WP/07/223

IMF Working Paper

Can Miracles Lead to Crises? The Role of Optimism in Emerging Markets Crises

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INTERNATIONAL MONETARY FUND

 WP/07/223

IMF Working Paper

IMF Institute

Can Miracles Lead to Crises? The Role of Optimism in Emerging Markets Crises

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Authorized for distribution by Enrica Detragiache

September 2007

Abstract

Emerging market financial crises are abrupt and dramatic, usually occurring after a period of high output growth, massive capital flows, and a boom in asset markets. This paper develops an equilibrium asset-pricing model with informational frictions in which vulnerability and the crisis itself are *consequences* of the investor optimism in the period preceding the crisis. The model features two sets of investors, domestic and foreign. Both sets of investors learn from noisy signals, which contain information relevant for asset returns and formulate expectations, or "beliefs," about the state of productivity. We show that, if preceded by a sequence of positive signals, a small, negative noise shock can trigger a sharp downward adjustment in investors' beliefs, asset prices, and consumption. The magnitude of this downward adjustment and sensitivity to negative signals *increase* with the level of optimism attained prior to the negative signal.

JEL Classification Numbers: F41, D82, G15

Keywords: financial crises, emerging markets, informational frictions, learning

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[1] This paper has benefited from the comments of Enrique Mendoza, John Rust, Guillermo Calvo, Carlos Vegh, John Shea, Carol Osler, Laura Veldkamp, Bora Durdu, the participants of 2005 Society for Economic Dynamics Meetings, and 2006 North American Winter Meetings of the Econometric Society. All errors are my own.

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I. INTRODUCTION

...That this region [East Asia] might become embroiled in one of the worst financial crises in the postwar period was hardly ever considered-within or outside the region-a realistic possibility. What went wrong? Part of the answer seems to be that these countries became victims of their own success. This success had led domestic and foreign investors to underestimate the countries' economic weaknesses. It had also, partly because of the large scale financial inflows that it encouraged, increased the demands on policies and institutions, especially but not only in the financial sector; and policies and institutions had not kept pace. The fundamental policy shortcomings and their ramifications were fully revealed only as the crisis deepened... IMF (1998)

The experience of the last decade suggests that emerging capital markets are vulnerable to significant shifts in investors' confidence in both upward and downward directions. Downward shifts in confidence and financial market collapses are abrupt and often take place unexpectedly after a large boom. Table 1 documents the magnitude of these booms for several pre-crisis episodes: Argentina and Mexico in 1994, Korea in 1997, and Turkey in 2000. Taking Turkey as an example, the year before its financial crisis in 2001, the country boasted an average quarterly current account-to-GDP ratio of 5.1 percent, consumption growth of 4.5 percent, an increase in equity prices of 57 percent, and GDP growth of 3 percent.[2]

Table 1. Magnitudes of Pre-Crisis Booms

Episode	GDP (%)	Private Consumption (%)	Equity Price (%)	CA/GDP (%)
Argentina , 1994Q1-Q4	1.72	2.67	12.97	-1.08
Mexico, 1994Q1-Q4	3.43	6.69	18.53	-2.00
Korea, 1996Q4-1997Q3	3.67	5.14	1.04	-3.69
Turkey, 2000Q1-Q4	3.08	4.51	57.30	-5.12

It is widely agreed that overconfidence and informational problems are at least partially responsible for recent crisis episodes, as the above opening quote by International Monetary Fund on the Asian crisis suggests. Whether these frictions in international capital markets can

[2] This empirical regularity has been documented by Calvo and Reinhart (2000) who conclude that "Sudden Stops," sharp negative reversals of capital flows, are usually preceded by a surge in capital inflows. In addition, the literature on exchange rate based stabilization programs confirms the existence of a "business cycle" associated with these programs. (Kiguel and Liviatan (1990), Vegh (1992), Calvo and Vegh (1994)). A more recent study by Tornell and Westerman (2002) document that the twin crises (banking and currency) are typically preceded by a real exchange rate appreciation and a lending boom along which bank credit grows unusually fast.

be large enough to explain pre-crisis periods of bonanza and the depth of the crises remains an open question.

In this paper, we aim to answer this question by studying the quantitative predictions of a model in which optimism, due to investors' underestimation of the weaknesses of emerging economies, acts as the driving force behind both the pre-crisis booms and the vulnerability that paves the way to financial turmoil and deep recessions. In the model, the pre-crisis bonanza is driven by a sequence of positive signals that investors interpret as an improvement in the true fundamentals of the economy. The crisis occurs as a sudden downward adjustment in investors' expectations of the true fundamentals is triggered and their optimism suddenly fades. The magnitude of this downward adjustment *increases* with the level of optimism attained prior to the crisis.

The *informational frictions* that are the key ingredient of the model, are likely to be prevalent in emerging markets for several reasons. One is the lack of transparency in policy-making, and data reporting which manifests itself in the form of inaccurate or misleading data.[3]

A second reason informational frictions pose particular challenges for emerging economies is the existence of high fixed costs associated withobtaining country-specific information and keeping up with the developments in emerging economies, as suggested by Calvo (1999). Such costs could arise due to idiosyncrasies affecting financial markets in these countries, including for example, each country's unique institutions, policies, political environment, legal structure, etc. From international investors' perspective, it might be optimal not to "buy" this information. Calvo and Mendoza (2000) provide two arguments for why this can be the case. First, if short selling positions are limited, the benefit of paying for costly information declines as the number of emerging economies in which to invest becomes sufficiently large. Second, if punishment for poor performance is high, managers of investment funds may choose to mimic each other's behavior instead of paying for costly information.

The model in this paper features two types of investors, domestic and foreign, both of whom trade a single emerging market asset. Domestic investors are consumer-investors who maximize the expected present discounted value of their lifetime utility. Foreign investors specialize in trading the emerging market asset, face trading costs, and maximize the expected present discounted value of profits from investing. We model the informational frictions as follows. Both sets of investors are imperfectly informed about the true state of current productivity, which contains information relevant for predicting future returns on the emerging market asset. They can only partially infer the true state of productivity by "learning" from publicly observed dividends (or signals) and, they share the same

[3] See IMF (2001).

information set. The dividends consist of two parts: a persistent component, which we interpret as “true productivity”, and a transitory component, which is a noise term that controls the accuracy of the signals. Modelled in this way, dividends serve an informational role since a dividend payment is a noisy signal that contains information about current and future realizations of productivity. Every period, foreign and domestic investors observe dividends, solve a signal extraction problem, and learn about productivity by updating their expectations or “beliefs” regarding true productivity.

When investors turn pessimistic (optimistic), asset prices are driven below (above) the “fundamentals price,” which is defined as the expected present discounted value of dividends conditional on full information. In these periods, asset prices and domestic investors’ consumption display swings that are not associated with changes in true productivity. We find that a sequence of positive signals can cause a boom in both the asset market and in consumption, and can be a source of economic vulnerability if true productivity is in fact low. If a negative signal is realized at the peak of a boom of this nature and, as a result, “challenges” current prevailing beliefs, an abrupt and large downward adjustment in asset prices and consumption takes place. If, however, the same signal “confirms” prevailing beliefs, its impact is smaller.[4]

Foreign and domestic investors trade due to differences in their objective functions particularly their risk aversions, but not for speculation (given that they have the same beliefs). From the domestic investors’ perspective, dividend shocks are important for two reasons. First, in order to intertemporally smooth consumption domestic investors would like to increase (decrease) their asset position in response to positive (negative) dividend shocks. Second, they play a critical informational role. In response to a negative dividend shock, changes in expectations due to the new information compounds the first effect, and as a result, domestic investors reduce their demand for the emerging market asset. Foreign investors also reduce their demand for the asset in response to this shock, since they receive a negative signal regarding future productivity. In equilibrium, we find that domestic investors’ demand decreases by more than that of their foreign counterparts, therefore, domestic investors become net sellers in response to a negative dividend shock. This result leads to a procyclical current account on average. However, we also find that for a given dividend shock, the higher the expectations about future productivity, the lower are the domestic investors’ asset holdings since higher expectations induce foreign investors to bid more aggressively, compared to their risk-averse domestic counterparts, for the same asset. Hence, the higher the investment optimism, the more the emerging economy can attract foreign investment, and therefore the more likely the country is to develop a potentially sizable current account deficit.

[4] Moore and Schaller (2002) establish the state dependence of responses to noisy signals. We borrow our terminology from them.

Given the inherent noisiness of signals obtained by calibrating the model to a typical emerging economy, we analyze the frequency, duration and magnitude of booms and busts that are due to misperceptions of investors.[5] The model generates these booms(busts) with 8.89(4.41) percent probability and with duration of 2.75(1.41) quarters on average. In addition, the model produces booms(busts) in asset prices and consumption of the size observed in the data (reported in Table 1) with probabilities 2.88(0) and 2.33(2.60) respectively.

With the introduction of informational frictions, the volatility of the emerging economy's consumption increases by 2 percentage points compared to the "full information" setup. Uncertainty about true current productivity leads to increased uncertainty regarding future asset returns and a more volatile consumption profile for the risk averse domestic investors. Moreover, informational frictions produce persistence in response to transitory noise shocks. If investors turn pessimistic in response to a misleading signal, it takes several periods for them to correct their beliefs. The mechanism behind this result is the Bayesian learning process: the posteriors of one period are used in the calculation of the following period's priors.

This paper is at the crossroads of two main strands of literature. The first is the literature on Sudden Stops and financial crises in open economies, and the second is that on informational frictions in finance. Most existing models of financial crises and Sudden Stops, focus on crash episodes, but not on the booms preceding the crashes that might indeed contain the seeds of the financial crises. In contrast, the model proposed in this paper emphasizes more the dynamics of pre-crisis booms. Studies explaining Sudden Stops focus on financial frictions and often utilize collateral constraints, (see, for example, Caballero and Krishnamurthy (2001), Paasche (2001), or Mendoza and Smith (2004)). Credit constraints are successful for producing amplification in the response of the economy to typical negative shocks.

In the international finance literature, shifts in investor sentiment have usually been analyzed within the context of currency crises. These studies often utilize sunspot models with multiple equilibria and therefore provide little guidance as to when and how the shifts in investor sentiment occcur. In this paper, we take a different approach by considering a model with a unique equilibrium that can endogenously produce shifts in investors' confidence and switches between good states and bad ones which allows us to predict when these shifts occur and how long it takes for the market to recover after a bust.

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[5] See Section 3.3 for a formal definition.

This paper is also related to the literature on learning in macro and finance. Particularly, Wang (1994), models dividends as noisy signals to analyze trading volume in stock markets, Albuquerque, Bauer and Schneider (2004) use noisy dividend signals to investigate the effects of investor sophistication on international equity flows, and Nieuwerburgh and Veldkamp (2006) use them to explain U.S. business cycle asymmetries in an RBC framework with asymmetric learning.

The rest of the paper proceeds as follows. We describe the model in Section 2, and in Section 3 we discuss the model's solution procedure, calibration, and numerical results. Finally, Section 4 concludes.

II. Model

The economy has two classes of agents, foreign investors and domestic household-investors, who are identical within each class. The domestic households maximize expected lifetime utility by making consumption and asset holding decisions conditional on their information set, that includes the noisy signals about the true state of productivity. Foreign investors choose their asset positions in order to maximize the expected present discounted value of profits based on their beliefs about the state of productivity. Foreign investors also face trading costs associated with operating in the asset market. Both domestic and foreign investors observe dividends, which are noisy signals about the true value of productivity. They form their beliefs by solving a signal extraction problem explained further below.

A. Domestic Households' Problem

Domestic households choose stochastic intertemporal plans for consumption, c_t, and asset holdings, α_{t+1}, in order to maximize expected life-time utility conditional on the information available to them:

$$U = E_0\left[\sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\sigma}}{1-\sigma} \mid I_0^U\right] \tag{1}$$

subject to

$$c_t + \alpha_{t+1} q_t = \alpha_t (q_t + d_t) \tag{2}$$

taking asset prices, q, evolution of beliefs and their information set I^U as given.[6] d denotes dividend payments of the emerging market asset, the parameter σ is the coefficient of relative risk aversion of domestic investors and β is the standard subjective discount factor.

[6] We discuss the role of the expectation operator and the information structure in Section 2.3.

At the beginning of each period, productivity shocks are realized and dividends are determined. Domestic investors make their decisions after observing dividends. The optimality conditions characterizing their decisions are:

$$\beta^t u'(c_t) - \lambda_t = 0 \tag{3}$$

$$\lambda_t q_t + E_t\left[\lambda_{t+1}\left(d_{t+1} + q_{t+1}\right) \mid I_t^U\right] = 0 \tag{4}$$

where λ_t denotes the Lagrange multiplier associated with the budget constraint. Combining these two first order conditions gives the Euler equation:

$$q_t u'(c_t) = \beta E_t\left[\left(q_{t+1} + d_{t+1}\right) u'\left(c_{t+1}\right) \mid I_t^U\right]. \tag{5}$$

This equation is familiar except that the expectations are taken conditional on the information set I_t^U. They form their beliefs by solving a signal extraction problem explained further below.

B. Foreign Investors' Problem

As in Mendoza and Smith (2004), foreign investors choose $\left\{\alpha_{t+1}{}^*\right\}_0^\infty$ in order to maximize the expected present discounted value of their profits conditional on their information sets:

$$E_0 \sum_{t=0}^{\infty} R^{-t}\left(\alpha_t^*\left(d_t + q_t\right) - \alpha_{t+1}^* q_t \frac{a}{2}\left(\alpha_{t+1}^* - \alpha_t^* + \theta\right)^2 \mid I_0^U\right) \tag{6}$$

where R is the gross world interest rate, $1/a$ is the price elasticity of foreign investors' demand, $q_t \frac{a}{2}\left(\alpha_{t+1}^* - \alpha_t^* + \theta\right)^2$ is the total trading cost associated with buying and selling equities in the emerging economies, θ is the recurrent cost. Similar to Aiyagari and Gertler (1999), and Mendoza and Smith (2004), we model the trading cost associated with buying and selling the asset as quadratic in the size of the asset trade. The first order condition of the foreign investors' problem is:

$$q_t\left(1 + a\left(\alpha_{t+1}^* - \alpha_t^* + \theta\right)\right) = R^{-1} E\left[d_{t+1} + q_{t+1}\left(1 + a(\alpha_{t+2}^* - \alpha_{t+1}^* + \theta)\right) \mid I_t^U\right]. \tag{7}$$

We can solve the above first order condition forward to obtain:

$$\alpha_{t+1}^* - \alpha_t^* = \frac{1}{a}\left(\frac{q_t^b}{q_t} - 1\right) - \theta. \tag{8}$$

q_t^b, called the *belief price*, is defined as the expected present discounted value of future dividends conditional on the current belief about productivity:

$$q_t^b = E\left[R^{-1}d_{t+1} + R^{-2}d_{t+2} + R^{-3}d_{t+3} + ... \mid I_t^U\right]. \tag{9}$$

Intuitively, foreign investors adjust their asset holdings depending on the gap between the market price q_t, and their belief price q_t^b. How much of this gap is reflected in the asset demand is determined by $1/a$.

C. Information Structure

Dividends are determined exogenously as follows:

$$d_t = e^{z_t + \eta_t}. \tag{10}$$

There are two types of uncertainty associated with dividends: persistent aggregate productivity shocks, z, and noise, in the form of transitory, additive, Normal i.i.d. shocks, η, with $E[\eta] = -\sigma_\eta^2/2$ and $E[\eta^2] = \sigma_\eta^2$.[7] Aggregate productivity shocks follow a Markov process with two states and transition probability matrix P. We denote the values z can take as $z \in \{z^L, z^H\}$ and assume $z^L < z^H$ without loss of generality.

Assumption $P >> 0$ *(irreducible Markov chain) and* $P_{ii} > P_{ji}$ *(positive autocorrelation) where* P_{ij} *is the probability of transiting from state* i *to state* j*;* $i, j \in \{L, H\}$ *and* $i \neq j$.

$P >> 0$ rules out absorbent states. $P_{ii} = P_{ji}$ would imply that the probability of transiting to state i is the same regardless of the current state. Therefore, in this case, information regarding the current state would not be useful for forecasting the following period's state (no autocorrelation).

We assume both sets of investors know the true distributions governing the productivity shocks z and the noise η. They observe the dividends d at the beginning of each period, but

[7] This specification for guarantees that changes in produce mean preserving spreads.

do not observe the current or past values of the productivity shock z or the noise η.[8] Both investors use the information revealed by dividends in order to infer the realization of the productivity shock in the current period.[9] Beliefs are defined as:

$$\tilde{z}_t = E\left[z_t \mid I_t^U\right] \tag{11}$$

where I_t^U includes the entire history of dividends observed by the investors:

$$I_t^U = \{d_t, d_{t-1}, ...\}. \tag{12}$$

Throughout the paper we refer to this information structure as the "incomplete information" scenario. The belief $\tilde{z}_t$ is formed by updating the previous period's belief $\tilde{z}_{t-1}$ using Bayes' rule:

$$\Pr\left(z_t = z^i \mid I_t^U\right) = \frac{f\left(d_t \mid z_t = z^i\right)\Pr\left(z_t = z^i \mid I_{t-1}^U\right)}{f\left(d_t \mid z_t = z^j\right)\Pr\left(z_t = z^j \mid I_{t-1}^U\right) + f\left(d_t \mid z_t = z^i\right)\Pr\left(z_t = z^i \mid I_{t-1}^U\right)} \tag{13}$$

where f is the conditional normal probability density that can be written as:

$$f\left(d_t \mid z_t = z^i\right) = \frac{1}{\sqrt{2\Pi}\sigma_\eta} e^{-\frac{1}{2\sigma_\eta^2}\left(d_t - z^i\right)^2} \tag{14}$$

for $i, j \in \{L, H\}$ and $i \neq j$. Equation (13) is used to update the probability assigned to being in the high productivity state, incorporating the additional information revealed by d_t at the beginning of period t. The priors that will be used in period $t+1$ for updating beliefs are obtained by simply adjusting for the probability of a change in state from period t to $t+1$ using the Markov transition matrix. That is:

$$\Pr\left(z_{t+1} = z^i \mid I_t^U\right) = \Pr\left(z_t = z^i \mid I_t^U\right)P_{ii} + \Pr\left(z_t = z^j \mid I_t^U\right)P_{ji}. \tag{15}$$

Once the posteriors of the current period are calculated, beliefs are:

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[8] One can imagine that investors observe productivity with such a long lag that, once received, the information is no longer useful for predicting current productivity any more.

[9] It is also possible to model different types of publicly observed signals, such as news reports, in addition to dividends. In any case, the model variables will be sensitive to the information content of the signals and this sensitivity will be qualitatively similar but quantitatively different depending on the informativeness of the publicly observed signals.

$$\tilde{z}_t = \Pr\left(z_t = z^L \mid I_t^U\right)z^L + \Pr\left(z_t = z^{Hi} \mid I_t^U\right)z^H . \tag{16}$$

Proposition 1 $0 < \Pr\left(z_t = z^i \mid I_{t-1}^U\right) < 1$ and $0 < \Pr\left(z_t = z^i \mid I_t^U\right) < 1$.

Proof See Appendix.

The interval to be considered for the prior and posterior probabilities is $(0,1)$. The prior $\Pr\left(z_0 = z^i \mid I_{-1}^U\right)$ or the posterior $\Pr\left(z_0 = z^i \mid I_0^U\right)$ can be set exogenously to "start" from 0 or 1. Afterwards, however, it can take these values with zero probability. From equation (16), we know that beliefs are convex combinations of low and high values of productivity, with weights defined by the Bayesian posterior probabilities assigned to each state. Hence, beliefs are always higher than the low value of productivity and lower than the high value, $z^L < \tilde{z} < z^H$. This implies that agents can never be exactly sure about being in a particular state. In addition, they never believe productivity to be lower (higher) than the low (high) value of true productivity. This is an unappealing feature of learning with discrete probabilistic processes. Also, as a result of this limitation, the standard deviation of beliefs is always less than or equal to that of productivity.

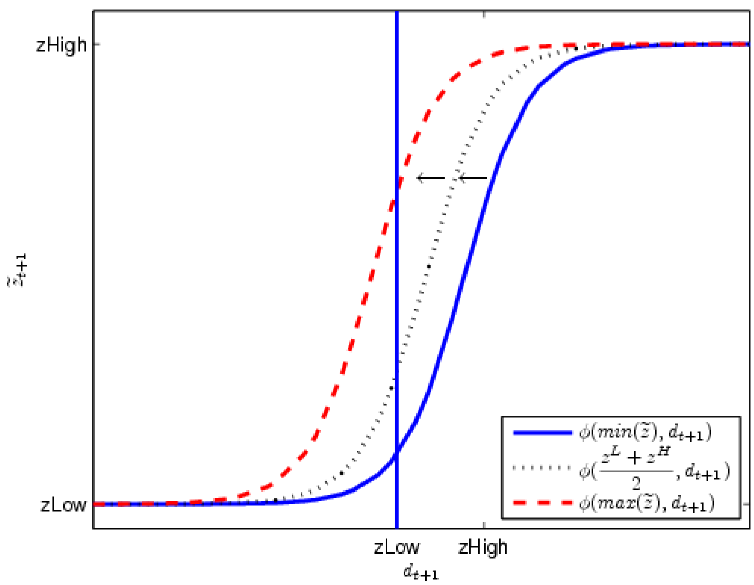
Equation (16) implies that beliefs are sufficient to backtrack the probabilities assigned to each state. Using equation (16) and $\Pr\left(z_t = z^i \mid I_t^U\right) = 1 - \Pr\left(z_t = z^j \mid I_t^U\right)$ for $i, j \in \{L, H\}$ and $i \neq j$, a given $\tilde{z}_t$ can be mapped to a unique $\Pr\left(z_t = z^i \mid I_t^U\right)$. The assumption that provides this simplification is having two states for productivity. This simplification is crucial for the numerical analysis since probabilities assigned to each state are continuous endogenous state variables for the problem. Given the computational difficulty of handling continuous state variables, we assume two states for productivity and carry $\tilde{z}_t$ as a state variable that is sufficient for backtracking the posterior probabilities assigned to each state of productivity.

We denote the evolution of investors' beliefs as $\tilde{z}_{t+1} = \phi\left(\tilde{z}_t, d_{t+1}\right)$. When investors make their decisions at date t, d_{t+1} is not known, but its distribution conditional on $\tilde{z}_{t+1}$ is known. As the signal-to-noise ratio (defined as $\dfrac{z^H - z^L}{\sigma_\eta}$) increases, distribution of dividends conditional on the high and low productivity overlap less, as a result, dividends become more informative. In the limit as σ_η approaches zero, the informational imperfection vanishes.

In Figure 1, we plot $\tilde{z}_{t+1} = \phi\left(\tilde{z}_t, d_{t+1}\right)$ for three different values of $\tilde{z}_t$ where d_{t+1} is on the horizontal axis and $\tilde{z}_{t+1}$ is on the vertical axis. The solid curve corresponds to

$\tilde{z}_{t+1} = \phi(\min(\tilde{z}), d_{t+1})$; that is, investors are "almost sure" that the economy is in the low state. Similarly, the dashed curve shows $\tilde{z}_{t+1} = \phi(\max(\tilde{z}), d_{t+1})$, or the case in which they are optimistic. All other beliefs would be represented by curves that lie between the solid and dashed curves, such as the dotted curve, which shows the case in which the investors assign equal probability to each state, $\tilde{z}_{t+1} = \phi\left(\frac{z^H + z^L}{2}, d_{t+1}\right)$.

Figure 1. Next Period's Beliefs for Different Values of Current Beliefs



Proposition 2 If $P_{ii} > P_{ji}$ then $\phi(\tilde{z}_t, d_{t+1})$ is strictly increasing in both of its arguments.
Proof See Appendix.

$P_{ii} < P_{ji}$ corresponds to a scenario in which knowing the current state is useful for forecasting future productivity: the information that the economy is in a particular state would reveal that the economy is more likely to transition to the other state than to stay in the same state in the subsequent period (negative autocorrelation). Although information is valuable and learning would still take place, we rule out the case $P_{ii} > P_{ji}$ in order to establish Proposition 2.

The elasticity of $\tilde{z}_{t+1}$ with respect to d_{t+1} varies depending on $\tilde{z}_t$. When the investors assign a high probability to being in the low state ($\tilde{z}_t$ is low), a low realization of d_{t+1} "confirms" the beliefs and as a result $\tilde{z}_{t+1}$ changes only marginally. On the other hand, if a high d_{t+1} is observed, the beliefs of investors are "challenged" and there is a large adjustment in the next period's beliefs.

In order to see this, consider the following scenario. Assume that true productivity is low and that investors' current beliefs are "almost correct". In this case, $\tilde{z}_t = \min(\tilde{z})$, as depicted by the solid curve in Figure 1. The vertical line in Figure 1 marks the mean of the signals conditional on the economy being in the low state. Hence, a small negative noise shock is a realization of dividends to the left of this vertical line. If investors observe a negative noisy signal at $t+1$, the response of beliefs to this signal is minimal (the solid curve is flat on the left side of the vertical line). On the other hand, if investors receive a *sequence of misleading positive* signals before the negative one, their optimism builds up and their beliefs can move to reach that reflected in dashed curve in Figure 1. When the economy ends up in this situation, the response to a small negative signal is large (the dashed curve is steep on the left side of the vertical line). Therefore, a stream of positive signals can move the economy to a vulnerable state in which a negative signal triggers a large downward adjustment.

Figure 2 shows the numerical derivative of $\phi(\tilde{z}_t, d_{t+1})$ with respect to d_{t+1} around $d_{t+1} = z^L$ as a function of $\tilde{z}_t$.[10] This derivative captures the response of the beliefs to a small, negative signal conditional on true productivity being low. Figure 2 illustrates that this derivative increases with the level of optimism attained prior to the negative signal.[11]

The quantitative analysis focuses on the model's competitive equilibrium defined as follows.

Definition A *competitive equilibrium* is given by allocations $\alpha'(\alpha, \tilde{z}, d)$, $c(\alpha, \tilde{z}, d)$, $\alpha^{*}{}'(\alpha, \tilde{z}, d)$ and asset prices $q(\alpha, \tilde{z}, d)$ such that:

i. Domestic households maximize U subject to their budget constraint and their information set, I^U, taking asset prices as given.

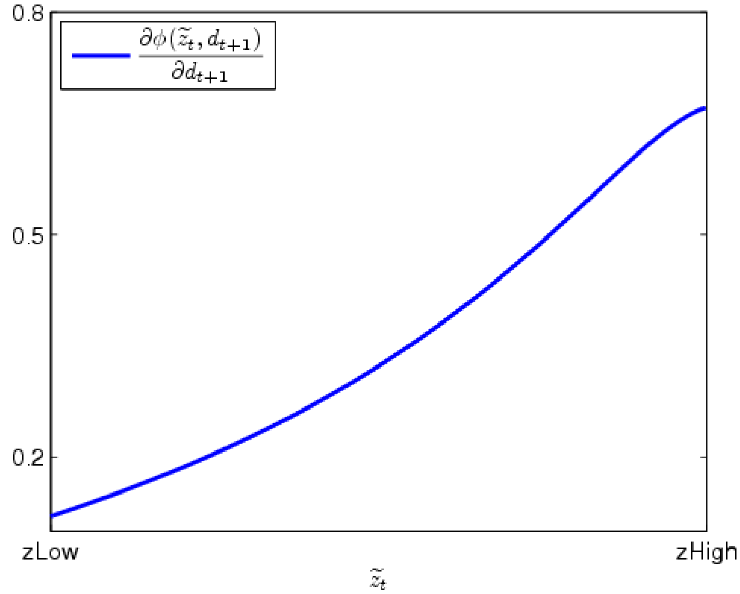
ii. Foreign investors maximize the expected present discounted value of future profits conditional on their beliefs about the state of productivity, taking asset prices as given.

iii. Goods and asset markets clear.

[10] We approximate this derivative numerically with **Error! Objects cannot be created from editing field codes.** for **Error! Objects cannot be created from editing field codes.** small and positive. In the figure, we plot this expression for different values of **Error! Objects cannot be created from editing field codes.**.

[11] Convexity of this derivative is due to the assumption that true productivity is a discrete random variable. In the case of continuous random variables, learning takes place in a linear fashion, that is, the posteriors are a convex combination of the priors and the signal with weights that depend on the signal-to-noise ratio. In that case, this derivative would be linearly increasing in the level of optimism prior to the negative signal.

Figure 2. Derivative of Belief Evolution Function



III. Quantitative Analysis

A. Computation

Dynamic programming representation of the domestic investors' problem for $i, j \in \{L, H\}$ and $i \neq j$ is:

$$V(\alpha,\tilde{z},d) = \max_{\alpha'} \left\{ \begin{array}{l} u(\alpha(q+d) - \alpha' q) \\ + \beta\left[\Pr(z = z^i \mid I^U)P_{ii} + \Pr(z = z^j \mid I^U)P_{ji}\right] \int V(\alpha', \phi(\tilde{z}, d'), d') f(d' \mid z' = z^i) dd' \\ + \beta\left[\Pr(z = z^i \mid I^U)P_{ij} + \Pr(z = z^j \mid I^U)P_{jj}\right] \int V(\alpha', \phi(\tilde{z}, d'), d') f(d' \mid z' = z^j) dd' \end{array} \right\} \quad 17)$$

Solution algorithm includes the following steps:

i. Discretize the state space. We use 102 equally spaced nodes for α and 40 equally spaced nodes for $\tilde{z}$ in the intervals [.83,1.00] and $[z^L, z^H]$ respectively. To discretize the noise component of dividends we use Gaussian quadratures with 20 quadrature nodes.

ii. Evaluate the evolution of beliefs $\tilde{z}_{t+1} = \phi(\tilde{z}_t, d_{t+1})$ using equations (13)-(16).

iii. For a conjectured pricing function $q^{old}(\alpha,\tilde{z},d)$, solve the dynamic programming problem described in equation (17) using value function iterations in order to get $\alpha'(\alpha,\tilde{z},d)$ and $c(\alpha,\tilde{z},d)$.

iv. Calculate the foreign investors' demand function using domestic investors' asset demand function obtained in Step 3 and the market clearing condition in the asset market, $\alpha^* + \alpha = 1$.

v. Using foreign investors' demand calculated in equation (8), calculate new prices $q^{new}(\alpha, \tilde{z}, d)$.

vi. Update conjectured prices with $\zeta q^{old}(\alpha, \tilde{z}, d) + (1-\zeta) q^{new}(\alpha, \tilde{z}, d)$ where ζ is a fixed relaxation parameter that satisfies $\zeta \in (0,1)$ and is set close to 1 in order to dampen hog cycles.

vii. Iterate prices until convergence according to the stopping criterion $\max\{|q^{new} - q^{old}| < 0.00001\}$ and get equilibrium asset prices $q(\alpha, \tilde{z}, d)$.

To check the accuracy of the solution of the dynamic programming problem, we evaluate Euler equation residuals as described in Judd (1992). To do so, we solve for $\hat{c}$ in the following Euler equation:

$$q_t u'(\hat{c}_t) = \beta E_t[(q_{t+1} + d_{t+1}) u'(c_{t+1})]. \tag{18}$$

Intuitively, we evaluate the consumption function that exactly satisfies the Euler equation implied by the solution of the dynamic programming problem. Then, we calculate $1 - (\hat{c}_t / c_t)$, which is a unitless measure of error. We find that the average Euler equation error is 0.0016.[12]

B. Calibration

The model is calibrated quarterly for Turkey using data for the 1987:1-2005:2 period. We set the risk free interest rate to average US Treasury Bill rate, $R = 1.0471^{.25} = 1.0115$ and $\beta = 0.9886$, $\sigma = 2$ following the business cycles literature. We set the trading costs of the foreign investors to $\{a = 0.001, \theta = 0.1\}$. With this calibration, total trading costs on average constitute 0.2589 percent of foreign investors' per period profits as specified in equation (6) and 1.8845 percent of the trade value. These costs are in line with the analysis of Domowitz, Glen and Madhavan (2001) covering the period 1996-1998 for a total of 42 countries among which 20 are emerging markets. They found that for emerging markets, trading costs are higher than the developed ones and they range between 0.58 percent (Brazil) and 1.97 percent (Korea) as percentage of trade value.

We estimate the parameters $\{\sigma_\eta, z^H, z^L\}$ and Markov transition probabilities $\{P_{HH}, P_{LL}\}$ using a Maximum Likelihood Estimation procedure similar to the one described in Hamilton (1989). For this exercise, we use quarterly GDP data for Turkey from 1987:1 to 2005:2 with a total of 74 observations. The data are from Central Bank of the Republic of Turkey's web site and are in constant 1987 prices. They are logged, seasonally adjusted (using the Bureau of Economic Analysis's X12 Method) and HP filtered using a smoothing parameter of 1600.

We denote the observed GDP series as y_t for $t \in \{1,2,...,T\}$ and the parameters to be estimated are $\psi \equiv \{z^i, z^j, \sigma_\eta, P_{ii}, P_{jj}\}$. The algorithm used for the estimation is as follows:

i. Calculate the ergodic distribution of the Markov process, $\Pi = [\Pi_i \Pi_j]$, using $\Pi_i = (1 - P_{jj})/(2 - P_{jj} - P_{ii})$. Π_j can be calculated using $\Pi_i + \Pi_j = 1$.

ii. Calculate the conditional density:

$$f(y_t, \psi \mid y^{t-1}) = \frac{1}{\sqrt{2\Pi}\sigma_\eta}\left(\Pr(z_t = z^i \mid y^{t-1}) e^{\frac{-(y_t - z^i)^2}{2\sigma_\eta^2}} + \Pr(z_t = z^j \mid y^{t-1}) e^{\frac{-(y_t - z^j)^2}{2\sigma_\eta^2}} \right) \tag{19}$$

where $\Pr(z_t = z^i \mid y^{t-1})$ denotes the posterior probability assigned to being in state i conditional on the observed history of y until period $t-1$.

iii. For $t = 1$, when no history is available, use the ergodic probabilities calculated in Step 1 instead of the conditional probabilities.

iv. Update the prior probability $\Pr(z_t = z^i \mid y^{t-1})$ using Bayesian updating equations (13) and (15).

v. Repeat Steps 2-4 for $\forall t \in \{1,2,...,T\}$.

vi. The log likelihood function is evaluated by simply adding the logged conditional density functions for all observations:

[12] Judd (1992) calls this measure the "bounded rationality measure," and interprets an error of 0.0016 as a $16 error made on a $10,000 expenditure.

$$L(\psi)=\sum_{t=1}^{T}\ln f\left(y_t;\psi \mid y_{t-1}\right). \tag{20}$$

vii. Maximize the log likelihood function:

$$\max_{\psi} L\left(\psi; y^T\right) \tag{21}$$

subject to $P_{ii} > 0$, $P_{jj} > 0$ and $P_{ii} > P_{ji}$ (see Assumption).

Table 2. Model Parameters

β	0.9881	Discount factor
R	1.0121	Risk free rate
σ	2	Risk aversion coefficient
P_{HH}	0.8933	Transition probability from H to H
P_{LL}	0.6815	Transition probability from L to L
z^L	-0.0427	Productivity in state L
z^H	+0.0175	Productivity in state H
σ_η	0.0362	Standard deviation of noise
$\dfrac{z^H - z^L}{\sigma_\eta}$	1.6638	Signal-to-noise ratio
$\{a,\theta\}$	$\{0.001,0.1\}$	Trading costs

The estimates of the productivity shock are $\left\{z^H, z^L\right\}=\left\{0.0175,-0.0418\right\}$ which translate into $\left\{e^{z^H}, e^{z^L}\right\}=\left\{1+0.0177,1-0.0418\right\}$. Transition probabilities are $P_{HH}=0.8933$, $P_{LL}=0.6815$, persistent component variance is $\sigma_z = 0.0260$, and the noise component variance is $\sigma_\eta = 0.0362$. With these parameters, signal-to-noise ratio is $\dfrac{z^H - z^L}{\sigma_\eta}=1.6638$. Productivity shocks and the transition probability matrix approximate a Normal AR(1) process: $z_{t+1}=(0.0004)+(0.5763)z_t+\varepsilon_{t+1}$, where $\sigma_\varepsilon = 0.0213$. This calibration implies $\dfrac{\sigma_\varepsilon}{\sigma_\eta}=0.5888$ which constitutes another measure of information content of the signals.[13]

[13] This, in fact, is the conventional measure of the information content of signals when learning is about continuous as opposed to discrete variables.

C. Quantitative Findings

Table 3 documents the long run moments of actual and simulated data for full and incomplete information scenarios, respectively.[14] "Full information" scenario corresponds to the case in which information set of both investors is $I_t^I \equiv \{d_t, d_{t-1}, ..., z_t, z_{t-1}, ...\}$.[15] Informational friction reduces the mean asset holdings of domestic investors. (Compare 86.1 percent with 84 percent.) This is because the informational imperfection increases the uncertainty associated with future asset returns, and, hence, risk averse domestic investors are demand less of these "riskier" assets. As a result of their greater asset holdings, domestic investors' consumption is also higher on average in the full information scenario than in the incomplete information. In the full information case, higher average consumption and lower consumption volatility lead to a higher level of welfare compared to the case in which investors have only incomplete information.

Going from full information setup to the one with incomplete information, standard deviation of consumption increases by 2 percentage points. On the other hand, standard deviation of asset prices and the current account to dividend ratio fall by 0.87 and 40 basis points, respectively. The decline in the standard deviation of asset prices is due to beliefs being a convex combination of the low and high value of true productivity. (See equation (16) and Proposition 1.)

Correlation between true productivity, z, and asset prices, q, falls from 0.9975 in the full information setup to 0.6883 in the incomplete information setup. This is due to booms-busts induced by imperfect information, which gives rise to misperceptions regarding the true state of productivity. In the full information case, all of the cycles are driven by changes in true productivity and noise shocks have negligible effects on asset prices. Although most of the booms and busts in the incomplete information scenario are also due to changes in true productivity, there is a significant number of optimism-pessimism driven cycles that is further explored below. Autocorrelation coefficient of $\tilde{z}$ is 0.5532 suggesting that transitory shocks have persistent effects on beliefs. The belief updating structure is the key element that induces this persistence: previous period's posteriors are current period's priors.

Another important observation from Table 3 is the decline in the correlation between dividends and the current account going from full information to imperfect information (0.90

[14] We simulate each scenario for 10,000 periods and calculate the moments after dropping the first 1,000 observations.

[15] One can model a full information scenario by setting **Error! Objects cannot be created from editing field codes.**. However, doing so would alter the distribution of the dividend process. As a result, it would not be possible to distinguish changes in results that are due to full information per se from those due to the change in the distribution of the dividend process.

vs. 0.48). In response to a positive dividend shock, domestic investors would like to increase their asset position so as to smooth consumption over time and *in addition*, their expectations for asset returns increase since they observe a positive signal. Foreign investors are modeled not to have a consumption smoothing motive therefore, for them only the second effect (positive signal) prevails. This second effect is stronger for foreigners compared to their domestic counterparts and they bid more aggressively for the asset when there is a positive signal due to their risk neutrality. Overall, we find that usually the first effect dominates the second for domestic investors, and therefore, the model produces a procyclical current account. However, as mentioned, the procyclicality is lower compared to the full information scenario where only the first effect is present.

Table 3. Long-Run Business Cycle Moments[16]

	Data	Full Information	Incomplete Info.
$E[d]$		1.0036	1.0036
$E[c]$		0.8642	0.8419
$E[\alpha]$		0.8609	0.8397
$E[q]$		83.1358	83.0617
$E[CA/d]$		-0.0001	0.0001
$\sigma(z)$ (%)	2.5884	2.5884	2.5884
$\sigma(\eta)$ (%)	3.6341	3.6341	3.6341
$\sigma(d)$ (%)	4.5694	4.5514	4.5514
$\sigma(c)/E[c]$ (%)	5.4597	2.2226	4.2168
$\sigma(q)/E[q]$ (%)	38.0997	0.0370	0.0283
$\sigma(CA/d)$ (%)	3.1168	3.6134	3.0060
$corr(d,c)$	0.6984	0.3153	0.6506
$corr(d,q)$	0.0718	0.5611	0.8327
$corr(d,CA)$	-0.4217	0.9019	0.4879
$corr(d,\alpha')$		0.0347	0.1125
$corr(\tilde{z},\tilde{z}_{-1})$		X	0.5532
$corr(z,q)$		0.9975	0.6883

[16] Simulated data is logged and HP filtered.

In Figure 3, we plot two sets of conditional forecasting functions; first, starting from a state where investors are optimistic (first column) and second, where they are pessimistic (second column). In the optimistic scenario, we set the state variables to $(\alpha, \tilde{z}, d) = (0.840, 0.017, 0.958)$: that is, beliefs are $\tilde{z} = \max(\tilde{z})$; dividends are set to signal that the productivity is low; $d = e^{z^L}$ and the domestic investors' asset position is set to its long-run mean. The pessimistic scenario is set to start at $(\alpha, \tilde{z}, d) = (0.840, -0.042, 0.958)$. These scenarios are identical except for the initial beliefs.[17]

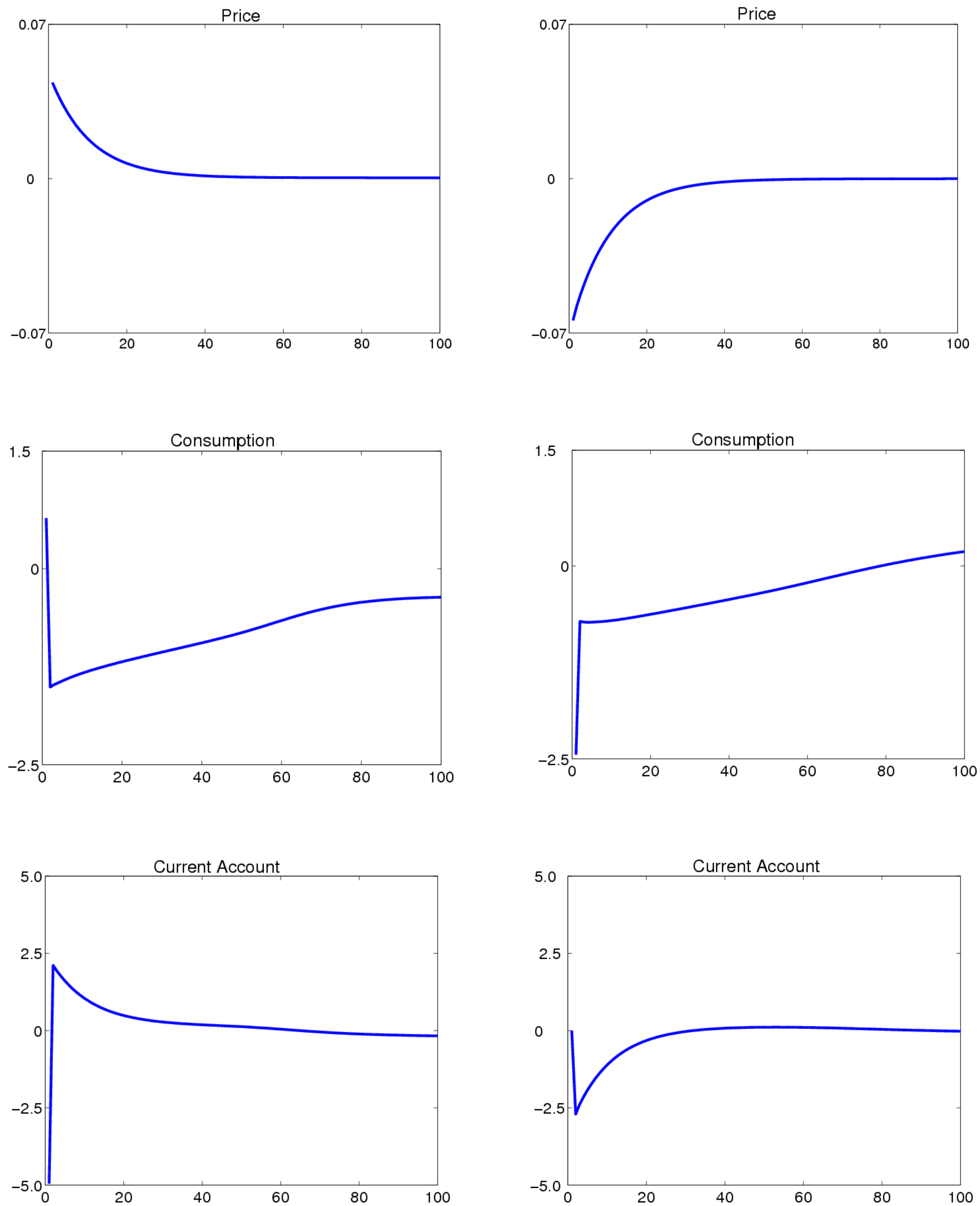
On impact in period one, the economy with optimistic investors is characterized by a current account deficit as well as a boom in consumption and asset prices. In period two, however, consumption falls sharply below its mean by 1.5 percent and the current account turns to a surplus of roughly 2.5 percent. The prices also adjust downwards but the adjustment is more gradual than those of consumption and the current account. After the second period, all variables slowly and monotonically converge to their long-run means.

Dynamics of the model economy starting with optimistic investors are similar to those of emerging market crises. As documented in Section 1, pre-crisis periods are characterized by current account deficits as well as consumption and asset price booms. Our model is able to forecast a drop in consumption and asset prices as well as reversal of the current account after this period of optimism.

The results in Table 3 suggested that the model produces a procyclical current account on average and in the imperfect information scenario this procyclicality is lower than in the full information case. Previously, we explained the model dynamics that lead to this result. The forecasting functions plotted in Figure 3 support the previous explanation and the results of Table 3. Particulary, the economy with optimistic investors has a current account deficit because, ceteris paribus, the higher the beliefs, the lower the current account.

[17] Consumption and asset prices are plotted as percentage deviations from long-run means whereas the current account is the ratio of the current account to dividends in percentage terms.

Figure 3. Forecasting Functions Conditional on Optimism (first column) and Pessimism (second column)



Given the inherent noisiness of signals obtained by calibrating the model to a typical emerging economy, Table 4 reveals how often investors turn optimistic-pessimistic due to misleading signals, how long these periods last, and more importantly, whether and how much optimism (pessimism) periods are associated with booms (busts) in asset prices and consumption and current account deficits (surpluses). In order to conduct the analysis, we use simulated data to identify periods in which investors assign a probability greater than 0.5 to productivity being high (low) even though the true productivity is low (high) and call them optimism (pessimism) periods.[18] In the first row of Table 4, we report the ratio of the number of optimism (pessimism) periods to the total number of observations.

Table 4. Analysis of Optimism (Pessimism) Driven Booms (Busts)[19]

	Booms	**Busts**
Probability(%)		
$\Pr[\Pr(z_t = z^i \mid I_t^U, z_t = z^j) > 0.5\}$	8.7900	4.4100
Probability of model producing cycles of the size in the data		
In percentage deviations:		
q	0	0
c	2.1837	2.5004
CA	0.2000	0
In standard deviations:		
q	2.8838	0
c	2.3337	2.6004
Duration (quarters)		
Average duration	2.7540	1.4149
Magnitude		
In percentage deviations:		
q	0.0334	-0.0528
c	2.0284	-5.3483
CA	1.04	-0.64
In standard deviations:		
q	1.2097	-1.9087
c	0.4865	-1.2827

[18] Note that by doing so, we are picking up only those periods in which optimism and pessimism are due to misperceptions of investors.

[19] Percentages except for the probabilities and interest rates are with respect to average output.

Unconditionally, the model produces optimism driven booms with a 8.79 percent probability, whereas it produces pessimism driven busts with a 4.41 percent probability. The former is more likely to happen because investors interpret positive signals to be more "credible" than negative signals due to the asymmetry of the Markov transition probability matrix. The optimism in response to a misleading positive signal is greater than the pessimism caused by a misleading negative signal with the same magnitude.

In addition, we report the probabilities that the model generates booms/busts of the size observed in the data. The size of booms are those reported in Table 1, that is the boom in Turkey in 2000. As for the bust, we take the average consumption, price drops and current account reversal in 2001 Q2-Q4 following the crisis in the first quarter of the year. These are -4.97, -13.21, 4.09 percent for consumption, prices and the current account respectively. In terms of matching the consumption figures, the model performs well by generating booms (busts) with probability 2.18 (2.50) percent. The model fails to match the fluctuations in the asset prices as the volatility of the asset price in the model is significantly lower than that in the data.

We calculate the average duration by calculating the average length of the distinct optimism-pessimism periods. On average, the model predicts an average duration of 2.75 (1.41) quarters for the optimism (pessimism) driven booms (busts). These cycles are relatively short lived because these cycles hinge on the realization of a sequence of positive or negative signals.

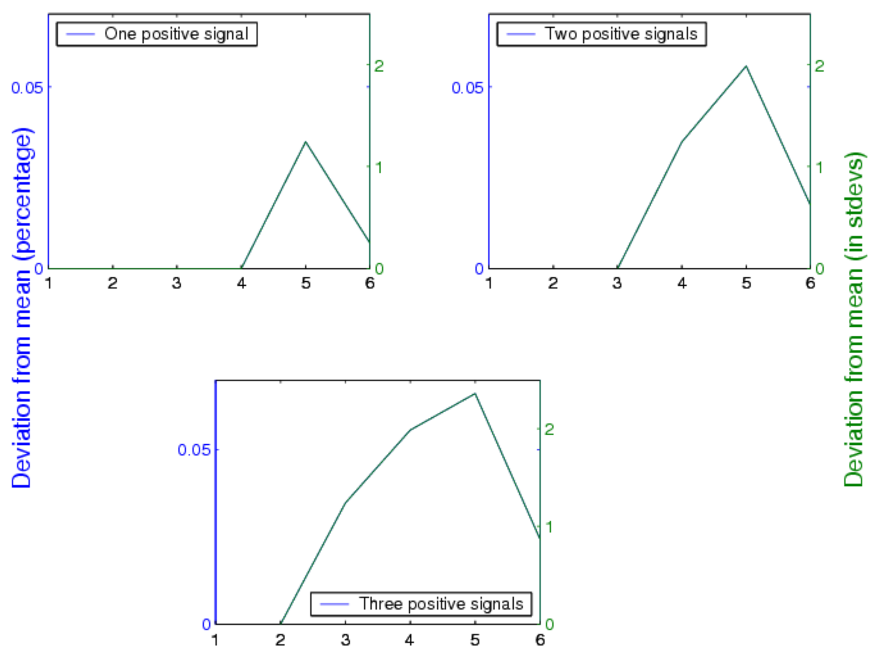
In the same table, we also report the size of these booms-busts as percentage deviations from the value that corresponding variables would have taken if investors had correctly estimated the true productivity instead of being optimistic or pessimistic. The magnitude for the asset price boom is small when we look at it as pecentage deviation because asset prices have low volatility. However, this magnitude is closer to the data in terms of standard deviations. The boom periods are characterized by asset prices and consumption that are on average 1.20 and 0.48 standard deviations above what they would have been if the investors were not optimistic. The over-pricing as well as over-consumption are evident in this table. Especially, the over-pricing of the emerging market asset is significant: during the booms on average we observe prices that are more than two standard deviations higher than what they would have been if investors were not optimistic. Similarly, we see under-pricing and under-consumption during the busts, with magnitudes that are larger than those observed during booms due to the asymmetry of the Markov process.

D. From Miracles to Crises

In Figure 4, we plot the response of asset prices to a sequence of positive signals, particularly to one, two, and three consecutive one standard deviation positive transitory shocks, respectively. Given the normal distribution of η, these scenarios occur with 16, 2.5 and 0.4

percent probability, respectively. In each of these scenarios, we set the true state to low $z = z^L$ and with the one standard deviation transitory shocks, the signals can be written as $d = e^{z^L + \sigma_\eta}$. After the positive signals, a truth revealing signal $d = e^{z^L}$ arrives. Figure 4 plots the response of asset prices as percentage deviations from its long run mean conditional on $z = z^L$.

Figure 4. Sequences of Positive Signals



In line with the analysis of Section 2, Figure 4 establishes the relation between the size of the booms and the magnitude of the downward adjustment due to the truth revealing signal that arrives after the peak of the boom. Although the signal that is observed after the positive signals is exactly the same in all of these scenarios, asset prices respond differently because beliefs respond more to challenging signals compared to the confirming ones.

E. Turkey vs. U.S.

In order to establish the difference of a developed economy from a typical emerging market economy, we estimate the model's parameters governing the informativeness of the signals using GDP data for the U.S. for the same time period using the same estimation procedure.[20]

[20] U.S. data are from OECD's web site, and are in constant prices, seasonally adjusted and HP filtered with a smoothing parameter 1600.

Not surprisingly, the total variance of U.S. GDP is significantly lower than that of Turkey (1.0121 vs. 4.5694).[21] Table 5 reports the results of the estimation for the U.S. and also reproduces those for Turkey. Comparing σ_z and σ_η for these two countries reveals that the variance for the persistent component as well as the noise is lower for the U.S. In the model at hand, informativeness of signals is determined by the signal-to-noise ratio which is estimated to be $\frac{z^H - z^L}{\sigma_\eta} = 2.7053$ for the US (vs. 1.6638 for Turkey) suggesting a more trivial learning for the case of the U.S.

Table 5. U.S. vs. Turkey, Parameters

	Turkey	**U.S.**	
P_{HH}	0.8933	0.9117	Transition probability from H to H
P_{LL}	0.6815	0.9317	Transition probability from L to L
z^L	-0.0427	-0.0054	Productivity in state L
z^H	+0.0175	0.0108	Productivity in state H
σ_η	0.0362	0.0060	Standard deviation of noise
$\frac{z^H - z^L}{\sigma_\eta}$	1.6638	2.7053	Signal-to-noise ratio
$\sigma(z)$	2.5884	0.8109	Variance of the persistent component
$\sigma(\eta)$	3.6341	0.6124	Variance of the transitory component
$\sigma(d)$	4.5694	1.0121	Total variance

To see the differences of these two economies visually, we plot time series simulations of the persistent and transitory shocks for the U.S. and Turkey in Figure 5. In addition to the observations made before, one can also see in this figure that for the case of Turkey, switches between the low and high states of the persistent component are more frequent. This is also consistent with the common argument that emerging market economies experience more frequent and dramatic changes in their fiscal and monetary policies potentially due to higher political instability. Motivated by this striking difference in the signal-to-noise ratios of these economies, we solve our model with the U.S. calibration.

[21] This volatility for the U.S. GDP is somewhat lower than those calculated by other studies in the literature because we only consider the 1987:1-2005:2 period that is characterized by a lower volatility compared to the period before 1980's, the so-called Great Moderation. We restrict our analysis to this time frame since quarterly Turkish data is available starting in 1987.

Figure 5. Time Series Simulations for U.S. and Turkey

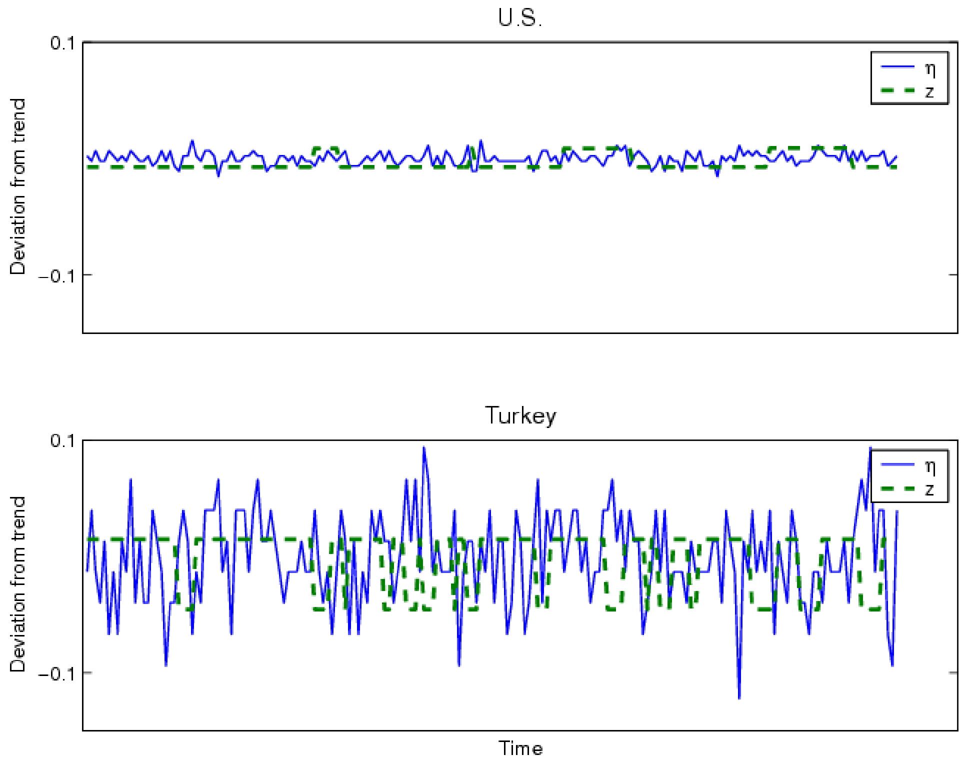


Table 6 documents the magnitude, frequency and the duration of booms and busts due to misperceptions of investors for the cases of U.S. and Turkey. All of the calculations are conducted the same way as those of Table 4. The first two rows of the table reveal that the probabilities of both booms and busts are lower for the case of U.S. compared to Turkey. This is mainly driven by the higher signal-to-noise ratio estimated for the U.S. leading to more informative signals and making it less likely for the investors to be misled. Another observation is the reversed asymmetry, for Turkey optimism driven booms occur with a higher probability than busts whereas pessimism driven busts are more likely for the U.S. A careful observation of Table 5 reveals that the low state is slightly more persistent than the high state (comparing P_{LL} with P_{HH}) for the U.S. which is in contrast with the case of Turkey. This difference in the Markov transition matrices estimated for these countries accounts for the reversed asymmetry.

Table 6. U.S. vs. Turkey, Booms and Busts

	Turkey	**U.S.**
Probability(%)	Booms/Busts	Booms/Busts
$\Pr[\Pr(z_t = z^i \mid I_t^U, z_t = z^j) > 0.5\}$	8.7900/4.4100	2.1500/2.2500
Duration (quarters)		
Average duration	2.7540/1.4149	1.2632/1.3857
Magnitude		
In percentage deviations:		
q	0.0334/-0.0528	0.0721/-0.0730
c	2.0284/-5.3483	1.0991/-1.0519
CA	1.04/-0.64	0.4759/-0.3298
In standard deviations:		
q	1.2097/-1.9087	1.5854/-1.6053
c	0.4865/-1.2827	1.0890/-1.0422

In terms of the durations, cycles generated by Turkey calibration are on average longer than those generated by the U.S. calibration. Noisier signals for the case of Turkey make it more likely for the investors to receive consecutive misleading signals and extend the time it takes for them to correct their beliefs leading to longer misperceptions driven booms and busts.

The size of consumption booms/busts are significantly larger for Turkey than the U.S. but this result does not hold for asset prices. The higher signal-to-noise ratio for the U.S. leads to a higher asset price volatility increasing the size asset price booms/busts in units of percentage deviations from mean.[22]

F. Sensitivity Analysis

We document the long run business cycle moments of the model with different calibrations for the noisiness of signals, σ_η, and trading costs, a and θ. The third column of Table 7 shows the results with $\sigma_\eta = 0.0265$ and we compare these results with those of the baseline model with $\sigma_\eta = 0.0362$ reproduced in the second column.[23] With lower σ_η, the standard deviation of dividends and consumption fall by 85 and 20 basis points, respectively. Average consumption among domestic investors increases due to the lower volatility of dividends and the associated decrease in uncertainty regarding future asset returns.

[22] Remember that the full information model produces more volatile asset prices than the incomplete information as documented in Table 3.

[23] With $\sigma_\eta = 0.0265$ the signal-to-noise ratio increases to 2.26 from 1.66 in the baseline scenario.

Table 7. Sensitivity Analysis

Incomplete Info.	Baseline	$\sigma_\eta = 0.0265$	$a = 0.002$	$\theta = 0$
$E[d]$	1.0036	1.0036	1.0036	1.0036
$E[c]$	0.8419	0.8472	0.8663	0.8417
$E[\alpha]$	0.8397	0.8448	0.8637	0.8398
$E[q]$	83.0617	83.0937	82.9521	83.0636
$E[CA/d]$	0.0001	0.0001	-0.0001	-0.0001
$\sigma(z)$ (%)	2.5884	2.5884	2.5884	2.5884
$\sigma(\eta)$ (%)	3.6341	2.6512	3.6341	3.6341
$\sigma(d)$ (%)	4.5514	3.6997	4.5514	4.5514
$\sigma(c)/E[c]$ (%)	4.2168	4.0287	4.4765	4.2153
$\sigma(q)/E[q]$ (%)	0.0283	0.0291	0.0288	0.0285
$\sigma(CA/d)$ (%)	3.0060	3.7166	4.5698	3.8472
$corr(d,c)$	0.6506	0.4318	0.2163	0.4519
$corr(d,q)$	0.8327	0.8505	0.8038	0.8313
$corr(d,CA)$	0.4879	0.6032	0.6591	0.5751
$corr(d,\alpha')$	0.1125	0.1403	0.0216	0.2064
$corr(\tilde{z},\tilde{z}_{-1})$	0.5532	0.5407	0.5532	0.5532
$corr(z,q)$	0.6883	0.7282	0.6694	0.6761

Lower σ_η implies that the signals are more informative and credible. Therefore, learning is faster compared to the baseline scenario. This leads to less persistence in beliefs. The autocorrelation of beliefs drops down to 0.54 from 0.55 in the baseline model. In addition, the probability of optimism-pessimism driven cycles falls leading to a stronger correlation between asset prices and true productivity.

The fourth column of the same table presents the results for the scenario with higher per trade costs, $a = 0.002$. The standard deviation of prices, consumption, and the current account increase by 0.05, 26, and 156 basis points, respectively. Due to higher per trade costs on the foreign investors' side, domestic investors hold more of the asset in equilibrium, leading to higher mean consumption but more volatile consumption.

Analysis of the scenario with no recurrent costs, $\theta = 0$, is reported in the fifth column. The results remain largely unchanged except for slight drops in the current account volatility and the correlation of the current account with dividends.

IV. CONCLUSION

The boom-bust cycles of emerging economies suggest that periods of apparent prosperity in these countries might contain the seeds of crises. This paper explores this possibility using an open economy equilibrium asset pricing model with imperfect information in which agents do not know the true state of productivity in the economy. The main contribution of the paper is its ability to endogeously generate (a) periods of optimism characterized by booms in asset prices and consumption followed by sudden reversals, (b) sensitivity to negative signals that increases with, and arises from, investor optimism attained prior to the negative signal. These results are due to the fact that informational frictions generate a disconnect between country fundamentals and asset prices. That is, busts (booms) in asset markets can occur even though the fundamentals of the economy are strong (weak). Asset prices display persistence in response to transitory shocks since investors cannot perfectly identify the underlying state of productivity. Due to the additional uncertainty created by informational frictions, the volatility of the emerging economy's consumption increases by 2 percentage points compared to the full information scenario. In addition, periods with high levels of optimism are more likely to be associated with current account deficits than periods of pessimism.

Although the informational frictions introduced in this paper can produce booms and busts in asset prices and consumption due to shifts in investor confidence, these booms and busts are short lived. In addition, even though the introduction of imperfect information provides an improvement in terms of matching the volatility of consumption and the current account dynamics observed in the data, the model cannot account for the volatility of asset prices.

The role of informational frictions in understanding emerging market regularities is an area ready for further research. For instance, the model presented in this paper endogenously produces sensitivity to negative signals given an *exogenous* sequence of positive signals. We could think of producing an *endogeous* sequence of positive signals by introducing strategic information manipulation into the model, especially prevalent during the run-ups to crises. If there is initially some sensitivity due to short-term and/or dollarized debt, a policymaker might find it optimal to manipulate or screen the signals to send positive signals. However, this would come at a cost because, by taking out the negative signals and sending only positive ones, the sensitivity of the economy to a sudden downward adjustment would only increase. This would create a feedback mechanism in which the policymaker, concerned about the country's ability to continue borrowing in international markets, has a self-perpetuating incentive to hide negative information from the public.

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APPENDIX

Throughout this section, we assume that $i, j \in \{L, H\}$ and $i \neq j$.

Proof of Proposition 1

Denote the prior $\Pr\left(z_t = z^i \mid I_{t-1}^U\right) = p_t(i)$ and the Normal density function $f\left(d_t \mid z_t = z^i\right) = f(i)$.

Priors:

Evolution of $p_t(i)$ is characterized by:

$$p_t(i) = \frac{p_{t-1}(i)f(i)P_{ii} + [1 - p_{t-1}(i)]f(j)P_{ji}}{p_{t-1}(i)f(i) + [1 - p_{t-1}(i)]f(j)}.$$

- $p_t(i) = 1 \Leftrightarrow p_{t-1}(i)f(i)P_{ii} + [1 - p_{t-1}(i)]f(j)P_{ji} = p_{t-1}(i)f(i) + [1 - p_{t-1}(i)]f(j)$ and $p_{t-1}(i)f(i) + [1 - p_{t-1}(i)]f(j) \neq 0$. Given $P >> 0$ (see Assumption), the first condition is satisfied iff
    - $p_{t-1}(i) = 0$ and $f(j) = 0$ or
    - $p_{t-1}(i) = 1$ and $f(i) = 0$, both of which violate the second condition.

- $p_t(i) = 0 \Leftrightarrow f(j)P_{ji} + p_{t-1}(i)[f(i)P_{ii} - f(j)P_{ji} = 0$ and $p_{t-1}(i)f(i) + [1 - p_{t-1}(i)]f(j) \neq 0$. The first condition is satisfied iff
    - $f(j) = 0$ and $f(i)P_{ii} = f(j)P_{ji}$. These two hold iff $f(j) = 0$ and $f(i) = 0$, in which case the second condition above does not hold.
    - $f(j) = 0$ and $p_{t-1}(i) = 0$. In this case, second condition is again violated.

See Liptser and Shiryayev (1977) Ch. 9 and David (1997) for the proof of entrance boundaries in continuous time.

Posteriors:

Rewrite equation (13):

$$\Pr\left(z_t = z^i \mid I_t^U\right) = \frac{p_{t-1}(i)f(i)}{p_{t-1}(i)f(i) + p_{t-1}(j)f(j)}$$

All terms on the right hand side of the equation are positive: $p > 0$ (see proof above) and $f > 0$ (Normal distribution). ■

Proof of Proposition 2

First Argument:

We need to show that $\frac{\partial \phi(\tilde{z}_t,.)}{\partial \tilde{z}_t} > 0 \forall \tilde{z}_t$. Denote the posterior probabilities $\Pr\left(z_t = z^i \mid I_t^U\right) = \gamma_t$ and $f(d_{t+1} \mid z_t = z^i) = f(i)$. We start with expressing γ_{t+1} as a function of γ_t:

$$\gamma_{t+1} = \frac{[\gamma_t P_{ii} + (1-\gamma_t)P_{ji}]f(i)}{[\gamma_t P_{ii} + (1-\gamma_t)P_{ji}]f(i) + [1-\gamma_t P_{ii} - (1-\gamma_t)P_{ji}]f(j)} \tag{i.}$$

Also:

$$\frac{\partial \phi(\tilde{z}_t, d_{t+1})}{\partial \tilde{z}_t} = \frac{\partial \tilde{z}_{t+1}}{\partial \tilde{z}_t} = \frac{\partial \tilde{z}_{t+1}}{\partial \gamma_{t+1}} \frac{\partial \gamma_{t+1}}{\partial \gamma_t} \frac{\partial \gamma_t}{\partial \tilde{z}_t} \tag{ii.}$$

Remember that $\tilde{z}_t = \gamma_t z^i + (1-\gamma_t)z^j$, so we can calculate the first and the third expressions in the above equation:

$$\frac{\partial \tilde{z}_{t+1}}{\partial \gamma_{t+1}} = z^i - z^j, \frac{\partial \gamma_t}{\partial \tilde{z}_t} = \frac{1}{z^i - z^j}. \tag{iii.}$$

The second expression can be calculated using equation (i.). After some manipulation:

$$\frac{\partial \gamma_{t+1}}{\partial \gamma_t} = \frac{f(z^i)f(z^j)(P_{ii} - P_{ji})}{\{[\gamma_t P_{ii} + (1-\gamma_t)P_{ji}]f(i) + [1-\gamma_t P_{ii} - (1-\gamma_t)P_{ji}]f(j)\}^2} \tag{iv.}$$

Plug in equations (iii.) and (iv.) into equation (ii.). To complete the proof, we need to establish $f(i), f(j) > 0$ and $P_{ii} > P_{ji}$. $f(i), f(j) > 0 \ \forall z^i, z^j$ since the Normal distribution is unbounded. $P_{ii} > P_{ji}$ follows from Assumption 2.3.

Second Argument:

We need to show that $\frac{\partial \phi(., d_{t+1})}{\partial d_{t+1}} > 0$. Write:

$$\frac{\partial \phi(., d_{t+1})}{\partial d_{t+1}} = \frac{\partial \tilde{z}_{t+1}}{\partial d_{t+1}} = \frac{\partial \tilde{z}_{t+1}}{\partial \gamma_{t+1}} \frac{\partial \gamma_{t+1}}{\partial d_{t+1}} \tag{v.}$$

Denote $A = P_{ij} + \gamma(P_{ii} - P_{ji})$. Then we can rewrite equation (i.):

$$\gamma_{t+1} = \frac{Af(i)}{Af(i) + (1-A)f(j)} = \frac{1}{1 + \frac{1-A}{A}\frac{f(j)}{f(i)}} \qquad \text{(vi.)}$$

Write $f(i)$ and $f(j)$ explicitly:

$$\frac{f(j)}{f(i)} = e^{\frac{1}{2\sigma^2}[(d_{t+1}-z^i)^2-(d_{t+1}-z^j)^2]} = e^{\frac{(2d_{t+1}-z^j-z^i)(z^j-z^i)}{2\sigma^2}}.$$

Then we can calculate its derivative with respect to d_{t+1}:

$$\frac{\partial[f(j)/f(i)]}{\partial d_{t+1}} = \frac{z^j - z^i}{\sigma^2} e^{\frac{(2d_{t+1}-z^j-z^i)(z^j-z^i)}{2\sigma^2}} \qquad \text{(vii.)}$$

Rewrite equation (v.):

$$\frac{\partial \tilde{z}_{t+1}}{\partial d_{t+1}} = \frac{\partial \tilde{z}_{t+1}}{\partial \gamma_{t+1}} \frac{\partial \gamma_{t+1}}{\partial[f(j)/f(i)]} \frac{\partial[f(j)/f(i)]}{\partial d_{t+1}} \qquad \text{(viii.)}$$

We know the first expression from equation (ii.). The second expression can be calculated using equation (vi.):

$$\frac{\partial \gamma_{t+1}}{\partial[f(j)/f(i)]} = \frac{-(1-A)/A}{\left(1+[(1-A)/A][f(j)/f(i)]\right)^2} \qquad \text{(ix.)}$$

Plugging in equations (ii.), (vii.) and (ix.) into (viii.) and rearranging we get:

$$\frac{\partial \tilde{z}_{t+1}}{d_{t+1}} = \left[\frac{z^i - z^j}{\sigma[1+(1-A)/A(f(i)/f(j)]}\right]^2 e^{\frac{(2d_{t+1}-z^j-z^i)(z^j-z^i)}{2\sigma^2}} > 0 .\blacksquare$$