Financial Markets and Real Economic Activity: has the Shadow Banking sector played a role in changing the relationship?

An analysis of the relationship between Financial Markets and Real Economic Activity, and the influence of the Shadow Banking sector in the United States Economy from 1953 to 2012.

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An Essay submitted to the Department of Economics in partial fulfillment of the requirements for the degree of Masters of Arts

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August 2013

Acknowledgements

I would like to thank my Supervisor, Professor Edwin Neave, for his guidance and support throughout the research and writing process. Thank you to my family and friends for their support and encouragement while I pursued this Master's program. And, of course, a big thank you to my classmates in the QED MA Class of 2013 – I couldn't have done it without all of you!

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ABSTRACT

This paper investigates the changing relationship between Financial Markets and Real Economic Activity in the United States from 1953 to 2012 by employing the use of cointegration testing, Vector Error Correction Model estimation and Ordinary Least Squares regression analysis. Using monthly and quarterly data, this paper explores the relationship between these two variables and a potential cause for the changes witnessed. Existing literature posits that while there was a relation between Financial Markets and Real Economic Activity, this relation has changed significantly since the 1980s. By extending the existing literature to include the most recent financial crisis, this paper finds that while the relationship between these two variables has weakened since the 1950s, the relationship may be improving in light of the most recent policy and regulatory changes made in the United States. Increased popularity of the Shadow Banking system and the new legislation following the 2008 Financial Crisis may be contributing factors in the breakdown and subsequent improvements in the relationship between these two variables. While Eugene Fama attributes changes and fluctuations in the relationship to real economic activity's sensitivity to changing business conditions and the influence of business cycles, this paper postulates that the economy's heavy reliance on Financial Sector health, and Financial Markets' responsiveness to regulatory and policy changes are potential explanations for the changes experienced in the relationship between Financial Markets and Real Economic Activity. Additionally, the importance and influence of financial markets and their role in the economy has grown since Fama conducted his study in 1990. Overall, the results of this paper suggest that while the once strong relationship between Financial Markets and Real Economic Activity has deteriorated, results from more recent years (following the legislative changes post-2008 Financial Crisis), including stronger OLS Regression results and potential for Granger Causality indicate a strengthening relationship that may prove to be beneficial for the health of the United States economy.

1. INTRODUCTION

Financial Market performance has long been tied to overall economic performance and health. "Black Tuesday", which occurred on October 29, 1929, was the most devastating stock market crash to hit the United States, eventually propelling the U.S. economy into the Great Depression. Similarly, a number of events and situations in financial markets in the early 2000s acted as a catalyst for the 2008 Financial Crisis. The bursting of the US housing bubble, poor stock market performance following the burst, increased bank bailouts, easy credit availability and asset securitization are just some of the events and factors that sent the U.S. into a devastating economic tailspin not experienced since the Great Depression.

The devastating economic consequences of the Great Depression and the 2008 Financial Crisis beg the question - is the relationship between financial markets and the domestic economy so strong and interconnected that poor performance in one can lead to devastation in the other? Eugene Fama, Mathius Binswanger and other notable economists have studied this relationship to understand just how much financial markets influence real economic activity and the health and performance of the overall economy. Results from their studies suggest that the relationship between financial markets and real economic activity has changed since the 1950s, and their results present differing viewpoints surrounding the behaviour of these variables. Fama's research concludes that there was a strong, statistically significant relationship between these two variables during the 1953 – 1987 time period, whereas Binswanger's results demonstrate a considerable separation beginning in 1984 lasting until 1996. Since Binswanger, however, there has been little exploration in the existing literature to investigate how the relationship between financial markets and real economic activity has changed since 1996, nor has there been much literature devoted to better understanding why this relationship may have changed so much.

The goal of this paper is twofold – to extend the analysis of Fama, Binswanger and other economists to include the 2008 Financial Crisis, as well as present a feasible explanation for the changing relationship. Using Cointegration analysis – both Johansen's Likelihood Ratio Test and the Engle & Granger Method – as well as Ordinary Least Squares Regression analysis, this paper will analyze the relationship between financial markets and real economic activity. Using the Standard & Poor's 500 Stock Price Index as a representative for financial market performance and the Industrial Production Index as a proxy for real economic activity, the relationship will be tested and compared across three different time periods:

- Fama's time period: 1953 – 1987
- Binswanger's time period: 1984 – 1997
- Additional time period: 1998 – 2012

With results to support Fama's strong relationship in the first time period, Binswanger's breakdown in the second, and evidence from the third time period to suggest that the relationship has improved slightly, this paper will take a critical look at the Shadow Banking sector and its potential role in the relationship between financial market performance and real economic activity. Specifically, the evolution of the Shadow Banking sector and the subsequent policy reformation that took place after the 2008 Financial Crisis presents a compelling argument for the changes experienced in the relationship between these two variables. Increased popularity of the Shadow Banking sector beginning in the 1980s put increased focus on financial market performance as an indicator of economic health. The relatively quick recovery of financial markets following a downswing can generate misleading economic results; real economic effects, including unemployment rates and Gross Domestic Product are not as quick to recover, and losses in these areas can persist for some time following an economic downturn. If the focus for overall economic health is based strictly on financial markets and real effects are ignored or overlooked, it may be hard to determine just how well the economy is performing. Increased use of securitization in the shadow banking sector gave financial institutions the ability to group lower quality loans with higher quality loans and package these off to investors as safe investments. When the housing bubble burst, a number of securitized assets containing lower quality mortgages defaulted. Additionally, some banks who were not able to meet the needs of their depositors were not offered liquidity support; some banks, like Bear Stearns and Lehman Brothers were allowed to fail and declare bankruptcy. Together, these events created a toxic economic environment that eventually developed into the worst financial crisis since the Great Depression. The legislative reforms and policy changes following the 2008 Financial Crisis are an important consideration – the Dodd Frank Wall Street Reform Act aims to rein in Shadow Banking activity to protect the economy while still allowing financial institutions to operate in the Shadow Banking sector. Policy changes and legislative reform have abandoned the ideology that financial markets alone predict economic health, and instead governments are beginning to focus on the performance of real economic variables in addition to financial markets. This realization could be part of the reason for a somewhat improved relationship between financial markets and real economic activity.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature; Section 3 outlines the Data and Methodology used; Section 4 presents the results; Section 5 discusses the results and the influence of the Shadow Banking sector; Section 6 concludes.

2. LITERATURE REVIEW

In 1990, Eugene Fama's work - *Stock Returns, Expected Returns and Real Activity* - was among the first to econometrically tackle the complicated relationship between financial markets and economic activity. Fama's results indicate that the relationship between future real economic activity and financial markets (specifically stock prices and industrial production) is undeniably strong[1]. Industrial Production is a real economic variable that Fama uses as a proxy for shocks to expected cash flows; he found that this real variable provided as much or more return variation for expected cash flows than any other real variable[2], and thus he uses industrial production throughout his work as a means of measuring shocks to expected cash flows, and to represent real economic activity. Fama argues that understanding shocks to expected cash flows, time-varying expected returns, and shocks to expected returns allowed for a more thorough evaluation of the rationality of stock prices, and thus their role in standard valuation models used in financial markets. From there, Fama outlines standard valuation models and their role in financial markets, specifically how explaining variation in stock returns can be related to real economic activity.

Fama posits that industrial production growth rates, when regressed on lagged values of stock returns, should have explanatory power on future production rates[3]. He goes on to show that using monthly/quarterly/annual data does not change the significance of the explanatory power (but concludes that monthly data yields the weakest predictor power), and concludes that real economic activity has stronger explanatory power for stock return variations over longer time horizons, regardless of the time variable (i.e. monthly vs quarterly vs annual) used[4]. Fama then runs a number of tests after introducing

[1] Fama, E. *Stock Returns, Expected Returns and Real Activity.* Journal of Finance. 1990. p. 1093
[2] ibid p. 1092
[3] ibid. p. 1096
[4] ibid p. 1092

new variables (changes in term structure, dividend yields etc.) that provide further support for his theory of the explanatory power of stock returns on industrial production. He then relates these results to consumption smoothing theories – an important argument to support Fama's theory. The general conclusion of Fama's results is that expected returns vary based on business conditions; expected returns are high when times are tough and vice versa[5]. Assuming output varies with business conditions, Fama's results suggest that if the "marginal return on capital declines with the level of investment, the desire to save more when income is high lowers the expected returns on securities"[6]. Saving more when income is high is a characteristic of consumption smoothing, and since Fama's results are related to business conditions, his results are then consistent with asset pricing and consumption smoothing theory. Overall, Fama's work suggests that a large fraction of the changes in stock returns can be explained by their relationship with industrial production[7], and he attributes the relationship to the importance of business cycles.

Fama's work inspired other economists to take a closer look at the relationship between these two variables, specifically to see how their relationship has evolved over time. Mathias Binswanger conducted two studies (2000 and 2004) that looked at real economic activity and stock market activity. In 2000, Binswanger replicated Fama's tests for United States data, but included an additional time period to better illustrate how the relationship has changed. Like Fama, Binswanger uses stock price data and industrial production data to model the relationship. Binswanger argues that real economic activity and financial market activity were more closely related in the time period Fama studied, but the relationship began to deteriorate in the 1980s as a result of different stock market booms and other activity in financial markets; Binswanger does not subscribe to Fama's view of business cycles and their influence, but instead believes that financial markets and their influence in the overall economy plays a larger factor. His 2004 study

[5] Fama, E. *Stock Returns, Expected Returns and Real Activity.* Journal of Finance. 1990. p. 1096
[6] ibid 1105-6
[7] ibid 1107

expands on his work done in 2000 by analyzing data from the G7 countries. Binswanger also incorporates tests for cointegration in his second paper to support his theory further.

Binswanger's 2000 paper – *Stock Market Booms & Real Economic Activity: Is this time different?* – outlines the two major stock market booms experienced by the United States in the post-World War II era; the first boom took place from the late 1940s to the early 1960s, and the second boom, which began in 1984 and lasted until 1997[8]. The first boom was covered in Fama's paper and his results suggest that stock returns led real economic activity until 1983. Binswanger postulates that the data from the time period of the second stock market boom suggests that the same relationship no longer exists; stock returns no longer lead real economic activity, and predictable return variations as a response to business conditions (the consumption smoothing argument and supporting results) cannot be detected[9]. The two growth periods tested by Binswanger generate different empirical results – the first time period (which is used to confirm Fama's results) indicates that results may have been driven by expectations of real activity, whereas the second boom period does not draw the same conclusion about expectations. The most important conclusion drawn by Binswanger's paper was the breakdown in the relationship between stock returns and real economic activity. His results indicate that the correlation between real activity and stock prices is statistically insignificant in the second boom period[10]. Binswanger does not offer much theoretical explanation for his findings; instead, he focuses heavily on the econometrics of the paper and how these results compare to those found by Fama.

Binswanger concludes that Fama's results do not hold for the time period following 1984[11]. However, these results only covered one of the channels through which real activity is [supposed to be] related to stock returns. As outlined by Fama, and again by Binswanger, the two channels through which these variables are related are:

[8] Some tests use 1982-1984 as a sub period, but Binswanger notes that following a Chow test, a structural break was detected in 1984, and thus he considers the official starting period for the tests to be in 1984.
[9] Binswanger, M. *Stock Market Booms & Real Economic Activity: Is this time different?* International Review of Economics and Finance. 2000 p.387
[10] ibid p. 396
[11] ibid

1. Expected growth rates of real activity can have a positive effect on future cash flows, which will increase stock prices[12]
2. A forecastable variation of future returns by variables that correlate with business conditions, and thus with real economic activity[13]

The first channel was tested by Fama and Binswanger – both found significant results for the first time period, but Binswanger did not generate statistically significant results for the second time period. The second channel was also tested by Fama, and is illustrated through his consumption smoothing argument and the supporting results. Recall that Fama used dividend yields and interest spreads in his analysis of the second channel to support this consumption smoothing argument[14]. Binswanger goes on to note that this analysis depends heavily on theoretical considerations of intertemporal market equilibrium models – these models suggest that stock returns and GDP are negatively related. Additionally, consumption smoothing behaviour can be explained by consumption functions where risk aversion increases as income decreases[15]. Binswanger then relates risk aversion to risk premia to better explain to the reader how the second channel is empirically tested. According to Binswanger, if income decreases, consumers will demand a higher risk premium; thus, risk premia are positively related to risk aversion[16]. Chen (referenced by both Fama and Binswanger) found that if the recent growth rate of the economy was used as a proxy for economic health, risk premiums should show negative correlations with the recent growth rates[17]. As was noted previously, Fama had strong results supporting this theory, while Binswanger's tests yield mixed results.

Overall, Binswanger's work confirms the strong leading relationship between stock returns and real economic activity for the time period also covered by Fama's work, but his results conclude that

[12] Binswanger, M. *Stock Market Booms & Real Economic Activity: Is this time different?* International Review of Economics and Finance. 2000 p. 396
[13] ibid
[14] ibid
[15] ibid p. 400
[16] ibid
[17] ibid p. 402

beginning in the 1980s, this relationship began to deteriorate. He attributes this breakdown to the possible effects of speculative bubbles in the economy, but he does not develop this statement further.

In 2004, Binswanger published another paper on this topic – *Stock Returns and Real Activity in the G7 Countries: Did the Relationship Change During the 1980s?* – which took the tests and results of his original [2000] paper and extended the analysis to the G7 countries. He also introduces cointegration analysis for this paper and focuses on Vector Error Correction Models and Ordinary Least Squares Regression analysis of the two variables. Binswanger (2004) takes a simpler approach to the question at hand, but generates interesting results that provided the foundation and inspiration for the work done in this essay.

Recall that Binswanger (2000) suggested that the traditionally strong relationship between stock returns and real activity has disappeared since the 1980s[18]. Since then, Binswanger suggests that financial markets have not led real economic activity in the U.S., as his results failed to establish a significant relationship between stock returns and industrial production[19]. Binswanger (2004) postulates that this breakdown is likely true for countries outside of the U.S., and thus extends his analysis to the G7 countries for the time period of 1960 to 1999[20]. Binswanger (2004) uses stock price indices, Industrial Production Indices, the Consumer Price Index and Gross Domestic Product data for the G7 countries.

Binswanger (2004) uses both the Johansen test for cointegration and the Engle and Granger method of testing for cointegration. His results conclude that industrial production and stock prices were not cointegrated in all of the G7 countries. When testing for cointegration, the null hypothesis is that no cointegration exists. In the cases of the U.S., Canada, France and Germany, the null hypothesis could not be rejected (i.e. no cointegration exists in these countries for the time period tested), whereas the null

[18] Binswanger, M. *Stock Returns and Real Activity in the G7 Countries: Did the Relationship Change During the 1980s?* Quarterly Review of Economics & Finance. 2004. p. 238
[19] ibid
[20] Note: the beginning of this time period includes the end of the first economic boom noted in Binswanger (2000). In this paper, Binswanger hopes to confirm Fama's results for the 1960s, and his own results for the period after 1980.

could be rejected for Japan and the aggregate European G7 countries (i.e. there is a cointegrating relationship between stock prices and industrial production in these countries). Binswanger then uses Ordinary Least Squares regression analysis to clear up the confusion encountered when testing for cointegration. When a cointegrating relationship does not exist (i.e. for U.S., Canada, France & Germany), a Vector Error Correction Model cannot be estimated[21]; without a VECM, changes in the relationship over time cannot be analyzed. As such, Binswager uses OLS to acquire statistical information about the relationship between the two variables, and uses the results from the regressions to quantitatively illustrate how the relationship has changed. The regression results corroborate Fama's findings for the 1960 -1999 time period, but for sub sample time periods of 1983 – 1999 and 1989 – 1999, results indicate that no statistical relationship exists between stock price returns and industrial production in the U.S., France, Japan and the G7 European aggregate[22]. The strength of the relationship between the two variables from 1960 – 1982 is strong enough to generate results that indicated a statistically significant correlated relationship throughout, but breaking down the sample into different time periods helps to illustrate the breakdown in the relationship between the two variables. Overall, Binswanger's (2004) study of the cointegrating relationship between financial markets and real economic activity supports his analysis of the U.S. economy from his previous work – "Since the 1980s stock markets do not lead real economic activity as regressions fail to establish any significant relation between stock returns and growth rates of real activity"[23]. Binswanger's work calls readers and economists to think more critically about how this changing relationship will affect domestic and global economies over time.

Jongmoo Choi, Shmeul Hauser and Kenneth Kopecky conducted research similar to Fama and Binswanger (2004) to evaluate the cointegrating relationship in the G7 countries. Their paper *Does the Stock Market Predict Real Activity?: Time Series Evidence from the G7 Countries* covers the time period

[21] Gregory, A. (2013). *ECON 853 Lecture Notes Chapter 11: Cointegration.* Queen's University Economics Department.
[22] Binswanger, M. *Stock Returns and Real Activity in the G7 Countries: Did the Relationship Change During the 1980s?* Quarterly Review of Economics & Finance. 2004. p. 243
[23] ibid p. 248

tested by Fama, and also extends the analysis to 1996 to include some of the data tested by Binswanger. Testing for cointegration, as well as conducting in and out of sample forecasts, Choi et. al. found that a cointegrating relationship exists between the two variables over the tested time period. Choi et. al. use these results to test for predictability power through sample forecasts and find that only four countries (U.S., Japan, Canada, France and Germany) generated forecasts that support the hypothesis that stock price returns can predict industrial production values[24]. Unlike Binswanger (2004), Choi et. al. do not break down their time period further to analyze cointegration over a number of sub samples. Nevertheless, their work contributes to a growing literature base for this specific topic, and their use of forecasting and ARIMA modelling also introduces a new facet of analysis to the problem.

The works of Fama and Binswanger provided the inspiration for this essay. Their work, and their varying analytical methods for tackling the problem at hand, has posed an interesting question that will become increasingly important as domestic and global economies continue to grow and change. Globalization and advanced financial technologies allowed for much more sophisticated relationships to develop and change in the economy, and also contributed to changes experienced in what were previously considered to be predictable and straightforward economic relationships. The goal of this essay is to not only analyze time periods and data similar to those covered by previous researchers, but also to extend the analysis to incorporate the most recent financial crisis, as well as to postulate potential reasoning for the changes experienced in recent years.

3. DATA & METHODOLOGY

To examine the relationship between financial markets and real economic activity, data sets similar to those used by Binswanger (2004) were compiled. Closing prices of the Standard and Poor's 500 (SP500) stock index, seasonally adjusted Consumer Price Index (CPIAUSCL) data and seasonally adjusted Industrial Production Index (INDPRO) data were collected. The stock price index data, the CPI data and

[24] Choi, J. Hauser, S., Kopecky, K. *Does the Stock Market Predict Real Activity?: Time Series Evidence from the G7 Countries.* Journal of Banking and Finance. p. 1791

Industrial Production Index data were collected from the Federal Reserve of St. Louis. Nominal closing stock prices were converted into real closing prices by dividing by the CPI, and all of the statistical and econometric tests conducted in this paper used natural log levels of real stock prices and industrial production. There are three time periods being tested:

1. The first time period (Fama), which looks at data from 1953 – 1987
2. The second time period (Binswanger), which looks at data from 1984 – 1997
3. The third time period looks at data from 1998 – 2012 (Note that this time period contains periods of rapid growth, a severe crash and a prolonged recovery period. More details on the sub-periods are outlined below)

Each time period was evaluated to determine whether a cointegrating relationship existed between stock prices and industrial production. Additionally, real economic activity was regressed on stock prices in each time period to better understand how the relationship between the two variables has changed over time. The first two time periods are evaluated in this paper in order to generate results consistent with those found by Fama and Binswanger, while the third time period allows for extended analysis of the relationship between the two variables in a more recent time period.

The credibility of monthly financial market data for leading monthly real economic activity was debated by both Binswanger and Fama. Both found that while monthly data produces results consistent with their ideologies, it was not as strong as quarterly data in predicting future behaviour. As such, in this paper, both monthly and quarterly data sets have been used. The results for both will be analyzed and compared across the three time periods, but in cases where the monthly and quarterly results conflict, quarterly results will be used for comparisons across time periods. .

3.1 TESTING FOR COINTEGRATION

Cointegration was developed by Clive Granger and Robert Engle to tackle problems involved when using linear regression models to try and fit non-stationary data. Even if data is combined with conventional de-

trending techniques it can still be non-stationary and linear regression results often contain spurious correlation as a result. The methodology of cointegration is essential when comparing and testing data sets that have unit roots present. Cointegration models are also used in econometrics to allow economic models to have long run components of variables that not only obey the constraints of economic equilibrium, but also have flexible, dynamic specifications when not in equilibrium[25].

Cointegration is a commonly used econometric tool to represent the relationship between two variables that share a common stochastic drift. Consider, for example, two time series variables - x_t and y_t - both of which follow some non-stationary process. The variables can be considered integrated of order d if differencing the data d times yields a stationary process for each of the variables. If x_t and y_t are both $I(1)$ - integrated of order one – it is possible to test for a cointegrating relationship between the two variables[26]. Generally, when two variables are $I(1)$, some linear combination of these variables will also yield an $I(1)$ process. If, however, these variables are cointegrated, they will generate an $I(0)$ process. That is, two time series variables integrated of order one are considered to be cointegrated if the process generated by some linear combination of the two is **stationary**.

x_t and y_t are $I(1)$ if:

$$x_t = x_{t-1} + e_t \text{ and}$$

$$y_t = y_{t-1} + e_t$$

Thus, when x_t and y_t are cointegrated, the following process is generated:

$$u_t = y_t - \beta x_t$$

[25] Gregory, A. (2013). *ECON 853 Lecture Notes Chapter 11: Cointegration.* Queen's University Economics Department.
[26] Variables that are integrated of different orders cannot be linearly combined to produced an I(0) – stationary – process. Thus, in order to conduct cointegration analysis, all variables must first have the same order of integration.

where u_t is $I(0)$. That is, u_t is an independently and identically distributed process with a mean of zero and a variance of σ_u^2. The e_t's are stationary and independently distributed of u_t. It's also important to note that the OLS estimation of the β of a cointegrated relationship is consistent and has an asymptotic normal distribution.

Once it has been determined whether or not the two variables being tested are integrated of the same order, cointegration testing can begin. There are two common methods for testing for cointegration – the Johansen Likelihood Ratio Test, and the Engle & Granger method. Both methods will be used to test each time period for cointegrating relationships.

3.1.1 The Johansen Likelihood Ratio Test for Cointegration

Suppose the data generating process is

$$\Delta z_t = \Gamma_1 \Delta z_{t-1} + \Gamma_2 \Delta z_{t-2} + \ldots + \Gamma_m \Delta z_{t-m} + \upsilon_t$$

The Johansen Likelihood Ratio Test tests the rank of Γ_m, which will dictate the degree of cointegration between the variables[27]. If the rank of Γ_m is 0, the variables are not cointegrated. If the rank of Γ_m is 1, there is one cointegrating relationship, and so on.

3.1.2 The Engle &Granger Test for Cointegration

If a series is cointegrated, then a linear combination of the data produces a stationary process:

$$y_t - \beta x_t = \mu_t$$

Since the process of μ is not usually known, β must be estimated using OLS, and then used to estimate the series μ and perform stationarity tests on this estimated data. The Engle and Granger method regresses one variable on the other, and then estimates the residuals (μ) and determines whether or not the residuals

[27] Gregory, A. (2013). *ECON 853 Lecture Notes Chapter 11: Cointegration.* Queen's University Economics Department.

of the regression are stationary; stationary residuals will indicate a cointegrating relationship between the variables.

3.2 VECTOR ERROR CORRECTION MODELS

Once a cointegrating relationship is established, it can be determined how the variables will influence each other over the long run. Cointegration, however, gives little to no information regarding the behaviour of cointegrated variables over the short run. A Vector Error Correction Model (VECM) helps to fill this void and depicts how cointegrated variables will behave together over the short run. A VECM takes on the following form:

$$\Delta y_t = v + \prod y_{t-1} + \sum_{i=1}^{p-1} \Gamma \Delta y_{t-i} + \epsilon_t$$

Letting $\prod = \alpha\beta'$, where α is a vector of short run adjustment parameters and β is a vector of the the coefficients of cointegration. $\prod$ has rank *r*, where *r* represents the number of cointegration vectors[28]. If *r* = 0, there are no cointegrating vectors. Additionally, v can be ignored since it is just a vector of parameters. As such, the VECM becomes:

$$\Delta y_t = \alpha\beta y_{t-1} + \sum_{i=1}^{p-1} \Gamma \Delta y_{t-i} + \epsilon_t$$

The α term represents the speed of adjustment to equilibrium, and βy_{t-1} is the error correction element, and is often used when constructing the cointegrating equation[29].

A VECM can only be estimated when a cointegrating relationship exists. The results of the VECM can illustrate how the two variables are related; for the purpose of this paper, the results of the VECM can

[28] Becketti, S. *Cointegrating Relationships and VECMs*. Introduction to Time Series using Stata. 2013. p. 387-392
[29] Bath University. (2009). *Estimating a VECM in Stata.* http://staff.bath.ac.uk/hssjrh/VECM%20STATA.pdf

help to understand how the relationship between financial markets and real economic activity has changed over time, and whether or not the relationship has experienced a breakdown.

If, however, a cointegrating relationship does not exist, Ordinary Least Squares regression results can be used to observe the change in the relationship between the variables over time.

3.3 OLS REGRESSION ANALYSIS

In the case that a cointegrating relationship is non-existent, OLS can be used to estimate the coefficient relating the variables and evaluating the regression results can help to explain the weakening/strengthening of the connection between financial markets and real economic activity. It is assumed that the reader has an understanding of the theory behind Ordinary Least Squares. As such, it will not be outlined here.

Similar to the methodology used by Binswanger (2004), regressing real economic activity on stock prices (i.e. real economic activity is the dependent variable, and stock price the independent) for the three different time periods being tested will illustrate if real economic activity is reliant on stock prices, and how this reliance has changed since the 1950s.

4. RESULTS

4.1 COINTEGRATION TESTING AND RESULTS

Using both the Johansen Likelihood Ratio Test and the Engle & Granger method, the data set for each time period is tested for cointegration between stock prices and industrial production. Cointegration is tested for both monthly data and quarterly data.

Before cointegration testing can begin, unit roots must be tested for. The Augmented Dickey Fuller test is a common unit root test. Dickey Fuller tests the null hypothesis that the process possesses a unit root. A

process containing a unit root is considered non-stationary. Table 1 below details the results of a Dickey Fuller test conducted on the leveled data.

Table 1: Dickey Fuller Unit Root Test Results

Levelled Data				
Variable		**Time Period 1 (1953 - 1987)**	**Time Period 2 (1984 - 1997)**	**Time Period 3 (1997 - 2012)**
S&P 500 Closing Price	Monthly Data	0.8966	0.6908	0.9924
	Quarterly Data	0.2559	0.7959	0.7959
Industrial Production	Monthly Data	0.8823	0.9927	0.249
	Quarterly Data	0.986	1.000	0.4576

From the results above, all three time periods (for both monthly and quarterly data sets) possess a unit root. The values in the table are the p values from testing the null hypothesis, and the high values indicate that the null hypothesis cannot be rejected at the 10%, 5% or 1% levels. Thus, the data must be stationarized, and then retested for unit roots.

A common technique used in econometrics to stationarize a data set is the first difference operator. Each variable was first differenced for its monthly and quarterly levels, and the Dickey Fuller test was conducted on the differenced data to determine stationarity. The results are detailed in Table 2 below.

Table 2: Dickey Fuller Unit Root Test Results

First Differenced Data				
Variable		**Time Period 1 (1953 - 1987)**	**Time Period 2 (1984 - 1997)**	**Time Period 3 (1997 - 2012)**
S&P 500 Closing Price	Monthly Data	0.000	0.000	0.000
	Quarterly Data	0.0001	0.000	0.0015
Industrial Production	Monthly Data	0.000	0.0002	0.0529
	Quarterly Data	0.000	0.0014	0.0028

These results indicate that both variables, for both monthly and quarterly observations, in all time periods are stationary; low p values from the Dickey Fuller test indicate that the null hypothesis can be rejected, meaning that the process does not possess a unit root.

4.1.1Johansen Likelihood Ratio Test for Cointegration

Recall that in order to test for cointegration, variables being tested must be integrated of the same order. Since applying the differencing operator to both variables once, this means that both the S&P500 Closing Price and Industrial Production are *I(1)* – both are integrated or order one. From here, testing for a cointegrating relationship begins.

Optimal lag selection for cointegration testing is based on the Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (SBIC) and the Hannan Quinn Information Criterion (HQIC). For some of the time periods, the results of the lag selection criterion were mixed (e.g. AIC would suggest 2 lags is optimal while HQIC and SBIC would suggest 4 lags). A paper from the Centre for Economic Policy Research suggests that when the lag selection options differ, considering the properties underlying data is important. The paper concludes that for quarterly data with more than 120 observations the HQIC is the most accurate lag selection criterion to consider, while the AIC criterion is the most accurate for monthly data; SBIC tends to be accurate regardless of the underlying characteristics of the data[30]. As such, HQIC was used for lag selection of quarterly data in each time period (since there are more than 120 observations in each period), and AIC for monthly data. The table below details the optimal lags used for each variable.

Table 3: Optimal Lag Selection

Optimal Lags to test for Cointegration			
	Time Period 1 (1953 - 1987)	**Time Period 2 (1984 - 1997)**	**Time Period 3 (1997 - 2012)**
Monthly Data	2	4	4
Quarterly Data	3	2	3

The Johansen Likelihood ratio test was conducted using the optimal number of lags suggested for each time period. To test for cointegration, Johansen constructs two likelihood-ratio tests: the trace statistic and

[30] Reyna-Torres, O. (n.d.). *Time Series.* Princeton University Data & Statistical Services. http://dss.princeton.edu/training/TS101.pdf

the eigenvalue statistic[31]. Both of these statistics are used determine to the appropriate number of cointegrating equations for each time period tested. The results are summarized below.

Table 4: Johansen's test for cointegration results

Time Period 1 (1953 - 1987) MONTHLY				
Maximum Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
0	3706.29	.	28.9555	15.41
1	3720.08	0.06209	1.3908*	3.76
2	3720.77	0.00323		
Time Period 1 (1953 - 1987) QUARTERLY				
Maximum Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
0	1093.09	.	15.44	15.41
1	1100.64	0.1008	0.3529*	3.76
2	1100.82	0.00248		
Time Period 2 (1984 - 1997) MONTHLY				
Maximum Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
0	1728.98	.	15.2302*	15.41
1	1735.85	0.07931	1.5131	3.76
2	1736.6	0.00907		
Time Period 2 (1984 - 1997) QUARTERLY				
Maximum Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
0	531.35	.	4.2579*	15.41
1	533.19	0.0658	0.5824	3.76
2	533.48	0.1073		
Time Period 3 (1998 - 2012) MONTHLY				
Maximum Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
0	592.09	.	6.6898*	15.41
1	595.3	0.10834	0.2681	3.76
2	595.44	0.00478		
Time Period 3 (1998 - 2012) QUARTERLY				
Maximum Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
0	584.61	.	14.2857*	15.41
1	590.79	0.19199	1.9211	3.76
2	591.75	0.03258		

The Trace Statistic values with an asterisk (*) correspond to a specific rank value – this rank value represents the number of cointegrating equations for each time period tested. For both quarterly and

[31] Becketti, S. *Cointegrating Relationships and VECMs*. Introduction to Time Series using Stata. 2013. p. 387-392

monthly data sets, the results above indicate that a cointegrating relationship exists between financial markets and real economic activity only in the first time period (Fama's time period). In the second time period, much like Binswanger's findings, there is no cointegrating relationship. Results for the third time period indicate that no cointegrating relationship existed between 1998 and 2012.

Considering the third time period covers two periods of significant economic growth (the Dot Com bubble and the run up to the 2008 Financial Crisis), a significant recession (the 2008 Financial Crisis), and the recovery period following the bubble burst and the recession, there may be some merit in examining sub-periods for the third time period. Performing the same tests above on sub-sample periods may generate results to help better understand why no cointegrating relationship exists in this period. By breaking the time period down into four sub samples – 1997 to 2000 (the Dot Com bubble period), 2000 to 2005 (Dot Com Recovery), 2006 to 2009 (2008 Financial Crisis) and 2010 – 2012 (2008 Financial Crisis recovery period) – the Johansen Likelihood Ratio test for cointegration is rerun for each sub-period. Using the same trace statistic analysis used above, the tests concluded that no cointegrating relationship exists in any of the sub sample time periods for both monthly and quarterly data.

Considering again the results for all time periods, the results indicate that a VECM can only be estimated for the first time period. The results of the estimated monthly and quarterly VECMs for time period one are below.

Period 1 VECM Results - Monthly

D_indpro	L._ce1	0.000
		(0.00)
	LD.indpro	0.416
		(9.44)**
	LD.sp500	0.629
		(1.39)
	_cons	0.002
		(3.19)**
D_sp500	L._ce1	-0.001
		(5.30)**
	LD.indpro	-0.000
		(0.05)
	LD.sp500	0.110
		(2.31)*
	_cons	0.000
		(0.16)
N		430

* p<0.05; ** p<0.01

Period 1 VECM Results – Quarterly

D_indpro	L._ce1	0.01
		(1.21)
	LD.indpro	0.337
		(4.55)**
	LD.sp500	4.76
		(4.95)**
	_cons	0.000
		(0.06)
D_sp500	L._ce1	-0.002
		(-3.65)**
	LD.indpro	-0.011
		(-1.98)*
	LD.sp500	0.542
		(7.56)**
	_cons	0.001
		(3.40)**
N		142

* p<0.05; ** p<0.01

Recall that the VECM has the form:

$$\Delta y_t = \alpha\beta y_{t-1} + \sum_{i=1}^{p-1} \Gamma\Delta y_{t-i} + \epsilon_t$$

With the results above, the VECM for the monthly data can be characterized by the following equations:

$$\Delta(indpro)_t = 0(\beta\, indpro)_{t-1} + 0.002(\beta\, sp500)_{t-1} + 0.416(indpro) + 0.629(sp500) \quad (1)$$

$$\Delta(sp500)_t = -0.001(\beta\, sp500)_{t-1} + 0(\beta\, indpro)_{t-1} + 0.110(sp500) - 0(indpro) \quad (2)$$

Similarly, the VECM for the quarterly data can be characterized by the following equations:

$$\Delta(indpro)_t = 0.01(\beta\, indpro)_{t-1} + 0(\beta\, sp500)_{t-1} + 0.337(indpro) + 4.76(sp500) \quad (3)$$

$$\Delta(sp500)_t = -0.002(\beta\, sp500)_{t-1} + 0.001(\beta\, indpro)_{t-1} + 0.542(sp500) - 0.011(indpro) \quad (4)$$

The equations above illustrate the relationship between the variables over the short run. Specifically, the first two terms in each equation represents how the variables are related through time. The coefficients on the first two terms in each equation determine whether the variables are positively or negatively related. If the coefficient on one of the first two terms is zero, the estimated VECM indicates that there is no relationship between the two variables.

The Error Correcting term is represented by the βy_{t-1} term in the VECM, where y_{t-1} is the variable under consideration (i.e. indpro or sp500). This term illustrates the relationship between the variables over the **long run,** and will also help to define the cointegrating equations as estimated by the VECM. The cointegrating equations for monthly and quarterly results are below.

Monthly:

$$indpro_t = indpro_{t-1} + 7.23(sp500)_{t-1} - 4.714 \quad (5)$$

$$sp500_t = sp500_{t-1} + 7.23 indpro_{t-1} - 4.714 \quad (6)$$

Quarterly:

$$indpro_t = indpro_{t-1} + 7.66(sp500)_{t-1} - 3.549 \quad (7)$$

$$sp500_t = sp500_{t-1} + 7.66 indpro_{t-1} - 3.549 \quad (8)$$

Equations (5) through (8) demonstrate the cointegrating equations as defined by the estimated VECM. There is a variety of post-estimation testing that can be applied to the VECM and cointegrating results

obtained above. The post-estimation results will reveal more characteristics about the cointegrating relationship between these two variables in the first time period. However, since no cointegrating relationship exists in any other time period, post-estimation testing would provide no knowledge about how the relationship between these two variables has changed over time. As such, post-estimation tests will not be conducted.

From here, the above cointegration results for all time periods will be compared with the Engle & Granger method, followed by OLS regression analysis.

4.1.2 Engle & Granger Test for Cointegration

Recall that the Engle and Granger method regresses one variable on the other and estimates the residuals (μ). If the Augmented Dickey Fuller test results for the residuals indicate that no unit root is present, then the process generated by the variables is stationary. Engle & Granger take stationary residuals to indicate that a cointegrating relationship exists between the variables being tested. The dependent variable (industrial production) was regressed on the independent variable (S&P500 closing price), for each time period, residuals were estimated and then the Dickey Fuller test was used to determine if the residuals possessed a unit root. The Dickey Fuller results are summarized below.

Table 5: Dickey Fuller Test Results for Residuals

Time Period	Monthly Results	Quarterly Results
1: 1953 - 1987	0.0057	0.0023
2: 1984 - 1997	0.9946	0.9970
3: 1998 - 2012	0.0229	0.0796

Recall that low p values indicate that the null hypothesis of unit roots can be rejected, indicating that the process generating the results is stationary. The results above are consistent with those observed using the Johansen Likelihood Ratio test for Cointegration. In period 1, the residuals for both monthly and quarterly values indicate that the residuals are stationary, meaning that a cointegrating relationship exists. However,

for time periods two and three, the high p values indicate that the process contains a unit root, meaning that the likelihood of a cointegrating relationship existing is low. Overall, the Engle & Granger results are consistent with those found using the Johansen Likelihood ratio test method, indicating that the cointegrating relationship that once existed between these two variables is not longer existent, but that the relationship has gained strength in recent history.

4.2 REGRESSION RESULTS

Similar to the tests used in Binswanger (2004), OLS was used to quantify the relationship between financial markets and real economic activity where cointegrating equations did not exist. Additionally, OLS was used to analyze the first time period as well (even though it had a cointegrating relationship) to allow for quantitative comparisons of the relationship between the two variables over time. The OLS regression can be represented by the following equation:

$$y_i = \beta x_i + \varepsilon$$

Where y_i represents the vector of industrial production values, x_i represents the vector of S&P500 closing price values, and β is the coefficient being estimated to determine the relationship between the two variables. This regression is run for each time period, and for monthly and quarterly values. Some important results from the regressions are summarized below.

Table 6: Regression Results

Time Period		Monthly Results	Quarterly Results
1: 1953 - 1987	Adj R^2	0.6771	0.0435
	Std. Error	0.2900603	0.9861
	F test	0.00	0.0071
2: 1984 - 1997	Adj R^2	0.0074	0.0076
	Std. Error	0.11858	2.3490
	F test	0.1368	0.2401
3: 1998 - 2012	Adj R^2	-0.0052	0.0797
	Std. Error	2.018	5.1439
	F test	0.7889	0.0200

Adj R^2 represents the Adjusted R^2 value for each regression; Std. Error represents the Standard Error and the F test value is the p value which represents the probability that the coefficient on stock price data is equal to zero

The Adjusted R^2, Standard Error and F test results are some of the most important values when interpreting regression results. The R^2 value represents the percentage of variation in the dependent variable that is explained by the model; the Adjusted R^2 accounts for errors as a result of the inclusion of too many variables. If the absolute value of the Adjusted R^2 is low, this generally indicates that there is a weak correlation between the variables being regressed. The standard error is the standard deviation value; lower standard deviation values indicate that there is not much variation from the expected value of the regression. The F test value is the p value that tests the probability that the coefficient on stock price returns is equal to zero; a higher value indicates that the coefficient is more likely to be equal to zero, indicating that there is a weak/non-existent relationship between the two variables being regressed.

The results from the first time period support both the results found by Fama and Binswanger. The Adjusted R^2 values for both the monthly and quarterly results in the first time period are relatively high, indicating strong correlation between the two variables. Similarly, the low F test values indicate that the probability of the coefficient on stock price data being zero is low, meaning that there is some relationship

that exists between the two variables. Finally, the standard error values are low indicating limited variation around the mean in the model.

Comparatively, the results for the second and third time periods paint a different picture about the relationship between the two variables. In both these cases, low adjusted R^2 values and relatively high p values indicate a very weak relationship between real economic activity and financial markets, for both monthly and quarterly data sets. However, comparing the F test values for monthly and quarterly results across the last two time periods generates some conflicting interpretations. Looking at monthly results, the F test values indicate that the relationship between the two variables has deteriorated further from 1998 onward, whereas the quarterly results indicate a slight improvement in the relationship beginning in 1998. Keeping in mind that Fama and Binswanger found that, although valuable for analytical purposes, monthly data does not provide results as robust as quarterly data when considering predictive power and the changes in the relationship between the variables[32]. As such, for interpretation and discussion of the changes in the relationship over time, this paper will focus on the results generated using quarterly data.

The adjusted R^2 values for both time periods are both low (when compared to the first time period), indicating a weaker relationship in more recent years. However, in the third time period, the adjusted R^2 value, while still low, is higher than the value for the second time period. This could be indicative of an improving relationship between the two variables in the third time period. The F test values for both time periods illustrate a similar observation for the second and third time periods – while the F test value for the third time period is still outside the 1%, 5% and 10% significance levels, the value is much lower than that of the second period. This means that for the third time period, the probability of the coefficient on stock price data in the regression being zero is lower than the probability of it being zero in the second period. This supports the adjusted R^2 results, indicating that the relationship may have improved in recent history.

[32] Fama, E. *Stock Returns, Expected Returns and Real Activity.* Journal of Finance. 1990. p 1098-1100

Recall that four sub-time periods of the third period were tested for cointegration - 1997 to 2000, 2000 to 2005, 2006 to 2009 and 2010 – 2012. The same regression analysis was also performed on the sub periods to determine if the strengthened relationship can be attributed to changes in most recent history. Interestingly, the Dot Com bubble and its recovery period exhibited results similar to those of the second time period; high p values, low adjusted R^2 values indicating a weak relationship between the variables. The 2008 Financial crisis period (2006 – 2009) also demonstrated these results, but with marginally stronger results. The fourth sub-period (2009 – 2012), however exhibited the lowest p values and the highest adjusted R^2 values. While the p value was still not significant at any of the standard significance levels, its value of 0.371 was still lower than those of the other three sub periods (0.481, 0.512 and 0.593 respectively). Ultimately, this suggests that the most recent time period has had an effect on these two variables, and that the strengthened relationship could be attributed to changes in the last 3-4 years.

4.2.1 Granger Causality

An interesting extension to regression analysis to consider is Granger Causality. Suppose once again that there are two time series variables – x and y. If x "Granger Causes" y, this means that past values of x provide more information about future y values than past values of y alone[33]. Inherently, Cointegration suggests that Granger Causality exists, but the direction of causality is unknown[34]. For the purposes of this paper, it will be interesting to determine if Granger Causality exists in the second and third time periods; although no cointegration relationship can be established in these time periods, perhaps there is some degree of Granger Causality that has led to an improvement in the relationship between the variables in recent years. If Granger Causality holds, this does not guarantee that stock price data causes industrial production, but it suggests that it *might* be causing it[35].

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[33] Koop, G. *Chapter 11: Regression with Time Series Variables – Granger Causality.* 2011. University of Strathclyde Department of Economics. p. 2-7

[34] Gregory, A. (2013). *ECON 853 Lecture Notes Chapter 11: Cointegration.* Queen's University Economics Department.

[35] ibid

Granger Causality must be tested using stationary data. Thus, first differenced data will be used to test for Granger Causality. Only time periods two and three will be tested for Granger Causality; period one's cointegrating relationship implies that Granger Causality already exists. To test for Granger Causality, first regress (the first differenced) industrial production data on the (first differenced) closing stock price data. Then, the p value for the coefficient on stock price data - β_1 - must be examined. If the coefficient is statistically significant (i.e. the p value is less than 0.05 for a 95% confidence interval), then stock price is said to "Granger Cause" industrial production[36]. This could mean that financial market performance may be influencing future levels of real economic activity. The table below summarizes the coefficient values as well as the p value for the coefficient on stock price in time periods two and three for monthly and quarterly results:

Table 7: Granger Causality Test Results

Time Period		Monthly Results	Quarterly Results
2: 1984 - 1997	β_1	-3.14	-2.79
	p value	0.002	0.24
3: 1998 - 2012	β_1	-0.54	12.3
	p value	0.789	0.0101

Note: $\boldsymbol{\beta_1}$ represents the coefficient value

The above results paint an interesting picture. In period 2, monthly results indicate that financial markets can Granger Cause real economic activity, whereas quarterly results for the same time period illustrate that financial markets do not Granger Cause real economic activity. The reverse is true for period 3 – monthly results suggest no Granger Causality while quarterly results suggest Granger Causality. Given the uncertainty regarding the credibility of results generated using monthly data, consider the results of quarterly results only. In time period 2, the quarterly results indicate no Granger Causality, while the time period 3 results suggest that financial markets could potentially Granger Cause real economic activity. Note that the coefficient for time period 3's quarterly results is only significant for the 90% confidence interval.

[36] Note: A joint F test is not required since this model is binomial. (Source: Koop, G. *Chapter 11: Regression with Time Series Variables – Granger Causality.* 2011. University of Strathclyde Department of Economics. p. 2-7)

These results are an important consideration for understanding how the relationship between financial markets and real economic data has evolved over time. Despite the fact that no cointegrating relationship exists in the third time period, a coefficient that is significant at a 90% confidence interval could be indicative of a stronger relationship between these two variables.

The next section of this paper will take a critical look at Shadow Banking as a potential factor in the breakdown of the relationship between financial markets and real economic activity, and it will also address how policy and regulatory changes in the Shadow Banking sector may have led to an improved relationship.

5. DISCUSSION

While Fama, Binswanger and a number of other economists have conducted research and contributed greatly to the literature surrounding the relationship between financial markets and economic activity, few have yet to offer a reason (or reasons) for how this relationship has changed over time. In both of his works (2000 and 2004), Binswanger spends the majority of his paper explaining how his research shows the breakdown in the relationship that Fama demonstrated in his previous work. Binswanger does not offer a cause for the breakdown in the relationship, and simply attributes it to "speculative bubbles and fads"[37] in financial markets. Without a comprehensive qualitative analysis to complement the quantitative analysis, it is difficult for policy makers and economists to understand how to strengthen this relationship to allow the economy to perform at its best. Financial market performance is vitally important to the health of the economy, and if the relationship between financial markets and economic activity is falling apart, governments and economic agencies should be focusing on improving the relationship to better support the economy. Despite the degradation of the relationship between the variables according to Binswanger, the economy still experienced growth during the time period covered by his study. Since this observation was made during a boom-time period, concern regarding the potential effects from this

[37] Binswanger, M. *Stock Returns and Real Activity in the G7 Countries: Did the Relationship Change During the 1980s?* Quarterly Review of Economics & Finance. 2004.. p. 402

changing relationship may have been overlooked. The third and final time period analyzed in this paper (1998 – 2012) not only encompasses the "Dot-com Bubble" of 1997 – 2000, but also covers the most devastating financial crisis since the Great Depression – the 2008 Financial Crisis. Taking a critical look at how the variables have evolved over time, while keeping in mind the economic differences between boom times and times of recession is essential for improving the relationship to ensure economic prosperity and safety.

This section of the paper will focus on offering a realistic and plausible explanation for the disparity between financial markets and real economic activity.

5.1 The Evolution of the Shadow Banking Sector

Shadow Banking, also known as Off-Balance-Sheet Financing, Maturity Transformation or Market Based Finance, evolved as a means for firms to achieve necessary financing, while still being protected through another form of deposit insurance. Increased competition from non-banks, decreased regulation and financial innovation all contributed to the growth of the Shadow Banking Sector. Shadow Banking has been growing in popularity since the 1980s, and in the early 2000s became so popular that it eventually contributed to the downfall the global economy. The lack of regulation in the Shadow Banking system is arguably one of the key contributing factors for the 2008 Financial Crisis, and increased "financialization" of the economy allowed the Shadow Banking sector to prosper. In their working paper *The Global Financial Crisis & the shift to Shadow Banking*, Nersisyan and Randall define "financialization" as "the rapid growth of leverage and financial layering [in the Shadow Banking System] allowed the financial sector to claim an ever rising proportion of national income"[38]. Essentially, Nersisyan and Randall argue that financial markets became a key area of focus in the early 2000s as a measure of economic growth, instead of traditional measures of growth such as Gross Domestic Product, Industrial Production and other real economic variables that typically illustrate growth (or lack of) in the

[38]Nersisyan, Y., Wray, R. *The Global Financial Crisis and the shift to Shadow Banking*. Levy Economics Institute Working Paper No 587. 2010. p. 2

economy. This financialization, they argue, created a false sense of security in that financial market performance was being used as a proxy for economic health, when in reality the shadow banking sector allowed financial markets to experience unprecedented gains. As a result, confidence in financial markets boomed, the shadow banking sector evolved even more, fostering fragility in financial markets, [39] which ultimately created a dangerous and risky environment.

Lack of regulation is part of the reason Shadow Banking became such a popular form of banking for many large financial institutions. The removal of interest rate ceilings in the 1970s decreased regulations surrounding banking activity, allowing banks to engage in a variety of other financial activities domestically and internationally[40]. Financial innovation in the form of derivatives, increased loan liquidity and the introduction of securitization allowed more diversified participation in capital markets[41].The Shadow Banking system was not subject to the same regulations as the Commercial Banking system, and it can be argued that a major banking panic (specifically a bank run) in the Shadow Banking sector was one of the leading causes of the most recent financial crisis. Additionally, further development of the shadow banking system allowed for repetitive bubbles to evolve into a financial crisis after they burst[42]. Recovery of financial markets following the burst perpetuated the false sense of security in many economies (including the U.S.) – while financial markets can recover relatively quickly after a speculative bubble bursts, decreased output and prolonged unemployment can persist for many quarters after, and eventually develop into a financial crisis with far reaching effects across the economy. Since financialization allowed for an increased focus on financial markets as an indicator of economic growth, these consequences of the bubble bursts were ignored until it was too late.

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[39] Nersisyan, Y., Wray, R. *The Global Financial Crisis and the shift to Shadow Banking*. Levy Economics Institute Working Paper No 587. 2010. p. 2
[40] ibid p. 3
[41] Gorton, G. *Slapped in the face by the invisible hand: Banking and the Panic of 2007*. Federal Reserve Bank of Atlanta. 2009. p.23
[42] Nersisyan, Y., Wray, R. *The Global Financial Crisis and the shift to Shadow Banking*. Levy Economics Institute Working Paper No 587. 2010. p. 3

Securitization also factored into the evolution of the Shadow Banking sector. Fragility of the financial system is largely dependent on the quality of loans issued into the market[43], and securitization played a large role in allowing lower quality loans to masquerade as high quality, safe investments. Securitization provided banks with deposit insurance that wasn't available in the Commercial Banking sector[44]. Increased use of securitization as a means of financing led to growth in the repurchase (repo) agreement market, increased rehypothecation of collateral and laid the foundation for a vulnerable and fragile financial market in the United States. Securitization and rehypothecation caused vast internalization of risk; that is, allowing lower quality loans to be packaged with higher quality loans, and allowing firms to purchase securities of other companies without transactions appearing on balance sheets created a vicious cycle in American financial markets that consolidated all the risk inside the financial system. Instead of diversifying the risk away into different industries – a traditional method used to mitigate risk in portfolio management – the United States financial market evolved into a large, solitary industry with no possibility of diversifying away the risk. Global diversification was also ineffective – many international economies were following suit and allowing financial institutions to conduct business in the same manner as many large American banks, only contributing to the already precarious situation in the global economy. After the housing bubble burst, mortgages defaulted, leading to securitized asset default, resulting in a ripple effect throughout financial markets.

Relating changes in financial markets prior to the onset of the 2008 Financial Crisis to the empirical results of the time period can help illustrate how the relationship between financial markets and real economic activity has transformed over time. Evidently, the lack of regulation in the Shadow Banking system and the Too Big to Fail ideology are major contributors to the change in the relationship, and could potentially be the reason that these two variables have experienced so much change in such a short

[43] Nersisyan, Y., Wray, R. *The Global Financial Crisis and the shift to Shadow Banking*. Levy Economics Institute Working Paper No 587. 2010. p. 10

[44] Commercial Banking Sector did not provide institutions with large cash holdings easy access to safe, interest earning short term investments because of a $1,000,000 cap on deposit insurance (source: Gorton, G. Metrick, A. *Regulating the Shadow Banking System.* National Bureau of Economic Research Working Paper Series. 2010. p.38)

period of time. Arguably, the lack of regulation in the Shadow Banking system allowed for such a devastating financial crisis to take place. This oversight in financial regulation also allowed for the "Too Big to Fail" (TBTF) legislation which fostered a false sense of security in the economy. TBTF states that many large financial institutions are so interconnected and interdependent that allowing them to fail in light of an impending financial crisis would have overwhelmingly destructive effects on the economy[45]. As such, should a financial crisis persist and failure of these financial institutions becomes a possible reality, government intervention would be necessary to alleviate stresses on these institutions and prevent their failure. Liquidity support from the government is provided to banks facing difficulties so that they can still meet the needs of their depositors while avoiding default[46]. In a number of ways, the availability of ex-post liquidity support cultivates an environment in which banks and large financial institutions can take on riskier activity without any consequences; knowing that if they are in danger of defaulting and causing mass financial failure, the government will effectively bail them out. Government reaction to other changes in the economy can be quite different than the reaction to a failing bank. If unemployment rates spike, or output falls drastically (whether as a result of financial market performance or not), the United States government is quick to release statements and develop action plans to combat the problem over the long term, but often times these economic issues are not addressed with the same urgency as a potentially failing bank. Lack of regulation in the Shadow Banking system was exacerbated further by the fact that Shadow Banks simply grew too quickly, making it difficult for regulators to pay the banking system the attention it needed to maintain control. Eventually, following the housing bubble burst and the defaulting of some major banks, the system collapsed in on itself before regulators or the government had the chance to step in, as they had not noticed how the situation had progressed until it was too late. While the Shadow Banking sector has presented risks and problems in the United States economy, the banking system is beneficial to the economy, it just requires more intensive monitoring to ensure that the full benefits of the system are realized. That being said, the lack of monitoring and financial institutions'

[45] O'Hara, M., Shaw, W. *Deposit Insurance and Wealth Effects: The Value of Being "Too Big to Fail"*. The Journal of Finance. 1990. p. 1589
[46] ibid

heavy dependence on the government's willingness to offer bailouts in the time leading up to the Financial Crisis presented an image of prosperity amidst a climate of economic uncertainty. With a heavy focus on financial market performance as an indicator of economic health, governments and policy makers overlooked other signs in the economy indicating a possible recession and concentrated mainly on positive gains and strength in financial markets.

5.2 Shadow Banking and its influence on the relationship between Financial Markets and Real Economic Activity

The disparity between actual economic health and financial market health is essential for better understanding the evolving relationship between real economic activity and financial markets. For the second and third time periods tested, there may be some merit in considering the arguments above regarding Shadow Banking, regulatory standards and the Too Big to Fail ideology as potential contributing factors and/or causes of the change in the relationship in recent years. Additionally, for the third period specifically, considering how new policy regimes and regulatory reform have influenced financial markets may help to paint a clearer picture of what has led to a slight improvement in the relationship, as well as how the relationship may continue to improve over time.

Fama's research established a significant correlation between the variables, while Binswanger suggested that later time period empirical results exhibit a failing relationship. Binswanger attributes the cause to speculative bubbles and fads, but does not develop the theory behind his argument very much. Additionally, Binswanger's time period relates mainly to economic boom times, so, one could argue that looking into the theory more deeply to explain behaviour in times of prosperity is unnecessary, and that looking at the data from a quantitative perspective to classify the relationship is sufficient. However, the data analysis for the latest time period (1998 – 2012) covers the Dot Com Bubble, the 2008 Financial Crisis, and their respective recovery periods. Arguably, recession data can sometimes paint a more

interesting picture of economic behaviour and relationships than boom times, making the most recent time period under analysis critical to the understanding of the relationship between the two variables.

Similar to Binswanger's findings, the data concluded that there is no cointegrating relationship between stock price returns and industrial production growth. However, the OLS results for the second and third time periods illustrate that, the relationship between the two variables has changed since the late 1990s. The results suggest that the relationship between industrial production and financial market activity has improved slightly from the second time period to the third. Considering how the U.S. economy has changed, especially since the 2008 Financial Crisis could provide some insight into how these results could be possible.

As noted above, the Shadow Banking Sector's rising popularity began in the 1980s, and continued into the 1990s and 2000s. The lack of regulation and the government's approach towards TBTF could be contributing factors to an increased focus on financial health as economic health, and could have led to the breakdown in the relationship between financial markets and real economic activity. If real economic variables like Industrial Production and GDP are ignored as indicators of economic health, and all focus is directed toward financial markets, this could be misrepresentative of what is actually going on in the economy. If financial markets are booming, then presumably the economy as a whole is booming and financial market health can be taken to represent overall economic health. While financial markets do contribute to overall economic health, taking prosperity in financial markets to fully represent the economy's health can be a dangerous assumption. Other factors, including real economic variables, should be considered when analyzing whether or not the domestic economy has been prosperous. The fact that financial market health may have been used as a proxy for economic prosperity in the 1980s and 1990s could be the reason that empirical results suggest a breakdown in the relationship – with increased popularity of Shadow Banking and financial health presumed to also represent economic health, as the economy began to experience trends differing from those in financial markets, the relationship may have started to change. If this trend continued until the early 2000s, the warning signs of a financial crisis could

have been missed, and when the economy fell apart in the aftermath of the crisis, governments, economists and policy makers alike may have opened their eyes to the fact that economic health depends on more than just stocks and indices performing well. Improved policy response and changes in regulatory regimes in the United States following the 2008 Financial Crisis have not only assisted with economic recovery, but may have also helped to close the gap between financial markets and real economic activity. Specifically, the Dodd Frank Wall Street Reform Act (Dodd Frank) has pushed for a greater focus on regulating the shadow banking sector, increasing accountability of shadow banking institutions, and protecting the United States economy in the event of another financial crisis. The Dodd Frank Act highlights the importance of financial markets in the American economy, but does not subscribe to the idea that financial market health is indicative of overall economic health. Instead, it focuses on "creating a sound economic foundation to grow jobs, protect consumers, rein in Wall Street Big banks, end bailouts and Too Big to Fail, and prevent another Financial Crisis[47]". Some of Dodd Frank's proposals to tackle these issues are summarized below:

1. End Too Big To Fail (TBTF) Bailouts: This part of the legislation aims to create a safe way to liquidate failed financial firms, as well as to impose tough new capital and leverage requirements that make getting "too big" unattractive for a particular firm[48]. Additionally, it will update the Federal Reserve's role in terms of their ability to provide assistance - The Federal Reserve will no longer be able to provide assistance to individual firms, but instead will only provide system wide support to protect the overall economy[49]. The Volcker Rule is a specific provision of the Dodd Frank act aimed at ending TBTF bailouts. The rule requires that "regulators implement regulations for banks, their affiliates and holding companies to prohibit proprietary trading, investment in and sponsorship of hedge funds and private equity funds. Non-bank financial institutions supervised by the Federal

[47] Neave, T. *Review of the Wall Street Reform & Consumer Protection Act.* Economics 871 Lecture Notes. April 2013. p. 1
[48] ibid p. 3
[49] ibid

Reserve also have restrictions on proprietary trading"[50]. This rule prevents financial institutions from trading on their own behalf to complement their normal business practices. This rule protects financial institutions and its clients by controlling the risk in the Shadow Banking sector and prevents the risk from being concentrated within the banks themselves. The Volcker rule encourages more transparent financial markets to provide better regulations to allow Shadow Banks access to the funds and security need, while also protecting its clients.

2. Advanced Warning System: Establishes a council in the Federal Reserve that identifies and addresses systemic risks posed by large, complex companies before economic stability is compromised[51].

3. Enforcing Regulation of the Books: Empower regulators to aggressively pursue manipulations of the financial system[52].

While the first point deals mainly with ending TBTF bailouts, it also complements the second two points to increase accountability and regulating activity in the Shadow Banking sector. These, and the other provisions in the Dodd Frank Act, have attempted to provide a stronger foundation for economic growth and prosperity. Dodd Frank may have also been responsible for putting the entire American economy under the microscope and shifting the focus from financial markets as the sole indicator of economic health.

Stricter regulations on shadow banks has led to more accountability, while still allowing shadow banks to get the funding they need to operate. This, and the new approach to end bailouts, have been made possible because policy makers and government officials identified the lack of regulation in the shadow banking sector as a problem that could severely damage the American economy. While there is a lot of literature – economic and legal – that criticizes Dodd Frank, the goals of the legislation and their proposed solutions

[50] Neave, T. *Review of the Wall Street Reform & Consumer Protection Act.* Economics 871 Lecture Notes. April 2013. p. 3
[51] ibid
[52] ibid

to pressing economic problems are of more interest here than the actual success or feasibility of the act. Dodd Frank is just the first step in the right direction – drawing attention to financial market activities and the devastating effects they can have on the economy, and proposing ideas and regimes to prevent and rectify these effects can potentially lead to an improved and stronger relationship between financial markets and real economic activity.

5.3 Schularick & Taylor Analysis

In their paper *Credit Booms Gone Bust: Monetary Policy, Leverage Cycles & Financial Crises, 1870 – 2008*, Moritz Schularick and Alan M. Taylor look at money, credit and the macro economy in the "long run regarding whether or not financial markets play a role in influencing economic activity"[53]. Their analysis covers 140 years in 12 developed countries, and focuses heavily on the relationship between money and credit and how these can factor into financial crises, but their work can also shed some light on the work done in this paper.

Their work separates economic history into two "eras of finance" – pre World War II (1870 – 1939) and post World War II (1945 – 2009). The event study conducted in their paper uses credit levels to determine if financial crises can be predicted. Using a dummy variable to represent whether or not a crisis occurred, Schularick & Taylor find that lagged credit growth is a significant predictor of financial crises. Their definition of a crisis follows the work of other economists, namely that of Reinhart & Rogoff, which defines a financial crisis as "two types of events: (1) [systemic, severe] bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions and (2) [financial distress, milder] if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions) that marks the start of a string of similar outcomes for other financial institutions"[54]. They simplify the definition of a financial crisis as a "credit boom gone

[53] Schularick, M., Taylor, A. *Credit Booms Gone Bust: Monetary Policy, Leverage Cycles & Financial Crises, 1870 – 2008*. National Bureau of Economic Research Working Paper Series. 2009. p. 4
[54] Reinhart, C., Rogoff, K. *This Time It's Different: Eight Centuries of Financial Folly – Chapter 1*. MPRA Paper No. 17452. 2009. p. 10

wrong", and they seek to test whether or not a country's history of credit growth can help predict a financial crisis. Schularick & Taylor also provide a timeline of financial crises in each of the 12 countries being studied. Additionally, they analyze the economic impact of financial crises, and find that financial market performance has a statistically significant impact in both time periods[55]. They also analyze monetary policy decisions and their impact on financial crisis response in the pre and post World War II eras. The results suggest that "policy makers learned lessons from the Great Depression. Following this, financial crises were fought with more aggressive monetary policy response and quick support for the financial sector". As a result of this willingness to provide quick support to the financial sector, loan growth remained high and leverage in financial sectors continued to grow[56]. In the United States, quick support to the financial sector takes on the form of "Too Big to Fail", and the loan growth and high leveraging highlighted by Schularick & Taylor is reminiscent of increased popularity in the Shadow Banking sector. Without deliberately analyzing the Shadow Banking sector and its role in contributing to Financial Crises, Schularick & Taylor still highlight the fact that endogenous lending booms in the financial system leads to instability in the market, and increases the risk of economic devastation. Furthermore, they acknowledge that central banks and governments should not "ignore potential financial bubbles and easily clean up after they burst"[57]. This idea – that economic authorities should not be complacent in their treatment of financial crisis – was the foundation for the Dodd Frank Wall Street Reform Act. Dodd Frank, as outlined above, aimed to identify financial crises before they worsen, and tackle the problem head on to minimize the negative effects. While some may argue that Dodd Frank is unrealistic and overzealous in its attempts to prevent financial crises, the fact remains that central banks and governments cannot and should not focus on cleaning up financial crises, but should instead focus on safeguarding economies from the crises in the first place.

[55] Schularick, M., Taylor, A. *Credit Booms Gone Bust: Monetary Policy, Leverage Cycles & Financial Crises, 1870 – 2008*. National Bureau of Economic Research Working Paper Series. 2009. p. 4-5
[56] ibid p 15
[57] ibid p. 4

Schularick & Taylor focus heavily on credit markets as a potential source for economic fragility, and although their argument is slightly different than that of this essay, their work still provides insight into the important connection between financial markets and real economic activity. Their event study of 12 different countries over 140 years stresses the importance of the relationship between these two variables, emphasizing that financial crises still have a real cost in the economy. Their work provides support for the argument that Shadow Banking may be to blame for the breakdown in the relationship, as exhibited by Binswanger, but it also provides support for the fact that regulation and policy reformation could be responsible for improving the relationship in recent years.

6. CONCLUSION

The relationship between Financial Markets and Real Economic Activity has undergone significant change since Fama's study in 1990. A strong, statistically significant leading relationship existed between the two variables from the 1950s until the early 1980s. This relationship, while consistent with economic theory and expectations, began to exhibit signs of deterioration in the mid-1980s. Binswanger's studies in 2000 and 2004 highlighted how the relationship established by Fama no longer applied to these two variables in the 1980s. Binswanger's studies focused on the volatility of financial markets and how this volatility was no longer consistently able to predict real economic activity. Fama, on the other hand, related the strong relationship between the two variables to the influence of business cycles on the economy as a whole and argued that asset pricing theory and consumption smoothing theory together helped to explain the leading relationship between the two variables. Binswanger's work, with its heavy focus on financial market volatility illustrates that despite the economy's highly sensitive response to changes in financial markets, the relationship between financial markets and real economic activity is no longer as predictable as was previously thought.

With the works of Fama and Binswanger serving as a foundation, this paper extended the analysis of the relationship between financial markets and real economic activity to include both the Dot Com bubble

and the most recent financial crisis. Financial market and real economic data surrounding the Dot-Com Bubble, the 2008 Financial Crisis and their respective recovery periods allows for the inclusion of highly volatile and economically interesting data.

As expected, the cointegration testing results for the first and second time periods tested yielded results similar to those found by Fama and Binswanger. The third time period, however, presented noteworthy results regarding the evolution of the relationship over time. Similar to Binswanger's results for the second time period, there was no cointegrating relationship detected for the third time period, but the OLS regression results indicated that the relationship between the variables may have improved since the time period covered by Binswanger's work.

The Shadow Banking sector could have been part of the reason that the relationship between these two variables has changed so much. Permissive regulation, guaranteed government bailouts and concentrated risk in the financial sector cultivated an environment for financial institutions to experience major gains, but also allowed for financial devastation once market performance began to worsen. Policy reform and legislative changes that took place following the Financial Crisis focused on better regulating the Shadow Banking sector to cushion the economy from any significant losses while still allowing financial institutions to use the system as a fully functioning banking sector. The Dodd Frank Wall Street Reform Act focused on instituting tighter regulations for Shadow Banks and looks to put an end to Too Big To Fail bailouts that foster an environment where banks undertake riskier activities than the otherwise normally would. Dodd Frank recognizes that the Shadow Banking system is an important sector of the modern economy, and that regulating the system and monitoring it more closely is important for overall success in the U.S. economy.

Future research opportunities in this area could include performing similar analysis on a number of different economies to observe how the 2008 Financial Crisis has influenced the relationship between Financial Markets and Real Economic Activity globally. Additionally, considering Shadow Banking as an

influencing factor in the relationship change, and performing analysis similar to that of Schularick & Taylor would incorporate more factors (i.e. credit markets and shadow banking activity) and allow for a more in depth analysis of the relationship between these two variables. Analyzing different financial sectors and their influence on real economic activity may also yield interesting results. For example, analyzing how energy markets' relationship with real economic activity has changed over time, compared to technology markets' relationship may provide more insight into the sectors of the economy that influence real activity the most.

Works Cited

Bath University. (2009). Estimating a VECM in Stata.*Bath University.* Retrieved July 2013, from Estimating a VECM in Stata: http://staff.bath.ac.uk/hssjrh/VECM%20STATA.pdf

Becketti, Sean. (2013). Cointegrating Relationships and VECMs. Introduction to Time Series using Stata. STATA Press.

Binswanger, Mathias. (2000) Stock Market Booms & Real Economic Activity: Is this time different*? International Review of Economics and Finance.* p. 387-415

Binswanger, Mathias. (2004) Stock Returns and Real Activity in the G7 Countries: Did the Relationship Change During the 1980s? *Quarterly Review of Economics & Finance*. p. 237-252

Choi, Jongmoo., Hauser, Shmuel., & Kopecky, Kenneth. (1997). Does the stock market predict real activity?: Evidence from the G7 countries. *Journal of Banking and Finance* , 1771-1792

Fama, Eugene. (1990) Stock Returns, Expected Returns and Real Activity. *The Journal of Finance*. 1089-1108

Gorton, Gary. (2009). Slapped in the Face by the Invisible Hand: Banking and the Panic of 2007. *Federal Reserve Bank of Atlanta* , 1-53.

Gorton, Gary ., Metrick, Andrew. (2010). Regulating the Shadow Banking System. *National Bureau of Economic Research Working Paper Series* , 1-41.

Gregory, Allan. (2013). ECON 853 Lecture Notes Chapter 11: Cointegration. *Queen's University Economics Department.*

Hendry, David F., & Juselius, Katarina. Explaining Cointegration Analysis: Part II. *Oxford University & University of Copenhagen*. Retrieved July 2013, from Explaining Cointegration Analysis Part II: http://www.econ.ku.dk/okokj/papers/kjdhengii.pdf

Koop, Gary. (2011) Chapter 11: Regression with Time Series Variables – Granger Causality. *University of Strathclyde Department of Economics.* p. 2-7

Neave, Edwin. (2013) Review of the Wall Street Reform & Consumer Protection Act. *Economics 871 Lecture Notes*

Nersisyan, Yeva, Wray, Richard. (2010). The Global Financial Crisis and the Shift to Shadow Banking. *Levy Economics Institute Working Paper No. 587*. 1-31

O'Hara, Maureen., Shaw, Wayne. (1990). Deposit Insurance and Wealth Effects: The Value of Being Too Big to Fail. *The Journal of Finance*. 1587-1600

Reinhart, Carmen., Rogoff, Kenneth. (2009). Chapter 1. *This Time its Different: Eight Centuries of Financial Folly.* 1-15

.
StataCorp. (2011). Introduction to Vector Error Correction Models. In StataCorp, *Stata Time Series Reference Manual* (pp. 447-467). Stata Press Publications.

Schularick, Moritz., Taylor, Allan M. (2009) *Credit Booms Gone Bust: Monetary Policy, Leverage Cycles & Financial Crises, 1870 – 2008*. National Bureau of Economic Research Working Paper Series. p. 1-40

Torres-Reyna, Oscar. (n.d.). *Princeton University Data & Statistical Services*. Retrieved July 2013, from Time Series : http://dss.princeton.edu/training/TS101.pdf