed markets shows strong supporting evidence. Using agricultural commodity models, results showed that price estimates of agricultural products under 2007 technological baseline levels would be higher by 5.8% for corn, 9.6% for soybean, and 3.8% for canola (Brookes, Yu, Tokgoz, Elobeid 2010). This evidence was signified while addressing the issue of relative price adjustments alongside the surge of biotechnology use in agricultural production. Evidence suggests a negative price effect on farmers who have not integrated technology use into harvesting, given reduced respective yields and cost inefficiencies. The research used statistical interpretations to develop findings relating biotech crop developments to relative production and price measures estimations. However, the data did not expand beyond price estimates, relative growth, and the limited commodity sample. Building on the research developed, agricultural commodities as significant assets in trade markets provide much more price variability with given improvements in efficiency. Additionally, given the nature in which agricultural commodities interact, the cereal and oilseed sectors narrow down results failing to demonstrate biotech's aggregate price impact.

Consistent development and integration of technology in agricultural production and trade markets have been substantially influential over supply and demand theories explaining these interactions. With farmers being introduced to advanced developments in an otherwise ancient practice and speculative traders accessing, analyzing, and trading based on virtually limitless amounts of data at incompressible speeds, an overall period of accelerated technological growth that has been consistent and gaining great momentum since the beginning of the 21st century is transforming economic foundations. It is an ideal time to assess the overall impact of technology, both financial and real, on agricultural production.

METHODOLOGY AND DATA

Testing consisted of two main phases: correlation and multivariable linear regression analysis. In efforts to break data into two separate spaces for deeper analysis in terms of the criteria of technology, real technological advancement was the first subcategory to begin testing. The natural order of analysis continued with correlation then linear regression, correlation results helping to distinguish any degree of stronger statistical significance among these relationship combinations to note patterns for further tests using multiple regression as a means of identifying independent relationships.

$$r = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma(x_i - \bar{x})^2 \Sigma(y_i - \bar{y})^2}} \tag{1.1}$$

The above notation, noted by equation 1.1, is the mathematical computation to calculate the correlation coefficient, r. Elaborating on the additional variables, x_i represents the values of the x-variables in the sample, whereas $\bar{x}$ is the respective mean of the values of x-variables from the sample. Similarly, y_i represents the values of the y-variable from the sample, thus $\bar{y}$ being the mean of the values of the y-variables. That is correlation ranging from (-1,1) demonstrating the strength and direction shared between variables as measured over time. Linear regression testing was conducted at the 95% confidence interval with the respective 0.05 significance level. That is, we could conclude we are 95% confident that the population correlation falls within the range of the correlation coefficient if results demonstrate a p-value less than our significance level at 0.05; thus, concluding variables are correlated.

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i \tag{1.2}$$

The above notation is representative of the mathematical equations supporting the statistical analysis used in the study. More precisely, the equation (1.2) demonstrates the formula used to conduct a multivariable linear regression analysis. In this case, Y represents the dependent variable, β_0 is the intercept, and β_1 through β_k denote the coefficients of the independent variables X_1, through X_n. The final variable ε_i is the error term reflecting possible errors in measurement and the effects of omitted variables on Y. STATA software was used to generate the results of our multivariable regression analysis with the respective y variable and x variables for the multiple tests conducted throughout this study with interchanged variables. The **options** category in our linear regression analysis code was used as needed by including a **robust** specification command to control for heteroscedasticity. Heteroscedasticity being further defined as difference in variances of errors. Variance measures the mean squared deviation of a variable from its mean.

Correlation of real technology usage and agricultural production was examined using monthly pricing data collected from 2007 to 2021 for the S&P500, S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT), Invesco DB Agriculture Fund (DBA), Bloomberg Agriculture Subindex (BCO) and World Bank Commodity Price Data. The indices specified begins with the S&P500, a stock market index consisting of the over 500 of the largest companies operating within the United States stock exchanges. This general index is the testing measure representative of average stock price and market performance as a proxy to refer to when collecting results. The S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index, similarly, is used as a general reference measure but is more complementary to agricultural production. Including this index allows to make any distinctions between potential industry specific fluctuations and mitigate overfitting risks with the capacity of the S&P500. Invesco DB Agriculture Fund (DBA) is a measure representative of agricultural commodity futures. Similarly, Bloomberg Agriculture Subindex (BCO) is an alternative measure representative of agricultural commodity futures. Lastly, World Bank Commodity Price Data is representative of an average for agricultural commodity prices.

Additional data collection was included to gauge a better understanding of the influence agricultural chemical complements may have on agricultural commodity trades. These agricultural chemical complements, in simpler terms, are the chemical treatments and fertilizers used in agricultural commodity production. Gross cash income of US agricultural commodity production alongside the NAICS industry code 325 for Chemical Manufacturing subsector in agricultural usage, the S&P500, and S5FERT were involved in testing for shared linear relationships. This group of testing identifies any potential relationship between commodity production income, agricultural chemical production income, and those agricultural chemical complements traded in the stock exchange.

Lastly, three of the 'Big Four' agricultural chemical producers, Bayer-Monsanto, BASF, and DowDuPont/Corteva were tested alongside the S&P500. It can be considered that results from testing among the 'Big Four' and the S&P500 may be disoriented due to the large-scale composition of the S&P500. Thus, ten series of hypothesis tests were run holding Bayer-Monsanto, BASF, and DowDuPont/Corteva against those ten smaller randomly generated samples consisting of 10 companies from S&P500. After pulling those ten random samples of ten companies from the complete S&P500 list, only those companies selected from the random sample that had quarterly price and volume data available from our testing period of 2007 to 2021 were included in the average generated and thus tested. These random samples were formed into a respective 'smaller slice' of the S&P500 to form an average of these for deeper analysis, given the possible overvaluation in the regression analysis with the complete S&500. Possible overvaluation can be further elaborated on as the concern selection biased my impose on results given only a single test under the scope of our random sample is conducted. Additionally, collecting several randomly selected samples from the S&P500 and generating the respective averages was included to reduce selection bias. The average of the quarterly price data for a given sample of companies and the average of the quarterly volume data was generated by taking the sum of the sample measures (price and volume) divided by the number of companies included in the sample.

$$\text{Price Average} = \frac{\Sigma p_k}{n} \quad \text{Volume Average} = \frac{\Sigma v_k}{n}$$

The following index level formula specifies P_k as the quarterly historical price data from 2007 to 2021 for each of the specified companies, V_k being the volumes, n being the total number of companies included in the sample.

The three progressions of testing, more easily categorized by the grouping of generalized indexes, industry specific data, and the 'Big Four' chemical producers was initiated in efforts to collect and gather evidence that would easily distinguish the elements of real and financial technologies while jointing them with the shared explanatory variable of S&P500 Fertilizers &

Agricultural Chemicals Sub-Industry Index (S5FERT) as well as Invesco DB Agriculture Fund (DBA) when necessary.

Transitioning into the second subcategory of testing, financial technology, a similar methodology was carried out. The correlation was tested among the S5FERT index, S&P500, and DBA in relation to monthly volume recorded during the period of 2007 to 2021. This testing was followed by using quarterly volume data from Bayer-Monsanto, BASF, and DowDuPont/Corteva relative to the S&P500 and then again with the ten series of ten count company samples drawn from the S&P500 that were generated as averages previously.

All correlation and linear regression series analyzed were followed by a Variance Inflation Factor (VIF) test to check model precision relative to any effects on inferences due to multicollinearity. Detection of multicollinearity is confirmed by two general conditions. These conditions specify if any single VIF measures report above the threshold of ten or if the mean VIF measure is reported above one, there is evidence of multicollinearity. The mathematical computation for Variance Inflation Factor testing is represented by the following formula:

$$VIF = \frac{1}{1 - R_k^2}$$

The preceding formula uses the variable R_k^2 to represent the R-squared value; that is the measure of how much the variation in the dependent variable is explained by the independent variable or variables in the model. The subscript i is used to represent the sequence of R-squared values of all variables included in the regression analysis.

Breusch-Pagan/Cook-Weisberg testing for heteroskedasticity was conducted if necessary, preceding VIF testing to test the null hypothesis that error variances are all equal. Testing is conducted using a chi-squared distribution under the null hypothesis, with the test statistic itself being calculated as follows:

$$Test\ Statistic = N * \ R^2$$

The preceding formula denotes the test sample size by N and the R-squared value by R^2. The R-squared value in this test is representative of the regressions involving quarterly volume data from Bayer-Monsanto, BASF, and DowDuPont/Corteva relative to the S&P500 and then again with the ten series of ten count company samples drawn from the S&P500. Using a significance value of 0.05, the null hypothesis of heteroskedasticity is rejected if the p-value is less than 0.05. It can be noted, heteroskedasticity testing was used for preliminary data progressing when determining significant models that inferences that could be drawn from. Indication of heteroskedasticity was followed by incorporating the **robust** command during linear regression testing to confirm improved clarity and adequacy in analysis.

My thesis is testing to identify any technology transfers relative to trade volumes among the general index and the complementary ag-tech stocks. It can be noted that the research is lacking high frequency/bid-ask spreads data for testing of this hypothesis. Given these circumstances, the impact of financial technologies on trade behavior relative to the agricultural commodities market cannot be explicitly inferred from my thesis hypothesis testing results. Considering these limitations posed by the lack of sufficient collected data, hypothesis testing was conducted as appropriately as possible by way of linear regression analysis relative to historical stock price and volume data as previously specified.

RESULTS

Generalized Index Measures

The introductory set of results were gathered by testing the correlation coefficient using categorization by the grouping of generalized indexes. That is, monthly pricing data from 2007 to 2021 for the S&P500 (SP), S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT), Invesco DB Agriculture Fund (DBA), Bloomberg Agriculture Subindex (BCO), and World Bank Commodity Price (CMO) were our variable measures of interest. The historical price data for this testing set was measured in terms of percent change. The correlation was then tested over the period, and observations were specified producing those results found below in Table 1.

As noted by the asterisk, any value followed by (*) reflected results in which the correlation coefficient is significant at the 5% level. In this case, the test demonstrated significant statistical evidence to conclude correlation between price percent change among S&P500, S5FERT, DBA, and BCO. Invesco DB Agriculture Fund (DBA) and Bloomberg Agriculture Subindex (BCO) monthly price data produced the highest correlation coefficient of 0.9049, thus providing sufficient evidence of strong positive correlation. Readdressing the significance of the incorporation of these variables in the study, DBA is an Exchange Traded Fund (EFT) investing in a futures-based basket of broad agricultural commodities. Similarly, Bloomberg Agriculture Subindex (BCO) is composed of futures contracts quoted in USD for coffee, corn, cotton, soybeans, soybean oil, soybean meal, sugar, and wheat. Therefore, this high degree of correlation is easily understood, given the nature of the index compositions.

To a more moderate degree, a positive correlation was noted among S5FERT and S&P500 with a correlation coefficient of 0.5908. This demonstrates that even the S5FERT index, as a subcategorization of the S&P500 specifically under the scope of agricultural chemical production, shows a moderate positive relationship to that of the general S&P500 index.

The remaining results indicating the correlation coefficient significant at the 5% level demonstrated a weak positive correlation among the S&P500 and S5FERT relative to DBA and BCO. That is, these cross-correlations ranged from 0.2950 to 0.4087. Conversely, the CMO price percent change demonstrated no correlation among any of the alternative variables at our 5% level.

Table 1 Price Percent Change Correlation Matrix

	SP_PCCHG	S5F~CCHG	DBA_PC~G	BCO_PC~G	CMO_PC~G
SP_PCCHG	1.0000				
S5FERT_PCCHG	0.5908*	1.0000			
	0.0000				
DBA_PCCHG	0.3092*	0.4087*	1.0000		
	0.0000	0.0000			
BCO_PCCHG	0.2950*	0.3913*	0.9049*	1.0000	
	0.0001	0.0000	0.0000		
CMO_PCCHG	0.0221	0.0623	0.0853	0.0396	1.0000
	0.7696	0.4089	0.2578	0.5995	

It can be concluded from the empirical evidence found that there is positive correlation among the percent change in price relative to our general index, agricultural chemical general index, and both agricultural commodity indexes. These results indicate of a degree of correlation among speculation with general indexes and agricultural commodity price levels over time.

Transitioning from correlation testing to multivariate linear regression analysis, S5FERT, S&P500, DBA, CMO, and BCO were again used as variables in this test to produce the following results. The results denoted by three asterisks (***) represented those results that tested significant with a p-value less than 0.001, two asterisks (**) with a p-value less than 0.01, and one asterisk (*) with a p-value less than the 0.05 significance level.

Regression analysis results in Table 2 first show those results for the analysis in which Invesco DB Agriculture Fund (DBA) is our dependent variable, relative to our single independent variable the S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT). Identified as the first column (1), these results were statistically significant at the 0.001 significant level showing a positive linear relationship. Similarly, in our second column (2), located in Table 2, holding the Bloomberg Agriculture Subindex (BCO) as our dependent variable against our independent variable S5FERT, the results are statically significant at the 0.001 significant level. Both columns 1 and 2 are representative of our agricultural commodity futures indices and demonstrate positive linear relationships with coefficient values under the value of one. World Bank Commodity Price (CMO) measured in price percent change is shown in Table 2 as identified by the third column (3). While results from the linear regression of the dependent variable CMO was not statistically significant, the coefficient similarly was less than one.

This positive relationship between our general ag-tech index and the agricultural commodity futures indices demonstrates a positive correlation between chemicals and these agricultural indices. Additionally, our coefficient results relative to DBA indicates that a 1% change in S5FERT corresponds to a 0.252% change in DBA. Similarly, the results infer that a 1% change in S5FERT corresponds to a 0.312% change in BCO. Both of these coefficients are statistically significant and less than 1; thus, these results support the hypothesis that our ag-tech index is more volatile and experiences more activity.

Table 2 Price Percent Change S&P500 Sub Index Linear Regression Analysis

	(1)	(2)	(3)
	DBA_PCCHG	BCO_PCCHG	CMO_PCCHG
S5FERT_PCCHG	0.252***	0.312***	0.488
	(0.0461)	(0.0619)	(0.580)
_cons	-0.274	-0.134	3.275
	(0.333)	(0.433)	(3.968)
N	179	179	178
R-sq	0.167	0.153	0.004
adj. R-sq	0.162	0.148	-0.002
rmse	4.294	5.608	59.61

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Elaborating more on the prior claim, the distinction of S5FERT demonstrating greater volatility while our dependent variables show less of a reaction to changes in the ag-tech index, it is noted that this could be a result of financial technologies. That is, the regression results in Table 2 indicate technology transfers impose effects on our general ag-tech index.

The following linear regression results shown in Table 3 address the same three dependent variables consisting of DBA, BCO, and CMO but include a second dependent variable switching over to the multivariable linear regression setting. The following results are conclusive of our independent variables: the S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index and the S&P500, measured again in price percent change. Addressing the variable names as they are presented in the output, they are the same as in Table 2 while including the additional independent variable of the S&P500(SP_PCCHG).

The results relative to the multivariable linear regression analysis including the additional independent variable of the S&P500 price percent change remain consistent with the previous results found in Table 2. While the agricultural commodity indices show a positive linear relationship below a value of one for our general market index (S&P500), being closely related to the coefficients found for the ag-tech index (S5FERT), these results are not statically significant as indicated by our significance values. Additionally, the commodity price measure (CMO) showed an opposing, inverse relationship lacking statical significance relative to the independent variable S&P500 (SP).

Table 3 Price Percent Change Multivariable Linear Regression Analysis

	(1) DBA_PCCHG	(2) BCO_PCCHG	(3) CMO_PCCHG
S5FERT_PCCHG	0.214***	0.266***	0.591
	(0.0606)	(0.0778)	(0.668)
SP_PCCHG	0.110	0.134	-0.299
	(0.129)	(0.148)	(0.300)
_cons	-0.324	-0.195	3.410
	(0.353)	(0.448)	(4.084)
N	179	179	178
R-sq	0.174	0.159	0.004
adj. R-sq	0.165	0.150	-0.007
rmse	4.288	5.603	59.77

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

The S&P500 was introduced into the multivariable linear regression setting to find the relationship between these agricultural technologies and the ag-tech index. Results found these relationships are independent of the market (as represented by the S&P500 independent variable), continuing to demonstrate results relative to S5FERT as positive and less than one. That being said, the results were robust. Table 3, in addition to Table 2 , supports the hypothesis that our ag-tech index is more volatile and may indicate technology transfers onto the general ag-tech related market.

In efforts to further investigate the high levels of correlation demonstrated in Table 1, relative to the linear regression analysis presented in table 3, a Variance Inflation Factor (VIF) test was reported. This test is used to measure any multicollinearity effect on standard errors of estimated coefficients. More simply put, multicollinearity can make it difficult to precisely estimate the separate effects of correlated independent variables. VIF testing reported mean VIFs of 1.54, 1.54, and 2.53 for Table 3, columns 1, 2, and 3. These values being slightly larger than 1 signify evidence of multicollinearity. Given that these values are slightly larger than the threshold of 1, Table 2, representing our linear regression analysis with the single independent variable of the S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index, is further emphasized. Correcting for multicollinearity we can still conclude these results came back in support of the hypothesis that technology transfers are imposing effects on the ag-tech trade market.

Industry Specific Data

This sub-category transitions over to results presented regarding industry specific data. These relative measures include S5FERT, the North American Industry Classification System (NAICS) 325 for chemical manufacturing for the agricultural sector, and Gross Cash Incomes of the United States agricultural commodity industry. The supporting data collected was representative of annual pricing data over the period of 2000 to 2021 at the indicated critical value of 0.05. As denoted in previous testing, any value followed by an asterisk (*) reflects results of a specified correlation coefficient which tested significant at the 5% level.

Results relative to this subcategory of testing provides sufficient statistical evidence to conclude various correlation coefficients with a p-value below the critical level of 0.05, as shown in Table 4. The respective column names denote the annual pricing data observed for the

S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT), The North American Industry Classification System (NAICS) code 325 for chemical manufacturing for the agricultural industry price average (Ind), and the Gross Cash Incomes of the United States agricultural commodity industry in both nominal (GCI_Nominal) and real (GCI_Real) dollars. In this sample, we used S5FERT as our industry specific general index, NAICS 325 as our ag-tech production variable, and GCI as our agricultural commodity production variable. At the 0.05 critical level, agricultural chemical manufacturing demonstrated a statistically significant and strong correlation relative to gross cash incomes in nominal terms of agricultural commodities at 0.9450. The NAICS correlation alongside both real and nominal GCI shows ag-tech and agricultural commodity production coincided. Additionally, S5FERT historical price data was statically significant with a strong positive correlation to all variables included in the testing.

Table 4 Industry Specific Correlation Matrix

	S5FERT~T	Ind_Pr~g	GCI_No~l	GCI_Real
S5FERT_LAST	1.0000			
Ind_Price_~g	0.8826*	1.0000		
	0.0000			
GCI_Nominal	0.8723*	0.9450*	1.0000	
	0.0000	0.0000		
GCI_Real	0.7248*	0.7977*	0.9413*	1.0000
	0.0003	0.0000	0.0000	

The empirical evidence collected provided results demonstrating a strong correlation among all variables included in the testing; thus, there is correlation among the Agricultural fertilizer index, agricultural chemical manufacturing, and gross cash incomes of agricultural commodities as shown in Table 4. The result is evidently in support of the hypothesis of a strong positive relationship between the ag-tech index price, ag-chemical production, and ag-commodity production.

Multivariable linear regression analysis was conducted proceeding correlation testing for industry specific data. As shown in Table 5, the regression analysis was conducted with the dependent variable being the NAICS chemical manufacturing for the agricultural industry Price Average (Ind_Price). Analysis followed with the dependent variables being the Gross Cash Incomes of the United States agricultural commodity industry in real dollars (GCI_Real) and the ag-tech index (S5FERT). A statistically significant, positive linear relationship between the ag-tech index (S5FERT) and chemical manufacturing price average (Ind_Price) is observed. These results show, at the 0.05 significance level, a one unit increase in S5FERT corresponds to a 0.05833 unit increase in Ind_Price. While not statically significant, the GCI_Real independent variable similarly demonstrates a positive coefficient.

Table 5 Industry Specific Linear Regression (GCI_Real)

```
Linear regression                               Number of obs     =         20
                                                F(2, 17)          =     122.66
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8316
                                                Root MSE          =     20.304

------------------------------------------------------------------------------
             |               Robust
Ind_Price_~g |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    GCI_Real |   2.43e-07   1.22e-07     1.99   0.063    -1.48e-08    5.00e-07
 S5FERT_LAST |     .05833   .0167812     3.48   0.003     .0229248    .0937353
       _cons |   64.23264   41.89772     1.53   0.144    -24.16381    152.6291
```

In brief, the results found were statistically significant in support of a shared positive relationship between the ag-tech index and actual ag-tech prices in the industry. These results can be further elaborated on when considering how financial changes (S5FERT) affect the actual market industry dynamics by changing prices. Drawing focus on advances in information technology and increased activity in this market, more trading could have a positive spillover into the actual market. In simpler terms, Table 5 in support of a positive link between financial activity and the actual prices in the industry.

After analysis of the linear regression results, a Variance Inflation Factor (VIF) test was incorporated for diagnosis of statistical accuracy. The mean VIF for our 'industry specific' sub-category linear regression analysis tested slightly above our threshold of 1 at 2.11. The VIF was tested again, accounting for the Gross Cash Incomes of the United States agricultural commodity industry in Nominal dollars (GCI_Nominal). However, VIF testing results provided a mean VIF of 4.18 when running the regression analysis using Gross Cash Incomes measured in Nominal dollars. These results, while both indicating a presence of multicollinearity, was nearly half as large with the GCI measured in Real dollars, as included in Table 5. This further supports the reasoning of including the real measure over the nominal measure in testing. While the mean VIF of 2.11 suggests greater precision of results in comparison to that of 4.18, the test still suggests a presence of heteroskedasticity with a mean VIF larger than the threshold of 1.

Accounting for slight correction in multicollinearity leaves Table 5 as the preferred model. The resulting analysis provided results that were statistically significant in support of a shared positive relationship between the ag-tech index and actual ag-tech prices in the industry.

While the inability to proceed testing using higher frequency data related to bid-ask spread and additional trade market components may pose hypothesis testing bias, this inability to come to a formal conclusion is somewhat supported with slight indications of technology transfers supported by these tests. That is, the findings showing results in favor of advances in financial technologies leading to increased activity in the agricultural commodity related market.

‘Big Four’ Chemical Producers

The assignment of the ‘Big Four’, including Bayer-Monsanto, BASF, and DowDuPont/Corteva after a series of mergers, are used to represent three of the largest agricultural chemical companies used for agricultural production. The monthly historical price data was collected from BASF, DowDuPont/Corteva (DD), and Bayer-Monsanto (BAYRY) from the period of 2007 to 2022. The average of ‘Big Four’ historical data was generated to emphasize model precision and interpretation clarity. This chemical price average (ChemAvgPrice) was then held relative to S5FERT, and the simple random sample price averages generated from the S&P500 (Priceavg1). The below results were generated for the first random sample S&P500 average at a 0.05 critical value. The S&P500 sample price average showed strong positive correlation with the S5FERT index and the ‘Big Four’ chemical price average.

Table 6 Big Four' Sample 1 Price Correlation Matrix

	Pricea~1	S5FERT~T	ChemA~ce
Priceavg1	1.0000		
S5FERT_LAST	0.7122*	1.0000	
	0.0000		
ChemAvgPrice	0.6679*	0.4418*	1.0000
	0.0000	0.0004	

Table 6 provides results in support a relationship between the general market index, the ag-tech index, and the 'Big Four' average representative of ag-tech producers. There is statistical evidence in favor of the hypothesis that general market index price, ag-tech index price and ag-tech company stock price are positively correlated.

Changing the scope of results from price to volume data, correlation results were generated for the historical volume data of the S&P500 random sample average, S5FERT Index, and the 'Big Four' chemical producer volume average. The data set used to produce results remained consistent with monthly volumes recorded from 2007 to 2021. Correlation tested at a 0.05 critical value found statistically significant, positive correlation between the 'Big Four' volume average and both S5FERT and the S&P500 random sample average. As denoted by the asterisk indicating statistical significance, there was a slight positive correlation for ChemAvgVolume relative to all other variables included in testing.

Table 7 'Big Four' Sample 1 Volume Correlation

```
             | Volume~1 S5FERT~E ChemA~me
-------------+---------------------------
  Volumeavg1 |   1.0000
             |
             |
S5FERT_VOL~E |   0.1167   1.0000
             |   0.3788
             |
ChemAvgVol~e |   0.4095*  0.2587*  1.0000
             |   0.0013   0.0459
             |
```

Table 7 indicates a positive relationship between the general market index, ag-tech index, and ag-tech chemical producer volumes. These results suggesting support for technology transfers between generalized indices and ag-tech related markets.

Having a strong foundation on the data being tested following interpreting correlation results, multivariable linear regression analysis follows. Table 8 demonstrates the first set of results collected in which our dependent variable is the S&P500 random sample price average relative to the independent variables S5FERT and the 'Big Four' price average. Results were statistically significant among both independent variables, showing positive linear relationships. S5FERT providing a statistically significant positive coefficient falling below the value of 1 indicates that a 1 percent change in S5FERT corresponds to a .053% change in the S&P500. Similarly, a 1 percent change in ChemAvgPrice corresponds to a 1.45% change in the S&P500.

Table 8 Sample 1 Price Multivariable Linear Regression

```
Linear regression                               Number of obs     =         59
                                                F(2, 56)          =      93.10
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6606
                                                Root MSE          =       18.8

------------------------------------------------------------------------------
             |               Robust
   Priceavg1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  S5FERT_LAST |   .0533801   .0087473     6.10   0.000     .0358572     .070903
ChemAvgPrice |   1.458591   .2741184     5.32   0.000     .9094657    2.007716
       _cons |  -40.35994   9.199765    -4.39   0.000    -58.78928   -21.93059
------------------------------------------------------------------------------
```

Table 8 can be further interpreted alongside the testing question providing results in support of the hypothesis. Given the statistically significant, positive linear relationship between our ag-tech index (S5FERT) and the general market index (PriceAvg1), the coefficient less than one could suggest S5FERT is more volatile. Furthermore, the coefficient value of .0533 could suggest the ag-tech index is less stable.

Comparing those results found in Table 8, representative of the multivariable setting, we can continue to address this analysis relative to the single independent variable setting. Table 9 below is representative of the dependent variable Priceavg1 as our general index measure relative to the single independent variable S5FERT as our ag-tech index. The coefficient value is statically significant, with a positive value of less than 1.

Table 9 Sample 1 Price Linear Regression S5FERT

```
Linear regression                               Number of obs     =         59
                                                F(1, 57)          =      95.00
                                                Prob > F          =     0.0000
                                                R-squared         =     0.5072
                                                Root MSE          =     22.453

------------------------------------------------------------------------------
             |               Robust
   Priceavg1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
S5FERT_LAST |    .0734968   .0075407     9.75   0.000     .0583968    .0885968
       _cons |  -15.21767   9.325608    -1.63   0.108    -33.89188    3.456534
------------------------------------------------------------------------------
```

These results offer the same interpretation gathered from the multivariable setting analyzed in Table 8, but the increased coefficient value from 0.0533 to 0.0734 is noted. While a one unit change in S5FERT would now correspond to a 0.0734 unit change in S&P500, this result is still in support of S5FERT being more volatile. Drawing focus to the alternative model represented by Table 10, the single independent variable setting relative to the ChemAvgPrice variable demonstrates a statistically significant effect. Given Priceavg1 is the dependent variable among the independent variable ChemAvgPrice, the results show a positive coefficient.

Table 10 Sample 1 Price Linear Regression ChemAvg

```
Linear regression                               Number of obs     =         59
                                                F(1, 57)          =      86.86
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4462
                                                Root MSE          =     23.803

-----------------------------------------------------------------------------
             |               Robust
   Priceavg1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ChemAvgPrice |   2.227027   .2389569     9.32   0.000     1.748524     2.70553
       _cons |  -.9169388     9.6413    -0.10   0.925    -20.22331    18.38943
------------------------------------------------------------------------------
```

As the coefficient increases from 1.4585 in Table 8 to 2.227 in Table 10, we can see a one unit change in ChemAvgPrice would now correspond to a 2.227 unit change in S&P500. These result interpretations supporting an alternative suggestion that the general market index price could be noted as less stable relative to the ag-tech price average. As shown by Table 10, there is plausible reasoning of these results when considering the strength of the S&P500 as the general market index in comparison to the ag-tech industry stock relative to stock performance growth over time. Relative to the testing objective, analysis of Tables 8 and 9, provide results in support of technological transfers and the ag-tech index demonstrating greater volatility. Moreover, the general market index and the ag-tech related independent variables demonstrate a positive relationship with respect to price.

Comparing the multivariable linear regression results relative to those found in the single independent variable setting helps to confirm model interpretation with improved accuracy by reducing any possible adverse effects of multicollinearity. With that being said, the following results are relative to volume data, rather than price data, for linear regression testing conducted. To reiterate, the variable names shown for this series of testing include the dependent variable of Volumeavg1to represent the S&P500 simple random sample volume average generated. Additionally, our independent variables once again include our ag-tech index (S5FERT), and 'Big Four' ag-tech average (ChemAvgPrice) measured relative to volume data.

Beginning with the multivariable linear regression model shown by Table 11, only the ChemAvgVolume independent variable provided results that were statistically significant. At the 0.05 significance value, results showed a positive linear relationship between the 'Big Four' ag-tech average and the general market index volumes. Table 11 proposes that a one unit change in S5FERT volume corresponds to a 0.337 unit change in the general market index volume

Table 11 Sample 1 Volume Multivariable Linear Regression

```
Linear regression                               Number of obs     =         59
                                                F(2, 56)          =       2.73
                                                Prob > F          =     0.0739
                                                R-squared         =     0.1678
                                                Root MSE          =    3.1e+07

------------------------------------------------------------------------------
             |               Robust
  Volumeavg1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
S5FERT_VOL~E |   .0063955   .0699395     0.09   0.927    -.1337102    .1465012
ChemAvgVol~e |   .3370784   .1495748     2.25   0.028      .037444    .6367127
       _cons |   1.64e+08   1.60e+07    10.26   0.000     1.32e+08    1.96e+08
------------------------------------------------------------------------------
```

The statistically significant coefficient value for ChemAvgVolume again falls below a coefficient value of 1, in support of the plausible explanation that the chemical industry is more volatile than the general market index. To further investigate these results, the single independent variable linear regression model with respect to the relationship between VolumeAvg1 and ChemAvgVolume is shown by Table 12. Table 12 results above demonstrate a similar outcome to those in the multivariable linear regression setting presented in Table 11. Once again, the test results are statistically significant and show a positive linear relationship. The only significant visible difference between the two results is the coefficient jumping to .3392 from 0.3370, which eludes the same response prediction.

Table 12 Sample 1 Volume Linear Regression ChemAvg

Linear regression

Number of obs	=	59
F(1, 57)	=	5.47
Prob > F	=	0.0228
R-squared	=	0.1677
Root MSE	=	3.1e+07

Volumeavg1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
ChemAvgVol~e	.33926	.1450131	2.34	0.023	.0488762	.6296437
_cons	1.65e+08	1.28e+07	12.93	0.000	1.39e+08	1.90e+08

Table 12 results distinguishing the explicit relationship between the 'Big Four' ag-tech average and the general market index (Volumeavg1) provide additional clarity and support for those inferences drawn from the multivariable linear regression setting in Table 11. There is statistically significant evidence of a positive linear relationship between the 'Big Four' ag-tech average and the general market index. Furthermore, these results, in a way, demonstrate that the chemical industry is more volatile. This could be due to more trading/financial sector involvements relative to agricultural commodity related markets.

After an in-depth analysis of the "Big Four" historical price and volume data relative to our initial S&P500 sample price and volume averages, a concentrated review of the results collected from the additional ten samples are addressed. These ten additional phases of testing providing those results shown in Tables 14 through 31 as listed in the Appendix. Variables names again correspond to the dependent variable of Priceavg and the independent variables S5FERT_LAST and ChemAvgPrice Beginning with multivariable linear regression testing relative to price, these additional trials confirmed the general premises of those found in the first sample analysis. Relative to the S5FERT, nine of the ten results provided statistically significant positive linear relationships below a coefficient value of 1. The average coefficient of the ten samples tested was 0.06171. Additionally, we found eight of the ten results relative to ChemAvgPrice provided statistically significant results, seven of which showed positive linear relationships. The average coefficient for ChemAvgPrice was 0.88313. The collective sample results relative to Priceavg can be interpreted in favor of the hypothesis that ag-tech stocks are more volatile, possibly as a result of more trade in these markets, relative to the general market index.

Switching focus to multivariable linear regression testing relative to volume, the results were somewhat distinguishable from our first sample alone. When drawing focus to results specific to the independent variable S5FERT_VOLUME, only one of the ten results could be considered statistically significant. To elaborate more on this finding, at a p-value of 0.047 there was significant statistical evidence of a positive relationship relative to Volumeavg with a coefficient value of .1369. However, the average coefficient for S5FERT_VOLUME was calculated at -0.005 with limited model adequacy. Alternativity, five of the ten samples provided statical significant evidence of a positive linear relationship between ChemAvgVolume and Volumeavg. The average of the coefficient results found for our independent variable ChemAvgVolume was calculated at 0.2362. These results draw a parallel to those found in the first sample regression. Overall, the collective multivariable linear regression results for the ten samples relative to volume supported the argument that the ‘Big Four’ ag-tech average (ChemAvgVolume) is more volatile as a result of technology transfers compared to the general market index (Volumeavg1).

Given the reported correlation and linear regression results from our S&P500 random samples relative to our "Big Four" ag-tech average, Variance Inflation Factor (VIF) testing was included to measure testing accuracy. Mean VIF values for all linear regression tests including the ten random samples indicated evidence of multicollinearity. All mean VIFs for price averages ranged from 1.01 to 41.25, averaging across the ten tests at 1.218. While these results were above our threshold of 1, the magnitude of the mean VIF value is only slightly indicative of multicollinearity. The mean VIF relative to the volume averages were only slightly above 1, ranging from 1.01 to 1.70 averaging at 1.06. These results being even less significantly indicative of multicollinearity relative to our threshold mean VIF of 1.

To better link the analysis of volume relative to interactions in the agricultural commodities market, correlation between the S5FERT Index, DBA, and S&P500 was conducted. The following results interpret an inverse relationship shared between S5FERT volumes and those of DBA at the 0.05 significance level. Alternatively, at the significance level there was an indication of a positive relationship between S&P500 and DBA volumes with a result of 0.4209.

Table 13 Agricultural Commodity Industry Correlation Matrix

	S5FERT~E	DBA_VO~E	SP_VOL~E
S5FERT_VOL~E	1.0000		
DBA_VOLUME	-0.1515*	1.0000	
	0.0424		
SP_VOLUME	0.0911	0.4209*	1.0000
	0.2240	0.0000	

Table 13 results support a shared increase in the growth of trade volumes overtime between a more generalized index (S&P500), and the exchange traded fund with focus in agricultural commodity futures (DBA). More simply put, these results support that the general market and commodity futures indexes share a strong relationship relative to trade volumes. That is, financial technologies provide a plausible explanation for growing trader activity in the agricultural commodities market relative to the general market.

Analysis of historical volumes relative to the agricultural commodities market is again approached by addressing the price-earnings (P/E) ratio and price-to-book (P/BV) ratio as a measure of stock price overvaluation. Line charts modeling the P/E and P/BV ratios for a ten-year period were generated for the S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT). Both Figure 1 and Figure 2 in the Appendix demonstrate the daily price-to-earnings ratio and price-to-book value ratio of S5FERT from the period of 2012 to 2022.

As demonstrated by Figure 1, the P/E ratio was at a slight incline until the drop in 2016. This drop later followed by a spike in 2018 until 2019 marking the Corona Virus Pandemic causing another drop. Since 2021, the P/E ratio has grown exponentially breaking new highs over this period. It can be noted in figure 2 that late 2018 marked the initial rise in the P/BV ratio following 6 years of relative consistence. A breakthrough occurred in late 2019 during wake of the Corona Virus Pandemic causing an abrupt dramatic incline. Since the 2019 spike, a higher P/BV ratio has been observed and maintained. Analysis of the spread of the price-earnings and price-to-book ratios support potential indication of strong overvaluation following mid-2020 for S5FERT. Overvaluation of the S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT) may indicate relative support of financial technology advancements causing more trade, and thus overvaluation of companies, relative to the ag-tech index.

CONCLUSION

In this thesis, research was conducted in an effort to elaborate on statistical evidence in support of the possible impact of advancements in real and financial technology on interactions in the agricultural commodities market. Real technology, in this instance, was reflective of the increased efficiency and accuracy of harvesting yields for farmers acting as suppliers in the trades markets. Drawing a parallel, financial technologies were defined as the access to, and those instruments used, allowing for reduced barriers to entry into trade markets for traders. That is, given the progression of technological availability, trade markets are not as exclusive as they previously were in the past. Three progressions of testing took place as series under the categorization of generalized indexes, industry specific data, and the 'Big Four' chemical producers. These series were initiated with the determinant of the coefficient correlation among variables included in the testing.

The first sub-category group tested included the S&P500, S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT), Invesco DB Agriculture Fund (DBA), Bloomberg Agriculture Subindex (BCO) and World Bank Commodity Price (CMO). These measures were included in correlation and linear regression testing using monthly price percent change data from 2007 to 2021. Results came at the 0.05 significance level with positive correlation among S5FERT, S&P500, DBA, and BCO. The results generally supporting the complementary speculation aspect of financial technologies in the agricultural industry. Price percent change linear regression results found were in support the hypothesis that our ag-tech index is more volatile and may indicate technology transfers onto the general ag-tech related market.

The next sub-category, and second series of testing, defined by industry specific data, proved evident at the 0.05 significance level of positive correlation. To elaborate more on the claim, the S5FERT index, NAICS price, and gross cash income of agricultural commodities all shared strong positive correlation relationships. This evidence is found supporting the basis of agricultural chemical production and agricultural commodity returns being strongly related to one another. Linear regression analysis showed a positive linear relationship between the ag-tech index (S5FERT) and the chemical manufacturing price average (Ind_Price). The general conclusion drawn from the results were in support of a positive link between financial activity and the actual prices in the industry. This empirical evidence supports the hypothesis that our ag-tech index is more volatile and may indicate technology transfers to the general ag-tech related market.

Lastly, testing of the 'Big Four' based chemical producers relative to the random samples drawn from the S&P500 were the final sub-category tested. Results reflective of the collective sample testing expressed a positive linear relationship between the S&P500 sample and the 'Big Four' ag-tech averages. Moreover, the collective sample results from multivariable linear regression testing relative to the general market index volume averages and ag-tech related indices supports the argument that ag-tech is more volatile than the general market index, possibly as a result of technology transfers.

Supplementary results were included upon completion of testing to confirm statistical results found prior. Correlation testing of the historical volumes of the S&P500, S5FERT, and DBA showed a strong positive relationship between the growth of trade volumes over time between the generalized index (S&P500) and agricultural commodity exchange traded funds. The price-earnings ratio and price-to-book ratio from 2012 to 2022 for the S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT) was included to investigate potential stock overvaluation. Figures 1 and 2 represent these two measures graphically to explicitly show any major indications, and consequently indicated that following mid-2020 the P/E and P/BV ratios had two major shocks and were followed by consistent higher levels. Analysis of the P/E ratio being consistent with the general argument in support of the complementary speculation aspect of financial technologies in the agricultural industry.

Evidence drawn from the multiple series of testing demonstrated a shared relationship relative to price movement between the general market index and ag-tech related indices. Additionally, empirical evidence found a shared relationship between ag-tech related stocks and agricultural commodity returns. In brief, testing provided statistically significant results in support of the hypothesis that technology transfers influence the general ag-tech market and financial technologies influence the actual market industry dynamics with respect to prices. Thus, findings supporting the proposition that the agricultural commodities market and their relative trade volumes are gaining moment as a result of technological advancements.

It is understood that with respect to the hypothesis question focused on financial technologies influencing trade behavior and the agricultural commodities market the testing used in this thesis lacks sufficient data to draw empirical evidence. Given the nature of lack of complete data for testing, the results found relative to financial technologies may serve as strong intermediate empirical evidence for greater analysis. As previously addressed, future testing utilizing high-frequency bid-ask spreads would further support the hypothesis identifying the role advancing financial technologies plays on trader behavior and interactions relative to the agricultural commodities market.

My following research may help to support future research regarding interactions in the agricultural commodities markets and their respective chemical usage. Moreover, as smartphone user volumes build a stronger foundation for historical data use in statistical testing, a greater link between naïve traders interacting with markets and the hedging aspect of commodities markets can be emphasized.

These findings can be used to suggest certain directions of future policy making and government intervention to protect the production of raw materials and their producers. With the understanding that trade behavior often dictated by monetary risk-reward potential is the link to farms hoping to hedge against risk, keeping the mechanics of safeguards for market uncertainty is significant. Further eluding the importance of trading for producers, authorities such as the Commodity Futures Trading Commission (DFTC) may need to more frequently update these regulations as smartphone platforms continue to emerge into this market with greater force.

REFERENCES

About CME Group - CME Group - CME Group. Accessed November 20, 2021. https://www.cmegroup.com/company/about-us.html.

Akerlof, George A. “The Market for ‘Lemons’: Quality Uncertainty and the Market Mechanism.” *The Quarterly Journal of Economics* 84, no. 3 (1970): 488. https://doi.org/10.2307/1879431.

Albert Wang, F. “Informed Arbitrage with Speculative Noise Trading.” *Journal of Banking & Finance* 34, no. 2 (2010): 304–13. https://doi.org/10.1016/j.jbankfin.2009.07.019.

Beddington, John. “Food Security: Contributions from Science to a New and Greener Revolution.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 365, no. 1537 (2010): 61–71. https://doi.org/10.1098/rstb.2009.0201.

“Biotechnology.” USDA. Accessed October 10, 2021. https://www.usda.gov/topics/biotechnology.

Black, Fischer. “Noise.” *The Journal of Finance* 41, no. 3 (1986): 528–43. https://doi.org/10.1111/j.1540-6261.1986.tb04513.x.

Brookes, Graham, Tun-Hsiang (Edward) Yu, Simia Tokgoz, and Amani Elobeid. The Production and Price Impact of Biotech Crops . Accessed March 31, 2022. https://www.card.iastate.edu/products/publications/pdf/10wp503.pdf.

“CBOT (Chicago Board of Trade) - CME Group.” Futures & Options Trading for Risk Management - CME Group. Accessed November 10, 2021. https://www.cmegroup.com/company/cbot.html.

Chen, James. “Free-Float Methodology Definition.” Investopedia. Investopedia, February 8, 2022. https://www.investopedia.com/terms/f/freefloatmethodology.asp.

Clor-Proell, Shana M, Ryan D Guggenmos, and Kristina Rennekamp. “Mobile Devices and Investment News Apps: The Effects of Information Release, Push Notification, and the Fear of Missing Out.” *The Accounting Review* 95, no. 5 (2019): 95–115. https://doi.org/10.2308/accr-52625.

Comtois, James. “Trading The Pencil For A Smartphone; Technological Advances Have Improved Efficiency While Also Making Money Management Increasingly Complex.” *Gale General OneFile* 41, no. 21 (October 14, 2013).

Cornish , Lisa. “What the 'Big Six' Agricultural Biotech Companies Think about the GMO Debate.” Genetic Literacy Project, May 16, 2018. https://geneticliteracyproject.org/2018/05/16/what-big-six-agricultural-biotech-companies-think-about-gmo-debate/.

Cuellar, Maria C, and Adrie JJ Straathof. “Downstream of the Bioreactor: Advancements in Recovering Fuels and Commodity Chemicals.” *Current Opinion in Biotechnology* 62 (2020): 189–95. https://doi.org/10.1016/j.copbio.2019.11.012.

Deconinck, Koen. “From Big Six to Big Four.” Seed World, May 6, 2019. https://seedworld.com/from-big-six-to-big-four/.

Fishe, Raymond P., Joseph P. Janzen, and Aaron Smith. “Hedging and Speculative Trading in Agricultural Futures Markets.” *American Journal of Agricultural Economics* 96, no. 2 (2014): 542–56. https://doi.org/10.1093/ajae/aat111.

"Green Revolution: Curse or Blessing?" International Food Policy Research Institute, 2002. https://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/64639/filename/64640.pdf.

Hamadi, Hassan, Charbel Bassil, and Tamara Nehme. "News Surprises and Volatility Spillover among Agricultural Commodities: The Case of Corn, Wheat, Soybean and Soybean Oil." *Research in International Business and Finance* 41 (2017): 148–57. https://doi.org/10.1016/j.ribaf.2017.04.006.

Kalda, Ankit, Benjamin Loos, Alessandro Previtero, and Andreas Hackethal. "Smart(Phone) Investing? A within Investor-Time Analysis of New Technologies and Trading Behavior." *National Bureau of Economic Research*, January 2021. https://doi.org/10.3386/w28363.

Keynes, John Maynard. "Chapter 12. the State of Long-Term Expectation." The General Theory of Employment, Interest and Money by John Maynard Keynes, 1935. https://www.marxists.org/reference/subject/economics/keynes/general-theory/ch12.htm.

Lammi, Minna, and Mika Pantzar. "The Data Economy: How Technological Change Has Altered the Role of the Citizen-Consumer." *Technology in Society* 59 (2019): 101157. https://doi.org/10.1016/j.techsoc.2019.101157.

Langager, Chad. "How Is the Value of the S&P 500 Calculated?" Investopedia. Investopedia, March 8, 2022. https://www.investopedia.com/ask/answers/05/sp500calculation.asp.

Osteen, Craig D, and Jorge Fernandez-Cornejo. "Economic and Policy Issues of U.S. Agricultural Pesticide Use Trends." *Pest Management Science* 69, no. 9 (2013): 1001–25. https://doi.org/10.1002/ps.3529.

Norman Cummins and Cassie Bable, Larry, Norman, Lorraine Lizana, and Brad Fourby. “Mobile Farms Move into Urban Settings.” USDA, February 21, 2017. https://www.usda.gov/media/blog/2015/05/19/mobile-farms-move-urban-settings.

Ross, Alice. “Faster Smartphone Trading Raises Risks: Apps.” *Financial Times*, September 24, 2010. https://www.proquest.com/newspapers/faster-smartphone-trading-raises-risks/docview/753937205/se-2?accountid=10003.

“Stata: Software for Statistics and Data Science | Stata.” Accessed March 5, 2022. https://www.stata.com/manuals13/rregresspostestimation.pdf.

Stephanie. “Breusch-Pagan-Godfrey Test: Definition.” Statistics How To, April 27, 2020. https://www.statisticshowto.com/breusch-pagan-godfrey-test/.

Stephanie. “Variance Inflation Factor.” Statistics How To, December 16, 2020. https://www.statisticshowto.com/variance-inflation-factor/.

“United States Department of Agriculture.” USDA, 2022. https://www.nass.usda.gov/Charts_and_Maps/Field_Crops/index.php.

Waryoba, Fulgence Dominick. “Online Trading and Adverse Selection in Smartphone Market.” *Academic Journal of Economic Studies* 4, no. 4 (December 2018): 96. https://link.gale.com/apps/doc/A569456186/AONE?u=orla57816&sid=bookmark-AONE&xid=0a4ded02.

APPENDIX

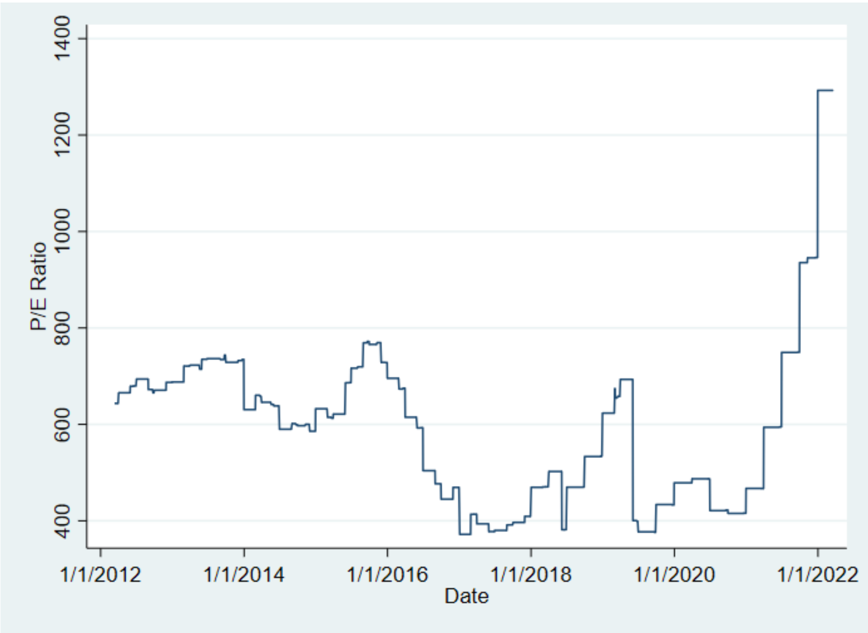

Figure 1: Historical daily price-earnings ratios for the S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT) from 2021-2022

Figure 2: Historical daily price-to-book ratios for the S&P500 Fertilizers & Agricultural Chemicals Sub-Industry Index (S5FERT) from 2012-2022

Table 14 Sample 2 Price Multivariable Linear Regression

Linear regression

Number of obs	=	60
F(2, 57)	=	80.37
Prob > F	=	0.0000
R-squared	=	0.6582
Root MSE	=	13.694

Price_Avg2	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
S5FERT_LA	.0436442	.006967	6.26	0.000	.0296932	.0575953
ChemAvgPrice	.8581411	.1995347	4.30	0.000	.4585798	1.257702
_cons	-21.6002	6.737401	-3.21	0.002	-35.09161	-8.108785

Table 15 Sample 2 Volume Multivariable Linear Regression

Linear regression

Number of obs	=	60
F(2, 57)	=	4.78
Prob > F	=	0.0120
R-squared	=	0.1983
Root MSE	=	2.5e+07

Volume_Avg2	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
S5FERT_V	.0933789	.0517465	1.80	0.076	-.0102417	.1969996
ChemAvgVol~e	.2472547	.1177348	2.10	0.040	.0114948	.4830145
_cons	8.32e+07	1.30e+07	6.43	0.000	5.73e+07	1.09e+08

Table 16 Sample 3 Price Multivariable Linear Regression

Linear regression

Number of obs	=	60
F(2, 57)	=	79.40
Prob > F	=	0.0000
R-squared	=	0.6677
Root MSE	=	22.339

Price_Avg3	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
S5FERT_LA	.0763419	.0126962	6.01	0.000	.0509181	.1017656
ChemAvgPrice	1.279843	.324478	3.94	0.000	.6300867	1.929599
_cons	-51.84707	11.0144	-4.71	0.000	-73.90303	-29.7911

Table 17 Sample 3 Volume Multivariable Linear Regression

```
Linear regression                               Number of obs     =         60
                                                F(2, 57)          =       2.81
                                                Prob > F          =     0.0683
                                                R-squared         =     0.1835
                                                Root MSE          =     2.3e+07
-------------------------------------------------------------------------------
              |               Robust
  Volume_Avg3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     S5FERT_V |  -.0181218   .0476544    -0.38   0.705     -.113548    .0773045
ChemAvgVolume |   .2696198   .1136502     2.37   0.021     .0420393    .4972004
        _cons |   3.82e+07   1.21e+07     3.16   0.003     1.40e+07    6.24e+07
-------------------------------------------------------------------------------
```

Table 18 Sample 4 Price Multivariable Linear Regression

```
Linear regression                               Number of obs     =         60
                                                F(2, 57)          =      76.85
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6849
                                                Root MSE          =      13.14
------------------------------------------------------------------------------
             |               Robust
  Price_Avg4 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   S5FERT_LA |   .0517786   .0074037     6.99   0.000      .036953    .0666042
ChemAvgPrice |   .5498165   .1878558     2.93   0.005     .1736418    .9259913
       _cons |  -27.02994   6.485965    -4.17   0.000    -40.01786   -14.04202
------------------------------------------------------------------------------
```

Table 19 Sample 4 Volume Multivariable Linear Regression

```
Linear regression                               Number of obs     =         60
                                                F(2, 57)          =       2.85
                                                Prob > F          =     0.0660
                                                R-squared         =     0.1420
                                                Root MSE          =     3.5e+07

-------------------------------------------------------------------------------
              |               Robust
  Volume_Avg4 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     S5FERT_V |  -.0816912   .0751791    -1.09   0.282    -.2322348    .0688525
ChemAvgVolume |   .3589471   .1592928     2.25   0.028     .0399687    .6779255
        _cons |   9.60e+07   1.78e+07     5.39   0.000     6.04e+07    1.32e+08
-------------------------------------------------------------------------------
```

Table 20 Sample 5 Price Multivariable Linear Regression

Linear regression

Number of obs	=	60
F(2, 57)	=	59.30
Prob > F	=	0.0000
R-squared	=	0.5628
Root MSE	=	28.476

Price_Avg5	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
S5FERT_LA	.0929294	.0129707	7.16	0.000	.0669559	.1189028
ChemAvgPrice	.5675934	.3798568	1.49	0.141	-.1930568	1.328244
_cons	-62.713	12.57029	-4.99	0.000	-87.88457	-37.54143

Table 21 Sample 5 Volume Multivariable Linear Regression

Linear regression

Number of obs	=	60
F(2, 57)	=	2.02
Prob > F	=	0.1426
R-squared	=	0.0819
Root MSE	=	1.1e+07

Volume_Avg5	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
S5FERT_V	.017749	.0242542	0.73	0.467	-.0308191	.0663171
ChemAvgVolume	.0741	.0436577	1.70	0.095	-.0133229	.161523
_cons	3.15e+07	5409178	5.82	0.000	2.06e+07	4.23e+07

Table 22 Sample 6 Price Multivariable Linear Regression

```
Linear regression                               Number of obs     =         60
                                                F(2, 57)          =      64.32
                                                Prob > F          =     0.0000
                                                R-squared         =     0.5927
                                                Root MSE          =     50.423

------------------------------------------------------------------------------
             |               Robust
  Price_Avg6 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    S5FERT_L |   .1683842   .0250482     6.72   0.000     .1182261    .2185423
ChemAvgPrice |   1.429791   .7199601     1.99   0.052    -.0119041    2.871487
       _cons |  -143.6333   23.05016    -6.23   0.000    -189.7904   -97.47612
------------------------------------------------------------------------------
```

Table 23 Sample 6 Volume Multivariable Linear Regression

```
Linear regression                               Number of obs     =         60
                                                F(2, 57)          =       1.87
                                                Prob > F          =     0.1638
                                                R-squared         =     0.0662
                                                Root MSE          =     3.3e+07

------------------------------------------------------------------------------
              |               Robust
  Volume_Avg6 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     S5FERT_V |  -.0885613   .0707482    -1.25   0.216    -.2302321    .0531095
ChemAvgVolume |   .2159032   .1321353     1.63   0.108    -.0486932    .4804996
        _cons |   8.03e+07   1.62e+07     4.96   0.000     4.79e+07    1.13e+08
------------------------------------------------------------------------------
```

Table 24 Sample 7 Price Multivariable Linear Regression

```
Linear regression                               Number of obs     =         60
                                                F(2, 57)          =      36.49
                                                Prob > F          =     0.0000
                                                R-squared         =     0.5703
                                                Root MSE          =     10.604

------------------------------------------------------------------------------
             |               Robust
  Price_Avg7 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    S5FERT_V |   7.83e-08   1.96e-08     4.00   0.000     3.90e-08    1.17e-07
ChemAvgPrice |   1.195144   .1520523     7.86   0.000     .8906645    1.499624
       _cons |   16.98974   6.098166     2.79   0.007     4.778375    29.20111
------------------------------------------------------------------------------
```

Table 25 Sample 7 Volume Multivariable Linear Regression

```
Linear regression                               Number of obs     =         60
                                                F(2, 57)          =       2.98
                                                Prob > F          =     0.0588
                                                R-squared         =     0.1817
                                                Root MSE          =     2.2e+07

-------------------------------------------------------------------------------
              |               Robust
  Volume_Avg7 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     S5FERT_V |   .0171184   .0490802     0.35   0.729     -.081163    .1153998
ChemAvgVolume |   .2438155   .1049985     2.32   0.024     .0335596    .4540713
        _cons |   5.08e+07   1.16e+07     4.39   0.000     2.76e+07    7.40e+07
-------------------------------------------------------------------------------
```

Table 26 Sample 8 Price Multivariable Linear Regression

Linear regression

Number of obs	=	60
F(2, 57)	=	68.97
Prob > F	=	0.0000
R-squared	=	0.5876
Root MSE	=	27.031

Price_Avg8	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
S5FERT_LA	.0869082	.0119736	7.26	0.000	.0629315	.1108849
ChemAvgPrice	.8823922	.3684774	2.39	0.020	.144529	1.620255
_cons	-57.68878	11.48682	-5.02	0.000	-80.69075	-34.68681

Table 27 Sample 8 Volume Multivariable Linear Regression

Linear regression

Number of obs	=	60
F(2, 57)	=	2.35
Prob > F	=	0.1047
R-squared	=	0.0775
Root MSE	=	2.6e+07

Volume_Avg8	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
S5FERT_V	-.093402	.0568956	-1.64	0.106	-.2073335	.0205295
ChemAvgVolume	.1761638	.1026234	1.72	0.091	-.029336	.3816635
_cons	6.30e+07	1.24e+07	5.09	0.000	3.82e+07	8.78e+07

Table 28 Sample 9 Price Multivariable Linear Regression

```
Linear regression                               Number of obs     =         60
                                                F(2, 57)          =      87.13
                                                Prob > F          =     0.0000
                                                R-squared         =     0.7657
                                                Root MSE          =     7.1254

------------------------------------------------------------------------------
             |               Robust
  Price_Avg9 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   S5FERT_LA |    .003417   .0028487     1.20   0.235    -.0022876    .0091215
ChemAvgPrice |   1.288029   .1262638    10.20   0.000      1.03519    1.540868
       _cons |   15.56067   3.717107     4.19   0.000     8.117288    23.00404
------------------------------------------------------------------------------
```

Table 29 Sample 9 Volume Multivariable Linear Regression

```
Linear regression                               Number of obs     =         60
                                                F(2, 57)          =       2.28
                                                Prob > F          =     0.1119
                                                R-squared         =     0.1617
                                                Root MSE          =     2.5e+07

-------------------------------------------------------------------------------
              |               Robust
  Volume_Avg9 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     S5FERT_V |  -.0416322   .0529719    -0.79   0.435    -.1477066    .0644421
ChemAvgVolume |   .2806746   .1359494     2.06   0.044     .0084406    .5529086
        _cons |   5.52e+07   1.42e+07     3.90   0.000     2.68e+07    8.35e+07
-------------------------------------------------------------------------------
```

Table 30 Sample 10 Price Multivariable Linear Regression

```
Linear regression                               Number of obs     =         29
                                                F(2, 26)          =      91.92
                                                Prob > F          =     0.0000
                                                R-squared         =     0.7591
                                                Root MSE          =     8.0124

------------------------------------------------------------------------------
             |               Robust
 Price_Avg10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   S5FERT_LA |   .0403488   .0031061    12.99   0.000     .0339642    .0467334
ChemAvgPrice |  -.6775422   .1668519    -4.06   0.000    -1.020511   -.3345734
       _cons |   48.28095   7.820504     6.17   0.000     32.20567    64.35623
------------------------------------------------------------------------------
```

Table 31 Sample 10 Volume Multivariable Linear Regression

```
Linear regression                               Number of obs     =         29
                                                F(2, 26)          =       3.24
                                                Prob > F          =     0.0556
                                                R-squared         =     0.1942
                                                Root MSE          =     2.2e+07

-------------------------------------------------------------------------------
              |               Robust
 Volume_Avg10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
     S5FERT_V |   .1369788   .0655678     2.09   0.047     .0022023    .2717553
ChemAvgVolume |   .1563483   .0906532     1.72   0.096    -.029992    .3426887
        _cons |   5.72e+07   1.54e+07     3.71   0.001     2.55e+07    8.89e+07
-------------------------------------------------------------------------------
```