6

Macroeconomic Volatility and Stock Market Volatility, World-Wide

Francis X. Diebold and Kamil Yilmaz

1. Introduction

The financial econometrics literature has been strikingly successful at measuring, modeling, and forecasting time-varying return volatility, contributing to improved asset pricing, portfolio management, and risk management, as surveyed for example in Andersen, Bollerslev, Christoffersen and Diebold (2006a, 2006b). Much of the financial econometrics of volatility is of course due to Rob Engle, starting with the classic contribution of Engle (1982a).

Interestingly, the subsequent financial econometric volatility, although massive, is largely silent on the links between asset return volatility and its underlying determinants. Instead, one typically proceeds in reduced-form fashion, modeling and forecasting volatility but not modeling or forecasting the effects of fundamental macroeconomic developments.[1] In particular, the links between asset market volatility and fundamental

Acknowledgments: We gratefully dedicate this paper to Rob Engle on the occasion of his 65th birthday. The research was supported by the Guggenheim Foundation, the Humboldt Foundation, and the National Science Foundation. For outstanding research assistance we thank Chiara Scotti and Georg Strasser. For helpful comments we thank the Editor and Referee, as well as Joe Davis, Aureo DePaula, Jonathan Wright, and participants at the Penn Econometrics Lunch, the Econometric Society 2008 Winter Meetings in New Orleans, and the Engle Festschrift Conference.

[1] The strongly positive volatility-volume correlation has received attention, as in Clark (1973), Tauchen and Pitts (1983), and many others, but that begs the question of what drives volume, which again remains largely unanswered.

volatility remain largely unstudied; effectively, *asset market volatility is modeled in isolation of fundamental volatility.*[2]

Ironically, although fundamental volatility at business cycle frequencies has been studied recently, as for example in Ramey and Ramey (1995) and several of the papers collected in Pinto and Aizenman (2005), that literature is largely macroeconomic, focusing primarily on the link between fundamental volatility and subsequent real growth.[3] Hence the links between fundamental volatility and asset market volatility again remain largely unstudied; *fundamental volatility is modeled in isolation of asset market volatility*.

Here we focus on stock market volatility. The general failure to link macroeconomic fundamentals to asset return volatility certainly holds true for the case of stock returns. There are few studies attempting to link underlying macroeconomic fundamentals to stock return volatility, and the studies that do exist have been largely unsuccessful. For example, in a classic and well-known contribution using monthly data from 1857 to 1987, Schwert (1989) attempts to link stock market volatility to real and nominal macroeconomic volatility, economic activity, financial leverage, and stock trading activity. He finds very little. Similarly and more recently, using sophisticated regime-switching econometric methods for linking return volatility and fundamental volatility, Calvet, Fisher and Thompson (2006) also find very little. The only robust finding seems to be that the stage of the business cycle affects stock market volatility; in particular, stock market volatility is higher in recessions, as found by and echoed in Schwert (1989) and Hamilton and Lin (1996), among others.

In this chapter we provide an empirical investigation of the links between fundamental volatility and stock market volatility. Our exploration is motivated by financial economic theory, which suggests that the volatility of real activity should be related to stock market volatility, as in Shiller (1981) and Hansen and Jagannathan (1991).[4] In addition, and crucially, our empirical approach exploits cross-sectional variation in fundamental and stock market volatilities to uncover links that would likely be lost in a pure time series analysis.

This chapter is part of a nascent literature that explores the links between macroeconomic fundamentals and stock market volatility. Engle and Rangel (2008) is a prominent example. Engle and Rangel propose a spline-GARCH model to isolate low-frequency volatility, and they use the model to explore the links between macroeconomic fundamentals and low-frequency volatility.[5] Engle, Ghysels and Sohn (2006) is another interesting example, blending the spline-GARCH approach with the mixed data sampling (MIDAS) approach of Ghysels, Santa-Clara, and Valkanov (2005). The above-mentioned Engle

[2]By "fundamental volatility," we mean the volatility of underlying real economic fundamentals. From the vantage point of a single equity, this would typically correspond to the volatility of real earnings or dividends. From the vantage point of the entire stock market, it would typically correspond to the volatility of real GDP or consumption.

[3]Another strand of macroeconomic literature, including for example Levine (1997), focuses on the link between fundamental volatility and financial market development. Hence, although related, it too misses the mark for our purposes.

[4]Hansen and Jagannathan provide an inequality between the "Sharpe ratios" for the equity market and the real fundamental and hence implicitly link equity volatility and fundamental volatility, other things equal.

[5]Earlier drafts of our paper were completed contemporaneously with and independently of Engle and Rangel.

et al. macro-volatility literature, however, focuses primarily on dynamics, whereas in this chapter we focus primarily on the cross-section, as we now describe.

2. Data

Our goal is to elucidate the relationship, if any, between real fundamental volatility and real stock market volatility in a broad cross-section of countries. To do so, we ask whether time-averaged fundamental volatility appears linked to time-averaged stock market volatility. We now describe our data construction methods in some detail; a more detailed description, along with a complete catalog of the underlying data and sources, appears in the Appendix.

2.1. Fundamental and stock market volatilities

First consider the measurement of fundamental volatility. We use data on real GDP and real personal consumption expenditures (PCE) for many countries. The major source for both variables is the World Development Indicators (WDI) of the World Bank.

We measure fundamental volatility in two ways. First, we calculate it as the standard deviation of GDP (or consumption) growth, which is a measure of unconditional fundamental volatility. Alternatively, following Schwert (1989), we use residuals from an AR(3) model fit to GDP or consumption growth. This is a measure of conditional fundamental volatility, or put differently, a measure of the volatility of *innovations* to fundamentals.[6]

Now consider stock market volatility. We parallel our above-discussed approach to fundamental volatility, using the major stock index series from the IMF's International Financial Statistics (IFS). Stock indices are not available for some countries and periods. For those countries we obtain data from alternative sources, among which are Datastream, the Standard and Poors Emerging Markets Database, and the World Federation of Exchanges. Finally, using consumer price index data from the IFS, we convert to real stock returns.

We measure real stock market volatility in identical fashion to fundamental volatility, calculating both unconditional and conditional versions. Interestingly, the AR(3) coefficients are statistically significant for a few developing countries, which have small and illiquid stock markets.[7]

2.2. On the choice of sample period

Our empirical analysis requires data on four time series for each country: real GDP, real consumption expenditures, stock market returns and consumer price inflation. In terms of data availability, countries fall into three groups. The first group is composed

[6]The latter volatility measure is more relevant for our purposes, so we focus on it for the remainder of this chapter. The empirical results are qualitatively unchanged, however, when we use the former measure.

[7]Again, however, we focus on the condition version for the remainder of this chapter.

of mostly industrial countries, with data series available for all four variables from the 1960s onward.

The second group of countries is composed mostly of developing countries. In many developing countries, stock markets became an important means of raising capital only in the 1990s; indeed, only a few of the developing countries had active stock markets before the mid-1980s. Hence the second group has shorter available data series, especially for stock returns.

One could of course deal with the problems of the second group simply by discarding it, relying only on the cross-section of industrialized countries. Doing so, however, would radically reduce cross-sectional variation, producing potentially severe reductions in statistical efficiency. Hence we use all countries in the first and second groups, but we start our sample in 1983, reducing the underlying interval used to calculate volatilities to 20 years.

The third group of countries is composed mostly of the transition economies and some African and Asian developing countries, for which stock markets became operational only in the 1990s. As a result, we can include these countries only if we construct volatilities using roughly a 10-year interval of underlying data. Switching from a 20-year to a 10-year interval, the number of countries in the sample increases from around 40 to around 70 (which is good), but using a 10-year interval produces much noisier volatility estimates (which is bad). We feel that, on balance, the bad outweighs the good, so we exclude the third group of countries from our basic analysis, which is based on underlying annual data. However, and as we will discuss, we are able to base some of our analyses on underlying quarterly data, and in those cases we include some of the third group of countries.

In closing this subsection, we note that, quite apart from the fact that data limitations preclude use of pre-1980s data, use of such data would probably be undesirable even if it were available. In particular, the growing literature on the "Great Moderation" – decreased variation of output around trend in industrialized countries, starting in the early 1980s – suggests the appropriateness of starting our sample in the early 1980s, so we take 1983–2002 as our benchmark sample.[8] Estimating fundamental volatility using both pre- and post-1983 data would mix observations from the high and low fundamental volatility eras, potentially producing distorted inference.

3. Empirical results

Having described our data and choice of benchmark sample, we now proceed with the empirical analysis, exploring the relationship between stock market volatility and fundamental volatility in a broad cross-section covering approximately 40 countries.

[8]On the "Great Moderation" in developed countries, see Kim and Nelson (1999a), McConnell and Perez-Quiros (2000) and Stock and Watson (2002b). Evidence for fundamental volatility moderation in developing countries also exists, although it is more mixed. For example, Montiel and Serven (2006) report a decline in GDP growth volatility from roughly 4% in the 1970s and 1980s to roughly 3% in the 1990s. On the other hand, Kose, Prasad, and Terrones (2006) find that developing countries experience increases in consumption volatility following financial liberalization, and many developing economies have indeed liberalized in recent years.

3.1. Distributions of volatilities in the cross-section

We begin in Figure 6.1 by showing kernel density estimates of the cross-country distributions of fundamental volatility and stock return volatility. The densities indicate wide dispersion in volatilities across countries. Moreover, the distributions tend to be right-skewed, as developing countries often have unusually high volatility. The log transformation largely reduces the right skewness; hence we work with log volatilities from this point onward.[9]

3.2. The basic relationship

We present our core result in Figure 6.2, which indicates a clear positive relationship between stock return and GDP volatilities, as summarized by the scatterplot of stock market volatility against GDP volatility, together with fitted nonparametric regression curve.[10] The fitted curve, moreover, appears nearly linear. (A fitted linear regression gives a slope coefficient of 0.38 with a robust t-statistic of 4.70, and an adjusted R^2 of 0.26.)

When we swap consumption for GDP, the positive relationship remains, as shown in Figure 6.3, although it appears less linear. In any event, the positive cross-sectional relationship between stock market volatility and fundamental volatility contrasts with the Schwert's (1989) earlier-mentioned disappointing results for the US time series.

3.3. Controlling for the level of initial GDP

Inspection of the country acronyms in Figures 6.2 and 6.3 reveals that both stock market and fundamental volatilities are higher in developing (or newly industrializing) countries. Conversely, industrial countries cluster toward low stock market and fundamental volatility. This dependence of volatility on stage of development echoes the findings of Koren and Tenreyro (2007) and has obvious implications for the interpretation of our results. In particular, is it a development story, or is there more? That is, is the apparent positive dependence between stock market volatility and fundamental volatility due to common positive dependence of fundamental and stock market volatilities on a third variable, stage of development, or would the relationship exist even after controlling for stage of development?

To explore this, we follow a two-step procedure. In the first step, we regress all variables on initial GDP per capita, to remove stage-of-development effects (as proxied by initial GDP). In the second step, we regress residual stock market volatility on residual fundamental volatility.

In Figures 6.4–6.6 we display the first-step regressions, which are of independent interest, providing a precise quantitative summary of the dependence of all variables (stock market volatility, GDP volatility and consumption volatility) on initial GDP per capita. The dependence is clearly negative, particularly if we discount the distortions to the basic relationships caused by India and Pakistan, which have very low

[9] The approximate log-normality of volatility in the cross-section parallels the approximate unconditional log-normality documented in the time series by Andersen, Bollerslev, Diebold and Ebens (2001).

[10] We use the LOWESS locally weighted regression procedure of Cleveland (1979).

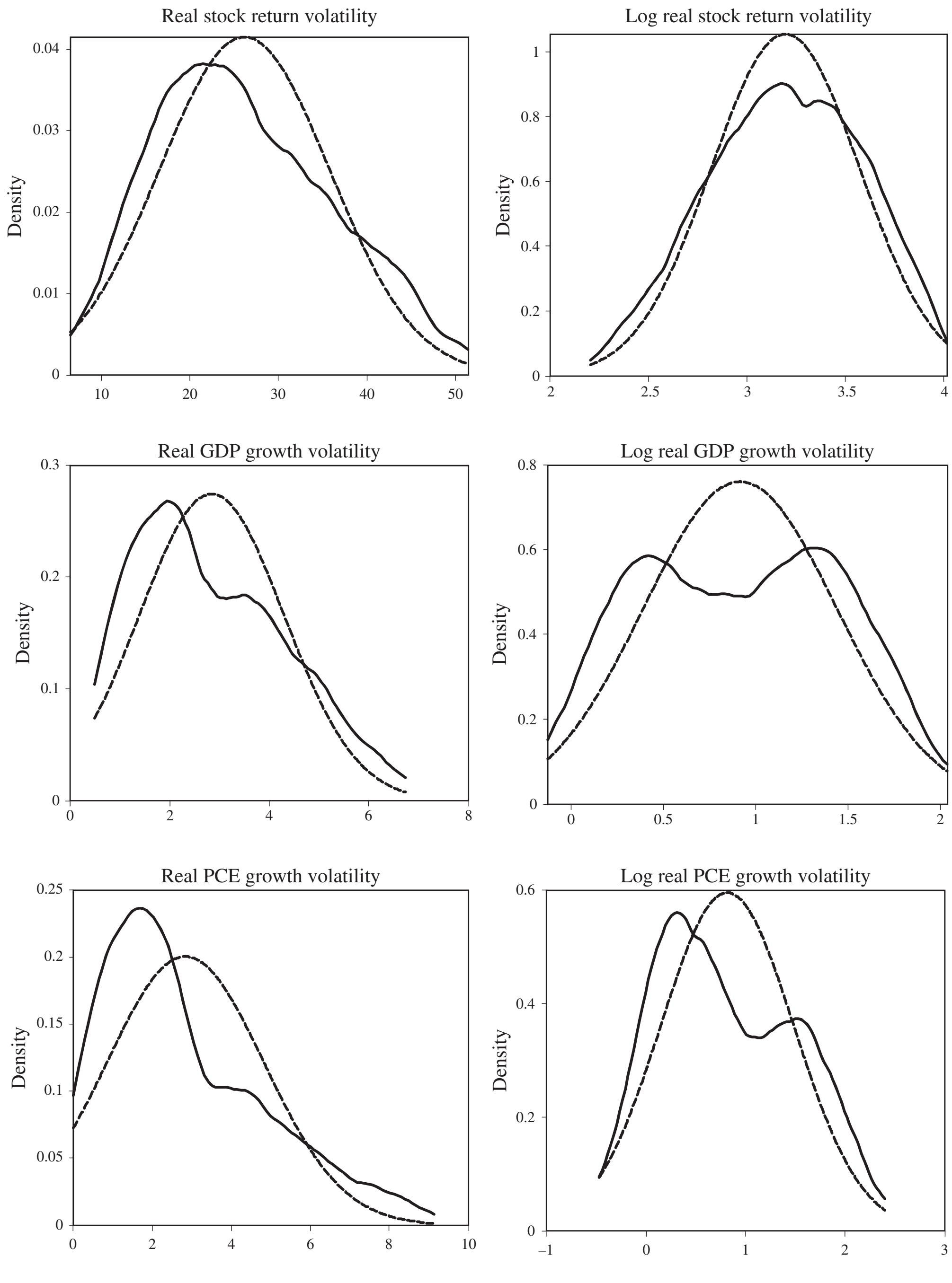

Fig. 6.1. Kernel density estimates, volatilities and fundamentals, 1983–2002

Note: We plot kernel density estimates of real stock return volatility (using data for 43 countries), real GDP growth volatility (45 countries), and real consumption growth volatility (41 countries), in both levels and logs. All volatilities are standard deviations of residuals from AR(3) models fitted to annual data, 1983–2002. For comparison we also include plots of bestfitting normal densities (dashed).

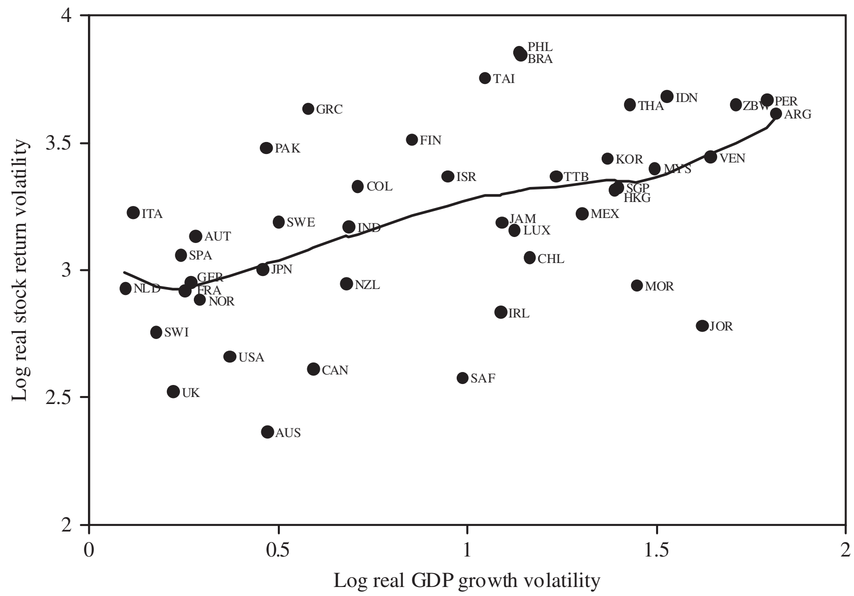

Fig. 6.2. Real stock return volatility and real GDP growth volatility, 1983–2002

Note: We show a scatterplot of real stock return volatility against real GDP growth volatility, with a nonparametric regression fit superimposed, for 43 countries. All volatilities are log standard deviations of residuals from AR(3) models fitted to annual data, 1983–2002.

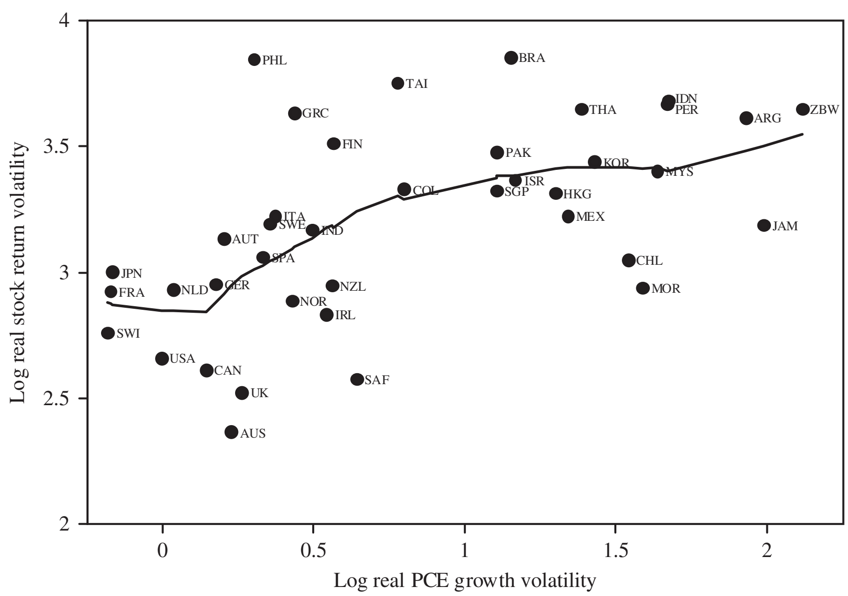

Fig. 6.3. Real stock return volatility and real PCE growth volatility, 1983–2002

Note: We show a scatterplot of real stock return volatility against real consumption growth volatility, with a nonparametric regression fit superimposed, for 39 countries. All volatilities are log standard deviations of residuals from AR(3) models fitted to annual data, 1983–2002.

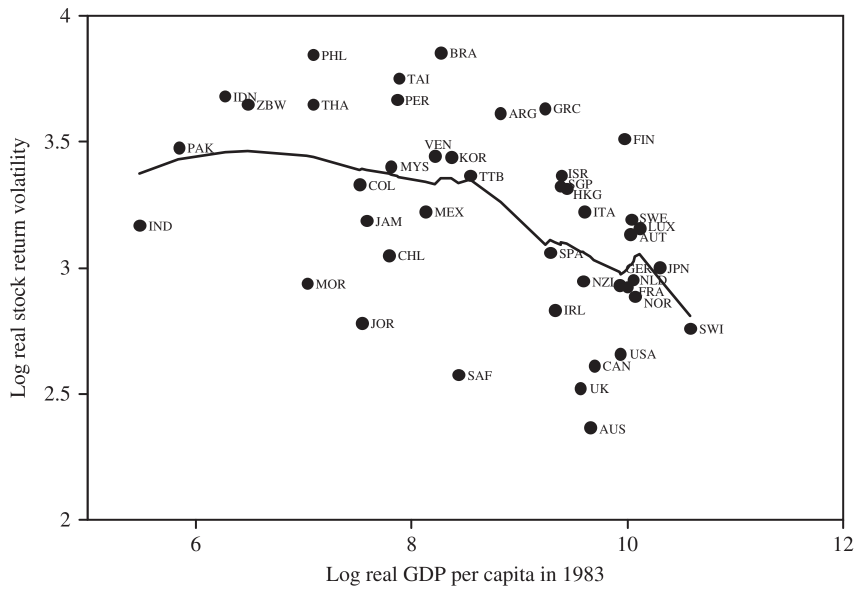

Fig. 6.4. Real Stock return volatility and initial real GDP per capita, 1983–2002

Note: We show a scatterplot of real stock return volatility against initial (1983) real GDP per capita, with a nonparametric regression fit superimposed, for 43 countries. All volatilities are log standard deviations of residuals from AR(3) models fitted to annual data, 1983–2002.

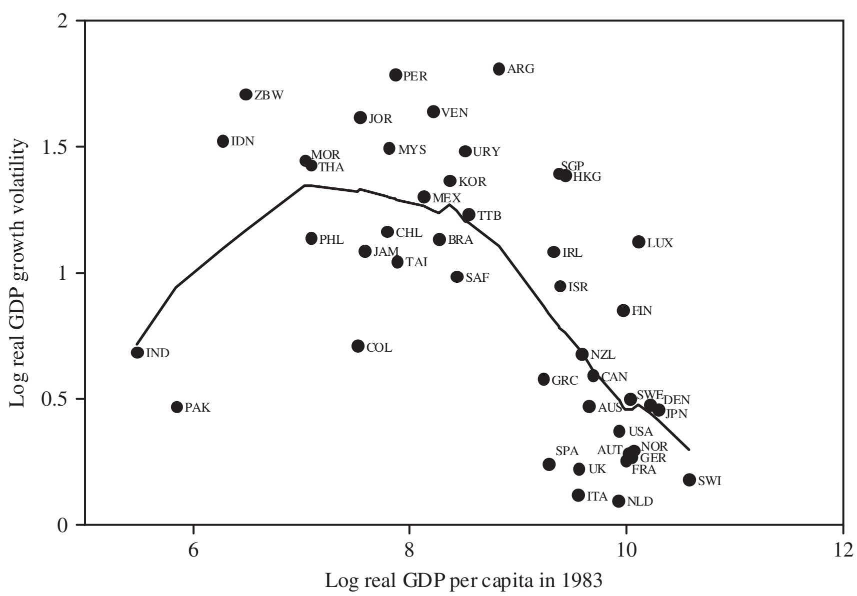

Fig. 6.5. Real GDP growth volatility and initial GDP per capita, 1983–2002

Note: We show a scatterplot of real GDP growth volatility against initial (1983) real GDP per capita, with a nonparametric regression fit superimposed, for 45 countries. All volatilities are log standard deviations of residuals from AR(3) models fitted to annual data, 1983–2002. The number of countries is two more than in Figure 2 because we include Uruguay and Denmark here, whereas we had to exclude them from Figure 2 due to missing stock return data.

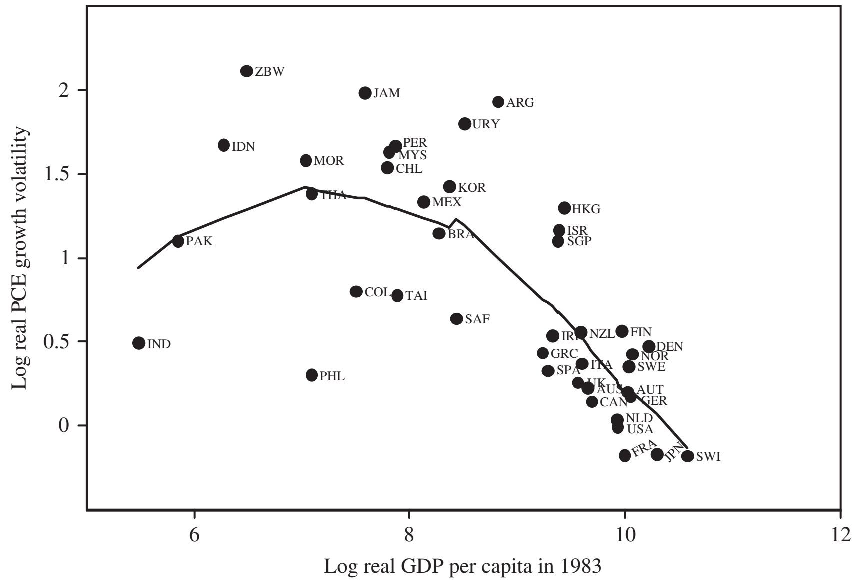

Fig. 6.6. Real PCE growth volatility and initial GDP per capita, 1983–2002

Note: We show a scatterplot of real consumption growth volatility against initial (1983) real GDP per capita, with a nonparametric regression fit superimposed, for 41 countries. All volatilities are log standard deviations of residuals from AR(3) models fitted to annual data, 1983–2002. The number of countries is two more than in Figure 3 because we include Uruguay and Denmark here, whereas we had to exclude them from Figure 3 due to missing stock return data.

initial GDP per capita, yet relatively low stock market, and especially fundamental, volatility.

We display second-step results for the GDP fundamental in Figure 6.7. The fitted curve is basically flat for low levels of GDP volatility, but it clearly becomes positive as GDP volatility increases. A positive relationship also continues to obtain when we switch to the consumption fundamental, as shown in Figure 6.8. Indeed the relationship between stock market volatility and consumption volatility would be *stronger* after controlling for initial GDP if we were to drop a single and obvious outlier (Philippines), which distorts the fitted curve at low levels of fundamental volatility, as Figure 6.8 makes clear.

4. Variations and extensions

Thus far we have studied stock market and fundamental volatility using underlying annual data, 1983–2002. Here we extend our analysis in two directions. First, we incorporate higher frequency data when possible (quarterly for GDP and monthly, aggregated to quarterly, for stock returns). Second, we use the higher frequency data in a panel-data framework to analyze the direction of causality between stock market and fundamental volatility.

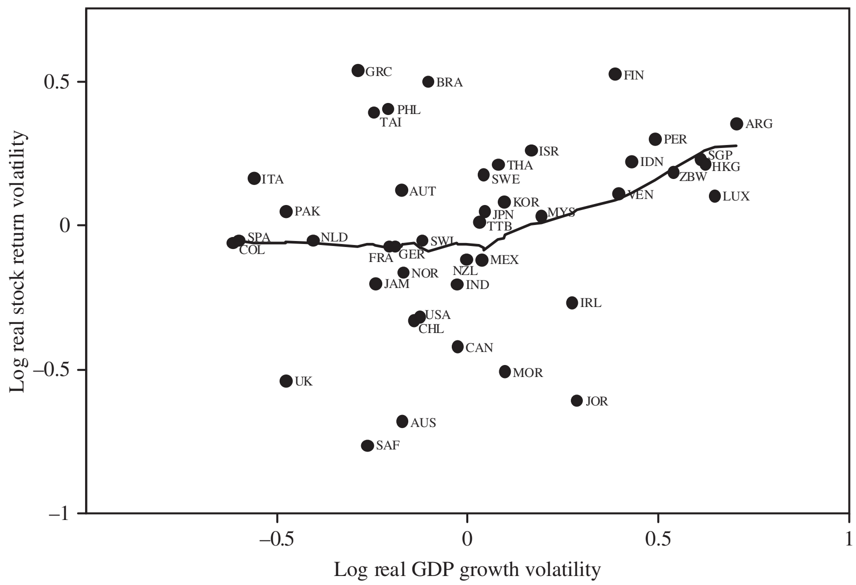

Fig. 6.7. Real stock return volatility and real GDP growth volatility, 1983–2002, controlling for initial GDP per capita

Note: We show a scatterplot of real stock return volatility against real GDP growth volatility with a nonparametric regression fit superimposed, for 43 countries, controlling for the effects of initial GDP per capita via separate first-stage nonparametric regressions of each variable on 1983 GDP per capita. All volatilities are log standard deviations of residuals from AR(3) models fitted to annual data, 1983–2002.

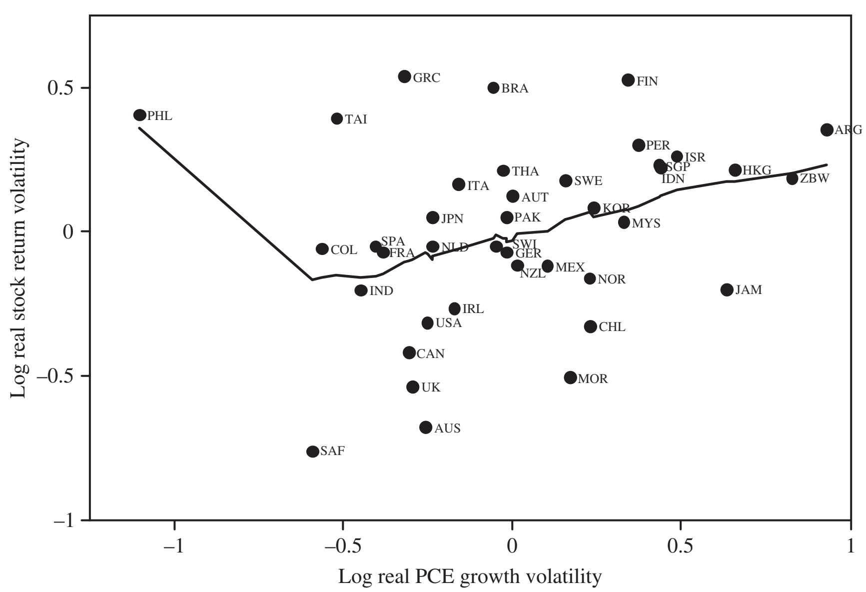

Fig. 6.8. Real stock return volatility and real PCE growth volatility, 1983–2002, controlling for initial GDP per capita

Note: We show a scatterplot of real stock return volatility against real consumption growth volatility with a nonparametric regression fit superimposed, for 39 countries, controlling for the effects of initial GDP per capita via separate first-stage nonparametric regressions of each variable on 1983 GDP per capita. All volatilities are log standard deviations of residuals from AR(3) models fitted to annual data, 1983–2002.

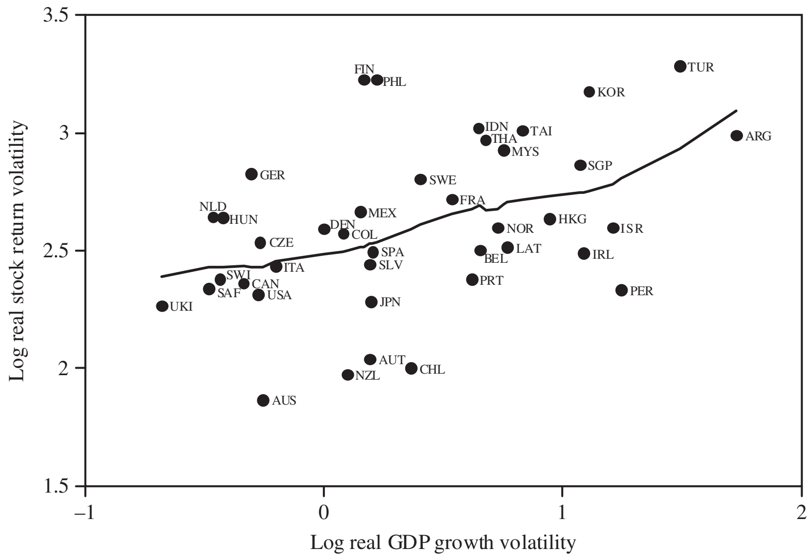

Fig. 6.9. Real stock return volatility and real GDP growth volatility, 1999.1–2003.3

Note: We show a scatterplot of real stock return volatility against real GDP growth volatility, with a nonparametric regression fit superimposed, for 40 countries. All volatilities are log standard deviations of residuals from AR(4) models fitted to quarterly data, 1999.1–2003.3.

4.1. Cross-sectional analysis based on underlying quarterly data

As noted earlier, the quality of developing-country data starts to improve in the 1980s. In addition, the quantity improves, with greater availability and reliability of quarterly GDP data. We now use that quarterly data 1984.1 to 2003.3, constructing and examining volatilities over four five-year spans: 1984.1–1988.4, 1989.1–1993.4, 1994.1–1998.4, and 1999.1–2003.3.

The number of countries increases considerably as we move through the four periods. Hence let us begin with the fourth period, 1999.1–2003.3. We show in Figure 6.9 the fitted regression of stock market volatility on GDP volatility. The relationship is still positive; indeed it appears much stronger than the one discussed earlier, based on annual data 1983–2002 and shown in Figure 6.2. Perhaps this is because the developing-country GDP data have become less noisy in recent times.

Now let us consider the other periods. We obtained qualitatively identical results when repeating the analysis of Figure 6.9 for each of the three earlier periods: stock market volatility is robustly and positively linked to fundamental volatility. To summarize those results compactly, we show in Figure 6.10 the regression fitted to all the data, so that, for example, a country with data available for all four periods has four data points in the figure. The positive relationship between stock market and fundamental volatility is clear.[11]

[11] Two outliers on the left (corresponding to Spain in the first two windows) distort the fitted curve and should be discounted.

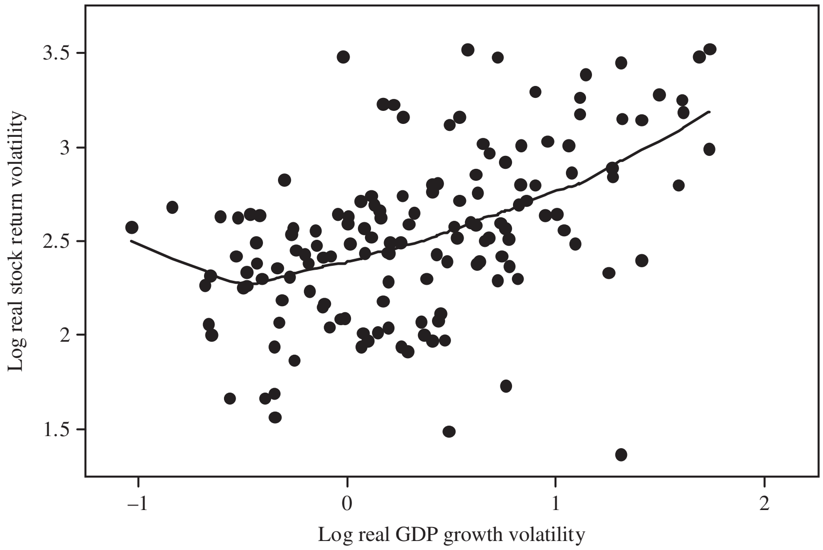

Fig. 6.10. Real stock return volatility and real GDP growth volatility, 1984.1–2003.3

Note: We show a scatterplot of real stock return volatility against real GDP growth volatility, with a nonparametric regression fit superimposed, for 43 countries. All volatilities are log standard deviations of residuals from AR(4) models fitted to quarterly data over four consecutive five-year windows (1984.1–1988.4, 1989.1–1993.4, 1994.1–1998.4, 1999.1–2003.3).

4.2. Panel analysis of causal direction

Thus far we have intentionally and exclusively emphasized the *cross-sectional* relationship between stock market and fundamental volatility, and we found that the two are positively related. However, economics suggests not only correlation between fundamentals and stock prices, and hence from fundamental volatility to stock market volatility, but also (Granger) causation.[12]

Hence in this subsection we continue to exploit the rich dispersion in the cross-section, but we no longer average out the time dimension; instead, we incorporate it explicitly via a panel analysis. Moreover, we focus on a particular panel analysis that highlights the value of incorporating cross-sectional information relative to a pure time series analysis. In particular, we follow Schwert's (1989) two-step approach to obtain estimates of time-varying quarterly stock market and GDP volatilities, country-by-country, and then we test causal hypotheses in a panel framework that facilitates *pooling* of the cross-country data.

Briefly, Schwert's approach proceeds as follows. In the first step, we fit autoregressions to stock market returns and GDP, and we take absolute values of the associated *residuals*, which are effectively (crude) quarterly realized volatilities of stock market and fundamental innovations, in the jargon of Andersen, Bollerslev, Diebold and Ebens (2001).

[12]There may of course also be bi-directional causality (feedback).

In the second stage, we transform away from realized volatilities and toward conditional volatilities by fitting autoregressions to those realized volatilities, and keeping the *fitted values*. We repeat this for each of the 46 countries.

We analyze the resulting 46 pairs of stock market and fundamental volatilities in two ways. The first follows Schwert and exploits only time series variation, estimating a separate VAR model for each country and testing causality. The results, which are not reported here, mirror Schwert's, failing to identify causality in either direction in the vast majority of countries.

The second approach exploits cross-sectional variation along with time series variation. We simply pool the data across countries, allowing for fixed effects. First we estimate a fixed-effects model with GDP volatility depending on three lags of itself and three lags of stock market volatility, which we use to test the hypothesis that stock market volatility does not Granger cause GDP volatility. Next we estimate a fixed-effects model with stock market volatility depending on three lags of itself and three lags of GDP volatility, which we use to test the hypothesis that GDP volatility does not Granger cause stock market volatility.

We report the results in Table 6.1, using quarterly real stock market volatility and real GDP growth volatility for the panel of 46 countries, 1961.1–2003.3. We test noncausality from fundamental volatility (FV) to return volatility (RV), and vice versa, and we present F-statistics and corresponding p values for both hypotheses. We do this for 30 sample windows, with the ending date fixed at 2003.3 and the starting date varying from 1961.1, 1962.1, . . . , 1990.1. There is no evidence against the hypothesis that stock market volatility does not Granger cause GDP volatility; that is, it appears that stock market volatility *does not* cause GDP volatility. In sharp contrast, the hypothesis that GDP volatility does not Granger cause stock market volatility is overwhelmingly rejected: evidently GDP volatility *does* cause stock market volatility.

The intriguing result of one-way causality from fundamental volatility to stock return volatility deserves additional study, as the forward-looking equity market might be expected to predict macro fundamentals, rather than the other way around. Of course here we focus on predicting fundamental and return *volatilities*, rather than fundamentals or returns themselves. There are subtleties of volatility measurement as well. For example, we do not use implied stock return volatilities, which might be expected to be more forward-looking.[13]

5. Concluding remark

This chapter is part of a broader movement focusing on the macro-finance interface. Much recent work focuses on high-frequency data, and some of that work focuses on the high-frequency relationships among returns, return volatilities and fundamentals (e.g., Andersen, Bollerslev, Diebold and Vega, 2003, 2007). Here, in contrast, we focus on international cross-sections obtained by averaging over time. Hence this chapter can be interpreted not only as advocating more exploration of the fundamental volatility/return

[13]Implied volatilities are generally not available.

Table 6.1. Granger causality analysis of stock market volatility and fundamental volatility

Beginning Year	RV not ⇒ FV		FV not ⇒ RV	
	F-stat.	p value	F-stat.	p value
1961	1.16	0.3264	4.14	0.0024
1962	1.18	0.3174	4.09	0.0026
1963	1.11	0.3498	4.21	0.0021
1964	1.14	0.3356	4.39	0.0015
1965	1.07	0.3696	4.33	0.0017
1966	1.06	0.3746	4.33	0.0017
1967	1.01	0.4007	4.48	0.0013
1968	1.00	0.4061	4.44	0.0014
1969	0.98	0.4171	4.38	0.0016
1970	0.96	0.4282	4.14	0.0024
1971	0.89	0.4689	3.86	0.0039
1972	0.78	0.5380	4.16	0.0023
1973	0.62	0.6482	4.06	0.0027
1974	0.84	0.4996	4.40	0.0015
1975	0.83	0.5059	3.90	0.0036
1976	0.83	0.5059	3.89	0.0037
1977	0.95	0.4339	3.93	0.0035
1978	0.88	0.4750	4.11	0.0025
1979	0.73	0.5714	4.02	0.0030
1980	0.74	0.5646	4.52	0.0012
1981	0.49	0.7431	4.67	0.0009
1982	0.47	0.7578	4.77	0.0008
1983	0.59	0.6699	5.15	0.0004
1984	0.71	0.5850	5.39	0.0003
1985	0.83	0.5059	5.58	0.0002
1986	1.07	0.3697	5.59	0.0002
1987	1.29	0.2716	5.76	0.0001
1988	1.29	0.2716	4.84	0.0007
1989	1.21	0.3044	3.86	0.0039
1990	1.23	0.2959	3.42	0.0085

We assess the direction of causal linkages between quarterly real stock market volatility and real GDP growth volatility for the panel of 46 countries, 1961.1 to 2003.3. We test noncausality from fundamental volatility (FV) to return volatility (RV), and vice versa, and we present F-statistics and corresponding p values for both hypotheses. We do this for 30 sample windows, with the ending date fixed at 2003.3 and the starting date varying from 1961.1, 1962.1, . . . , 1990.1.

volatility interface, but also in particular as a call for more exploration of volatility at *medium* (e.g., business cycle) frequencies. In that regard it is to the stock market as, for example, Diebold, Rudebusch and Aruoba (2006) is to the bond market and Evans and Lyons (2007) is to the foreign exchange market.

Appendix

Here we provide details of data sources, country coverage, sample ranges, and transformations applied. We discuss underlying annual data first, followed by quarterly data.

Annual data

We use four "raw" data series per country: real GDP, real private consumption expenditures (PCE), a broad stock market index, and the CPI. We use those series to compute annual real stock returns, real GDP growth, real consumption growth, and corresponding volatilities. The data set includes a total of 71 countries and spans a maximum of 42 years, 1960–2002. For many countries, however, consumption and especially stock market data are available only for a shorter period, reducing the number of countries with data available.

We obtain annual stock market data from several sources, including International Financial Statistics (IFS), the OECD, Standard and Poor's Emerging Market Data Base (EMDB), Global Insight (accessed via WRDS), Global Financial Data, Datastream, the World Federation of Exchanges, and various stock exchange websites. Details appear in Table 6.A1, which lists the countries for which stock market index data are available at least for the 20-year period from 1983–2002. With stock prices in hand, we calculate nominal returns as $i_t = \ln(p_t/p_{t-1})$. We then calculate annual consumer price index (CPI) inflation, π_t, using the monthly IFS database 1960–2002, and finally we calculate real stock returns as $r_t = (1 + i_t)/\ (1 + \pi_t) - 1$.

We obtain annual real GDP data from the World Bank World Development Indicators database (WDI). For most countries, WDI covers the full 1960–2002 period. Exceptions are Canada (data start in 1965), Germany (data start in 1971), Israel (data end in 2000), Saudi Arabia (data end in 2001), and Turkey (data start in 1968). We obtain Taiwan real GDP from the Taiwan National Statistics website. We complete the real GDP growth rate series for Canada (1961–1965), Germany (1961–1971), Israel (2001–2002) and Saudi Arabia (2002) using IFS data on nominal growth and CPI inflation. We calculate real GDP growth rates as $GDP_t/\ GDP_{t-1} - 1$.

We obtain real personal consumption expenditures data using the household and personal final consumption expenditure from the World Bank's WDI database. We recover missing data from the IFS and Global Insight (through WRDS); see Table 6.A2 for details. We calculate real consumption growth rates as $C_t/C_{t-1} - 1$.

Quarterly data

The quarterly analysis reported in the text is based on 46 countries. Most, but not all, of those countries are also included in the annual analysis.

For stock markets, we construct quarterly returns using the monthly data detailed in Table 6.A3, and we deflate to real terms using quarterly CPI data constructed using the same underlying monthly CPI on which annual real stock market returns are based.

For real GDP in most countries, we use the IFS volume index. Exceptions are Brazil (real GDP volume index, Brazilian Institute of Geography and Statistics website), Hong

Kong (GDP in constant prices, Census and Statistics Department website), Singapore (GDP in constant prices, Ministry of Trade and Industry, Department of Statistics website), and Taiwan (GDP in constant prices, Taiwan National Statistics website).

Table 6.A4 summarizes the availability of the monthly stock index series and quarterly GDP series for each country in our sample.

Table 6.A1. Annual stock market data

Country	Period covered	Database/Source	Acronyms
Argentina	1966–2002	1966–1989 Buenos Aires SE[(1)] General Index 1988–2002 Buenos Aires SE Merval Index	ARG
Australia	1961–2002	IFS[(2)]	AUS
Austria	1961–2002	1961–1998 IFS 1999–2002 Vienna SE WBI index	AUT
Brazil	1980–2002	Bovespa SE	BRA
Canada	1961–2002	IFS	CAN
Chile	1974–2002	IFS	CHL
Colombia	1961–2002	IFS	COL
Finland	1961–2002	IFS	FIN
France	1961–2002	IFS	FRA
Germany	1970–2002	IFS	GER
Greece	1975–2002	Athens SE General Weighted Index	GRC
Hong Kong, China	1965–2002	Hang Seng Index	HKG
India	1961–2002	IFS	IND
Indonesia	1977–2002	EMDB–JSE Composite[(3)]	IDN
Ireland	1961–2002	IFS	IRL
Israel	1961–2002	IFS	ISR
Italy	1961–2002	IFS	ITA
Jamaica	1969–2002	IFS	JAM
Japan	1961–2002	IFS	JPN
Jordan	1978–2002	Amman SE General Weighted Index	JOR
Korea	1972–2002	IFS	KOR
Luxembourg	1970–2002	1980–1998 IFS 1999–2002 SE–LuxX General Index	LUX
Malaysia	1980–2002	KLSE Composite	MYS
Mexico	1972–2002	Price & Quotations Index	MEX
Morocco	1980–2002	EMDB–Upline Securities	MOR
Netherlands	1961–2002	IFS	NLD
New Zealand	1961–2002	IFS	NZL
Norway	1961–2002	1961–2000 IFS 2001–2002 OECD–CLI industrials	NOR
Pakistan	1961–2002	1961–1975 IFS 1976–2002 EMDB–KSE 100	PAK

(*cont.*)

Table 6.A1. (*Continued*)

Country	Period covered	Database/Source	Acronyms
Peru	1981–2002	Lima SE	PER
Philippines	1961–2002	IFS	PHL
Singapore	1966–2002	1966–1979 Strait Times Old Index 1980–2002 Strait Times New Index	SGP
South Africa	1961–2002	IFS	SAF
Spain	1961–2002	IFS	SPA
Sweden	1961–2002	IFS	SWE
Switzerland	1961–2002	OECD–UBS 100 index	SWI
Taiwan	1967–2002	TSE Weighted Stock Index	TAI
Thailand	1975–2002	SET Index	THA
Trinidad and Tobago	1981–2002	EMDB–TTSE index	TTB
United Kingdom	1961–2002	1961–1998 IFS, industrial share index 1999–2002 OECD, industrial share index	UK
United States	1961–2002	IFS	USA
Venezuela, Rep. Bol.	1961–2002	IFS	VEN
Zimbabwe	1975–2002	EMDB–ZSE Industrial	ZBW

(1) SE denotes Stock Exchange.
(2) IFS denotes IMF's International Financial Statistics. IFS does not provide the name of the stock market index.
(3) EMDB denotes Standard & Poors' Emerging Market Data Base.

Table 6.A2. Annual Consumption Data

Country	Database	Country	Database
Argentina	1960–2001 IFS[1] 2002 WRDS[2]	Malaysia	1960–2002 WDI
Australia	1958–2000 WDI[3], 2001–2002 WRDS	Morocco	1960–2001 WDI, 2002 WRDS
Austria	1959–2002 WDI, 2002 WRDS	Mexico	1959–2001 WDI, 2002 WRDS
Brazil	1959–2001 WDI, 2002 WRDS	Netherlands	1959–2001 WDI, 2002 WRDS
Canada	1960–1964 IFS; 1965–2000 WDI, 2002 WRDS	New Zealand	1958–2000 WDI, 2001–2002 IFS
Chile	1960–2001 WDI, 2002 WRDS	Norway	1958–2000 WDI, 2001–2002 WRDS
Colombia	1960–2001 WDI, 2002 WRDS	Pakistan	1960–2002 WDI
Denmark	1959–2001 WDI, 2002 IFS	Peru	1959–2001 WDI, 2002 WRDS
Finland	1959–2001 WDI, 2002 WRDS	Philippines	1960–2001 WDI, 2002 WRDS

(*cont.*)

Table 6.A2. (*Continued*)

Country	Database	Country	Database
France	1959–2001 WDI, 2002 WRDS	Singapore	1960–2002 WDI
Germany	1960–1970 IFS, 1971–2001 WDI, 2002 WRDS	South Africa	1960–2002 WDI
Greece	1958–2000 WDI, 2001–2002 WRDS	Spain	1959–2001 WDI, 2002 WRDS
Hong Kong, China	1959–2001 WDI, 2002 IFS	Sweden	1959–2001 WDI, 2002 WRDS
India	1959–2001 WDI, 2002 WRDS	Switzerland	1959–2001 WDI, 2002 WRDS
Indonesia	1960–2002 WDI	Taiwan	1964–2002 National Statistics Office
Ireland	1960–2000 WDI, 2001–2002 WRDS	Thailand	1960–2002 WDI
Israel	1960–2000 WDI, 2001–2002 WRDS	United Kingdom	1959–2001 WDI, 2002 WRDS
Italy	1959–2001 WDI, 2002 IFS	United States	1958–2000 WDI, 2001–2002 WRDS
Jamaica	1959–2001 WDI, 2002 IFS	Uruguay	1960–2001 WDI, 2002 WRDS
Japan	1959–2001 WDI, 2002 WRDS	Zimbabwe	1965–2002 WDI
Korea	1960–2002 WDI		

(1) IFS denotes IMF's International Financial Statistics.
(2) Data taken from the Global Insight (formerly DRI) database which is available through Wharton Research Data Service (WRDS).
(3) WDI denotes World Development Indicators.

Table 6.A3. Monthly Stock Index Data

Acronym	Country	Definition	Period covered	Source
ARG	Argentina	Buenos Aires Old (1967–1988) Merval Index (1989–2003)	1983:01–2003:12	GFD[1]
AUS	Australia	19362...ZF..., Share Prices: Ordinaries	1958:01–2003:12	IFS[2]
AUT	Austria	12262...ZF..., Share Prices	1957:01–2003:12	IFS
BEL	Belgium	12462...ZF...	1957:01–2003:12	IFS
BRA	Brazil	22362...ZF...	1980:01–2003:12	IFS
CAN	Canada	15662...ZF...	1957:01–2003:11	IFS
CHL	Chile	22862...ZF...	1974:01–2003:10	IFS
COL	Colombia	23362...ZF...	1959:01–2003:12	IFS

(*cont.*)

Table 6.A3. (*Continued*)

Acronym	Country	Definition	Period covered	Source
CZE	Czech Republic	PX50 Index	1994:01–2003:12	EMDB(3)
DEN	Denmark	12862A..ZF...	1967:01–2003:12	IFS
FIN	Finland	17262...ZF...	1957:01–2003:12	IFS
FRA	France	13262...ZF...	1957:01–2003:11	IFS
GER	Germany	13462...ZF...	1970:01–2003:12	IFS
GRC	Greece	Athens General Index	1980:01–2003:09	GFD
HKG	Hong Kong	Hang Seng Index	1980:01–2003:05	GFD
HUN	Hungary	BSE BUX Index	1992:01–2003:12	EMDB
IDN	Indonesia	Jakarta SE Composite Index	1983:03–2003:12	GFD
IRL	Ireland	17862...ZF... (May 1972 missing)	1957:01–2003:11	IFS
ISR	Israel	43662...ZF...	1957:01–2003:11	IFS
ITA	Italy	13662...ZF...	1957:01–2003:12	IFS
JPN	Japan	15862...ZF...	1957:01–2003:11	IFS
JOR	Jordan	ASE Index	1986:01–2003:02	EMDB
KOR	S. Korea	KOSPI Index	1975:01–2003:12	GFD
LAT	Latyia	94162...ZF...	1996:04–2003:12	IFS
MYS	Malaysia	KLSE composite	1980:01–2003:12	GFD
MEX	Mexico	IPC index	1972:01–2003:12	GFD
NLD	Netherlands	13862...ZF...	1957:01–2003:11	IFS
NZL	New Zealand	19662...ZF...	1961:01–2003:09	IFS
NOR	Norway	14262...ZF... (Sep 1997 missing)	1957:01–2003:12	IFS
PER	Peru	Lima SE Index	1981:12–2003:12	GFD
PHL	Philippines	56662...ZF...	1957:01–2003:11	IFS
PRT	Portugal	PSI General Index	1987:12–2003:12	EMDB
SGP	Singapore	Old+New Strait Times Index	1966:01–2003:11	GFD
SLV	Slovakia	SAX Index	1996:01–2003:12	EMDB
SAF	South Africa	19962...ZF...	1960:01–2003:10	IFS
SPA	Spain	18462...ZF...	1961:01–2003:12	IFS
SWE	Sweden	14462...ZF...	1996:06–2003:12	IFS
SWI	Switzerland	14662...ZF...	1989:01–2003:12	IFS
TAI	Taiwan	SE Capitalization Weighted Index	1967:01–2003:12	GFD
THA	Thailand	SET Index	1980:01–2003:12	GFD
TUR	Turkey	ISE National-100 Index	1986:12–2003:12	GFD
UKI	United Kingdom	FTSE 100 Index	1957:12–2003:11	WRDS(4)
USA	United States	11162 ZF	1957:01–2003:12	IFS

(1) GFD denotes Global Financial Data.
(2) IFS denotes IMF's International Financial Statistics.
(3) EMDB denotes Standard & Poors' Emerging Market Data Base.
(4) WRDS denotes Wharton Research Data Services.

Table 6.A4. Availability of monthly stock returns and quarterly GDP series

Acronym	Country	1984. I–1988.IV		1989.I–1993.IV		1994.I–1998.IV		1999.I–2003.IV	
		Stock index	GDP	Stock index	GDP	Stock index	GDP	Stock index	GDP
ARG	Argentina	✓	✓	✓	✓	✓	✓	✓	✓
AUS	Australia	✓	✓	✓	✓	✓	✓		✓
AUT	Austria	✓	✓	✓	✓	✓	✓	✓	✓
BEL	Belgium	✓	✓	✓	✓	✓	✓	✓	✓
BRA	Brazil	✓		✓		✓	✓	✓	
CAN	Canada	✓	✓	✓	✓	✓	✓	✓	✓
CHL	Chile	✓	✓	✓	✓	✓	✓	✓	✓
COL	Colombia	✓		✓		✓		✓	✓
CZE	Czech Republic					✓		✓	✓
DEN	Denmark	✓	✓	✓	✓	✓	✓	✓	✓
FIN	Finland	✓	✓	✓	✓	✓	✓	✓	✓
FRA	France	✓	✓	✓	✓	✓	✓	✓	✓
GER	Germany	✓	✓	✓	✓	✓	✓	✓	✓
GRC	Greece	✓	✓	✓		✓		✓	
HKG	Hong Kong	✓	✓	✓	✓	✓	✓		
HUN	Hungary					✓		✓	✓
IDN	Indonesia	✓		✓		✓		✓	✓
IRL	Ireland	✓		✓		✓		✓	✓
ISR	Israel	✓	✓	✓	✓	✓	✓	✓	✓
ITA	Italy	✓	✓	✓	✓	✓	✓	✓	✓
JPN	Japan	✓	✓	✓	✓	✓	✓	✓	✓
JOR	Jordan			✓		✓	✓	✓	
KOR	S. Korea	✓	✓	✓	✓	✓	✓	✓	✓
LAT	Latvia							✓	✓
MYS	Malaysia	✓		✓	✓	✓	✓	✓	✓
MEX	Mexico	✓	✓	✓	✓	✓	✓	✓	✓
NLD	Netherlands	✓	✓	✓	✓	✓	✓	✓	✓
NZL	New Zealand	✓	✓	✓	✓	✓	✓	✓	✓
NOR	Norway	✓	✓	✓	✓	✓	✓	✓	✓
PER	Peru	✓	✓	✓	✓	✓	✓	✓	✓
PHL	Philippines	✓	✓	✓	✓	✓	✓	✓	✓
PRT	Portugal			✓	✓	✓	✓	✓	✓
SGP	Singapore	✓	✓	✓	✓	✓	✓	✓	✓
SLV	Slovakia							✓	✓
SAF	South Africa	✓	✓	✓	✓	✓	✓	✓	✓
SPA	Spain	✓	✓	✓	✓	✓	✓	✓	✓
SWE	Sweden							✓	✓
SWI	Switzerland			✓		✓	✓	✓	✓
TAI	Taiwan	✓	✓	✓	✓	✓	✓	✓	✓
THA	Thailand					✓	✓	✓	✓
TUR	Turkey			✓	✓	✓	✓	✓	✓
UKI	United Kingdom	✓	✓	✓	✓	✓	✓	✓	✓
USA	United States	✓	✓	✓	✓	✓	✓	✓	✓