



Volatility: A dead ringer for downside risk

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ABSTRACT

Volatility is as widely used as is widely criticized as a risk metric. This short article argues that despite its many shortcomings volatility is pervasive for two mutually-reinforcing reasons: First, it is very widely known; and second, it is a very good proxy for the downside risk that investors really dislike. The evidence discussed here shows that a ranking of assets by volatility is very highly correlated with rankings made by different metrics that directly assess downside risk.

1. Introduction

The standard deviation is a statistic widely known and widely used in many and varied fields. Finance academics and practitioners have been using the standard deviation of returns, usually referred to as volatility, as a measure of risk from the beginning of modern finance in the early 1950s. Interestingly, despite its many shortcomings as a risk metric and its lack of intuitive meaning, volatility remains pervasive in finance. Why?

Two mutually-reinforcing reasons may help to answer this question. First, unlike many other risk metrics, volatility is known essentially by all market participants, from institutional to individual investors, and from academics to practitioners. Second, and central to the issue addressed in this article, volatility is a very good proxy for the downside risk that investors really dislike; that is, a ranking of assets by volatility is very highly correlated with rankings made by different metrics that directly assess downside risk.

It should not be surprising that individuals have a general tendency to use a tool that most other people use, have been using for a long time, and roughly does its job, even if it has obvious limitations. When assessing the risk of financial assets, volatility is that tool. In fact, despite its shortcomings, volatility is very widely used, has been used for decades, and as shown here, it properly captures and conveys the downside risk that, all else equal, investors want to avoid.

The rest of the article is organized as follows. Section 2 discusses the origin of volatility as a measure of risk, some of its limitations, and some

metrics designed to capture downside risk; section 3 discusses the evidence that explains the widespread use of volatility as a measure of risk; and section 4 provides an assessment. An appendix with exhibits concludes the article.

2. The issue

2.1. Volatility – origin

Modern finance theory begins with the publication of Markowitz's (1952) seminal article and Markowitz's (1959) follow-up book, which for the first time formally define the risk of an asset as the variance of its returns, and by extension as the standard deviation of its returns; that is, volatility. His simple (but revolutionary) idea was to capture the dispersion of returns around their mean, with higher dispersion implying higher uncertainty, and therefore higher risk.²

Importantly, from the very beginning Markowitz noticed some limitations of volatility as a risk metric and for this reason he also considered assessing risk with the semideviation, a related metric that captures volatility only below, but not above, a benchmark; see Markowitz (1959), chapter IX. However, due to "cost, convenience, and familiarity" he ultimately chose the standard deviation over the semideviation, albeit recognizing the limitations of the former.

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¹ I would like to thank John Rekenhaller for his comments. Pol Delgado provided valuable research assistance. The views expressed and any errors that may remain are entirely my own. Web: <https://blog.iese.edu/jestrada>.

² Volatility aims to capture the total risk of an asset, part of which that can be diversified away through the combination of assets in a portfolio (unsystematic risk), and part of which that has to be born even when holding a fully diversified portfolio (systematic risk). Treynor (1961), Sharpe (1964), Lintner (1965), and Mossin (1966) introduced beta to quantify the systematic risk of an asset, and the Capital Asset Pricing Model (CAPM) to estimate the asset's required/expected return.

2.2. Volatility – shortcomings

It is both curious and perhaps surprising that a risk metric as widely used as volatility has so little intuitive meaning. Consider an asset with an annual volatility of 15%. What does that mean? Strictly speaking, 15% is the square root of the average quadratic deviation with respect to the arithmetic mean return; but that is a mouthful that conveys no intuition. Interestingly, Goldstein and Taleb (2007) argue that this lack of intuition leads even finance professionals to confuse the standard deviation with the mean absolute deviation, thus leading them to underestimate risk.

If the asset in question had a mean annual return of 10%, a volatility of 15% could be used to argue that one would expect the annual return of the asset to be between –20% and 40% with a probability of 95%. But that is only a helpful way of *using* volatility, not of explaining the meaning of 15%; and importantly, it requires the assumption of normality, which is very far from guaranteed in practice.

Critically, one of the main limitations of volatility as a measure of risk, and one of its main criticisms, is that it gives the same weight to deviations above and below the mean. Needless to say, investors do not feel the same way when they experience a return 10 percentage points above or below the mean; and yet both returns would have the same impact in the calculation of a volatility figure. Estrada (2006) considers the case of Oracle over the 1995–2004 period, calculates a very high annual volatility of 91.7%, and highlights that it is mostly driven by Oracle's 289.8% positive return in 1999.

2.3. Downside risk

As already mentioned, from the very beginning of modern finance the semideviation was viewed by Markowitz as a serious contender of volatility as a measure of risk. In fact, when receiving the 1990 Nobel prize in Economics, Markowitz (1991) stated that “[s]emivariance seems more plausible than variance as a measure of risk, since it is concerned only with adverse deviations.” And Markowitz et al (1993) further argue that because “... an investor worries about underperformance rather than overperformance, semideviation is a more appropriate measure of investor's risk than variance.”

Moreover, the semideviation as a measure of risk can also be defended on theoretical grounds. In fact, Estrada (2004) justifies mean-semivariance behavior along the same lines used by Levy and Markowitz (1979) to justify mean-variance behavior; that is, as a criterion that is highly correlated with expected utility. And importantly, the reasons that Markowitz gave in 1959 for favoring variance over semivariance, such as computational cost and convenience, hardly apply nowadays.

Formally, the *semideviation* with respect to any chosen benchmark B (SSD_B) is given by the expression

$$SSD_B = \left\{ (1/T) \cdot \sum_{t=1}^T \text{Min}[(R_t - B), 0]^2 \right\}^{1/2} \quad (1)$$

where R denotes returns, t indexes time, and T is the number of observations in the sample. Thus, returns below B add to the calculation of the semideviation figure, but returns above it do not. For ease of exposition, from this point on the benchmark B will be assumed to be 0, in which case (1) turns into

$$SSD = \left\{ (1/T) \cdot \sum_{t=1}^T \text{Min}(R_t, 0)^2 \right\}^{1/2} \quad (2)$$

Importantly, in the same way that (2) can be easily generalized for any benchmark B , as shown by (1), the same goes for the rest of the expressions below in which B will be set equal to 0.

Needless to say, the semideviation is but one of the many metrics designed to capture downside risk. Investors are also typically interested

to know how often they should expect to experience losses. Assume that out of T observations in a sample, N of them are losses ($L = R < 0$) and M of them are gains ($G = R > 0$), such that $N + M = T$. Then, the *probability of loss* (PL) is given by the expression

$$PL = N/T \quad (3)$$

that is, by the proportion of negative returns in the sample, which (if history is any guide) is an estimate of the probability of experiencing periodic losses in the future.

Investors are also typically interested to know how much they would lose in the periods in which they expect to experience losses. Thus, the *average loss* (AL) is given by the expression

$$AL = (1/N) \cdot \sum_{t=1}^N L_t \quad (4)$$

Combining the probability of loss as defined in (3) and the average loss as defined in (4) yields the *expected loss* (EL), which is formally given by

$$EL = PL \cdot AL = (1/T) \cdot \sum_{t=1}^N L_t \quad (5)$$

Investors are also often concerned with ‘worst-case’ scenarios, which can be quantified in at least three different ways. One of them is the *worst loss* (WL), which is formally given by

$$WL = \text{Min}(L_1, L_2 \dots L_T) \quad (6)$$

and is expressed in the same frequency as the data in the sample. Another is with the *maximum drawdown* (MD), which is formally given by

$$MD = (PVB - TV)/PVB \quad (7)$$

where PVB denotes the peak value before the trough and TV denotes the trough value. In words, a maximum drawdown is the largest drop from peak to trough before a new peak is achieved.

Finally, ‘worst-case’ scenarios can be quantified with the value at risk (Var_c) metric, which under the assumption of normality can be calculated as

$$Var_c = AM - z_c \cdot SD \quad (8)$$

where AM and SD denote the arithmetic mean return and standard deviation of returns of the sample considered, and z_c is the cutoff point for the standard normal distribution for a confidence level of $c\%$. This VaR can be calculated for any chosen data frequency and confidence level.³

The metrics in expressions (2–8) are not an exhaustive list of all the downside risk metrics that have been proposed by academics and practitioners; see, for example, (Rockafellar et al 2006a, 2006b, 2006c). Moreover, the metrics considered here omit variables that focus on relative (rather than on absolute) risk, such as downside beta or downside capture. Nawrocki (1999) provides a brief history of downside risk measures and Estrada (2006) provides a primer on downside risk for practitioners Exhibit 1, Exhibit 2.

3. Evidence

3.1. Data and methodology

The data used in this article consists of the MSCI database of 47

³ There are several variations of VaR, such as conditional value at risk (CVar), conditional autoregressive value at risk (CAViaR), and systemic conditional value at risk (ΔCoVar); see Rockafellar and Uryasev (2000), Engle and Manganelli (2004), and Adrian and Brunnermeier (2016). This article focuses on VaR as the representative metric for all VaR-related metrics.

Exhibit 1

Spearman correlations – countries. This exhibit shows, over the whole sample period available for each country, Spearman correlations between volatility and the semideviation (SSD), the probability of loss (PL), the average loss in periods with losses (AL), the expected loss (EL), the worst loss (WL), the maximum drawdown (MD), and value at risk (VaR), all in monthly terms. AL, EL, WL, MD, and VaR in absolute value. The last column shows the average (Avg) of the figures in the previous columns. The data is described in [Exhibit A1](#) in the appendix.

	SSD	PL	AL	EL	WL	MD	VaR	Avg
Developed	0.96	0.64	0.91	0.9	0.62	0.71	0.99	0.82
Emerging	0.96	0.29	0.97	0.97	0.81	0.62	1	0.8
All countries	0.98	0.53	0.97	0.96	0.77	0.74	1	0.85

Exhibit 2

Spearman correlations – industries and countries. This exhibit shows, over the whole sample period available for each industry and country, Spearman correlations between volatility and the semideviation (SSD), the probability of loss (PL), the average loss in periods with losses (AL), the expected loss (EL), the worst loss (WL), the maximum drawdown (MD), and value at risk (VaR), all in monthly terms. AL, EL, WL, MD, and VaR in absolute value. The last column shows the average (Avg) of the figures in the previous columns. The data is described in [Exhibit A1](#) in the appendix.

	SSD	PL	AL	EL	WL	MD	VaR	Avg
Industries	0.96	0.51	0.95	0.94	0.73	0.64	0.98	0.82
Industries & Countries	0.97	0.66	0.95	0.96	0.79	0.71	0.99	0.86

countries (23 developed and 24 emerging) and 65 industries, each considered from its inception in the database and through Dec/2024. All returns are nominal, in dollars, and account for both capital gains/losses and dividends. [Exhibit A1](#) in the appendix shows the countries and industries in the sample, their inception month in the database, and their annualized mean return and volatility over their whole sample period. Note that each asset in the sample is a portfolio of stocks, not an individual stock.

The first step of the analysis is to calculate, for the whole series of monthly returns available for each country and industry in the sample, all the risk metrics considered here; that is, volatility, the semideviation (SSD), the probability of loss (PL), the average loss (AL), the expected loss (EL), the worst loss (WL), the maximum drawdown (MD), and value at risk (VaR).

The second step is to rank countries (first developed, then emerging, then all pooled), industries, and countries and industries pooled by each risk metric considered here. Because SSD and PL are non-negative numbers, and AL, EL, WL, MD, and VaR are negative numbers, the rankings for these five metrics are based on the absolute value of these variables (as they are shown in [Exhibit A2](#) and [Exhibit A3](#) in the appendix).

Finally, in order to assess the similarity between the *rankings* made by each risk metric, the Spearman correlation is used. This statistic is the non-parametric version of the more common Pearson correlation and measures the degree of association between two variables based on their rankings; or, put differently, the degree of similarity between their rankings.

The ultimate issue explored here is whether a ranking of assets by volatility is similar to (highly correlated with) a ranking of the same assets by metrics designed to capture downside risk. Thus, if the rankings are highly correlated, using a rather unintuitive metric such as volatility would be justified on the grounds that, first, ‘everybody’ knows it and uses it; and second, the relevant risk of the assets is properly assessed and conveyed.

3.2. Results

[Exhibit 1](#) shows, for developed countries, emerging countries, and all countries pooled, the Spearman correlations between volatility and the seven risk metrics considered here. The first row of the exhibit shows correlations for the 23 developed countries in the sample, all of which are statistically significant.⁴ The ranking made by volatility is most similar to those made by SSD, AL, EL, and VaR, with correlations 0.90 or higher; and less similar to those made by PL, WL, and MD, although their correlations are still fairly high, in the 0.62-0.71 range. The average correlation across all the downside risk metrics considered is 0.82.

The results for the 24 emerging countries in the second row of the exhibit are rather similar to those for developed countries, the main difference being that in this case the correlation for PL is not significant (the only one in the exhibit). On average, the correlation across all the downside risk metrics considered is 0.80, very similar to that for developed countries. For the pooled sample of developed and emerging countries, in the third row of the exhibit, the results are again fairly similar, with an average correlation of 0.85 across all the downside risk metrics.

[Exhibit 2](#) repeats the analysis, first for industries and then for countries and industries pooled. For industries (in the first row of the exhibit), the results are fairly similar to those already discussed for countries, with very high correlations for SSD, AL, EL, and VaR; somewhat lower, but still clearly sizeable, correlations for PL, WL, and MD; and an average correlation across all downside risk metrics of 0.82.

Finally, for industries and countries pooled (in the second row of the exhibit), the results are again similar to those already discussed for countries and industries separately. In this case, the lowest correlation is a sizeable 0.66 for PL, with the rest of correlations above 0.7, and four of them at or above 0.95. The broadest correlation of all those calculated in this article, considering all countries and industries in the sample and all downside risk metrics, is 0.86.

This last figure, perhaps better than any other, largely explains the ubiquity of volatility as a measure of risk. Being known by ‘everybody’ by itself is not a good reason for using it; being known by ‘everybody’ *and* properly capturing the downside risk that investors dislike, is. A volatility of 15% may not convey a lot of intuition about the risk of an asset. But relative to an asset with a volatility of 5% and to another with a volatility of 25%, volatility does properly capture and convey the idea of the very different downside potential of these three assets.

4. Assessment

The fact that finance academics and practitioners widely use volatility as a measure of risk is blindingly clear; *why* that is the case is somewhat less clear. This article argues that it is due to two mutually-reinforcing reasons: First, volatility is very well known by all market participants; and second, it properly captures the downside risk that investors really dislike.

In fact, rankings of assets by volatility are very similar to (are very highly correlated with) rankings of assets by metrics specifically designed to capture downside potential. Across all the countries and industries considered here, a ranking by volatility has an average correlation of 0.86 with respect to rankings by the semideviation, the probability of loss, the average loss, the expected loss, the worst loss, the maximum drawdown, and value at risk.

[Rekenthaler \(2024\)](#) evaluates the loss potential of actively-managed, large-blend U.S. stock funds and finds that volatility and downside capture perform in a very similar way. He therefore concludes that volatility should be the preferable choice because it “is a conventional and widely known calculation,” and whenever possible “researchers

⁴ Unless otherwise stated, statistical significance is evaluated at the 5% level of significance.

should use a common language.” The findings in this article are fully consistent with his conclusion.

To be sure, this article is *not* a defense of volatility as a measure of risk; this metric does have some serious limitations and, arguably, there are better ways to assess the risk that investors dislike. Rather, this article aims to answer the question of why volatility is so pervasive in finance; being very well known and doing properly the job it is supposed to do may go a long way toward answering that question.

CRedit authorship contribution statement

Javier Estrada: Writing – review & editing, Writing – original draft,

Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author has no conflicts of interest.

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Appendix

Exhibit A1

Data. This exhibit shows all the countries and industries in the sample, their inception month in the MSCI database (IM), and their mean compound return (MR) and volatility (SD), both annualized. All returns are in dollars and account for capital gains/losses and dividends. MR and SD in %.

Countries	IM	MR	SD	Industries	IM	MR	SD
<i>Developed</i>				1. Aerospace & Defense	Dec-94	11.9	20
Australia	Dec-69	8.6	23.5	2. Air Freight & Logistics	Dec-94	7.5	19.8
Austria	Dec-69	7.8	24.1	3. Automobile Components	Dec-94	4.8	20.7
Belgium	Dec-69	9.7	20.2	4. Automobiles	Dec-94	8.5	23.5
Canada	Dec-69	9.2	19.4	5. Banks	Dec-94	5.6	20.8
Denmark	Dec-69	13	19.3	6. Beverages	Dec-94	8.2	14.6
Finland	Dec-87	7.5	28.3	7. Biotechnology	Dec-94	10.2	23.7
France	Dec-69	9.5	21.9	8. Broadline Retail	Dec-94	9.1	18.7
Germany	Dec-69	9	21.6	9. Building Products	Dec-94	5.9	21
Hong Kong	Dec-69	12.3	32.5	10. Capital Markets	Apr-03	7	22.8
Ireland	Dec-87	4.9	21.9	11. Chemicals	Dec-94	7.6	18.6
Israel	Dec-92	5.3	22.5	12. Commercial Services & Supplies	Dec-94	6.9	14.9
Italy	Dec-69	5.7	25.1	13. Communications Equipment	Dec-94	6.7	27.8
Japan	Dec-69	8.7	20.1	14. Construction & Engineering	Dec-94	4.6	20.5
Netherlands	Dec-69	11.6	19.4	15. Construction Materials	Dec-94	6.2	22.2
New Zealand	Dec-87	6.1	22.2	16. Consumer Finance	Apr-03	8.4	27
Norway	Dec-69	9.6	26.3	17. Consumer Staples Distribution & Retail	Dec-94	7.7	13
Portugal	Dec-87	2	22.2	18. Containers & Packaging	Dec-94	4.7	19.8
Singapore	Dec-69	9.9	26.9	19. Distributors	Dec-94	0.5	25.6
Spain	Dec-69	8	23.3	20. Diversified Consumer Services	Apr-05	-5.4	32.9
Sweden	Dec-69	12.1	23.4	21. Diversified Telecommunication Services	Dec-94	4.2	16.5
Switzerland	Dec-69	10.8	17.6	22. Electric Utilities	Dec-94	7.3	13.1
UK	Dec-69	9	21	23. Electronic Equipment, I&C	Dec-94	4.5	23.4
USA	Dec-69	10.7	15.4	24. Energy Equipment & Services	Dec-94	4.1	34.8
<i>Emerging</i>				25. Entertainment	Dec-18	9.3	24.4
Brazil	Dec-87	11.6	46.1	26. Food Products	Dec-94	7.3	12.7
Chile	Dec-87	10.6	24.7	27. Financial Services	Dec-94	7.2	23.2
China	Dec-92	1	31.8	28. Gas Utilities	Dec-94	7.4	13.5
Colombia	Dec-92	8.8	31.5	29. Ground Transportation	Dec-94	7.7	15.7
Czech Rep.	Dec-94	10	26.7	30. Health Care Equipment & Supplies	Dec-94	10.5	15.6
Egypt	Dec-94	8.2	32.2	31. Health Care Providers & Services	Dec-94	9.2	19.3
Greece	Dec-87	-0.4	37.1	32. Health Care Technology	Apr-06	5.7	25
Hungary	Dec-94	9.8	34.3	33. Hotels, Restaurants & Leisure	Dec-94	9.2	17.9
India	Dec-92	9.2	27.2	34. Household Durables	Dec-94	3.1	21.9
Indonesia	Dec-87	8.4	42.5	35. Household Products	Dec-94	9.9	14.7
Korea	Dec-87	5.5	33.5	36. Independent Power and R.E.P.	Apr-05	2.2	18.8
Kuwait	May-05	4.5	19.9	37. Industrial Conglomerates	Dec-94	7.3	20.1
Malaysia	Dec-87	5.8	25	38. Insurance	Dec-94	7.6	19.3
Mexico	Dec-87	13.5	28.9	39. Interactive Media & Services	Dec-18	20.7	23.4
Peru	Dec-92	12.8	29.9	40. IT Services	Dec-94	6.2	23.2
Philippines	Dec-87	6	28.1	41. Leisure Products	Dec-94	2.4	17.4
Poland	Dec-92	8.3	42.1	42. Life Sciences Tools & Services	Apr-06	12.1	20.7
Qatar	May-05	4	24.2	43. Machinery	Dec-94	7.7	21.6
S. Arabia	Aug-14	4.6	20	44. Marine Transportation	Dec-94	5.9	26.5
S. Africa	Dec-92	7.9	26.2	45. Media	Dec-94	6	19.7
Taiwan	Dec-87	8.6	31.7	46. Metals & Mining	Dec-94	5.3	26.7
Thailand	Dec-87	6.5	33.2	47. Mortgage Real Estate Investment Trusts	Sep-16	2	26.9
Turkey	Dec-87	6.8	50.5	48. Multi/Utilities	Dec-94	4.5	18
UAE	May-05	1.4	30.1	49. Oil, Gas & Consumable Fuels	Dec-94	8.5	21.4
				50. Paper & Forest Products	Dec-94	2.2	23.1
				51. Passenger Airlines	Dec-94	1.8	23.4

(continued on next page)

Exhibit A1 (continued)

Countries	IM	MR	SD	Industries	IM	MR	SD
				52. Personal Care Products	Dec-94	9.2	18.4
				53. Pharmaceuticals	Dec-94	9.6	14.1
				54. Professional Services	Aug-08	10.6	18.8
				55. Real Estate Management & Development	Apr-06	1.1	21.5
				56. Semiconductors & SE	Dec-00	12.3	28.1
				57. Software	Dec-94	15.5	24.1
				58. Specialty Retail	Dec-94	10.2	18.8
				59. Technology Hardware, S&P	Dec-94	15	25.3
				60. Textiles, Apparel & Luxury Goods	Dec-94	9	21.6
				61. Tobacco	Dec-94	12.9	20.6
				62. Trading Companies & Distributors	Dec-94	7.4	21.9
				63. Transportation Infrastructure	Dec-94	6.9	18.9
				64. Water Utilities	Dec-94	12.1	16.4
				65. Wireless Telecommunication Services	Dec-94	8.9	20.2

Exhibit A2

Metrics – Countries. This exhibit shows, over the whole sample period available for each country, volatility (SD), the semideviation with respect to 0 (SSD), the probability of loss (PL), the average loss in periods with losses (AL), the expected loss (EL), the worst loss (WL), the maximum drawdown (MD), and value at risk (VaR), all in monthly terms. All figures in %. AL, EL, WL, MD, and VaR in absolute value. The data is described in [Exhibit A1](#).

Country	SD	SSD	PL	AL	EL	WL	MD	VaR
<i>Developed</i>								
Australia	6.8	4.6	42.7	4.8	2.1	44.5	62.6	10.2
Austria	7	4.6	43.5	4.7	2	37	78.6	10.6
Belgium	5.8	3.8	40.8	4.2	1.7	36.6	72.9	8.7
Canada	5.6	3.7	41.4	4.1	1.7	26.9	55.8	8.3
Denmark	5.6	3.4	39.7	4.1	1.6	25.7	56.4	8
Finland	8.2	5.2	45.7	5.6	2.6	31.8	72.6	12.5
France	6.3	4.1	42.4	4.7	2	23.2	56.9	9.5
Germany	6.2	4.1	42.3	4.6	2	24.4	63.6	9.4
Hong Kong	9.4	5.7	41.4	6.1	2.5	43.4	88	14
Ireland	6.3	4.5	42.8	5	2.1	26	82.7	9.8
Israel	6.5	4.5	41.9	5.1	2.2	18.8	61.4	10
Italy	7.3	4.7	45.5	5.3	2.4	23.6	72.8	11.2
Japan	5.8	3.5	43.3	4.1	1.8	19.4	61.1	8.7
Netherlands	5.6	3.6	37.6	4.3	1.6	25.1	59.7	8.1
New Zealand	6.4	4.2	44.6	4.8	2.1	22.4	63.1	9.8
Norway	7.6	4.9	44.7	5.4	2.4	33.4	68.9	11.4
Portugal	6.4	4.4	47.3	4.9	2.3	26.2	68.9	10.2
Singapore	7.8	4.9	42.1	5.1	2.2	41.3	70.2	11.7
Spain	6.7	4.3	44.8	4.7	2.1	27.3	70	10.2
Sweden	6.8	4.2	42.9	4.8	2	26.7	72.4	9.9
Switzerland	5.1	3.2	40.8	3.7	1.5	17.6	47.1	7.4
UK	6.1	3.6	40.8	4.3	1.7	21.5	68.2	9.1
USA	4.4	2.8	37.3	3.4	1.3	21.2	50.6	6.3
<i>Emerging</i>								
Brazil	13.3	8.1	44.6	8.5	3.8	66.6	74.6	20.1
Chile	7.1	4.5	45.7	4.9	2.3	29.1	62.4	10.6
China	9.2	6	45.8	6.8	3.1	27.1	87.5	14.6
Colombia	9.1	6	42.7	6.9	2.9	40.9	71.3	13.8
Czech Rep.	7.7	5	41.4	5.7	2.4	29.4	64	11.6
Egypt	9.3	5.8	46.9	6.1	2.9	33.5	73	14.2
Greece	10.7	7.1	45.5	7.7	3.5	36.7	98.1	17.1
Hungary	9.9	6.6	42.8	7	3	43.3	77.6	15
India	7.9	5	44.3	5.7	2.5	28.5	68.9	11.9
Indonesia	12.3	7	43.2	7.5	3.2	40.5	93.6	18.8
Korea	9.7	5.8	48	6.3	3	31.3	82.1	15
Kuwait	5.8	4	45.1	4.2	1.9	22.8	66.3	8.9
Malaysia	7.2	4.6	44.4	4.8	2.1	30.2	87.3	11.2
Mexico	8.3	5.4	41.4	6	2.5	34.3	67.2	12.3
Peru	8.6	5.4	42.7	6.1	2.6	36	61.7	12.8
Philippines	8.1	5.2	43.9	5.9	2.6	29.2	87.7	12.5
Poland	12.1	6.8	45.6	7.6	3.5	34.8	75.6	18.7
Qatar	7	4.8	46.4	4.7	2.2	26.5	62	10.9
S. Arabia	5.8	3.9	42.7	4.7	2	14.3	41	9
S. Africa	7.6	5.1	43.2	5.8	2.5	30.5	59.5	11.5
Taiwan	9.2	5.6	45.3	6.2	2.8	33.7	77.9	13.9
Thailand	9.6	6.2	44.4	6.6	2.9	34	92.3	14.8
Turkey	14.6	8.6	48.4	9.6	4.6	41.2	82.9	22.4
UAE	8.7	5.9	46.8	6	2.8	33.4	85.7	13.8

Exhibit A3

Metrics – Industries. This exhibit shows, over the whole sample period available for each industry, volatility (SD), the semideviation with respect to 0 (SSD), the probability of loss (PL), the average loss in periods with losses (AL), the expected loss (EL), the worst loss (WL), the maximum drawdown (MD), and the value at risk (VaR), all in monthly terms. All figures in %. AL, EL, WL, MD, and VaR in absolute value. The data is described in [Exhibit A1](#).

Industry	SD	SSD	PL	AL	EL	WL	MD	VaR
1	5.8	3.8	33.9	4.5	1.5	27	51.5	8.4
2	5.7	3.7	39.2	4.3	1.7	21.2	52.7	8.6
3	6	4.1	40.6	4.7	1.9	23.9	63	9.3
4	6.8	4.2	42.2	4.6	1.9	25.9	58.1	10.2
5	6	4.2	39.4	4.6	1.8	27.1	70.8	9.2
6	4.2	2.8	36.4	3.2	1.2	21.1	35	6.2
7	6.8	4.3	40.6	4.5	1.8	40.7	57	10.2
8	5.4	3.5	37.2	4.2	1.6	25.5	63.8	8
9	6.1	4.2	39.7	4.8	1.9	24	66.8	9.3
10	6.6	4.5	40.8	5.3	2.2	24.3	72.6	10
11	5.4	3.5	38.3	4.2	1.6	21.3	54.2	8.1
12	4.3	3	36.7	3.6	1.3	15.3	51.2	6.4
13	8	5.4	39.2	6.3	2.4	38.3	89.2	12.3
14	5.9	4.1	41.7	4.6	1.9	25.7	64.9	9.2
15	6.4	4.4	38.1	5.2	2	29.7	65.9	9.8
16	7.8	5.1	38.5	5.6	2.2	33.4	83.5	11.9
17	3.7	2.4	37.2	2.9	1.1	16.6	44.5	5.5
18	5.7	3.9	38.3	4.7	1.8	20.2	55.7	8.9
19	7.4	5.3	41.4	5.7	2.4	32.7	83.3	11.8
20	9.5	7.3	50	6.5	3.3	67.5	92.4	15.5
21	4.8	3.2	41.1	3.7	1.5	14.5	74.4	7.4
22	3.8	2.5	35.3	3.3	1.2	12.4	39.2	5.5
23	6.7	4.5	40.3	5.3	2.2	21.9	79.2	10.5
24	10	6.5	45	6.8	3.1	48.2	87.6	15.7
25	7	4.7	41.7	5.3	2.2	23.1	50.9	10.6
26	3.7	2.4	34.4	3.1	1.1	13.2	36.4	5.4
27	6.7	4.6	38.3	5	1.9	30	80.3	10.2
28	3.9	2.6	36.1	3.2	1.1	13.2	38	5.7
29	4.5	2.9	37.5	3.7	1.4	15.1	44	6.8
30	4.5	2.9	35.6	3.5	1.2	19.3	39.5	6.5
31	5.6	3.7	36.1	4.5	1.6	22.7	53.9	8.3
32	7.2	5	42	5.7	2.4	24.6	69.3	11.1
33	5.2	3.4	36.7	4	1.5	23.7	52.5	7.6
34	6.3	4.3	41.1	5.1	2.1	21.5	70.2	10
35	4.2	2.6	37.8	3	1.1	17.9	33	6.1
36	5.4	3.9	45.3	4.1	1.8	27.5	61.8	8.6
37	5.8	3.9	38.9	4.4	1.7	26.6	68.7	8.8
38	5.6	3.9	36.7	4.4	1.6	30.1	66	8.4
39	6.8	4.2	33.3	6.2	2.1	15.5	50.3	9.3
40	6.7	4.7	35.3	5.5	1.9	34.7	82.6	10.3
41	5	3.7	39.4	4.3	1.7	21.7	60.4	7.9
42	6	4	37.1	4.7	1.7	28	43.3	8.7
43	6.2	4.1	39.4	4.8	1.9	28.7	62.6	9.4
44	7.6	5.1	38.9	6.2	2.4	29.2	70.5	11.8
45	5.7	3.9	36.4	4.8	1.7	21.1	70	8.7
46	7.7	5.1	44.2	5.7	2.5	32.5	75.9	12
47	7.8	6	39.4	6.3	2.5	32.1	45.9	12.3
48	5.2	3.7	38.6	4.1	1.6	25.4	81	8
49	6.2	4	37.5	4.7	1.8	30.7	51.2	9.3
50	6.7	4.6	41.1	5.1	2.1	29.2	72.3	10.6
51	6.7	4.8	39.7	5.6	2.2	32.2	63	10.7
52	5.3	3.6	35	4.3	1.5	24.8	48.8	7.8
53	4.1	2.5	36.4	3.2	1.2	11.8	34.3	5.8
54	5.4	3.6	34.7	4.6	1.6	21.3	32.9	7.9
55	6.2	4.2	47.3	4.6	2.2	21	67.8	9.9
56	8.1	5.2	40.3	6.1	2.4	27.9	61.4	12.1
57	6.9	4.1	35	5.2	1.8	22	70.8	10
58	5.4	3.4	38.1	4.2	1.6	17.4	57.5	8
59	7.3	4.5	36.7	5.7	2.1	25.7	72.6	10.6
60	6.2	4	36.9	5	1.8	22.6	55.4	9.3
61	5.9	3.7	36.4	4.6	1.7	20.1	56.3	8.6
62	6.3	4.2	38.6	5	1.9	23	61.8	9.6
63	5.4	3.8	36.9	4.4	1.6	26.7	61.9	8.2
64	4.7	2.7	37.5	3.4	1.3	14.9	39	6.7
65	5.8	3.7	35.8	4.5	1.6	21.8	78	8.7

Data availability

IESE Business School is subscribed to

The data for this research was downloaded from a database to which

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