Stock Market Volatility and the Business Cycle

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In this paper we provide a review of the literature on the link between stock market volatility and aggregate demand. In particular, we focus on the implications of the so-called uncertainty hypothesis according to which it is primarily the uncertainty associated with stock market fluctuations that influences aggregate demand. Empirical studies find that stock market volatility indeed feeds back into the real economy.

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Although conventional wisdom holds that the stock market plays an important role for macroeconomic developments and the business cycle, the precise linkages between the stock market and macroeconomic aggregates are not well understood. Several transmission channels have been proposed in the literature: For instance, stock market fluctuations influence the wealth of stock holders and therefore influence consumption spending (e.g. Poterba, 2000). In addition, stock price fluctuations may also influence investment spending via their impact on financing conditions.

Moreover, it is not clear how important the effects of financial market fluctuations are for real economic activity in a quantitative sense. For example, although is generally claimed that the Great Crash in 1929 was the starting point of the Great Depression, several economists argue that these two events were only loosely related at best. Temin (1976), for instance, finds that direct wealth effects were fairly small due to the small fraction of consumers that actually invested in the stock market (see also Romer, 1990).

More generally, the main problem of theories that seek to establish a causal link between stock market fluctuations and real economic activity is that potential effects appear to be too small, quantitatively, to have a large impact on macroeconomic variables. In this sense, the stock market appears to be a sideshow from a business cycle point of view. This point of view is also consistent with Barro and Ursua (2009), who show that although stock market crashes have predictive power for business cycle downturns, only 30% of stock market crashes are associated with depressions, while severe depressions are almost always associated with stock market crashes. Put differently, stock market crashes occur with substantially higher frequency than depressions. If crashes are related to economic downturns in a causal way, one would expect to see that a larger fraction of crashes are associated with periods of economic slowdowns.

Romer (1990) proposes an additional channel through which stock market fluctuations, albeit not necessarily stock market crashes themselves, impact upon aggregate demand. In her theory, the so-called uncertainty hypothesis, volatility of the stock market leads to uncertainty about future economic conditions and may thereby result in lower consumption and investment spending. According to this view, stock market volatility can lead to substantial effects on, say, consumption spending even if the fraction of asset-holding households is small, as long as non-asset-holding households also view the stock market

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as a predictor of future economic activity. Thus, stock market uncertainty can have large effects despite the fact that households' direct stock market participation is rather limited. Similarly, if stock market volatility can be viewed as an indication of how uncertain firms regard future developments, it can have a large effect on investment even if only a small fraction of firms in an economy are subject to financing conditions determined by stock price movements.

In this paper, we provide empirical evidence on the relationship between stock market volatility and the business cycle and review the existing literature.

The remainder of this paper is structured as follows: Section 1 describes methods used to measure conditional stock market volatility and provides some indication of how volatility and the business cycle are related. Section 2 summarizes the empirical literature, and section 3 concludes the paper.

1 Stock Market Volatility, Crashes and Recessions

1.1 Volatility, Stylized Facts and Measurement

Share prices can fluctuate for numerous reasons. For example, share prices may respond to new firm-specific information, change due to the changing risk aversion of investors or react to changes in expectations about the future course of the economy. Volatility reflects the magnitude of such price fluctuations. If volatility is high, the chance that we see large positive or negative price changes is high, too. By contrast, low volatility implies that deviations from expected price changes are small on average. Volatility is therefore widely used as a measure of risk in financial markets.

Chart 1 shows the daily returns (i.e. the logarithmic daily price changes) on the S&P 500 index over the period from 1960 to the end of 2008. As can be seen, the magnitude of the returns varies considerably. Turbulent periods of highly fluctuating returns tend to follow periods in which return fluctuations are rather modest. This phenomenon, called "volatility clustering" in the literature, suggests that volatility varies over time. Another phenomenon, which is more specific to stock returns, is volatility asymmetry. Volatility tends to increase more strongly after negative returns than after equally large positive returns (French et al., 1987).

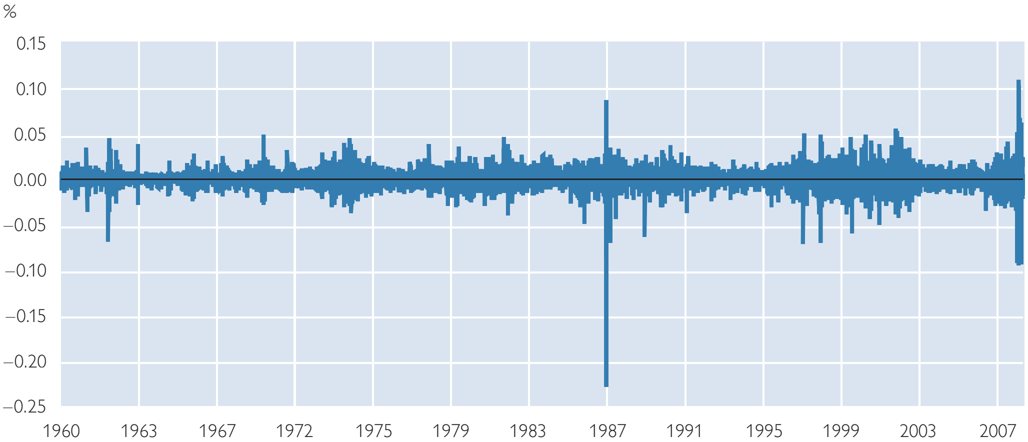
Unfortunately, volatility cannot be observed directly and must therefore be estimated. Moreover, the presence of volatility clustering and asymmetry calls for models that are able to adequately capture the dynamics of volatility. Four different approaches are popular for modeling and forecasting volatility. These include historical volatility, autoregressive conditional heteroskedasticity (ARCH)-type models, stochastic volatility models and option implied volatility. There exists an extensive literature on the specification, estimation and performance of the aforementioned models. Li et al. (2002), Poon and Granger (2003), and Andersen et al. (2006) provide recent surveys of this literature.

In this paper, we only describe three alternative models that we use here to illustrate the evolution of stock market volatility over time. Ultimately, we are interested in the relationship between stock market volatility and the business cycle. The macroeconomic data used in our calculations are available on a quarterly frequency; therefore we focus on quarterly stock market volatility.

A simple model from the class of historical volatility models is the standard deviation s_t of financial returns based on a rolling time window with fixed window length. Using daily log

Chart 1

S&P 500 Daily Stock Market Returns



Source: OeNB.

returns r_i the estimator of volatility is given by

$$s_t = Q\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_i - \bar{r})^2} \qquad (1)$$

where $\bar{r}$ denotes the average daily return over a quarter, N is the number of trading days within a quarter and $Q = \sqrt{365/4}$ is a scaling factor that converts daily volatility into quarterly volatility. Due to the rolling window, this estimator captures volatility clustering, albeit in a rather simple manner. However, the estimator does not account for volatility asymmetry because the estimator does not discriminate between positive and negative returns.

A more sophisticated model that accounts for volatility clustering as well as for volatility asymmetry is the asymmetric GARCH (generalized ARCH) model proposed in Glosten, Jagannathan and Runkle (GJR) (1993). In the GJR model, stock market volatility may respond differently to positive and negative shocks. We obtain these shocks implicitly by filtering monthly returns r_{mt} with a first order autoregressive process

$$r_{mt} = \alpha_0 + \alpha_1 r_{mt-1} + \sqrt{h_t}\,\varepsilon_t \qquad (2)$$

where the shocks ε_t are assumed to be independently and identically distributed with zero mean and unit variance. The conditional variance h_t of the returns is given by

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \Pi_{t-1}^{-} \varepsilon_{t-1}^2 + \beta_3 h_{t-1} \qquad (3)$$

In (3) the variable Π_t^- equals 1 if $\varepsilon_t<0$ and 0 otherwise. If $\beta_2>0$ then negative shocks have a larger impact on volatility than positive shocks. We estimate equations (2) and (3) jointly with maximum likelihood methods using monthly stock index return data. To obtain a measure of quarterly volatility, we take the square root of the sum of the estimated monthly conditional variances over a given quarter.

The models introduced so far use historical data of financial returns to estimate volatility. Alternatively, volatility can also be backed out from quoted prices of traded financial derivatives if volatility is required as an input parameter to price these instruments. Volatility obtained in this way is called implied volatility. It is often argued that implied volatility is superior to time series-based volatility because implied volatility reflects the current view in the market about future volatility. The most popular index of U.S. implied stock market volatility is the VIX provided by the Chicago Board Option Exchange (CBOE). The VIX is based on implied volatility backed out from prices of S&P 500 index options. We use this index of implied S&P 500 volatility as our third measure of U.S. stock market volatility.

1.2 Volatility, Crashes and Recessions

Stock market crashes are periods where the prices of many stocks traded in the market suddenly drop dramatically. These extreme price declines often occur at the end of a speculative bubble and may be caused by sharp revisions of market participants' expectations, by overreaction to new information, herd behavior or panic. The economic uncertainty associated with financial crashes is typically reflected in high levels of stock market volatility.

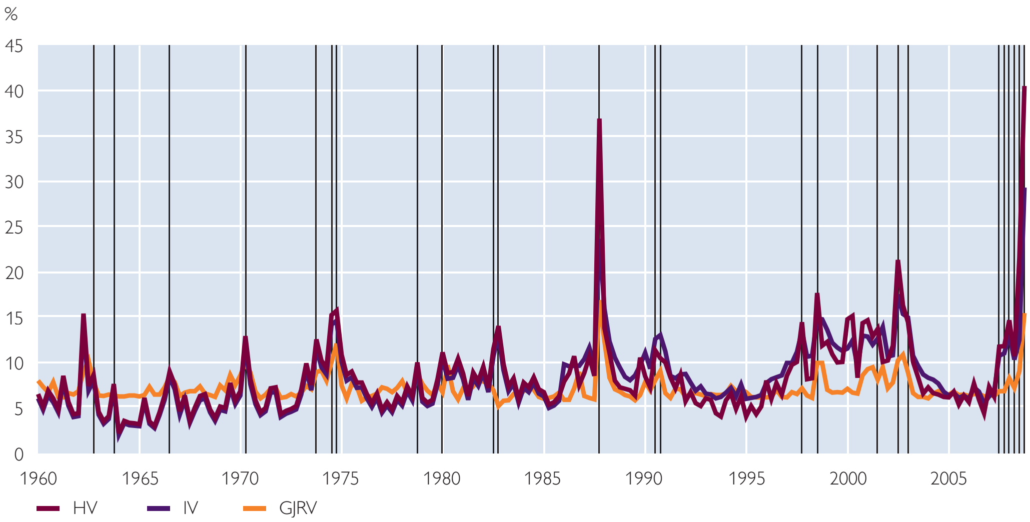
Chart 2 shows the evolution of quarterly U.S. stock market volatility over the period from 1960 to the end of 2008 together with a dummy variable that takes on the value of 1 during quarters belonging to crash periods and 0 otherwise. Our classification into crash periods follows Bloom (2009). Volatility is measured by historical volatility (HV) based on (1), GARCH-type volatility (GJRV) based on (2) and (3), and implied volatility (IV) based on the VIX index.

Our data cover 196 quarters, from which 171 are classified as normal periods and 25 are classified as crash periods. In chart 2 it is easy to see that volatility skyrockets during crash periods no matter how volatility is measured. The crashes of 1987 and 2008 stand out as episodes where volatility was extraordinarily high.

Table 1 contains summary statistics for our volatility measures. As can be anticipated from chart 2, the level of volatility is considerably higher during crash periods than in noncrash periods.

Chart 2

Quarterly U.S. Stock Market Volatility and Stock Market Crashes



Source: OeNB.

Note: Vertical lines denote crash quarters.

Table 1

U.S. Quarterly Stock Market Volatility during Crashes and Normal Times

No crash	HV	GJRV	IV
Mean	7.3	7.0	7.5
Median	6.8	6.6	6.9
Maximum	16.3	12.4	15.9
Minimum	2.2	5.8	2.1
Number of observations	171	171	171
Crash	**HV**	**GJRV**	**IV**
Mean	15.2	9.0	13.2
Median	12.9	8.4	12.6
Maximum	40.5	16.9	29.3
Minimum	7.6	5.2	7.1
Number of observations	25	25	25

Source: OeNB.

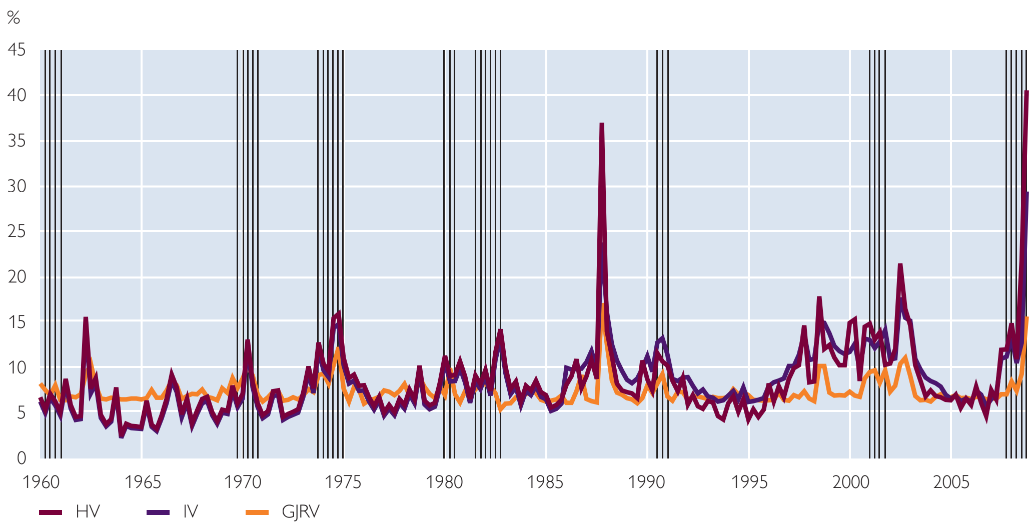
Moreover, all three volatility measures take on their highest value in a crash period.

Stock market crashes often precede recessions. Barro and Ursua (2009) investigate the long term economic history for 30 countries and conclude that stock market crashes have indeed some predictive power for recessions. However, not every crash results in a recession. For example, the spectacular "Black Monday" of October 19, 1987, when the S&P 500 index dropped by more than 20% within a day and stock markets crashed around the world, was not followed by a serve recession. However, stock market volatility tends to be higher during a recession (e.g. Schwert, 1989). This can be seen in chart 3, where our measures of U.S. stock market volatility are plotted together with a dummy variable that takes on the value of 1 when a quarter belongs to a recession period as classified by the U.S. National Bureau of Economic Research (NBER) and 0 otherwise.

Table 2 shows summary statistics for our volatility measures over economic expansions and recessions of the U.S. economy over the period from 1960 to 2008. Over this sample period 160 quarters are classified as expansionary and 36 quarters are classified as contractions. Again, stock market volatility is larger on average during recessions.

Chart 3

Quarterly U.S. Stock Market Volatility and Recessions



Source: OeNB.

Note: Vertical lines denote recession quarters.

Table 2

U.S. Quarterly Stock Market Volatility in Periods of Expansion and Recession

No recession	HV	GJRV	IV
Mean	7.6	7.0	7.7
Median	6.8	6.6	7.0
Maximum	36.9	16.9	23.6
Minimum	2.2	5.8	2.1
Number of observations	160	160	160

Recession	HV	GJRV	IV
Mean	11.3	8.3	10.4
Median	10.4	8.0	10.3
Maximum	40.5	15.5	29.3
Minimum	4.9	5.2	4.5
Number of observations	36	36	36

Source: OeNB.

1.3 Volatility and Output

The empirical observation that stock market volatility tends to be higher during recessions points toward a negative relationship between stock market volatility and output. Chart 4 shows a scatter plot of U.S. quarterly percentage growth of real GDP against implied U.S. stock market volatility together with a fitted regression line.

The negative relationship between volatility and output growth is clearly visible. Scatter plots using historical volatility or GJR-based volatility instead of implied volatility show a similar negative relationship.

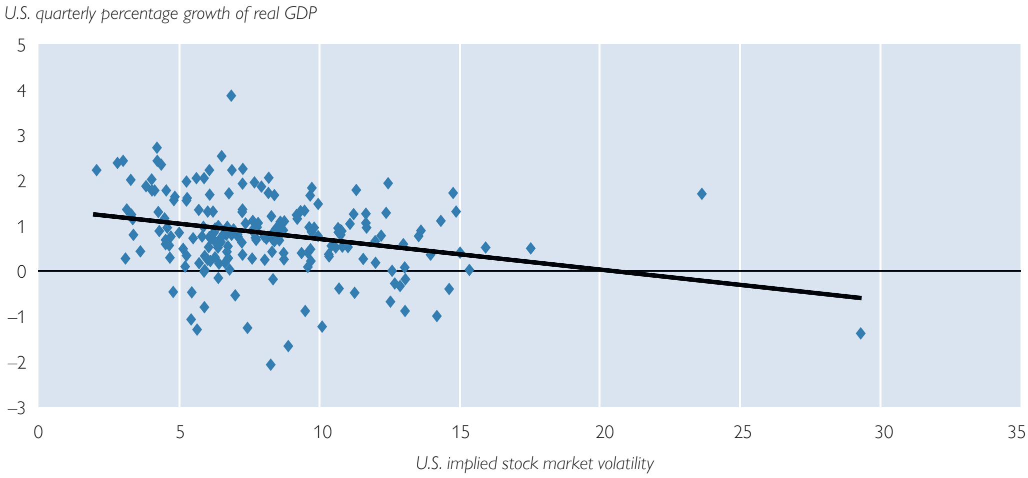
2 Stock Market Volatility and the Business Cycle; Empirical Evidence

Although the empirical evidence presented in the previous section indicates a close relationship between stock market volatility and economic fluctuations, the evidence is only suggestive. However, several papers document similar linkages using more detailed empirical approaches. We now turn to this literature in greater detail.

The empirical study of Romer (1990) deals primarily with the onset of the Great Depression. However, Romer also presents estimates of the relationship between stock market volatility and consumption in the U.S.A.

Chart 4

U.S. Stock Market Volatility and GDP Growth



Source: OeNB.

for the post-war period.[2] Using annual U.S. data ranging from 1949 to 1986, she concludes that a doubling of stock market volatility reduces durable consumer goods output by about 6%, whereas the effect on nondurables is essentially 0. This ordering of the magnitudes of the effects is consistent with the idea that stock market volatility is closely related to uncertainty about future real economic activity. This is because nonreversibility gives rise to a lock-in effect that is particularly pronounced during periods of high uncertainty. Consider for instance a consumer deciding to buy a durable consumption good. Given the durable nature of the good and the uncertainty about future income, it may turn out that the good is either too modest or too luxurious with respect to future income. However, if the consumer waits until uncertainty is resolved, it may be easier to choose an appropriate good. Thus, by postponing the purchase of the good, the lock-in effect can be avoided and the benefit of doing so increases with the level of uncertainty. It follows that decisions that are irreversible to a larger extent are postponed, resulting in particularly pronounced reactions of durable consumption expenditures and investment expenditures to increasing stock market volatility.

Since investment decisions are presumably the least reversible, one would expect that stock market volatility has the largest effect on investment spending, followed by durable consumption and nondurable consumption. Note that if households substitute away form durable consumption goods into nondurable consumption goods because of higher uncertainty, then nondurable consumption may even rise during periods of high stock market volatility.

Raunig and Scharler (2010) evaluate the uncertainty hypothesis by estimating the influence of stock market volatility on durable consumption growth, nondurable consumption growth and investment growth. Their analysis is based on quarterly time series data for the U.S.A.

Based on a number of different estimates of time-varying stock market volatility, Raunig and Scharler (2010) find that stock market volatility exerts an economically and statistically significant effect on aggregate demand. Moreover, they find that the adverse effect of stock market volatility on aggregate demand depends on the extent to which decisions are reversible. Based on their richest specification (table 3), they find that an increase in volatility by one standard deviation reduces the quarterly growth of durable consumption by around –0.70 percentage points, whereas the effect on the growth of nondurable consumption is only –0.14 percentage points. Investment growth responds with a lag of one quarter and declines by 1.12 percentage points.

Table 3

Effect of an Increase in Stock Market Volatility by one Standard Deviation on U.S. Consumption and Investment Growth

	Volatility	Lagged volatility
Growth of durable consumption	–0.70	×
Growth of nondurable consumption	–0.14	×
Investment growth	×	–1.12

Source: OeNB.

[2] *See Romer (1990), Table III.*

Hence, the decline in the growth of durable consumption and investment is larger during periods of increased volatility than the decline in the growth of nondurable consumption, which is again fully consistent with the predictions of the uncertainty hypothesis.

In addition to being statistically significant, the estimated effects are also substantial in an economic sense. Stock market returns, in contrast to volatility, have a quantitatively smaller and often statistically insignificant influence on consumption and investment. This result is consistent with Lettau and Ludvigson (2004), who also find that returns exert only a limited influence on consumption. The reason is that although permanent shocks to stock prices have a strong effect on consumption, most fluctuations in prices are transitory and exert only small effects on consumption.

Alexopoulos and Cohen (2009) identify uncertainty shocks using vector autoregressive methods. To measure uncertainty, they use stock market volatility measures, as in Raunig and Scharler (2010) and Choudhry (2003), and also an index based on the number of New York Times' articles on economic uncertainty. They find that uncertainty shocks play an important role for the business cycle. In particular, uncertainty measured by the New York Times' index accounts for up to 25% of the short-run variation in employment and output.

Choudhry (2003) analyzes the influence of stock market volatility on GDP and the components of GDP using an error-correction framework. Under the assumption that volatility follows a nonstationary stochastic process, he estimates the short-run and long-run dynamics of GDP components using an error-correction framework. His results confirm that stock market volatility has adverse effects on consumption and investment.

A different, but closely related, issue is analyzed in Jansen and Nahius (2003). They analyze how stock market fluctuations influence consumer sentiment in a sample of eleven countries. They find that in the vast majority of countries under consideration, consumer sentiment and stock returns are positively related. They also find that causality runs from stock returns to consumer sentiment rather than vice versa. Moreover, they conclude that the correlation between stock returns and consumer sentiment mirrors expectations about future economic conditions. Therefore, the evidence presented in their paper also provides some backing for the uncertainty hypothesis, in the sense that stock market fluctuations give rise to uncertainty about future economic conditions.

Note that although the uncertainty hypothesis suggests that causality runs from stock market volatility to the business cycle, this need not necessarily be the case. Although the early literature on the determinants of stock market volatility (e.g. Schwert, 1989) finds only weak linkages between stock market volatility and macroeconomic variables, recent empirical research (e.g. Engle et al., 2008; Diebold and Yilmaz, 2010) establishes important linkages between macroeconomic fundamentals and stock market volatility. In particular, Arnold and Vrugt (2008) find a strong link between macroeconomic uncertainty and stock market volatility using survey data from the Survey of Professional Forecasters maintained by the Federal Reserve Bank of Philadelphia. The authors find that rising uncertainty about future macroeconomic developments increases stock market volatility. Thus, taken together with the evidence presented above, it appears that causality between macroeconomic outcomes and stock market volatility is bidirectional.

3 Concluding Remarks

In this paper, we review the theoretical and empirical literature dealing with the link between the stock market and real economic activity. Our particular focus is on the so-called uncertainty hypothesis according to which it is not stock market fluctuations per se which influence aggregate demand, but the volatility associated with such fluctuations.

The main idea is that increased volatility results in higher uncertainty about future economic conditions. Increased uncertainty, in turn, leads to lower consumption and investment spending, and this shortfall in aggregate demand causes an economic slowdown. Empirical evidence suggests that this indirect channel through which stock market developments feed back into the real economy is quantitatively important.

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