# Bryant University HONORS THESIS

## The Dangers in the Rise of Passive Investing: Impacts on Equity Market Functionality

BY Ryan Donovan

ADVISOR • John Fellingham EDITORIAL REVIEWER • Jeffrey Koplik

Submitted in partial fulfillment of the requirements for graduation with honors in the Bryant University Honors Program April 2022

### **Table of Contents**

Abstract	1
Introduction	2
Passive vs. Active Investing	2
Factors Contributing to the Shift	3
Methodology	4
Results	6
Liquidity	6
Comovement	8
Discussion of Results	11
Liquidity Discussion	11
Comovement Discussion	12
Significance of Findings	13
Conclusion	14
References	15
Appendix	16
Daily return correlations to \$SPY each year	16
Average Daily Return Correlation By Year- S&P 100 Components	17

### ABSTRACT

Most investments into equity markets can be categorized into two general strategies: active investments and passive investments. These strategies impact equity markets in different ways. Over the past few decades, market participants have witnessed a radical shift from active management to passive management. This paper reviews how this shift impacts market dynamics generally, and liquidity and comovement effects, in particular. Robust statistical analysis of total passive domestic equity assets under management (AUM), individual security, and market index data demonstrates that dramatic increases in passive investment flows correlates with decreased broad market liquidity and increased security-index comovement for securities in the technology sector. Both liquidity loss and increased comovement can potentially impact the pricing efficiency of equity markets. These potential pricing inefficiencies that the statistical analysis points towards can allow active management to realize excess returns in the future. It also points to a possible cycle which, if identified, may also lead to excess returns.

### **INTRODUCTION**

As technological advances have continued and markets have adapted, participants in equity markets during the past few decades have witnessed a radical shift in investment styles. This shift is best categorized as one from active management to passive management. In evaluating whether passive investing, and its dramatic increase over the past few decades, is causing pricing inefficiency within equity markets, we first define the difference between active and passive investing. Second, we assess potential explanations for the shift from investment styles. After understanding the rationale behind the trend, utilizing empirical research and statistical analysis, its impact on equity markets will be evaluated. Lastly, we put the significance of these impacts into context, including ramifications of liquidity loss and increased degrees of security comovement in specific sectors.

#### Passive vs. Active Investing

In evaluating the differences between the two differing investment styles, Turner and Shushko (2018) note that passively managed funds are investment vehicles that offer diversified and low fee portfolios with low turnover. This contrasts with actively managed funds, which seek to earn higher returns than their chosen benchmark through discretionary security selection or trading in anticipation of market turning points, resulting in higher turnover. The rise in popularity of exchange-traded funds (ETFs) is a clear example of equity market's transition from active to passive management. In a survey conducted by Nanigan (2019), in working with clients, over eighty-seven percent of financial advisors surveyed in 2018 reveal that they currently use or recommend ETFs with their clients. Additionally, the proportion that suggested they plan to increase these ETF recommendations stood at forty-six percent. Figure 1 shows a closer look at the magnitude of this trend, from Morningstar Inc. In evaluating the data in figure 1, in 1995 passive investing's share of assets under management was less than 2% of total assets under management. Its share has grown to over 40% as of 2019. As of March 2022, passive investing's share of domestic equity funds stands at 53% (Bloomberg Intelligence).



Figure 1: Total assets in active and passive MFs and ETFs and passive share of total

Another study by Tokic (2019) points out the significance of this shift in a profound way, noticing that in 2009 assets under management in active funds tripled that of passive funds; however, by 2019, passive funds had quickly closed that gap, and overtook active funds by market share. Why would this be fundamentally alarming? Because passive investment strategies can be best described as set-it-and-forget-it, hands-off strategies, an intuitive market participant likely infers that, if 18% of all global equities are held passively as a study by the Boston Federal Reserve indicates (Kenechukwu, 2019), then 18% of all global equities are not contributing to global market liquidity (or, at the very least, rarely are). Evidence as to whether this is occurring will be evaluated later within the paper. Other effects of passive investing's increase in popularity will be discussed throughout the paper as well, but the most widespread are liquidity and security comovement. Both effects potentially contribute to declines in pricing efficiency of the stock market. When stock valuations are not representative of true intrinsic valuations of the underlying companies, this kind of valuation dislocation on the upside (overvalued) can cause a bubble, or an opportunity if dislocated on the downside (undervalued).

#### Factors Contributing to the Shift

It is apparent that this shift from active to passive investment vehicles has accelerated over the past few decades, but what might explain that? According to Vanguard (2021), a provider of

Figure 1

over fifty exchange-traded funds, ETFs (classically passive investment vehicles) provide several benefits that traditional mutual funds do not, including lower investment minimums (virtually zero with the rise of fractional trading) and more hands-on control over the price of a given trade (since spot prices update more frequently throughout the day in ETFs vs. MFs). Similarly, a study by Narend (2016) points to the expense ratio (a transaction cost) as a major factor that drives investment decisions. Theoretically, both an ETF and a mutual fund can replicate an index, but according to Vanguard, most of their MFs require a \$3,000 investment minimum. Conversely, ETFs have basically no investment minimum, as fractional trading has allowed investors to buy fractional shares at a desired dollar amount. Because of these facts, ETFs in this technology-driven market are typically much more attractive investment vehicles, as they offer generally lower investment minimums and transaction costs.

Another driving factor of passive investing adoption appears to be performance. According to Hamilos (2015), despite active investing's focus on the outperformance of benchmarks, 78 percent of active domestic equity managers trailed their relevant benchmarks in 2014. Other studies have also found similar outcomes. According to Prondzinski and Miller, who studied passive investing from 2009-2017, during that period, on a risk-adjusted basis in the nine hypotheses tested, the mean daily Sharpe ratios per week were not significantly higher for the active indices (proxies for active management) as compared to the passive indices (proxies for passive management). As investors usually pay a premium for active management to outperform benchmarks, the fact that risk-adjusted returns are not meaningfully higher disincentivizes investors to seek active management without outperformance. Lessening interest in active investment vehicles means increasing interest in passive vehicles- but what affect could this have on equity markets?

### **METHODOLOGY**

First, we separate the two dependent variables and statistically analyze them with total passive domestic equity investment assets under management (AUM) as the independent variable. To address liquidity, we obtained data from NASDAQ Inc, a company that manages, operates, and provides market services, investment intelligence, and market technology. This data includes yearly bid-ask spread data for S&P 500 components from 2015 through 2021 at

various VIX levels. The separation of VIX (or, commonly referred to as the markets "Fear Gauge") levels was crucial. Since it is a common measure of market volatility, it is typical for bid-ask spreads to vary across different VIX levels. Typically, spreads are tight at lower VIX levels and wider at higher VIX levels. I ran a statistical regression between total passive assets in domestic equity markets and the bid-ask spread of these S&P500 components, providing a predictive model that explains how changes in passive investment flows impact liquidity across S&P500 components.

My statistical analysis of security comovement took a far more robust process, which is laid out below:

- Input every ticker of each component of the S&P100 into a MS Excel "master spreadsheet"
- 2. Download historical data from Jan-1-2010 to Dec-31-2021 for each security
- 3. Use return formula: ((New-Old)/Old) to get daily returns
- 4. Input daily return data for each component into master spreadsheet, separating by each year; also do for \$SPY, an ETF that replicates the S&P500 (once)
- Using data analysis tool on excel, correlate daily returns of each security for each year with \$SPY returns; this provided what we'll refer to as the "degree of comovement value" (DCV)

This process gave me the correlation of daily returns between each S&P100 component and \$SPY for every year from 2010-2021 (for securities, such as \$FB, whose IPO was after 2010, the first full year was used). In other words, this process showed comovement trends for individual components from 2010-2021. The next step was to see what correlation these trends had to passive investment assets over time. To do so, I:

Used the =AVERAGE function on excel to get average correlation for *all* securities each year (giving me an average correlation value for each year from 2010 to 2021).

7. Used data analysis function on excel to run a statistical regression model to correlate comovement over time with total passive assets over time, giving me a model that explains how changes in total passive assets impacts comovement.

### **RESULTS**

We separated the results by the two different dependent variables analyzed: liquidity and comovement. In order to analyze each dependent variable, a slightly different process was needed, in large part due to differences in data sources. First, we will explore how total passive investment flows impact market-wide liquidity.

### Liquidity

Figure two shows the summary output which displays findings of how total passive domestic equity assets under management (AUM) impacts market-wide liquidity. Based on the statistical findings, and this regression model, it is *estimated* that for every \$1 trillion increase in total passive domestic equity AUM, our independent/explanatory variable, the bid-ask spread for S&P500 components will increase by .29 basis points. In more digestible terms, this model estimates that every ~\$3.44 trillion increase in passive domestic equity would translate to a single basis point increase in the average bid-ask spread of all S&P500 components. At first, a single basis point increase as a result of a \$3.44 *trillion* increase in passive assets may not seem significant, but when considering the fact that this spans across *every component of the S&P500*, it really is worth paying attention to, and ramifications will be discussed further.

SUMMARY OUTPUT									
Regression Statistics									
Multiple R	0.76350394								
R Square	0.582938266								
Adjusted R Square	0.499525919								
Standard Error	0.429280452								
ANOVA									
	df	SS	MS	F	Significance F				
Regression	<u>df</u> 1	SS 1.287877184	MS 1.287877	F 6.988633	Significance F 0.045777318				
Regression Residual	<u>df</u> 1 5	SS 1.287877184 0.921408531	MS 1.287877 0.184282	F 6.988633	Significance F 0.045777318				
Regression Residual Total	<u>df</u> 1 5 6	SS 1.287877184 0.921408531 2.209285714	MS 1.287877 0.184282	F 6.988633	Significance F 0.045777318				
Regression Residual Total	<u>df</u> 1 5 6	SS 1.287877184 0.921408531 2.209285714	MS 1.287877 0.184282	F 6.988633	Significance F 0.045777318				
Regression Residual Total	<u>df</u> 1 5 6	SS 1.287877184 0.921408531 2.209285714	MS 1.287877 0.184282	F 6.988633	Significance F 0.045777318				
Regression Residual Total	df 1 5 6 Coefficients	SS 1.287877184 0.921408531 2.209285714 Standard Error	MS 1.287877 0.184282 t Stat	F 6.988633 P-value	Significance F 0.045777318				
Regression Residual Total Intercept	<u>df</u> 1 5 6 Coefficients 3.394032831	SS 1.287877184 0.921408531 2.209285714 Standard Error 0.600120705	MS 1.287877 0.184282 t Stat 5.655584	F 6.988633 P-value 0.002401	Significance F 0.045777318				
Regression Residual Total Intercept Passive Assets	<u>df</u> 1 5 6 <u>6</u> <u>7</u> <u>7</u> <u>8</u> 3.394032831 0.293867196	SS 1.287877184 0.921408531 2.209285714 Standard Error 0.600120705 0.111161653	MS 1.287877 0.184282 t Stat 5.655584 2.643602	F 6.988633 P-value 0.002401 0.045777	Significance F 0.045777318				

Figure 2

Further analyzing the regression output beyond the significance of our coefficient value, the model showed an R-squared value of .583. This means that 58.3% of the *variability* in the average bid-ask spread of S&P500 components can be *explained* by changes in total passive domestic equity holdings. Importantly, these findings were statistically significant at a 95% confidence level, evidenced by the p-value of .0457, which is less than .05. This means that this correlation is due to something *other than chance*. Also, important to note is the regression controls for VIX levels throughout the year. Since higher VIX levels signal more volatility (and, therefore, heightened bid-ask spreads), this was a factor that simply had to be controlled in order to achieve meaningful statistical analysis. By analyzing yearly spreads at a standard VIX level of 15 for each year, volatility can be removed as a potential source of statistical error. Figure 3 shows a basic graph showing the relationship between total passive domestic equity AUM and the bid-ask spread of S&P500 components on a yearly basis.



Figure 3

#### Comovement

Among our entire sample size (the S&P100, or largest 100 companies in the S&P500) there was not an apparent statistically significant relationship between the entirety of component's degree of comovement over time with increases in passive investment flows. The regression output can be seen in figure 4, where the r square value was miniscule, and the p-value did not show statistical significance.

		Regression S	tatistics		
		Multiple R	0.225604421		
		R Square	0.050897355		
		Adjusted R Square	-0.04401291		
		Standard Error	0.109097259		
		Observations	12		
ANOVA					
	df	SS	MS	F	Significance F
Regression	1	0.006382778	0.006382778	0.536268179	0.480794625
Residual	10	0.11902212	0.011902212		
Total	11	0.125404898			
	Coefficients	Standard Error	t Stat	P-value	Lower 95%
Intercept	0.646421712	0.068370773	9.45464981	2.65114E-06	0.494082137
Total Passive Equity AUM	-0.01158475	0.015819612	-0.73230334	0.480794625	-0.04683305
Figure 4					

The next logical step in the analysis of this data was to see if there was a trend among those components whose degrees of comovement over time *did* appear to show a relationship with total passive domestic equity AUM. The findings were intriguing. Utilizing the IF() function in MS Excel, these components were sorted out, and figure 5 is a list of those that did show a relationship in the form of stronger correlations compared to other components:

Component	<b>Correlation Value</b>	
Apple		0.483
Amazon		0.642
Broadcom		0.539
Facebook		0.628
Google		0.537
Netflix		0.725
ServiceNow		0.706
Paypal		0.519
Visa		0.531
Zoetis		0.639
Figure 5		

All of these companies showed a relatively strong correlation between yearly comovement values and increases in total passive domestic equity AUM. The next step to further analyze and achieve increased context was to look deeper into these components and see if they shared any similarities. I looked into the size of each company, by market capitalization, and the sector that they are in, and my results are shown in figure 6:

Component	Market Cap (end of '21)	Sector
Apple	\$2.89T	Technology
Amazon	\$1.69T	Cons. Disc.
Broadcom	\$269B	Technology
Facebook	\$914B	Technology
Google	\$1.91T	Technology
Netflix	\$265B	Technology
ServiceNow	\$130B	Technology
Paypal	\$201B	Technology
Visa	\$455B	Technology
Zoetis	\$115B	Technology

Figure 6

The trend here is clear: every company that showed a strong correlation between increased comovement trends and increases in total passive domestic equity AUM were very large technology companies (Amazon is technically in the consumer discretionary sector due to the size of their retail business, but AWS has become an increasingly large portion of their business and FCF driver, which may explain why they are included). Those polished in financial markets jargon will notice that every member of "FAANG" (Facebook, Apple, Amazon, Netflix, and Google) show this special relationship between comovement and passive flows. Notably, Microsoft just narrowly missed the parameters for relationship strength, but it still showed a stronger-than-average correlation value of .44.

Noticing this trend- the fact that large cap technology stocks showed the strongest correlation between increases in degrees of comovement and total passive domestic equity assets under management- brought me to the next natural question that would allow me to further dig down into my results: If these large technology companies showed a strong relationship, but the S&P100 did not, what kinds of companies showed the weakest relationship? Utilizing a similar process to sort out these companies, we developed the table below:

Component	Correlation Value	Sector
Moderna	-0.872	Biotechnology
<b>General Electric</b>	-0.696	Industrials
Wells Fargo	-0.684	Financials
UPS	-0.635	Transportation
ConocoPhillips	-0.595	Energy
3M	-0.566	Industrials
Exxon	-0.547	Energy
Pfizer	-0.536	Pharmaceuticals
US Bancorp	-0.532	Financials
Truist Financial	-0.528	Financials
PNC Financial	-0.500	Financials
Honeywell	-0.478	Industrials
Boeing	-0.443	Aerospace

Figure 7

### **DISCUSSION OF RESULTS**

#### Liquidity Discussion

One can readily observe the trend in S&P500 components' liquidity through figure 8:



Figure 8

Figure 8, which includes the average bid-ask spread for *all* S&P500 components from 2015-2021, shows a clear trend: the average bid-ask spread (in basis points), while controlling for the level of the VIX, has shown a relatively steady increase since 2015. As noted previously, our model predicted that for every trillion dollar increase in total passive domestic equity AUM, the average bid-ask spread for S&P500 components is *expected* to increase by .29 basis points. Though .29 basis points may not seem like a significant amount, when one thinks about how *frequently* every component of the S&P500, the world's most popular index, is traded on a daily basis, an increase in the spread to this degree suggests massive increases in transaction costs. One study finds that, increases in transactions costs, resulting from less liquidity, could deter market participants from engaging in firm-specific information gathering activities, thereby leading to less informative stock prices in the firm-specific

component (Doron, 2017). This study ultimately points to the prediction that, due to decreases in liquidity (therefore, increases in transaction costs) as a byproduct of increases in passive investment activity, investors will be less willing to take their time to gather informational asymmetries, as transactions costs will cut into investment gains. With investors less willing to discover true price, intrinsic value will deviate from stock price further than normal. This deviation from intrinsic value would be a textbook market inefficiency, in broader terms.

#### **Comovement Discussion**

When first analyzing any statistical significance between changes in degree of comovement and increases in total passive domestic equity AUM within S&P100 components over the past decade, there did not appear to be any robust statistical relationship. This is conveyed by an insignificant p-value of .48 and a weak adjusted r-squared value of -0.04; however, once I analyzed which components showed a robust correlation and which showed a weak correlation, the results were incredibly interesting. I found that the components that demonstrated the highest correlation (that is, the components in which the variability in degree of comovement is best *explained* by increases in total passive investment flows) were all large-cap technology stocks. Though the statistical model used does not show causation, it can be stated that there was a correlation between increases in total passive investment flows and increases in degree of comovement with \$SPY among large-cap technology stocks. Put in simpler terms, the data shows that large-cap technology stocks have become more correlated with the S&P500 in the past decade, and the statistics show that this is a result of *something* other than chance. Conversely, those components that showed the *least* correlation between total passive investment flows and degree of comovement with the underlying index in the past decade were more cyclical stocks belonging to the industrial, energy, and financial sectors. Interestingly, the components that showed the *least* correlation were Moderna (\$MRNA) and General Electric (\$GE). Analyzing these companies and how the market operates, this makes fundamental sense:

Moderna underperformed in the first year or so after its initial IPO, falling from roughly \$18 per share to \$13 pre-covid, while \$SPY saw gains; additionally, during 2020 Moderna often saw increases in share price when the pandemic worsened (due to vaccine potential) which

often coincided with declines in the \$SPY. These factors would explain the lack of correlation.

General Electric saw firm-specific underperformance from 2016-2020, seeing its share price crater from ~\$240 to ~\$50 per share while the \$SPY saw gains. Given this underperformance, one could see how degree of comovement lowered over time while total passive investment flows increased.

The point of these anecdotes is to show that dramatic negative correlations were often found to be firm-specific anomalies, and enough of these strong negative correlations can lower the correlation of the entire S&P100 benchmark as a whole. This is one of my educated guesses as to why the benchmark did not show a strong relationship between degrees of comovement and total passive investment flows over the past decade or so.

#### Significance of Findings

Its important to once again note that certain sectors (technology) saw much greater degrees of correlation than others (industrials, financials, energy). This means that increases in total passive domestic equity AUM will increase large-cap technology stocks' degree of comovement with \$SPY in the future and decrease large-cap companies in the industrial, financial, and energy sector's degree of comovement with \$SPY. Why is this significant? In my opinion, it all comes down to active vs. passive investment trends. Based on my findings, I theorize that these trends may open the door for active management to capitalize on these trends. For example, if large-cap technology stocks are more likely to be brought up (or down) by the S&P500 due to increased degrees of comovement, there may be pricing inefficiencies that active management may have the opportunity to exploit in the future. Conversely, if those components in the industrial, financial, and energy sector continue to lose degrees of comovement with the S&P500, they may be underinvested in on index upside (as market/economy-wide trends may not translate immediately to these companies' stock prices). If these factors do open the door for active management to capitalize, I theorize that this may cause a predictable feedback loop within the market in the future:



We saw steps "A" and "B" across the past decade or so and based on the data analyzed I theorize that we are currently in step "C". I expect step "D" to come soon, and once more and more active capitalize on this trend, there will be less returns (it would become a "crowded trade") leading back towards "C". If managers can stay in touch with how total passive domestic equity AUM impact the underlying components of the index, they may be able to stay ahead on this feedback loop, likely providing excess returns.

### **CONCLUSION**

Through my statistical analysis, a strong, positive, and statistically significant relationship was found between total passive domestic equity AUM and bid-ask spreads for S&P500 components. This trend, if it continues, should be alarming for market participants, as, since most technological advancements that have historically reduce spreads have already been implemented, it appears that spreads are destined to continue to rise with total passive domestic equity AUM. These increases in transaction costs could reduce the incentive for firms to search for informational asymmetries, therefore potentially causing some security values to deviate from intrinsic value. This would infer a less efficient market. Additionally, increases in passive flows have a positive correlation to increased degrees of comovement for large-cap technology stocks and a negative correlation for those in the industrial, financial, and energy sectors. Active management may be able to analyze these trends and ultimately achieve excess returns due to these market inefficiencies, potentially opening the door for a period of active manager outperformance in the future.

### **REFERENCES**

- Ben-David, I., Franzoni, F., & Rabih, M. (2015). Do ETFs Increase Volatility? *Securities and Exchange Commission*.
- Gregoire, V. (2019). The Rise of Passive Investing and Index-Linked Comovement. North American Journal of Economics and Finance.
- Hamilos Paul, A., & Ribando, J. M. (2015). Benchmark buyer beware: How well do you know your index? *Journal of Asset Management*.
- Kenechukwu, A., Mathias, K., Patrick, M., & Emilio, O. (2020). The Shift from Active to Passive Investing: Risks to Financial Stability? *Federal Reserve Bank of Boston*.
- Malkiel, B. (2003). The Efficient Market Hypothesis and its Critics. *Journal of Economic Perspectives*.
- Nallareddy, S., & Glosten, L. (2020). ETF Activity and Informational Efficiency of Underlying Securities. *Management Science Vol.* 67 No. 1.
- Nanigan, D. (2019). What Matters in Exchange-Traded Fund Selection? *Journal of Financial* Services Professionals .
- Narend, S., & Thenmozhi, M. (2016). What drives fund flows to index ETFs and mutual funds? *Crossmark*.
- Prondzinski, D., & Miller, M. (2018). Active vs. Passive Investing; Evidence from the 2009-2017 Market. *Journal of Accocunting and Finance*.
- Tokic, D. (2019). The passive investment bubble . *Wiley Corporate Accounting & Finance*, 7-11.
- *Vanguard ETFs*. (2021, March 4). Retrieved from Vanguard : https://investor.vanguard.com/etf/etf-vs-mutual-fund

### APPENDIX

#### Daily return correlations to \$SPY each year

Stock	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
SAAPL	0.708766818	0.677420466	0.537406281	0.237899989	0.438491879	0.663621076	0.566594687	0.517126979	0.748373893	0.74095548	0.830607098	0.683226959
SARRY				0.464946047	0.632701886	0.508198347	0.435563933	0.320717386	0.543354303	0.434000387	0.696013506	0.375512123
CART	0.639656445	0.697369097	0 \$11\$22599	0 560990121	0.669493693	0.812192261	0.59799702	0.421221655	0.8057155	0.670075949	0 245220696	0.217271742
CACH	0.6393056465	0.30403043	0.300101005	0.536363601	0.603001303	0.301032400	0.53730705	0.46547030	0.014020055	0.373606681	0.063435056	0.005201547
CADDE.	0.376263370	0.75402542	0.700191893	0.353502391	0.037631337	0.701033433	0.003800009	0.40347050	0.014079033	0.727000001	0.003#23330	0.053301347
SAUBE	0.49875218	0.772594347	0.652009849	0.491061319	0.577699529	0.667579753	0.70548358	0.38664191	0.765137602	0.710190866	0.776237552	0.618199344
SADI	0.733725117	0.778664748	0.757119095	0.716434453	0.598374732	0.624862628	0.694585818	0.421821785	0.690587988	0.683297417	0.820388139	0.654412312
SADP	0.835721047	0.89259871	0.774943139	0.694123529	0.764990709	0.818354974	0.750719919	0.324192631	0.777346279	0.715760526	0.853854557	0.595758313
SAMAT	0.770764454	0.764515359	0.682637303	0.569841141	0.566444133	0.603483275	0.63928797	0.509014974	0.680429706	0.589950573	0.83839873	0.640219872
\$AMD	0.709304748	0.670628132	0.533869664	0.302574193	0.340706495	0.32145251	0.313297549	0.282749154	0.476492952	0.609089876	0.650625649	0.511323145
\$AMGN	0.565023784	0.631092368	0.616457711	0.450281361	0.618873227	0.736483666	0.616480509	0.474374997	0.719915119	0.423685894	0.715907758	0.384100969
\$AMT	0.674985217	0.638962708	0.463687778	0.507781482	0.547472826	0.663143594	0.587142787	0.098027164	0.381360632	0.110231757	0.766432956	0.39458631
\$AMZN	0.198805122	0.580343052	0.436510054	0.502335435	0.510414634	0.522385997	0.494320783	0.400139377	0.769512647	0.73952247	0.608823358	0.554874273
SANTM	0.538379617	0.781756208	0.388665431	0.479378384	0.506767466	0.509692906	0.52180744	0.34599321	0.611035549	0.37997054	0.752819756	0.355224699
\$AVG0	0.495793994	0.607554659	0.596018664	0.429474797	0.591723692	0.536888049	0.674783737	0.465888025	0.528293028	0.60629432	0.828719598	0.674319238
\$AXP	0.784993979	0.844881556	0.711564411	0.673861045	0.800479281	0.599215872	0.420690006	0.565538806	0.750836036	0.7751896	0.789966594	0.527600129
\$BA	0.765068506	0.842930236	0.687394189	0.503017936	0.597321333	0.716907772	0.651061884	0.358240765	0.709471292	0.425838912	0.680767846	0.526086047
SBAC	0.76957695	0.772476609	0.662218582	0.640645734	0.632120773	0.755266268	0.704911782	0.601533205	0.75708464	0.668578315	0.821779965	0.469275863
\$RKNG	0 539277317	0.631866054	0.434937867	0 572239971	0.621227648	0.572475084	0.652974211	0.288920822	0.64434714	0.547191795	0.729496443	0.547411775
SRIK	0.649278796	0.892024792	0.657468385	0.814708435	0.829189173	0.811537262	0.821877477	0.668368587	0.77504987	0.809262745	0.844905389	0.755450261
CRAAV	0.473917411	0.66/000912	0.446614286	0.515297266	0.510127542	0.601719197	0 241127912	0 175967048	0.473618115	0 447704046	0.710004239	0 147712212
CROV R	0.661434046	0.004909015	0.762863038	0.926756925	0.763607420	0.979966769	0.700677766	0.650527999	0.472010113	0.751267722	0.995304075	0.634342345
SPRK-D	0.001424040	0.672234631	0.765863028	0.636/39623	0.762007439	0.878900709	0.790677266	0.630327888	0.813233732	0.751567722	0.865504975	0.624245245
SC	0.674876922	0.844863672	0.717945571	0.749033024	0.697048796	0.816586217	0.784252245	0.578530661	0.742937109	0.759837674	0.799774956	0.458580677
SCAT	0.825057655	0.881054914	0.712854414	0.563459535	0.606190677	0.62118898	0.669120112	0.4/1325114	0.76729836	0.6656/58/1	0.76164748	0.47989705
SCB	0.706656497	0.803244544	0.654230617	0.742279564	0.697881342	0.794538247	0.682039286	0.325024208	0.625827345	0.307628916	0.731270935	0.324642849
SCHTR	0.180195154	0.652670665	0.494485122	0.324691625	0.429650198	0.539499724	0.453065013	0.207962054	0.494466526	0.407687641	0.718245585	0.314062864
SCMCSA	0.662811398	0.816221816	0.676545103	0.531310343	0.643953543	0.735970284	0.591605147	0.326204277	0.559635995	0.538652222	0.807857249	0.459440614
SCOP	0.865551164	0.818077662	0.708186855	0.62509935	0.578606532	0.611127828	0.528734501	0.320396971	0.613575161	0.475392705	0.693797801	0.413696245
\$COST	0.565041604	0.69595475	0.450607185	0.582146952	0.511635635	0.633329742	0.416778064	0.267724726	0.653219029	0.551580524	0.697513609	0.521710179
\$CRM	0.565679112	0.650728454	0.509375867	0.457459982	0.567601636	0.563543986	0.54517904	0.506469745	0.7439923	0.615352181	0.677905725	0.533737731
\$CSCO	0.62825636	0.693062832	0.523439153	0.363970864	0.579000261	0.718020581	0.627187651	0.492625697	0.833517264	0.661202351	0.804987897	0.57554439
\$CV5	0.669195815	0.741102545	0.473907639	0.615732684	0.637336931	0.721450493	0.35724336	0.232506434	0.521368945	0.406078142	0.70445949	0.32303801
\$CVX	0.855307487	0.865267078	0.751694504	0.687062997	0.591499035	0.668232249	0.62618777	0.265335929	0.662314314	0.540620159	0.761762653	0.49553525
SDE	0.768227448	0.859379391	0.681421535	0.464069069	0.444954724	0.602340066	0.401457979	0.4574964	0.699856719	0.626777189	0.800968572	0.477256226
SDHR	0.824003625	0.889056549	0.735703517	0.72023916	0.757481404	0.81306891	0.661902106	0.391547831	0.772787158	0.595477159	0.77247422	0.346683926
SDIS	0.774939297	0.842286195	0.666768773	0.693854832	0.756774876	0.625926686	0.658876212	0.20408605	0.714022741	0.437472637	0.743129554	0.48315789
\$EB.			0.020037497	0.210828349	0.543209899	0.64207308	0 501642087	0.487810503	0 56673287	0 570643386	0 740583914	0 560953757
SOF	0.820024634	0.861534494	0.775000925	0.651054179	0.737878314	0.690397677	0.744410808	0.290962606	0.350127827	0.443948886	0.680325278	0.407226411
\$GUD	0.520024034	0.614285987	0.212822194	0.596761285	0.445181412	0.65605218	0.447534492	0.2672904	0.630793194	0.482012871	0.442520272	0.258465021
\$0000	0.552119075	0.014203507	0.512035154	0.350701503	0.443101412	0.03003310	0.447324495	0.2072904	0.020/52104	0.402012071	0.445350275	0.230403021
\$0000	0.045175524	0.000373029	0.405050470	0.463/09/6/	0.080575095	0.300442871	0.021910449	0.337199830	0.829595677	0.002400109	0.030021004	0.067/12/33
203	0.330349314	0.790091912	0.711294907	0.72551254	0.744087031	0.041/9/39	0.752939749	0.0145/010/	0.770055810	0.6398012	0.857210726	0.515/5/542
SHD	0.70840444	0.761780282	0.004906788	0.34501985	0.55524595	0.767490482	0.638734764	0.325999964	0.757421732	0.59087907	0.856965511	0.520290698
SHON	0.876219878	0.896411964	0.759294589	0.784285751	0.81820285	0.830118939	0.706330971	0.578839881	0.801875806	0.764934983	0.827957594	0.616579202
SIBM	0.782505038	0.784200974	0.661150977	0.443073936	0.477177053	0.737668588	0.616293402	0.279347794	0.661248705	0.648817735	0.83413909	0.29195036
SINTC	0.769681396	0.730000585	0.648999981	0.463548023	0.539224319	0.636599688	0.71245258	0.432111134	0.686045131	0.598918157	0.741099338	0.553249703
SINTU	0.592015864	0.748986047	0.646906027	0.426851618	0.662894151	0.70243933	0.723262486	0.331092888	0.772517452	0.6373716	0.852518712	0.63461565
SISRG	0.581238687	0.661409592	0.534894957	0.166991928	0.335291988	0.525525298	0.458268136	0.327404709	0.74317694	0.620136013	0.8500166	0.621762295
\$JNJ	0.661110025	0.775019768	0.598814976	0.656437735	0.667819301	0.780660471	0.525119705	0.290518259	0.582622411	0.395563617	0.762483942	0.358738159
\$JPM	0.785008674	0.852362513	0.653174661	0.716182755	0.720300436	0.845004585	0.760459702	0.598112353	0.769782306	0.703967139	0.808831573	0.503323726
\$KO	0.624167965	0.770617496	0.638416014	0.573639716	0.347901255	0.694367557	0.510555192	0.096137166	0.516787381	0.329977372	0.801785451	0.469124019
SLIN	0.769933795	0.873952253	0.728333369	0.634526551	0.72109802	0.710532107	0.662356081	0.51584155	0.648777526	0.535594653	0.870259279	0.663412834
\$LLY	0.568481866	0.688968381	0.497209288	0.533529377	0.501570348	0.562222027	0.394274991	0.242433226	0.568290367	0.407808921	0.590827962	0.226547592
\$LMT	0.676394742	0.667101246	0.661395004	0.575904038	0.569127331	0.749929129	0.359333299	0.359742085	0.575334019	0.527441545	0.726680057	0.285007623
\$LOW	0.720813837	0.680883332	0.438583176	0.58567071	0.506512606	0.705722515	0.566963343	0.363196276	0.651894297	0.504301788	0.801095901	0.467663637
\$LRCX	0.738074333	0.677871689	0.597316935	0.638723919	0.550061509	0.623015884	0.682915715	0.470703492	0.684492861	0.563458135	0.814975212	0.612323355
SMA	0.545398519	0.744673204	0.621402567	0.622005894	0.716765423	0.823828876	0.720778242	0.577989705	0.813557529	0.752928325	0.871970649	0.607099598
ŚMCD	0.661006477	0.686723346	0.494689476	0.481925578	0.489947905	0.676096053	0.468554096	0.266725061	0.429272338	0.349404991	0.797618265	0.552425129
SMDLZ	0.582731339	0.717428303	0.189189914	0.555097486	0.56082513	0.668371533	0.611266005	0.329216346	0.541506943	0.475217643	0.840995121	0.416698698
SMDT	0.650131572	0.766768845	0.710731154	0.62986359	0.62289761	0.758638848	0.481527417	0.323288412	0.714324403	0.463366177	0.802055772	0.524209309
SMMC	0.773959217	0.810880012	0.70791275	0.75549926	0.769173809	0.887163222	0.746569709	0.347641704	0.696161539	0.669424827	0.806711314	0.600982237
CLARADA	0.771163502	0.004103010	0.910342561	0.732405927	0.773963151	0.739966043	0.695317035	0.260067144	0.799675947	0 596774520	0 755559543	0.229001166
SMO	0.651961006	0.662400265	0.010342391	0.614400127	0.003767744	0.6153300043	0.03531/025	0.300007144	0.700073042	0.225059225	0.755556563	0.350003453
CAADY	0.051801906	0.002409765	0.451051968	0.614400134	0.504767744	0.015239895	0.314246206	0.190187895	0.353736014	0.335058335	0.080801533	0.350093457
OWIKK.	0.000019835	0.765509913	0.501257755	0.423383969	0.48845299	0./10922/8/	0.540939662	0.22031947	0.582285508	0.44158672	0.732805147	0.149292396
SMRNA		0.000000000							0.383746563	0.263719713	0.014126783	0.039775129
SMS	0.716674218	0.787377405	0.688324089	0.706370171	0.683794964	0.810153902	0.769056469	0.626189839	0.788828697	0.711064754	0.856111735	0.55612499
SMSFT	0.726835922	0.807156312	0.673508321	0.375148838	0.56682051	0.680784832	0.704982259	0.567163171	0.866164993	0.812331001	0.87327806	0.71158671
SNEE	0.585404943	0.786831386	0.477675984	0.548046492	0.425686357	0.54076191	0.230055701	0.013780791	0.211820412	0.123131626	0.762484794	0.456695338
SNFLX	0.236562906	0.30837759	0.195006442	0.199745744	0.331401922	0.426444596	0.362883932	0.406585727	0.680071919	0.514426736	0.480918681	0.400501859
SNKE	0.73856814	0.707897255	0.36281208	0.479065575	0.583043615	0.662518613	0.500441831	0.213154722	0.606861358	0.684497549	0.782674213	0.458621332
\$NOW			0.230918665	0.37688495	0.531529557	0.549764881	0.505927212	0.447340044	0.654224088	0.560004211	0.707140155	0.560245058
\$NVDA	0.60019022	0.632333084	0.521937884	0.461142309	0.561484568	0.524685265	0.357196563	0.350963948	0.653620913	0.698202167	0.787401096	0.582852632
SORCL	0.651933464	0.80700461	0.682403165	0.499612537	0.653178693	0.746680943	0.73445243	0.321420144	0.666970655	0.667525355	0.775360398	0.343596402
SPEP	0.614318489	0.616335076	0.518414838	0.548409369	0.495140303	0.760808822	0.509836629	0.182932444	0.411403252	0.470151922	0.832784877	0.458368569
\$PFE	0.655736775	0.784794956	0.53971819	0.565148331	0.58629575	0.715987459	0.483872049	0.344481179	0.681484352	0.487293603	0.651007424	0.005969353

\$0G	0.639699149	0 700169971	0.474977996	0.404525210	0 40075705	0 736540397	0 5017257/9	0 100003034	0.40030410	0 2010/2260	0 749673943	0 340597196
SPLD	0.9074345	0.83982175	0.724009529	0.636165277	0.611977482	0.658057049	0.572647064	0.361149694	0.511903609	0.454185792	0.819896094	0.507410869
SPA	0.677947619	0.698784604	0 52184088	0 51602346	0.525953127	0.65421736	0.446285836	0 252317974	0.289683455	0 331435671	0.780480608	0.38110024
SPNC	0.735365251	0.85512969	0.697526493	0.653378753	0.720359792	0.804095888	0.715041494	0.586010094	0.639318198	0.632247146	0.803622121	0.514077968
COVPE	0.10000202	0.00046909	0.037320433	0.033370733	0.720337172	0.600110771	0.532023748	0.453792131	0.205085086	0.641282213	0.253220126	0.577714286
SOCOM	0.504622855	0.807812376	0.667994331	0.460607669	0.566431209	0.432478703	0.604662342	0.349381704	0.645057115	0.385355253	0.752744883	0.587075546
ŚRTX	0.842581808	0.890150984	0.763417387	0.742184191	0.690061996	0.72501152	0.620264825	0.397648957	0.717198877	0.743754678	0.728608189	0.60071241
SSRUX	0.720490028	0.695887101	0.413854108	0.633565909	0.531913425	0.722123809	0.596248006	0.280993049	0.493760334	0.531557998	0.848855975	0.55772803
SSCHW	0.670661122	0.834959514	0.705524302	0.606638818	0.747065286	0.704427829	0.726714028	0.567711588	0.759128177	0.556136335	0.705881455	0.549774785
\$50GI	0.611650861	0.701962072	0.622794353	0.420755487	0.725801345	0.721896094	0.737029589	0.493623862	0.783657205	0.657762762	0.821630012	0.610860103
SSYK	0.685104206	0.79657426	0 714797889	0.697956282	0.688062187	0.747552263	0.484302027	0.420644803	0.716531891	0.55409012	0.795906578	0.673132979
\$T.	0.662362404	0.748628126	0.542507395	0.531084258	0.43506772	0.694099949	0.423390441	0.255860141	0.476408399	0.384144293	0.795182349	0.253601944
STEC	0.699474819	0.841313377	0.682533474	0.695504083	0.657917728	0.784136403	0.713963178	0.537791572	0.619080579	0.595884336	0.75402327	0.533795091
STGT	0.665418196	0.602742548	0.43864179	0.418792795	0.434240304	0.546384842	0.364507765	0.133197937	0.507612821	0.287261472	0.606208685	0.48565077
STMO	0.661169696	0.789927763	0.676191902	0.650273342	0.745400445	0.790887207	0.723323945	0.320846855	0.805766603	0.668175112	0.670460794	0.346514794
STSLA	0.194265006	0.539843939	0.385066578	0.181803489	0.454388479	0.45052069	0.389793569	0.25311534	0.394897652	0.340403761	0.475622936	0.456562995
STXN	0.726850999	0.782201601	0.715479416	0.673021287	0.658642606	0.683014801	0.699197987	0.585387341	0.703794812	0.663049211	0.861260944	0.714852436
SUNH	0.535025211	0.740183694	0.4362091	0.433809283	0.595305791	0.636356488	0.556829466	0.402862349	0.734524739	0.356045708	0.806698605	0.44366233
SUNP	0.801501524	0.831712287	0.676852469	0.698253074	0.70201375	0.693117532	0.576633908	0.47368532	0.69957848	0.608148039	0.831651362	0.592260321
SUPS	0.767570045	0.880439573	0.60587953	0.626427568	0.678930422	0.697407922	0.707925855	0.438350251	0.663002967	0.551928937	0.652512741	0.40160977
SUSB	0.76325972	0.855897053	0.744606031	0.614897256	0.757856468	0.819326334	0.767544552	0.597550908	0.689719981	0.695702543	0.761647227	0.463140136
\$V	0.499814019	0.693705785	0.571720765	0.542058676	0.639922594	0.737434204	0.72235744	0.542287622	0.848864491	0.730580861	0.904880238	0.59080397
\$VZ	0.569561445	0.692797998	0.477554567	0.446440414	0.449405779	0.713839091	0.453920087	0.209545877	0.3767486	0.26226195	0.725960865	0.197906495
SWEC	0.780839963	0.85106553	0.771802463	0.69948131	0.772890645	0.855184914	0.668152334	0.550757347	0.656803912	0.586190557	0.768105896	0.45406505
SWMT	0.494373466	0.656748772	0.3228868	0.440776142	0.463575239	0.545982801	0.325643498	0.208737028	0.494996268	0.429135413	0.55177909	0.397069144
\$XOM	0.840283166	0.863961976	0.784949457	0.676150559	0.635161151	0.727376765	0.579954078	0.342760102	0.668377973	0.634332165	0.719265935	0.440512415
SZTS				0.40682208	0.434098053	0.5178144	0.550255195	0.356243304	0.746575192	0.556654296	0.805653781	0.546175143
Avg	0.65867386	0.753764978	0.585888061	0.552805408	0.597121656	0.678034939	0.581463358	0.382457844	0.644760742	0.552961353	0.754515481	0.481331857

#### Average Daily Return Correlation By Year- S&P 100 Components

