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The effects of systemic crises when investors can be crisis ignorant.*

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Abstract

Systemic crises can largely affect asset allocations due to the rapid deterioration of the risk-return trade-off. We investigate the effects of systemic crises, interpreted as global simultaneous shocks to financial markets, by introducing an investor adopting a crisis ignorant or crisis conscious strategy. Including the possibility of a systemic crisis is a substantial improvement. Investments in risky assets fall, while allocations to countries less sensitive to a crisis grow relatively. An increasing probability of a crisis exacerbates these effects. The certainty equivalent costs of ignoring systemic crises are large, ranging from 0.65% per year unconditionally, to over 5% per month conditionally on a high probability for the occurrence of a crisis.

Key words: asset allocation, systemic risk, international finance, regime switching

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1 Introduction

In this paper we study the impact of systemic risk on asset allocation. We interpret systemic risk as the risk that all financial markets encounter a simultaneous negative shock[1]. Indeed, financial markets witnessed events that had severe global repercussions during the last two decades, such as the stock market crash of October 1987, the Mexican crisis of 1994, the Asian crisis of 1997 and the tumbling of Enron in 2001. Their features include a sharp, global drop in returns, a general upswing in volatility and a rise of the correlation between financial markets. These are the ingredients that constitute a systemic crisis. Though systemic shocks occur irregularly, they do happen every now and then. As such, it is difficult to include them in asset allocation decisions, since models used to support those decisions may regard them as outliers. However, a systemic crisis can largely affect portfolios, because the risk-return trade-off deteriorates dramatically. Consequently, ignoring systemic risk may seriously harm investors.

In order to investigate the relationship between systemic shocks and investors' asset allocations, we introduce an investor that can follow a crisis conscious or crisis ignorant strategy. If a systemic crisis is important, the investor should in general make more defensive decisions (i.e. invest a smaller proportion of his wealth in risky assets), when he changes his strategy from crisis ignorant to crisis conscious. Within the risky asset part, investment should shift to countries that are less sensitive to a systemic crisis. Furthermore, the differences between the two allocations should be larger if the probability that a crisis occurs grows.

There is a rich literature that analyses the effect of crises on returns, without however establishing a direct link with asset allocation. The important resulting stylized fact is that the normal distribution, which is popular in modelling asset allocation problems, does not accurately capture the behavior of asset returns during crises. Longin (1996)

[1]Systemic risk encompasses more than global, simultaneous shocks to financial markets. De Bandt and Hartmann (2000) provide a detailed survey of systemic risk. For asset allocation decisions, simultaneous global shocks are most relevant.

shows that a fat-tailed distribution describes extreme returns better than exponentially tailed distributions such as the normal distribution. Furthermore, extreme returns are commonly followed by an increase in volatility, particularly if they are negative. Most important, however, is the tendency of markets to move downwards together[2], which is only limitedly captured by the normal distribution, as shown by Longin and Solnik (2001), Ang and Chen (2002), Bae et al. (2003) and Hartmann et al. (2004). When investigating the influence of a systemic crisis on asset allocation, a model of systemic crisis should capture these three characteristics.

Several authors have investigated the influence of extreme events on asset allocation. Das and Uppal (2004) model systemic risk as a perfectly correlated jump in the jump-diffusion process for the returns in different countries. As a consequence, expected returns and volatility change only instantaneously, making a systemic crisis an event of infinitesimal length, which is at odds with their observed persistence. Liu et al. (2003) propose a model that combines stochastic volatility and jumps in both the level and the volatility process. However, their model is limited to a univariate setting with one risky asset.

In order to capture the mentioned characteristics, to allow for persistence and to obtain a tractable multivariate extension, we use a Markov regime switching model for the return process. Based on such a process and his strategy, the investor derives his optimal asset allocation. The crisis ignorant strategy uses a basic version of the regime switching model, while the crisis conscious strategy extends the model with a crisis regime, turning the crisis ignorant model into a restricted version of the crisis conscious model. We model a systemic crisis as a global, simultaneous shock to financial markets to which markets can have a different sensitivity. We formulate the asset allocation problem in a continuous-time, expected utility framework and derive the optimal asset allocation analytically along the lines set out by Merton (1969). An expected utility framework also enables the use of certainty equivalents to determine the economic cost of ignoring the possibility of a crisis.

This design makes our research closely related to Ang and Bekaert (2002), who study

[2]It is widely discussed whether this phenomenon is a form of contagion or can be explained by joint shocks (see Forbes and Rigobon, 2002; Corsetti et al., 2002).

international asset allocation in a regime switching framework. However, they do not concentrate on the effect of a systemic crisis. Furthermore, they assume that the investor knows the actually prevailing regime with certainty. In contrast, we assume that the investor learns the likelihood of a crisis from the data.

We apply the crisis ignorant and conscious strategies to a US investor with power utility who can invest in stock markets in the US, Japan, Hong Kong, Korea and Thailand, and a riskless asset. This investment set has interesting features, since it contains the US as home country, two developed and two emerging markets. We use monthly returns from 1975 to 2003 to estimate the parameters of the regime switching models. Subsequently, we consider the asset allocations produced by the crisis conscious and crisis ignorant strategies, unconditionally as well as conditionally on actual observed return series. We compare the actual allocations and determine the certainty equivalent cost of ignoring a crisis.

This paper contributes to the existing literature theoretically as well as empirically. Starting with the theoretical part, we propose a tractable, relatively simple model that includes the possibility of a systemic crisis, characterized by a decrease in expected returns as well as an increase in volatilities and correlations. Second, we show how to link the discrete-time regime switching model to a continuous-time asset allocation problem. Our empirical results show the following. First, we find that including a crisis improves the fit of the return process. Second, the unconditional probability for the occurrence of a systemic crisis indicates that it may be deemed rare but not highly unlikely. Third, differences in regimes are mainly driven by differences in volatility. Including a crisis regime yields estimates for the quiet regimes that are more in line with financial theory: a higher volatility is accompanied by a higher mean. Fourth, the possibility of a systemic crisis has a strong impact on asset allocation. Unconditionally, the proportion invested in risky assets decreases, within which investments shift from emerging markets to the US. Conditionally on the actual occurrence of crisis, allocations exhibit large differences: a leveraged long net position based on the crisis ignorant strategy versus a large short net position for the crisis conscious strategy. Fifth, the costs of ignoring the possibility of a crisis are considerable. Unconditionally, the investor requires a compensation of at most 0.65% per year of his wealth for using the crisis ignorant strategy. If a crisis actually occurs, this compensation can easily exceed 5% per month.

The outline of the paper is as follows. In Section 2 we introduce the crisis conscious and crisis ignorant strategies. Section 3 formulates the asset allocation problem, discusses how to solve it, how to link it to the regime switching model and explains how the outcomes can be compared. Section 4 presents the concrete design of the study, including the data. In section 5 we discuss the estimation results. In section 6 we derive and compare the allocations produced by the crisis conscious and crisis ignorant strategies. Section 7 concludes.

2 The crisis conscious and the crisis ignorant strategy

Because the investor we consider can adopt either a crisis ignorant or a crisis conscious strategy, we split the return process into two parts: a quiet part and a crisis part which can be added to the quiet part. We use a Markov regime switching model for the quiet part in order to capture heteroskedasticity and fat tails. We model a crisis as a global shock. First, we consider the regime switching model for the quiet part. Next, we discuss how to include the crisis part.

We assume that the investment set consists of n risky assets. A risky asset i can be in a regime Q_i from a set of K regimes. The prevailing state for the complete investment set is then given by the combination of regimes for the n assets. We represent this state by the vector Q, which has K^n permutations, collected in the set $\mathbb{Q}$. The state process $\{Q_\tau\}$ follows a Markov chain, characterized by the transition matrix P, which is assumed to be constant over time.

Let the joint distribution of the quiet part of the return x conditional upon a specific state vector Q be the multivariate normal distribution, parameterized by a mean vector μ_Q and variance matrix Ω_Q that depend on that state. Mathematically:

$$x|Q \sim N(\mu_Q, \Omega_Q), \quad Q \in \mathbb{Q}. \tag{1}$$

Furthermore, we assume that the marginal distribution of asset return i, given a state vector Q, depends only on the regime Q_i in the state vector.

We model the systemic crisis as a global shock x^c in addition to the quiet part. The shock has a univariate normal distribution with mean μ^c and variance ω^c. The global shock itself is independent of the quiet part. Each asset has a sensitivity δ_i to the global shock, which is restricted to be nonnegative in order to make the direction of the shock equal for all assets. The global shock can be either present or absent, represented by a new state variable Q^c that has value 0 if a crisis is absent, or 1 if a crisis is present. Hence, the marginal distribution of return i if a crisis is prevailing, depends on the specific regime Q_i, the parameters that characterize a shock and the sensitivity to the shock. While a shock hits all countries, differences between the marginal distributions can exist due to differences in the quiet part and in the sensitivities.

The complete model for the return process is a combination of the two parts:

$$r = x + Q^c x^c \delta, \quad Q^c \in \{0, 1\}, \tag{2}$$

where δ is the column vector of sensitivities. Hence, it depends on both the state process $\{Q_\tau\}$ for the quiet part and the crisis part $\{Q^c_\tau\}$. Let $\tilde{Q} \equiv (Q, Q^c)$ denote the combination of the quiet state vector and the crisis state indicator. The complete state space consists of the cartesian product of the set of quiet state vectors and the two crisis states: $\tilde{\mathbb{Q}} \equiv \mathbb{Q} \times \{0, 1\}$. Since the conditional distributions are both normal, the return process conditional on both states is also normal. More formally:

$$r|\tilde{Q} \sim N(\mu_{\tilde{Q}}, \Omega_{\tilde{Q}}), \quad \tilde{Q} \in \tilde{\mathbb{Q}} \tag{3}$$

The mean and variance satisfy:

$$\mu_{\tilde{Q}} = \mu_Q + Q^c \mu^c \delta, \tag{4}$$

$$\Omega_{\tilde{Q}} = \Omega_Q + Q^c \omega^c \delta\delta', . \tag{5}$$

Since we require nonnegativity for each sensitivity parameter, the covariance between return i and j will rise if a crisis hits. In that case, the correlation will rise if the relative increase in covariance exceeds the product of relative increase in volatilities. This condition will generally be satisfied for correlations not too close to 1. The change in correlation if a crisis hits, is completely due to a common factor. In terms of Forbes and Rigobon (2002) we assume only interdependence and no contagion.

We introduce a new transition matrix $\tilde{P}$ that characterizes the Markov chain of the combined state processes $\{\tilde{Q}_\tau\} \equiv \{Q_\tau, Q^c_\tau\}$. Consequently, the distribution of $r_{\tau+1}$, conditional only on the filtration of the return process up to time τ, denoted by $\mathcal{F}_\tau$, is a mixture of normals. In other words, the conditional probability density function g of $r_{\tau+1}$ is given by

$$g(r_{\tau+1}|\mathcal{F}_\tau) = \sum_{\tilde{Q}_{\tau+1}\in\tilde{\mathbb{Q}}} f\left(r_{\tau+1}|\tilde{Q}_{\tau+1}, \mathcal{F}_{\tau+1}\right) Pr\left(\tilde{Q}_{\tau+1}|\mathcal{F}_{\tau+1}\right), \tag{6}$$

where f is the normal density corresponding to (3) and $Pr(A)$ denotes the probability of event A.

We stress again that the difference between the crisis conscious and the crisis ignorant strategy is caused by the perception of the crisis part. The crisis conscious strategy acknowledges that a crisis state $Q^c = 1$ can be prevailing, and will result in decisions based on the mixture model specified in (6), using all information available up to that time. Adopting a crisis ignorant strategy, the investor assumes that a switch to $Q^c = 1$ will never take place, putting restrictions on $\tilde{P}$. This implies that (6) still applies, with the restriction that $Pr(\tilde{Q}_{\tau+1}|\mathcal{F}_{\tau+1}) = 0$ for $Q^c = 1$. The consequences of this restriction are twofold. First, the crisis ignorant strategy will lead to different inferences and forecasts about the prevailing regime. Second, if the investor follows an ignorant strategy and estimates the parameters of the process, the estimates for the parameters (both the distribution parameters and the transition matrix) will be affected if the possibility of a crisis is incorrectly ignored.

3 Asset allocation

In this section we consider the model for the investor's asset allocation. First we formulate and solve the asset allocation problem he faces in a continuous-time expected utility framework. The optimal portfolio has a similar structure as the basic optimal portfolio, when asset prices follow a geometric Brownian motion. However, the parameters that define the optimal portfolio depend on the realization of the return process up to that time and time itself. We present and discuss the exact formulation of these parameters in the second subsection. In the third subsection we decompose the differences in asset allocation due to the different strategies. In the final subsection we explain how to compare the optimal portfolios of the crisis conscious and crisis ignorant strategies by means of certainty equivalents.

3.1 The asset allocation problem

The investor is risk averse and maximizes his utility over terminal wealth W_T. We assume he has a power utility function:

$$U(W_T) = \frac{W_T^{1-\gamma}}{1-\gamma}, \quad \gamma > 0, \gamma \neq 1, \tag{7}$$

where γ is the investor's coefficient of relative risk aversion[3]. To focus on the effect of a systemic crisis on asset allocation, we rule out intermediate consumption. These assumptions are quite common in empirical studies on asset allocation empirically, making our analysis comparable to other studies. The investor can trade in continuous time.[4] At each point in time t, $0 \leq t \leq T$, he will choose to invest proportions of his wealth in the n risky assets, denoted by the vector ϕ_t and the remaining part $1 - \phi_t' \iota_n$ in the riskless asset (ι_n being a column vector of size n with ones) in order to maximize expected utility:

$$\max_{\{\phi_t, 0 \leq t \leq T\}} E_0 \left[U(W_T) \right]. \tag{8}$$

Assuming the investor receives only an initial endowment W_0, he faces a self-financing constraint, which describes the dynamics of the wealth process. To derive it, we need a process for the asset prices first. As we will describe later, we use a specific Itô process in

[3]For $\gamma = 1$ the utility function is defined as log utility $U(W_T) = \ln W_T$.

[4]We use t to denote points in continuous time and τ for points in discrete time. The units are the same.

continuous time that is consistent with the discrete time return process described in the previous section. For the moment, let the (multivariate) Itô process be given by:

$$dr = \mu dt + \Lambda dZ, \tag{9}$$

where $\mu \equiv \mu(r,t)$ is the column vector of instantaneous drift rates, which can depend on the return up to time t and time itself, $\Lambda \equiv \Lambda(r,t)$ is a lower triangular $n \times n$ matrix that can also be a function of r and t, and dZ is a vector of n independent Wiener processes. Consequently, the instantaneous variance rate Ω is given by $\Omega = \Lambda\Lambda'$. We assume that the price for asset i can be constructed from r_i as $S_{i,t} = \exp(r_{i,t})S_0$ with S_0 known. Using Itô's lemma, we derive the following process for the asset prices:

$$\frac{dS}{S} = \left(\mu + \frac{1}{2}\mathrm{diag}(\Omega)\right) dt + \Lambda dZ, \tag{10}$$

where $\mathrm{diag}(\Omega)$ denotes a column vector containing the diagonal elements of Ω. Given the one-to-one relation between r and S for given S_0, μ and Λ can be written as functions of S and S_0 as well. The riskless asset pays the risk-free rate r_f. The self-financing condition reads:

$$\frac{dW}{W} = \phi' \left(\mu + \frac{1}{2}\mathrm{diag}(\Omega)\right) dt + \phi'\Lambda dZ + \left(1 - \phi'\iota_n\right) r_f dt, \tag{11}$$

with both S_0 and W_0 given.

The asset allocation problem constituted in (8) and (11) can be solved using standard stochastic control techniques[5]. First, the indirect utility function is given by

$$V(W,t) = \max_{\phi_s, t \leq s \leq T} E_t[U(W_T)]. \tag{12}$$

The Hamilton-Jacobi-Bellman equation takes the form:

$$\max_{\phi} \left(\frac{\partial V}{\partial t} + \left(r_f + \phi' \left(\mu + \frac{1}{2}\mathrm{diag}(\Omega) - r_f \iota \right) \right) W \frac{\partial V}{\partial W} + \frac{1}{2}\phi'\Omega\phi W^2 \frac{\partial^2 V}{\partial W^2} \right) = 0. \tag{13}$$

We conjecture (and verify) that the indirect utility function is of the form:

$$V(W,t) = C(t)\frac{W^{1-\gamma}}{1-\gamma}, \quad \gamma \neq 1. \tag{14}$$

[5] See for example Léonard and Van Long (1992).

Based on this functional form[6], we derive expressions for the derivatives in (13) and substitute them. We can now differentiate (13) with respect to ϕ, which gives the following first-order condition:

$$(\mu + \mathrm{diag}(\Omega)/2 - r_f\iota) - \gamma\Omega\phi = 0. \tag{15}$$

Consequently, the optimal portfolio weights for the risky assets ϕ^* are given by:

$$\phi^* = \gamma^{-1}\Omega^{-1}\left(\mu + \mathrm{diag}(\Omega)/2 - r_f\iota\right). \tag{16}$$

Though this expression looks familiar, we shall see that both μ and Ω depend on time and the observed returns, making the weights varying over time and dependent on the returns so far. This expression applies to the log-utility investor as well.

3.2 The Itô process for returns

Brigo (2002) describes a way to derive continuous time processes whose corresponding density at a certain point in time is a mixture of densities from the same family[7]. Since the distribution of $r_{\tau+1}$ conditional on its filtration $\mathcal{F}_\tau$ as given in (6) is a mixture of normal distributions, we can apply a multivariate extension of Theorem 2 in Brigo (2002). Consequently, the Itô process in (9) starting at $t_0 = \tau$ with $r_{t_0} = 0$ has a mixture density at time $t = \tau + 1$ given by (6), if the instantaneous drift rate $a(r,t)$ and instantaneous variance rate $\Omega(r,t)$ are given by:

$$\mu(r,t) = \sum_{\tilde{Q}\in\tilde{\mathbb{Q}}} \pi(\tilde{Q}, r, t)\mu_{\tilde{Q}} \tag{17}$$

$$\Omega(r,t) = \sum_{\tilde{Q}\in\tilde{\mathbb{Q}}} \pi(\tilde{Q}, r, t)\Omega_{\tilde{Q}} \tag{18}$$

with

$$\pi(\tilde{Q}, r, t) = \frac{\xi_{\tau+1|\tau}(\tilde{Q}) \cdot f\left(r_{\tau+t}; \mu_{\tilde{Q}}t, \Omega_{\tilde{Q}}t\right)}{\sum_{\hat{Q}\in\tilde{\mathbb{Q}}} \xi_{\tau+1|\tau}(\hat{Q}) \cdot f\left(r_{\tau+t}; \mu_{\hat{Q}}t, \Omega_{\hat{Q}}t\right)}, \tag{19}$$

[6]For $\gamma = 1$ we use $V = \ln[C(t)W]$.

[7]Applications of this technique can be found in Alexander and Narayanan (2001), Alexander and Scourse (2003) and Brigo et al. (2003).

where $\xi_{\tau+1|\tau}(\tilde{Q}) = Pr(\tilde{Q}_{\tau+1}|\mathcal{F}_\tau)$ gives the forecast probability that state $\tilde{Q}$ is prevailing at time $\tau + 1$.[8] $B(r, t)$ can then be found by applying a Cholesky decomposition to $\Omega(r, t)$.

The drift and variance rate constructed by (17), (18) and (19) have an appealing interpretation. First, notice that the drift and variance are a weighted average of the mean and variance parameters for the different states. Since the weights are bounded between one and zero and sum to one by construction, they can be interpreted as probabilities. Moreover, (19) has the same structure as the inference probabilities used in regime switching models (see Hamilton, 1994, eq. 22.4.5). It can be interpreted as a Bayesian update rule, with $\xi_{\tau+1|\tau}(\tilde{Q}) = Pr(Q_{\tau+1}|\mathcal{F}_\tau)$ as prior probability for the prevailing regime and $\pi(\tilde{Q}, r, t) = Pr(Q_{\tau+1}|r_t, \mathcal{F}_\tau)$ as its posterior probability. Consequently, the weight $\pi(\tilde{Q}, r, t)$ can be interpreted as the probability that state $\tilde{Q}$ is prevailing from τ until $\tau + 1$, inferred from the realization of r from τ till t, $\tau < t \leq \tau + 1$. If the probability that state $\tilde{Q}$ is prevailing rises, the weight with which its parameters constitute the instantaneous drift and variance rate increases linearly with it. In the limiting case that state $\tilde{Q}$ is prevailing with certainty, the return at time $\tau+t$ will be normally distributed with parameters $\mu_{\tilde{Q}}t$ and $\Omega_{\tilde{Q}}t$. For $t = 0$, the distribution of $r_{\tau+t}$ is degenerate and (19) reduces to $\pi(\tilde{Q}, 0, 0) = \xi_{\tau+1|\tau}(\tilde{Q})$.

3.3 Decomposing portfolios

Though the expression for the optimal portfolio (16) is the same for both the crisis conscious and the crisis ignorant strategy, the resulting portfolios will differ due to differences in the underlying processes, as described in Section 2. These differences are due to differences in the estimates for the quiet regimes and the absence of crisis regimes in the inference regarding the state process. An analysis of these differences provide insights into the importance of both sources. Suppose that the differences in parameter estimates explain just a small part of the changes in the optimal allocations. In that case, the crisis regime is the main driver of the portfolio adjustments because of the resulting deterioration of the risk-return trade-off. If it is the other way round, i.e. the differences in parameter estimates

[8] We follow the notation in Hamilton (1994).

explain most of the changes in optimal portfolios, the influence of the crisis is limited. The observations that belong most likely to the crisis regime cause outlier problems in the crisis ignorant case.

To analyze the differences between the optimal allocations produced by the crisis conscious and ignorant strategies we introduce a myopic strategy. This strategy uses the same estimates as the crisis conscious strategy, but excludes a crisis regime in the forecasts it makes. Instead of forecasts for state vectors in the complete state space $\xi_{\tau+1|\tau}(\tilde{Q})$, only forecasts for the quiet states: $\xi^m_{\tau+1|\tau}(Q)$ are constructed. Their mathematical relation is:

$$\xi^m_{\tau+1|\tau}(Q) = \xi_{\tau+1|\tau}(Q, Q^c = 0) + \xi_{\tau+1|\tau}(Q, Q^c = 1), \quad Q \in \mathbb{Q}. \tag{20}$$

The myopic strategy produces an allocation, denoted by ϕ^m. Let ϕ^c and ϕ^i denote the optimal portfolios resulting from the crisis conscious and crisis ignorant strategy, respectively. We define the difference due to deviating estimates as

$$\phi^e \equiv \phi^m - \phi^i, \tag{21}$$

and the difference due to the recognition of the crisis regime as

$$\phi^s \equiv \phi^c - \phi^m. \tag{22}$$

As a consequence, we have $\phi^c = \phi^i + \phi^e + \phi^s$.

Besides comparing the vectors ϕ^e and ϕ^s on an element-by-element basis, we apply two other techniques to determine which of the two effects (i.e. the effect of estimation differences or the effect of the crisis regime) is most important in explaining the differences between the optimal portfolios for the crisis conscious and crisis ignorant strategy. We determine the magnitude of both effects by calculating the length of both vectors, defined as the Euclidean norm and denoted by $|\phi|$. This enables us to determine which effect is largest in size. Subsequently, we determine the angle between the two vectors: $\angle(\phi^e, \phi^s) = \arccos(\phi^{e\prime}\phi^s/|\phi^e||\phi^s|)$. If the angle is close to $0°$, both effects reinforce each other since they work almost in the same direction. If the angle is close to $90°$, the effects can be regarded as orthogonal to each other. Finally, if the angle is close to $180°$ the effects are opposite to each other. If the magnitudes are also comparable the effects cancel, but if the effects differ in size, the situation looks like 'two steps forward, one step back'.

The difference ϕ^s has a clear interpretation as a hedging demand. It reveals how the investor changes his optimal portfolio in order to take the effects of a crisis into account. In our model a crisis affects both the expected returns and the covariance matrix of the returns. We can disentangle these effects by splitting up ϕ^s in a part related to changes in the drift ϕ^μ and a part related to changes in variances ϕ^Ω:

$$\phi^s = \phi^\mu + \phi^\Omega. \tag{23}$$

The parts are given by:

$$\phi^\mu = \gamma^{-1}(\Omega^c)^{-1} \sum_{Q\in\mathbb{Q}} \left(\pi_{Q,1}\alpha_{Q,1} - \pi_{Q,0}\frac{\xi_{Q,1}}{\xi_{Q,0}}\alpha_{Q,0} \right) \tag{24}$$

$$\phi^\Omega = -\gamma^{-1}(\Omega^c)^{-1} \left[\sum_{Q\in\mathbb{Q}} \left(\pi_{Q,1}\Omega_{Q,1} - \pi_{Q,0}\frac{\xi_{Q,1}}{\xi_{Q,0}}\Omega_{Q,0} \right) \right] (\Omega^m)^{-1}\alpha^m, \tag{25}$$

where Ω^c and Ω^m are the instantaneous variance rates constructed for the crisis conscious strategy and the myopic strategy according to (18), $\alpha^m \equiv \mu^m + \mathrm{diag}(\Omega^m)/2 - r_f\iota$, with μ^m the instantaneous drift rate for the myopic strategy according to (17). The second subscripts in π, α, ξ and Ω indicate whether a crisis is prevailing (1) or not (0), while π_{Q,Q^c} is defined in (19), $\alpha_{Q,Q^c} \equiv \mu_{Q,Q^c} + \mathrm{diag}(\Omega_{Q,Q^c})/2 - r_f\iota$, Ω_{Q,Q^c} is defined in (5) and $\xi_{Q,Q^c} \equiv \xi_{\tau+1|\tau}(Q, Q^c)$. The derivation of these expressions can be found in the appendix. Again we can determine the lengths of the two vectors and the angle between them to compare both effects.

The parts of the hedging demands have a similar structure. First, the drift and variances given that a crisis regime is prevailing are included, weighted by the respective probability $\pi_{Q,1}$. Second, a correction is made for the weights with which the drift and variances given that a crisis does not occur, are included in the myopic instantaneous drift and variance rate. The myopic weights overstate their influence by a factor $\xi_{Q,1}/\xi_{Q,0}$, which is the relative increase in the myopic forecast probability for regime Q with regard to its original value (dividing both sides of (20) by $\xi_{\tau+1|\tau}(Q, 0)$ produces this result).

3.4 Comparing portfolios

To assess the economic impact of the differences in portfolios we calculate the certainty equivalent needed to compensate the investor for using the crisis ignorant strategy. Since the crisis ignorant strategy does not take a crisis into account in determining the optimal portfolio, this strategy is suboptimal. Consequently, utility will be lower than what would have resulted from the crisis conscious strategy. Calculating certainty equivalents answers the question by how much the wealth of the investor at time t should be raised to compensate him for adopting the crisis ignorant strategy. Hence, it shows the cost of ignoring a crisis. We derive the certainty equivalent by comparing the value functions given the crisis ignorant portfolio and given the crisis conscious portfolio.

We define the certainty equivalent in terms of returns. The certainty equivalent return is determined as the certain return needed to equal the indirect utility given the suboptimal strategy ϕ^i to the indirect utility given the optimal strategy ϕ^c. We adopt the notation introduced by Das and Uppal (2004), and include the portfolio that is used to calculate the value function (12) as a parameter. The certainty equivalent return $\bar{r}$ can then be found as the solution to:

$$V\left(e^{\bar{r}}W_t, t; \phi^i\right) = V\left(W_t, t; \phi^c\right). \tag{26}$$

Using the functional form in (14), we find after some rearrangements that

$$\bar{r} = \frac{\ln C(t;\phi^c) - \ln C(t;\phi^i)}{1-\gamma}, \tag{27}$$

which is independent of wealth[9]. To identify $C(t)$, consider the Hamiltonian (13) at the presumed optimal solution ϕ^*, with actual derivatives based on (14). This equation implies

[9]Other papers such as Ang and Bekaert (2002), Liu et al. (2003) and Das and Uppal (2004) define the certainty equivalent as the relative increase in wealth needed to equal the value functions. Hence the certainty equivalent CEQ is defined as the solution to $V((1+CEQ)W_t, t; \phi^i) = V(W_t, t; \phi^c)$. While this definition comes naturally in a discrete time environment, since it makes CEQ a discrete return, we choose to work with the continuous-time version in which $\bar{r}$ has the interpretation of a log return.

an ordinary differential equation for $C(t)$:

$$dC = -(1-\gamma)\left[r_f + \phi^{*\prime}\left(a + \text{diag}(\Omega)/2 - r_f\iota\right) - \frac{1}{2}\gamma\phi^{*\prime}\Omega\phi^*\right]C(t).$$

This differential equation can be solved straightforwardly, yielding:

$$C(t;\phi^*) = \eta\exp[-(1-\gamma)(r_f + h(\phi^*))t],$$

with integration constant η and $h(\phi^*)$ defined as:

$$h(\phi^*) = \phi^{*\prime}\left(a + \text{diag}(\Omega)/2 - r_f\iota\right) - \frac{1}{2}\gamma\phi^{*\prime}\Omega\phi^*. \tag{28}$$

Finally, we can solve for η by using the boundary condition $V(W,T;\phi^*) = U(W_T)$, which gives $\eta = \exp[(1-\gamma)(r_f + h(\phi^*))T]$. Substituting this for η produces the final result

$$C(t;\phi^*) = \exp[(1-\gamma)(r_f + h(\phi^*))(T-t)]. \tag{29}$$

We can combine the more general expressions (27) and (29) to find an expression for the certainty equivalent return that is specific for the type of models in this paper[10]:

$$\bar{r} = [h(\phi^c) - h(\phi^i)](T-t). \tag{30}$$

This expression is interesting in several ways. First, we observe that it only depends on the coefficient of risk aversion γ via the function h and the portfolio ϕ^*. It is easy to show that $h(\gamma^{-1}\phi^*) = \gamma^{-1}h(\phi^*)$. Consequently, the certainty equivalent return needed to compensate any power utility investor for using the crisis ignorant strategy can be derived from the certainty equivalent return for the log utility investor and the risk aversion of the specific power utility investor. Second, the certainty equivalent return is a linear function of the investor's horizon T. Third, in a similar way we can determine the economic value of the two components ϕ^e and ϕ^s defined in the previous subsection by calculating $h(\phi^m)$, where ϕ^m denotes the myopic portfolio. Letting $\bar{r}^e$ denote the contribution of the differences in

[10]For the log utility investor we have $V = \ln[C(t)W]$, $\bar{r} = \ln C(t;\phi^c) - \ln C(t;\phi^i)$ and $C(t;\phi^*) = \exp[h(\phi^*)(T-t)]$, and arrive again at (30).

the parameter estimates for the quiet regimes and using $\bar{r}^s$ to denote the value of the hedge due to the crisis regime, we have:

$$\bar{r}^e = [h(\phi^m) - h(\phi^i)](T - t) \tag{31}$$

$$\bar{r}^s = [h(\phi^c) - h(\phi^m)](T - t) \tag{32}$$

4 Design of the analysis

This section explains how we apply the models from the previous sections. Central in our analysis is a US investor who considers Asia to diversify his portfolio. His investment set consists of the stock market in the US, two developed Asian markets (Japan and Hong-Kong), two emerging markets (Korea and Thailand) and the riskless asset. We assume that each country in our analysis can be in 2 regimes. The resulting model allows a large number of regime combinations (in total $2 \times 2^5 = 64$). Some state vectors may be badly identified, and some state transitions may be unrealistic. Therefore, we impose more structure to the model. First, to guarantee positive definiteness of the variance matrix in each state, the correlation matrix implied by the covariance matrix for the quiet part is assumed to be independent of the regimes. Second, if a global shock hits, we require that all assets move to the regime (in $\mathbb{Q}$) that has the highest volatility. As such, global stress arouses local stress and prohibits illogical switches from high volatility regimes to low volatility regimes (both in $\mathbb{Q}$), while a crisis remains present. This restricts the number of regimes to 33. Finally, if a shock dies out, the assets move to the highest volatility regime (in $\mathbb{Q}$) first. So, if a shock has taken place, markets calm down at their own pace.

In the following subsection we present the data. Then we discuss the estimation procedure we use. We finish with describing how we construct asset allocations based on both strategies.

4.1 Data

We approximate the markets we consider by indices: the gross return indices from Morgan Stanley Capital International (MSCI) for the US, Japan and Hong Kong, and the gross return indices from International Financial Corporation (IFC) for Korea and Thailand. We collected the monthly prices of these indices in dollars terms over the period from 31/12/1975 to 31/12/2003, yielding a data set of 336 returns. We use the 1-month EuroDollar LIBOR as a proxy for the risk free rate. To filter out movements in the risk free rate, we construct excess returns. All data are obtained from DataStream.

A summary of the data is provided in Table 1. We observe the familiar picture of small, positive means, non-zero skewness (except probably for Japan) and fat tails. Generally, the minimum exceeds the maximum in absolute value. The correlation matrix shows low levels of correlation, implying the presence of diversification possibilities. However, Hong Kong, Korea and Thailand may be less attractive due to their relatively high level of volatility.

[Table 1 about here.]

4.2 Estimation procedure

The regime switching models we propose in Section 2 belong to the standard regime switching models as discussed in Hamilton (1994). Two algorithms are available to estimate these models: expectation maximization and maximum likelihood estimation. Central in both algorithms is a filtering technique to determine the state probabilities at each point in time, which can also be found in Hamilton (1994). Since the expectation maximization algorithm is less sensitive to the initial solution, we use this algorithm first. If the improvement in the likelihood function falls below a specified limit, we change to maximum likelihood estimation. If the optimal solution is reached, we calculate standard errors using the analytically constructed Hessian matrix of the likelihood function.

It turns out that some transitions from one state vector to another are highly unlikely, having an estimated probability below 10^{-10}. To avoid numerical problems in the maximum likelihood part, caused by parameter values that are too small (i.e. close to zero), we decided to fix these variables at the value they have after the expectation maximization part. After an optimal solution is reached we check whether we can restrict these transition probabilities to zero. The decrease in log likelihood value turns out to be lower than 10^{-5}. We interpret this negligible difference as a support for this approach[11].

4.3 Constructing optimal portfolios

The expression for the optimal portfolio in (16) defines an asset allocation strategy in continuous time. This means that we can derive a path of portfolios, given a price path. We decide to construct paths of portfolios based on daily prices. The data we use are the daily prices of the mentioned gross return indices in dollar terms, also gathered from DataStream. To keep the daily and monthly data sets consistent, we use the 1-month EuroDollar LIBOR that was prevailing at the beginning of the month to compute the daily excess returns during that month.

In this approach the portfolio path from the beginning of month τ till its end reflects two sources of information. First, it is based on the forecast probability $\xi_{\tau+1|\tau}(\tilde{Q})$. This is the forecasted probability with which a state vector $\tilde{Q}$ is prevailing at time $\tau+1$, based on all information available up to time τ. It can be interpreted as the outcome of an investor's thorough analysis of the economic situation. Because of it thoroughness such an analysis is conducted at a limited frequency, i.e. once per month. Since we do not want to model the economic situation itself, we use a Markov chain to represent it. The second source of information is the return process from τ to t, $\tau \leq t \leq \tau+1$. The cumulative return in this period is used to update the forecast into an inference about the actual probability with which a state vector is prevailing. The allocation is based on the inference probabilities constructed in this way. Hence, each state vector is assigned a prior probability, based on the Markov chain which reflects the dynamics of the economy. This prior probability is

[11]This procedure enables a straightforward determination of the Hessian matrix, whereas otherwise the methods described by Andrews (1999) have to be used to determine standard errors.

updated to a posterior probability, based on actual observed returns, which is in turn used to construct the allocation.

5 Estimation results

In this section we present and discuss the results from the estimation of the models that the different strategies imply. The parameter estimates are reported in Tables 2 to 7. We list our main findings and will discuss them in more detail hereafter. First, we consider the estimates for the parameters that characterize the normal distributions. We see that the two regimes can distinguished from each other based on volatility. Extending the model with a crisis regime improves the fit of the model substantially. In the crisis regime, we observe the expected deterioration of the risk-return trade-off, particularly for emerging markets. Next, we turn to the transition matrices. For both the model with and without the crisis, we find that the number of likely transitions is limited. We calculate unconditional inference probabilities to get a better insight in the likelihood of the different regimes. The low volatility regimes have the highest probability to occur unconditionally. Unconditionally, the crisis regime has a probability of 0.044, or once every 23 months, to occur. An inspection of the smoothed inference probability indicates two periods during which the crisis regime was prevailing with a high probability.

The estimates for the parameters that characterize the marginal normal distributions can be found in Table 2. We observe that the quiet regimes can be distinguished by a considerable difference in the estimated variances. Therefore, we will use the terms low volatility regime and high volatility regime to distinguish the regimes. A distinction based on volatility has been reported before in Ramchand and Susmel (1998), Ang and Bekaert (2002) and Graflund and Nilsson (2003).

[Table 2 about here.]

The estimates and standard errors for the mean and variance of the shock and the sensitivities of the different countries provide mild evidence in favor of the addition of a crisis regime. The ratio of the likelihoods[12] equals 9.65, which is a clear difference. However standard statistical tests cannot be used, because several parameters can be unidentified under the null hypothesis[13]

Including a crisis in the model causes some clear differences between the parameter estimates, particularly for the estimates for μ. In the model that excludes a strategy, the means in the high volatility regime tend to be lower and sometimes even negative (except for Korea). If a crisis regime is included, the means in the low volatility regime decrease (except for Hong Kong), while they increase in the high volatility regime. For Japan, Korean and Thailand, the means in the high volatility regime exceed those in the low volatility regime, whereas the difference for the US is small. This seems more in accordance with standard financial theory, stating that higher risk requires a higher expected return. The introduction of a crisis regime also lowers the estimates for the variance, except for the US, where we observe a slight increase. The decrease is most considerable for the emerging markets.

The estimated correlation matrices in Table 3 show relative low levels of correlation. The correlation estimates are not much affected by including a crisis regime. This indicates that the investment set offers ample diversification possibilities, though the relatively high volatility in emerging markets may diminish their attractiveness.

[Table 3 about here.]

To analyze the return process in the crisis regime we combine the estimates for the high volatility regime and the shock (see Table 4). To enable a comparison, the marginal parameters of the high volatility regimes are also included. The estimates for the shock

[12]The log likelihood values for the model without and with a crisis equal -5521.922 and -5512.273, respectively.

[13]Hansen (1992) proposes a method to formally test whether the addition of a regime is a significant improvement. In this method, the likelihood function is maximized over different combinations of fixed values for the restricted and nuisance parameters. The number of combinations grows exponentially in the number of parameters, which makes the method less attractive to test the significance of the crisis regime in this design.

in the crisis regime cause what we had expected: a sharp drop in expected returns (also compared with the means in the quiet regimes), an increase in volatility and a rise in correlations. The rise in correlation is conform results in Ang and Chen (2002) and Forbes and Rigobon (2002). The effect is most pronounced for the emerging markets, which is explained by their high sensitivities reported in Table 2. These higher sensitivities can offer an explanation for the fat tails in emerging markets reported by Susmel (2001). If the investor uses the crisis ignorant strategy, while a crisis has actually occurred, he will assign returns that belong to the crisis regime to the state vector of regimes with high volatility. Consequently, the estimates for those regimes will reflect the crisis as well. This can be observed when the first column of the table is compared with the other two: both mean and volatility are in between the values estimated for the crisis conscious strategy.

[Table 4 about here.]

The second group of estimates for the regime switching models, those for the transition probabilities, are reported in Tables 6 and 7. Because we consider 5 countries that can all be in two regimes, we include 32 different state vectors. The different vectors have been given a unique number, which can be found in Table 5. Our main finding is that only a limited number of transitions are likely. This follows from the fact that both transition matrices are sparse. For many transition probabilities, the estimates were close to zero and have subsequently been fixed at zero. The non-zero transition probabilities exhibit a pattern. First, in most cases the probability that the state (vector) process remains in the same state (vector) is unequal to zero. Second, if a switch takes place, the (country specific) regimes that switch, all switch in the same direction (i.e. all from low volatility to high volatility or vice versa). Whereas most state vectors have a non-zero probability of prevailing subsequent periods, some states are always followed by another state. These states are badly identified. Since the parameters that characterize the normal distributions never depend on only one state vector, the effects of these badly identified states are limited. Standard errors have not been reported because of their uninformative nature for probabilities close to 0 and 1.

[Table 5 about here.]

In Table 7 we observe that switches in the state process from a quiet state vector to the crisis state have a positive probability only for state vector 2 and 8. In other words, if Thailand or Thailand, Korea and Japan are in the high volatility regime, it is possible that a global crisis hits. If a crisis dies down, the state process moves to the state vector of high volatility regimes. Subsequently, the state process moves to state 4, in which Korea and Thailand are in the high volatility regime. The other countries move to the low volatility regime.

[Table 6 about here.]

[Table 7 about here.]

To get a better insight in the different regimes, we compute unconditional probabilities per state vector, and aggregate them into unconditional probabilities per regime. The results are presented in Table 8. In the model for the crisis ignorant strategy, each state has a positive unconditional probability. In the model for the crisis conscious strategy this is no longer the case: both state 27 and 31 have a probability of zero to occur. This is caused by their rows in the transition matrix, which consist entirely of zeros. For both models, the combination of low volatility regimes has the highest unconditional probability. A crisis has an unconditional probability of 0.044, which implies that a crisis can be expected to occur once per 23 months, which seems reasonable. Incorporating a crisis regime causes some minor adjustments in the unconditional probabilities.

The second panel of Table 8 aggregates the unconditional probabilities for each state vector into probabilities per country specific regime. The probability that the high volatility regime is prevailing ranges from 0.215 to 0.387 in the crisis ignorant model. Korea has the highest probability of being in the high volatility regime. Introducing a crisis regime has a mixed effect on the probability for low and high volatility regimes. For the US the probability of a low volatility regime rises, whereas it decreases for all other countries. The probability of a high volatility regime decreases for the US, Japan and Korea, while it increases for Hong Kong and Thailand. Of course, the estimates for high and low volatility regimes have changed too, which makes it difficult to compare the regimes for different models.

[Table 8 about here.]

Finally, we use the filtering and smoothing technique described in Hamilton (1994) to find out when each state vector was most likely to be prevailing. Figure 1 shows the series of smoothed inference probabilities for the crisis regime. The first peak in the figure represents the crash of October 1987. The crisis regimes dies down quickly: it is prevailing during October 1987 with probability 0.997, and with only 0.117 the month thereafter. The second, longer peak starts in the summer of 1997. The crisis regime is prevailing with probability (close to) 1 from October 1997 to September 1998. This period includes both the Asian crisis and Russian crisis. We conclude that the model picks up exactly those periods that have been marked as crises.

[Figure 1 about here.]

6 Portfolio construction

Based on the estimates of the previous section we construct optimal portfolios for the crisis conscious and crisis ignorant strategies. The portfolios vary over time and depend on the filtration of the return processes. As such, one general analysis of the different portfolios will not suffice. Instead, we concentrate on two situations. First, we consider the influence of a crisis for the unconditional case. This situation shows the effects of a crisis, when investors do not have prior knowledge on the state of the economy. In the second situation we analyze the effects of a crisis conditional on a period in which the probability that a crisis was actually prevailing was high. For this situation, we consider the optimal portfolios during the second half of 1997, when the Asian crisis took place. We concentrate on October 1997, the month in which the Hong Kong market crashed, and briefly consider the two months before and after it.

For both cases we conduct an analysis consisting of the same steps. We present and motivate the steps here, together with the main outcomes. In the next two subsections we report the actual analysis in more detail. We start by deriving and comparing the optimal allocations. We concentrate on the log utility investor. Though the assumption of log utility is unrealistic due to its low degree of risk aversion, the log utility is popular in asset allocation studies. The optimal portfolio for a power utility investor is the log utility portfolio scaled by the inverse of his coefficient of relative risk aversion and an investment in the riskless asset to meet the budget constraint. We find considerable differences between the crisis conscious and crisis ignorant strategies, which indicate that the crisis conscious strategy produces less aggressive portfolios. An inspection of only the risky part shows that the crisis conscious strategy shifts investment to countries less prone to a crisis, compared to the crisis ignorant strategy.

Next, we investigate what can explain the differences between the crisis conscious and crisis ignorant portfolio: the differences in the parameters estimates for the quiet part in both models, or the hedging demand due to the possibility of a crisis in the crisis conscious strategy. To accomplish this we use the myopic strategy introduced in Section 3.3. This strategy uses the same estimates for the quiet part as the crisis conscious model, but excludes the crisis regime from the forecasts it makes. Consequently, the differences between the portfolios produced by the crisis ignorant and the myopic strategy are due to different parameter estimates for the quiet part. On the other hand, the differences between the myopic strategy and the crisis conscious strategy are due to the crisis regime. These latter differences have the clear interpretation of a hedging demand. We compare both portfolio differences, and determine their magnitude and direction. We find that the investor hedges against a crisis by taking a long position in the US and the riskless asset and a short position in the stock markets of the other countries.

We decompose the hedging demands further to find out whether unattractive means or variances drives them. We compare both effects, and determine again their magnitude and direction. In general we see that the changes in means and the changes in variances due to the global shock have the same effect: either both changes make a country more attractive or both make it less attractive. If a crisis has a low probability of occurring, the effects are equally important, but if a crisis is hitting with almost certainty, the increase in variances has the strongest influence.

We finish the analysis by determining the costs of the crisis ignorant strategy under the assumption that the crisis conscious strategy is the most accurate. To that end we calculate the certainty equivalents needed to compensate the investor for using the crisis ignorant strategy as presented in 3.4. For the unconditional case, the costs of ignoring the possibility of a systemic crisis are limited, but large enough not to neglect them, particularly for longer horizons. In the second situation, so if a crisis takes place with almost certainty, the costs rise dramatically, also for more risk averse investors.

6.1 Unconditional analysis

In the unconditional case, we concentrate on the portfolios that are constructed based on the probabilities in Table 8. These probabilities are taken as inference probabilities, based on which a forecast is made. We do not assume a certain price path, but concentrate on the initial allocation instead. We present the allocations produced by the crisis ignorant and crisis conscious strategies in Table 9, together with a decomposition of the differences.

[Table 9 about here.]

The log utility portfolio reported in Table 9(a) reveals several valuable insights. Most importantly we observe that the crisis conscious strategy results in a less aggressive allocation than the crisis ignorant strategy. Overall, the position is less leveraged: the investor lends 1.8 times his initial wealth opposite to 2.2 under the crisis ignorant strategy. Furthermore, the investments in Hong Kong, Korea and Thailand are decreased (in size). Das and Uppal (2004) report similar, though less pronounced results.

The effect of rising risk aversion is now easy to determine. An investor with power utility and coefficient of relative risk aversion γ will choose the same allocation to risky assets as the log utility investor, with all weights divided by γ, and will invest the rest in the riskless asset. Panel b of Table 9 reports the allocation of a power utility investor with risk aversion coefficient $\gamma = 4$. We observe a substantial decrease in overall riskiness: the total proportion in risky assets does not exceed 1.

Panel c of Table 9 concentrates on the risky asset part in the portfolios. The ignorant strategy leads to an investment of half of his (risky) portfolio in the US, 33% in emerging markets, 23% in Hong Kong and a short position in Japan. If it is changed to crisis conscious, more is allocated to the US and less to emerging markets. Estimates indicate that emerging markets are more sensitive to a crisis.

The differences between the crisis ignorant and crisis conscious strategies can be decomposed in a part related to differences in the estimates for the quiet regimes, called the estimation effect, and a part related to the presence of a crisis regime in the crisis conscious strategy, called the crisis effect. The estimation effect causes a slight decrease of investments in the US, Hong Kong and Japan but increases the exposure to the Thai and Korean market, which is mostly financed by shorting the riskless asset. The crisis effect is almost opposite to the estimation effect: investments are shifted from the Thai and Korean market to the US market and the riskless asset. The proportion invested in Hong Kong and Japan are further reduced. The crisis effect is largest, as is revealed by the lengths of both vectors: $|\phi^e| = 0.879$ and $|\phi^s| = 1.336$. The angle both effects make is 171°, which shows again that both effects are opposite. We conclude that the estimation effect boosts investments in risky assets, whereas the crisis effect curbs it. Since the effects are opposite and the crisis effect dominates, the crisis ignorant strategy leads to some prudence due to periods with high volatility and low expected returns but fails to fully incorporate the effect of a systemic crisis.

We can use (24) and (25) to further analyze the crisis effect. Overall, both the expected returns and the variances during a crisis make investments in stocks less attractive (the angle between both vectors equals 9°). Of course, this does not come as a surprise[14]. More

[14] Because we consider initial asset allocations, the inference and forecast probabilities coincide, $\pi_{Q,Q^c} = \xi_{Q,Q^c}$. Consequently, (24) and (25) can be expressed solely in terms of the crisis parts $\pi_{Q,1}$, μ^c and ω^c and δ. This results in a large common factor.

interesting is the observation that in this setting the increase in variances contributes most. Each element in ϕ^Ω is larger (in size) than its corresponding element in ϕ^μ (except for Japan). Calculating lengths confirms this: $|\phi^\Omega| = 0.774 > |\phi^\mu| = 0.567$.

We address the economic impact of the different strategies by calculating the certainty equivalent return needed to compensate the investor for adopting crisis ignorant strategy. A log utility investor with a horizon of 1 month requires a certainty equivalent return of 0.054% when he follows the crisis ignorant strategy. The certainty equivalent rises proportional to the horizon. If the horizon is 1 year, the certainty equivalent return amounts to 0.65%. For more risk-averse investors, the certainty equivalent can be found by dividing the certainty equivalent return by the risk aversion coefficient.

Though the certainty equivalent return is relatively small, the contributions of the constituting estimation and crisis effect are larger: the estimation effect corresponds with a return of -0.377% and the crisis effect with a return of 0.432%. This shows again the opposite direction of both effects. The estimation effect worsens the investors allocation, because it makes it more aggressive. The crisis effect on the other hand improves the allocation by making it more prudent. Therefore, it has a positive certainty equivalent return. We still observe that the crisis effect dominates, but the difference between the two effects (in absolute sense) has become smaller.

6.2 October 1997: the Asian crisis

After studying the unconditional effects of a systemic crisis in the previous section, we now turn to a conditional setting. We investigate the implications of the crisis ignorant models for asset allocation in October 1997, the month during which the Hong Kong market crashed. This enables us to observe how the dive of the Hong Kong market influenced the inference probabilities and consequently the asset allocation. The decompositions can help us to understand the changes in the asset allocation over time.

The Asian crisis hit financial markets during the second half of 1997.[15]. In August 1997

[15]See Kamin (1999) for a broad discussion of the symptoms of the Asian crisis Kaminsky and Schmukler

the Thai market crashed. Only after the crash of the Hong Kong market, the shocks in Asia were considered as a global crisis. An inspection of the inference probabilities of our model produces a similar picture. By the end of August, the inferred probability for the crisis regime was 0.16, in September it decreased to 0.03 but by the of October it had risen to 0.99992. The smoothed inference probabilities resulting from our model confirm the view that the sharp drop in the Thai market could be seen as an overture to the Asian crisis. For August, the smoothed inference probability of a crisis regime was 0.46, in September it climbed to 0.52, and from October onwards it remained close to 1.

Figure 2(a) plots the cumulative excess gross returns for the different countries. All cumulative returns, except for the US, are already negative during the beginning of the month. However, after October 17, 1997 the Hong Kong market starts to dive: from -9.5% to -50% in 7 days. The Thai and Korean market move in lock step, while the US and Japanese market are falling as well, though not as much as the other three. At the end of October 20, a Monday, the inference probability for the crisis regime in the crisis conscious model climbs to 0.57 and remains above 0.50 for the rest of the month (except 0.48 for October 23). So the conscious strategy deems the crisis regime the most likely for the second half of the month.

[Figure 2 about here.]

To see what happened if a crisis had not been taken into account, we also plot the inferences for the crisis ignorant model. In the first half of the month, it is inferred that the Thai market, probably accompanied by the Hong Kong and Korean market, is in its high volatility regime (state vector 2 or 12). After the sharp decline in the Hong Kong market, the inference probability for state vector 12 is close to 1. If he adopts the crisis ignorant strategy, the investor deems it highly uncertain that all markets are in their high volatility regime. The inference probability for the high volatility state vector 32 does not exceed 0.004.

(1999) investigate the causes of daily market fluctuations during the Asian crisis.

The allocations produced by the crisis conscious and crisis ignorant strategies during the month are plotted in Figure 3. First consider the solid lines of the crisis conscious strategy. The investment in the US market is the most stable during the month. In the first half of the month, the investor maintains a leveraged position in the US, but after the crash of the Hong Kong market he reduces his investment to 0.5 - 0.75. The investments in the other markets are more volatile. In Japan, he always maintains a short position, ranging from -0.5 to -1.7 in the first half of the month. However, after the increase in the inference probability for the crisis regime, this position is reduced to -0.2. The Hong Kong market becomes less and less attractive during the month: its weight decreases gradually from around 2.0 to -0.44 by the end of October. It is interesting to see, that the position has already been reduced during the first half of the month. At the end of October 17, its position is only 0.28. After the crash it becomes and remains negative. The investments in Korea and Thailand look a bit symmetric: if the investor takes a short position in Korea, he takes a long position in Thailand (and vice versa), and he either increases or reduces both positions. This may be caused by the inferences in the first half of the month, that put either Korea or Thailand in their high volatility regimes. After the crisis regime becomes prevailing with a high probability, both positions are reduced, though the short position in Thailand remains relatively large (-0.75). The net effect of these adjustments over time are reflected in the last graph in Figure 3. It shows a gradual increase of the investment in the risk-free asset. In the beginning of the month it is shorted, indicating an overall leveraged position. During the first half, we see that the positions become less leveraged, probably due to the possibility of high volatility regimes in Hong Kong, Korea and Thailand. From October 20 onwards, the investor takes a long position in the risk-free asset. This position exceeds his initial wealth by maximally 60%.

[Figure 3 about here.]

The question how the presence of a crisis regime affects asset allocation can be answered by paying attention to the evolution of the allocations resulting from the crisis ignorant strategy, which is also included in Figure 3. The differences between the allocations based on the crisis conscious and crisis ignorant strategy are quite pronounced, particularly regarding the US investments. The crisis ignorant strategy yields a leveraged position during the complete month, and even extends it during the second half of the month, implying that the US is perceived as a safe haven. For Hong Kong we see overall a similar tendency of decreasing exposure. However, in the first days of the month the crisis ignorant strategy highly speculates in the Hong Kong market. Contrary to the crisis conscious strategy, it keeps a stable and limited exposure in the Thai and Korean markets. This is due to the inference that Thailand and Korea are in a high volatility regime with a high probability.

In order to explain the differences between the crisis ignorant and crisis conscious portfolios we consider the decomposition of those differences in an estimation and a crisis effect, also included in Figure 3. Both effects reveal interesting insights. Based on the crisis effect we conclude that also during a crisis, the US and the riskless asset can be used to hedge against a crisis at the expense of investments in the other countries. We observe a positive demand for the US asset, and a strong and increasing positive demand for the riskless asset. Positions in other markets are more and more reduced, particularly in the emerging markets Korea and Thailand, which are most prone to a crisis.

The estimation effect presents a less clear picture. In the unconditional case, the estimation effect shifts investments from the riskless asset to the risky assets, and within the risky part it favored the emerging markets over the other 3 countries. We still observe a preference for Korea and Thailand, but also a growing interest in Hong Kong and Japan. So within the risky asset part we observe a tendency to more aggressive allocations. For the portfolio as a whole, we observe an increase of leverage first. However, in the second half of the month the US asset is shorted to finance the portfolio adjustments.

To increase the understanding of the cooperation of both effects, we plotted the length and the angle for the adjustment vectors of the effects in Figure 4. The estimation effect has the largest influence, since the length of the corresponding vector is longer than the crisis effect on most days. The impact of both effects in this conditional setting exceeds their impact in the unconditional case by far. Most striking, however, is the fact that the effects work in a different direction: their angle is close to 90°. This implies that the crisis ignorant strategy fails to react accurately on a crisis when it actually hits. This is a clear contrast with the unconditional situation where the ignorant strategy included at partial reaction to a crisis and shows again the importance of accurately including the possibility of a crisis.

[Figure 4 about here.]

Whether the hedging demands for the crisis are due to the decline in means or the rise in variances is considered in Figure 5. This figure plots the crisis effect and a decomposition of it in a part caused by changes in the drift (mean effect) and another part caused by changes in the variance (variance effect). During the first half of the month, the effects of a possible shock on asset allocation via a decrease in expected returns and via an increase in variance are similar, and mostly in the same direction. However, when the inference probability for a crisis increases during the second half of the month, we see differences occur. The attraction of the US asset is mainly due to the limited decrease in its expected return. Japan, but particularly Thailand are hurt by a crisis, because both the change in means and variances make them unattractive. For Korea and Hong Kong the overall effect is negative, but both effects cancel at least partly. The riskless asset shows the net-effects: at first they equal, but in the second half the variance effect dominates. Figure 6(a) confirms this observation, while Figure 6(b) shows that both effects reinforce each other.

[Figure 5 about here.]

[Figure 6 about here.]

The economic importance of including the likelihood of a crisis in asset allocation decisions is investigated in Figure 7, which presents the certainty equivalent return needed to raise the investor's utility, if he adopts the crisis ignorant strategy (assuming log utility). This figure is interesting in several ways. First, the certainty equivalent costs for the ignorant strategy are high, mostly above 0.5 %, compared to the 0.054 % reported for the unconditional case. This finding applies to the complete month, not only to the second half. Second, the certainty equivalents rise dramatically after the crash of the Hong Kong market. Third, the certainty equivalent costs of missing the hedging components for a crisis are also considerable. These costs exceed 0.5% as well, with an exception for 4 days at the beginning of the month. Of course, missing the hedging components becomes extremely expensive after a crisis has occurred. The estimation effect does not always harm the investor's utility. Furthermore, the estimation effect influence utility less (in absolute sense) than the crisis effect. We conclude that during the complete month of October, before and after the crash of the Hong Kong market, taking a crisis into account is economically important.

[Figure 7 about here.]

To investigate the robustness of our findings based on October 1997, we conduct similar analyses for August, September, November and December. These analyses reveal large similarities for those months and October and support our conclusions based on October. We briefly discuss the main findings for each month. August shows a crash for the Thai market (amounting to -35%), whereas in September the Korean market goes down. Other markets remain fairly stable. Consequently, the inference probabilities for the crisis regime remain at a low level. We observe strongly leveraged portfolios for both the crisis conscious and crisis ignorant strategy. The differences between the portfolios can be large, and are mainly driven by the estimation effect. However, their economic impact is limited, with certainty equivalent returns around 1.5%. As such, August and September show a similar picture as the beginning of October. On the contrary, November and December have more in common with the second half of October: the markets go down and are volatile. The inference probabilities for a crisis are high (close to 1). As was the case for the second half of October, the crisis ignorant model deems a high volatility regime for Hong Kong, Korea and Thailand and a low volatility regime for the US and Japan most likely. Correspondingly, we see large differences in asset allocation, with again more aggressive investments for the crisis ignorant strategy and more prudence for the crisis conscious one. These differences can be best explained by the crisis effect, which is positive for the US and the risk-free asset and negative for the other countries. The economic impact of the differences is again large (around 5%).

7 Conclusions

In this paper we studied the effect of systemic crises, interpreted as a global simultaneous shock to financial markets, on asset allocation. Due to the crisis, expected returns decrease, while volatilities and correlations increase, leading to a severe and rapid deterioration of the risk-return trade-off. Because of its global and simultaneous nature, a systemic crisis can have dire consequences for international investors. However, due to their irregular and relatively rare occurrence, standard models to support asset allocation decisions typically fail to capture systemic crises. Inappropriately ignoring systemic risk can seriously harm investors.

To establish a link between systemic crises and asset allocation we introduce an investor that can determine his optimal portfolio based on a crisis ignorant or a crisis conscious strategy. Both strategies are based on Markov regime switching models for the return process. In addition to a basic quiet part, which is present in both strategies, the crisis conscious scenario extends the model for the return process by including crisis regimes. These regimes are a combination of a basic regime and a shock. The shock hits all markets simultaneously, but markets have a different sensitivity to it. Based on the two different models, we solve the investor's asset allocation problem in a continuous-time, expected-utility framework. We use certainty equivalents to determine the economic cost of ignoring systemic crises.

We use both strategies to evaluate the allocations made by a US investor who can invest in the riskless asset and stock markets in the US, Hong Kong, Japan, Korea and Thailand. The models for the strategies are estimated on monthly stock returns from 1975 to 2003. The estimates for the quiet part show the typical picture of regimes that differ mainly on volatility. The crisis regime is characterized by a decrease in expected returns and an increase in volatilities and correlations, particularly for emerging markets. Based on the estimates we conclude that an accurate model for return processes should incorporate the possibility of a systemic crisis. Not only do we observe a statistical improvement, but also estimates that link a higher volatility to a higher expected return.

The allocations based on the estimates for the different strategies indicate that the possibility of a crisis has a considerable impact on asset allocations. If a crisis is taken into account, allocations become less aggressive: the proportion invested in risky assets decrease and investments shift to countries less prone to a crisis. If the likelihood of a crisis grows, these effects become more pronounced. Using models in asset allocation decisions that incorrectly ignore a crisis is costly, also to more risk averse investors.

This paper can motivate further research in several ways. Some parts of our model are kept at a basic level for clarity. It will be interesting, however, to see the influence of a crisis, when other economic variables are used to predict the likelihood of a crisis or the corresponding means and variances. A more normative model for a crisis can also be interesting. Finally, our finding that crisis conscious strategies shift allocations from countries that are relatively prone to a crisis to countries that are less prone to it can add to the research on the home bias puzzle (see Lewis, 1999, for an overview), particularly in relation to emerging markets. These are issues for future research.

A Disentangling hedging demands

To show how the hedging demand for a crisis can be split up in a mean effect and a variance effect, we first determine the relation between $\pi(\tilde{Q}, r, \tau)$ in the crisis conscious and the myopic strategy. Since r and τ are the same for both strategies, we suppress them in this part. To further ease notation, we write the state vector on which the value of a variable depends as a subscript, and split the state vector in the quiet part Q and the crisis part which can be 0 or 1. A c or m as superscript indicates whether we consider the crisis conscious or myopic strategy. Consequently, we can rewrite (19) to:

$$\pi^c_{Q,Q^c} = \frac{\xi^c_{Q,Q^c} f_{Q,Q^c}}{\sum_{(\hat{Q},\hat{Q}^c)\in\tilde{\mathbb{Q}}} \xi^c_{\hat{Q},\hat{Q}^c} f_{\hat{Q},\hat{Q}^c}} \tag{33}$$

We can use (20) to construct a similar expression for the myopic strategy:

$$\pi^m_Q = \frac{(\xi^c_{Q,0} + \xi^c_{Q,1}) f_{Q,0}}{\sum_{(\hat{Q},\hat{Q}^c=0)\in\tilde{\mathbb{Q}}} \xi^c_{\hat{Q},\hat{Q}^c} f_{\hat{Q},\hat{Q}^c}} \tag{34}$$

Since the myopic strategy uses the same parameters as the crisis conscious strategy to characterize the quiet regimes, f is the same for both. The values of f for the different state vectors and given values for r and τ can be reconstructed from ξ_{Q,Q^c} and π^s_{Q,Q^c} up to a scale factor (interpreting (33) as a system whit the different f_{Q,Q^c}'s constituting a set of k unknowns, with k equal to the number of elements in $\tilde{\mathbb{Q}}$, and $k-1$ equations (one equation is redundant) reveals the existence of 1 free variable). Letting $f_{Q^0,0}$ denote the scale factor, we find:

$$f_{Q,Q^c} = \frac{\pi^s_{Q,Q^c}}{\xi^c_{Q,Q^c}} \frac{\xi^c_{Q^0,0}}{\pi^s_{Q^0,0}} f_{Q^0,0} \tag{35}$$

Substituting this expression in (34) yields

$$\pi^m_Q = \pi^c_{Q,0}\left(1 + \xi^c_{Q,1}/\xi^c_{Q,0}\right) \Bigg/ \sum_{(\hat{Q},\hat{Q}^c=0)\in\tilde{\mathbb{Q}}} \pi^c_{\hat{Q},0}\left(1 + \xi^c_{\hat{Q},1}/\xi^c_{\hat{Q},0}\right) \tag{36}$$

Now consider the optimal portfolio defined in (16), which we rewrite to

$$\phi^* = \gamma^{-1}\Omega^{-1}\alpha, \tag{37}$$

with $\alpha \equiv a + \mathrm{diag}(\Omega) - r_f\iota$. The variables α and Ω differ dependent on the myopic and crisis conscious strategy, since they depend on π as given in (17) and (18). For the myopic strategy's instantaneous variance we have:

$$\Omega^m = \sum_{Q\in\mathbb{Q}} \pi^m_Q \Omega_{Q,0} = \frac{\sum_{Q\in\mathbb{Q}} \pi^c_{Q,0}(1 + \xi^c_{Q,1}/\xi^c_{Q,0})\Omega_{Q,0}}{\sum_{Q\in\mathbb{Q}} \pi^c_{Q,0}\left(1 + \xi^c_{Q,1}/\xi^c_{Q,0}\right)} \tag{38}$$

We can use this expression to relate Ω^s and Ω^m:

$$\Omega^s = \eta\Omega^m - \sum_{Q\in\mathbb{Q}} \pi^c_{Q,0}\frac{\xi^c_{Q,1}}{\xi^c_{Q,0}}\Omega_{Q,0} + \sum_{Q\in\mathbb{Q}} \pi^c_{Q,1}\Omega_{Q,1}, \tag{39}$$

where we have defined the auxiliary variable $\eta \equiv \sum_{Q\in\mathbb{Q}} \pi^c_{Q,0}(1+\xi^c_{Q,1}/\xi^c_{Q,0})$. Upon defining $\alpha_{Q,Q^c} = \mu_{Q,Q^c} + \mathrm{diag}(\Omega_{Q,Q^c})/2 - r_f\iota$, we can derive a similar relation between α^s and α^m.

This enables us to rewrite the difference between ϕ^c and ϕ^m as:

$$\begin{aligned}
\phi^c - \phi^m &= \gamma^{-1}(\Omega^c)^{-1}\alpha^c - \gamma^{-1}(\Omega^m)^{-1}\alpha^m \\
&= \gamma^{-1}(\Omega^c)^{-1}\left(\alpha^c - \Omega^c(\Omega^m)^{-1}\alpha^m\right) \\
&= \gamma^{-1}(\Omega^c)^{-1}\Bigg[\eta\alpha^m - \sum_{Q\in\mathbb{Q}}\pi^c_{Q,0}\frac{\xi^c_{Q,1}}{\xi^c_{Q,0}}\alpha_{Q,0} + \sum_{Q\in\mathbb{Q}}\pi^c_{Q,1}\alpha_{Q,1} - \\
&\qquad \left(\eta\Omega^m - \sum_{Q\in\mathbb{Q}}\pi^c_{Q,0}\frac{\xi^c_{Q,1}}{\xi^c_{Q,0}}\Omega_{Q,0} + \sum_{Q\in\mathbb{Q}}\pi^c_{Q,1}\Omega_{Q,1}\right)(\Omega^m)^{-1}\alpha^m\Bigg] \qquad (40)\\
&= \gamma^{-1}(\Omega^c)^{-1}\Bigg[\sum_{Q\in\mathbb{Q}}\left(\pi^c_{Q,1}\alpha_{Q,1} - \pi^c_{Q,0}\frac{\xi^c_{Q,1}}{\xi^c_{Q,0}}\alpha_{Q,0}\right) - \\
&\qquad \sum_{Q\in\mathbb{Q}}\left(\pi^c_{Q,1}\Omega_{Q,1} - \pi^c_{Q,0}\frac{\xi^c_{Q,1}}{\xi^c_{Q,0}}\Omega_{Q,0}\right)(\Omega^m)^{-1}\alpha^m\Bigg],
\end{aligned}$$

which produces the given expressions in (24) and (25).

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(a) univariate statistics

	US	Hong Kong	Japan	Korea	Thailand
mean	0.438	0.599	0.224	0.302	0.290
volatility	4.44	9.43	6.52	10.66	10.35
skewness	-0.75	-1.07	0.07	0.37	-0.45
kurtosis	5.84	8.26	3.47	5.73	5.91
minimum	-24.5	-57.6	-22.2	-41.3	-41.9
maximum	11.9	28.3	21.1	53.1	38.0

(b) correlation matrix

	US	Hong Kong	Japan	Korea	Thailand
US	1	0.419	0.300	0.279	0.314
Hong Kong	0.419	1	0.304	0.209	0.397
Japan	0.300	0.304	1	0.365	0.255
Korea	0.279	0.209	0.365	1	0.396
Thailand	0.314	0.397	0.255	0.396	1

Table 1: *Descriptive statistics for the data set consisting of the monthly excess gross returns (in %) for the MSCI US, MSCI Hong Kong, MSCI Japan, IFC Korea and IFC Thailand indices, running from January 1976 to December 2003. Panel (a) presents univariate statistics, panel (b) shows the correlation matrix.*

country		crisis ignorant		crisis conscious	
		estimate	standard error	estimate	standard error
US	μ_1	0.813	0.215	0.519	0.220
	μ_2	-0.889	0.783	0.446	0.945
	ω_1	11.2	1.09	13.0	1.17
	ω_2	48.7	8.95	53.2	10.22
	δ			1	
Hong Kong	μ_1	1.027	0.384	1.144	0.389
	μ_2	-0.193	1.588	0.218	1.327
	ω_1	39.8	3.51	38.2	3.45
	ω_2	253.1	39.42	207.7	31.00
	δ			3.33	1.77
Japan	μ_1	0.210	0.325	0.065	0.328
	μ_2	0.026	0.908	0.754	0.849
	ω_1	25.9	2.37	25.5	2.36
	ω_2	89.4	13.28	79.3	11.46
	δ			1.77	1.14
Korea	μ_1	0.221	0.476	-0.542	0.450
	μ_2	0.904	1.268	2.757	1.137
	ω_1	46.8	5.09	38.4	4.32
	ω_2	214.6	26.39	171.0	23.38
	δ			6.33	4.36
Thailand	μ_1	0.615	0.410	-0.337	0.417
	μ_2	-0.025	1.678	2.031	0.948
	ω_1	37.5	3.89	27.1	3.27
	ω_2	257.4	39.16	130.2	17.35
	δ			7.30	4.45
crisis	μ^c			-1.344	1.243
	ω^c			9.42	12.74

Table 2: *Estimates for the parameters of the marginal distributions of the excess monthly equity return (in %) for the US, Hong Kong, Japan, Korea and Thailand under the different regimes (indicated by subscripts). The first two columns present the estimates for the crisis ignorant strategy; the last two for the crisis conscious strategy. The sensitivity of the US market to a crisis has been normalized to 1.*

(a) crisis ignorant

	US	Hong Kong	Japan	Korea	Thailand
US	1				
Hong Kong	0.50 (0.043)	1			
Japan	0.33 (0.050)	0.34 (0.049)	1		
Korea	0.27 (0.053)	0.22 (0.054)	0.40 (0.046)	1	
Thailand	0.30 (0.052)	0.35 (0.050)	0.22 (0.054)	0.27 (0.054)	1

(b) crisis conscious

	US	Hong Kong	Japan	Korea	Thailand
US	1				
Hong Kong	0.48 (0.044)	1			
Japan	0.34 (0.050)	0.33 (0.050)	1		
Korea	0.26 (0.055)	0.20 (0.054)	0.38 (0.048)	1	
Thailand	0.27 (0.055)	0.35 (0.054)	0.17 (0.055)	0.21 (0.055)	1

Table 3: *Estimates for the correlations between the different countries for the crisis ignorant (panel a) and crisis conscious strategy (panel b). The correlations are assumed to be independent of the regimes. Standard error are reported in parentheses.*

(a) parameters for the marginal distribution

		crisis ignorant high volatility	crisis conscious high volatility	crisis
US	mean	-0.889	0.446	-0.898
	variance	48.7	53.2	62.7
	volatility	6.98	7.30	7.92
Hong Kong	mean	-0.193	0.218	-4.26
	variance	253.1	207.7	312.2
	volatility	15.9	14.4	17.7
Japan	mean	0.026	0.754	-1.63
	variance	89.4	79.3	108.9
	volatility	9.45	8.90	10.4
Korea	mean	0.904	2.757	-5.75
	variance	214.6	171.0	548.5
	volatility	14.6	13.1	23.4
Thailand	mean	-0.025	2.031	-6.89
	variance	257.4	130.2	632.3
	volatility	16.0	11.4	25.1

(b) resulting correlation for the crisis regime

	US	Hong Kong	Japan	Korea	Thailand
US	1				
Hong Kong	0.58	1			
Japan	0.47	0.53	1		
Korea	0.46	0.57	0.61	1	
Thailand	0.46	0.65	0.53	0.79	1

Table 4: *The effects of a crisis. This table presents the parameters that characterize the normal distribution when a crisis occurs (panel a, last column; panel b) and compares the parameters for the marginal distributions with those for the high volatility regimes for both the crisis ignorant and crisis conscious strategy (first two columns, panel a). The parameters for the crisis state are computed using equations* (4) *and* (5).

	US	Hong Kong	Japan	Korea	Thailand
1	1	1	1	1	1
2	1	1	1	1	2
3	1	1	1	2	1
4	1	1	1	2	2
5	1	1	2	1	1
6	1	1	2	1	2
7	1	1	2	2	1
8	1	1	2	2	2
9	1	2	1	1	1
10	1	2	1	1	2
11	1	2	1	2	1
12	1	2	1	2	2
13	1	2	2	1	1
14	1	2	2	1	2
15	1	2	2	2	1
16	1	2	2	2	2
17	2	1	1	1	1
18	2	1	1	1	2
19	2	1	1	2	1
20	2	1	1	2	2
21	2	1	2	1	1
22	2	1	2	1	2
23	2	1	2	2	1
24	2	1	2	2	2
25	2	2	1	1	1
26	2	2	1	1	2
27	2	2	1	2	1
28	2	2	1	2	2
29	2	2	2	1	1
30	2	2	2	1	2
31	2	2	2	2	1
32	2	2	2	2	2

Table 5: *Combinations of country specific regimes and the number of the resulting state vector.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0.93	0	0	0	0	0	0	0	0	0	0	0	0.57	0.22	0	0
2	0.03	0.90	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0.02	0	0	0	0	0	0	0	0	0	0.46	0	0	0	0	0
4	0	0	0	0.46	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0.86	0.30	0	0	0.05	0.00	0	0	0	0	0	0
6	0	0	0	0	0	0.70	0	0	0	0	0	0	0	0	0	0
7	0.01	0	0	0	0	0	0.79	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0.15	0	0	0	0	0	0	0	0	0
9	0.01	0	0	0	0	0	0	0	0.83	0	0	0	0.32	0	0	0
10	0	0	0	0	0	0	0	0	0	0.00	0	0	0	0	0	0
11	0	0	1.00	0	0	0	0	0	0	0	0	0	0	0	1	0
12	0	0.05	0	0	0	0	0	0	0	0	0	0.90	0	0	0	0
13	0	0	0	0	0	0	0	0	0.00	0.00	0	0	0.10	0	0	0
14	0	0	0	0	0.06	0	0	0	0	0	0	0	0	0.78	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.22
17	0	0	0	0.04	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0.06	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0.42	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0.08	0	0	0	0	0	0	0	0	0	0	0	0.78
21	0	0	0	0	0.09	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0.35	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0.06	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	1.16E-06	0	0.65	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0.03	1	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0.09	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0.29	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0.10	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
1	0.12	0	0	0	0	0	0	0	0	0	0.11	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
7	0	0	0	0	0.24	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0.15	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0.75	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.74
17	0.83	0.65	0	0	0	0	0	0	0	0	0	0	0	1	0	0
18	0	0.35	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0.76	0	0.32	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0.68	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0.05	0	0	0	0	0	0	0	6.62E-05	0	0	0	0	0	0	0
30	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0.26

Table 6: *Estimates for the transition probabilities p_{ij} from state vector j to state vector i for the model for the crisis ignorant strategy.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0.91	0	0	0.02	0	0	0	0	0	0	0	0	0	0.34	1	0	0.15
2	0.02	0.90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0.06	0.10	0	0	0	0	0	0	0	0	0	0	0
4	0	0.00	0	0.95	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0.86	0	0	0	0	0.41	0	0	0	0	0	0	0
6	0	0	0.73	0	0	0.85	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0.86	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0.85	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0.87	0	0	0	0.49	0	0	0	0
10	0.01	0	0	0	0	0	0	0	0	0.59	0	0.50	0	0	0	0	0
11	0	0.03	0	0	0	0	0	0	0	0	0.88	0	0	0	0	0	0
12	0	0	0	0	0	0.04	0	0	0	0	0	0.50	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0.51	0	0	0	0
14	0	0	0	0	0.08	0	0	0	0	0	0	0	0	0	0	1	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0.66	0	0	0
17	0	0	0	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0.85
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0.04	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0.14	0	0	0	0	0	0	0	0	0	0
23	0.05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0.27	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0.12	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0.13	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
crisis	0	0.03	0	0	0	0	0	0.15	0	0	0	0	0	0	0	0	0

	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	crisis
1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0
2	0	0	0	0	0	0.76	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0.24	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0.51	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0.73	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0.25	0	0.60	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0.75	0.67	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0.40	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0.49	0.17	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0.83	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0.85	1	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0.33	0	0	0	0	0	0	0	0	0	0.15	0	0	0	0
30	0	0	0	0	0	0	0	0	0.27	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.13
crisis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.87

Table 7: *Estimates for the transition probabilities p_{ij} from state vector j to state vector i for the model for the crisis conscious strategy.*

(a) unconditional probability per state vector

	crisis ignorant	crisis conscious		crisis ignorant	crisis conscious
1	0.276	0.202	17	0.060	0.025
2	0.071	0.123	18	0.006	0.006
3	0.034	0.010	19	0.033	0.015
4	0.078	0.118	20	0.009	0.008
5	0.053	0.035	21	0.032	0.005
6	0.016	0.049	22	0.003	0.014
7	0.050	0.017	23	0.010	0.010
8	0.007	0.017	24	0.005	0.003
9	0.055	0.069	25	0.004	0.009
10	0.003	0.012	26	0.005	0.015
11	0.065	0.125	27	0.019	0
12	0.032	0.004	28	0.003	0.009
13	0.011	0.018	29	0.003	0.006
14	0.013	0.008	30	0.003	0.004
15	0.017	0.009	31	0.017	0
16	0.004	0.005	32	0.004	0.006
			crisis		0.044

(b) unconditional probability per regime per country

	crisis ignorant		crisis conscious	
	low volatility	high volatility	low volatility	high volatility
US	0.785	0.215	0.822	0.134
Hong Kong	0.743	0.257	0.658	0.298
Japan	0.753	0.247	0.750	0.206
Korea	0.613	0.387	0.600	0.356
Thailand	0.737	0.263	0.553	0.403

Table 8: *Unconditional probability for each state vector (panel a) and unconditional probability for each regime for each country (panel b). The unconditional probabilities for the state vector are calculated from the estimates in Table 6 and Table 7 following Hamilton (1994), Eq. 22.2.26. The unconditional probabilities for the different regime per country are found by summing the relevant state vector probabilities.*

(a) log utility investor

investor	ignorant	conscious	ϕ^e	ϕ^s	ϕ^μ	ϕ^Ω
US	1.645	1.751	-0.057	0.163	0.042	0.121
Hong Kong	0.728	0.632	-0.021	-0.075	-0.040	-0.034
Japan	-0.248	-0.299	-0.015	-0.036	-0.037	0.001
Korea	0.592	0.519	0.360	-0.433	-0.173	-0.260
Thailand	0.463	0.206	0.416	-0.674	-0.259	-0.414
risk free	-2.180	-1.809	-0.683	1.054	0.468	0.586

(b) power utility, $\gamma = 4$

investor	ignorant	conscious	ϕ^e	ϕ^s	ϕ^μ	ϕ^Ω
US	0.411	0.438	-0.014	0.041	0.010	0.030
Hong Kong	0.182	0.158	-0.005	-0.019	-0.010	-0.009
Japan	-0.062	-0.075	-0.004	-0.009	-0.009	0.000
Korea	0.148	0.130	0.090	-0.108	-0.043	-0.065
Thailand	0.116	0.051	0.104	-0.168	-0.065	-0.104
risk free	0.205	0.298	-0.171	0.264	0.117	0.147

(c) all risky assets portfolio

investor	ignorant	conscious	ϕ^e	ϕ^s
US	0.517	0.623	-0.106	0.212
Hong Kong	0.229	0.225	-0.046	0.042
Japan	-0.078	-0.106	0.010	-0.038
Korea	0.186	0.185	0.060	-0.062
Thailand	0.146	0.073	0.082	-0.154
risk free	0	0	0	0

Table 9: *Optimal portfolios for the crisis ignorant and crisis conscious strategies for different situations: log utility, power utility with $\gamma = 4$ and an investment in risky assets only. The portfolios are the initial portfolios ($t = 0$) based on the unconditional inference probabilities given in Table 8. The portfolio weights for the different countries and the risk-free asset are reported in the first two columns. The differences between the allocations are decomposed in an estimation effect ϕ^e and a crisis effect ϕ^s. The crisis effect is split up in a mean effect ϕ^μ and a variance effect ϕ^Ω.*

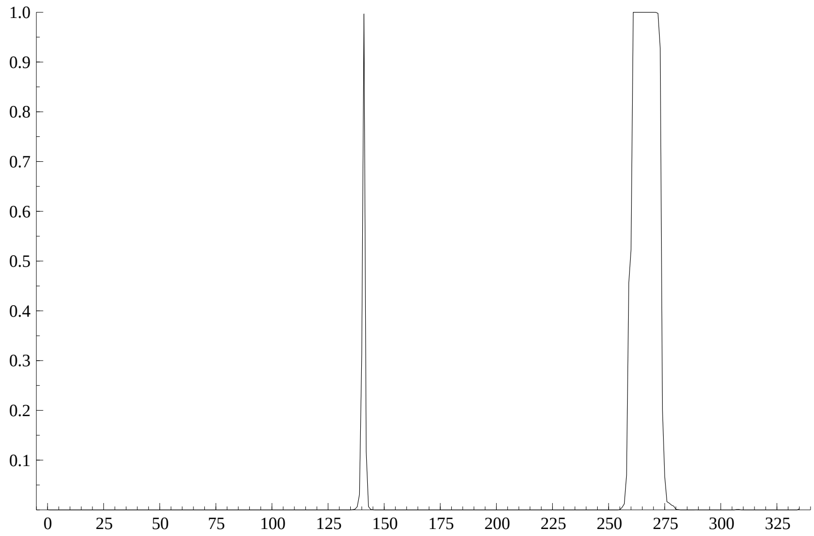
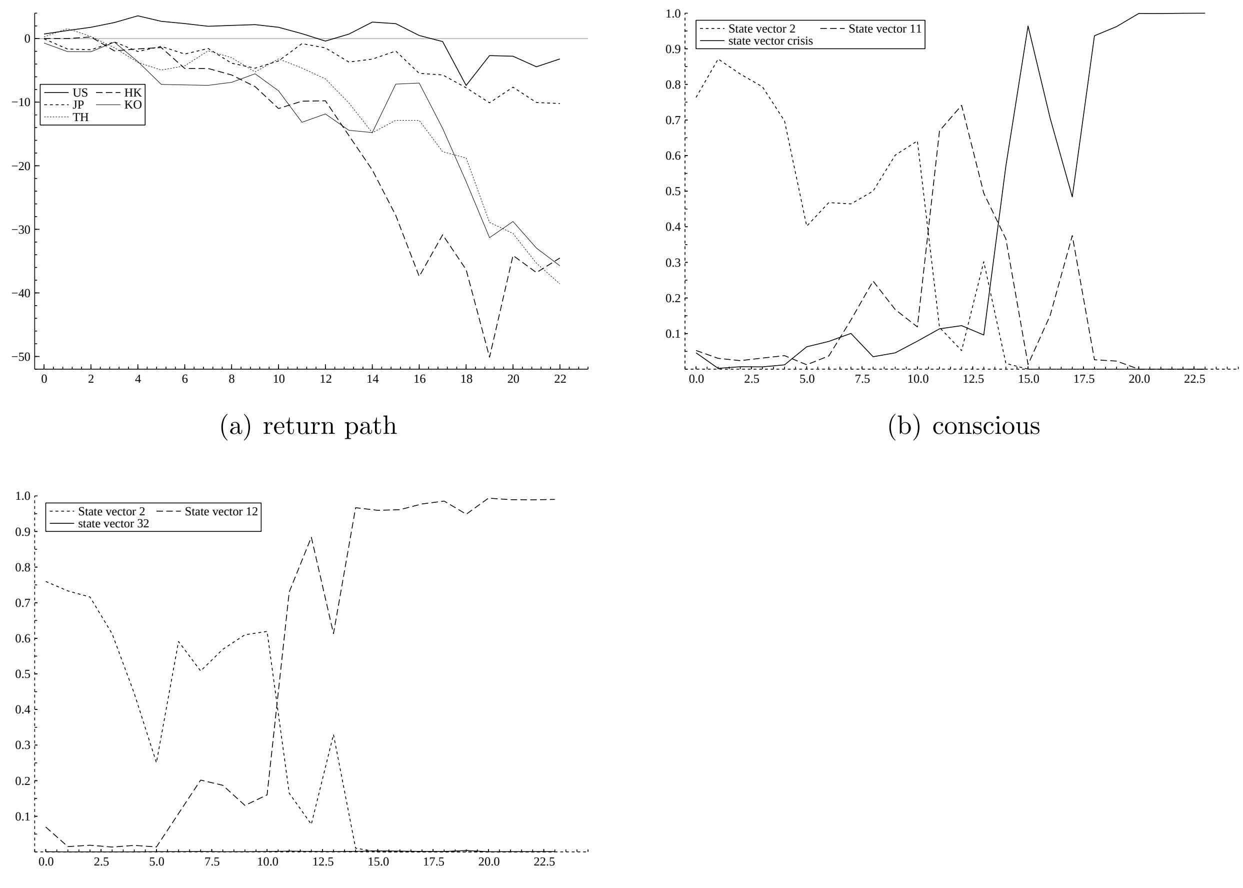


Figure 1: *Smoothed probability that the crisis regime is prevailing. A smoothed probability is defined as the probability on a state, given the complete set of observations. It is constructed using the filtering technique described in Hamilton (1994) and the smoothing technique from Kim (1994).*

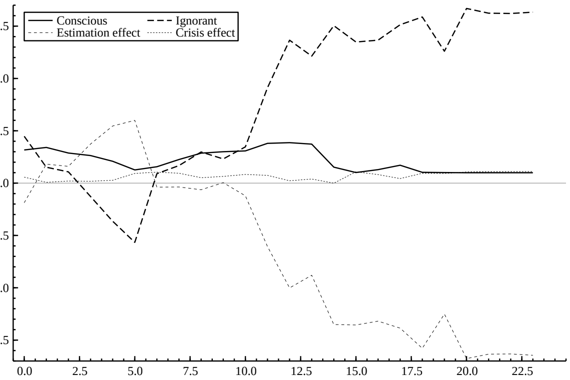


(a) return path

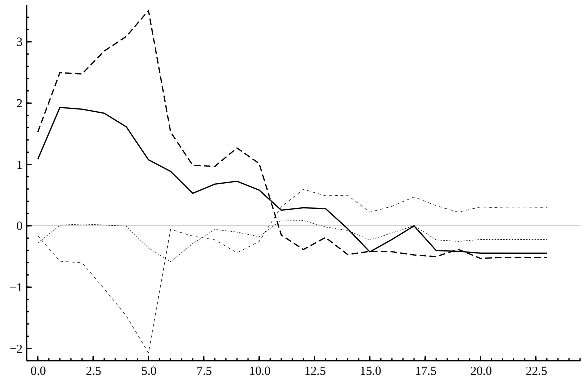
(b) conscious

(c) ignorant

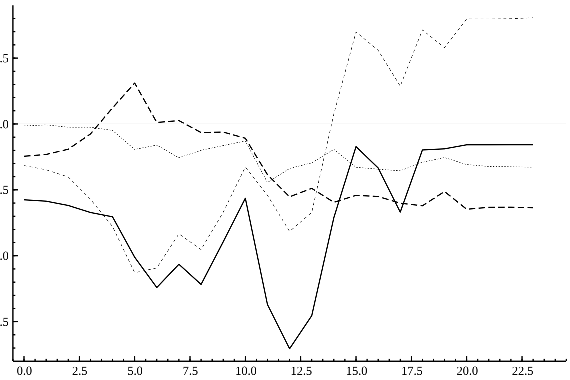
Figure 2: *The return path (excess returns, in %) of the indices for the US, Hong Kong (HK), Japan (JP), Korea (KO) and Thailand (panel a) and the resulting inferences for the different investors during October 1997. The inference probabilities are constructed using* (19). *We only report the inferences for a state vector, if the inferences have exceeded 0.5 at least once. The state vectors have received a number according to Table 5.*



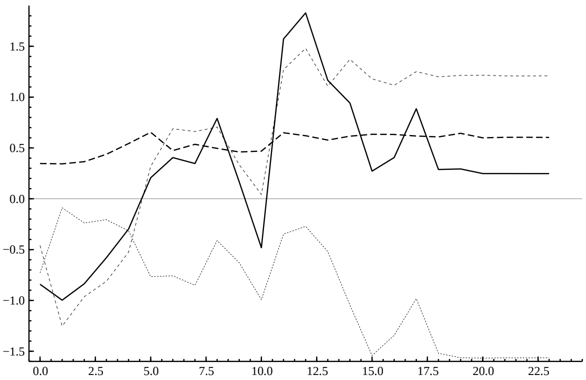
(a) US



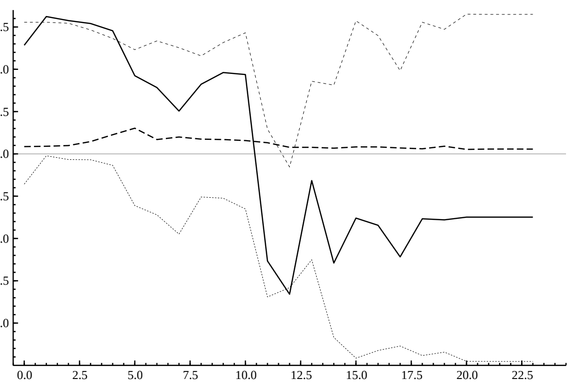
(b) Hong Kong



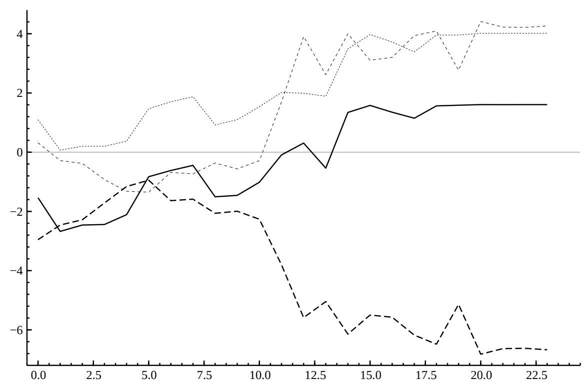
(c) Japan



(d) Korea

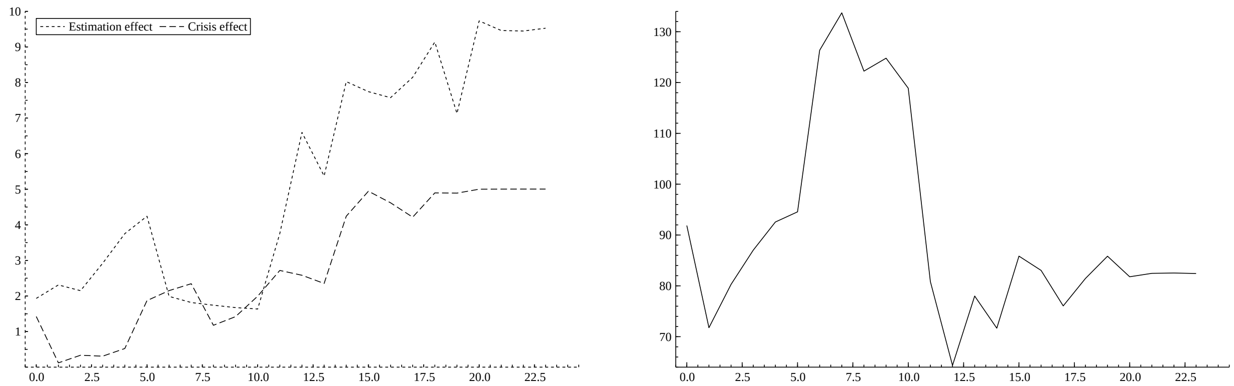


(e) Thailand



(f) risk free asset

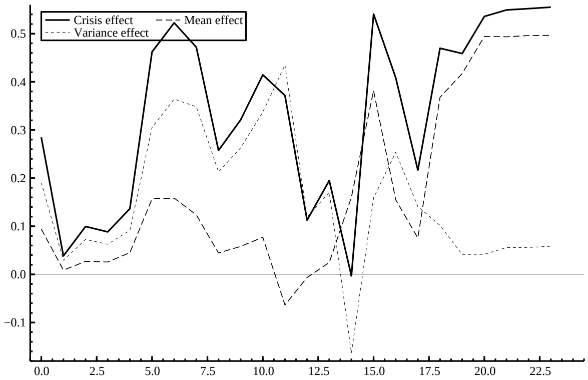
Figure 3: *The proportion invested in the different countries for the crisis conscious and crisis ignorant strategy and a decomposition of the differences over time during October 1997. We assume the investor has a log utility function. The portfolios are based on the estimates in Tables 2 and 3 and the inferences presented in Figure 2. The portfolio differences between the two portfolios are decomposed in an estimation and a crisis effect.*



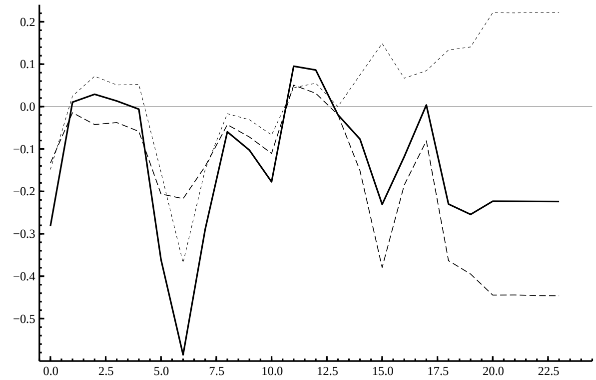
(a) Norm

(b) Angle

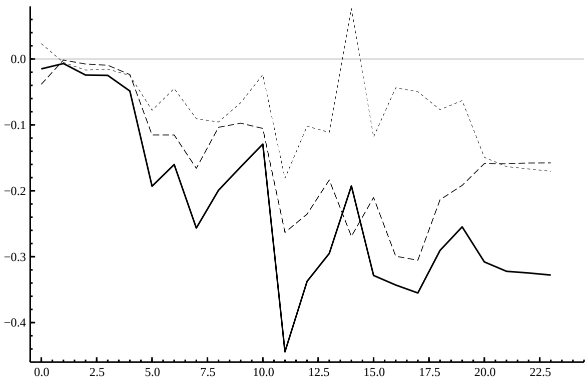
Figure 4: *Geometric comparison of the estimation and crisis effect over time during October 1997. The estimation and crisis effect are constructed as a decomposition of the differences between the crisis conscious and crisis ignorant portfolio, as reported in Figure 3. Panel (a) shows the length of both effects. Panel (b) shows the angle the two effects make.*



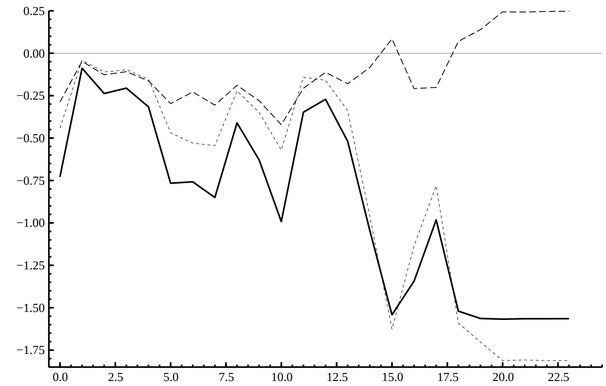
(a) US



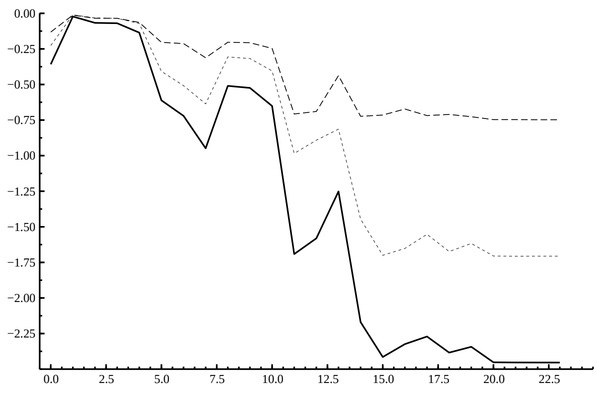
(b) Hong Kong



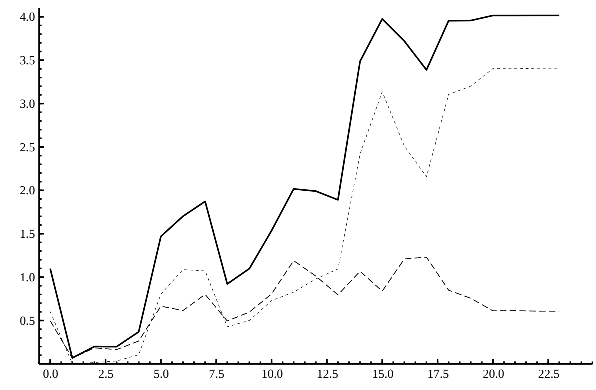
(c) Japan



(d) Korea

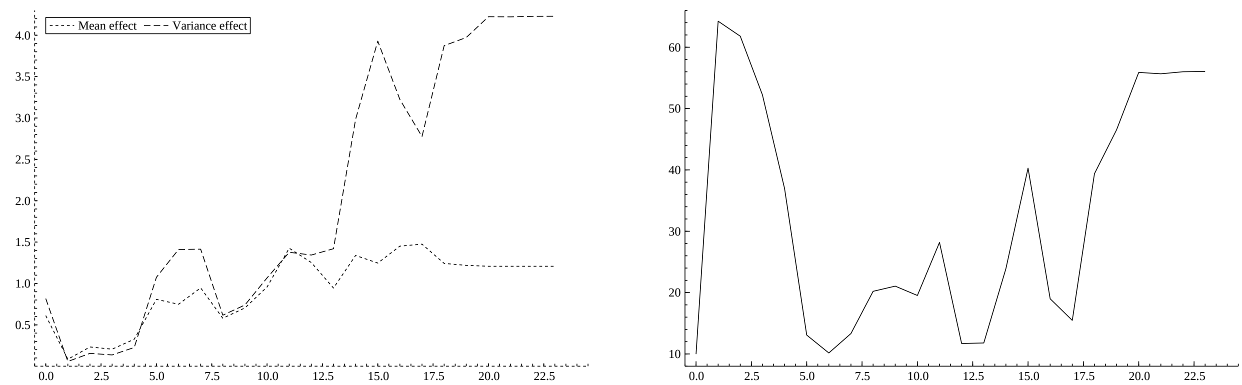


(e) Thailand



(f) riskless asset

Figure 5: *The crisis effect on asset allocation and its decomposition in a part related to changes in means and a part related to changes in variances over time during October 1997. We assume the investor has a log utility function. The crisis effect is derived as a part of the decomposition of the differences between the crisis ignorant and crisis conscious portfolio, reported in Figure 3. The decompositions in a mean and a variance effect are defined in* (24) *and* (25).



(a) Norm (b) Angle

Figure 6: *Geometric comparison of the mean and variance effect over time during October 1997. The mean and variance effect are constructed as a decomposition of the crisis effect which is part of the decomposition of the differences between the crisis conscious and crisis ignorant portfolio, as reported in Figure 3. Panel (a) shows the length of both effects. Panel (b) shows the angle the two effects make.*

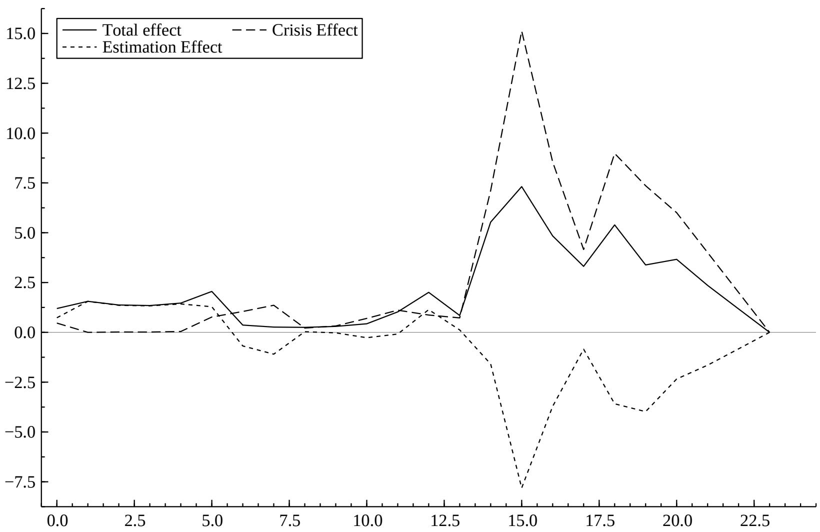


Figure 7: *Certainty equivalent return (in %) needed to compensate the investor for adopting the suboptimal ignorant strategy and a decomposition in an estimation and crisis effect. We assume the investor has a log utility function and a horizon of 1 month. The portfolios during October 1997 and there decompositions are given in Figure 3.*

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