# THE EVOLUTION OF STOCK MARKETS IN CENTRAL AND EASTERN EUROPE[1]

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**Abstract:** A significant autocorrelation of returns, also called predictability, may indicate market inefficiency. To test whether market efficiency has improved in transition economies we develop a methodology based on a time varying parameter model. We apply this methodology to a set of recently established stock markets over the period April 1994 through June 1999. We find that the Hungarian market always satisfies weak efficiency. For the Czech and Polish market, we document convergence towards efficiency. On the other hand, a constantly significant level of predictability characterizes the Russian market. For this market we cannot draw any conclusions concerning market efficiency.

**JEL Classification Number: G14, G15, C22.**

## 1. INTRODUCTION

Recently emerged stock markets such as the Czech, Hungarian, Polish, and Russian market, represent interesting opportunities for an investor who wishes international diversification.[2] Indeed, optimal portfolio theory teaches that the introduction of an asset into a portfolio decreases that portfolio's risk for a given level of expected return as long as the asset introduced is not perfectly correlated to any of the other portfolio's assets.

The tradeoff for diversification into recently emerged stock markets is that they may not be fair. Financial economists generally refer to market fairness as market efficiency. According to Roberts (1967) and Fama (1970), a market is weakly efficient if it is not possible to reap abnormal benefits by using past stock prices and dividends as the only source of information for investment decisions. It follows that a market is inefficient, in the weak sense, if there exists a stable statistical relation linking, for example, changes of stock prices during one day to changes during the next day. An example of such a statistical relation is a significant autocorrelation between subsequent returns. A significant autocorrelation between returns has been defined as predictability in the literature, e.g. Fama (1991) and Classens, Dasgupta, and Jack (1995). If one measures a positive autocorrelation, then one can theoretically realize a positive profit by systematically purchasing the day after stocks have risen and reselling the next day. Because the seller of the stock suffers from an opportunity cost, one may challenge the fairness of such a market. Many studies have investigated the possibility of recurrent patterns in asset prices; the works by Keim (1987), Fama (1991), and Taylor (1986) are surveys of this literature.

At this stage we understand that a market may reveal its inefficiency because of its predictability. More recently, Fama (1991) and Malkiel (1992) have suggested that a market may be predictable yet efficient. Several examples may be given to demonstrate how a predictable market can be efficient. First, it is known that investors take a certain risk by investing in financial assets. The capital asset pricing model then states that risk taking should be rewarded by a certain expected return. Thus, the fact that certain investment strategies are profitable, if played long enough, may be the compensation for risk taking. Second, markets may be very illiquid. In such a case, as pointed out by Lo and MacKinlay (1990), if a piece of news hits the market, it may be incorporated into prices at different time periods and, therefore, it may generate autocorrelation once the assets get aggregated into a single index.

It appears that the list of known examples why a predictable market may still be efficient is rather small. This observation may be used to design a test for weak efficiency by checking for predictability and by simultaneously controlling the elements likely to generate predictability. As shown further ahead, predictability can be made a function of time. This variability of predictability makes it possible to measure whether markets have become fairer through time.

Our strategy to measure improvements of efficiency may at first seem tortuous. On second thought, though, it appears to be the only way of measuring whether market efficiency has increased. Improvements in market efficiency may indeed not be measurable by direct means. As a first example of this assertion, consider the case of shareholder protection. There may well be laws that protect foreign investors, but if no law enforcement exists then the laws are useless. A second related example concerns insider trading. Regulations may exist on paper, but in a fledgling market economy these may not be enforced. A third example concerns disclosure practice, which may improve

as managers of companies become acquainted with general accounting principles (GAP). In all of these examples we notice that there exists no observable variable for emerging markets that might be used to quantify improvements in stock market efficiency. In developed markets there may exist polls on how investors perceive the efficiency of a market. No systematic inquiry appears to exist for investors in emerging markets.

Our testing strategy should now be clear. We develop a model that allows us to measure how autocorrelation evolves through time. If we find that there exists no autocorrelation, hence no predictability, we conclude that the market under investigation satisfies one criterion of weak market efficiency. If we find that predictability indeed exists, we consider additional features such as the liquidity of the market. If we find that there are no elements justifying predictability we conclude that the market is inefficient. If there exist factors that may explain predictability, e.g. a very illiquid market, we cannot come to a conclusion concerning market efficiency.

Other studies have also examined the predictability of emerging markets. Recently, Claessens, Dasgupta, and Glen (1995) tested for return anomalies and predictability in twenty countries using the International Finance Corporation (IFC) database. Given the large number of countries investigated, it was not possible for these authors to consider the evolution of the financial markets. At the time of their study, insufficient information was available on the markets considered in this paper.

Other contributions, e.g. Bekaert and Harvey (1997) and Harvey (1995), have investigated the change in the volatility of emerging markets. In our econometric model, residuals are distributed as in a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, thereby allowing for time varying volatility.[3] Bekaert and Harvey (1995) and Campbell (1996) have addressed the question of whether emerging markets have become more integrated with other markets. However, this issue

is beyond the scope of this paper. Other authors, e.g. Jenssen (1999), provide anecdotal evidence concerning the transition of Eastern European markets.

This paper is organized as follows. In Section 2 we introduce a first order autoregressive, (AR(1)), model with time varying parameters and possibly heteroskedastic residuals to test whether stock market predictability has decreased over time. In section 3 we provide a short description of our dataset and we discuss the evolution of the market's predictability over time. Section 4 presents our conclusion.

## 2. THEORETICAL ISSUES

In this section, we introduce a time varying model similar to the one proposed by Emerson, Hall, and Zalewska-Mitura (1996).[4] It tests whether the Central and Eastern European financial markets, (CEEFM), become more efficient over time, that is, whether the predictability of returns decreases. Since changes in the market microstructure may be detected more easily at high frequency, we focus on daily data. Let $r_t$ denote the daily returns of a given index; the model, allowing for a time changing intercept and slope (AR(1) parameter), is given by:

$$r_t = \alpha_{0,t} + \alpha_{1,t} r_{1,t-1} + y_t , \qquad (1)$$

$$y_t = \sigma_t \varepsilon_t , \ \varepsilon_t \sim N(0,1) , \qquad (2)$$

$$\alpha_{i,t} = \alpha_{i,t-1} + \eta_{i,t} , \qquad (3)$$

where $\eta_{i,t}$ is distributed as $N(0, q_i^2)$. All random noises are assumed to be independent. Equation (1) decomposes returns into a time varying intercept, $\alpha_{0,t}$, a prediction term, $\alpha_{1,t} r_{1,t-1}$, and an error term, $y_t$. The time varying intercept captures the long run trend of the stock market and the $\alpha_{1,t}$ parameter measures predictability. Since equation (1) represents, at best, an approximation of the very complex way in which asset returns

evolve, the error term, $y_t$, will capture that part of the returns that cannot be explained by the general trend and the predictability part. Non-predictability, i.e. autocorrelation, at time t implies that $\alpha_{1,t} = 0$. This parameter has a subscript and can vary over time, so that we may measure a trend towards non-predictability.

Equation (3) defines the parameters' dynamics. Following the literature, it is assumed that the best predictor of the future value of a parameter is its present value. This means that the future value equals the present value but for an error term $\eta_{i,t}$. If a given parameter does not vary through time then all of its values have to be equal, i.e. if there is no variability in the parameter then $q_i$=0.

Equation (2) states that the errors are the product of a normal variate, $\varepsilon_t$, with mean 0 and variance 1, and a standard deviation $\sigma_t$. In finance this standard deviation is called volatility. We specify volatility as a GARCH model that allows for asymmetries similar to those suggested in the literature by Campbell and Hentschel (1992), Glosten, Jagannathan, and Runkle (1993), and Zakoïan (1994).[5] The specification of $\sigma_t^2$ takes the following form:

$$\sigma_t^2 = \theta_0 + \theta_1 y_{t-1}^2 \Lambda_{y_{t-1}>0} + \theta_2 y_{t-1}^2 \Lambda_{y_{t-1}<0} + \theta_3 \sigma_{t-1}^2 \qquad (4)$$

The variable $\Lambda_{y_{t-1}>0}$ represents a dummy taking the value 1 when the last period's error $y_{t-1}$ is positive, and taking the value 0 otherwise. Similarly $\Lambda_{y_{t-1}<0}$ takes the value 1 if the last period's error is negative, and 0 otherwise.

In order to understand the dynamic of this model, suppose that a particularly good piece of news hits the market in the last period. In this case its return will be exceptionally high. This exceptional behavior will be reflected in an abnormally high level of the error term which will have an impact on the present period through two

channels. First, according to equation (1), if $\alpha_{1,t}$ is positive then one expects that the current return will be higher than the normal. If $\alpha_{1,t}$ is smaller than 1, as will generally be the case, then the impact of the initially abnormally large return will slowly die out. Second, in equation (4), in the event of an abnormally large error, $\Lambda_{y_{t-1}>0}$ will take the value 1 and $\Lambda_{y_{t-1}<0}$ will take the value 0. This means that the standard deviation of period t will be determined by $\sigma_t^2 = \theta_0 + \theta_1 y_{t-1}^2 + \theta_3 \sigma_{t-1}^2$, demonstrating that the parameter $\theta_1$ measures the impact of a past positive error on the current variability of returns.

In the traditional time-varying parameter model (Harvey, 1989), the error term $\varepsilon_t$ is assumed to have constant variance. Our general specification of the residuals improves the efficiency of the parameter estimates as shown by Bollerslev and Wooldridge (1992).

## 3. EMPIRICAL RESULTS

We begin by describing the model implementation, then we describe the series used, and finally we report and discuss the empirical results.

### 3.1 Empirical implementation

The implementation of such a time varying model is straightforward within the Kalman filter framework (Harvey, 1989). The Kalman filter is a Bayesian technique in which learning occurs with each additional observation. As initial conditions, the estimates $a_{0,0}$ and $a_{1,0}$ of $\alpha_{0,0}$ and $\alpha_{1,0}$ must be specified. The variance-covariance estimates of $\alpha_{0,0}$ and $\alpha_{1,0}$ must also be specified; these are given by the diagonal matrix containing $q_0$ and $q_1$. This framework yields smoothed estimates of $a_{i,t}$ and of its variance $P_{i,t}$. In the Kalman filter framework, a smoothed estimate is defined as being constructed with the entire sample, in contrast to a filtered estimate for which only the preceding observations are used. If one of the variance estimates $q_i$ is equal to 0, the associated

parameter will not be time varying. Since $q_i$ cannot take negative values, the distribution of its t-statistic, to test the null hypothesis $q_i = 0$, is non standard, and care must be taken in interpreting the standard errors.[6]

### 3.2 The stock indices considered

The empirical results are based on the use of indices at daily frequency expressed as end-of-day values for all countries except for Russia for which we use a daily average.[7] The sample runs from April 1994 through June 1999.

For the Czech Republic, we use the **PX-50** index, which is available beginning on April 7, 1994. The PX-50 is the leading representative index in terms of turnover and capitalization of a family of 22 Czech indices from various sectors and levels of aggregation. The index is revised quarterly. The market value of the companies included in the PX-50 corresponds to about 80% of the total market capitalization of the PSE.

For Hungary, we use the **BUX,** which has existed since December 12, 1991. This index replaced the unofficial Budapest Stock Exchange Index that was used during the initial phase of economic transition. At the end of 1998, the BUX contained the 24 most liquid Hungarian stocks. To qualify for the index, a stock must comply with several requirements, including a certain minimum nominal value, a defined minimum price, a minimum number of transactions, and a cumulated minimum turnover of 10% of the registered capital during the six months preceding the revision of the index.

For Poland, we use the **WIG**, which was introduced on December 6, 1991. The WIG was the first index to be introduced after the reopening of the Warsaw Stock Exchange. Since January 1997, it has contained 66 stocks, though it had been down to only 39 stocks in April 1995. This index is calculated as a weighted index for the main market once per trading day after each trading session. The weight of an individual stock

to its market capitalization is limited to 10% of the index sample. Furthermore, a single sector may not account for more than 30% of the index. The index is revised every three months, mainly to account for the introduction of new stocks.

For Russia we selected the Credit Suisse First Boston **ROS** index since it has been available as early as December 11, 1993. The index is capitalization weighted and includes the 30 most liquid stocks. This index is published in US dollar units and has been available on a daily basis since August 1, 1994.

**[Insert Figure 1 about here]**

Figure 1 shows the evolution of the dollar denominated indices after they were scaled to 100 on April 6, 1994. The vertical axis is in log scale. A $100 investment in the Czech market would have resulted in a final wealth of about $47.48 by the end of June 1999. For Hungary, Poland, and Russia, the final values would be $168.11, $78.48, and $120.37, respectively. Figure 1 shows that the variability of the Hungarian and especially the Russian index is greater than that of the Czech and Polish indices.

### 3.3 Model estimation

In the following section, we use daily U.S. dollar denominated series. There are several reasons for using daily data. First, since we investigate whether the time series properties of the indices have changed, the highest available frequency is relevant.[8] Ideally, we would have liked to use intra-day data but such market microstructure information does not appear to exist. Second, the time series behavior at other frequencies can be inferred by aggregation of the parameter estimates obtained for daily data. Third, the specification of the time series behavior at a high frequency is of prime importance for the pricing of derivative instruments. Fourth, using weekly data would reduce the sample to 275 observations. This would be too small a sample to estimate a complex econometric model such as ours.

In this study we use US dollar denominated indices so as to give ourselves the perspective of an international investor. However, we did estimate the model using local currency as well and we found similar results. Since the exchange rate in these countries is partially pegged, it appears as a rather smooth series relative to stock market data. In this context, changing the currency unit is like multiplying by a constant.

**[Insert Table 1 about here]**

In Table 1, we report the results from estimating equations (1) through (3) with the asymmetric GARCH model (4). We first test if there are asymmetric effects on volatility, i.e. if $\theta_1=\theta_2$ . To do so, we construct a likelihood ratio test based on the values of the log-likelihood, LL, obtained from the model where $\theta_1$ and $\theta_2$ are estimated freely, and based on the values of the restricted log-likelihood, RLL, obtained by re-estimating the model under the constraint $\theta_1=\theta_2$. Under its restricted version, the asymmetric GARCH model collapses to the standard GARCH (1,1) of Bollerslev (1986). The values taken by the likelihood ratio-statistic are reported in the last row. These values show that the hypothesis that there are no asymmetries, i.e. $\theta_1=\theta_2$, must be rejected for Hungary and for Russia. An examination of the coefficients $\theta_1$ and $\theta_2$ reveals that the coefficient $\theta_2$ is larger than $\theta_1$. This implies that for these countries, bad news has a larger impact on volatility than good news. For Poland and the Czech Republic, however, we cannot reject the hypothesis that both good and bad news have the same impact on future volatility.

The parameter $a_{0,0}$, and its associated standard error $q_0$, capture the perceived variability of the mean return over time. For both the Czech and the Polish market, the model yields $q_0 = 0$, implying that there is no statistically significant modification of the average return for these countries. Returning to Figure 1, we notice that, for the above

mentioned markets, the evolution of the stock index is indeed rather smooth. The sign of the $a_{0,0}$ estimates indicates that, on average, one would have lost money on the Czech market (negative sign) and earned money (positive sign) on the Polish market. For Hungary and Russia, we find that there have been changes in the indices because $q_0$ is no longer 0. The Hungarian market was dropping at the beginning of our sample ($a_{0,0} = -0.2256$) whereas the Russian market was very bullish ($a_{0,0} = 1.9441$). Again, this can be confirmed by examining Figure 1.

Given that the variability of the average return is greatest for Russia ($q_0 = 0.0863$), we focus on that market and provide anecdotal evidence of possible causes that may have moved the conditional mean of returns.[9] The plot of the smoothed estimates of $a_{0,t}$ for Russia is represented in Figure 2.

**[Insert Figure 2 about here]**

If we compare Figure 1 and Figure 2 we see that the Russian index rose from 100 in April to 414 in August 1994. By April 1995, it had plummeted to 53.70. Figure 2 shows that $a_{0,t}$ took a positive value between April and August 1994 and a negative value following this period. A similar comparison between the trend of the index found in Figure 1 and in the intercept displayed in Figure 2 reveals that the intercept appropriately captures the long trends in the market. We may find some explanations for why the market evolved in certain ways in the IFC Factbook. For example, the slowdown between summer 1995 and spring 1996 may be explained by investors' uncertainty concerning the outcome of the 1996 presidential election. Later on, the upswing that starts in January 1997 seems due to an inflow of foreign capital: "…the index surged to a …high… thanks to an inflow of US and British institutional money on renewed optimism over election

results and the general consensus that the market was fundamentally undervalued." (See the IFC 1997 Factbook, p. 214).

We now turn to the AR(1) coefficients.[10] Inspection of the standard error $q_1$ reveals that the AR(1) parameter varies for all countries except for Hungary where $q_1 = 0$. For this country we find a constant correlation of 0.037 which turns out to be non-significant. This result suggests that the Hungarian market cannot be predicted and, therefore, satisfies one of the criteria of weak market efficiency. This does not come as a surprise given that the Budapest Stock Exchange was founded on June 21, 1990, several years before the other markets. Also, the Hungarian market has an independent supervisory authority with a reputation for being a strict regulator.

Since the Czech, Polish, and Russian markets reveal a non-constant autocorrelation, we turn to a graphical analysis of their smoothed parameter estimates.

**[Insert Figure 3 about here]**

Figure 3 represents the estimates of the time-varying autocorrelation coefficient, $a_{1,t}$, for the PX-50, the Czech stock index. In April 1994, we notice a very high value of autocorrelation of 0.6, which is followed by a downward trend for the remainder of the sample period.

According to our methodology, during periods when predictability is indistinguishable from zero, we can conclude that a criterion of weak efficiency is satisfied. We notice that the confidence interval around the estimates includes 0 between May 1995 and August 1996. This means that during this period the autocorrelation coefficient had became statistically insignificant and that the value of past returns could no longer be used to infer future returns. Non-predictability was again reached in October

1997 for a short period. Since March 1999 the confidence interval has included 0, suggesting that the Czech market has become efficient, at least since then.

For the Czech market, the period April 1994 through March 1995 is particularly interesting because it allows us to show how our methodology is able to detect when unobservable factors are at work. The IFC Factbook documents that liquidity had diminished during that period because American investors repatriated their capital since they could get a higher interest rate at home.[11] Furthermore, since no change in politics or economics occurred during that period, we could not find a reason to justify a changing risk premium. According to theoretical arguments, e.g. Lo and MacKinlay (1990), predictability should have increased due to the diminishing liquidity. However, examination of Figure 3 shows that predictability decreased. Since we are unable to explain this improvement with explicit economic or political events, we derive from our methodology that unobservable forces such as better enforcement of shareholder protection, better enforcement of insider trading, or better disclosure practices, must have been at work, leading to a more efficient market.

Other periods, such as that between June 1996 and March 1997 or that between March 1998 and mid 1999, are characterized by predictability. Our methodology suggests that during these periods markets may have been efficient if there were elements justifying predictability. For the period between June 1996 and March 1997, the IFC Factbook documents that there were fears that the newly elected coalition government would weaken and that the pace of reform might slow down. Thus, predictability can be explained by less liquidity and by the request for a higher risk premium.

**[Insert Figure 4 about here]**

The interpretation of the results for the Polish market, whose smooth estimates of $a_{1,t}$ are displayed in Figure 4, is very similar to the interpretation of the results for the Czech market. If we focus on 1994, in April we find a rather high degree of autocorrelation that decreases rapidly. The 1995 IFC Factbook (p. 192) indicates that at the beginning of 1994 the average daily value traded ranged between $ 57 million (for March 1994) and $ 75 million (for February 1994). In April 1994, the daily value dropped to $ 24 million and remained roughly constant until the beginning of September 1994. In September and October, volume dropped even further. This suggests that liquidity had decreased. One would expect an increase in predictability if a non-trading bias were present. There is, however, a drop in the predictability coefficient. Thus, other forces must have been at work to pull autocorrelation down. Anecdotal evidence provides an answer to why autocorrelation was so high at the beginning of 1994. According to the 1995 IFC Factbook (p. 193), [at the beginning of 1994] "…domestic investors started liquidating their equity position because of the very high P/E ratios on the WSE. Panic selling among domestic investors fueled declines in the WIG." This suggests that prices were dropping because stock prices were too high with respect to fundamentals. Also, during a panic sell, one expects investors to sell even more if they observe a large drop in prices. The market plunge then becomes self-sustaining and one expects high autocorrelation. This is in contrast to a fully informationally efficient market in which we expect complete and instantaneous adjustments upon receiving a bad piece of news.

After this initial period which ended towards the end of 1994, autocorrelation decreased to about 0.2 and became statistically insignificant by the end of 1994. Occasionally, the lower bound of significance of the smoothed parameter estimates moves above 0, suggesting rejection at the 5% level of non-autocorrelation. A careful

study of the IFC handbook reveals that these variations are due to changes in liquidity, suggesting that the predictability of the market may be due more to a loss in liquidity than to inefficiency. As with the Czech market, we cannot reject non-predictability from the beginning of 1999. Again, from that moment, the market appears to satisfy our weak efficiency measure.

**[Insert Figure 5 about here]**

In Figure 5 we display the smoothed estimates of $a_{1,t}$ for Russia. In April 1994, when our sample starts, the autocorrelation coefficient was 0.16 (see also Table 1). Even though the graph displays some variation in auto-correlation, the fact that 0 is never included in the confidence interval implies that the Russian index is always predictable. Therefore, Russia shows a different evolution and pattern of significance for $a_{1,t}$ than the other countries considered. Also, from an institutional point of view there exist differences from the other markets considered. For example, the Czech, Hungarian and Polish markets are centralized, whereas the Russian market remains decentralized with regional exchanges. The Central European Countries chose a computer driven exchange system, while Russia adopted an US-NASDAQ type dealers' market. Also, ownership registration follows similar rules across the Central European countries. In these countries there is usually a deposit at an exchange-registrar which is modified according to share ownership. The situation is different in Russia. Transactions concluded through the Russian Trading System require official registration where the buyer's name gets registered. The seller or his nominee are responsible for this re-registration. For foreign investors, Russian brokers take the responsibility for re-registration, which takes about 5 days on average.

These institutional differences may explain why the Russian market evolved differently than the others. According to our methodology, in order to see whether this market was efficient even though predictable, it is necessary to discuss other stock-market characteristics.

Careful inspection of Figure 5 and anecdotal evidence, discussed below, indicates that the variations of predictability for the Russian market may be explained by political and economic risk-premium or by market illiquidity. Between April 1994 and August 1994, autocorrelation increases due to low liquidity. Indeed, even though at that stage 70% of Russia's largest enterprises were privatized through voucher actions, yielding an increase in market capitalization from $2 billion at the end of 1993 to $30 billion at the end of 1994, the demand by foreign investment funds was rationed by an insufficient supply of stock.

From August 1994 on, liquidity decreased in the Russian market, this time because of diminished demand. Indeed, higher domestic interest rates led to foreign capital withdrawals. The Mexican peso crisis reinforced this withdrawal in December 1994. The trend of increasing predictability continued until June 1995. From then until April 1997 predictability decreased. From April 1997 on, predictability increased again. At that time investors had to face the political instability caused by the dismissal of the Prime Minister and the appointment of a new cabinet. Also, a fall in oil prices rose concerns about the State budget which depended on oil export revenues. Then, in the second quarter of 1997, foreign investors were concerned by the sustainability of the exchange rate. After the Russian central bank had resisted for some time, paying 100% interest, by August the financial system had become paralyzed, i.e. a three month moratorium on debt payments was instated, the ruble was devaluated by more than 50%, and foreign exchange trading was halted. Also, news of debt-rescheduling diminished

liquidity strongly. As we notice in Figure 5, predictability peaked in December 1998 after "the most dismal year in the history of the Russian capital market," i.e. IFC Factbook, 1999, p. 290. In December 1998, the daily volume was 1% of what it was one year earlier. From December 1999 on, predictability decreased because of higher liquidity due to foreign capital inflows. These inflows are due to investors considering Russian equities as substantially undervalued.

As our econometric model indicates, the Russian market was always predictable. However, this predictability may arise - because of little liquidity or as a risk premium for adventurous investors - we cannot conclude that this market was inefficient.

## 4. CONCLUSION

An investor may realize an easy profit if there exists a statistically stable relation between asset price variations. One such relation, called predictability, occurs when stock market returns are autocorrelated. The existence of such a relation may contradict market efficiency, the notion that prices fully reflect information and that the market is fair. As a consequence, if asset returns are not predictable, a criterion for market efficiency is satisfied. On the other hand, a market may be predictable yet efficient, since predictability may be a risk premium or a consequence of low liquidity. We designed a methodology to investigate efficiency in a predictable market by systematically studying market characteristics. This methodology allows for the possibility of an evolving market and makes it possible for us to detect whether unobservable changes have occurred, e.g. improvements in regulation enforcement.

In an empirical study, we investigated the evolution of the Czech, Polish, Hungarian, and Russian stock markets over the period of April 1994 to June 1999.

Our research shows that the Hungarian market is non-predictable over the entire sample and, therefore, satisfies our criteria for weak efficiency. This result is in line with the fact that this market has existed for ten years longer than the other markets and appears to be strongly regulated.

The Czech market becomes less predictable between April 1994 and December 1994, yet according to its market characteristics, predictability should have improved during this period. Hence, according to our methodology, it must be that latent factors were active in making that market more efficient. For the other periods, careful inspection of anecdotal evidence suggests a link between predictability and liquidity. Thus, this market may have been efficient since spring 1995. Since spring 1999 even predictability has disappeared, ensuring that weak market efficiency held.

The Polish market shows an evolution of predictability very similar to the Czech market. At the beginning of our sample we find anecdotal evidence that investors were behaving irrationally, as if the market were inefficient. Through time we find convergence towards non-predictability, as for the Czech market.

The Russian market was one of the world's best performers in 1996 and one of the worst in 1997. Its structure is rather different from the other markets. There are several exchanges where trades occur on an over the counter basis. The registration of shares is rather burdensome, fees are higher than elsewhere, and the liquidity measures appear more questionable than for the other markets considered. Our model suggests that predictability is significant for the Russian market. Considering the small amount of evidence available concerning stock market characteristics, we cannot determine if this market becomes more or less efficient.

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FIG. 1: Stock Market Indices ( US $ Denominated). April 1994-June 1999.

Czech Republic: PX-50; Hungary: BUX; Poland: WIG; Russia: ROS.

FIG. 2: Smoothed estimates of $a_{0,t}$ for the Russian Index (ROS)

FIG.3: Smoothed estimates of $a_{1,t}$ for the Czech Index (PX-50)

FIG.4: Smoothed estimates of $a_{1,t}$ for the Polish Index (WIG-50)

FIG.5: Smoothed estimates of $a_{1,t}$ for the Russian Index (ROS-50)

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[2] Stock markets exist in other transition countries, e.g. Bulgaria, Slovenia, Romania, Croatia, and Estonia. However, we did not consider them due to a lack of history and available information. Also, these countries have high barriers to international capital flows.

[3] The autoregressive conditional heteroskedasticity model (ARCH) was proposed originally by Engle (1982) and extended to GARCH by Bollerslev (1986). For a survey of this type of model, see Bollerslev et al. (1992).

[4] In a companion paper, Rockinger and Urga (1998) propose a model to test for efficiency and integration across markets.

[5] For a summary of this literature and an encompassing model, see Crouhy and Rockinger (1997).

[6] Further details concerning this particular testing situation may be found in Harvey (1989, p. 236) and Chernoff (1954).

[7] A detailed presentation of the rules used to construct and update these indices is covered in Urga and Riera (1998). Price indices exclude dividends and, therefore, approximate returns. However, the BUX index is an exception in that it includes dividends.

[8] If we were to consider a portfolio allocation problem, we would use weekly or monthly data.

[9] Time varying performance can be modeled directly as in Ferson and Schadt (1996) but, given the poor macroeconomic data available, such an implementation seems impossible for the time being.

[10] The comparison of the reported parameter estimates in Table 1 with those obtained from a model without GARCH effects reveals that the introduction of time varying volatility changes those estimates dramatically. In fact, a correlation coefficient involves a covariance and a variance. If the latter changes over time, clearly, we expect the correlation to change as well, making for very complicated non-linearities.

[11] Even though we were unable to obtain a time series of shareholder structure, a Salomon Smith Barney guide to World equity markets indicates that in 1998 about 19% of the capitalization of the PX-50 was held by foreign investors. This can be subdivided into roughly equal parts held by foreign funds and individual investors.

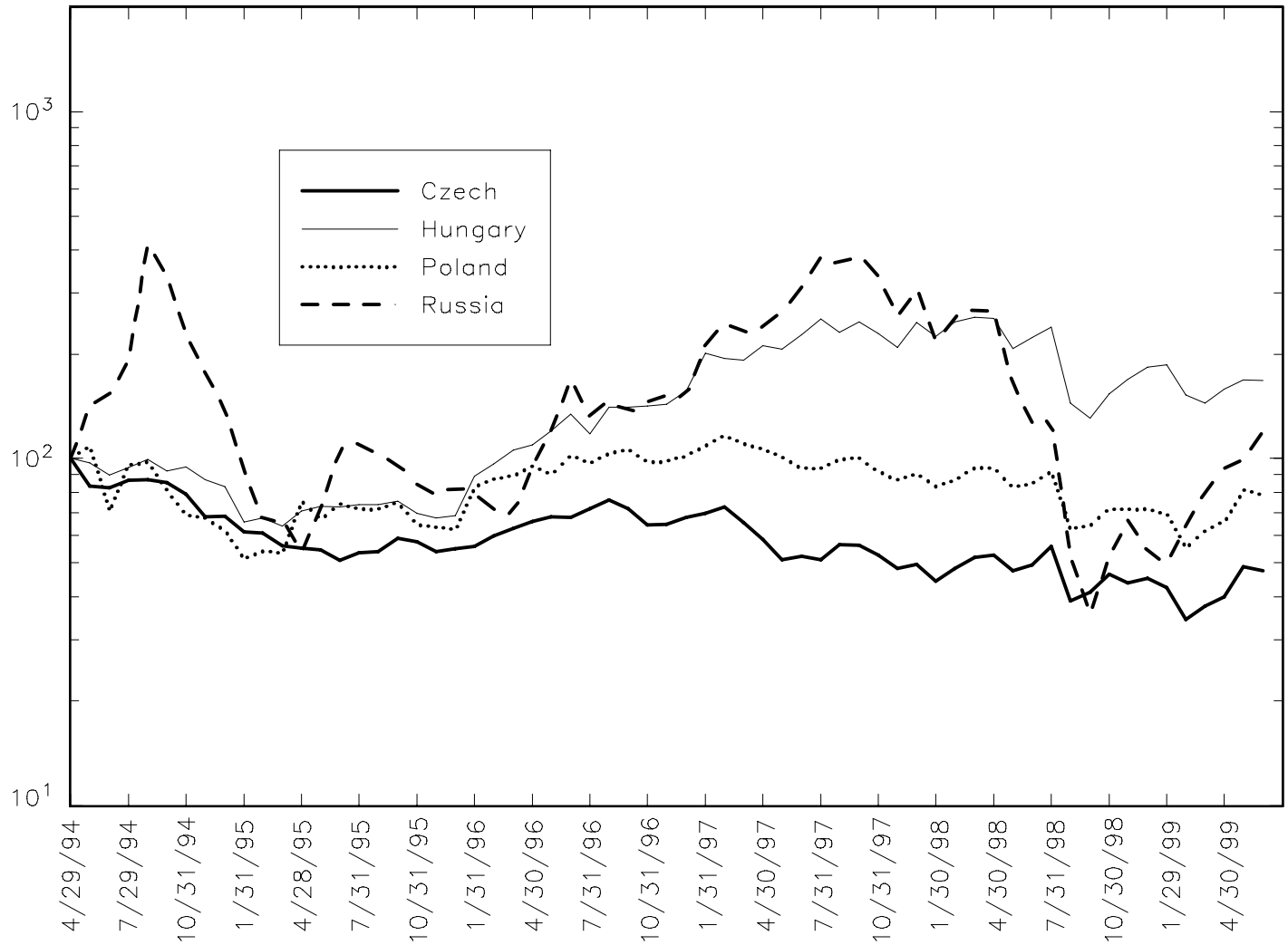
TABLE 1

Estimates of a time varying coefficients model with GARCH effects

| | Czech Republic PX-50 | Hungary BUX | Poland WIG | Russia ROS |
|---|---|---|---|---|
| $a_{0,0}$ | -0.0555 | -0.2256 | 0.0208 | 1.9441 |
| | (0.0518) | (0.1314) | (0.0246) | (2.0876) |
| $a_{1,0}$ | 0.6432 | 0.0370 | 0.9126 | 0.1624 |
| | $(0.1428)^a$ | (0.0364) | $(0.2337)^a$ | (0.3020) |
| $q_0$ | 0.0000 | 0.0066 | 0.0000 | 0.0863 |
| $q_1$ | 0.0185 | 0.0000 | 0.0232 | 0.0062 |
| $\theta_0$ | 0.1496 | 0.6459 | 0.5286 | 1.0867 |
| | $(0.0613)^a$ | $(0.1904)^a$ | $(0.1879)^a$ | (0.8675) |
| $\theta_1$ | 0.2179 | 0.2705 | 0.2907 | 0.0715 |
| | $(0.0712)^a$ | $(0.0811)^a$ | $(0.0656)^a$ | (0.1184) |
| $\theta_2$ | 0.2829 | 0.4967 | 0.3054 | 0.2377 |
| | $(0.0829)^a$ | $(0.1948)^a$ | $(0.0721)^a$ | $(0.1093)^a$ |
| $\theta_3$ | 0.6770 | 0.5187 | 0.5861 | 0.7841 |
| | $(0.0815)^a$ | $(0.1022)^a$ | $(0.0863)^a$ | $(0.1609)^a$ |
| LL | -2153.30 | -2720.28 | -2750.96 | -3640.20 |
| RLL | -2154.01 | -2724.56 | -2750.98 | -3649.49 |
| LRT | 1.42 | $8.57^a$ | 0.03 | $18.58^a$ |

We report here the estimates of an AR(1) regression with time changing intercept and slope. Estimations are done for 1367 daily US dollar denominated returns. The parameters $a_{0,0}$ and $a_{1,0}$ represent estimates of the values taken by the parameters at time 0. The parameters $q_0$ and $q_1$ measure the variability of the parameters. We also report the results of the estimates of a GARCH model with asymmetries. $\theta_0$ represents the constant in the volatility equation. $\theta_1$ and $\theta_2$ measure the contribution of positive and negative shocks on volatility. $\theta_3$ measures the persistency of a given shock. LL represents the log-likelihood for a model without restrictions. RLL, represents the restricted log-likelihood obtained by estimating the model with $\theta_1 = \theta_2$. LRT=-2(RLL-LL) represents the likelihood-ratio test statistic of the null hypothesis that there is no asymmetry between positive and negative shocks.

The parameters in parenthesis represent standard errors. We do not report standard errors for $q_0$ and $q_1$ since these parameters follow non-standard distributions. The superscript $a$ indicates that a given statistic is statistically different from 0 at the 5% level.


Czech
Hungary
Poland
Russia
$10^3$
$10^2$
$10^1$
4/29/94
7/29/94
10/31/94
1/31/95
4/28/95
7/31/95
10/31/95
1/31/96
4/30/96
7/31/96
10/31/96
1/31/97
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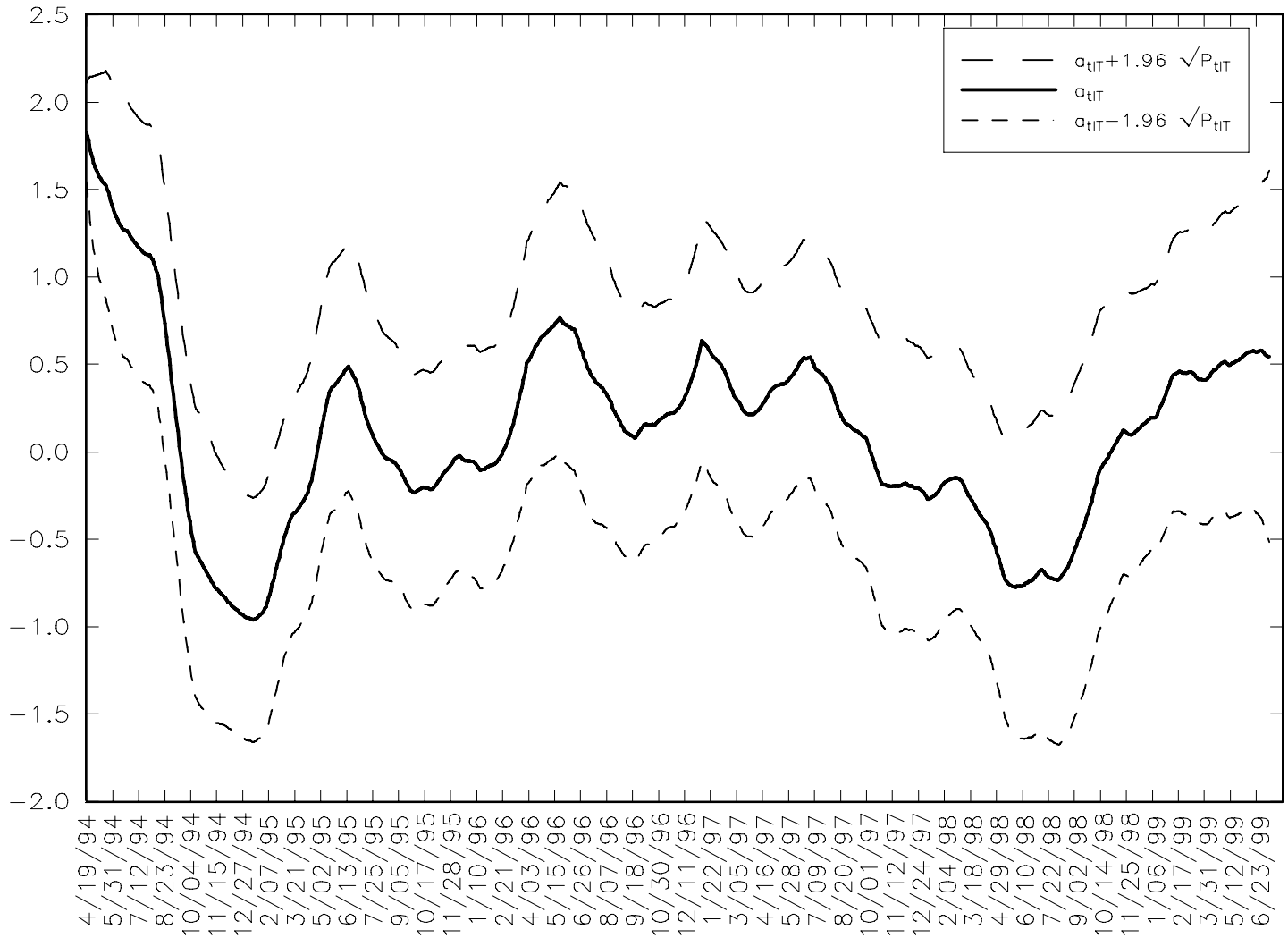
1/29/99
4/30/99


2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
$a_{t|T}+1.96\sqrt{P_{t|T}}$
$a_{t|T}$
$a_{t|T}-1.96\sqrt{P_{t|T}}$
4/19/94
5/31/94
7/12/94
8/23/94
10/04/94
11/15/94
12/27/94
2/07/95
3/21/95
5/02/95
6/13/95
7/25/95
9/05/95
10/17/95
11/28/95
1/10/96
2/21/96
4/03/96
5/15/96
6/26/96
8/07/96
9/18/96
10/30/96
12/11/96
1/22/97
3/05/97
4/16/97
5/28/97
7/09/97
8/20/97
10/01/97
11/12/97
12/24/97
2/04/98
3/18/98
4/29/98
6/10/98
7/22/98
9/02/98
10/14/98
11/25/98
1/06/99
2/17/99
3/31/99
5/12/99
6/23/99

0.8
0.6
0.4
0.2
−0.0
−0.2
$a_{t|T}+1.96\sqrt{P_{t|T}}$
$a_{t|T}$
$a_{t|T}-1.96\sqrt{P_{t|T}}$
4/19/94
5/31/94
7/12/94
8/23/94
10/04/94
11/15/94
12/27/94
2/07/95
3/21/95
5/02/95
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5/15/96
6/26/96
8/07/96
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10/30/96
12/11/96
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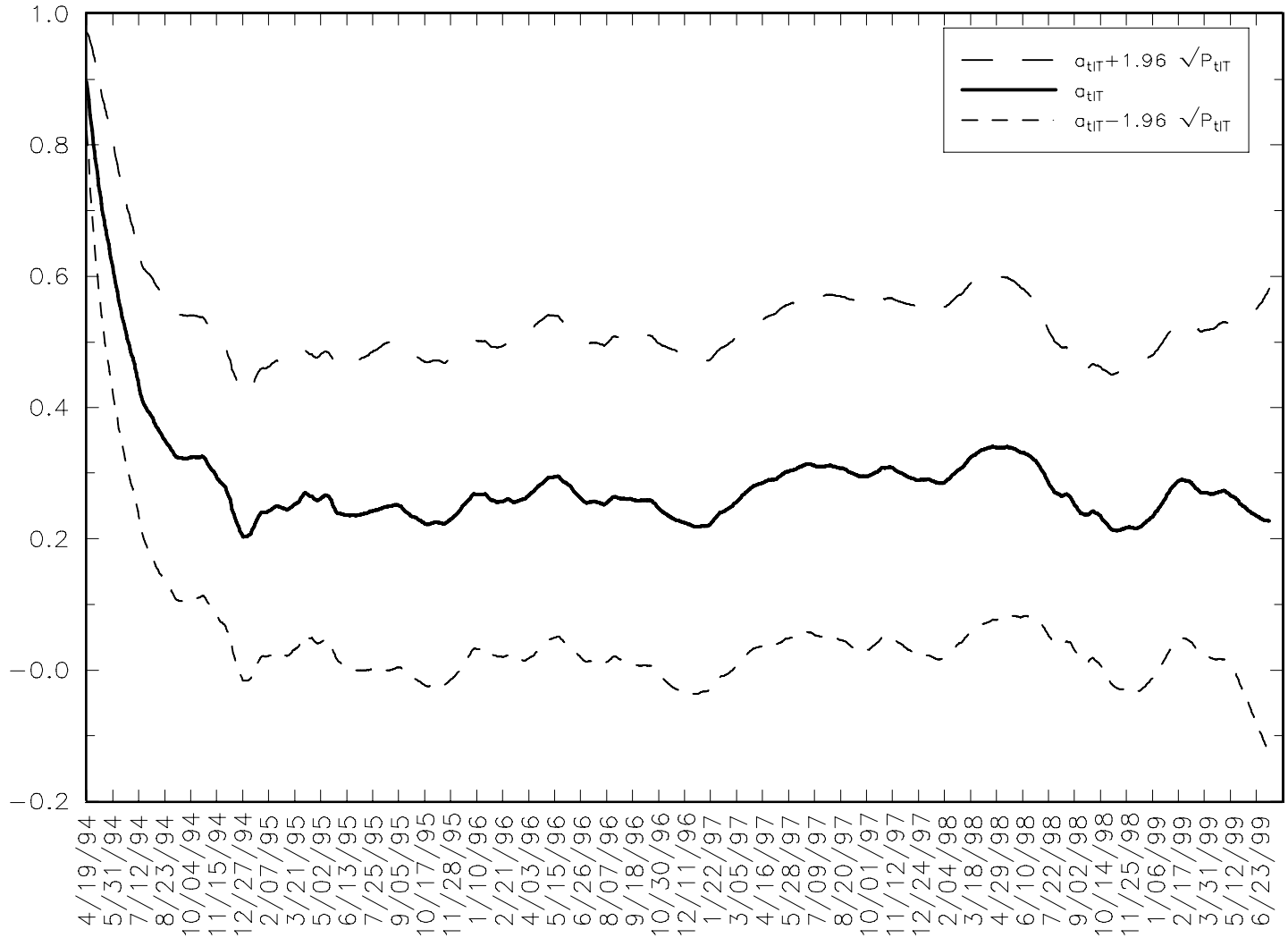
1.0
0.8
0.6
0.4
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$a_{t|T}+1.96\sqrt{P_{t|T}}$
$a_{t|T}$
$a_{t|T}-1.96\sqrt{P_{t|T}}$
4/19/94
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7/12/94
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10/04/94
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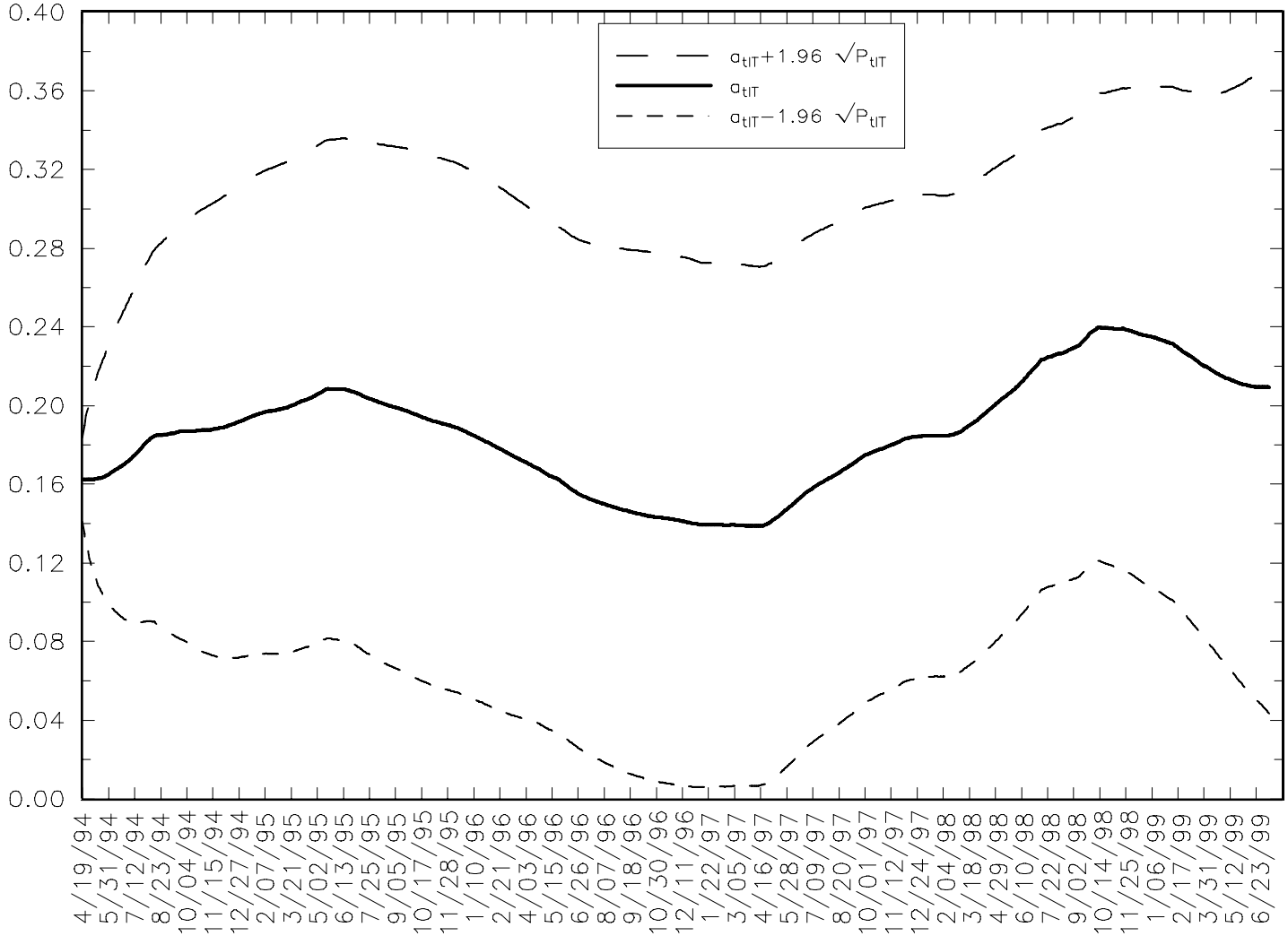
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$a_{t|T}+1.96\sqrt{P_{t|T}}$
$a_{t|T}$
$a_{t|T}-1.96\sqrt{P_{t|T}}$
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