Fundamental Volatility's Effect on Asset Volatility

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Abstract This paper examines the effect of macroeconomic variable volatility on implied and realized asset price level volatilities in the U.S. using monthly data from 1986 - 2008. Two approaches are taken: An autoregressive distributed lag model using rolling standard deviations and a GARCH model. The S&P 500's volatility is used as a proxy for historical (actual) volatility and the VIX is used as a proxy for implied volatility. For the distributed lag model, each linear regression tests granger causality (using Newey-West robust standard errors) of a single macroeconomic variable by incorporating lagged values (as determined by comparing Bayesian Information Criteria of both the constructed macroeconomic variable and the dependent asset volatility variable). Capacity utilization, PPI, and employment volatility are found to be significant for predicting S&P volatility, while PPI and M2 volatility are significant for the VIX. For the GARCH regressions, terms of trade, employment, and capacity utilization volatility are statistically significant. Forecasts are then constructed using those variables shown to be granger casual, but a two-sided t-test rejects the null hypothesis that forecast errors are zero in every case.

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1 Introduction

Risk is defined as volatility[1] (variance) of an asset's return. In common usage, risk measures the potential negative impact on an asset's value that may arise from future price level changes. It is a function of both the expected losses which may be caused by a future event, such as a price drop, and the probability of such an event occurring, so risk increases with both the likelihood of the event and the magnitude of loss associated with the event. In a financial context, risk is defined as the probability that an asset's return will deviate from the expected return. As such, risk is generally measured in a historical sense by the standard deviation of historical returns.

Generally markets are good at assessing the cost but not the probability of a bad event. As recent events all too well remind us, markets often are likely to underestimate the downside risk inherent in a given situation. In asset markets, when volatility (variance) rises it is a measure of an increase in risk. The rise in variance indicates that the market has no consensus regarding where the asset should be priced, even when all economic players have similar information.

Risk is important in financial markets because it affects returns. The higher the risk, the higher the return. In addition risk is an important component in diversification, and, at a macroeconomic level, it has a real effect on quality of life. Hence, the ability to measure risk and accurately gauge it has a wide range of practical implications for a many economic agents. Multinational corporations may desire to predict world market risk by examining prevalent macroeconomic indicators in order

[1]Fundamental Volatility, also known as macroeconomic variable volatility, is defined as the volatility of macroeconomic indicators such as GDP and consumption. In other words, fundamental volatility is the standard deviation of these macroeconomic variables.

Implied Volatility is the forward-looking expect volatility in any given time frame which is an input into options pricing models. Implied volatilities may or may not actually come true, they are simply the market's view on what the volatility will be in the future. They are often above actual predicted volatilities so that investment banks have a pricing buffer in case they underestimated volatility when selling options.

Realized Volatilities are the actual historical volatilities which can be measured using historic asset prices.

to adopt hedging strategies. Portfolio managers may wish to examine how risks differ across countries during current economic times in order to make informed investment decisions and achieve the greatest possible risk-adjusted returns. Individuals may find it beneficial to gauge risk in order to plan and invest for the future.

Financial markets, in fact, always have an opinion on level of risk in the future. This opinion can be extracted from options, since one input into option pricing models is the expected volatility of the underlying asset for the future. By looking at an array of options on a market index, such as the S&P 500, for a variety of expiration and strike prices, one can extract the markets view on future risk. This view is known as implied volatility, or options-implied volatility. These implied volatilities are the result of investment bankers pricing options for different assets. Implied volatility is an input into their models. It is used to calculate a value on the options they are pricing.

It is beyond the reach of the average investor to extract the implied volatility on U.S. markets from an array of option prices on market indices. However, in 1986 a volatility index known as the VIX and traded on the Chicago Board Options Exchange came into existence. This index allowed a layperson to trivially look at one number and understand the markets view, or the implied volatility numbers, which had been priced into options on the S&P 500, a major U.S. stock index. The VIX is a weighted average of prices for a range of different options on the S&P 500 index. It represents the implied volatility as reflected by the pricing of S&P 500 30-day options. Therefore, use of the VIX enables us to measure the options-implied volatilities on the U.S. market without involving complicated mathematical techniques.

The VIX index is also known as the "fear gauge" because, in essence, it gauges the level of anxiety of investors. Most recently in October and November of 2008 the VIX captured the wild ride which has characterized financial markets. The Wall Street Journal reported on November 13 that "for more than five weeks, the Chicago Board

Options Exchange's volatility index, or the VIX, has closed above 50 on every single day with the exception of one. Should this phenomenon continue, it could match the market volatility last seen during the Great Depression, according to derivatives analysts at Credit Suisse". The VIX historically has traded around 20, indicating that a 20% annual standard deviation in return on the S&P is expected. Most recently, however, VIX values as high as 50 have underestimated the actual, or realized volatility of financial markets. These markets have experienced approximately a 57% annualized standard deviation during the last weeks of 2008. Such unprecedented levels certainly indicate that a great deal of fear and uncertainty has been present in the minds of economic agents.

Hence, this study will investigate potential sources of asset price volatility. The research presented here investigates the effect of macroeconomic variable volatility, or fundamental volatility (such as standard deviation of return on GDP), on implied (options-derived) and realized (historical) asset price level volatilities in the U.S. using monthly data from 1986 - 2008. Since one of the underpinnings of economic growth is business and the productivity of business, and in theory, stock prices put a value on the discounted future profitability of these businesses, it would make sense that asset prices and macroeconomic variables are closely related.

This study differs from previous ones in three main ways: first, it considers the effect of fundamental volatility on implied volatilities as well as realized volatilities. Secondly, it considers the varying effect of fundamental volatility during different stages of the business cycle. Finally, it takes advantage of a unique data set by utilizing the VIX index and more contemporaneous data than other studies (with a sample period ending in 2008). By examining implied volatilities, insight can be made into the "average" inputs considered by financial analysts when they set implied volatilities in their options pricing models. If the volatility of a certain macroeconomic variable is strongly predictive of future volatility, perhaps that variable is often used as an input of implied volatility models for the S&P 500.

2 Related Literature

This literature review is organized into four sections. The first section profiles literature which examines the determinants of asset prices and those factors which affect asset prices. The second section examines existing literature that develops the relationship between macroeconomic variable levels (but not their volatilities) and asset price volatilities. The third section outlines those few papers that explore the relationship between fundamental volatility and asset price volatility. The final section places the approach produced here in the existing literature.

2.1 Influences on Asset Prices

Much work has been done on international asset-pricing models by Stulz (1981) and Adler and Dumas (1983). Their research extends the Capital Asset Pricing Model for an international bundle of stocks by specifying that an assets expected return is based not only on its covariance of the assets return with the return on world market portfolios but also by the covariance of the assets return with the returns on foreign exchange rates. This adjusts for differences in real returns between countries caused by fluctuations in currency value for the respective country versus the world.

Some studies have attempted to explain changing volatility by looking at the relationship between conditional stock market volatility and the release of new macroeconomic information. Fraser and Power (1997) examine the UK, US, and a number of Pacific Rim equity markets and find that the importance of new information plays a small role in the conditional stock market volatility. Cutler et al. (1989) also investigate influences of macroeconomic news on volatility and find that only one-fifth to one-third of movements of a stock market index can be explained by macroeconomic news.

Much research has been performed to determine influences of stock market returns and risk. By the last quarter of the twentieth century, economists had shown that macroeconomic variables influence stock markets and security prices (Fama, 1981). Additionally, research demonstrated that risk exposures (covariance of asset returns with a market portfolio) are also related to economic variables (Shanken, 1990 and Fama and French, 1993). More recently, Patro, Wald, and Wu (2006) reaffirm this finding on an international selection of 16 OECD[2] countries.

The derivatives market provides an additional perspective on market risk. Stock prices provide only one price point on a given day for an infinite time horizon. Options[3], however, provide a rich wealth of information because they are priced for a limited time frame and for a range of strike prices. Embedded in the pricing of these options are assumptions about the risk of return and the probability of a variety of different returns. A probability density function can be derived from these options prices to determined the implied, or market predicted, probability of different rates of return on the underlying asset. Studies by Day and Lewis (1993), Jorion (1995), and Christensen and Prahhala (1998) have found that options-implied volatilities provide much better estimates of future volatilities than do regressions of previous volatilities[4].

Other studies examine the options-implied volatilities which can be extracted by looking at an array of options, all for the same underlying asset, at different strike prices and expiration dates. Glatzer and Scheicher (2005) point out that "information extracted from the cross section of option prices by means of the probability density function (PDF) is more comprehensive than that contained in a time series of stock

[2]Organization of Economic Cooperation and Development: 30 mostly high-income, developed countries that believe in representative democracy and free markets.

[3]"A stock option is a financial contract that gives the holder the right to trade a certain number of shares of a specified common stock by a certain date for a specified price." (Tsay 2005)

[4]Although Martens and Zein (2004) provide improvements to the historical data method of volatility forecasting.

returns". Option prices allow the probability density functions of implied returns on an asset to be dissected each day for a constant time horizon. Glatzer and Scheicher use this rich information to examine the left tail of option-implied probability density functions in Germany's DAX. This approach captures the likelihood that assets or markets would take a large dive downward. The left tail is of interest to them because the high probability of stock price declines is largely responsible for skewing the PDF of stock returns. They find strong influences on the option-implied PDF from the U.S. Stock market, confirming evidence of international interaction between stock markets of industrialized countries. Glatzer and Scheicher also point out that the option-implied PDF also allows for risk aversion to be estimated as in Beber and Brandt (2003).

2.2 Macroeconomic Variables and Asset Price Volatility

In finance, one prevailing question is that of why asset risk, or the standard deviation of asset prices, varies over time. What is it that causes the standard deviation of asset prices to vary over time? What variables explain this variance in asset price volatility? Other studies have investigated these questions, exploring the explanatory power of different variables on asset price volatility, or how to better predict or forecast future levels of risk in financial markets. Some studies starting in the 1980s began to investigate the link between macroeconomic variables levels, such as GDP, inflation, and productivity, and the resulting effect on risk, or standard deviation of asset returns.

Though the literature has largely neglected the relationship between fundamental volatilities and asset price volatility, many studies have covered the relationship between macroeconomic variables (but not their volatilities) and implied and realized volatilities. One such study, Al-Khazali (2004), examines the relationship between inflation rates and stock prices in nine countries in the Pacific-Basin. He finds that while regression analysis yields a short-term negative correlation, co-integration tests show a positive relationship between inflation and stock prices in the long run. This relationship may be motivated by the fact that stocks in Asia, as in the U.S. and Europe, serve as a reasonably good hedge against inflation.

Another study that regresses absolute levels of macroeconomic variables against volatilities is Patro, Wald, and Wu (2006). They examine the relationship between risk exposure (betas) and their risk adjusted excess returns (alphas) and macroeconomic variables for a set of 16 OECD countries. A GARCH model is used to estimate world market alphas and betas, taking into consideration weekly data for both exchange rates and equity indices for the countries. Panel regressions are employed to compensate for a small sample size. By utilizing weekly, as opposed to monthly, data, they produce more precise estimates of betas and alphas. The GARCH model is used because of the natural assumption that the volatility stock returns and expected volatilities and risks are time-varying. After the betas and alphas are calculated, a likelihood ratio test is employed to reject the null hypothesis at the 1% level for all 16 countries that alphas are equal. Therefore, on the 1% it can be proven that countries have different excess returns (alphas) beyond their risk expected returns. The researchers next use GLS regressions with a panel approach with just country dummies, a panel approach with just year dummies, and a panel approach with both country and year dummies. With these country and year dummies, 72.8% of variation in world market betas can be explained by their regressions, or by the macroeconomic variables considered in their regressions. This finding supports the notion that macroeconomic variables have explanatory power for market alphas and betas. To estimate future explanatory power, the same regressions are run with explanatory variables lagged one period. Adjusted R-Squares are similar, with 63.4% of the variation in world market betas being explained. This result suggests that it may be possible to use macroeconomic data to predict market alphas and betas in the next period.

Many other economists have also investigated the relationships between macroeconomic variables and the stock market. Stock and Watson (2003) attempt to predict output and inflation based on asset returns. Kavussanos, Marcoulis, and Arkoulis (2002) find that the long run impacts of economic news have different implications in different industries. They look at global risk factors, including oil prices, returns on the MSCI World Equity Index, the Eurodollar-Treasury yield spread, an aggregate measure of exchange rate risk, industrial production, and inflation. They find that each of these factors has different effects on different aggregate global industries. Guidolin and Ono (2006) employ multivariate regime switching VAR models on a monthly U.S. data set for eight different economic variables. Andersen, Bollerslev, Diebold, and Wu (2005) use a standard N-dimensional Brownian motion to measure the effects of macroeconomic factors on volatility (or at least a function of volatility, beta). They break the market into 25 portfolios corresponding to 5 stratifications of size (market capitalization) and value (book to market ratios). They find that for industrial productivity growth shocks there is strong corresponding shock to market betas with a slow reversion to the mean. This movement in beta is more pronounced for portfolios consisting of larger market capitalization firms. Davis and Kutan (2003) use a battery of GARCH models on international stock market volatility. Their main finding is that inflation and real output have a weak predictive power for both stock market volatility and returns. Their GARCH models use both inflation and real output as exogenous variables to simultaneously estimate effects on returns and volatility. Predictive power is limited to only about 1 out of 13 countries in their sample for both returns and volatility, suggesting that inflation and real output are generally not good predictors.

2.3 Macroeconomic Variable Volatility and Asset Price Volatility

Through the 80s, econometric advancements allowed researchers to more thoroughly model a variety of factors which were hypothesized to effect risk. With the advent of the Autoregressive Conditional Heteroskedastic (ARCH)[5] model by Engle (1982) it became possible to calculate a model which allowed conditional variance, a measure of volatility, to change freely over time. A few studies came about that looked not simply at the levels of macroeconomic variables versus asset price standard deviations, but also at the standard deviation of macroeconomic variables versus the standard deviation of asset returns. Early studies found relatively weak results that asset volatility was influenced by the volatility of macroeconomic variables. The literature, however, has since largely ignored the modeling of macroeconomic volatility (also known as fundamental volatility) against the volatility of asset prices. Though asset price volatility, or risk, has been modeled against macroeconomic variables, it has been largely modeled in isolation of fundamental volatility.

Schwert (1989) employs US data to examine the explanatory power of macroeconomic volatility on stock market volatility. He analyzes many factors related to stock volatility. He is careful to note, however, that these relationships are not necessarily causal. He estimates a regression equation which incorporates these different factors. For most macroeconomic variables, coefficients are positive. Schwert finds that if the volatility of inflation rates, money growth, and industrial production all increase one percent, stock volatility increases by .45 percent. Overall, there is more evidence that

[5] In econometrics, an autoregressive conditional heteroskedasticity (ARCH) model considers the variance of the current error term to be a function of the variances of previous periods' error terms. It is commonly used to model financial time series, especially those demonstrating time-varying volatility clustering (markets often experience periods of high volatility in clusters). If a time series is assumed to have errors following an autoregressive moving average model (ARMA, which has an autoregressive part and a moving average part), the more specific generalized autoregressive conditional heteroskedasticity (GARCH) model applies. These models are used throughout the literature to estimate effects of macroeconomic data on market returns and volatilities.

financial asset volatility is a stronger predictor for macroeconomic volatility than vice versa. One of the questions the paper asks is why stock volatilities do not have a more pronounced relationship to macroeconomic volatilities. For instance, during periods of war macroeconomic volatilities greatly increase while stock market volatilities display a more tempered response.

In a related study, Liljeblom and Stenius (1997) use Finnish data to first estimate conditional monthly volatilities both from simple weighted moving averages and also from GARCH estimations. They find that between one-sixth and more than two-thirds of changes in conditional stock market volatility is related to conditional macroeconomic volatility; in particular they study industrial productivity, the money supply M2, terms of trade (export price index divided by the import price index) and find that inflation, industrial production, and money supply changes are primarily responsible for stock market volatility fluctuations. The researchers find significant predictive relationships between macroeconomic volatility and stock market return volatility, and predictive power (causation) appears to run in both directions.

In another related study, Morelli (2002), examines the relationship between conditional stock market volatility and conditional macroeconomic volatility in the UK from 1967 to 1995. He estimates volatilities between periods for both macroeconomic and stock market data using a GARCH model. He then employs a VAR model to test different lag periods. He finds that macroeconomic data does a poor job of explaining stock market return data and vice-versa.

In a more recent working paper Diebold and Yilmaz (2008) investigate the relationship between real volatility of macroeconomic variables in a cross section of 46 countries. They collect data on real GDP, real consumption expenditure, stock market returns, and consumer price inflation for each of the countries. Their primary finding is that a clear positive relationship exists between stock return volatilities and GDP volatilities. They later employ a panel regression to determine the causal direction of this relationship and find that GDP volatility leads stock market variation rather than vice-versa. This working paper notes, however, that the one-way causal relationship deserves additional study with implied as opposed to realized (historical) volatilities, because implied volatilities may be more forward-looking.

In conclusion, the existing literature utilizes a variety of models for volatility estimators (primarily ARCH and GARCH regressions). It also strongly links macroeconomic variable levels with asset price volatilities. The literature has, however, largely neglected the link between macroeconomic variable volatility and asset price volatility. The few studies which have investigated this link have produced inconclusive evidence for a relationship, although their sample periods and country choices vary. One of these studies inspects the UK instead of the US, while none take into account how macroeconomic volatility relates to implied volatility (as opposed to realized volatility). By employing the VIX index as a proxy for implied volatility, utilizing a data set ending in 2008, and investigating business cycle effects, this paper distinguishes itself from the existing literature and contributes to existing research regarding the effects of macroeconomic variable volatility on asset price volatility.

3 Theoretical Framework

The efficient market hypothesis (EMH) (Gourieroux and Jasiak, 2001) asserts that financial markets are informationally efficient and have priced in all publicly available information into the price of traded assets such as stocks, bonds, and property. Though some economic agents may overreact to news and others may under react, it is expected that on average these reactions are random and follow a normal distribution so that market prices cannot be exploited for abnormal profit. In this way, individuals can be wrong but the market as a whole is correct. Consequently, only new information matters, and only unanticipated information should move stock prices. A strict interpretation would yield the proposition that at any given time all macroeconomic news is factored into the market's capitalization as well as its volatility. Some of the new information which investors are constantly pricing in to asset prices is macroeconomic data which is reported to them regularly. As such, even if the EMH holds, volatility of asset prices can be interpreted as a metric of information flow. If macroeconomic variable volatility is high, investors will be unable to anticipate future movements, and we can expect underlying asset price volatilities to increase as the distribution of expected asset prices spreads. Thus it follows that it is possible to produce a model for future volatilities based on lagged macroeconomic volatilities.

The capital asset pricing model (CAPM) provides some motivation for a link between macroeconomic indicators and asset prices. CAPM is used to determine the theoretically appropriate required rate of return on an asset by examining its systemic (non-diversifiable) risk. According to CAPM, the excess return above the risk-free rate (treasury bonds) for an asset should be some multiple of a function of that asset's volatility (its beta) times the excess return on a market bundle (such as the S&P). In other words, assets that are more volatile should have greater returns. Asset prices reflect future potential rates of growth, with higher expected growth rates rewarded by higher prices on the underlying asset. Because the CAPM provides this justification between greater volatility and greater returns, market volatilities should be related to the macroeconomic growth potential for the country as a whole; if the country is experiencing high levels of growth on the underlying businesses, which collectively produce the nation's output, we should expect overall growth in GDP. In other words, an entire country can be thought of as a business in the world market. If the business (country) is experiencing a higher volatility on its stock (a higher total market volatility), then the business can be expected to produce a higher return (which may manifest as higher rates of GDP growth). In this way, by looking at countries themselves as assets in a world market bundle of countries, there should be some link between asset volatility of a country's market and its macroeconomic variables.

Another large theoretical justification for a relationship between fundamental volatility and asset volatility lies in examining the pricing of assets. In theory, the price of an asset is simply the net present value of all expected future cash flows that the asset will produce. From such a discounted cash flow model[6] for stock price, one can argue that the expected conditional variance of future cash flows and future discount rates (and the covariance between them) may directly affect the conditional variance of stock prices. As stock price volatility can also be thought of as disagreement in the market about what the actual value of the underlying asset should be priced, we can expect that disagreement about asset prices (great asset volatility) may be accompanied with additional disagreement (volatility) about macroeconomic volatility (and thus future cash flows / discount rates for the company). Another way to think of this is that a company's valuation (stock price) depends on future cash flows, and that the link between future cash flows of a company and factors such as GDP growth, productivity, and money supply is obvious; companies which sell goods can clearly can be expected to have larger cash flows when the economy is booming and the macroeconomic environment is favorable.

Much of this theoretical section has considered a link between macroeconomic variables and asset market volatility, instead of inspecting the relationship between the volatilities of these macroeconomic variables and asset market volatility. The work of Shiller (1981) and Hansen and Jagannathan (1991) provide an implicit link between volatility of real activity and stock market volatility. Hansen and Jagannathan (1991) use Sharpe ratios to relate fundamental volatility with equity volatility.

[6] A discount cash flow is one method of valuing an asset in which the asset's future cash flows are discounted to their present value. The discount rate used to perform this calculation is representative of the risk inherent in the future cash flows of the asset, or the likelihood that these cash flows will occur as scheduled.

4 Data

This paper uses a model which incorporates asset volatility as the dependent variable and volatility of varying macroeconomic variables as the independent variables. The independent variables used are listed and described in Table 1.

Table 1: Independent Variables

Variable	Description
EmploymentV	Volatility of Employment
TofTV	Volatility of Terms of Trade
M2V	Volatility of Change in Money Supply (M2)
PPIV	Volatility of PPI (Inflation Rate)
CapacityV	Volatility of Capacity Utilization
Recession	Dummy Variable for Recession according to NBER (recession=1; otherwise 0)

The choice of the independent variables in Table 1 is motivated both by conventional wisdom that these are key economic variables and by the results of previous research outlined in Section 2. Stock market and macroeconomic data are readily available from a variety of sources. The variables chosen are on monthly release schedules, allowing for a higher frequency examination of relationships. As such, variables such as GDP which are on a quarterly release schedule could not be used. Instead, proxies (such as capacity utilization and employment) are used. The sample period is 1986 - 2008. This period takes into account at least two full business cycles and includes the most recent period, 2006-2008.

Implied volatilities for the U.S. Stock Market will be proxied by the VIX index which is traded on the Chicago Board Options Exchange. This index estimates the market expectations of near-term volatility by measuring the square root of the implied variance across all options of a given time to expiration. The use of the VIX index will allow this paper to avoid complex calculations of implied volatilities that would otherwise be required to extract implied volatilities from asset prices.

Stock Market Indices and macroeconomic variable data is retrieved from Thomson Datastream as well as the Economic Report of the President. As volatility measures of macroeconomic variables are not readily available, these series are calculated. To do this, a rolling standard deviation is taken, beginning in January 1986. The standard deviation is executed over the following 8 months of data (240 days). A step of 1 month (30 days) is taken and a new standard deviation was calculated. This procedure is repeated for each macroeconomic variable and for the S&P from 1986 to 2008, producing 268 observations (volatility measures) for each variable. Macroeconomic volatilities referenced in Tables 2 to 4 and Figures 1 and 2 use this 8-month rolling standard deviation window. The same procedure is then repeated with a tighter window of 3 months (90 days) and a step of 1 month (30 days) for each macroeconomic variable to construct similar macroeconomic volatility measures.

Since the VIX is the implied volatility of the S&P, no standard deviation need be taken. The VIX, however, must correspond to the monthly macroeconomic data. Therefore, to transform the daily VIX number into a less frequent, monthly number, a point estimate of the VIX level is taken at the beginning of each month. This level is calculated by taking the mean VIX level for the first five days of each month. [7]

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Observations
SandPV	36.169	27.792	270
Vix	19.422	6.079	270
TermsOfTradeV	1.376	0.945	270
PPIV	0.811	0.941	270
M2V	30.858	26.473	270
EmploymentV	455.879	233.706	270
CapacityV	0.738	0.604	270

Trailing "V" indicates that all variables represent volatilities

Table 2 presents the summary statistics of all of the constructed volatility variables. Each macroeconomic variable has a different mean, or average, volatility level over the period 1986 - 2008. Each variable is logged to facilitate interpretation of the

[7]Though a mean could be taken over the month, this would throw away much of the activity of the VIX over the month and would wash away much of the data which the VIX contains, as it often fluctuates greatly around the mean.

coefficients. By utilizing logs, each variable's volatility can be examined in terms of percentages instead of in absolute terms.

4.1 Independent Variables Explained

Capacity Utilization measures the extent to which the country is using its installed productive capacity. It is measured as the percent of output a country is producing divided by the total amount of output which that country could produce if using all of its capital stock (such as plants). It has averaged about 81.6% since 1967 in the U.S. according to the Federal Reserve. Capacity utilization is theoretically positively correlated with market demand, and hence GDP, so in this paper it is used as proxy for GDP because GDP is only published quarterly and this paper employs monthly macroeconomic variables.

Employment is defined by the Bureau of Labor Statistics based on a monthly sample (the current population survey). Individuals are counted as employed if they did any work at all for pay or profit during the survey week, including part-time and temporary work. Employment also includes individuals who work without pay for 15 hours or more per week in a family-owned enterprise.

Terms of Trade (of commodities) is the relative price of a countrys exports to imports. An improvement in a countrys terms of trade is positive in the sense that it indicates that the country has to pay less for the products which the country buys from the rest of the world. Terms of trade are calculated by dividing a price index of exports over a price index of imports. The Laspeyres price index is used because it captures inflation. It is important to note that terms of trade do not take into account the volume of imports or exports.

M2 is a measure of money supply, or the total amount of money available in an economy. M2 is measured as cash and any assets which can be quickly converted into cash, money in checking accounts, and time deposits[8], savings deposits, and non-institutional money market funds. M2 is important because it has a documented affect on both output (GDP) and on the price level. It is also commonly used to quantify the amount of money in circulation.

The PPI, or producer price index, is a measure of inflation. Inflation is the rise in the level of prices over a period of time and therefore the loss of purchasing power. When levels of inflation are unpredictable, as occurs during times of very high inflation, investment is discouraged as it is impossible to determine the real (or after inflation) rate of return. The PPI measures the average change over time in the prices which domestic producers receive for their output and pay for inputs. This is the best proxy of the inflation experienced by businesses.

The recessionary dummy variable follows the definition of a recession by the National Bureau of Economic Research, which states that a recession is any two consecutive quarters of decline in real GDP.

4.2 Correlations

Table 3: S&P500 Cross-correlation table

Variables	SandPV	TermsOfTradeV	CapacityV	EmploymentV	M2V	PPIV
SandPV	1.000					
TermsOfTradeV	0.139	1.000				
CapacityV	0.395	0.184	1.000			
EmploymentV	-0.102	-0.102	0.190	1.000		
M2V	0.689	-0.138	-0.135	-0.079	1.000	
PPIV	0.461	0.352	0.041	-0.085	0.607	1.000

As can be seen in Tables 3 and 4, the chosen macroeconomic variable volatilities are not correlated with the Vix index. M2 and PPI volatility, however, are strongly positively correlated with the S&P, with R^2 values of .689 and .461, respectively. Capacity utilization volatility is also correlated with the S&P, with an R^2 of .395.

[8]money which cannot be withdrawn for a period of time

Table 4: VIX Cross-correlation table

Variables	Vix	TermsOfTradeV	CapacityV	EmploymentV	M2V	PPIV
Vix	1.000					
TermsOfTradeV	0.222	1.000				
CapacityV	0.187	0.184	1.000			
EmploymentV	-0.065	-0.102	0.190	1.000		
M2V	0.285	-0.138	-0.135	-0.079	1.000	
PPIV	0.062	0.352	0.041	-0.085	0.607	1.000

These correlations do not seem strong enough to cause multicollinearity problems, but they should be noted, as this creates a situation in which two regressors are quite correlated in the autoregressive distributed lag model outlined in the data section (the autoregressive lagged S&P terms would be correlated with the lagged M2V, PPIV, and CapacityV terms). These correlations should be noted when interpreting the data, as they may create coefficients which are significant only because of this relationship.

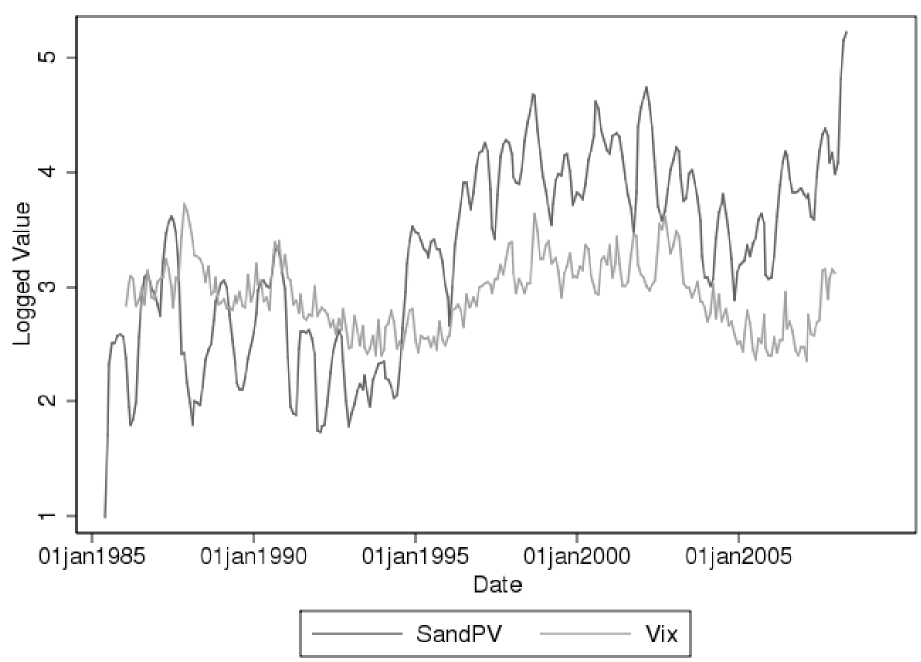

Figure 1 - Implied Volatility (VIX) vs. Historical Volatility (1986-2008)

Figure 1 shows the relationship between historical volatility and implied volatility for the S&P (as measured on the S&P 500 ETF[9] "IVV" which closely mimics the S&P by holding all of its assets). As evident in Figure 1, there is a strong positive correlation between historical and implied volatility for the S&P 500. As a general rule, asset returns are typically negatively correlated with that asset's volatility, and implied and historical volatility often closely mimic one another. Still, historical and implied volatilities sometimes diverge (as can be seen from October to December 2008) because options-traders do not have perfect foresight when predicting future volatility. This divergence is especially large during periods of high volatility (i.e. bear markets). Divergence is the justification for employing two different dependent variables, one using realized (historical) volatility (measured by the volatility of the S&P 500), while the other uses implied volatility for the dependent variable Y (as measured by the VIX). The documented phenomenon that higher volatility occurs during downturns (Schwert 1989) also supports inclusion of a dummy variable for recessionary periods (as determined by the NBER).

[9]An exchange-traded fund (ETF) is an investment vehicle traded on stock exchanges. It is often a conglomerate of other assets, such as stocks, bonds, or real estate. An ETF trades close to the value of its underlying assets.

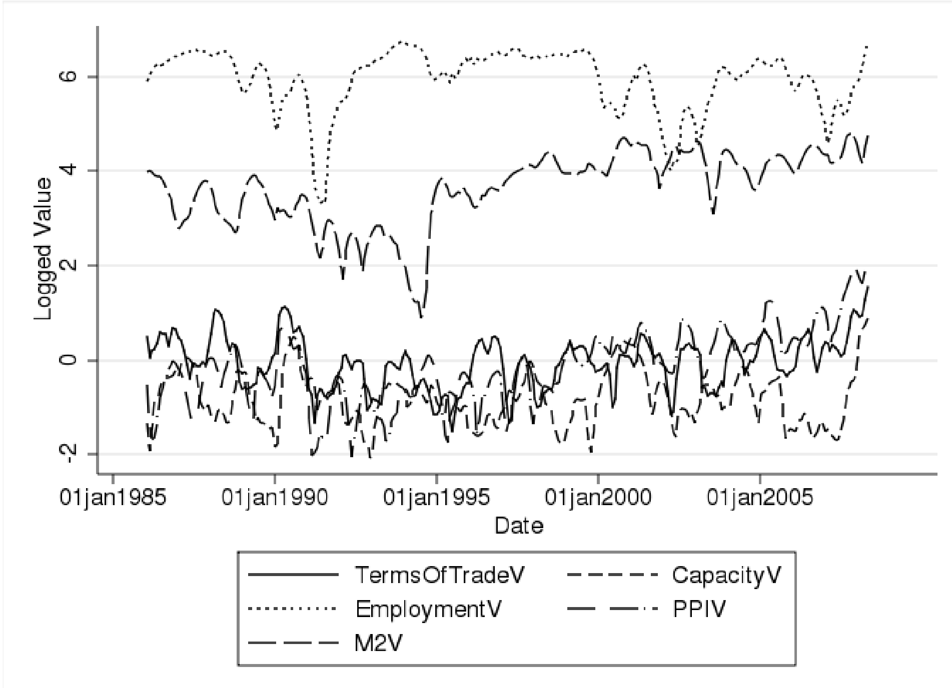

Figure 2 - Independent Variables - Macroeconomic Volatilities Plotted

In Figure 2, the volatilities of all of the logged independent variables are plotted. In the figure, it is easy to see that volatilities change over time, with periods of high volatility followed by periods of low volatility. Volatility clustering is demonstrated in Figure 2 by the flat peaks seen in many macroeconomic variables – periods of high volatility are followed by more periods of high volatility more often than not. This volatility provides some of the motivation for the GARCH regressions as discussed in the empirical specification section. Though in general these macroeconomic variable volatilities seem subjectively unaffected by major events, such as the September 11, 2001 attacks on the United States, the volatility plot of M2 has some large jumps that may be explainable by the Savings and Loan crisis and subsequent passage of legislature that was occurring during the 1980's and 1990's.

4.3 Data Concerns

The VIX index algorithm changed in 2003 to take into account a wider variety of option expiration prices and thus to more accurately represent implied volatility. In order to consolidate the old and new VIX series into one data series for the VIX, a univariate linear regression was run (Y = New VIX, X = Old VIX). The old VIX was then multiplied by the resulting coefficient in order to create a single VIX series which ran from 1986 to 2008.

Macroeconomic data is adjusted frequently in order to increase accuracy as more data becomes available and mistakes are corrected. This means, however, that the numbers used in regressions of historical figures are not the exact numbers economic agents are responding to at the time of the release. This becomes important if, for instance, one is studying the effects of macroeconomic data on stock market prices. Ideally, the economic data used in this paper would be the data as it was upon initial release. This would allow the regression to more fully capture the effects of macroeconomic volatility on options-implied asset volatility, as economic players utilize the macroeconomic data available at the time to generate their volatility forecasts. This is one shortcoming of this study, as it is difficult to obtain macroeconomic data without revisions. The Philadelphia Fed has a real-time database for this sort of analysis.

5 Empirical Specification

An autoregressive distributed lag model is specified in which the dependent variable is either the Vix or S&P volatility. The independent variables include a recessionary dummy variable, lagged terms of the independent variable, and lagged terms of each macroeconomic volatility variable. To estimate the regressions volatilities for each macroeconomic variable are calculated as described in Section 4.

A log is taken of all variables. This allows the coefficients on the independent variables to be standardized and interpreted as the percent change of the independent variable which corresponds to a percent change in the dependent (asset volatility) variable.

The previous methodology creates 8-month window volatility measures, which are stepped one month between successive data points, and separate 3-month window volatility measures which are also stepped one month. This study uses the NBER definition of a recession. In order to enter the binary variable for recessionary periods, any 3 or 8 month period which contained at least one month of a recession (as defined by the NBER) was set to 1.

Macroeconomic variable volatility in one month could affect volatility in asset markets contemporaneously or with a lag. In order to determine the appropriate lag structure to use for macroeconomic variables, the Bayesian Information Criterion (BIC) is employed. This test is a model selection tool which helps to determine which model causes the smallest loss in data. By comparing BIC numbers for different lag periods (with the same dependent variable), the optimal number of lagged periods for the macroeconomic variables can be determined[10]. Lower BIC values indicate, generally, a better fit (as additional lagged periods are added).

Next, in order to specify the regression equation above, the optimal lag period is determined by comparing the Bayesian Information Criterion (BIC) for a regression with only one lagged independent variable ($\beta X_{1,t-1}$), a regression with two lags of the independent variables ($\beta X_{1,t-1} + \delta X_{1,t-2}$), et cetera. A lower BIC indicates a better fitting regression. X is a matrix of explanatory independent variables. Starting with one lag, lagged terms were added up to maximum lag of 8. The lowest BIC value was then selected[11] The same process was followed to determine the number of autoregres-

[10]The macroeconomic volatility variables are lagged enough in both the univariate and GARCH regressions so that the window for the macroeconomic variable volatility calculation ends just before the window for the asset volatility calculation begins (or before the vix measurement is taken). As the windows never overlap, the coefficients could be interpreted as what an agent knew of the past at time t in order to predict asset volatility at time t+1.

[11]Lag selection using BIC was performed with an a priori comparison of models with lags added

sive lags for the dependent variable. For all variables except the S&P500, the optimal number of lags was found to be one. For the S&P500, three lags were optimal. With this information, equations 1 and 2 were fully specified for all independent variables, where $X_{i,t}$ is a matrix of explanatory variables:

$$Y_t^{S\&P} = \gamma Y_{t-1}^{S\&P} + \gamma Y_{t-2}^{S\&P} + \gamma Y_{t-3}^{S\&P} + \beta X_{1,t-1} + u_t \tag{1}$$

$$Y_t^{VIX} = \gamma Y_{t-1}^{VIX} + \beta X_{1,t-1} + u_t \tag{2}$$

The equations above were run once for each of the macroeconomic volatility variables in the data section as independent variables, with S&P500 volatility as the dependent variable, and again with the VIX as the dependent variable. Each regression was run with only one macroeconomic variable at a time in order to capture granger-causality. In addition a regression is estimated for the VIX and S&P including all of the macroeconomic variable volatilities at once. Robust standard errors are used to correct for the autocorrelated error terms that resulted from using an overlapping standard deviation window when calculating the volatility series. The "overlapping moving-window" standard deviation approach causes the usual OLS standard errors for cross-sectional data to no longer be consistent because they are serially correlated. For this reason, it is necessary to use heteroskedasticity and autocorrelation-consistent (HAC) standard errors. Even though the OLS coefficients would still be consistent, these robust standard errors allow for the construction of accurate confidence intervals and interpretation of the data. Specifically, the HAC variance estimator used is the Newey-West estimator.

The resulting 10 (5 regressions with a distinct macroeconomic variable for each of the two dependent variables) regression results are displayed in Tables 6-9. To

up to the maximum lag. The lowest BIC value indicates that the addition of another lagged term past this optimal lag would not increase the overall fit of the model.

determine granger causality, an F-test was run after each regression to determine the joint probability of all lagged macroeconomic variables being 0.

Next forecasts are generated from the independent variables which granger-cause the two dependent volatility measures. These forecasts are plotted and the mean and standard deviation of the forecast error for each forecast is examined. All forecasts errors were then tested with a one sided t-test against the null hypothesis that the forecast error was zero, and hence the forecast performed well.

Due to the fact that volatility of asset markets usually vary with time, a generalized autoregressive conditional heteroskedasticity (GARCH) model is also specified. Such a specification allows for the volatility clustering often found in asset markets. The regression results are displayed in Tables 10 to 14. The previous rolling standard deviation model was common practice before Engle's creation of the ARCH model. A rolling standard deviation model is like an ARCH model that assumes that the variance of the next period's return is an equally weighted average of the squared residuals from the length of the window used (either 90 or 240 days in this case). Using the GARCH model, the error term is modeled as being normally distributed and a function of past squared values of the error term (as in an ARCH model), which are not necessarily equally weighted, and also to depend on squared lags of the variance itself (the GARCH term). As Engle points out (2001), this assumption of equal weights is inaccurate, as more recent events should be weighted more heavily. Furthermore, the GARCH term allows the influence of past variances to never completely go to zero, because the variance from the previous period is included in the variance of the current period. Therefore, to be complete, GARCH models are specified in addition to the rolling standard deviation method described previously for the aforementioned reasons.

The GARCH models is specified by matrix equations 3 and 4 below, where σ represents the volatility (standard deviation) of the S&P 500 and $\sigma_t \varepsilon_t$ is the error term. Specifically, a GARCH(1,1) model is used to include one lag each of both the autocorrelated volatility term and the error term. One GARCH(1,1) regression is specified for each macroeconomic variable with S&P level data as the independent variable and the respective macroeconomic variable added to the conditional variance equation, as seen in equations 3 and 4 below.

$$r_t = m_t + \sigma_t \varepsilon_t \tag{3}$$

$$\sigma_{t+1}^2 = \omega + \alpha(r_t - m_t)^2 + \beta\sigma_t^2 + \gamma\sigma_{t-1}^{MacroVariable} \tag{4}$$

Equation 3 represents the mean equation of each GARCH(1,1) regression, while equation 4 is the conditional volatility equation for each GARCH regression variable. In the mean equation, r is the return on the S&P, while m_t is the mean return, or the expected value of the return based on past information and the variance is σ_t^2, a matrix of macroeconomic volatility variables. This makes the return in the current period r the expected value of the return based on past information plus the standard deviation of the variance $\sqrt{h_t}$ times the error term ε_t. In equation 4, α_1 is the ARCH term, which allows the conditional variance σ_{t+1}^2 to depend on past squared values of the error term ε times the variance σ^2 (the value $(r_t - m_t)^2 = h_t\varepsilon_t^2$) and past variances σ_t^2 with an GARCH coefficient of β. The γ term is added to the conditional variance equation to capture the effect of macroeconomic variable volatility in the model. In total, 5 GARCH regressions were run: one for each macroeconomic volatility variable. The GARCH regressions were run using macroeconomic variable volatilities constructed using 8-month rolling standard deviation windows, as volatilities using this window are found to be more significant in the autoregressive distributed lag model results than those using a 3-month window.

6 Estimation results

6.1 Autoregressive Distributed Lag Model

In all of these regressions, one would expect to find that macroeconomic variable volatility is positively correlated with asset market volatility; as turbulence increases in the economic climate the financial markets can't help but notice. However, most of the macroeconomic variables are found to be insignificant. In the regressions which use the 3 month rolling volatility calculation, the only variable found to be significant at the 10% level is M2 volatility when regressed on the Vix.

Each macroeconomic volatility variable is lagged so that it accounts for a rolling standard deviation window which ends just before the window begins for the calculation of S&P volatility (for the realized volatility regressions), or right before the Vix index is measured (for the implied volatility ones). As this is a log-log regression, the coefficients are interpreted as the effect in percentage terms on Y if there is a 1% increase in the independent variable X. This means that the coefficients for the autoregressive distributed lag model regressions answer the question: "If one is trying to predict future asset volatility using both past asset volatility data for the last 3 months (or 8 months, depending on the window), and all volatility movements are weighted equally during this past period, what is the expected percent increase in realized or implied asset volatility if the macroeconomic variable is increased by 1%?". For example, the coefficient on M2 for the Vix is .107, indicating that a one percent increase in M2 volatility yields a .107 percent increase in implied volatility.

The results using the 8 month rolling volatility window calculations yielded more significant results. In the regression on S&P volatility using the 8 month volatility windows, both capacity utilization volatility and employment volatility are found to be significant at the 1% and 5% levels, respectively. The coefficient on employment volatility was .185, a positive number which intuition suggests, because as macroeconomic volatility increases, one would expect that economic players would have less certainty about the level at which financial markets should trade in response. Stated another way, macroeconomic fluctuations should increase the divergence of opinions held by market players, and this could reasonably increase asset market volatility. Capacity utilization volatility has a negative coefficient, however. These negative coefficients suggest that as volatility of capacity utilization increases, there is a negative response in asset market volatility. These results are puzzling, as economic intuition does not suggest an immediate explanation for them, and they have not been found by other researchers. Negative coefficients are found in three out of eight significant variables (at the 10% level) between both the distributed lag model and the GARCH regressions. Others have found that macroeconomic variable volatility is positively related to asset market volatility.

The regression on the Vix with 8 month windows found that PPI was significant at the 10% level. When a regression was run that incorporated all of the variables, however, PPI lost its significance level in this case. M2, however, gained significance to the 1% level for both 3 month and 8 month windows against the Vix, and at the 10% level with 3 month windows for the S&P.

When examining the results of these regression, it is interesting to realize that a long-run effect exists that may not be immediately apparent. This long-run effect exists because of the model specification, in which a shock in one period propagates out to all future periods. When the lag in question is lagged once, this long-run effect simplifies to the sum of a infinite geometric series, $\beta/(1-\gamma)$, where γ is the coefficient on the autoregressive lag term and β is the coefficient on the macroeconomic volatility variable. If γ is less than 1, this equation converges to some finite value N. To run through an example calculation, M2 volatility in the Vix regression with 3 month windows will be used due to its statistical significance. Then $\beta/(1-\gamma) = .0319/(1-.682) = .1003$, with a resulting interpretation that .1003 is the iterative long run effect of the lagged autoregressive and macroeconomic volatility terms. Other long run effects can be seen in Table 5.

Table 5: Long-run Effects on VIX (using 3-month volatility windows)

Variable	Short Run Effect	Long Run Effect
TermsOfTradeV	-0.0328	-0.1176
PPIV	-0.0233	-0.0768
M2V	0.0319	0.1003
EmploymentV	0.0166	0.0395
CapacityV	0.00190	0.0065

In all regressions using both the 3 month and the 8 month volatility windows, the recessionary dummy variable was found to be very important, indicating that an economic downturn, as defined as two consecutive quarters of decline in real GDP, has a strong effect on asset market volatility. This makes sense, for as recessions in the U.S. become official by proclamation of the NBER, and as real GDP stays deflated, investors surely become wary of the financial climate and turn to safer investments. As trading volume and uncertainty increase during recessionary times, so too does volatility.

The adjusted R^2 of the VIX regressions were generally smaller than those for the S&P, indicating that macroeconomic variables may be a better predictor of the S&P than the VIX. Additionally, the R^2 of those regressions which use 3-month volatility windows were generally higher than those which use 8-month windows for volatility calculations.

The fact that both money supply volatility and PPI (inflation) volatility are significant explanatory variables for realized volatility, are consistent with the findings of Liljeblom and Stenius (1997), who find that inflation, industrial productivity, and money supply changes were primarily responsible for stock market volatility fluctuations. They Finish data and study a different time period; this study echoes their claims that money supply and inflation volatility are significant using U.S. data for a more recent period. Liljeblom and Stenius (1997) also find that M2 volatilty was not explanatory.

Results additionally echo Schwert (1989), who finds that if the volatility of inflation rates, money growth, and industrial productivity all increase by one percent, stock volatility increases by .45 percent. This paper's finding that M2 and inflation (PPI) volatility are significant and that the coefficients exhibit similar orders of magnitude is consistent with this previous research. Schwert, however, was working with a 12-order VAR model using data from 1885 to 1987. Morelli (2002), using UK data, found that money supply, inflation, and industrial production, among other variables, were not significant. This contradicts the results of this paper, but may be explained by the differences in countries and time periods studied.

This paper finds that only M2 volatility explains implied volatility. At the end of the day, implied volatility is predicted by humans working in finance, and these humans may not use any of the chosen variables in their modeling of future volatility. Realized volatility, however, seems to be influenced by money supply and inflationary volatility signals.

6.2 Pseudo Out-of-sample Forecasts

Forecasting future volatility is useful: forecasting variances allow one to obtain accurate forecast intervals (Stock and Watson 2007, p666). For example, in forecasting future realized and implied volatilities, one can check the forecast error of the forecast. The forecast error is the difference between the predicted level for a variable and the actual value of the variable. So, if macroeconomic variables predict future volatilities to be 20%, but the volatility was actually 24%, a forecast error of .04 would result. These forecast errors can be compared over time. If a the variance of this forecast error is constant, then a smaller forecast confidence interval can be used. If the variance of the forecast error changes throughout time, then the forecast

Table 6: S&P vs Fundamental Volatility using 3 Month Volatility Windows, Granger Causality Test with Newey-West Robust Errors

VARIABLES	(1) SandPV	(2) SandPV	(3) SandPV	(4) SandPV	(5) SandPV	(6) SandPV
L3_SandPV	0.348***	0.389***	0.405***	0.387***	0.389***	0.359***
	(0.0640)	(0.0589)	(0.0576)	(0.0570)	(0.0586)	(0.0642)
L4_SandPV	0.119	0.0753	0.0809	0.0753	0.0760	0.130
	(0.0872)	(0.0731)	(0.0716)	(0.0703)	(0.0731)	(0.0885)
L5_SandPV	0.382***	0.394***	0.434***	0.396***	0.393***	0.432***
	(0.0746)	(0.0724)	(0.0753)	(0.0700)	(0.0722)	(0.0729)
L3_PPIV	0.0178					0.0220
	(0.0353)					(0.0390)
L3_TermsOfTradeV		0.00305				-0.00139
		(0.0533)				(0.0537)
L3_M2V			-0.0800			-0.0940*
			(0.0492)			(0.0514)
L3_CapacityV				0.0605		0.0605
				(0.0410)		(0.0417)
L3_EmploymentV					0.00715	0.00876
					(0.0567)	(0.0554)
Recession	0.208***	0.224***	0.224***	0.214***	0.227***	0.199***
	(0.0681)	(0.0772)	(0.0769)	(0.0751)	(0.0872)	(0.0725)
Constant	0.442***	0.393***	0.433***	0.480***	0.355	0.542*
	(0.148)	(0.122)	(0.119)	(0.123)	(0.304)	(0.324)
Observations	270	270	270	270	270	270
Adjusted R^2	0.676	0.676	0.680	0.679	0.676	0.680
F-Test ($Prob > F$)	0.615	0.954	0.105	0.142	0.900	0.2635

An "L" with a number indicates a lag of that number, e.g. L3 is a three period lag.

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Table 7: S&P vs Fundamental Volatility using 8 Month Windows, Granger Causality Test with Newey-West Robust Errors

VARIABLES	(1) SandPV	(2) SandPV	(3) SandPV	(4) SandPV	(5) SandPV	(6) SandPV
L8_SandPV	0.504***	0.541***	0.548***	0.623***	0.576***	0.559***
	(0.164)	(0.170)	(0.176)	(0.165)	(0.170)	(0.168)
L9_SandPV	-0.407*	-0.448**	-0.441*	-0.354	-0.430*	-0.291
	(0.219)	(0.226)	(0.230)	(0.230)	(0.231)	(0.236)
L10_SandPV	0.587***	0.663***	0.564***	0.509***	0.614***	0.439**
	(0.175)	(0.171)	(0.193)	(0.176)	(0.170)	(0.202)
L8_PPIV	0.171*					0.163
	(0.102)					(0.118)
L8_TermsOfTradeV		0.124				-0.0225
		(0.117)				(0.114)
L8_M2V			0.107			0.0276
			(0.185)			(0.167)
L8_CapacityV				-0.344***		-0.345***
				(0.120)		(0.123)
L8_EmploymentV					0.185**	0.182***
					(0.0758)	(0.0630)
Recession	0.228*	0.299**	0.295**	0.327***	0.405***	0.316***
	(0.122)	(0.137)	(0.138)	(0.117)	(0.136)	(0.112)
Constant	1.099***	0.825***	0.711	0.455	-0.307	-0.462
	(0.301)	(0.254)	(0.438)	(0.315)	(0.462)	(0.591)
Observations	270	270	270	270	270	270
Adjusted R^2	0.581	0.569	0.567	0.615	0.584	0.649
F-Test ($Prob > F$)	0.095	0.289	0.566	0.004	0.016	0.000

An "L" with a number indicates a lag of that number, e.g. L3 is a three period lag.

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Table 8: VIX vs Fundamental Volatility using 3 Month Windows, Granger Causality Test with Newey-West Robust Errors

VARIABLES	(1) Vix	(2) Vix	(3) Vix	(4) Vix	(5) Vix	(6) Vix
L3_Vix	0.697***	0.721***	0.682***	0.707***	0.706***	0.673***
	(0.0430)	(0.0472)	(0.0483)	(0.0427)	(0.0439)	(0.0497)
L3_PPIV	-0.0233					-0.0283*
	(0.0164)					(0.0169)
L3_TermsOfTradeV		-0.0328				-0.0245
		(0.0215)				(0.0210)
L3_M2V			0.0319*			0.0435***
			(0.0164)			(0.0136)
L3_CapacityV				0.00190		0.00357
				(0.0249)		(0.0261)
L3_EmploymentV					0.0116	0.0164
					(0.0274)	(0.0256)
Recession	0.124***	0.110***	0.0983***	0.106***	0.112***	0.127***
	(0.0355)	(0.0359)	(0.0361)	(0.0361)	(0.0367)	(0.0403)
Constant	0.842***	0.776***	0.830***	0.844***	0.783***	0.696***
	(0.126)	(0.146)	(0.126)	(0.122)	(0.148)	(0.142)
Observations	270	270	270	270	270	270
Adjusted R^2	0.534	0.542	0.546	0.538	0.539	0.5431
F-Test ($Prob > F$)	0.157	0.129	0.053	0.939	0.674	0.009

An "L" with a number indicates a lag of that number, e.g. L3 is a three period lag.

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Table 9: VIX vs Fundamental Volatility using 8 Month Windows, Granger Causality Test with Newey-West Robust Errors

VARIABLES	(1) Vix	(2) Vix	(3) Vix	(4) Vix	(5) Vix	(6) Vix
L8_Vix	0.615***	0.615***	0.561***	0.589***	0.596***	0.536***
	(0.0738)	(0.0772)	(0.0853)	(0.0729)	(0.0743)	(0.0716)
L8_PPIV	-0.0603*					-0.108***
	(0.0331)					(0.0326)
L8_TermsOfTradeV		-0.0422				0.0153
		(0.0526)				(0.0444)
L8_M2V			0.0455			0.0909***
			(0.0342)			(0.0291)
L8_CapacityV				0.0263		0.0404
				(0.0487)		(0.0459)
L8_EmploymentV					-0.00751	0.000339
					(0.0545)	(0.0549)
Recession	0.238***	0.209***	0.182***	0.200***	0.199***	0.221***
	(0.0558)	(0.0562)	(0.0564)	(0.0563)	(0.0583)	(0.0715)
Constant	1.074***	1.088***	1.091***	1.191***	1.193***	1.003***
	(0.208)	(0.220)	(0.206)	(0.214)	(0.391)	(0.369)
Observations	270	270	270	270	270	270
Adjusted R^2	0.069	0.412	0.419	0.409	0.4071	0.456
F-Test ($Prob > F$)	0.425	0.424	0.185	0.590	0.891	0.002

An "L" with a number indicates a lag of that number, e.g. L3 is a three period lag.

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

interval of the series should also vary with time. It should be smaller during periods of low volatility in forecast error and higher in periods of relatively higher turbulence.

A pseudo out-of-sample forecast is performed to check the power of macroeconomic variable volatility to predict future levels of both realized and implied volatility. Granger-causality is proven for volatility of M2 and the PPI for the Vix, and for PPI volatility, employment volatility, and capacity volatility for S&P volatility. In-sample granger causality does not necessarily imply out-of-sample forecasting ability. For this reason, a pseudo out-of-sample forecast was constructed for the S&P and the Vix index for the regressors which were found to be causal for the entire sample of 1986-2009. The original regression equations (equation 1 and 2) are re-estimated for a period ending in December 2006 to obtain coefficients for the subsample. Forecasts for one period (one month) ahead are then made using these new coefficients. New regression coefficients are then estimated for a period containing one additional month into the future, and a new forecast is made. Using this iterative process, the forecasting power of these models is graphed in Figure 3.

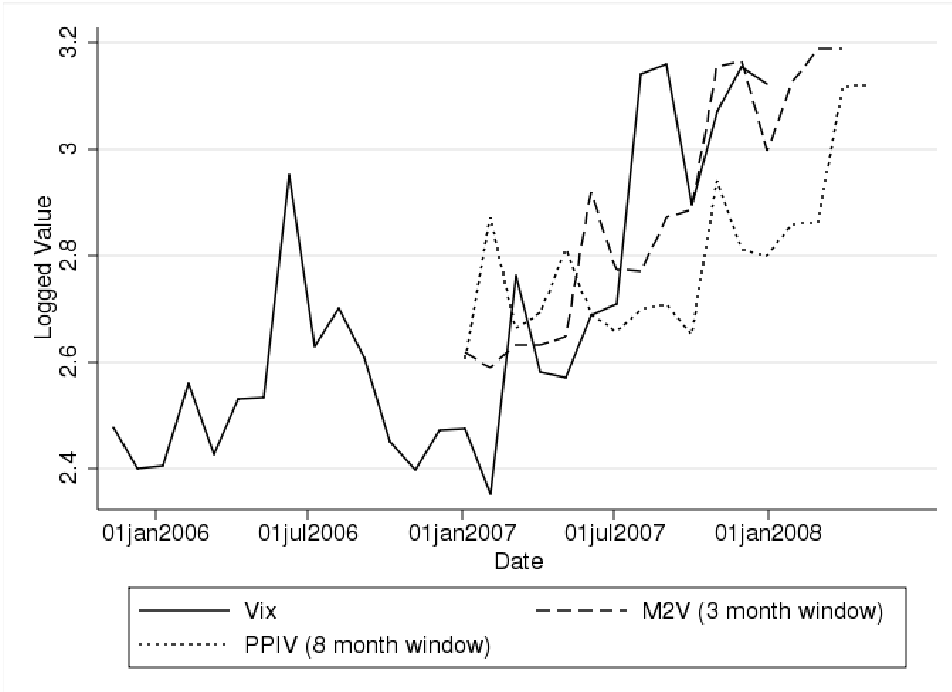

Figure 3 - Forecast of Vix from M2V and PPIV

As figure 3 shows, M2 volatility using a 3 month window and PPI volatility using an 8 window are relatively predictive for future implied volatility levels (as they generally capture the turning points). The forecast errors, or the difference between the predicted and actual Vix, is plotted in Figure 4. A forecast error of zero would indicate that the model predicted future implied volatility perfectly.

For PPI volatility model prediction, the mean value of the forecast error is .1733 and the standard deviation is .0460. Testing the null hypothesis that the mean of the forecasting error is zero using a two-sided t test zero yields a t-value of 18.8359 and probability of 0.00. Similar results are found when analyzing the forecast errors of the other models. For the M2 volatility forecast, the forecast error has a mean .0420, standard deviation of .0107, and p-value of 0.0000 when testing the null hypothesis that the forecast error was zero.

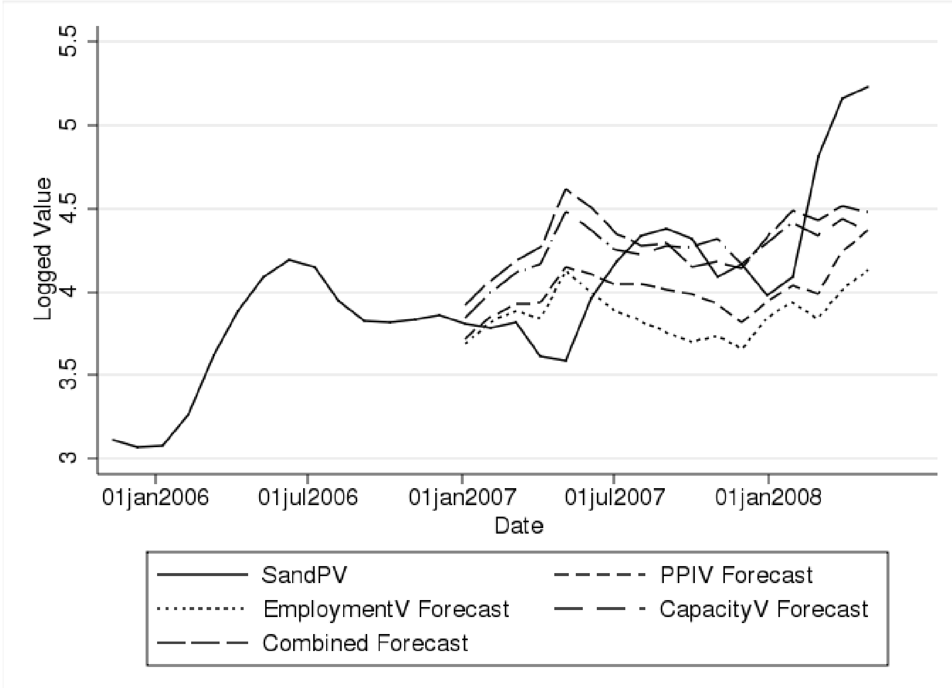

Figure 4 - Forecast of SandPV from PPIV, EmploymentV, and CapacityV with an 8 month window

The same process is repeated for those variables which are shown to Granger-cause the S&P volatility index. Employment volatility's forecast error has a mean of .1388 and standard deviation of .0255. In a null hypothesis test that the forecast error mean is zero, the resulting p-value was 0.000. Capacity utilization volatility has a mean of .1696, standard deviation of .0409, and p-value of 0.000. PPI volatility has a mean of .1733, standard deviation of .0092, and p-value of 0.0000.

Finally, an analysis is performed of the combined forecasting ability of a model including all of the significant variables: capacity volatility, employment volatility, and PPI volatility. The combined forecast has a forecast error with a mean of .2046, standard deviation of .0526, and p-value in a hypothesis test of 0.000. This forecast can be seen in Figure 4.

One measure of the strength of a forecast is whether or not that forecast model captures the turning points of the series being forecast. From a subjective visual perspective, the models seem to capture some of the turning points but not all of them. This bolsters the two sided t-test evidence that these macroeconomic variable volatility models have weak forecasting ability for implied and realized volatility series.

6.3 GARCH model

The GARCH(1, 1) regression results can be found in Tables 10 through 14. Employment and capacity utilization volatility are found to be significant at the 5% level. Terms of Trade volatility is significant at the 10% level, despite being insignificant in the autoregressive distributed lag model regressions. These variables are different in magnitude than the variables in the rolling standard deviation regressions. This may be expected, however, as the GARCH model improves upon the rolling standard deviation model as discussed earlier.

Capacity utilization volatility has a coefficient of -9.761 in the GARCH regression. This negative coefficient matches the negative coefficient on capacity utilization volatility from the autoregressive distributed lag model regressions. The coefficient in the GARCH regressions, however, is about one order of magnitude greater than in the univariate regressions.

Employment volatility, like capacity utilization volatility, has a positive coefficient in both the distributed lag model and GARCH regressions. The coefficient is 16.242, again about two orders of magnitude greater for the GARCH specification. M2 and PPI volatility are not significant in the GARCH regressions.

Capacity utilization has a puzzling negative coefficient and is significant in the GARCH specification. This is the only negative coefficient in the GARCH regressions.

The ARCH term of matrix equation 4, α, is significant in every regression. The GARCH term, which captures the asset market volatility's dependence on its own past variance, is only significant for regressions on employment and capacity utilization volatility. Even in these two regressions, the magnitude of the term is small. This is a different result than in matrix equations 1 and 2, in which the autoregressive lag terms of the dependent variables are found to be highly significant.

Table 10: Garch: S&P with PPIV

Variable	Coefficient (Std. Err.)
Mean Equation	
Intercept	936.632**
	(1.816)
Conditional Variance Equation	
L240.PPIV	0.387
	(0.591)
Intercept	4.792**
	(0.560)
L.arch	0.999**
	(0.072)
L.garch	0.000
	(0.000)
N	3359
Log-likelihood	-24480.146

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

7 Concluding remarks

This paper has investigated the relationship between fundamental volatility and asset market volatility. By explaining causes of fundamental volatility, risk can be more accurately forecast and analyzed. This is useful to many economic agents. Corporations would find this useful when crafting hedging strategies, portfolio managers when determining money-at-risk, and econometricians when constructing volatility series.

In all, capacity utilization, PPI, and employment volatility are found to be significant for predicting S&P volatility, while PPI and M2 volatility are significant for

Table 11: Garch: S&P with M2V

Variable	Coefficient (Std. Err.)
Mean Equation	
Intercept	938.059**
	(1.716)
Conditional Variance Equation	
L240.M2V	0.451
	(1.473)
Intercept	2.965
	(5.664)
L.arch	0.999**
	(0.071)
L.garch	0.000
	(0.000)
N	3359
Log-likelihood	-24480.384

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 12: Garch: S&P with TermsOfTradeV

Variable	Coefficient (Std. Err.)
Mean Equation	
Intercept	1126.349**
	(0.488)
Conditional Variance Equation	
L240.TermsOfTradeV	0.391†
	(0.236)
Intercept	4.078**
	(0.146)
L.arch	0.973**
	(0.103)
L.garch	0.032
	(0.045)
N	3359
Log-likelihood	-57280.44

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 13: Garch: S&P with EmploymentV

Variable	Coefficient (Std. Err.)
Mean Equation	
Intercept	933.220**
	(0.128)
Conditional Variance Equation	
L240.EmploymentV	16.242*
	(7.266)
Intercept	-101.824*
	(47.245)
L.arch	1.000**
	(0.067)
L.garch	0.001*
	(0.000)
N	3359
Log-likelihood	-41209.425

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 14: Garch: S&P with CapacityV

Variable	Coefficient (Std. Err.)
Mean Equation	
Intercept	930.990**
	(0.188)
Conditional Variance Equation	
L240.CapacityV	-9.761*
	(3.812)
Intercept	-9.673†
	(5.401)
L.arch	1.001**
	(0.064)
L.garch	0.001**
	(0.000)
N	3359
Log-likelihood	-41214.662

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

the VIX. For the GARCH regressions, terms of trade, employment, and capacity utilization volatility are statistically significant.

However, when further examining the data, M2 volatility is significant with a positive coefficient using 3-month volatility windows on the VIX, but has a negative coefficient using 3-month volatility windows on S&P volatility (in the regression with all other volatility regressors included). Additionally, M2 is not significant in the GARCH specification. For these reasons, the result that M2 volatility explains fundamental volatility is questionable. PPI volatility also has both positive and negative coefficients in the distributed lag model regressions and is not significant in the GARCH. For these reasons, M2 and PPI volatility may not be very explanatory.

Unlike M2 and PPI volatility, capacity utilization and employment volatility do have consistent results. Capacity utilization and employment are significant at the 1% and 5% levels, respectively, in the autoregressive distributed lag model specification. They are both also significant in the GARCH regression (at the 5% level), and maintain the same sign. Although the positive coefficient on employment is intuitive, the negative coefficient on capacity utilization is puzzling. This is the only negative coefficient that is not contradicted by a positive sign on the same variable in another regression. Another consistent finding in this study is that volatility increases during periods of economic downturn. Officer (1973), Schwert (1989), and Hamilton and Lin (1996) also find that stock market volatility is higher during a recession.

When those variables which are found to be significant vary depending on the specification, the specification should be determined by economic theory instead of the empirics. Here, economic theory would suggest that a GARCH model is a more sound approach, as volatility unarguably demonstrates clustered periods of turbulence, and it would make more sense to allow the autoregressive volatility term to be weighted differently during each period (instead of weighted equally across the entire window and then quickly going to zero).

It is also possible that macroeconomic variable volatility does not cause stock market volatility, but that stock markets become more volatile in expectation of the economy becoming more uncertain and therefore more volatile. Along a similar line, it is possible that financial asset volatility predicts macroeconomic volatility, rather than the other way around, as Schwert (1989) mentions. Finally, if macroeconomic volatility were predictive of equity volatility, an arbitrage situation might exist in which market participants would trade away the forecasting power of the macroeconomic volatility until it no longer exists.

Future research could extend this study. For instance, using the Federal Reserve Bank of Philadelphia's real-time database would allow for the macroeconomic variables used to be those which economic agents react to at the time of release (instead of corrected numbers). Additionally, analyzing the forecast errors with a Diebold-Mariano test may be useful. This test checks if forecast errors change when the macroeconomic variable volatility term is included in the forecast versus when only autoregressive lags of the dependent variable are included. One final area of future research could be to investigate the validity of the negative coefficient found on capacity utilization.

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