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Determinants of financial crises—An early warning system based on panel logit regression

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Abstract

Despite the fact that different types of financial crises are rooted in similar weaknesses of economy or may have common determinants, the very transmission mechanism may determine one category as leading or lagging behind others. We are focused on financial crises that necessarily have the features of systemic banking crises and assess econometric early warning system of 64 systemic banking crises that occurred in the period from 1977 to 2013. The paper employs two different procedures, based on panel logit regression. The dynamic discrete-choice (binary) early warning model clearly outperformed the static model. The set of significant explanatory variables changed relative to the findings of the static model. The most significant predictor of the crises in the better performing model is deposit insurance system, followed by international reserves, M2-to-international reserves ratio, M2 multiplier, bank deposits, and bank reserves ratio. The statistical significance of the lagged variable confirmed the necessity to take the effect of crisis persistence into account.

KEYWORDS

dynamic model, financial regulation, logit estimation, systemic banking crises

JEL CLASSIFICATION

C52; E58; G21; G28

1 | INTRODUCTION

Financial crises are not frequent, but they could be rather costly economic phenomena. The most severe crises ultimately result in years or even decades of lost economic growth and diverted development trajectories. It is no surprise that such an important economic phenomenon attracts vast interest both in academia and policy circles.

One of the largest issues that a researcher faces in studying financial disturbances comes from the fact that financial crises in real life rarely come as elegant as it appears in theory. It is often a mixture of problems faced by financial intermediaries, governments to handle public debt, or an economy inability to sustain foreign exchange peg or defend against rapid devaluation of currencies. Most frequently, researchers concentrate on a specific set of developments, ignoring that problems often come as twin crises or even joined in trinity (tripled; e.g., Bussiere & Fratzscher, 2006). Recently, the interest for studying systemic financial disturbances having in focus links between different types of this phenomena notably increased (Babecký et al., 2014; Breuer, 2004; Bruinshoofd, Candelon, & Raabe, 2010; Candelon & Palm, 2010; Lestano, Jacobs, & Kuper, 2003; Reinhart & Rogoff, 2014). Treating a disturbance as if it belonged exclusively to any of those three generic types leads to losing valuable information about complexity and multifaceted nature of systemic financial disturbances.

An equally important research issue is how to address variable duration of pulled crisis events within the limitation of most popular crisis prediction models. The problem is known as crisis duration bias or postcrisis bias. How long a crisis will be there is depended not only on specific crisis manifestations and dynamics but also on authorities' reaction. Early warning system (EWS) literature implicitly assumes that a crisis has its roots in either market or policy failures (Caprio & Klingebiel, 1996b). For sure, market may go wrong, but systemic disturbances often can be traced back to wrong policy choices. If it is true for any policy measure with potential to trigger vicious cycle, it must be also true for crisis resolution measures. Wrong policy undertaken during the resolution phase amplifies actual crisis, prolongs, or even contributes to changing nature of it. Therefore, those two issues are closely linked. If systemic problems in banking sector go together with sovereign default or currency disturbances, they will be likely to last longer and cost a society more than sole banking, debt, or currency crises (Kaminsky & Reinhart, 1999). If crisis resolution package includes measures that are targeted to cure one type of crises with a potential to harm others, it will probably be effective and the financial crisis will eventually last longer. There is vast narrative evidence that makes this point strong. For example, extensive and massive support of troubled banking sector with public funds will be likely to damage sustainability of public finances. On the other hand, there are cases where the right solution to problems in one sector leads to the measures originally tailored for the other sectors. For example, if the problems in banking sector come from exposure to bad public debt, consolidation of public finances will help solve problems in both banking sector and public debt markets. Moreover, fragility of any subsystem will be likely to limit the scope for an effective resolution initiative. Specifically, a banking system sensitive to currency depreciation will limit manoeuvrability of government in managing exchange rate. Thus, despite the assumption that authorities know more than the market, they will behave as if they had tied hands and refrain to prick bubble even if the bubbling is well understood and anticipated.

In this paper, we are focused on financial crises that necessarily have the features of systemic banking crises, whether at the same time showing defining features of other generic types of financial crises. We use dataset of systemic banking crises that occurred in the period from 1977 to 2013. However, the selection of explanatory variables gathers most powerful predictors that economic theory identified as joint determinants of all types of financial crises. As far as we know, this is the first attempt to delve into research on banking crises forecasting based on dynamic discrete-choice methodology. The remainder of the article proceeds as follows: Section 2 considers the interrelation between different categories of financial crises. Section 3 reviews operational definitions of banking systemic crises. Section 4 explains the methodology we adopt, including the selection of explanatory variables and construction of the banking crisis-dependent variable. Section 5 presents our results, comparing the performance of a static and dynamic model, and Section 6 concludes.

2 | INTERRELATION BETWEEN DIFFERENT CATEGORIES OF FINANCIAL CRISES

In this section, we will try to summarize main arguments why those three categories of financial crises, banking, currency, and debt crises, are preferable to treat within a common framework. Novel empirical research (inter alia Babecký et al., 2014) underlined joint occurrence of those categories, with banking and debt crises interrelated and both preceding currency disturbances. This empirical regularity indicates that different categories of financial crises are rooted in similar weaknesses of economy or may have common determinants, but the very transmission mechanism may determine one category as leading or lagging behind others. For example, output losses will harm government ability to collect fiscal revenues, undermine quality of bank assets, and be likely to lead to or deepen an existing external disequilibrium. In what follows, we will try to illustrate the connection between the different types of financial crises, propagating mechanisms, possibility that a running type ignites the next one, starting with currency crises.

Currency crises are featured by a severe and abrupt change in currency value (exchange rate), which is per se a feature of floating exchange rate regimes, or abandoning of exchange rate parity in case of a peg or a similar rigid regime. Depending on the nature of the regime, it may also be followed by massive unbalanced official intervention on currency market, and eventually lost international reserves. Authorities that are not able to sustain the parity anymore will be forced to abandon peg. If some market participants foresee the reaction of authorities, they may act with additional pressure on the currency market and precipitate impending crisis (also known as speculative attack). This is why empirical literature (e.g., Bussiere & Fratzscher, 2006; Eichengreen, Rose, & Wyplosz, 1995) defines a currency disturbance based on exchange market pressure, which takes in account variability of a real effective exchange rate, interest rate, and foreign exchange reserves. The last two variables are policy tools, available in protecting currency value against speculative attacks, so that variable composed this way allows capturing both successful speculative attacks and their failures.

Early literature on currency crises usually terms this kind of disturbances as balance of payment crisis. What is now

known as first generation of models (Krugman, 1979) depicts speculative attacks on local currency as an anticipated failure of inconsistent economic policy, merely the goal to sustain a peg within expansive monetary and fiscal policy.[1] Eventual breakdown of exchange rate parity becomes inevitable and solely fundamentally driven. Models of second generation (Obstfeld, 1986) rely on the same set of fundamental variables but, opposite to the first-generation models, allow private agents to form different expectations about future course of very fundamentals. Each set of private expectations corresponds to specific equilibrium, so that there must be multiple (a continuum of) equilibriums. There may be no fundamental weaknesses of economic policy, but there is inherent external fragility that derives from inequality of the amount of international reserves and total possible claims on it, known as fractional reserves system (Kaufman, 2000). In the second generation of models, speculative attacks on currencies are not necessarily fundamentally driven nor inevitable. The attacks are self-fulfilling in the sense that there are strong incentives for speculators to join the race, that is, change local currency holdings for foreign (reserve) currency holdings if they believe that the majority of speculators will do the same. Any state of beliefs corresponds to the specific outcome.

How does currency crisis transmit to banking crisis? According to financial theory, a link between a currency and a banking crisis goes through incoherent macroeconomic policies. In particular, an uncontrolled monetary expansion or monetized excessive public deficits is well understood as theoretical explanation for the joint occurrence of currency and banking crisis (Flood & Garber, 1984). Specifically, for all international parity relationships (interest rate parity, purchasing power parity, etc.), the nominal money supply is the only pure policy variable. From the monetary policy point of view, excessive money supply can be used for monetizing fiscal deficits as long as the level of international reserves may soak up any money that public is not willing to hold at the prevailing exchange rate. Melting down of international reserves, no matter which exchange rate regime is in place, will shift the pressure on the exchange rate and make currency peg unsustainable or depreciation inevitable. If a government hesitates to abandon expansionary fiscal policy (in some cases, even to enact fiscal austerity measures), it must abandon the policy of strong currency.

It is well known in banking theory that banks are well insulated against direct exchange rate exposure (Buch & Heinrich, 1999). Contemporary banking prudential regulations demand bank books to be matched in terms of exchange rate exposure, in order to avoid that the change in exchange rate level adversely influences bank equity. However, even if bank books are perfectly matched, abrupt changes in currency value will still influence ability of debtors to service credit obligations. If there is no so-called natural hedge, the currency mismatch will ruin both solvency and liquidity of the nonfinancial sector. In that case, exchange rate exposure of debtors will be translated into default risk exposure of creditors, with a potential to harm even solvency and liquidity of banking (financial) sector. According to Candelon and Palm (2010), this will be likely to decrease demand of distressed financial sector for governmental bonds and put in jeopardy attempts of a government to refinance at favourable conditions. Not in all banking turmoils does a government have the role of a prime culprit (at least not that obvious). Some problems may arise in nonfinancial sector (households and businesses) and easily transmit to banking and other sectors (e.g., bursting of real estate bubbles). If the banking sector solvency is strong enough to withstand credit losses, there is still possibility that, because of maturity mismatch, banks experience liquidity shortage and pull away from public debt market or cut off credit exposure to nonfinancial sector, which will ignite a new vicious cycle of mutation and resurgence of the crisis in another type of turmoil.

Banking systems that extensively use foreign currency in deposit and lending arrangements (financial dollarization) are extremely sensitive to the currency/banking turmoil (Mishkin, 1999). It is not only a bank run that can contribute to the melting down of international reserves but also vice versa; the melting down of international reserves possibly triggers bank run. Specifically, in dollarized financial systems, international reserves serve multiple roles. The need for reserves comes from implicit contingent claims created by public sector commitments to a fixed exchange regime (or local currency protection) and protection from systemic banking crises (Rosenberg et al., 2005). Nonetheless, in the case of extensive foreign currency public (or private) debt, even capacity of a sovereign to pay back or roll over external (or domestic foreign currency) debt is put in danger with drainage of international reserves.

For instance, the financial turmoil that hit Serbian economy in fall 2008 was a kind of twin disturbance. It started on the local currency market with anxiety of foreign banking subsidiaries that prompted capital flight and initial leakage of international reserves (Marinković, 2015). Soon after the first strike, less informed creditors (depositors) joined the race. In a few weeks, one fifth of previous amount of foreign currency savings was withdrawn from the banking system, consequently melting down international reserves. Thanks to immediate reaction of authorities (firefighting enactment of new law on deposit insurance that increased coverage as well as currency-aware changes in mandatory reserves policy), depositors rush was calmed down in a month.

Massive currency devaluations, associated with full-blown currency crises, have detrimental effects on trade flows. If it happens after a prolonged period of accumulation of currency overvaluation, it may be seen as a return to

equilibrium. However, if existing structure of an economy is generated based on calculations that use the overvalued exchange rate as an input, rapid devaluations will, in total and in short term, create more losers than winners.

The same as with banking and currency crises, debt crises are equally challenging to define precisely. One of the most comprehensive operational definitions is given in Ciarlone and Trebeschi (2005). The authors defined a debt crisis as an event when alternatively, or simultaneously, the following conditions occur: A country has officially declared a moratorium on public or external debt payments, accumulated arrears of or incurred missed external debt services payment toward official and commercial creditors to a significant extent. The same holds if a country has signed a debt restructuring or rescheduling agreement with a creditor, as well as if it has received a large (in excess of quota) assistance package from the IMF.

Thus, the debt crisis phenomenon is defined as the case when a country faces defaulting on its debt services, that is, the events of official defaults, seriously challenged ability to service debt obligations, or excessive emergency support from multilateral organization such as IMF. Interestingly, the support of the same purpose, but from any regional organization or integration, is here ignored. Please note that debt-to-output ratio plays no role in the definition above (applied inter alia in Dawood, Horsewood, & Strobel, 2017). This is because the prudent level of this ratio is often considered country specific. The indicator itself also ignores cost of debt that can be very informative about how market perceives the risk of a government to slip into default (Candelon & Palm, 2010). Inability of a government to handle its debt at sound levels increases costs of sovereign borrowing, the same as still moderate cost of debt, at which a government is able to refinance, despite of high debt-to-output ratio, may indicate that the threshold is not reached yet. The tension on the sovereign debt market is tolerable, and there is some margin for additional debt left. The definition above is concentrated largely on external debt, because internal (domestic) debt should be handled a lot easier, with inflation tax raised on all local currency holders.[2]

How can a sovereign debt crisis be related to a banking crisis? First and foremost, systemic importance of financial intermediation (externality) leads to an involvement of a government as an intervenient in public money financed resolution attempts in case of an evident systemic banking disturbances, whether the government can be taken guilty or not. In some cases, the problems in the banking sector even start with the government. Moreover, there is also a risk that the banking crisis is hibernating as it slowly morphs into a government debt crisis (Candelon & Palm, 2010).

A costly banking crisis may induce sovereign debt crisis if public money is used to bail out troubled banking sector. In one of the most extensive databases on systemic bank insolvencies, Caprio and Klingebiel (1996a) assessed direct transfer of public funds to insolvent banks up to 55% of GDP (Argentina banking crisis). Similarly, Reinhart and Rogoff (2009) assessed historical average of cumulative increase in real public debt in 3 years after the banking crisis as 86%. In some extreme cases (e.g., Colombia, 1998), debt almost tripled. However, even if a government does not intervene, a distressed banking industry (credit or capital crunch) will increase cost of credit intermediation (Bernanke, 1983) and harm possibility of businesses and households to finance current business undertakings or refinance their obligation. More recent empirical investigation with more extensive country coverage (Dell'Ariccia, Detragiache, & Rajan, 2008) supports above-mentioned argumentation, stressing that right those industries that are more dependent on external (credit) finance would perform worse during credit crunch, which is also true for countries that are isolated from international financial market. Because businesses and households are ultimate taxpayers, their problems will affect government itself. Government revenues will shrink, whereas government spending will expand due to its role in social security, for example, unemployment benefits and so forth. A banking crisis that adversely impacts real economy will have not only immediate budgetary consequences but also increased contingent claims in case of an extended explicit or implicit governmental guarantees of bank debt (deposit insurance). If public debt has already reached its limits, the government involved in resolution of banking crisis will not avoid budget cut-offs or austerity measures, which will trigger a new vicious cycle of adverse events and have adverse impact on domestic demand, business default, and business mortality rate, as well as unemployment, making it worse for bank asset quality in return. At least in historical perspective (Reinhart & Rogoff, 2014), coincidence between banking and debt crises seems obvious, with (sovereign) debt crises more likely to follow the problems in banking sector.

Transmission from one to another type of financial crisis may go also the other way around. Recent developments within the European Union show that the solvency of banking sector significantly exposed to public debt may be undermined if government finds itself unable to refinance its debt stock (at reasonably favourable conditions). However, those developments are not unique for the recent financial turmoil. It is also found in a number of historical crises (Reinhart & Rogoff, 2014) and in some more contemporary banking crises. For example, Khallouli and Nabi (2013) found banks' exposure to public sector amongst the most significant explanatory variables in case of two banking and currency crises of modern Turkey. This way, whenever the problem arises, it will soon spread throughout the whole economic system. In his research, Breuer (2004) emphasized the importance of institutions in identifying the causes of

banking and currency crises. The negative effects on the economy are more pronounced and even last longer when financial crisis have the features of systemic banking crises. Thus, we assess econometric EWS to explore the commonalities of 64 systemic banking crises that occurred in the period from 1977 to 2013.

3 | OPERATIONAL DEFINITIONS OF BANKING CRISIS

In order to come out with a robust crisis prediction model, EWS literature must first define the crisis event in an operable way. All existing definitions include inputs from vast financial theory, but, as we will present below, there are some differences throughout empirical literature. Lack of generally accepted operating definition of those events is what further complicates deciding on timing and duration of the crisis, which is per se a crucial input in prediction models based on EWS.

For example, Demirgüç-Kunt and Detragiache (2005, p. 8) include in the dataset of systemic banking crises events that alternatively satisfy the following conditions: (a) the ratio of nonperforming assets to total assets in the banking system exceeds 10%; (b) the cost of the rescue operation at least 2% of GDP; (c) banking sector problems leading to a large-scale nationalization of banks; and (d) extensive bank runs taking place or emergency measures, such as deposit freezes, prolonged bank holidays, or generalized deposit guarantees that were enacted by the government in response to the crisis.

Specific research methodology (signal extraction method) limited Kaminsky and Reinhart (1999, p. 476) to using data that enables precise timing of the crisis event. The authors define (beginning of) a crisis as follows: (a) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions; (b) if there are no runs, the closure, merging, takeover, or large-scale government assistance to an important financial institution (or group of institutions) that mark the start of a string of similar outcomes for other financial institutions. Therefore, definitions that fit silent type of banking crisis are here excluded.

In this paper, we adapt the approach taken by Laeven and Valencia (2012), who defined systemic banking crisis if two conditions are met simultaneously: (a) There are significant bank runs, losses in the banking system, or bank liquidations, and (b) there are significant intervention policy measures undertaken, which the authors further defined as extensive liquidity support (5% of deposits and liabilities to nonresidents), restructuring costs that exceed 3% of GDP, bank nationalization, extensive guarantees put in place, assets purchases arrangements (above 5% of GDP), and deposit freezes or bank holidays. A full-blown systemic crisis is taken to begin if at least three out of six measures are implemented at the same time.

The definitions given above are used for panel logistic regression or signal extraction models. Those models operate with ex ante dated crisis events, and prediction models are then calibrated so as to give the best possible guesses (Edison, 2003, p. 12). Some other authors experimented with a definition of banking crisis, which is based on twin crisis literature. Specifically, Khallouli and Nabi (2013) used a composite index of twin crisis intensity-based on four indicators: monthly variations of exchange rate, international reserves, interbank interest rate, and central bank loans in total bank liabilities. Those indicators are good enough for currency disturbances joined with bank liquidity crisis, the type of banking crisis formally modelled in Bryant (1980), or Diamond and Dybvig (1983), but it will probably miss more silent solvency type of banking disturbances, also known as bank distress.

4 | RESEARCH METHODOLOGY: A LOGISTIC PANEL REGRESSION MODEL

The basic virtue of EWSs is to provide authorities with some lead time to take corrective actions that would help avert or mitigate the social costs associated with an upcoming crisis. Traditionally, EWSs aimed to detect impending financial disturbances are designed as macroprudential monitoring tool, based on two alternative methodologies. Signal extraction method is the nonparametric statistical technique, intuitive and easier to implement.[3] However, far most popular are the so-called qualitative response models (logit or probit).

Standard crisis prediction models develop binomial logit models, where dependent variable may take either one or zero value depending on whether in any specific year a crisis was there or not. The basic issue with those models comes from the assumption that all included crisis episodes last the same period of time. In recent literature, this potential drawback is studied as the so-called crisis duration bias. The bias arises from the decision to treat crisis years after the onset of a crisis as noncrisis years or simply remove them from the dataset. A valuable approach to deal with the crises that normally last for more than a year is to use multinomial approach, which, along with the so-called tranquil years, recognizes a year when a crisis erupts and subsequent crisis years (Bussiere & Fratzscher, 2006; Caggiano, Calice, & Leonida, 2014; Caggiano, Calice, Leonida, & Kapetanios, 2016; Hamdaoui, 2016). Such an approach also recognizes tranquil phase, when fundamentals are largely sound, but, opposite to binomial models, it is able to distinguish between a precrisis regime and postcrisis or recovery periods, when

economic fundamentals go through an adjustment before reaching a sustainable level.

However, no matter how a researcher defines presence of the crisis conditions, all approaches are of static nature and assume that the probability of a crisis depends only on a set of macroeconomic variables. Considering that, after a crisis, it takes time for the economy to recover, it is important to assess the impact of the regime prevailing in previous periods on the crisis probability we assessed. The easiest way to take into account the persistence of the crisis phenomenon is to include a lagged dependent variable into the set of explanatory variables and run a logistic panel regression. The model that we get that way is known as dynamic discrete-choice (binary) EWS, and it was first introduced by Candelon, Dumitrescu, and Hurlin (2014) for constructing a currency crises EWS.

In order to make those methodological notes complete, we would mention other approaches. For example, Markov switching regression family of models enriches the analytical framework, introducing crisis probability as an outcome instead of two or more discrete choices. Recently, Dabrowski, Beyers, and de Villiers (2016) found those models outperforming standard logit panel regression or signal extraction models. Khallouli and Nabi (2013) applied Markov switching regression model in the case of Turkey and managed to identify two twin crises that happened in Turkey in the sample period.

4.1 | The selection of explanatory variables

Coincidence of some economic phenomena is just the first clue in defining the set of variables that are likely to determine incidence of financial crises. This is why researchers heavily rely on time-series models. If there is strong regularity, meaning that some developments appear more often than they are absent in the dataset, then we have a list of candidates for crisis manifestations (Table 1).

The researchers found some indicators worth considering in generating EWS models able to predict financial crises. In Table 1, we have listed results from the selected most recent or most influential empirical studies that have dealt with all generic types of financial crises or separately with banking, currency, or debt crises. Some studies are listed according to the survey results presented there, and they might relate to dozens of empirical studies. For instance, Frankel and Saravelos (2012) summarized results for a total of 83 studies of currency crises that appeared in the period before 2009, whereas Dawood et al. (2017) present the choice of variables that appear in a number of sovereign debt crisis studies. As obvious from Table 1, there is huge overlapping between the chosen sets of explanatory variables across variety of studies. It is particularly notable for variables that belong to external and real sector.

We extract three groups of indicators from vast empirical literature (external, domestic, and financial), by adopting a crisis events dating scheme as in Laeven and Valencia (2012). As much as a banking crisis episode is related to disturbances on currency and debt markets, it may be followed by related disturbances in external balance. Let us explain several most used determinants. Real exchange rate is a widely used criterion for the concept of price competitiveness of export. Overvalued local currency here means that *ceteris paribus* national economy is likely to have unbalanced foreign trade because of plummeted export and boosted import. However, this external position can be sustained rather long and even without negative consequences for the quality of banking assets if banks expose themselves largely to import-related business activities. A period of currency overvaluation often ends with huge currency depreciations and can be treated as a macroeconomic shock that triggers cyclical downturn with ability to downgrade bank assets quality. In some occasions, appreciation of real exchange rate may be just a follower of favourable change in productivity differentials (Balassa, 1964), and it will indicate moving towards new equilibrium. Such appreciations are not related to trade deficits, so that we need to include export and import data independently.

As long as the currency value can be supported through official foreign exchange interventions, exchange rate return will be smoothed and unable to detect real pressure on the currency market. The pressure on the currency market will then appear in international reserves data. Therefore, we expect also that some indicators of international liquidity help explaining incidence of currency and banking crises. For example, ratio of M2 to international reserves is amongst most frequently used indicators across the banking, currency, and even debt crises EWS. Although reserves coverage ratio can be constructed by using different money stock concepts, M2 (includes also foreign currency deposits) better suits financially dollarized economies. If an access to data is not limited, there is also an option to use net reserves data (excluded foreign currency bank mandatory reserves) or to change numerator into the sum of foreign currency deposits and short-term external debt, which will probably better explain an incidence of sovereign debt crises. Usually, a drop of international reserves signals an incoming financial crisis but may be equally present during the acute phase of the crisis and even afterwards. Therefore, ratio of M2 to international reserves is expected to rise before the crisis.

Slowing down of economic growth may precede or follow years after the banking crisis erupted. In the first case, economic growth may be taken as a leading indicator, although the same indicator is often used to measure intensity and the ultimate social costs of the crisis, so that it is taken as a consequence of the crisis. The slowdown of economic growth may indicate incoming problems of business

TABLE 1 Explanatory variables: Summary of empirical findings

	All financial			Banking					Currency			Debt	
Variables	Lestano et al. (2003)	Rose and Spiegel (2011)	Babecký et al. (2014)	DD (2005), DK (2008), Barrell, Phillip Davis, Karim, and Liadze (2010)	RR (2011), LV (2012)	Caggiano et al. (2014), Caggiano et al. (2016)	Qin and Luo (2014)	Hamdaoui (2016)	Bussiere and Fratzscher (2006)	Mendoza (2010)	Frankel and Saravelos (2012)	Ciarlone and Trebeschi (2005)	Dawood et al. (2017)
External sector													
Exchange rate[a]	*		*	*		*	*	*	*	*	*	*	*
Trade[b]	*	*	*				*	*	*	*	*	*	*
Terms of trade	*		*	*	*			*			*		
Reserves[c]	*			*	*	*	*	*	*		*	*	*
Capital flows[d]							*	*		*	*	*	*
Real and public sector													
Output	*	*	*	*	*	*	*	*	*		*	*	*
Debt[e]	*	*	*					*		*	*	*	
Inflation	*		*	*	*	*	*				*	*	*
Fiscal balance[f]	*			*							*	*	*
Financial sector													
Credit[g]	*	*	*	*		*	*	*	*	*	*		*
Money[h]	*		*			*				*	*		
Interest rate[i]	*		*	*			*				*		
Lending to deposit rate	*							*					
Deposits	*												

(Continues)

TABLE 1 (Continued)

Variables	All financial			Banking					Currency			Debt	
	Lestano et al. (2003)	Rose and Spiegel (2011)	Babecký et al. (2014)	DD (2005), DK (2008), Barrell, Phillip Davis, Karim, and Liadze (2010)	RR (2011), LV (2012)	Caggiano et al. (2014), Caggiano et al. (2016)	Qin and Luo (2014)	Hamdaoui (2016)	Bussiere and Fratzscher (2006)	Mendoza (2010)	Frankel and Saravelos (2012)	Ciarlone and Trebeschi (2005)	Dawood et al. (2017)
Bank reserves	*												

Abbreviations: DD stands for Demirgüç-Kunt and Detragiache (2005), DK for Davis and Karim (2008), RR for Reinhart and Rogoff (2011), and LV for Laeven and Valencia (2012).

[a]Exchange rate: Real, real effective, nominal or nominal effective, deviations from trend.

[b]Trade: Current account or trade balance, relative to GDP, imports, exports.

[c]Reserves: Change in amount of international reserves, reserves relative to M2.

[d]Capital flows: FDI or short term (hot money).

[e]Debt: External or total, debt service ratios.

[f]Fiscal balance: Related to GDP; government expenditures.

[g]Credit: Domestic credit to private sector, or total, relative to GDP.

[h]Money: Money supply, money stock, multiplier, excess money balances.

[i]Interest rate: Credit or market rate, nominal or real, or differential.

units in servicing credit obligations and, in extreme cases, even clustering of bankruptcies across the economy. However, although GDP data better represents overall economic activity output dynamics, researchers often use some indexes of industrial production (output) because EWS demands more frequent data.

Some indicators from monetary sphere may also benefit predictive models, and it seems equally beneficial for banking and currency crisis prediction. For example, inflation rate is a common input in a large number of structured models of equilibrium exchange rate, public debt yield curve, and so forth. It indicates monetary policy mismanagement with a threat to ignite asset price booms (stocks, real estate, etc.). Not only monetary but also fiscal developments (fiscal balance-to-GDP ratio) can tell something about the overall economy fragility. Overly expansive fiscal policy may boost domestic demand, which will be likely to carry over instability onto internal (rise of inflation and interest rates) and external sphere (twin deficits hypothesis).

Outstanding volume of domestic credit appears as the best candidate from the financial sector subsample of predictors. Credit aggregates are used in majority of studies and in various definitions and constructions. Although domestic credit to private sector relative to GDP is often used to represent how mature financial intermediation is, in some occasions, it may also indicate overheating of the economy. A rapid rise of credit volume goes hand in hand with loose credit standards and policy and accumulation of credit risk. Theoretical grounds for adding this indicator are found in credit cycle literature (see, for review, Fielding & Rewilak, 2015), which found capital inflow surges and credit booms significant in explaining probability of banking crises, but only in relatively fragile financial systems. A switch between stringent credit policy and the one that is loose contributes to credit growth acceleration. Modern empirical literature operates with a concept of excessive credit growth (Hume & Sentence, 2009). There is no consensus in terms of what should be assessed as excessive in any specific episode. However, putting aside all the discussion about what determines what, that is, whether GDP drives credit volume or vice versa, changing the ratio of credit to GDP is the simplest way to judge on how excessive was the credit growth. Depending on data availability, researchers may opt for total credit figures (Borio & Drehmann, 2009) instead of credit given only to private sector. For more mature financial systems, the former is to be an option colourful enough, but for transitional or emerging market economies, total credit figures will likely mask important structural changes in credit activity.

There is also a rationale that justifies including various monetary aggregates, for example, money supply/stock variables, or money multiplier, with money stock having more or less the same justification as the credit aggregates. M2

multiplier is the ratio of M2 to money base (high-powered money). It will depend on the forces that drive changes in both numerator and denominator and largely witnesses episodes of surge in foreign currency deposits (residents' or nonresidents') and subsequent changes in bank mandatory reserves. Higher multiplier would indicate larger exposure to bank runs, especially those induced by currency disturbances. In order to identify the determinants of banking crises, Von Hagen and Ho (2007) developed an index of money market pressure, but the results showed that the effects of monetary base growth on the probability of banking crises are negligible.

Although some financial sector (financial development) variables are not that frequent in the listed logit-based studies, they appeared in a seminal signal extraction model for twin crises (Kaminsky & Reinhart, 1999). Some indicators directly express the stance of matters on the main banking markets. For instance, lending to deposit interest rate ratio is a common variable that analysts use to portray how efficient banking intermediation is. The more efficient a banking industry, the less the ratio between lending and deposit interest rate. The rise in the ratio most likely indicates aggravation of nonperforming assets issue, because the spread between those rates is there to compensate banks for perspective credit losses.

A good addition to the previous indicator is real interest rate. This variable explains how big a creditor return is over the level that compensates it for purchasing power that is lost overtime. Steep rise in real interest rate is a common follower of financial (especially capital account) liberalization and more often than not comes joined with surge in capital inflow that itself may jeopardize stability of financial intermediation of less developed economies and an immature banking industry (Qin & Luo, 2014). Inoue and Rossi (2008) analysed a large number of predictors using a new diffusion index and identified output growth, interest rates, and money growth as economic variables with significant predictability power. Researchers sometimes use nominal credit or market rates, or even nominal or real interest rate differential. The last measure is able to indicate the change in relative attractiveness of local to relevant foreign (credit or debt) markets, which will further explain cross-border capital movements.

Although the credit-volume-related variables stay a number one choice for describing what happens on the asset side of bank balance sheet, the change in commercial banks deposits serves the role of the prime variable to portray problems that arise from the liability side. If a bank run features a specific financial crisis episode, it will appear in abrupt change of deposits.

Bank reserves ratio expressed as the share of bank most liquid assets in the total assets is another variable that indicates systemic exposure to liquidity risk and the likelihood of liquidity type of banking crises. Higher ratio of liquid assets (bank liquidity ratio) indicates better chances that banking industry will withstand a massive withdrawal of deposits or credit outflow (see inter alia Barrel et al., 2010). This variable usually substitutes for some monetary variables, like excess money balances. Both variables correspond to the level of abundance/shortage of liquidity with the difference that the liquidity ratio is per se an indicator of bank assets' liquidity, whereas excess money balances includes only the part of bank reserves, that is, money deposited at central bank in excess of mandatory reserves.

The last variable included in our dataset is an institutional feature of banking systems. Similar to Demirgüç-Kunt and Detragiache (2005), we have included deposit insurance dummy that takes the value of one if a country applies an explicit deposit insurance scheme, otherwise zero. This variable is included to describe how sensitive a banking system is to moral hazard.

EWSs sometimes extend set of explanatory variables towards individual bank performance data, specifically some proxies for credit risk (contamination of asset portfolio), interest rate risk, or exchange rate risk exposure. These data proved its importance in single country studies (Khallouli & Nabi, 2013), as well as in models that predict individual bank failures (Demyanyk & Hasan, 2010; Kimmel, Thornton, & Bennett, 2016; Oet, Bianco, Gramlich, & Ong, 2013; Tanaka, Kinkyo, & Hamori, 2016). Unfortunately, our choice of methodology leaves no space for any of those extensions.

5 | THE RESULTS AND DISCUSSION

Logistic regression is used to assess how well a set of predictor variables predicts or explains the categorical dependent variable, *there is/there is no crisis* in this case. We used a binary logistic because the dependent variable is dichotomous. Direct logit regression is derived to check the impact of 15 predictor variables on the occurrence of 64 systemic banking crises that occurred in the period from 1977 to 2013 (Table A1). Predictor variables in the model are fiscal balance-to-GDP ratio, M2 multiplier, domestic credit to private sector-to-GDP ratio, total bank deposits, bank reserves ratio, export volume, import volume, real exchange rate, international (FX) reserves, ratio of M2 to international reserves, industrial production, real interest rate, inflation, lending-to-deposit rate ratio, and deposit insurance system. All predictor variables, except for the deposit insurance system, which is a dichotomous variable, are standardized, and the standardized value of the real exchange rate variable is additionally transformed by differentiation.

After descriptive statistics for variables used in the model (Table A2), stationarity of time series is checked (ADF

stationarity test; Table A3). Stationarity is tested using ADF test. The value of ADF test statistics with all variables is significantly lower than the critical value, which means that variables do not have a unit root and that they are stationary. Before testing the model, it is necessary to determine the level of correlation between variables, because logistic regression is sensitive to high correlation between predictor variables. The study reveals high correlation between the two independent variables, imports and exports (not enclosed). This means that there is no need to include them both in the model. The criterion variable, occurrence of crisis, is dichotomous, where 0 indicates that there is no crisis and 1 that there is crisis (Table 2).

Eight predictor variables make statistically significant and unique contribution to the model (M2 multiplier, domestic credit-to-GDP ratio, bank deposits, bank reserves ratio, international reserves, M2-to-international reserves ratio, real interest rate, and deposit insurance system), $p < .05$. The negative values of the β coefficient are recorded with the following indicators: M2 multiplier, domestic credit-to-GDP ratio, bank deposits, bank reserves ratio, and real interest rate, indicating that these variables are inversely proportional to the emergence of crisis, that is, the lower the value of these variables, the higher the likelihood of the crisis. With other statistically significant variables (international reserves, M2 to international reserves, and deposit insurance system), the value of β coefficient is positive, indicating that the rise in the value of these variables increases the likelihood of a crisis. The strongest predictor is international reserves, with odds ratio of 538. This means that if volume of international reserves increases by a single unit of measure, chance that the crisis will occur increases 538.48 times. This claim is made with 95% confidence interval between 69.23 and 4187.89. If ratio of M2 to international reserves increases by one unit of measure, chance that the crisis will occur increases 52.38 times. This claim is made with 95% confidence interval between 13.10 and 209.46. If there is an explicitly defined deposit insurance system, the chance of the crisis is 22.51 times higher. This confirms the fact that the lack of an adequate system of supervision in this period created a favourable environment for the outbreak of crisis. If M2 multiplier, bank deposits, bank reserves ratio, and real interest rate increase by one unit of measure, chance that the crisis will occur decreases 0.20, 0.02, 0.07, and 0.40 times, respectively. Rise in the value of credit-to-GDP ratio by one unit of

TABLE 2 Results of the evaluated logit model with 14 independent variables

							95% Confidence interval for odds ratio	
Indicators	***β***	**Standard error**	**Wald**	***df***	***p***	**Odds ratio**	**Lower limit**	**Upper limit**
ZFiscal balance to GDP	.079	.249	.101	1	.750	1.083	.664	1.765
ZM2 multiplier	−1.619	.657	6.071	1	.014	.198	.055	.718
ZCredit-to-GDP ratio	−11.568	2.261	26.175	1	.000	.000	.000	.001
ZBank deposits	−3.979	.912	19.056	1	.000	.019	.003	.112
ZBank reserves ratio	−2.708	.698	15.067	1	.000	.067	.017	.262
ZImport volume	−.534	.634	.709	1	.400	.586	.169	2.032
ZReal exchange rate	−3.742	2.168	2.978	1	.084	.024	.000	1.661
ZInternational reserves	6.289	1.047	36.108	1	.000	538.478	69.237	4187.898
ZM2 to international reserves	3.959	.707	31.339	1	.000	52.384	13.100	209.463
ZIndustrial production	−.151	.412	.135	1	.713	.860	.384	1.926
ZReal interest rate	−.929	.392	5.618	1	.018	.395	.183	.851
ZInflation	−.157	.283	.311	1	.577	.854	.491	1.486
ZLending-to-deposit rate ratio	−.197	.637	.095	1	.757	.821	.236	2.864
Deposit insurance system	3.114	1.053	8.751	1	.003	22.507	2.860	177.119
Constant	−5.144	1.260	16.669	1	.000	.006		

Source: Authors' calculations.

Note. The model includes 253 cases, and when it does not have any predictor variables, 52.4% of cases are correctly classified. A model that includes all predictor variables is statistically significant, $\chi^2(14) = 155.63$, $p = .00$, which indicates that the model can distinguish cases with crisis from those with no crisis. Hosmer and Lemeshow test supports the model given that the test result is not statistically significant, $\chi^2(8) = 15.39$, $p = .05$. The model explains between 46.1% (Cox and Snell R^2) and 61.5% (Nagelkerke R^2) of variations in the dependent variable, and it correctly classifies 86.1% of cases. The model correctly classifies 80.3% of the cases without crisis and 92.5% of the cases with crisis. Positive predictive value is 81.02%, indicating that the model correctly predicts 81% of the crisis events. Negative predictive value is 91.17%, indicating that the model correctly predicts 92% of the cases of no crisis.

measure does not alter the chances that the crisis will occur.

5.1 | Logit regression model with dynamic variable

In order to improve results of previous model, we include a lagged dependent variable into the set of explanatory variables and run a logistic panel regression. The model that we get that way is known as dynamic discrete-choice (binary) EWS. A dynamic variable is derived from criterion variable, with a lag of 10 periods (lag = 10). Because there is no objective criterion, we decided to work with a lag of 10 periods, because it is the earliest period when the dynamic variable is statistically significant. This practically means that the dynamic variable, in combination with other statistically significant variables in the model, can point to the emergence of the crisis 10 months before it occurs (Table 3).

Eight predictor variables make a statistically significant and unique contribution to the model: M2 multiplier, credit-to-GDP ratio, bank deposits, bank reserves ratio, international reserves, M2-to-international reserves ratio, deposit insurance system, and the lagged (dynamic) variable. The negative values of the β coefficient are recorded with the following indicators: M2 multiplier, credit-to-GDP ratio, bank deposits, and bank reserves ratio. With other statistically significant variables (international reserves, M2-to-international reserves ratio, deposit insurance system, and dynamic variable), the value of β coefficient is positive. The most significant predictor of the crises is deposit insurance system, with odds ratio calculated at 743.42. This suggests that, if there is an explicitly defined deposit insurance system, the chance of the crisis is 743 times higher. This claim is made with 95% confidence interval between 33.16 and 16669. If volume of international reserves increase by a single unit of measure, chance that the crisis will occur increases 450.26 times. This claim is made with 95% confidence interval between 39.51 and 5131.23. If ratio of M2 to international reserves increases by one unit of measure, chance that the crisis will occur increases 56.92 times. This claim is made with 95% confidence interval between 10.06 and 322.27. When the value of dynamic variable is 1, meaning that there is a crisis, odds of crisis increase 63.80 times. If M2 multiplier, bank deposits, and bank reserves ratio increase by one unit of measure, chance that the crisis will occur decreases 0.11,

TABLE 3 Results of logit model with dynamic variable

							95% Confidence interval for odds ratio	
	β	Standard error	Wald	*df*	*p*	Odds ratio	Lower limit	Upper limit
ZFiscal balance to GDP	.221	.296	.556	1	.456	1.247	.698	2.230
ZM2 multiplier	−2.199	.788	7.779	1	.005	.111	.024	.520
ZCredit-to-GDP ratio	−13.652	2.962	21.240	1	.000	.000	.000	.000
ZBank deposits	−5.186	1.172	19.576	1	.000	.006	.001	.056
ZBank reserves ratio	−4.339	.907	22.896	1	.000	.013	.002	.077
ZImport volume	.582	.827	.496	1	.481	1.790	.354	9.053
ZReal exchange rate	−2.029	2.603	.608	1	.436	.132	.001	21.598
ZInternational reserves	6.110	1.241	24.220	1	.000	450.257	39.509	5,131.226
ZM2 to international reserves	4.042	.885	20.879	1	.000	56.924	10.055	322.267
ZIndustrial production	−.679	.562	1.458	1	.227	.507	.168	1.527
ZReal interest rate	−.650	.525	1.531	1	.216	.522	.187	1.461
ZInflation	−.060	.199	.091	1	.763	.942	.637	1.391
ZLending-to-deposit rate ratio	1.063	.872	1.484	1	.223	2.895	.524	16.001
Deposit insurance system	6.611	1.587	17.359	1	.000	743.419	33.156	16,669.028
CRISIS_LAG_10	4.156	.670	38.442	1	.000	63.801	17.151	237.333
Constant	−10.806	2.006	29.013	1	.000	.000		

Note. A complete model, which contains all predictor variables, is statistically significant, $\chi^2(15) = 220.02$, $p = .00$, which indicates that the model can distinguish cases with crisis from those with no crisis. Hosmer and Lemeshow test supports the model given that the test result is not statistically significant, $\chi^2(8) = 8.84$, $p = .36$. The whole model explains between 58.2% (Cox and Snell R^2) and 77.7% (Nagelkerke R^2) variations regarding the status of crisis, and it correctly classifies 89.7% of cases. The model correctly classifies 90.2% of the cases without crises and 89.2% of the cases where the crisis occurs. The positive predictor value is 89.17%, which indicates that the model correctly predicted 89% of the crisis events. The negative predictor value is 90.15%, which indicates that the model correctly predicted 90% of the cases of no crisis.

TABLE 4 Comparison of static versus dynamic model

	AUC	*SE*	*p*	95% Confidence interval	
				Lower limit	Upper limit
Static model	.897	.022	.000	.855	.939
Dynamic model	.960	.011	.000	.938	.981

0.01, and 0.01 times, respectively. Rise in the value of credit-to-GDP ratio by one unit of measure does not alter the chances that the crisis will occur.

In order to test goodness-of-fit of these two models, ROC curve is used. Both models are significant ($p < .05$), indicating that both the static model and the model with dynamic variable better classify cases of crisis or its absence than mere chance. The area under the curve (AUC) is 0.897 in a model without a dynamic variable, and 0.96 in a model with a dynamic variable (Table 4). Testing the significance of the difference between the two AUCs is done by DeLong test for two ROC curves. The obtained result ($D = -2.2858$, $df = 3909.9$, $p = .0228$) indicates that we can reject the zero hypothesis, that is, that there is a statistically significant difference between the two curves.

The AUC is larger for model with a dynamic variable than with the static model, which indicates that the model with dynamic variable with higher accuracy classifies cases of actual crisis or its actual absence than the static model (Figure 1).

5.2 | Out of sample analysis

In order to test goodness of previous models, we used out of sample analysis. The both models are tested with two crises that were not included in the sample used to predict the crisis likelihood. The first model (without a dynamic variable) correctly classified 61.76% of the total number of cases, which is slightly (2.94%) less than the model without any predictor variable, which correctly classified 64.70% of cases. The model with training data correctly classified 86.1% of cases, which is 24.34% more than this model tested with other data (out of sample). The model correctly classified 81.82% of the cases without crises (specificity) and 25% of the cases where there is crisis (sensitivity). The positive predictor value is 42.86%, which indicates that the model correctly predicted 43% of crisis cases. The negative predictor value is 66.67%, which indicates that the model correctly predicted 67% of the no crisis cases. In a model without a dynamic variable, the AUC is 0.585, which is slightly above the 0.5 threshold and points to the weak predictive power of the model.

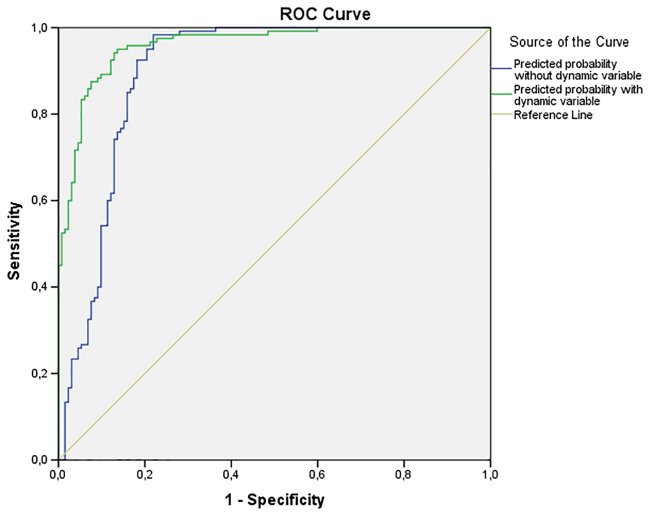

FIGURE 1 Source of the Curve in Legend [Colour figure can be viewed at wileyonlinelibrary.com]

The second model (with a dynamic variable) correctly classified 65.38% of the total number of cases, which is by 11.53% more than the model without any predictor variable, which correctly classified 53.85% of cases. The model with training data correctly classified 89.7% of cases, which is 24.32% more than this model tested with other data (out of sample). The model correctly classified 100% of the cases without crises (specificity) and 25% of the cases where there is crisis (sensitivity). The positive predictor value is 100%. The negative predictor value is 60.87%, which indicates that the model correctly predicted 61% of the no crisis cases. In a model with a dynamic variable, the AUC is 0.585, which is slightly above the 0.5 threshold and points to the weak predictive power of the model.

6 | CONCLUSION

The paper builds an econometric EWS of 64 systemic banking crises that occurred in the period from 1977 to 2013. The selection of explanatory variables gathers most powerful predictors that economic theory identified as joint determinants of various types of financial crises: systemic banking crises, currency crises, and debt crises. Specifically, empirical regularity indicates that different types of financial crises are rooted in similar weaknesses of economy or may have common determinants, but the very transmission mechanism may determine one category as leading or lagging behind others. We are focused on financial crises that necessarily have the features of systemic banking crises, whether at the same time showing defining features of other generic types of financial crises. We extract three groups of indicators from vast empirical literature (external, domestic, and

financial), by adopting a crisis events dating scheme as in Laeven and Valencia (2012), and have tested up to 15 predictors.

The paper employs two different procedures, based on panel logit regression. The dynamic discrete-choice (binary) early warning model clearly outperformed the static model. The set of significant explanatory variables changed relative to the findings of the static model. The most significant predictor of the crises in the better performing model is deposit insurance system, followed by international reserves, M2-to-international reserves ratio, M2 multiplier, bank deposits, and bank reserves ratio. The statistical significance of the lagged variable confirmed the necessity to take the effect of crisis persistence into account. In order to test goodness of previous models, we used out of sample analysis. The both models are tested with two crises that were not included in the sample used to predict the crisis likelihood. The both models have the weak predictive power.

ENDNOTES

[1] Saxena (2004) graphically demonstrated how the nature of currency crises has changed over time.

[2] Reinhart and Rogoff (2014) classified economic (merely financial) crises into five varieties: banking crises, currency crashes, external default, domestic default, and inflation outbursts.

[3] See more about differential diagnostics of banking and currency crises in (Joy et al., 2017).

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APPENDIX A

TABLE A1 Banking crises in the sample

Country and date	
Argentina 1980, 2001	Republic of Korea 1982
Austria 2008	Lebanon 1990
Belgium 2008	Lithuania 1995
Brazil 1994	Luxembourg 2008
Bulgaria 1996, 2008	FYR Macedonia 1993, 2008
Burundi 1994	Mexico 1994
Cameroon 1987, 1995	Netherlands 2008
Chile 1981	Nigeria 1991, 2009
Republic of Congo 1992	Norway 1991
Croatia 1998	Poland 1992
Croatia 2008	Portugal 2008
Czech Republic 1996	Romania 1990
Dominican Republic 2003	Russian Federation 1998, 2008
Ecuador 1982, 1998	Slovak Republic 1998

(Continues)

TABLE A1 (Continued)

Country and date	
France 2008	Slovenia 1992, 2008
Germany 2008	Spain 1977, 2008
Greece 2008	Sweden 1991, 2008
Guinea-Bissau 1995	Switzerland 2008
Hungary 1991, 2008	Tanzania 1987
Iceland 2008	Thailand 1997
Indonesia 1997	Turkey 2000
Ireland 2008	Ukraine 1998, 2008
Italy 2008	United States 1988, 2007
Jamaica 1996	Uruguay 1981, 2002
Jordan 1989	Venezuela 1994

TABLE A3 Augmented Dickey–Fuller Tests

Variables	ADF	*p*
ZFiscal balance to GDP	−11.86	.01
ZM2 multiplier	−4.29	.01
ZCredit-to-GDP ratio	−7.86	.01
ZBank deposits	−2.14	.03
ZBank reserves ratio	−2.44	.02
ZVolume of export	−3.05	.01
ZVolume of import	−2.95	.01
ZReal exchange rate	−14.80	.01
ZInternational reserves	−2.94	.01
ZM2 to international reserves	−4.29	.01
ZIndustrial production	−2.53	.01
ZReal interest rate	−3.00	.01
Zinflation	−15.40	.01
ZLending to deposit rate	−2.13	.03

TABLE A2 Descriptive statistics

Variable	Mean	Median	*SD*	Min	Max
Fiscal balance to GDP	0.00	0.00	0.02	−0.37	0.31
M2 multiplier	5.10	3.57	3.93	0.00	28.96
Credit-to-GDP ratio	1.46	0.36	43.26	0.00	2,159.05
Bank deposits	1.378E+13	1.097E+11	6.459E+13	57.90	5.997E+14
Bank reserves ratio	0.12	0.06	0.56	−0.08	16.73
Volume of export	5.461E+9	1.1565E+9	1.448E+10	6,213.69	1.168E+11
Volume of import	7.010E+9	1.367E+9	2.400E+10	1,266,450.99	2.087E+11
Real exchange rate	94.57	96.09	31.70	27.76	273.49
International reserves	1.433E+10	3.823E+9	3.827E+10	450,603.26	3.625E+11
M2 to international reserves	43.12	5.52	184.09	0.00	2,891.49
Industrial production	45.65	38.58	44.07	−26.90	150.45
Real interest rate	−76.69	−5.22	400.28	−6821.28	156.20
Inflation	104.42	100.69	186.20	−2,320.00	8,730.00
Lending to deposit rate	2.69	1.73	4.15	0.65	45.50
Deposit insurance system	0.54			0.00	0.31