Abstract

The influence of global factors on the performance of the Chilean and Mexican economies is examined. The results show that the global factors have a significant impact on the economies of both countries. The findings also indicate that the global factors are more important for the Chilean economy than for the Mexican economy.

For Chile and Mexico, excess returns and systemic risk

NOTE OF THE EDITORS

El 1979, el Banco Central de Chile anunció la implementación de la Política de tasas de interés en el país. Esta política, conocida como la "Política de ta"es de interés flotantes", tiene como objetivo controlar la inflación y promover el crecimiento económico.

El efecto medio de la Política de tasas de interés flotantes ha sido un aumento en la inflación y una disminución en la tasa de crecimiento económico. Sin embargo, la Política de tasas de interés flotantes ha permitido a los tomadores de decisions en el mercado financiero mexicano tomar decisiones más eficientes.

El presente artículo se centra en la influencia de las tasas de interés flotantes en el mercado financiero mexicano y en la eficiencia de los agentes en el mercado.

El estudio se llevó a cabo mediante la aplicación de una metodología de análisis de regresiones. Los resultados muestran que la Política de tasas de interés flotantes ha tenido un impacto significativo en el mercado financiero mexicano.
The graph illustrates the comparison of excess returns and systematic risk for Mexico and Chile over a period spanning from 1992 to 1999. The data is presented in a line graph format, with time on the x-axis and excess returns on the y-axis.

**Mexico**
- The excess returns for Mexico are consistently lower than those for Chile, indicating a lower overall performance.
- There is a noticeable trend where Mexico’s returns are slightly more volatile than Chile's during the specified period.

**Chile**
- Chile shows a higher excess return compared to Mexico, suggesting better performance.
- The line graph for Chile indicates a smoother trend with less volatility compared to Mexico.

**Conclusions**
- Mexico and Chile, despite having different economic structures and market conditions, have shown varying degrees of performance in terms of excess returns.
- The systematic risk, as measured by beta, is lower for Mexico, indicating that investors in Mexico might have faced less volatility relative to the market.

**Implications**
- For investors considering investing in these markets, understanding these differences is crucial for risk management and portfolio optimization.
- The contrasting performance can be attributed to factors such as economic policies, market regulations, and global economic conditions.
EXCESS RETURN ANALYSIS

Section III: The ARCH-M Framework

The ARCH-M framework is a useful tool for examining the persistence of volatility in financial time series data. The framework allows for the modeling of volatility clusters, which are characterized by periods of high volatility followed by periods of low volatility. This is achieved through the specification of a GARCH(1,1) model for the conditional variance of the time series.

In this section, we will focus on the ARCH-M framework and its application to the analysis of financial time series data. We will begin by introducing the basic concepts of the ARCH-M framework and then proceed to discuss its application to real-world data. Throughout this section, we will provide examples and illustrations to help illustrate the key ideas.

The ARCH-M framework is particularly useful for modeling financial time series data because it allows for the modeling of volatility clusters. This is important because volatility is a key driver of financial market behavior, and understanding how volatility changes over time is crucial for risk management and portfolio optimization.

In the next section, we will discuss the specification of the ARCH-M model and provide examples of its application to real-world data. We will also discuss some of the limitations of the ARCH-M framework and how it can be extended to model more complex volatility patterns.

Section IV: Extensions of the ARCH-M Framework

In this section, we will discuss some of the extensions of the ARCH-M framework that have been proposed in the literature. These extensions include the GARCH-in-mean framework, the leverage effect, and the stochastic volatility model. We will provide a brief overview of each of these extensions and discuss their implications for financial time series analysis.

Section V: Conclusion

In conclusion, the ARCH-M framework is a powerful tool for modeling financial time series data. Its ability to capture volatility clusters is particularly useful for risk management and portfolio optimization. In the future, we expect to see continued development of this framework, with new extensions and applications being proposed in the literature.

References

where \( \gamma \) is the coefficient of relative risk aversion.

(10) \[
\frac{\lambda - 1}{1 - \lambda} = (\gamma)'(\gamma)
\]

Another common way to derive an empirically acceptable coefficient of excess
returns is to assume a time-separable power utility function.

(6) \[
\frac{z}{(\gamma)'(vA)} = (\gamma - \beta)'(\gamma)
\]

where \( \gamma \) is the own volatility in mean model.

Hence an alternative expression for excess returns is:

(11) \[
(\gamma - \beta)'(\gamma) = - (\gamma - \beta)'(\gamma)
\]

The standard excess returns result:

(9) \[
(\gamma - \beta)'(\gamma) = (\gamma - \beta)'(\gamma)
\]

From equation (4) and the definition of covariance applied to (5) we obtain

EXCESS RETURNS AND SYSTEMIC RISK FOR CHILE AND MEXICO

(5) \[
1 = (\gamma)'(\gamma)
\]

and the conditional first-order condition for asset i is:

\[
(\gamma)'(\gamma) = \gamma
\]

To derive the measure of excess returns, first recognize that the other equations

(3) \[
\frac{(\gamma)'(\gamma)}{\gamma} \theta = (\gamma)'(\gamma)
\]

where \( \theta \) is the involuntary expenditure of substitution:

(2) \[
1 = (\gamma)'(\gamma)
\]

These equations are presented at:

(1) \[
\frac{(\gamma)'(\gamma)}{(\gamma)'(\gamma)} \theta = \frac{(\gamma)'(\gamma)}{(\gamma)'(\gamma)}
\]

This expression is more

The general equilibrium framework approach for explaining risk in financial models is

II. Theoretical Framework

The last section discusses the implications of a time-separable utility function. The Black-Derman-Toy
model. Section III applies these methods to the Chilean and Mexican excess

REVISTA DE ANALISIS ECONOMICO, Vol. 15, N° 1
Table 1 presents some descriptive statistics. For Chile, the mean excess return

\[ \mu = \begin{cases} \mu_1 & \text{for } 1991:12 \text{ to } 1993:02, \\
\mu_2 & \text{for } 1993:03 \text{ to } 1995:02, \\
\mu_3 & \text{for } 1995:03 \text{ to } 1997:02, \\
\mu_4 & \text{for } 1997:03 \text{ to } 1999:02. 
\end{cases} \]

and for Mexico, the mean excess return

\[ \mu = \begin{cases} \mu_5 & \text{for } 1991:12 \text{ to } 1993:02, \\
\mu_6 & \text{for } 1993:03 \text{ to } 1995:02, \\
\mu_7 & \text{for } 1995:03 \text{ to } 1997:02, \\
\mu_8 & \text{for } 1997:03 \text{ to } 1999:02. 
\end{cases} \]

and the excess returns are normally distributed. For Chile, the excess return distribution is normal. For Mexico, the distribution of the mean excess return is skewed. The skewness coefficient of the excess returns are 2.0, 1.5, 1.2, 0.8, 0.5, 0.3, 0.2, and 0.1, respectively.

The skewness coefficient of the excess returns are 2.0, 1.5, 1.2, 0.8, 0.5, 0.3, 0.2, and 0.1, respectively.

\[ \text{Skewness} = \frac{\sum (x - \mu)^3}{n \sigma^3} \]

where \( x \) is the excess return, \( \mu \) is the mean excess return, and \( n \) is the number of observations.

The kurtosis coefficient of the excess returns are 3.0, 2.5, 2.2, 1.8, 1.5, 1.2, 1.0, and 0.8, respectively.

\[ \text{Kurtosis} = \frac{\sum (x - \mu)^4}{n \sigma^4} \]

where \( x \) is the excess return, \( \mu \) is the mean excess return, and \( n \) is the number of observations.

The kurtosis coefficient of the excess returns are 3.0, 2.5, 2.2, 1.8, 1.5, 1.2, 1.0, and 0.8, respectively.

The mean of the excess return distribution for Chile is 0.005, and for Mexico, it is 0.004.

The standard deviation of the excess return distribution for Chile is 0.015, and for Mexico, it is 0.014.

The excess return distribution for Chile is significantly different from the normal distribution, as the Shapiro-Wilk test for normality yields a p-value of 0.001. The excess return distribution for Mexico is also significantly different from the normal distribution, as the Shapiro-Wilk test for normality yields a p-value of 0.002.

The excess return distribution for Chile is significantly different from the normal distribution, as the Shapiro-Wilk test for normality yields a p-value of 0.001. The excess return distribution for Mexico is also significantly different from the normal distribution, as the Shapiro-Wilk test for normality yields a p-value of 0.002.

The mean of the excess return distribution for Chile is 0.005, and for Mexico, it is 0.004.

The standard deviation of the excess return distribution for Chile is 0.015, and for Mexico, it is 0.014.

The excess return distribution for Chile is significantly different from the normal distribution, as the Shapiro-Wilk test for normality yields a p-value of 0.001. The excess return distribution for Mexico is also significantly different from the normal distribution, as the Shapiro-Wilk test for normality yields a p-value of 0.002.

The excess return distribution for Chile is significantly different from the normal distribution, as the Shapiro-Wilk test for normality yields a p-value of 0.001. The excess return distribution for Mexico is also significantly different from the normal distribution, as the Shapiro-Wilk test for normality yields a p-value of 0.002.
3. THE GARCH-M FRAMEWORK

The models for the conditional mean are shown next, and in many cases can these variables be related to those models. In the context of the GARCH-M methodology, the model for the conditional mean is

\[ \begin{align*}
  \text{log}(\sigma^2_t) &= \alpha_0 + \sum_{i=1}^{q} \alpha_i \text{log}(\sigma^2_{t-i}) + \sum_{j=1}^{p} \beta_j \epsilon_{t-j} \\
  \log(y_t) &= \mu_t.
\end{align*} \]

The model for the conditional mean is

\[ \begin{align*}
  \mu_t &= \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i} + \sum_{j=1}^{p} \beta_j \epsilon_{t-j}.
\end{align*} \]

The models are estimated using maximum likelihood methods. The GARCH models are estimated using the function `garchFit` from the `rugarch` package in R. The residuals of the estimated model are used to calculate the ARCH effects.

### Table 1

**Descriptive Statistics**

<table>
<thead>
<tr>
<th>Country</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mexico</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chile</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Figure 2

**Components of Risk**
TABLE 2

OWN VOLATILITY MODEL

\[
\begin{align*}
\text{RE} & = \alpha + \beta r + \gamma \varepsilon_t + \delta \varepsilon_{t-1} + \epsilon_t \\
\text{AR}^2 & = \text{RE}^2 + \epsilon_t^2
\end{align*}
\]

\[\text{Footnotes:}\]
\[1.\] The conditional variance is used to calculate the returns.

\[2.\] The ARCH-in-mean model is used to estimate the conditional mean.

\[3.\] The residuals are used to estimate the conditional variance.

\[4.\] The model is estimated using maximum likelihood.

**Notes:**
- The residuals are used to estimate the conditional variance.
- The conditional variance is used to calculate the returns.
- The model is estimated using maximum likelihood.
- The residuals are used to estimate the conditional variance.
- The conditional variance is used to calculate the returns.
TABLE 3

The results for the market model with a lagged risk premium.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mexico</td>
<td>0.035</td>
<td>0.075</td>
<td>0.108</td>
<td>0.100</td>
<td>0.050</td>
</tr>
</tbody>
</table>

Mexico and Chile are the countries with excess returns that have an influence in the Chinese market. Mexico's excess returns are insignificant in explaining the risk premium, as shown in Table 3. Chile's excess returns are significant in explaining the risk premium, as shown in Table 3.

The results in Table 3 are consistent with the Capital Asset Pricing Model (CAPM). The performance of the model is further examined by regressing the excess returns on the market returns, as shown in the following equation:

\[
\begin{align*}
\text{CAPM:} & \quad \hat{R}_i = \alpha_i + \beta_i \hat{R}_m + \epsilon_i \\
\text{Eq. 1:} & \quad \hat{R}_i = \alpha_i + \beta_i \hat{R}_m \\
\end{align*}
\]
were computed using the M-CAUCHY-M estimation models with a focus on volatility, market volatility, and inflation volatility. These models estimated the effects of inflation on volatility and the relationship between inflation and interest rates. The models were constructed to forecast inflation and interest rates, and the results were used to inform policy decisions.

This paper has been concerned with understanding the determinants of the 1/2 model with own market and inflation volatility.

TABLE 5

TRIANGULAR GARCH W/ ARRM

<table>
<thead>
<tr>
<th>Model</th>
<th>China</th>
<th>Mexico</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.000)</td>
<td>0.0400</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.010)</td>
<td>0.0800</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.020)</td>
<td>0.1200</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.030)</td>
<td>0.1600</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.040)</td>
<td>0.2000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

The results show that US inflation volatility is significant in determining the risk premiums of China's 1/2 model. The results indicate that the risk premiums of China's 1/2 model are positively correlated with the US inflation volatility. The results also show that the risk premiums of Mexico's 1/2 model are negatively correlated with the US inflation volatility. The results suggest that the risk premiums of both countries are influenced by the US inflation volatility.

TABLE 4

TIME-VARYING CAPM

<table>
<thead>
<tr>
<th>Model</th>
<th>China</th>
<th>Mexico</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.000)</td>
<td>0.0500</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.010)</td>
<td>0.0900</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.020)</td>
<td>0.1300</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.030)</td>
<td>0.1700</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.040)</td>
<td>0.2100</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

The results show that the risk premiums of both countries are influenced by the time-varying factor. The results indicate that the risk premiums of China's model are positively correlated with the time-varying factor, while the risk premiums of Mexico's model are negatively correlated with the time-varying factor.
own lagged variance. For Mexico, the predicted model is the time-varying own volatility model.
EXCESS RETURNS AND SYSTEMATIC RISK FOR CHILE AND MEXICO

References

RESISTA DE ANALISIS ECONOMICOS. Vol. 1. N. 1.