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A closer look at financial development and income distribution

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Abstract

This paper analyzes the under-investigated relationship uniting financial development and income distribution. We use a novel approach taking into account for the first time the specific channels linking banks, capital markets and income inequality, the time-varying nature of the relationship, and reciprocal causality. We construct a set of annual indicators of banking and capital market size, robustness, efficiency and international integration. We then estimate the determinants of income distribution using a panel Bayesian structural vector autoregressive (SVAR) model, for a set of 49 countries over the 1994-2002 period. We uncover a significant causality running from financial sector development to income distribution. In addition, the banking sector seems to exert a stronger impact on inequality. Finally, the relationship appears to depend on the characteristics of the financial sector, rather than on its size.

JEL classification: C33; D63; G15; O16
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1. Introduction

Although financial development is, over the long run, beneficial to economic growth, the normative question of the allocation of generated wealth remains largely unexplored to this date (Bekaert and Harvey, 2002). As shown by the recent financial crisis, how financial development impacts different categories of the population determines nonetheless the legitimacy of policy choices. In addition, understanding the distributional impact of financial reforms would permit to better tailor the content and sequencing of economic policy in emerging countries (Das and Mohapatra, 2003). More generally, one may wonder whether and how can financial sector policy be used as an instrument to alter income distribution, in the objective of generating 'pro-poor' economic growth.

In spite of an increasing academic focus on the subject, empirical studies remain relatively scarce. A set of pioneering studies analyzed the impact of market size on income distribution (often using domestic banking sector development as a proxy for the development of the financial industry as a whole), and suggested that financial development exerts a negative impact on the growth rate of the Gini coefficient (Beck, Demirgüc-Kunt and Levine, 2007). Size, however, may not entirely capture the complex mechanisms uniting finance and income distribution. Indeed, the ongoing financial crisis demonstrates that the relationship between finance and economic welfare depends ultimately on banks' and capital markets' ability to identify profitable projects, to monitor internal and external risk levels, and to ease transactions. Taking this into account, this paper attempts to extend the existing empirical literature in two directions.

First, we seek to model the complex transmission mechanisms uniting banks, capital markets and income distribution. This implies constructing a set of time-varying variables capturing the size, robustness, efficiency and international openness of banks and capital markets.

In addition, income distribution tends to follow a nonlinear path (Kuznets, 1955). Structural breaks and reciprocal causality should therefore be incorporated into the empirical framework. Our modelling strategy hence relies on a panel version of Bayesian vector autoregressive (VAR) model, which permits detecting potential structural breaks in the relationships through the analysis of variance decomposition and impulse response functions, while also controlling for reciprocal causality and stationarity issues. To the best of our knowledge, there are no other existing papers looking at the issue through these two angles.

This two step detailed approach should yield valuable information for policy makers seeking to design the content and sequencing of financial reforms, especially in developing countries.

Our results highlight a significant causality mechanism running from financial sector development to income distribution. In addition, we find that the banking sector exerts a stronger distributional impact than capital markets. Finally, the relationship appears to depend on the financial sector's transparency and ability to allocate resources optimally, rather than its size and level of international integration.

The remainder of the paper is structured as follows. Section 2 discusses the theoretical linkages uniting financial sector development and income distribution. Section 3 presents our database and some methodological notes on the construction of our variables. Section 4 describes our modelling framework, section 5 discusses our results and section 6 brings together our conclusions.

2. Financial sector and income distribution

2.1. Banking sector development and inequalities

On a theoretical level, the development and international integration of domestic banks exert contradictory effects on income distribution. If credit markets are underdeveloped, access to finance is conditional on dynastic assets (i.e. personal wealth, political connections...)

(Banerjee and Newman, 1993). This generates entry barriers, less opportunities for the neediest, slower economic growth and higher income inequality (Rao, 2006). By contrast, competitive financial institutions improve resource mobilization, align project selection with expected risk-adjusted returns, and widen the entrepreneurial base (Demirgüc-Kunt and Levine, 2009). Banking development also smoothes household consumption and saving decisions, with desirable implications for income volatility, human capital accumulation, and even child labour.

However, credit market imperfections restrict access to credit to the least risky segment of households and firms (i.e. those enjoying high income and collateral), regardless of the sector's size (Banerjee and Newman, 1993). These imperfections could be due to institutional factors, such as oligopolistic sector structure and connections between large bank managers and policy-makers (Narayana, 2000). Ex-ante moral hazard among creditors also restricts access to finance: low income individuals need to incur larger loans for a given investment project, which diminishes their return on investment and their incentive to invest (Ferreira, 1999). In addition, financial development increases returns to skills and entrepreneurship, and could therefore widen inequalities if human capital is unevenly distributed.

International integration and shock vulnerability constitute a separate issue. High risk aversion levels, short termism, sudden expectation shifts and herding behavior in international financial markets made local banks extremely vulnerable to liquidity crises for the past two decades. However, international risks were often magnified by lax prudential supervision, fast credit expansion and moral hazard in domestic banking systems (Büyükkarabacak and Valev, 2010). Banking crises impact income distribution via two channels (Honohan, 2005). If high income households and firms export their capital ahead of the crash, then only the most vulnerable agents suffer, resulting in higher inequality levels. If wealthier households and firms are affected by the crisis too, inequalities could temporarily narrow, but the ensuing increase in domestic bankruptcies and lay-offs would first impact most vulnerable households, with, again, undesirable consequences for income distribution. Overall, the mechanisms uniting banks and income distribution are complex and may vary over time according to the domestic institutional context.

2.2. Capital market and inequalities

International finance suggests that equity market development lowers discount rates and provides additional financing sources to the real sector, resulting in increased investment levels. This dynamic could improve income distribution in the middle run by transferring wealth from creditors to debtors (Aghion and Bolton, 1997). Valuation gains and losses may nonetheless impact different income quintiles asymmetrically if equity market participation is segmented by income groups. Lower discount rates also result in an upward shift in average NPV, which can increase inequalities if operating cash flows are not reinvested in the real sector but distributed as dividends instead (Das and Mohapatra, 2003). Finally, recent studies suggest that market-based economies tend to be more unequal due to the fact that large firms disproportionately benefit from stock market development (Aggarwal and Goodell, 2009).

It should be noted that market microstructures also affect the relationship. Without adequate informational efficiency levels, a restricted set of dominant players would cause stock prices to deviate from their intrinsic value, so that the gains of equity market development and integration would be captured by crony institutions and rent-seeking individuals.

Capital account convertibility has separate distributional implications. On the one hand, long term capital flows ease the financing constraint for local projects, and should have a similar distributional impact than domestic market development. On the other hand, foreign direct investment usually increases the demand for skilled workers. This boosts returns to skills and flattens the income distribution curve if human capital is unevenly distributed in the host economy. In the absence of adequate efficiency levels, financial integration favours insiders by giving them access to international capital. Capital flights to offshore accounts are a related issue implying fiscal losses, less investment, and less redistribution (Claessens and Perotti, 2007).

Analyzing the impact of financial development on income distribution should therefore take into account not only the size, but also the characteristics of banks and financial markets as well as time-varying dynamics. In what follows, we thus first develop annual variables capturing the size, efficiency, liquidity, and international exposure of the banking sector. Turning to capital markets, we measure size as well as *de facto* international integration, volatility, and efficiency. We then analyze the impact of these factors on income inequality, controlling for nonlinearities and reciprocal causality. This approach should raise useful information for policy makers operating in developed and emerging countries.

3. Dataset

3.1. Income distribution data

Most existing empirical research papers on inequality rely on GINI coefficients as taken from Deininger and Squire (1996). However, this master dataset suffers from a few inconsistencies. It mixes three data types: gross versus net income data, household versus individual income data and income versus expenditure data. In addition, observation frequency is low, and the series are plagued by many unexplained jumps. To correct for these biases, researchers sometimes extrapolated coefficient values between two surveys, or used extended data interval. This, however, creates serial dependencies in measurement errors and affects the robustness of estimation parameters.

To avoid these problems, we rely on an alternative inequality indicator named Estimated Household Income Inequality (EHII). This indicator was originally developed by Galbraith and Kum (2003) and subsequently updated by Daymon and Gimet (2009). It proxies income inequality by combining information from the GINI coefficient with a more precise (although more restrictive) Theil-index based measure of dispersion of pay within the industrial sector, which is taken from the UTIP-UNIDO database. Assuming that all measurement errors except those related to data type are random, Galbraith and Kum (2003) used the following OLS model:

$$GINIDS = \alpha + \beta T + \gamma X + \varepsilon \qquad (1)$$

In (1), *GINIDS* represents the Denninger and Squire (1996) GINI coefficient, α is a constant, T is the Theil-index based measure of wage inequality within the industrial sector, and X is a vector of conditioning variables including a set of dummies reflecting data source and the manufacturing employment to total population ratio (a time-varying indicator of sector specialization). In its logarithmic form, the EHII indicator is then defined as:

$$EHII = \hat{\alpha} + \hat{\beta} T + \hat{\gamma} X \qquad (2)$$

In (2), *EHII* stands for Estimated Household Income Inequality, *T* is the UTIP-UNIDO pay inequality index, and *X* is the matrix of conditioning variables. The intercept ($\hat{\alpha}$) and coefficients ($\hat{\beta}$ and $\hat{\gamma}$) are deterministic terms extracted from equation (1). This approach permits an appropriate filling-in of missing inequality observations by replicating the UTIP-UNIDO data set with estimated measures of household inequality. Although not perfect, the updated EHII database is to the best of our knowledge the most precise and extensive source of information on international income distribution to this date.

3.2. Control macroeconomic variables

In line with previous literature, we control for economic development levels, trade integration and international financial integration. Data is taken from the IMF International Financial Statistics CD-Rom (2009) and the World Bank's World Development Indicators database

(2009). We proxy for economic development levels through GDP and GDP per capita in current US dollars (*gdp*, *gdpcap*). We measure trade integration by calculating the openness rate as defined by the sum of imports and exports to GDP ratio (*openness).* Finally, we use the standard flow-related international financial integration indicator developed by Lane and Milesi-Ferretti (2006). This variable is defined as the sum of the stock portfolio equity and the stock of direct investment assets and liabilities to GDP (*milesi*). Finally, all our models include time and country effects as well as the lagged EHII variable to control for unobserved factors.

3.3. Banking sector variables

We seek to include both the size and the characteristics of the banking sector in our analysis. We measure the banking sector's ability to mobilize resources by calculating domestic credit as a percentage of GDP (*domcred*). We proxy for banking efficiency by calculating the difference between the lending rate and the deposit rate (*spread*). A higher value of this indicator suggests weak competition in the banking sector, high transaction costs and low efficiency. We may also hypothesize that weak competition implies higher fragility, in line with the concentration-fragility argument (Uhde and Heimeshoff, 2009). In addition, we capture country specialization in financial services by taking financial and insurance industry exports as a percentage of commercial exports (*insurfi*). Finally, we measure shock vulnerability and fragility through the liquid reserves to asset ratio (*liq*). A lower value of this indicator suggests that banks are more vulnerable to a sudden deterioration of international lending conditions.

3.4. Capital market variables

Two ubiquitous market development indicators often found in the literature are the market capitalization of listed companies to GDP ratio (*mc2gdp*) and the turnover ratio (t*urnover*). In an effort to better capture stock market characteristics, we also construct a number of time-varying proxies for market characteristics. These are computed using daily dollar stock market index series for each country, as well as for the S&P 500 as a global benchmark. Data ranges from 1/1/1994 (the earliest stock market data point for most emerging countries) to 12/31/2002 (the latest data point in the EHII database). We use national indices rather than rating agencies indices in order to include the broadest segment of companies into the analysis. All indices are downloaded from *Datastream International*. When the methodology requires it, indices are transformed into logarithmic returns. For each included country, we develop a battery of annual *de facto* indicators capturing important dimensions such as informational efficiency, volatility, transaction costs and international integration.

3.4.1. Efficiency

Recursive random-walk test (PV1)

A wide body of research developed tests for random walks in financial time-series. Within this literature, Wright's (2000) non-parametric test based on ranks was shown to have high power against a wide range of alternative models displaying serial correlation. Given T observations of first differences of a variable, $\{y_1 \dots y_T\}$ Wright's R1 test statistic is defined as:

$$R_1(k)\left(\frac{\frac{1}{Tk}\sum_{t=k}^{T}\left(r_{1t}+\dots+r_{1t-K+1}\right)^2}{\frac{1}{T}\sum_{t=1}^{T}r_{1t}^2}-1\right)\times\phi(k)^{-\frac{1}{2}} \tag{3}$$

$$r_{1t} = \left(r(y(t) - \frac{T+1}{2} \right) \Big/ \sqrt{\frac{(T-1)(T+1)}{12}} \tag{4}$$

In (3), $\phi(k) = \frac{2(2k-1)(k-1)}{3kT}$ and r_{1t} is the rank of y_t among observations $y_1 ... y_T$. The exact distribution of $R_1(k)$ and critical values are obtained from a bootstrap method on $r(x_t)$. In order to control for size distortion, we run the test sequentially over several values of *k* and select the appropriate statistic using the extremum approach suggested in Kim and Shamsuddin (2008). Following Lagoarde-Segot (2009), annual p-values from this test are used as indicators of relative efficiency.

Test of evolving efficiency (kalman)

As a robustness check, we also measure weak-form efficiency hypothesis through an explicit time-series modelling framework, as suggested in Emerson et.al (1997):

$$r_t = \beta_{0t} + \sum_{i=1}^{p} \beta_{it} r_{t-i} \tag{5}$$

Where *r* denotes returns and *t* is the time subscript. Controlling for changing variance in the error process, they combined the above specification with a GARCH-in-mean model:

$$\begin{aligned} r_t &= \beta_{0t} + \sum_{i=1}^{p} \beta_{it} r_{t-i} + \partial h_t + e_t \quad e_t \sim \mathrm{N}(0, \mathrm{h_t}) \\ h_t &= \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 e_{t-1} \end{aligned} \tag{6}$$

This model is then estimated via the following Kalman filter procedure:

$$r_t = \beta_{0t} + \sum_{i=1}^{p} \beta_{it} r_{t-i} + \partial h_t + e_t \quad e_t \sim \mathrm{N}(0, \mathrm{h_t}) \tag{7a}$$

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 e_{t-1} \tag{7b}$$

$$\beta_{it} = \beta_{it-1} + v_{it} \quad v_{it} \sim \mathrm{N}(0, \sigma_{\mathrm{i}}^2) \tag{7c}$$

Where (7a) is the space equation and (7b) and (7c) are the two state equations, respectively. In equation (7c), β_{it} tracks time-varying deviations from the random walk. We estimate the model over the entire sample and then use the annual average of β_{it} (taken in absolute value) as an indicator of relative market inefficiency for each country.

3.4.2. Volatility and transaction costs

GARCH modelling (garch)

We give a formal structure to stock market volatility using an intuitive GARCH (1,1) specification. We then use annual average predicted variance of daily returns as an indicator of equity market volatility. The model is described as follows:

$$r_t = \alpha + \beta r_{t-1} + e_{t-1} \tag{8}$$
$$\sigma_t^2 = \delta + \gamma_1 \sigma_{t-1}^2 + \gamma_2 e_{t-1}$$

In (8), the first equation describes the stock return mean r_t which depends on a constant, its lagged value and i.i.d residual ε_{t-1}. The second equation describes the variance of the error term, which has three components: a constant, the last period's variance (the GARCH term), and the last period's squared residual (the ARCH term). The unit variance assumption for the innovation process, ε_{t-1}, ensures that σ_t^2 is the variance of r_t, depending on the information set, F_{t-1}, that contains the past history of the process up to period $t - 1$.

Transaction costs (DNI)

Turnover ratios are included as control variables and provide an intuitive proxy for liquidity levels. However, the structure of auto-covariance in stock market returns better tracks the evolution of bid-ask spreads and transaction costs. We follow De Nicolò and Ivaschenko (2009) and capture market frictions through a simple decomposition of return variance. For a given time horizon *t* divided in *K* trading day and s subintervals, returns at time t satisfy:

$$R_t = \sum_{s \in K} R_s$$
$$Var_t(R_t) = \sum_{s \in K} Var(R_s) + 2\sum_{i,j \in K, i \neq j} Cov(R_i, R_j) \tag{9}$$

The magnitude of the auto-covariance term in equation (9) reflects the presence of transaction costs and market frictions. In the next step, a transaction costs indicator is constructed:

$$L_t = \frac{2\left(\left|\sum_{i,j \in K, i \neq j} \mathrm{cov}(R_i, R_j)\right|\right)}{\sum_{s \in K} \mathrm{var}_t(R_s) + 2\left(\left|\sum_{i,j \in K, i \neq j} \mathrm{cov}(R_i, R_j)\right|\right)} \tag{10}$$

Where K is the annual horizon, i and j denote daily observations. Covariances and variances are estimated from a GARCH(1,1) model. Absolute values are used in order to capture all possible sources of market frictions. The indicator ranges from 0 to 1 and increases with transaction costs and inefficiency. This indicator is calculated on an annual basis.

3.4.3. Equity market integration

Recursive trace statistic (trace)

Following a vast literature, we implement annual bi-variate cointegration tests between country indices and the world benchmark using the standard methodology of Johansen and Juselius (1990):

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + (...) + \Gamma_{k-1} \Delta Y_{t-k+1} + \pi Y_{t-k} + \mu + \varepsilon_t \tag{11}$$

In (11), Y_t=(2×1) is a vector of stock prices, π=(2×2) is a parameter matrix, and μ=(2×1) are intercept terms. The lag length (k) is chosen based on the Akaike information criterion (AIC) applied on the undifferenced VAR models. The parameter matrix π indicates whether the vector of stock prices (Y_t) has a long-run dynamic relationship or not. If the rank of π equals the number of variables (*2*), i.e. if π has full rank, the long-run equilibrium is given by *2* independent equations and the two stock price series are stationary in levels. If rank of π is zero, the stock price series (Y_t) are unit root processes, there is no error correction and thus no cointegration. For the bivariate case, cointegration is suggested if the rank of π is equal to 1. In line with standard practice, we use annual Trace statistics as indicators of time-varying long term integration. Higher statistics indicate higher level of integration, while lower statistics suggest the opposite.

Systematic risk exposure (akdogan)

As a robustness check, we also monitor country exposure to international shocks through a standard time-varying risk-decomposition model. Consider a standard asset pricing model:

$$R_i = \alpha + \beta R_g + \varepsilon_i \tag{12}$$

Where R_i is the rate of return on the ith country, R_g is the global rate of return, b is the beta of the ith country with respect to the global index, and ε_i is the error term. Following Akdogan (1997), the variance of country returns can then be broken down into:

$$Var(R_i) = \beta^2 Var(R_g) + Var(\varepsilon_i) \tag{13}$$

$$\frac{VarR_i}{VarR_i} = \frac{\beta^2 VarR_g}{VarR_i} + \frac{Var\varepsilon_i}{VarR_i} \tag{14}$$

$$1 = p_i + q_i \tag{15}$$

In equation (15), p_i measures the country's exposure to worldwide systemic risk. This score is calculated on an annual basis and constitutes a time-varying indicator for shock vulnerability.

Taking the intersection of our income distribution, macroeconomic and financial datasets leaves us with an unbalanced panel of annual observations for the 1994 to 2002 period, for a total of 49 countries. Our sample is well diversified and includes 21 high-income countries, 12 upper-middle income countries, 12 lower middle-income countries and 4 low-income countries. These are spread over 7 regions: 10 Asian countries, 11 Western European countries, 4 Central and Eastern European countries, 10 Middle East and North African countries, 8 Latin American countries, 4 Sub-Saharan African countries and 2 North American countries. Summary statistics on the final database is shown in table 1.We then proceed to the analysis of the relationships uniting financial development and income inequality.

4. Methodology

4.1. The Bayesian S-VAR model

A Bayesian panel S-VAR model appears appropriate for the purpose of our study. The VAR method permits to estimate the dynamic impact of financial development on income distribution and control for reciprocal causality. Given that to our sample is constituted of a high number of countries and a relatively limited time span, panel data analysis seems appropriate as it brings out individual heterogeneity and permits to identify effects that are not easily detected in time series or cross-sectional data. Finally, we use a Bayesian inference in order to overcome problems of interdependencies and time variations in estimation coefficients. In addition, this approach ensures that the model is not affected by unit-root problems, which permits to take all variables in levels and to increase the number of degrees of freedom (Sims and Uhlig, 1991). In line with common practice, all variables are taken in logarithms (except for the volatility variables).

The Structural Bayesian VAR model is estimated according to the method developed by Sims and Zha (1999). The reduced form of the vector auto-regression model VAR(q) is given as:

$$Y_{i,t} = \sum_{i=1}^{n} \sum_{j=1}^{q} A_j Y_{i,t-j} + e_{i,t} \tag{16}$$

In (16), q is the number of lags, n is the number of countries, $Y_{i,t}$ is the vector of endogenous variable, Y_{t-j} is the n x 1 vector of lagged variables for each i, A_j is the n x n parameter matrix, and e_{it} is the vector of errors with $e_{it} = b_i + b_t + b_{it}$ where b_i is the individual fixed effect, b_t is the time fixed effect and b_{it} is the disturbance term whose variance-covariance matrix has no restrictions, i.e. $E(b_{i,t}, b_{i,t}^T) = \Omega$ and $E(b_{i,t}) = 0$. Letting L be the lag operator, the VAR(q) model can be rewritten as:

$$A(L)Y_{i,t} = e_{i,t} \tag{17}$$

This process is transformed in moving average infinite structural form to yield the impulse response functions and the forecast error variance decomposition. An intermediate step consists in reversing the canonical VAR model using the Wold Theorem. This yields the moving average form:

$$Y_{i,t} = \sum_{i=1}^{n} \sum_{k=0}^{\infty} C_k e_{i,t-k} = C(L)e_{i,t} \tag{18}$$

where e_t represents the vector of canonical innovations. The structural Moving Average representation is then:

$$Y_{i,t} = \sum_{i=1}^{n} \sum_{k=0}^{\infty} \Theta_k \varepsilon_{i,t-k} = \Theta(L)\varepsilon_{i,t} \tag{19}$$

where $\varepsilon_{it} = d_i + d_t + d_{it}$

$$b_{i,t} = Pd_{i,t} \tag{20}$$

P is an n x n invertible matrix which has to be estimated to identify the structural shocks. Short-run constraints are imposed by setting some elements of the P matrix to zero. The Θ_j matrix represents the response functions of $Y_{i,t}$ to structural shocks d_{it}. These are assumed to be uncorrelated and to have a unit variance:

$$E(d_{i,t}, d_{i,t}^T) = I_n \tag{21}$$

Letting Ω be the variance-covariance matrix of the canonical innovations $b_{i,t}$, we have :

$$E(b_{i,t}, b_{i,t}^T) = PE(d_{i,t}, d_{i,t}^T)P^T = PP^T = \Omega \tag{22}$$

4.2. Specification and contemporaneous restrictions

Each model includes six variables. Two control variables appear in all specifications: economic size (GDP per capita (*gdpcap*) or GDP (*gdp*)) and trade integration (*openness*)).

These variables capture the powerful impact of economic growth and economic openness on the distribution of income (e.g. Kuznets effect, HOS effect). Unobserved determinants of income distribution are controlled for by including fixed time and country effects, as well as the lagged EHII variable in each specification.

We seek to measure the impact of size, international integration, efficiency of banking and financial markets on inequality levels. From a modeling point of view, this implies identifying the n^2 elements of the P matrix. In our case $n(n+1)/2$ (i.e. 21) orthogonality constraints are already set since Ω is a symmetrical matrix. Given that the variables used in this study are new in the existing Structural VAR literature, we apply a Cholesky decomposition to determine the $n(n-1)/2$ (i.e. 15) remaining constraints.

To do so, we follow a restrictive hypothesis and posit that financial variables are faster to respond to a shock than real variables. We also assume that the more volatile variables will be impacted first. Therefore, we place the flow-related variables ahead of the price-related variables within the vector of endogenous variables. Keeping our control variables, we experiment different specification in two sets of separate banking and financial market models.

4.2.1. Modelling the impact of financial development on EHII

Beginning with the banking sector models, we include size, profitability, efficiency or liquidity variables in each model, in addition to the two control real variables and the EHII indicator.

We let $Y = \begin{pmatrix} openness \\ gdp | gdpcap \\ domcred \\ spread \\ liq \;|\; insurfi \\ ehii \end{pmatrix}$ be the vectors of endogenous variable, and $\varepsilon_t = \begin{pmatrix} \varepsilon_{exts} \\ \varepsilon_s \\ \varepsilon_{bs} \\ \varepsilon_{risk} \\ \varepsilon_{liq \;|\; eff} \\ \varepsilon_{so} \end{pmatrix}$ be the vector of structural shocks, where ε_{exts} represents trade integration levels, and ε_s, ε_{bs}, ε_{risk}, ε_{liq} or ε_{eff}, ε_{so} represent the real domestic supply, banking sector size, risk, illiquidity, efficiency, and inequality shocks, respectively. Turning to capital market models, we let $Y = \begin{pmatrix} openness \\ gdp \;|\; gdpcap \\ milesi \;|\; mcgdp \\ kalman \;|\; pv1 \;|\; garch \;|\; turnover \\ akdogan \;|\; dni \;|\; trace \\ ehii \end{pmatrix}$ be the vectors of endogenous variables, and

$\varepsilon_t = \begin{pmatrix} \varepsilon_{exts} \\ \varepsilon_s \\ \varepsilon_{mfin|ms} \\ \varepsilon_{eff|\,fivol|liq} \\ \varepsilon_{pfin|illiq} \\ \varepsilon_{ehii} \end{pmatrix}$ be the vector of structural shocks, where ε_{exts} represents trade integration levels, and ε_s represent the domestic supply shock. Following the Choleski decomposition, the next variables are ε_{mfin} or ε_{ms} and capture shocks on macroeconomic international financial integration and market size. Finally, ε_{eff}, ε_{fivol} and ε_{liq} represent shocks on informational efficiency, volatility and liquidity, while ε_{pfin} and ε_{illiq} represent shocks on asset pricing integration and transaction costs. Results are shown in table 2 (models 1 to 11)

4.2.2. Robustness check: modeling the impact of EHII on financial development

We check for bidirectional causality by implementing two additional models. The first model focuses on flow-related variables. We let $Y = \begin{pmatrix} openness \\ gdp \mid gdpcap \\ ehii \\ milesi \\ domcred \\ mcgdp \end{pmatrix}$ be the vectors of endogenous variables, and $\varepsilon_t = \begin{pmatrix} \varepsilon_{exts} \\ \varepsilon_{s} \\ \varepsilon_{ehii} \\ \varepsilon_{mfin} \\ \varepsilon_{bs} \\ \varepsilon_{ms} \end{pmatrix}$ be the vector of structural shocks. The second model focuses on price-related variables. We let $Y = \begin{pmatrix} openness \\ gdp \mid gdpcap \\ ehii \\ pv1 \mid kalman \\ garch \mid dni \\ akdogan \mid trace \end{pmatrix}$ be the vectors of endogenous variables, and $\varepsilon_t = \begin{pmatrix} \varepsilon_{exts} \\ \varepsilon_{s} \\ \varepsilon_{ehii} \\ \varepsilon_{eff} \\ \varepsilon_{fivol \mid illiq} \\ \varepsilon_{pfin} \end{pmatrix}$ be the corresponding vector of structural shocks. All models include two lags following the Schwartz, Akaike and Hannan-Quinn information criteria. We also checked for the absence of autocorrelation in residuals[1]. Results are shown in table 3.

[1] Results are available upon request.

4.2.3. Robustness check: the mixed model

As a final step, we select the most significant variables (from variance decomposition and impulse response function analysis) from the banking and financial market models and plug them into a mixed financial sector model. This constitutes a robustness check on the patterns observed in section 4.2.2, but also on the relative importance of the banking and capital markets. Results are shown in table 2 (model 12).

5. Results

5.1. Variance decomposition analysis

Inspection of table 2 shows that macro-economic variables have a significant impact: taken individually, *openness*, *gdp*, and *milesi* explain up to 7.42%, 10.36%, and 9.64% of the total variance of EHII, respectively. In line with previous research, this suggests that economic size, financial integration and trade integration are important determinants of income distribution dynamics.

Turning to banking sector development, we find that resource mobilization is an important factor. The *domcred* variable captures 8.22% of the variance of EHII. However, *spread* and *liq* capture 14.08% and 9.14% of the variance of EHII, respectively. This suggests that the efficiency and the robustness of the banking sector matter more than its size when it comes to determining income distribution.

The most significant capital market development variables are *mc2gdp*, *turnover*, *PV1* and *garch*. These variables account for a maximum of 5.17%, 6.99%, 6.44% and 5.69% of the total variance of EHII, respectively. However, stock market characteristics seem to exert a stronger impact on income distribution than stock market size: *PV1*, *kalman*, *trace*, *DNI* and *garch* capture up to 6.44%, 1.15%, 1.61%, 1.17% and 5.69% of EHII's variance, respectively. Not surprisingly, price variables capture less of EHII's variance than flow variables. Overall, these results suggest that income distribution depends more on the features of financial systems than on their size. The lower observed coefficients for the capital market variables also suggest that the banking sector has a stronger impact on income distribution.

Finally, the mixed model confirms these results (model 12): when jointly modelling the most significant banking and capital market variables, we find that the bulk of EHII's variance is explained by banking sector design and governance (*domcred* and *spread* capture up to 9.71% and 8.96% of EHII's variance respectively, versus 3.76%, 3.82% and 1.24% for *mc2gdp*, *PV1* and *garch*, respectively).

Interestingly, table 3 shows that the initial income distribution does not seem to impact size-related financial development levels: a shock on EHII contributes to a maximum impact of 2.66% on the variance of *domcred*. Interestingly, income distribution seems to exert a significant impact on stock market volatility (through a 6.49% effect on the *garch* variable). This suggests that uneven wealth distribution may increase market speculation and induce sudden valuation shifts in the stock market. Taken together, these results suggest that (i) finance does matter for income distribution; (ii) the causality runs from financial development to inequality; (iii) banks matter more than capital markets; and (iv), financial sector design matters more than sector size. This echoes the view that the development of functional financial systems can simultaneously improve entrepreneurship and educational opportunities, align income with individual skills and initiatives, and increase the demand for labour through a more efficient allocation of capital (Demirgüc-Kunt and Levine, 2009). Inspection of impulse response functions will yield additional information on the sign and dynamics of these causality relationships[2].

[2] Impulse response functions for the various models described in section 4.2.2 are not shown for space-savings consideration but are available from the authors upon request.

5.2. Impulse response function analysis

The impulse response functions showed in figure 1 display the responses of EHII to a variation of one standard deviation of the various financial variables. Confidence intervals are calculated through a Monte Carlo integration method[3]. Finding similar results for different model specification indicates a robust relationship.

Inspection of the figures highlight that the response of EHII to economic growth (*gdpcap* and *gdp*) and economic integration (*openness*) is significant and negative, indicating a stable relationship (figure 2 to 11). However, economic integration seems to exert a positive short-run impact on inequality levels (figure 2, 5, 6, 7, 8, 9, 10 and 11). This suggests that the lower quintiles of the workforce benefit from economic openness in the middle run and that trade integration carries short-run distributional costs, in line with Rodrik (2002).

Turning to banking sector variables, we find that increased banking credit tends to increase inequalities (figure 1, 2, 3, 4 and 12). This provides backing for the argument that increased returns to entrepreneurship could increase inequality if human capital and collateral are unevenly distributed. It also echoes the literature on finance, absorptive capacities and convergence clubs. However, this size-related variable does not reflect the actual performance of the banking system in mobilizing and allocating resources.

Interestingly, interest spread and lower liquidity levels tend to increase inequalities (figure 1, 2, 3, 4 and 12). Credit market imperfections can indeed restrict access to credit to the high income, high collateral, politically-connected segment of households and firms (Banerjee and Newman, 1993; Narayana, 2000). Banking crises caused by insufficient liquidity have also been showed to widen income inequalities (Honohan, 2005). Overall, these results suggest

[3] Following Sims and Zha (1999), error bands correspond to the 0.16 % and 0.84 % fractiles, i.e. a confidence interval of 68%.

that policies seeking to improve the governance and robustness of local banks should be prioritized over size-enhancing reforms from a normative point of view.

Turning to capital markets, we find that increased market size (*mcgdp*) and liquidity (*turnover*) have a negative impact on inequality levels (figure 7, 8, 12 and 10, 11, respectively). In addition, the efficiency score (*PV1*) has a significant and negative impact on inequalities (figure 6, 8 and 12), while the inefficiency score (*kalman*) has a positive impact on inequalities (figure 7). Reforms seeking to improve information disclosure, corporate governance in the stock exchange therefore also have a role to play, as they ensure that financial development does not disproportionately benefit insiders.

Not surprisingly, volatility shocks (*garch*) exert a positive and significant impact on inequality levels (figure 5, 6, 7, 9 and 12). This variable responds positively to the activity of noise traders and domestic and foreign investors, to the implementation of pump and dump strategies by informed brokers, and to financial crises. This could suggest that transaction costs (*DNI*) do not seem to impact income distribution. This suggests that fiscal policy initiatives seeking to dampen financial volatility at the cost of higher transaction costs (e.g., Tobin tax-type proposals) would be distributionally neutral.

Finally, international financial integration (as measured by *milesi*) has a negative short-run impact but tends to increase inequality levels over the long run (figure 1, 2, 3, 5, 6, 9, 10 and 11). International asset integration (*trace*) also seems to be related to higher long run inequality levels (figure 5). All in all, these results suggest that full capital account liberalization should be considered with caution in developing countries. From a larger perspective, it should be noted that recent studies focusing on the impact of financial development for the poor came to similar conclusions regarding the discriminating impact of financial sector governance (rather than financial sector size), as well as the importance of tackling the issue of finance-led economic destabilization (Akhter and Daly, 2009).

6. Concluding remarks

This paper examined the relationship uniting financial development and income distribution, taking into account the specific channels linking banks, capital markets and income inequality, as well as the time-varying nature of the relationship. We constructed a set of annual indicators of banking and capital market size, robustness, efficiency and international integration. We then estimated the dynamic impact of these variables on income distribution using a panel Bayesian structural vector autoregressive (SVAR) model, for a set of 49 countries over the 1994-2002 period. We found that financial sector development has a significant effect on income distribution controlling for reciprocal causality and other factors. While this echoes and confirms previous studies, our approach permitted to detect that the banking sector exerts a stronger impact on inequality, and that the relationship depends on the characteristics of the financial sector, more than its size.

Our findings have a few normative implications for the content and sequencing of financial reforms, especially in developing countries. First, it appears that large crony domestic banks are a bigger threat to equality than capital market and international investors. Second, reforms seeking to improve the ability of banks and capital markets to monitor risks and allocate resources should be prioritized over other initiatives. In the first stage of reforms, prudential supervision and anti-monopolistic policies could be implemented in the banking sector, while corporate governance and information disclosure is improved in capital markets. Financial sector expansion policy programs (IPO, privatization etc) could then take implemented as a second step. During the entire process, international financial integration levels should be monitored carefully.

We may suggest future directions for research in finance and inequality. First, new theoretical models need be developed to formalize the suggested inductive mechanisms. Second, constructing a new database capturing the characteristics of the banking sector (e.g. banking sector concentration, ownership type, project screening procedures) across developing countries would permit to further refine the analysis and policy recommendation. Finally, empirical research on the determinants of income distribution would greatly benefit from an updated international inequality database.

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Appendix 1. Descriptive statistics

Table 1 Database: average values

Country	ehii	openness	gdpcapdol	mc2gdp	dni	akdogan	garch	pv1	domcredbank	insurfi	spread	milesi	liq	trace	kalman	gdp
AUS	1.58	1.61	4.30	1.91	0.36	0.01	0.03	0.47	1.93	0.74	0.68	1.90	0.14	12.32	0.03	5.60
AUT	1.57	1.91	4.36	1.17	0.34	0.01	0.03	0.48	2.09	0.71	0.56	1.53	0.24	9.21	0.04	5.33
BGR	1.62	2.01	3.18	0.05	0.38	0.01	0.31	0.82	1.50	0.34	1.18	1.08	0.92	5.42	0.14	4.09
BOL	1.69	1.68	2.99	0.69									0.88			
CAN	1.58	1.89	4.33	1.94	0.42	0.45	0.04	0.27	2.13	0.97	0.52	1.99	0.32	9.83	0.16	5.81
CHL	1.66	1.77	3.67	1.94	0.36	0.14	0.04	0.00	1.94	0.49	0.66	1.85	0.62	9.85	0.21	4.86
COL	1.64	1.57	3.31	1.18	0.47	0.00	0.04	0.00	1.58	0.62	0.93	1.26	1.00	6.55	0.20	4.95
CRI	1.61	1.94	3.58	1.07									1.59			
CYP	1.60	1.98	4.09	1.55									0.94			
DEU	1.55	1.75	4.34	1.60	0.42	0.16	0.06	0.45	2.14	0.80	0.82	1.71	0.18	11.59	0.02	6.33
DZA	1.65		3.24										0.32			
EGY	1.68	1.64	3.14	1.35	0.39	0.00	0.04	0.27	1.97	0.05	0.63		1.17	10.71	0.32	4.90
ERI	1.67		2.30										1.69			
ESP	1.59	1.72	4.12	1.74	0.39	0.10	0.05	0.43	2.04	0.53	0.33	1.77	0.44	9.87	0.12	5.78
FIN	1.52	1.83	4.33	1.96	0.38	0.09	0.12	0.45	1.78	0.33	0.58	1.95	0.70	13.97	0.08	5.09
GBR	1.56	1.75	4.36	2.17	0.35	0.12	0.03	0.33	2.11	1.32	0.41	2.15		14.62	0.05	6.13
HKG	1.59	2.43	4.38	2.43	0.40	0.02	0.09	0.59	2.16	1.04	0.56		-0.65	11.34	0.03	5.21
HUN	1.60	2.05	3.62	1.21	0.37	0.04	0.10	0.39	1.81	0.37	0.69	1.64	0.95	10.77	0.26	4.69
IDN	1.67	1.79	2.91	1.36	0.39	0.01	0.36	0.03	1.75	-1.42	0.46	1.15	0.72	10.62	0.22	5.25
IND	1.69	1.39	2.62	1.49	0.40	0.01	0.07	0.15	1.69	0.44		0.88		9.82	0.21	5.62
IRL	1.64	2.20	4.33	1.78	0.35	0.05	0.03	0.18	1.95	1.28	0.70	2.44	0.23	8.94	0.16	4.94
IRN	1.62		3.18	1.02									1.67			
ISR	1.63	1.89	4.24	1.67	0.44	0.05	0.06	0.42	1.92	-0.81	0.70	1.55	0.99	10.83	0.04	5.00
ITA	1.56	1.68	4.26	1.54	0.35	0.19	0.07	0.60	1.97	0.66	0.75	1.61	0.42	11.60	0.04	6.07
JOR	1.66	2.06	3.24	1.85	0.40	0.00	0.02	0.27	1.96	-0.87	0.59	1.16	1.47	9.16	0.09	3.89
JPN	1.62	1.29	4.56	1.82	0.40	0.01	0.06	0.32	2.47	0.44	0.33	1.29	0.01	9.70	0.03	6.64
KEN	1.66	1.74	2.62	1.16	0.41	0.00	0.04	0.46	1.63	-0.01	1.13	1.05	1.15	10.54	0.45	4.07
KOR	1.57	1.83	4.00	1.54	0.36	0.01	0.12	0.20	1.90	0.08	0.02		0.50	9.07	0.13	5.68
KWT	1.73	1.95	4.25	1.81	0.37	0.00	0.00	0.25					0.06	8.73	0.39	
LKA	1.65	1.91	2.89	1.07	0.42	0.00	0.07	0.00	1.60	0.66	0.74	1.09	1.07	8.63	0.39	4.17
LUX	1.54		4.62	2.19									-0.62			
MAC	1.52	2.19	4.14													
MAR	1.68	1.80	3.07	1.43	0.36	0.01	0.00	0.04					0.80	9.45	0.12	
MEX	1.64	1.76	3.74	1.42	0.38	0.28	0.09	0.11	1.59	0.89	0.91	1.45	0.69	13.17	0.12	5.67
MLT	1.56	2.27	3.96	1.24	0.44	0.00	0.02	0.09	2.11	0.37	0.45	1.73	0.64	11.41	0.14	3.55
MYS	1.58	2.30	3.57	2.23	0.43	0.01	0.08	0.07	2.28	0.03	0.54	1.93	0.94	9.89	0.41	4.94
NOR	1.53	1.86	4.55	1.55	0.36	0.06	0.04	0.46	1.91	0.51	0.39	1.76	0.17	10.26	0.07	5.20
PAN	1.68	2.20	3.57	1.29									10.35			
POL	1.57	1.72	3.60	0.95									0.87			
RUS	1.63	1.75	3.23	0.92	0.39	0.03	0.37	0.22	1.47	0.05	1.46		1.08	9.33	0.17	5.52
SEN	1.68	1.84	2.61										0.76			
SGP	1.57	2.57	4.32	2.18	0.37	0.02	0.06	0.26	1.94	0.79	0.53	2.46	0.52	10.44	0.16	4.94

Country	ehii	openness	gdpcapdol	mc2gdp	dni	akdogan	garch	pv1	domcredbank	insurfi	spread	milesi	liq	trace	kalman	gdp
SYR	1.72		3.05										0.94			
TTO	1.72	1.98	3.76	1.61									1.20			
TUN	1.70	1.96	3.27	1.15	0.40	0.00	0.01	0.66	1.85	0.28		1.79	0.57	7.75	0.45	4.28
TUR	1.67	1.72	3.45	1.37	0.33	0.01	0.27	0.43	1.63	0.28		0.95	1.01	9.97	0.19	5.24
URY	1.66	1.60	3.78	0.00									1.14			
USA	1.58	1.38	4.51	2.09	0.40	1.00	0.03	0.26	2.28	0.75		1.83	0.15	9.79	0.03	6.94
ZAF	1.65	1.70	3.48	2.20	0.36	0.04	0.06	0.17	2.17	0.93	0.69	1.79	0.41	9.38	0.07	5.13

Note: this table shows averaged values for the variables used in the panel. Averages are computed based on 9 observations per country over the 1994-2002 time period.

Appendix 2. Variance decomposition

Table 2 Variance decomposition analysis: response of EHII to a shock on financial development

Model #1	OPENNESS	GDPCAPDOL	MILESI	DOMCREDBANK	SPREAD
1	0.117	4.821	0.232	0.098	5.948
2	0.704	4.160	4.610	0.685	12.872
3	2.314	3.873	4.177	0.721	12.806
6	2.401	3.938	3.999	0.766	13.990
9	2.387	4.045	4.031	0.772	14.083
12	2.389	4.057	4.039	0.787	14.080
Model #2	OPENNESS	GDPCAPDOL	MILESI	DOMCREDBANK	LIQ
1	0.628	2.000	0.190	0.164	1.759
2	2.222	2.190	9.651	1.144	2.002
3	3.280	2.281	9.665	1.142	1.943
6	3.412	2.442	9.582	2.186	1.980
9	3.427	2.473	9.639	2.258	1.978
12	3.427	2.474	9.645	2.260	1.978
Model #3	OPENNESS	GDPCAPDOL	MILESI	SPREAD	LIQ
1	0.030	3.578	0.414	1.965	0.053
2	0.349	5.374	4.644	4.980	7.860
3	3.305	4.603	6.256	6.743	6.701
6	5.337	4.301	7.974	8.676	9.149
9	6.041	4.424	7.991	8.837	8.986
12	6.106	4.430	7.980	8.868	8.975
Model #4	OPENNESS	GDP	DOMCREDBANK	SPREAD	INSURFI
1	0.304	0.004	1.514	0.007	0.025
2	0.63	0.04	3.485	0.124	0.041
3	1.058	1.498	3.781	0.843	0.256
6	4.988	2.849	7.481	1.675	1.025
9	5.629	2.862	8.068	1.919	1.052
12	5.868	2.844	8.229	1.989	1.092
Model #5	OPENNESS	GDP	MILESI	GARCH	TRACE
1	0.112	1.046	0.888	0.913	0.11
2	4.744	8.65	5.129	1.205	1.424
3	4.666	9.95	5.09	1.19	1.451
6	5.334	10.351	5.08	2.391	1.61
9	5.334	10.355	5.192	2.399	1.608
12	5.334	10.356	5.197	2.4	1.609
Model #6	OPENNESS	GDPCAPDOL	MILESI	PV1	GARCH
1	0.462	0.575	0	0.016	0.375
2	2.069	2.965	3.483	0.45	2.432
3	3.354	2.801	3.275	5.221	2.506
6	3.305	3.329	4.453	5.878	2.92
9	3.406	3.591	4.513	5.885	2.949
12	3.448	3.654	4.512	5.879	2.945
Model #7	OPENNESS	GDP	MC2GDP	KALMAN	GARCH
1	0.17	0.939	0.625	0.034	0.295
2	7.882	1.254	1.867	0.453	3.332
3	7.629	1.792	2.291	0.478	5.17
6	7.436	3.038	3.257	0.993	5.627
9	7.429	3.131	3.245	1.126	5.697
12	7.428	3.137	3.246	1.147	5.697
Model #8	OPENNESS	GDPCAPDOL	MC2GDP	PV1	AKDOGAN
1	0.134	0.021	0.484	0.116	0.189
2	1.875	0.386	2.46	0.611	0.183
3	1.76	1.916	3.67	6.446	0.659
6	1.922	4.687	5.196	6.27	1.153
9	1.914	5.179	5.165	6.251	1.168
12	1.916	5.218	5.171	6.253	1.171

Model #9	OPENNESS	GDPCAPDOL	MILESI	GARCH	DNI
1	0.436	0.267	0.001	0.371	0.71
2	3.645	0.248	1.753	0.368	0.938
3	4.021	0.275	3.028	0.347	0.847
6	6.573	1.747	3.207	0.441	1.17
9	6.604	1.788	3.28	0.467	1.169
12	6.611	1.792	3.286	0.471	1.17
Model #10	OPENNESS	GDP	MILESI	TURNOVER	AKDOGAN
1	0.216	0.216	0.404	0.443	1.148
2	2.584	1.777	2.438	1.043	1.051
3	5.856	1.671	2.653	1.492	2.165
6	6.337	1.824	5.286	1.561	2.971
9	6.282	1.822	5.854	1.796	2.967
12	6.268	1.831	5.965	1.926	2.971
Model #11	OPENNESS	GDP	MILESI	TURNOVER	KALMAN
1	0.080	0.201	0.823	0.831	0.344
2	0.073	1.812	0.819	6.995	1.345
3	1.030	2.151	0.679	5.839	1.867
6	1.043	2.843	2.190	6.595	2.913
9	1.044	2.772	2.489	6.601	3.455
12	1.085	2.758	2.594	6.595	3.670
Model #12	MC2GDP	DOMCREDBANK	SPREAD	PV1	GARCH
1	0.802	0.538	0.638	0.026	0.051
2	2.899	1.005	8.966	2.980	0.304
3	2.467	5.140	7.831	3.041	0.765
6	3.749	8.031	8.379	3.441	1.227
9	3.751	9.645	8.637	3.709	1.202
12	3.762	9.708	8.603	3.827	1.236

Table 3 Variance decomposition analysis: response of financial development to a shock on EHII

Model #1	MILESI	DOMCRED	MC2GDP
1	0.209	0.020	0.502
2	0.127	0.156	0.352
3	0.107	1.708	0.750
6	0.955	2.518	1.329
7	1.175	2.534	1.322
9	1.373	2.604	1.319
12	1.411	2.656	1.316
Model #2	PV1	GARCH	AKDOGAN
1	0.285	0.147	0.884
2	0.528	6.490	0.855
3	1.534	5.747	1.662
6	1.567	5.407	1.679
7	1.565	5.389	1.676
9	1.565	5.381	1.673
12	1.565	5.375	1.673
Model #3	KALMAN	DNI	TRACE
1	0.640	0.645	0.005
2	1.126	0.671	1.618
3	0.968	0.661	1.585
6	1.015	1.473	2.016
7	1.189	1.473	2.017
9	1.421	1.484	2.017
12	1.521	1.488	2.017

Appendix 3. Impulse response functions

Figure 1 Impulse response functions

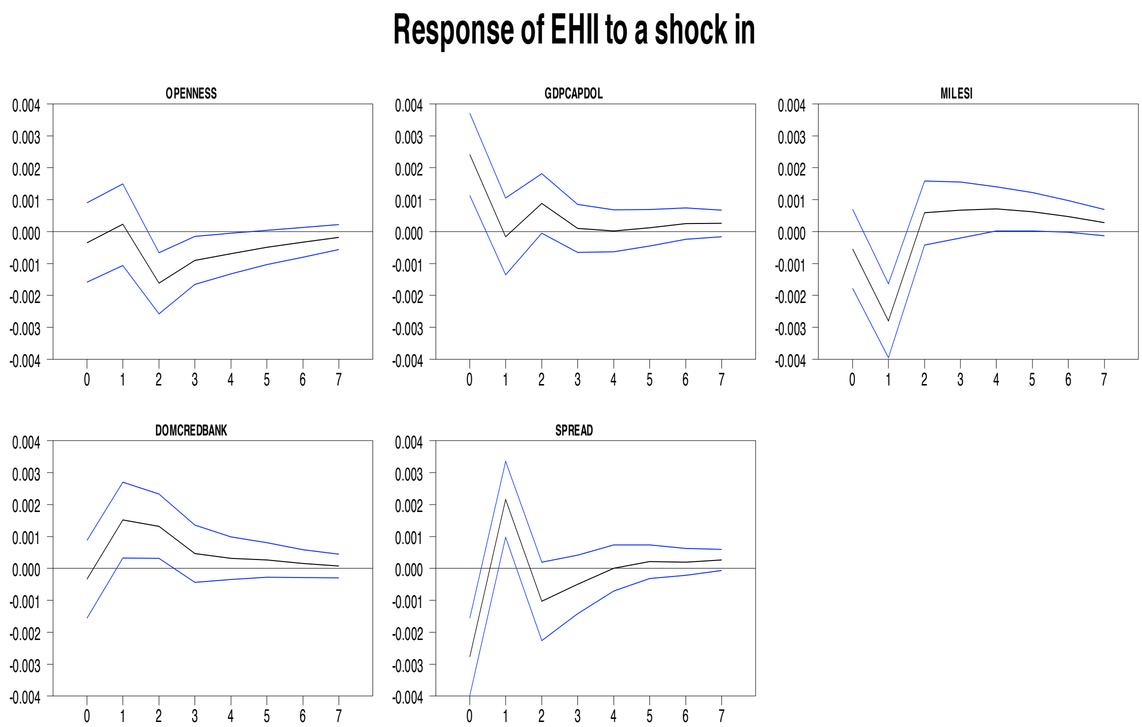


Figure 2 Impulse response functions

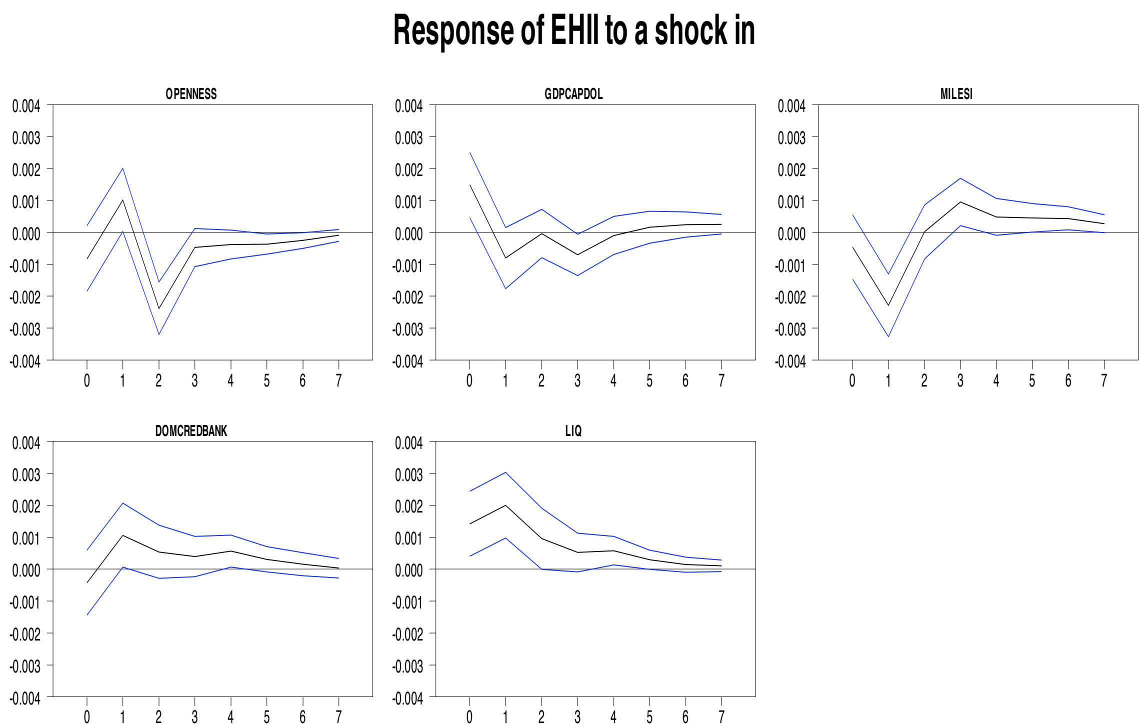


Figure 3 Impulse response functions

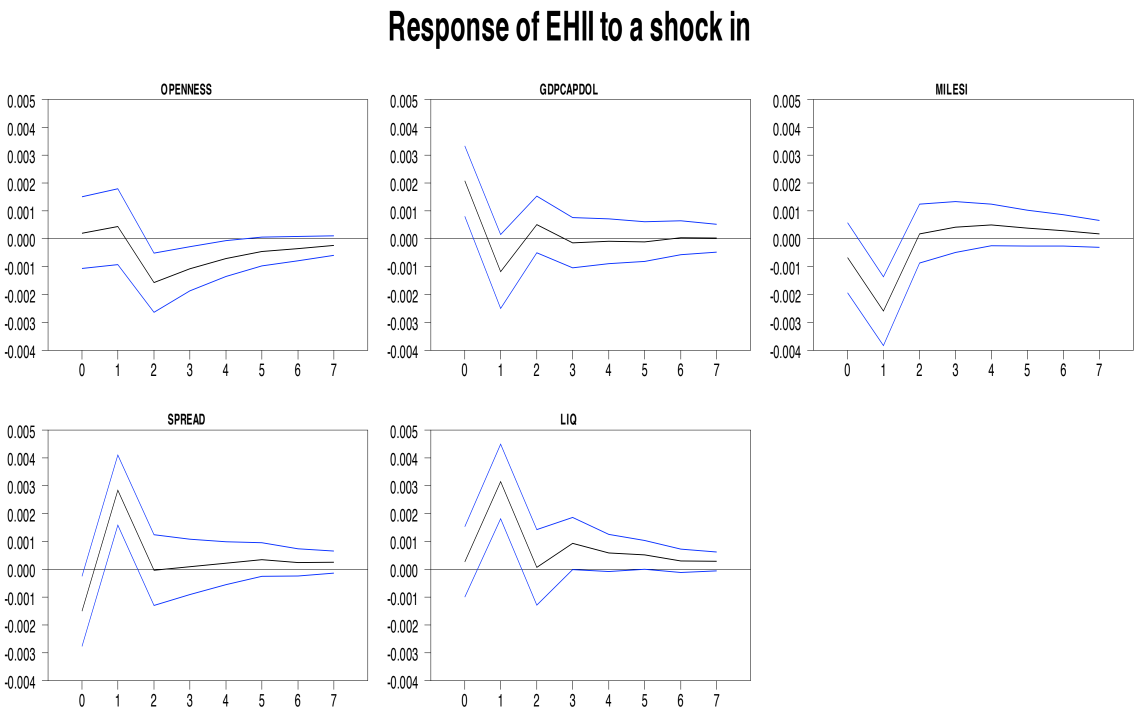


Figure 4 Impulse response functions

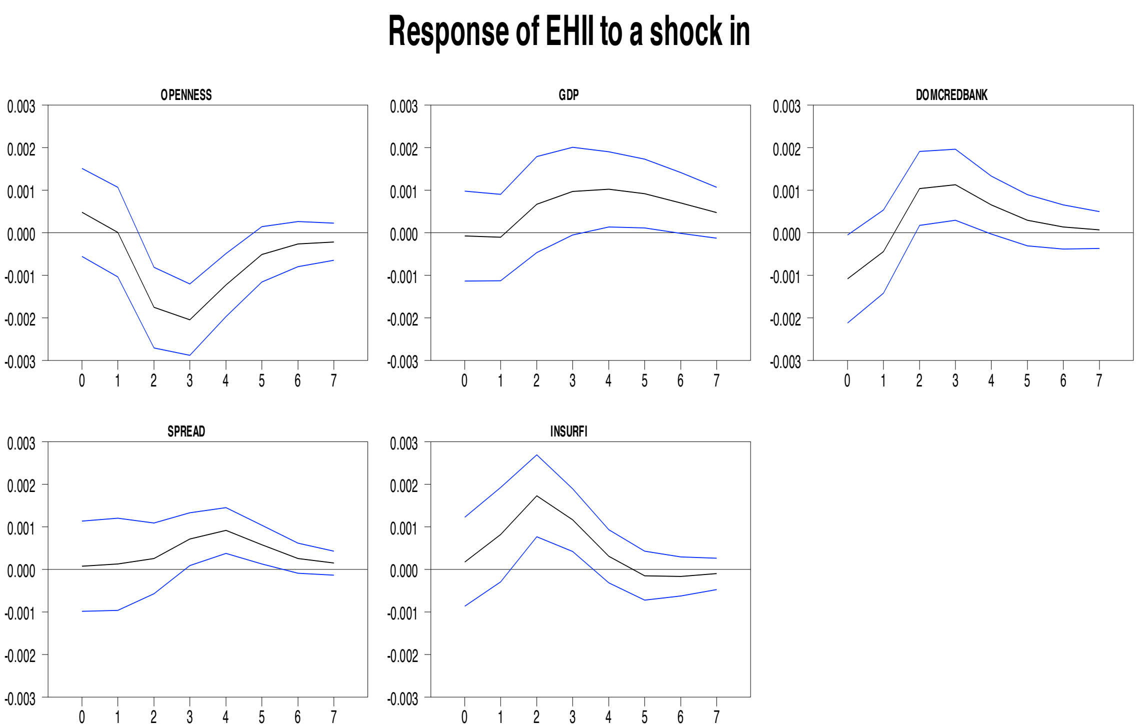


Figure 5 Impulse response functions

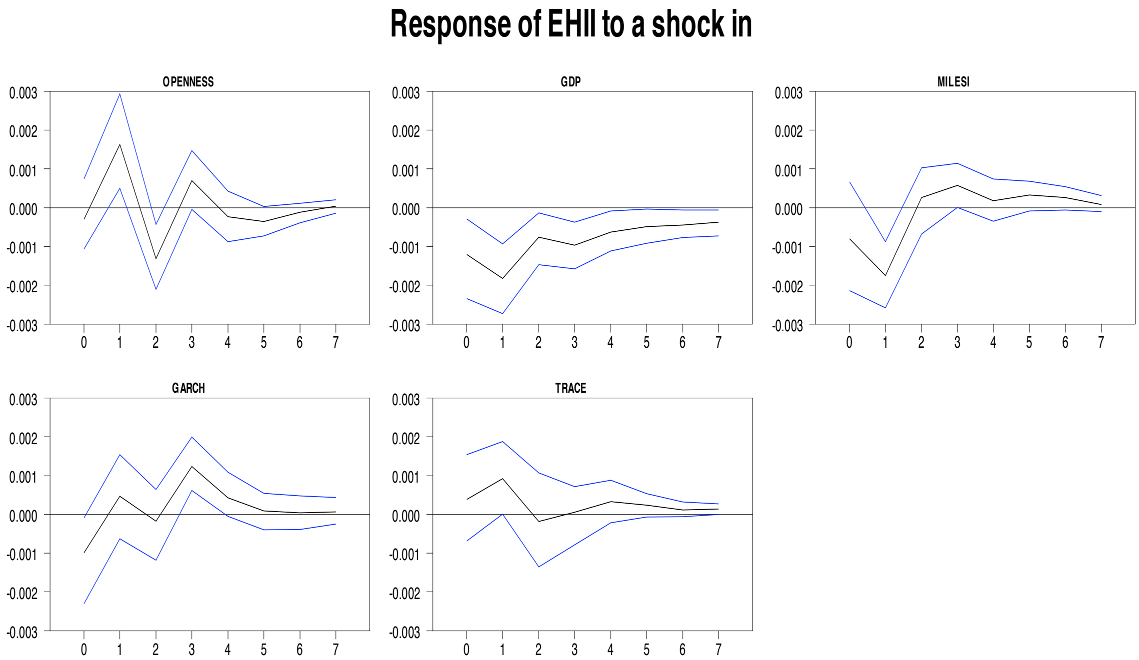


Figure 6 Impulse response functions

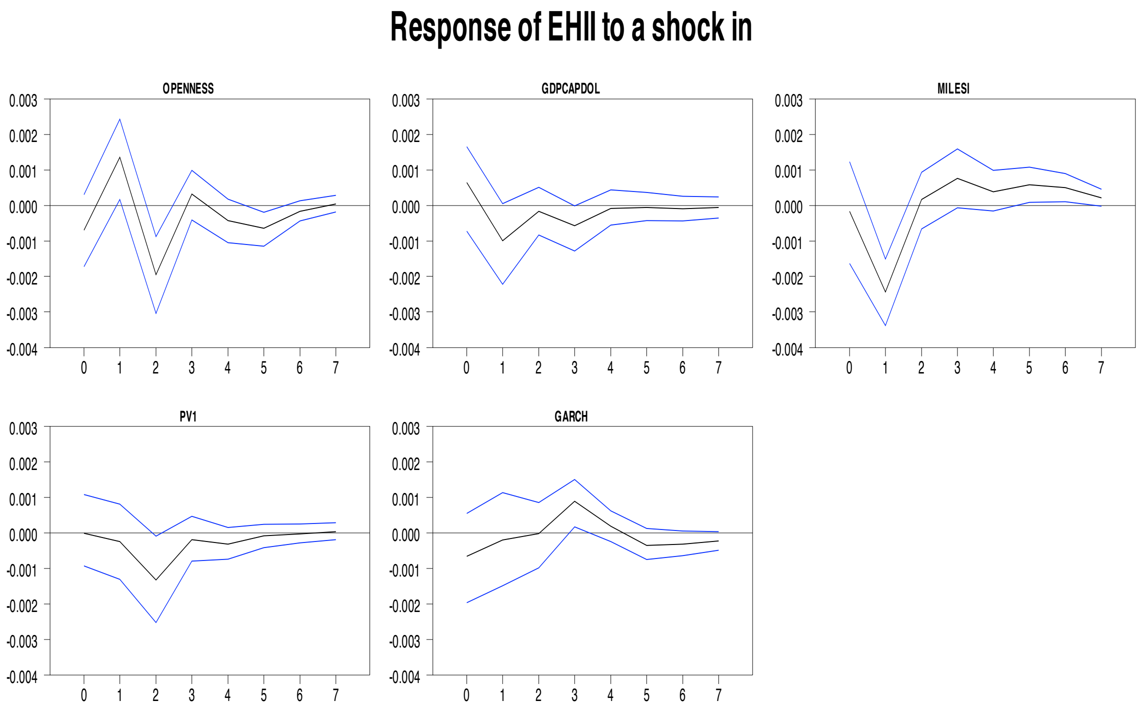


Figure 7 Impulse response functions

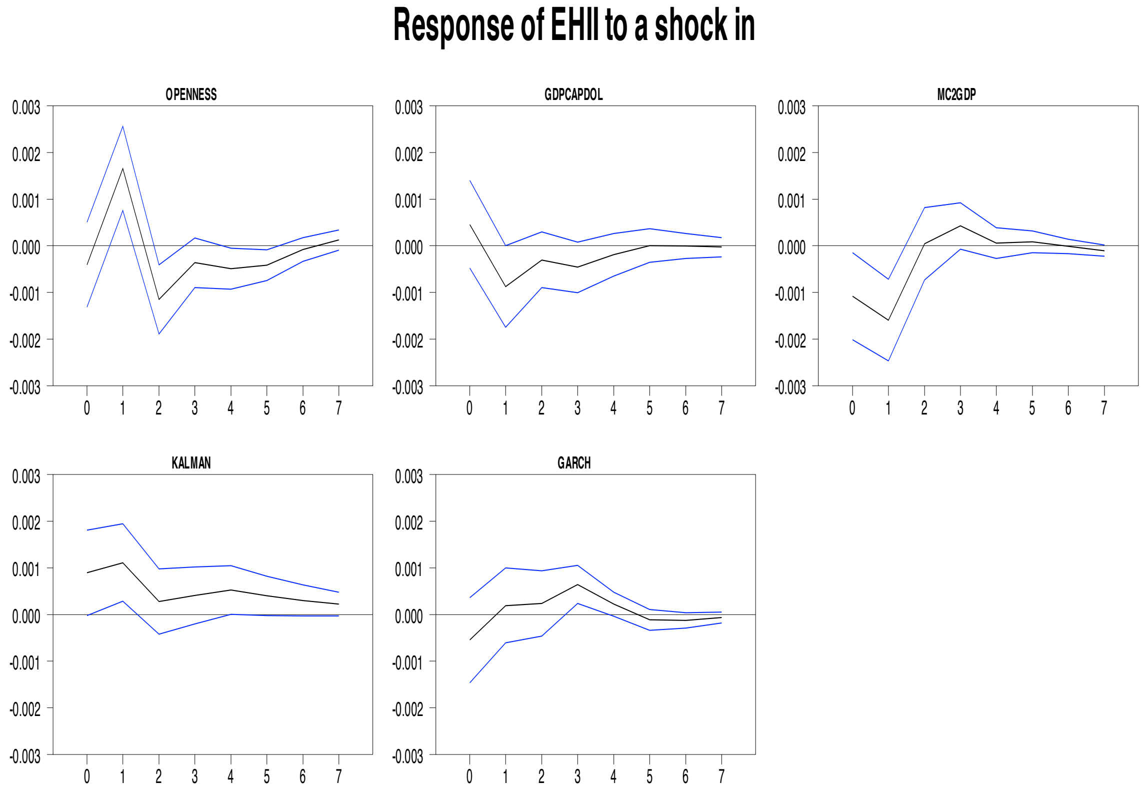


Figure 8 Impulse response functions

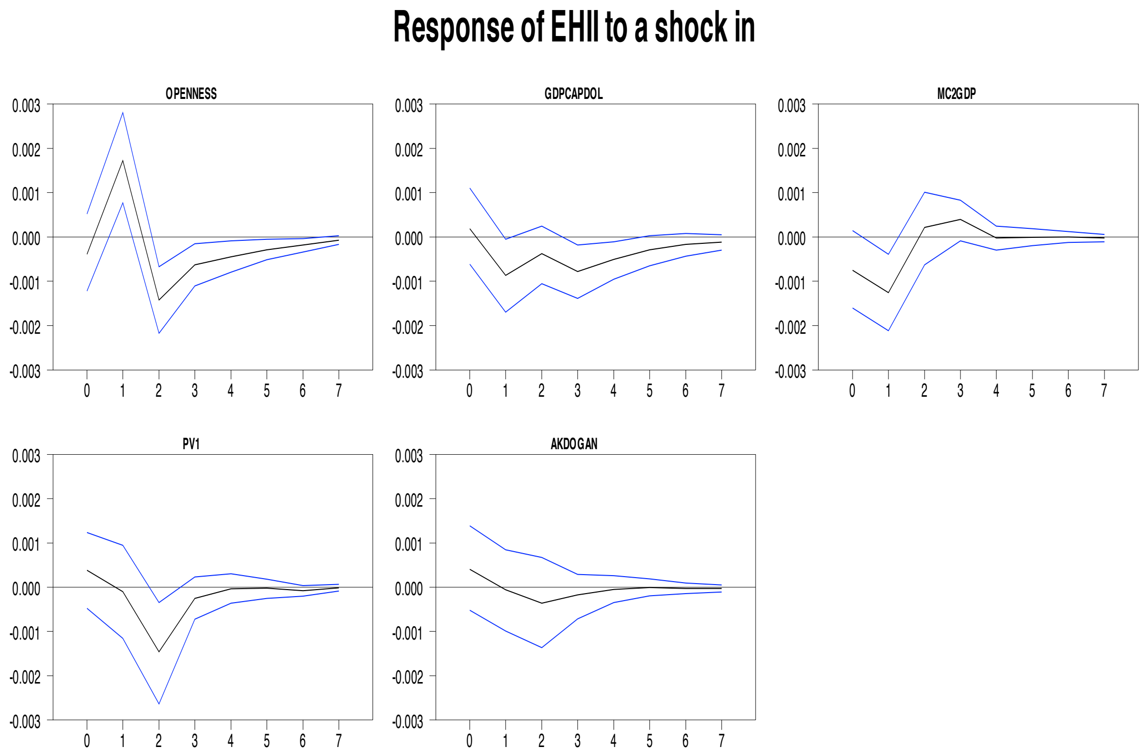


Figure 9 Impulse response functions

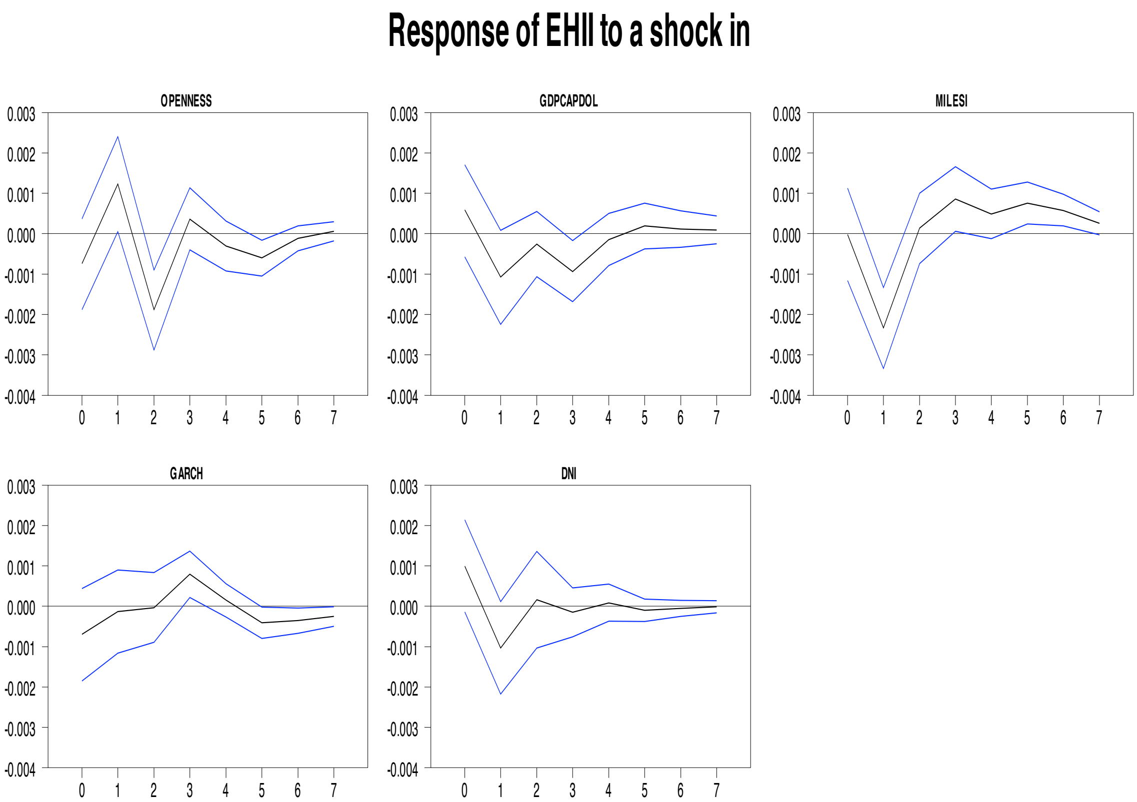


Figure 10 Impulse response functions

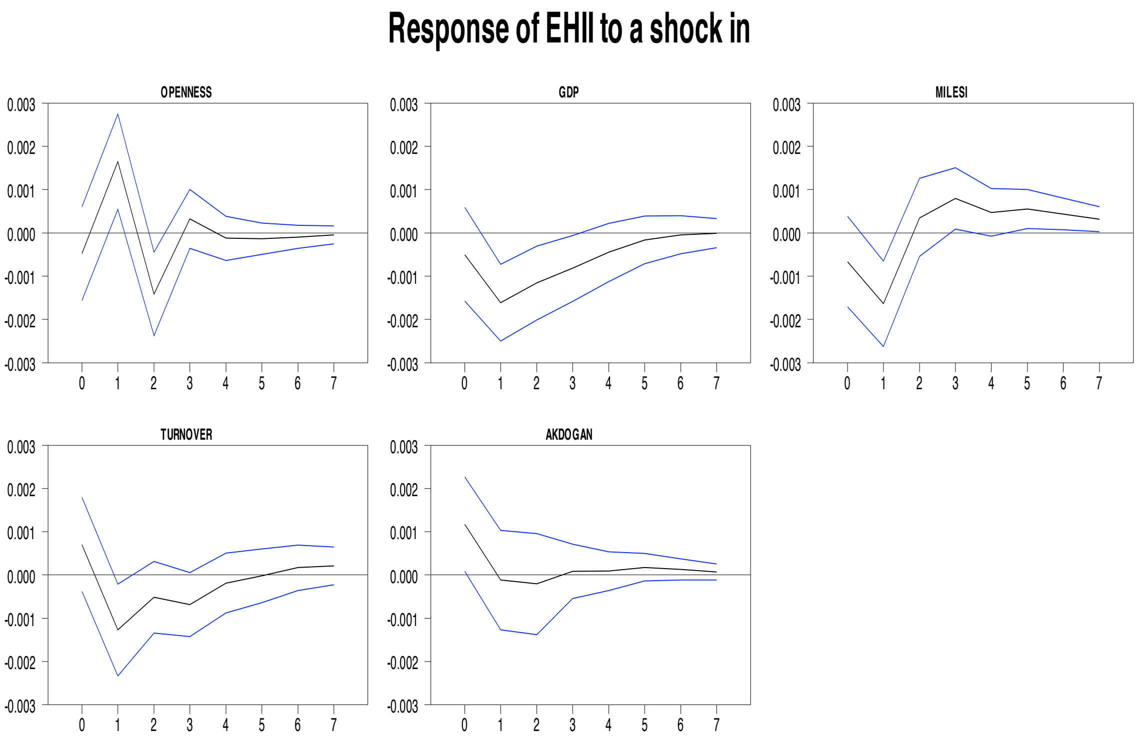


Figure 11 Impulse response functions

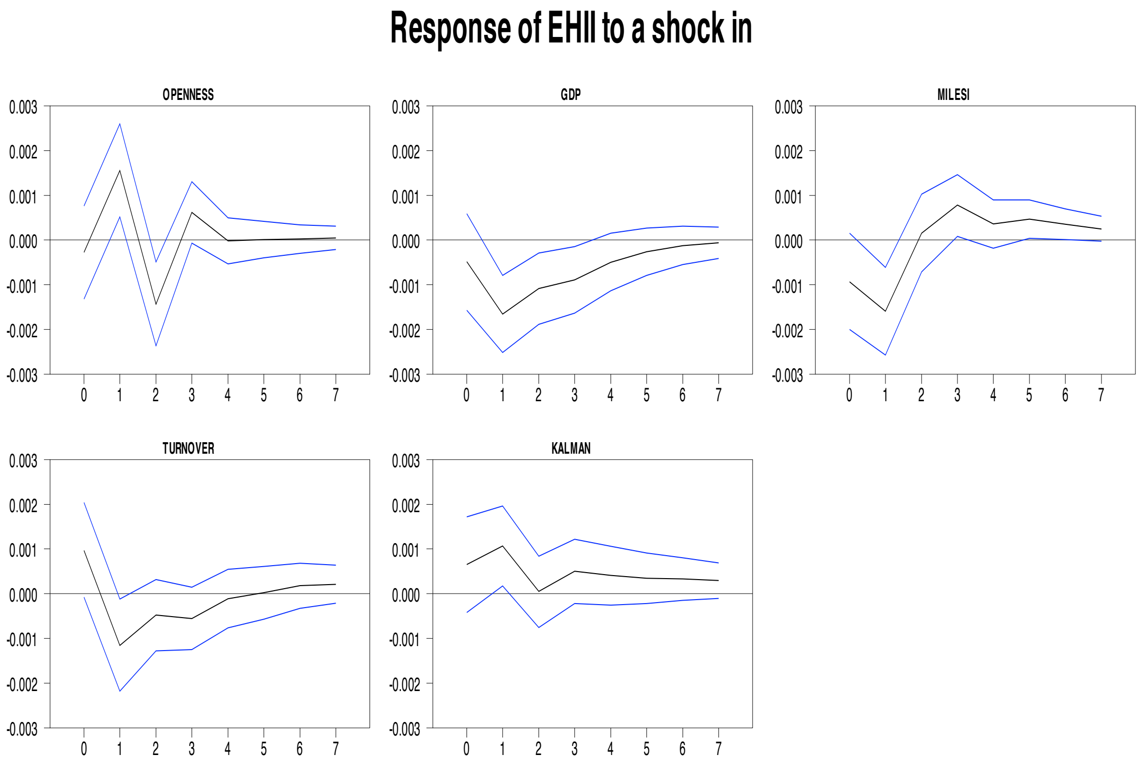
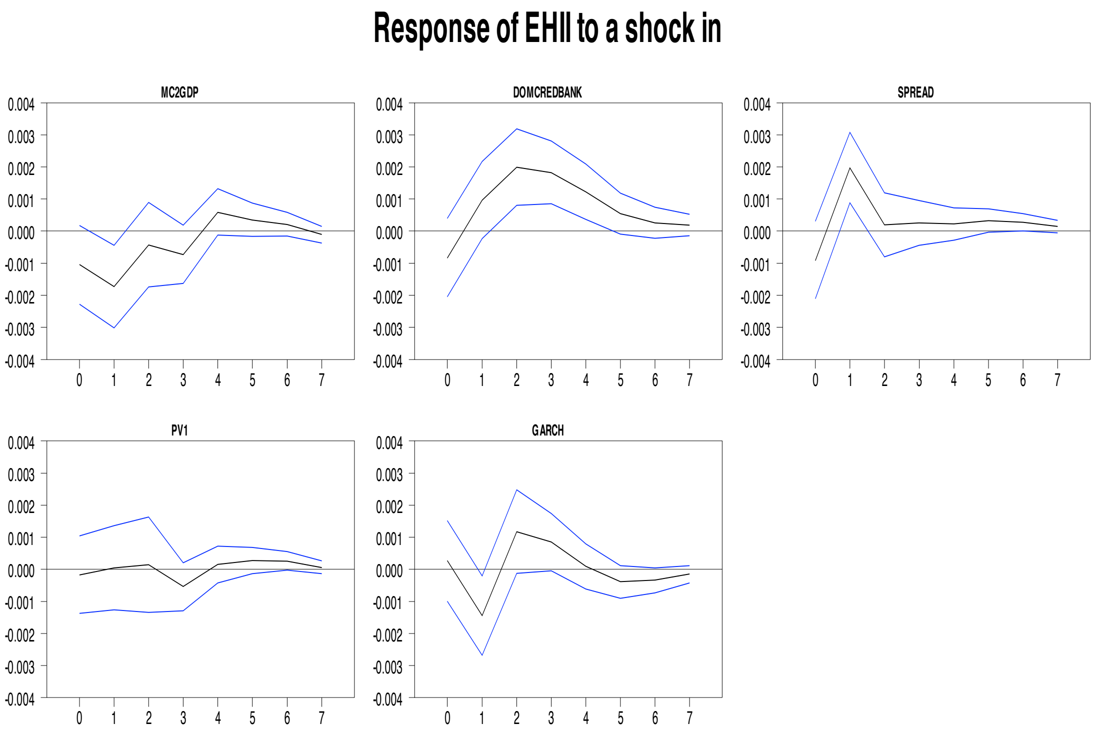


Figure 12 Impulse response functions



Appendix 4. The S-VAR model

The representation of the reduced form of the vector auto-regression model VAR(q) is:

$$Y_{i,t} = \sum_{i=1}^{n} \sum_{j=1}^{q} A_j Y_{i,t-j} + e_{i,t}$$

Where q is the number of lags and n the number of countries, $Y_{i,t}$ the vector of endogenous variable, Y_{t-j} the n x 1 vector of lagged variables for each i, A_j the n x n matrix parameters, e_{it} the vector of errors with $e_{it} = b_i + b_t + b_{it}$ with b_i the individual fixed effect, b_t the time fixed effect and b_{it} the disturbance term whose variance-covariance matrix has no restrictions, that is to say $E(b_{i,t}, b_{i,t}^T) = \Omega$ and $E(b_{i,t}) = 0$. Letting L be the lag operator, the VAR(q) model can be rewritten as:

$$A(L)Y_{i,t} = e_{i,t}$$
$$with \quad A(L) = I_n - A_1 L - ... - A_q L^q$$

$Y_{t,i}$ is supposed to be stationary meaning that $A(L)$ is invertible[4]. In other words, the matrix C_k has n x n parameters, $C_0 = I_n$ and $\sum_{j=0}^{\infty} C_k C_k^T$ is finite. This corresponds to $A(L)^{-1} = C(L)$ with

$$C(L) = I_n + C_1 L + C_2 L^2 + ... = \sum_{k=0}^{\infty} C_k L^k$$

The moving average form of the canonical VAR is thus:

$$Y_{i,t} = \sum_{i=1}^{n} \sum_{k=0}^{\infty} C_k e_{i,t-k} = C(L) e_{i,t}$$

where e_t represents the vector of canonical innovations, where $\varepsilon_{it} = d_i + d_t + d_{it}$

The vector of canonical innovations $b_{i,t}$ is supposed to be a linear combination of the structural impulses $d_{i,t}$ at the same time. Thus $b_{i,t} = Pd_{i,t}$. Thus, the structural Moving Average representation

[4] T represents the transposed matrix.

is:

$$p^{-1}Y_{i,t} = P^{-1}\sum_{i=1}^{n} \sum_{k=0}^{\infty} C_k e_{t-k} \Leftrightarrow Y_{i,t} = \sum_{i=1}^{n}\sum_{k=0}^{\infty} C_k PP^{-1} e_{i,t-k} \Leftrightarrow \sum_{i=1}^{n} \sum_{k=0}^{\infty} \Theta_k \varepsilon_{i,t-k} = \Theta(L)\varepsilon_{i,t}$$

With $\Theta(L) = PC(L) = P + PC_1 L + ...$ and $\Theta(L) = \sum_{k=0}^{\infty} \Theta_k L^k$