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Monetary Policy and Bank Lending Rates in Low-Income Countries: Heterogeneous Panel Estimates[1]

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Abstract

This paper studies the transmission of monetary shocks to lending rates in a large sample of advanced, emerging, and low-income countries. Transmission is measured by the impulse response of bank lending rates to monetary policy shocks. Long-run restrictions are used to identify such shocks. Using a heterogeneous structural panel VAR, we find that there is wide variation in the response of bank lending rates to a monetary policy innovation across countries. Monetary policy shocks are more likely to affect bank lending rates in the theoretically expected direction in countries that have better institutional frameworks, more developed financial structures, and less concentrated banking systems. Low-income countries score poorly along all of these dimensions, and we find that such countries indeed exhibit much weaker transmission of monetary policy shocks to bank lending rates than do advanced and emerging economies.

Keywords: monetary policy, bank lending, panel VAR

JEL Codes: E5, O11, O16

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1. Introduction

The Great Recession of 2007-10 has witnessed a resurgence of discretionary countercyclical fiscal policy. Until these dramatic recent events, however, doubts about the efficacy of fiscal policy, as well as recognition of the substantial "inside" and "outside" lags involved in its implementation, have left short-run stabilization policy almost entirely in the hands of monetary policy in almost every country. Despite the central role that monetary policy plays as a short-run stabilization instrument around the world, there continues to be considerable doubt about its efficacy as well as about the channels through which it exerts its effects on the real economy. Even in the United States, where these issues have received substantial attention, evidence about the effects of monetary policy on the real economy has long been controversial.

It has long been recognized that both the efficacy of monetary policy and the channels for its transmission are strongly influenced by a country's financial structure (see, for example, Monti, 1971 and Modigliani and Papademos, 1982), and that financial structures differ substantially among economies, even industrial ones. These differences are even more pronounced when comparing low-income countries (LICs) to advanced and emerging ones. The financial structures of low-income countries share many features that differentiate them systematically from both high-income as well as emerging economies. As documented by Mishra, Montiel, and Spilimbergo (2012), low-income countries tend to be poorly integrated with international financial markets, their central banks intervene heavily in foreign exchange markets, and their domestic macroeconomic environments are often unstable. Mishra, Montiel, and Spilimbergo (2012) argue that these characteristics suggest that the bank lending channel should dominate monetary transmission in low-income countries.

However, they also argue that other characteristics of the financial structures of LICs tend to undermine the effectiveness of the bank lending channel. For example, such countries suffer from a weaker domestic institutional environment (e.g., poorly defined property rights, inefficient legal systems, poor legal protection for creditors, weak accounting and disclosure standards), they have small and illiquid securities markets, and their banking systems are small, highly concentrated, poorly capitalized, and many banks are publicly owned. Mishra, Montiel, and Spilimbergo indeed find impressionistic evidence that this channel tends to be weak and unreliable in such countries – specifically, that in regressions of commercial bank lending rates on central bank policy rates, the latter have both smaller short-run as well as long-run coefficients, and policy rates tend to explain a substantially smaller share of the variance in lending rates than they do in high-income and emerging economies. A review by Mishra and Montiel (2012) of country-specific empirical work on the transmission of monetary policy to aggregate demand in a large number of low-income countries, much of which is based on individual country VAR evidence, is consistent with this finding, in the sense that their review failed to turn up much systematic evidence of strong and reliable monetary transmission in such countries.

Given the dominant role of monetary policy as a short-run stabilization instrument in low-income countries, this state of affairs, if true, is alarming, because it suggests very little scope for the conduct of stabilization policy by central banks. However, the cross-country evidence provided by Mishra, Montiel, and Spilimbergo was only impressionistic, and the country-specific VAR evidence surveyed by Mishra and Montiel suffers from a number of flaws, generally failing to give careful attention to the identification issues that have been the overriding concern in research on monetary policy effectiveness in advanced countries.

This paper attempts to investigate the effectiveness of monetary policy in low-income countries more systematically. Specifically, we are interested in exploring the effectiveness in such countries of the first step of monetary policy transmission through the bank lending channel – from monetary policy innovations to bank lending rates – leaving aside the question of whether changes in bank lending rates subsequently affect aggregate demand. We seek to do so subject to the double challenge of employing credible identifying restrictions while deriving results for a large group of possibly quite heterogeneous countries. Our objective is to investigate whether the effects of monetary policy shocks on bank lending rates are systematically different in low-income countries from what they tend to be in advanced and emerging economies and, if so, whether these differences are consistent with conventional theory.

The first step in doing so is to obtain estimates of the effects of monetary policy innovations on bank lending rates for a large group of countries. Since the data from many countries are available for too short a time span or are too noisy to reliably investigate using structural VARs at the individual country level, we employ a panel methodology that allows individual country responses to structural shocks to be heterogeneous. Conventional dynamic panel methods are not appropriate in light of the fact that they require the dynamics of individual country responses to be identical among all countries. Furthermore, it is important to take into consideration the fact that individual countries are likely to be linked cross-sectionally via common global and regional shocks. To address these issues in the context of structural identification, we use the panel SVAR methodology developed in Pedroni (2008).

The paper has two main findings. First, there is a wide variation in impulse responses of the lending rate to a domestic monetary policy shock across countries. Second, countries with better institutional environments, more developed financial structures, and more competitive banking systems are those where monetary policy is the most effective in influencing commercial bank lending behavior. Given that LICs score poorly on all of these dimensions, we find the predicted transmission to be significantly weaker in these countries than in advanced and emerging ones.

The structure of the paper is as follows: the next section describes our strategy for identifying monetary shocks in our panel VARs, while Section 3 describes our empirical methodology and data sources. Our empirical results are presented and discussed in Section 4, while Section 5 summarizes and concludes.

2. Identification strategy

A central challenge in estimating monetary policy effects is to identify policy innovations. This essentially requires imposing *a priori* theoretical restrictions on the vector moving average (VMA) representation of the economy. The literature on estimating monetary policy effects has pursued several alternative techniques to generate these restrictions that are not suitable for our purposes. Sims' original "a-theoretic" approach involved implementing a Choleski decomposition, which essentially involves assuming that the relationship between the reduced form innovations and the initial period responses is recursive. However, these restrictions are understood to be *ad hoc*, and there is no reason to suppose that they would appropriately identify monetary policy innovations. Much of the subsequent literature on the estimation of monetary policy effects has been devoted to finding identification assumptions based on sound economic theory. Key contributions include Bernanke (1986), Blanchard (1989), Sims (1986), Bernanke and Blinder (1992), and Christiano, Eichenbaum, and Evans (1996).

All of these, however, are short run approaches to identification, since they are based on restrictions on the contemporaneous response of the variables to the structural shocks. Unfortunately, none of them serves our purposes well because they all require specific assumptions about the timing of information flows and of macroeconomic responses that would be hard to justify across a large group of very diverse economies. For example, the contemporaneous information on the state of the economy available to the monetary authorities, as well as the speed with which monetary policy shocks affect macroeconomic variables, are likely to differ from country to country. We therefore require an approach that places less reliance on country-specific information.

Our approach is to achieve identification by relying on long-run restrictions instead, as developed originally in Blanchard and Quah (1989). While long-run identifying restrictions have been subject to criticisms, they serve our particular objectives well in that they are more likely to be applicable across a broad group of heterogeneous countries than are assumptions based on contemporaneous relationships among the variables in a VAR. Our strategy is based on the following underlying intuition: we are interested in detecting the effect of an innovation in monetary policy on commercial bank lending rates. The central bank implements monetary policy by altering the size of its outstanding liabilities – the monetary base. But a one-time change in the monetary base represents a level change in a nominal variable, and a monetary policy innovation engineered by the central bank is therefore a nominal shock. Long-run monetary neutrality suggests that level changes in nominal variables should leave the inflation rate unchanged in the long run, and should therefore leave both the real and nominal lending rates unaffected in the long run. We can use this property to distinguish between the types of monetary shocks that we are interested in, namely level shocks to the monetary base and other shocks that may affect the lending rate, including those engineered by central bank actions, such as changes in inflation targets, which we will want to control for in our analysis.

To make use of monetary neutrality for identification, a minimal system for our purposes would therefore have to include the lending rate as the observable variable whose behavior we are trying to explain as well as some other nominal variable which is affected by a monetary policy shock in the long run. Among possible nominal variables, the monetary base is ideal as it will allow us to measure the size of the monetary policy shock in terms of its effect on the money base over any desired time frame, and to see the consequences of this on the nominal lending rate. The long-run structural form of the system can therefore be expressed as:

$$[nLR^*, nM0^*]' = A(1)\ [\varepsilon_R , \varepsilon_N]'$$

where nLR^* and $nM0^*$ are respectively the steady state values of the nominal lending rate and nominal monetary base, $A(1)$ is the $2x\ 2$ matrix of long-run impulse responses, with $A(1)_{12} = 0$. We refer to the second shock, $\varepsilon_{N,}$ as a nominal shock to reflect the notion that it is a shock which is neutral in the long run on real variables. By contrast, the first shock, ε_R captures all remaining shocks to the economy that have a long run impact on real variables, including inflation. Notice that this implies that shocks to the demand for real money balances will be captured by our ε_R shock. Only shocks to the supply of the nominal money base are captured by $\varepsilon_{N,.}$ Finally, to identify the sign of the shocks, we define a positive nominal shock as one that leads to a long run *increase* in the nominal monetary base, $nM0^*$ so that $A(1)_{22} > 0$, and likewise a positive real shock is defined as one which increases the nominal lending rate, nLR^* in the long run, so that $A(1)_{11} > 0$. The short run dynamics of all of the responses to all of the shocks, including the response of the lending rate to the nominal shock, is left entirely unrestricted, and is the object of our interest.

3. Empirical methodology and data sources

In this section we describe in greater detail the methodology we use to estimate the effects of monetary policy shocks on bank lending rates. The methodology is based on the panel structural VAR technique developed in Pedroni (2008).

Identification with long-run restrictions

The nature of structural identification in panels differs from identification in conventional time series only to the extent that both idiosyncratic country specific shocks and common global shocks are identified. But aside from this, the manner in which identification is achieved is similar to how it is achieved in conventional time series. While in general panel structural VARs can be based on any of a number of identifying restrictions, including short run or long run restrictions, our particular identification relies on long run restrictions. For this reason, it is worth clarifying briefly how the long run identification is accomplished before discussing the details of the panel aspects of our analysis.

Toward this end, we start by reviewing briefly how our identifying restrictions allow us to recover the structural form representations in the context of a standard time series VAR. Specifically, , we will refer to our vector of demeaned variables as $z_t = (z_{1,t},...,z_{M,t})'$ so that our structural form vector moving average representation can be expressed as $\Delta z_t = A(L)\varepsilon_t$, where $A(L) = \sum_{j=0}^{Q} A_j L^j$ are the moving average coefficients that give us the structural impulse responses and variance decompositions of interest, and $\varepsilon_t = (\varepsilon_{1,t},...,\varepsilon_{M,t})'$ is our vector of white noise structural shocks. Notice for convenience that evaluating $A(L)$ at 0, written $A(0)$, gives us A_0, the first period structural response of the differenced variables to the shocks, and evaluating $A(L)$ at 1, written $A(1)$ gives us the accumulated response of the differenced variables to the shocks, $\sum_{j=0}^{Q} A_j$, which is equivalent to the long run response of the levels of the variables to the shocks.

Using similar notation, the actual VAR that one estimates from the data, which we refer to as the reduced form VAR, can be expressed as $R(L)\Delta z_t = \mu_t$, where $R(L) = I - \sum_{j=1}^{P} R_j L^j$ are the VAR coefficients to be estimated and $u_t = (\mu_{1,t},...,\mu_{M,t})'$ is the vector of white noise reduced form innovations to be estimated. The process of identification involves finding a set of suitable economic restrictions on the structural form that allow us to find a unique mapping between the estimates of the reduced form VAR coefficients and innovations, $R(L)$, μ_t and the structural form impulse response coefficients and shocks $A(L)$, ε_t. Toward that end, it is worth noting that if we express the reduced form estimates in moving average form as $\Delta z_t = R(L)^{-1}\mu_t$ so that $R(0)^{-1} = I$, then by evaluating $R(L)^{-1}\mu_t = A(L)\varepsilon_t$ at $L = 0$ we see that the structural shocks are related to the reduced form innovations as

$$\varepsilon_t = A(0)^{-1}\mu_t \tag{1}$$

Similarly, using equation 1 to substitute out μ_t gives us the relationship between the structural moving average coefficients and the reduced form VAR coefficients as

$$A(L) = R(L)^{-1} A(0) \tag{2}$$

Finally, evaluating equation 2 at $L = 1$ gives us a key relationship that relates the first period structural response of the differenced variables to the long run response of the variables in levels, namely

$$A(0) = R(1) A(1) \tag{3}$$

These are the three key equations that map the reduced form VAR estimates to the structural form shocks and impulse response coefficients that interest us. However, these mappings are not unique. For the mappings to become unique, we must use our identifying restrictions. The first of these is our assumption regarding the structural shocks. Since the shocks are thought of as the structural forcing processes for the underlying economic model, it is natural to think of them as conceptually distinct and therefore orthogonal to one another. Furthermore, since they are conceptual and unobserved, their units are arbitrary, so that we are free to scale them as we wish. Accordingly, we scale their variance to 1. These two features lead to the assumption that the covariance matrix for the structural shocks is a simple identity matrix, so that we have $E(\varepsilon_t \varepsilon_t') = I_{M \times M}$. Consequently, using equations 1 and 2 we get two useful results that relate estimates of the reduced form covariance matrices to the structural form contemporaneous response coefficients. Specifically, for the contemporaneous covariance of μ_t, we get

$$E(\mu_t \mu_t') = E(A(0)\varepsilon_t \varepsilon_t' A(0)') = A(0)A(0)' \tag{4}$$

We can derive a similar expression for the long run covariance, $\Omega(1)$. Conceptually, the long run covariance for the reduced form can be thought of as the covariance that occurs in the steady state, namely after the variables have fully adjusted to the shocks, which is equivalent to

$R(1)^{-1}\mu_t$ in the reduced form vector moving average representation. Consequently using equations 1 and 2 we can relate the reduced form long run covariance as

$$\Omega(1) = E(R(1)^{-1}\mu_t\mu_t' R(1)^{-1}{}') = A(1)A(1)' \tag{5}$$

Notice from these equations that the assumptions on the structural shocks gave us $(M^2+M)/2$ restrictions on $A(0)$ and $A(1)$ in equations 4 and 5 respectively, which means we require an additional $(M^2-M)/2$ restrictions. Short run structual VARs impose the restrictions directly on $A(0)$. Long run structural VARs impose the restrictions on $A(1)$ and then use equation 3 to map back to $A(0)$. In our case, since our long run restrictions are recursive, we can express them as $A(1)_{(j,k)} = 0 \ \forall j < k$. Consequently, using these restrictions with equation 5, we get:

$$A(1) = Chol(\Omega(1)) \tag{6}$$

where $Chol(\Omega(1))$ denotes the lower triangular Cholesky decomposition of the long run covariance matrix $(\Omega(1))$. Consequently, this gives us $A(0)$ by equation 3, which in turn gives us $A(L)$ and ε_t by equations 1 and 2, and thereby provides us with our structurally identified impulse response coefficients and shocks.

Heterogeneous panel estimation

Our interest is in how these impulse response coefficients vary across countries, and in particular whether they tend to be systematically weaker in countries with specific characteristics. However, implementing our structurally identified VAR in order to estimate these coefficients for a large group of countries poses two empirical challenges. The first of these is that many of the countries in our sample have relatively short spans of data available. For such countries a standard time series-based structural VAR analysis would not be reliable. The second is that the data from many of the countries are fairly noisy, so that even when more data are present, a conventional time series-based analysis for any one country may not be reliable. For these reasons, we wish to exploit the panel dimension of the data to increase the reliability of the inferences relative to simply basing our analysis on a large number of relatively unreliable individual country structural VAR results. Precisely because what we are interested in is the heterogeneity of country responses, we are led to use heterogeneous panel methods.

This poses its own challenges, however, stemming from the fact that countries are interdependent and often respond to common external shocks that are not directly observed by the econometrician. If we wish to use the panel dimension to improve inference relative to individual country results, then we must take into account this form of cross sectional dependence. If potential cross sectional dependence is naively ignored, then confidence intervals and standard errors associated with the panel estimation are no longer valid.

Consequently, to employ our structural identification in a manner that addresses these issues, we follow the panel structural VAR methodology as developed in Pedroni (2008). This methodology exploits the panel dimension to compensate for short or noisy individual country data, while allowing for complete heterogeneity among countries, as well as cross sectional dependence. It does so by taking a so-called group mean approach to estimation and inference, and reporting properties of the corresponding distribution of the structurally identified individual country results. It accounts for cross sectional dependence by identifying structural shocks that are common to all the countries in the sample, while allowing individual countries to respond to these common shocks heterogeneously.

The methodology is implemented as follows. First, we estimate the reduced form VAR for each country separately. We apply our identification scheme as described above to each of these estimated VARs to obtain a series of composite structural shocks for each country separately, yielding a panel of composite structural shocks. These composite shocks ε_{it} will need to be decomposed into common global shocks $\bar{\varepsilon}_t$ and idiosyncratic country specific shocks, $\tilde{\varepsilon}_{it}$. To do so, we use the raw panel data to compute the cross sectional averages of each of our $m = 1 \ldots M$ variables for each point in time over our sample. This gives us a pure $M \times 1$ dimensional time series vector of average values for our variables, which we use to estimate a reduced form VAR for the averages. Applying our identification scheme to the reduced form VAR for the averages then gives us an $M \times 1$ dimensional vector series of common structural shocks, $\bar{\varepsilon}_t$.

The relationship between the composite, idiosyncratic, and common structural shocks can be modeled as a panel common factor structure, whereby the composite shocks depend on the common shocks via an $M \times M$ country specific loading matrix λ_i, so that we have $\varepsilon_{it} = \lambda_i \bar{\varepsilon}_t + \tilde{\varepsilon}_{it}$. Furthermore, since shocks have been identified as orthogonal structural shocks, the loading matrix is a diagonal matrix and the composite shocks can be decomposed by simple OLS. Accordingly, for each composite structural shock $m = 1 \ldots M$ of our panel, we estimate

$$\varepsilon_{m,it} = \lambda_{m,i} \bar{\varepsilon}_{m,t} + \tilde{\varepsilon}_{m,it} \tag{7}$$

to obtain the country specific loading vectors and the idiosyncratic country specific structural shocks.

Once we have the loading vectors and the decomposition into common and idiosyncratic structural shocks, these can be used to obtain the country specific structural impulse responses to both common and idiosyncratic shocks, as well as variance decompositions for both common and idiosyncratic shocks. By virtue of the common factor extraction of the orthogonal structural shocks, the structural impulse responses and variance decompositions can now be treated as cross sectionally independent. This allows us to use the cross-country spatial distribution of the responses and variance decompositions to produce confidence intervals for the median impulse responses and variance decompositions. Furthermore these spatial distributions can also be used to study cross-country patterns in the signs and magnitudes of the responses. This allows us to examine which country-specific features, such as depth of the financial sector, might explain the relative effectiveness or non-effectiveness of monetary policy among different types of economies. For further details on the technique, we refer readers to Pedroni (2008).

Data sources

The data used in this paper are drawn from the International Financial Statistics of the IMF. The two key variables used in the panel VAR analysis are (i) nominal base money or M0, and (ii) the commercial bank lending rate. The nominal base is drawn from line 14. It typically includes currency in circulation and banks' reserves at the central bank. The bank lending rate is taken from line 60. This is the “rate that usually meets the short- and medium-term financing needs of the private sector” (IMF, 2008).

We first compile the dataset at a quarterly frequency. Our estimation sample covers a total of 63 countries over the period 1980-2008, which includes 20 advanced, 14 emerging, and

29 LICs.[2] The sample is selected based on the availability of data. In order to implement our empirical methodology in an unbalanced panel, some additional restrictions are imposed on the sample. For example, we require a certain minimum number of observations over time in order to search over a suitable range of possible lag truncations for each country and still retain enough degrees of freedom for estimation. To ensure this, we use a span of 5 years of continuous data as our cut-off for the minimum sample length for any one country. If a country has fewer than 5 years of continuous data for our variables of interest, we drop the country from our sample. Similarly, to ensure that the average variable values and corresponding common structural shocks are estimated reasonably well in an unbalanced panel, we must ensure that we have a sufficient cross-sectional dimension present for each time period of our sample. Accordingly, we use 15 as our cutoff, meaning that if for any given period we do not have data available for at least 15 countries, we drop that period from our sample.

Finally, we need to ensure that we have both cross sectional and temporal variation in our data. For example, if a country has fixed its nominal lending rate over the sample, then there is no country-specific variation in the variable, so it should not be used. Similarly, for some countries, certain variables are only available at the annual frequency, but are nonetheless reported at the quarterly frequency with no variation from quarter to quarter. Such data should also not be used in our analysis, since there will be no quarterly shocks present in the data. Consequently, to guard against the absence of temporal variation due to either of these possibilities, we drop any country from our sample for which the data values are identical for

[2] For the purposes of our survey, the classification of countries into advanced, emerging and LICs follows Rogoff et. al. (2004). Emerging market economies are those that are included in the Morgan Stanley Capital International (MSCI) index. With the exception of Israel, which is in the MSCI index, advanced economies are those that are classified as upper income economies by the World Bank. All other economies constitute low-income countries (LICs).

four or more consecutive quarters. The list of countries and time periods used in the study is provided in the appendix.

In order to study the variation in impulse responses across countries, we use data on a number of correlates which are drawn from the dataset compiled by Mishra, Montiel and Spilimbergo (2012), and are averaged over 1980-2010. These variables include measures of institutional quality, the ratio of deposit bank assets to GDP, the ratio of stock market capitalization to GDP, a measure of bank concentration, and an index of *de facto* international financial integration. A detailed description of all these variables is provided in the appendix.

4. Results

The structural VAR methodology outlined above is used to generate impulse response functions that capture the dynamic effects of a monetary policy innovation on bank lending rates in each country of our sample. In this section we use these estimated effects to answer three questions: 1) what is the median response of the lending rate to a country-specific monetary shock? 2) how much cross-country variation is there in this response? 3) what factors determine the response of the lending rate to monetary policy shocks?[3]

Impulse responses and variance decomposition

Our most important finding is that there is wide variation in the impulse responses of the (log) lending rate to a domestic monetary policy shock across countries. We find the expected negative response for a large group of countries, but by no means for all. As an illustration,

[3] In what follows, we will interpret the "nominal shock" as a monetary policy shock, given that we consider innovations to the monetary base.

consider the estimated responses over a four-quarter horizon for the United States and Uganda, shown in Figure 1. For the United States, the response of the lending rate to the monetary policy shock is negative, but small, in the first quarter, but it becomes progressively larger over the next two quarters, before reversing in the fourth quarter. For Uganda the initial effect is similarly small, but actually *positive*, and subsequent effects are very difficult to detect.

Figure 2 reports the median as well as the 25th and 75th percentile responses for the 63 countries in our sample.[4] The median response is actually *positive*, but very close to zero. While this is surprising, a similar result has previously been derived for a sample consisting only of advanced countries (Bernanke and Mihov, 1998). The 25th percentile response suggests that a one-unit monetary policy shock (or a shock which results in a 3% long-run increase in money balances) reduces the lending rate by about 1% in the following quarter, and up to 2% in the long run. The effect is therefore economically significant for at least the bottom 25th percentile of the countries.

Figure 3 reports the median as well as the 25th and 75th percentile fractions of the variance in the lending rate that is explained by the monetary innovation.[5] On average, country-specific monetary innovations explain about 4-7% of the variation in the bank lending rate over all response periods. Once again, the interesting finding is that there is significant variation across countries. While the short-run (1 quarter response period) variation ranges from close to 0 to 12 percent, in the long run (24 quarters response period) it ranges from 2% to 32%.[6]

[4] Note that the country that has the median response at response period S is not necessarily the same as the country with the median response in other response periods; the 25th and 75th percentile responses are constructed in the same way. Hence the curves shown in Figure 2 do not trace the responses for any particular country.
[5] Also in this case, the country with median fraction of variance in lending rate is not necessarily the same as the country with median fraction of variance in other periods.
[6] The impulse responses and variance decompositions for all the other variables in the system are provided in the appendix (Figures A1 and A2).

The key question is, of course, what accounts for this cross-country heterogeneity in the effectiveness of monetary policy? Next we examine the role of specific country characteristics in explaining the cross-country pattern in the responses of lending rates to monetary policy.

Variation across countries in impulse responses

Our results so far suggest that the strength of the link between central bank monetary policy actions and commercial bank lending behavior, as reflected in lending rates, varies widely across countries. Is there a systematic pattern to this variation in the impulse responses across countries, or it purely random? Mishra, Montiel, and Spilimbergo (2012) argued that in low-income countries with rudimentary financial structures monetary transmission is likely to operate primarily through the bank lending channel, but they also argued that when the domestic institutional structure is weak, the domestic financial system is poorly developed, and the domestic banking sector is not competitive, even this channel may prove to be weak.

In order to explore the determinants of the variation in impulse responses, we next examine the cross-section association between certain country characteristics, including those mentioned above, and the strength of the impulse responses. In particular, we test the hypotheses of Mishra, Montiel and Spilimbergo by considering three factors that may influence the strength of monetary transmission: (i) the strength of the domestic institutional environment, (ii) the development of the domestic financial system, and (iii) the degree of competition in the domestic banking system. Our regressions will also include the degree of integration of the domestic economy with international financial markets as a control variable. The need to control for the degree of financial integration arises from the fact that higher integration may tend to dampen the impact of monetary policy shocks on domestic interest rates. Under fixed exchange rates, this is a direct consequence of the loss of monetary autonomy as implied by the "impossible trinity." Under floating rates it reflects the fact that as financial integration increases, relatively more of the burden of monetary transmission falls on the exchange rate, rather than on the domestic interest rate, implying that monetary policy actions have smaller effects on domestic interest rates.

We measure the degree of institutional development using the index of the quality of regulation developed by Kaufman, Kraay and Mastruzzi (2009). We rely on two familiar complementary indicators of financial development from Beck, Demirguc-Kunt and Levine (2009): the ratio of the assets of deposit money banks to GDP and the ratio of stock market capitalization to GDP. In order to measure competition in the banking system, we use the concentration ratio in the domestic banking industry. Finally, we measure financial integration in *de facto* terms as the ratio of the sum of external assets and liabilities to GDP, after removing foreign exchange reserves from the asset side and concessionary loans from the liability side, following Dhungana (2008).

Measuring the effectiveness of the bank lending channel using impulse responses to a positive nominal shock is complicated by the fact that the response typically varies quarter by quarter, implying that no single number provides an unambiguous measure of the size of the response. Accordingly, we examine the magnitude of each of the responses over 1-4 quarter horizons, as well as by the magnitude of the average response coefficient over a four-quarter horizon. We also examine the effects of our covariates on the size of the peak response of the lending rate over the four-quarter horizon as a summary measure. Because a larger response (a more effective bank lending channel) would be recorded as a more *negative* impulse response coefficient, this involves explaining the *minimum* value of the impulse response over the four-quarter horizon. We expect the effects of an improved institutional environment and our two financial development indicators on each of these coefficients to be negative, indicating a more powerful effect of the monetary shock on the lending rate in the theoretically-expected direction, and that of increased bank concentration to be positive, after controlling for the effect of financial integration, which should itself be expected to have a positive coefficient, consistent with a weakening of the interest rate response.

Before proceeding to the regression analysis, we examine the bivariate relationship between the impulse responses and each of the potential correlates. The scatter plots are shown in Figures 4a-4e. Each figure has six plots showing the bivariate relationship between the six impulse responses (four quarters, average and the minimum), and one covariate. The signs of almost all the bivariate correlations (27 out of 30) are consistent with the hypotheses outlined above. Better institutional quality and a higher degree of financial development are associated with a larger reduction in lending rates in response to a monetary shock; whereas more concentrated domestic banking sectors are associated with a smaller decrease in the lending rates. The estimated correlation coefficents on institutional quality are always statistically significant.

Our full regression results are presented in Table 1, where each column reports the regression of the impulse response coefficient at each horizon, listed along the top row of the table, on each of the five variables mentioned above. Because of the noisiness of both the regressands as well as the regressors, we focus initially on the signs of the estimated coefficients, rather than their precision.

The multivariate regression results are consistent with the bivariate correlations in Figure 4. First, the partial effect of higher institutional quality on the impulse responses in each of the first three quarters, as well as the average response over the four quarters, is consistently negative. This is consistent with the hypothesis that monetary expansion is more effective in reducing bank lending rates in countries with better institutional environments. Although a weak positive effect appears in the fourth quarter, this may simply indicate that after the lapse of a year's time, the lending rate has returned close to its original value, as in the impulse response function for the United States shown in Figure 1. Second, monetary transmission tends to be more effective in countries with more developed financial systems. The partial effects of the ratio of banking sector assets to GDP as well as stock market capitalization to GDP on the impulse response is negative over all horizons, and is of course therefore negative for the average four-quarter response. The effect of stock market capitalization in particular is not only negative over all four quarters, but it is statistically significant in all but the fourth quarter, again consistent with the interpretation that in a strong institutional environment for the financial sector, the lending rate responds more quickly to monetary policy shocks. Third, the more concentrated the banking sector, the *less* negative is the response of lending rates. Again, this result holds over all horizons. In countries where the banking system is imperfectly competitive, changes in policy interest rates may have weak effects on market rates, since imperfectly competitive banks may not pass on changes in policy rates.[7] If so, changes in policy rates may largely affect banking spreads, rather than market rates. Fourth, the higher the degree of *de facto* financial integration; the weaker (or more positive) is the response of bank lending rates to monetary policy shocks. As indicated above, this result is consistent with increased financial

[7] Mishra and Montiel (2012) provide a simple model illustrating why this may be so.

integration resulting in a loss of monetary autonomy under fixed exchange rates, as well as a reallocation of the transmission burden from interest rates to exchange rates under floating rates.

While not all of our coefficients are statistically significant, this is to be expected with only 36 observations and in a regression that is designed to explain the cross-section values of very noisy estimated parameters. We note that the F-test for all of these equations is significant at the 10 percent level or better, and place special weight on the remarkable consistency in the signs of estimated parameters. Of the twenty estimated coefficients over the four quarters, nineteen carry the expected sign. As an illustration, if the true values of these coefficients were zero, and if coefficient were drawn independently from a symmetrical distribution, the probability of drawing 19 of 20 coefficients with the expected sign would be 1.91×10^{-5}.

The natural interpretation of these findings is that countries with better institutional environments, more developed financial structures, and more competitive banking systems, are those where monetary policy is most effective in influencing commercial bank lending behavior. On the other hand, countries with weaker institutional environments, less developed financial structures, and less competitive banking systems are those where monetary policy shocks do not tend to get transmitted to bank lending rates.

Table 2 shows how these characteristics differ among advanced, emerging, and low-income countries in our sample. As is evident in the table, the advanced economies in our sample have stronger institutional environments, more highly developed financial systems (as indicated by larger banking systems and larger stock markets), and more competitive banking systems. Emerging economies occupy an intermediate position, and the low-income countries in our sample are significantly more disadvantaged along all of these dimensions. We can see the implications of these differences in characteristics for the dynamic responses of bank lending rates to monetary policy shocks in each of these groups of countries by computing the predicted quarter-by-quarter impulse responses for each group based on these group-specific characteristics.[8] The results are shown in Figure 5. Both advanced and emerging economies display the expected negative response, larger on impact and more muted over time, with advanced economies displaying significantly larger responses than emerging economies. By contrast, low-income countries fail to display a negative response in three out of four quarters, and the negative response that they exhibit in the third quarter is extremely small.

Figure 5 summarizes our central result: in contrast to advanced and emerging economies, the transmission of monetary policy shocks to bank lending rates in low-income countries appears to be problematic. The poor institutional environment in which the financial sector operates in these economies, as well as the limited degree of concentration in their banking systems, appear to significantly weaken the impact that central bank monetary policy actions exert on commercial bank lending rates in these economies. The implication is that these characteristics of LIC financial structures are likely to significantly undermine the strength of the bank lending channel.

5. Conclusions

The links between central bank actions and ultimate effects on the real economy remain poorly understood. In the case of low-income countries, a strong *a priori* case can be made (see Mishra, Montiel, and Spilimbergo, 2012) that those links should operate primarily through the bank lending channel. Yet there are independent reasons, related to poor domestic institutions

[8] Since we use financial integration only as a control variable, the predicted responses are computed for each group using the average value of the financial integration measure over the whole sample.

and weak competition in the banking sector, to suspect that the bank lending channel may itself be weak and unreliable in such countries. If so, the classic analysis of Brainard (1967) suggests caution in the application of monetary policy, and in particular restraint in the use of monetary policy for stabilization purposes.

This paper is a first attempt at systematically documenting and providing tentative explanations for the variation in the effectiveness of the bank lending channel across countries. Using a 63-country sample and a heterogeneous panel VAR approach with relatively agnostic economically motivated identification restrictions, we have found that there is evidence of substantial cross-country variation in the strength of the first stage of the bank lending channel, as measured by the impulse responses at various horizons of commercial bank lending rates to monetary policy shocks. Partial correlations of the magnitudes of these responses with various country characteristics suggested by theory as potentially affecting the strength of the bank lending channel are consistent with theoretical predictions. The implication is that monetary policy may be a highly unreliable instrument with which to pursue macroeconomic stabilization in countries that are characterized by a poor institutional environment and an uncompetitive banking sector, both of which are common characteristics in low-income countries. If this conclusion is correct, it raises the natural follow-up questions of how the central bank should behave in such an environment, whether it would indeed be desirable for it to have stronger and more reliable effects on aggregate demand, and if so, how the environment can be changed so as to achieve this goal.

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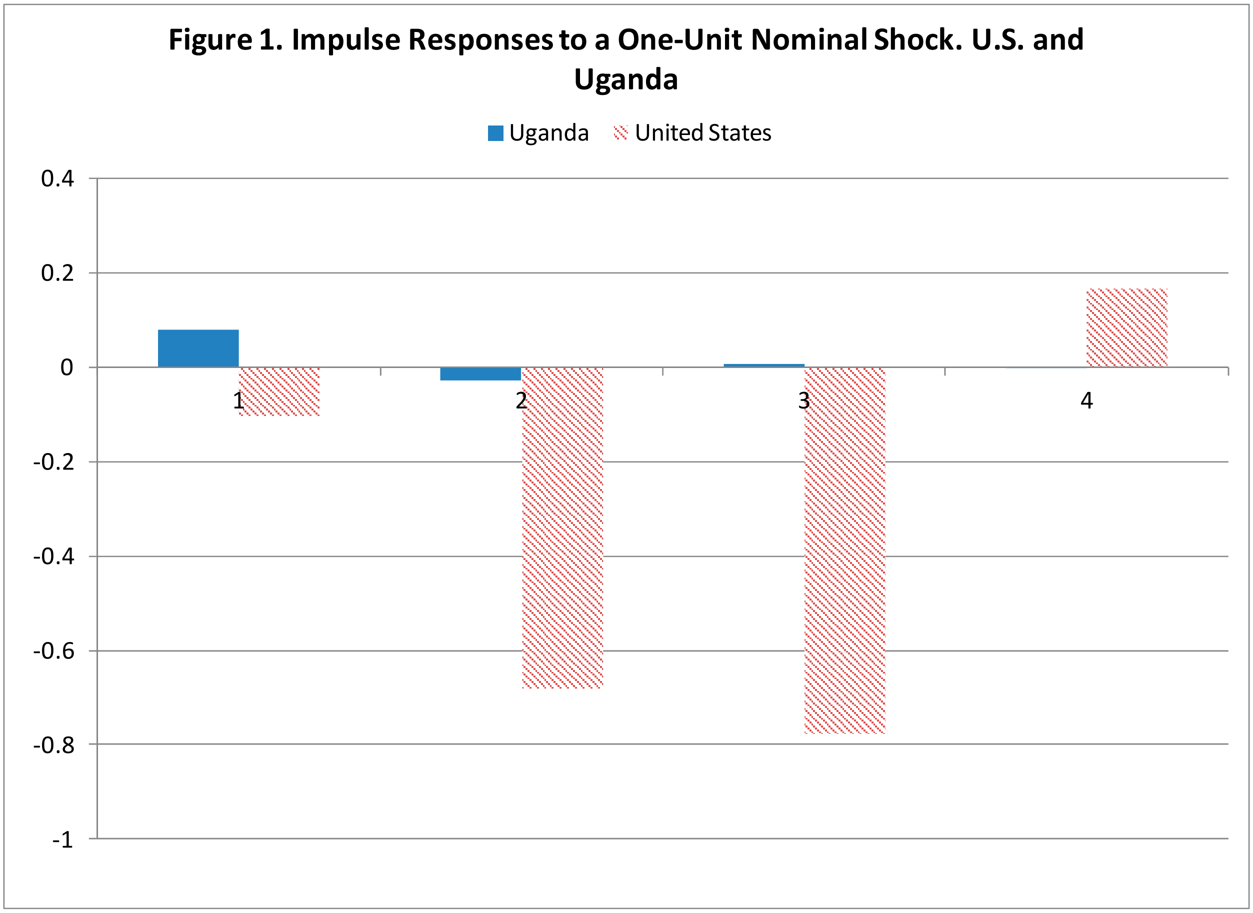


Figure 1. Impulse Responses to a One-Unit Nominal Shock. U.S. and Uganda
Uganda
United States
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
1
2
3
4

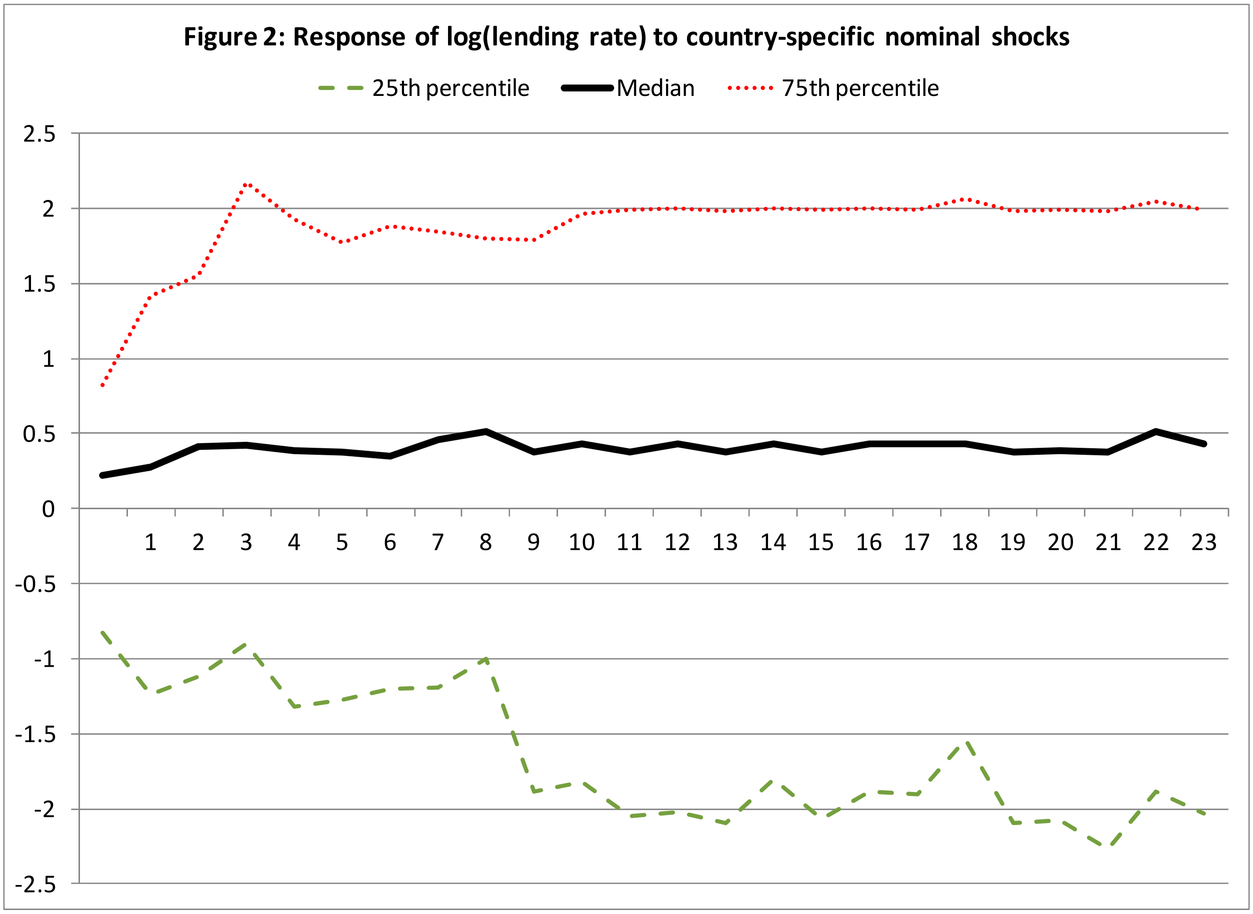


Figure 2: Response of log(lending rate) to country-specific nominal shocks
25th percentile
Median
75th percentile
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23

Figure 3: Percent share of the variance of log(lending rate) due to country-specific nominal shocks

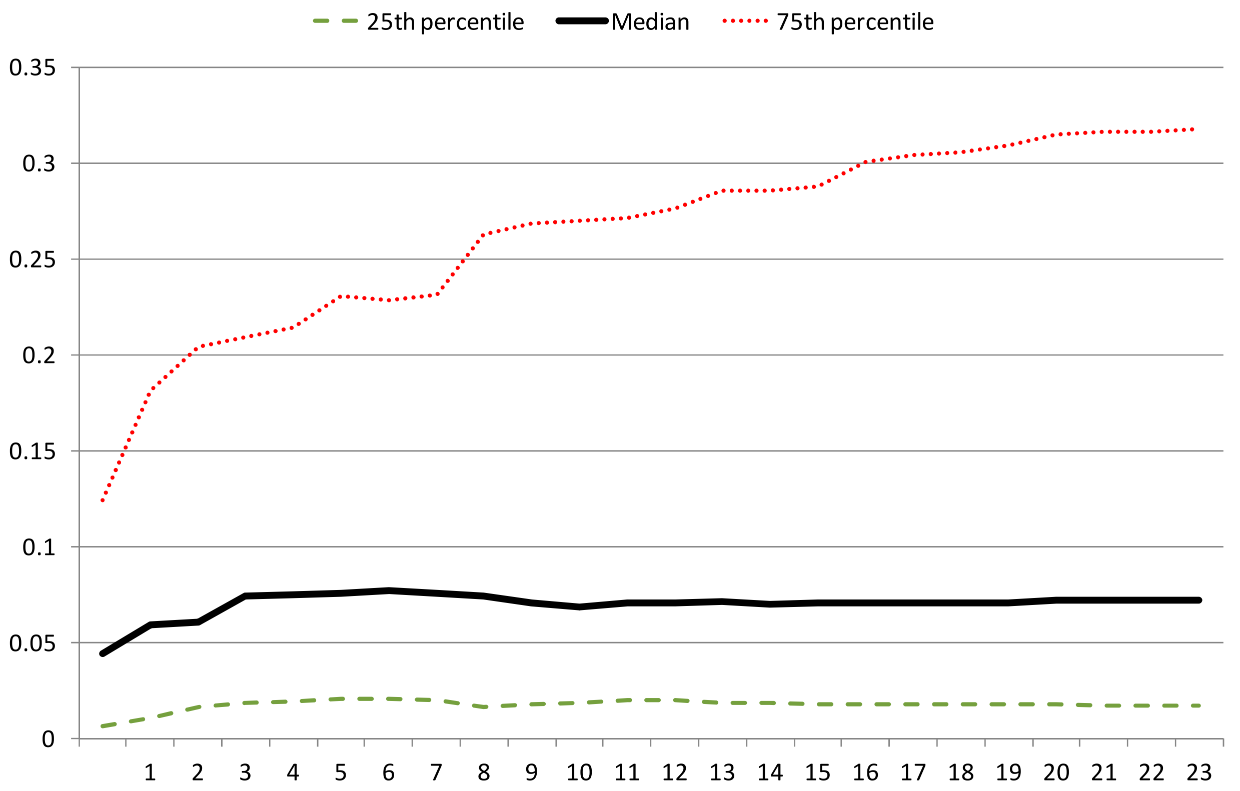


Fig 4a: Impulse Responses and Regulatory Quality

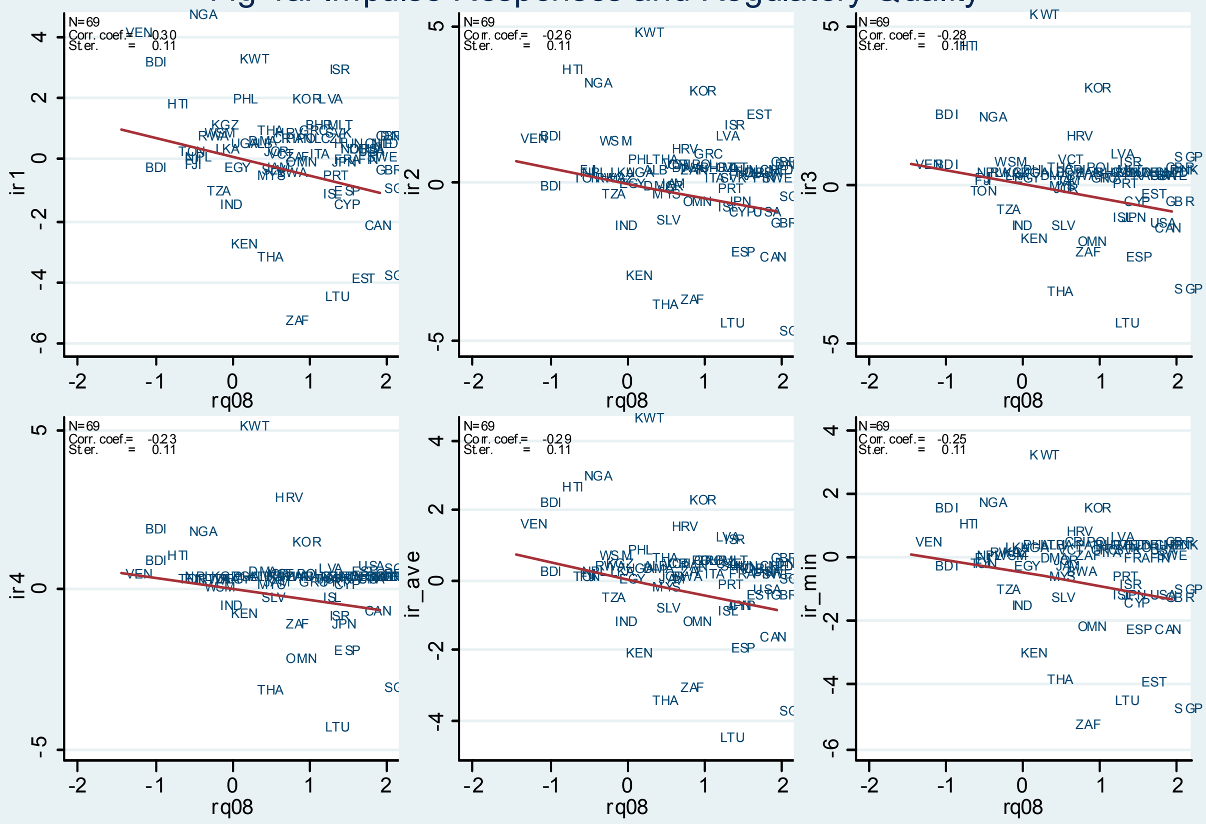


Fig 4b: Impulse Responses and Size of Banking Sector

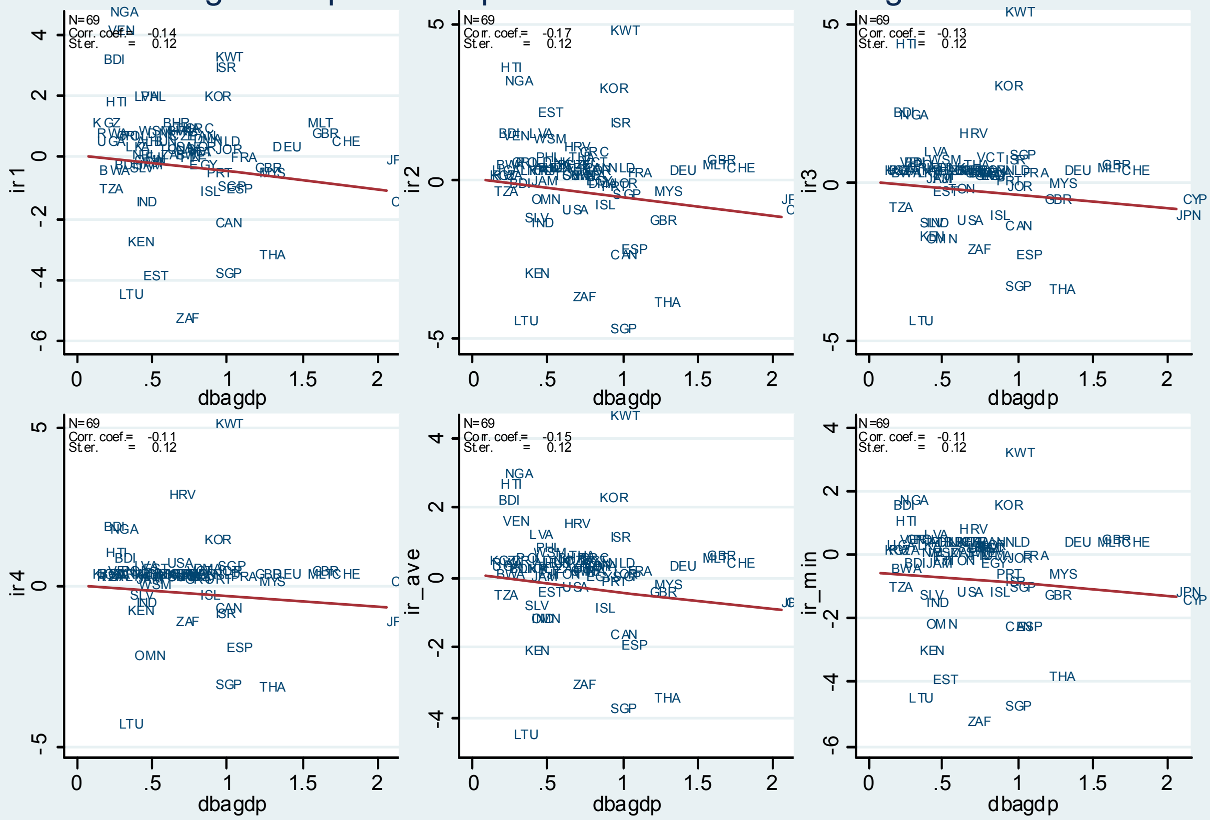
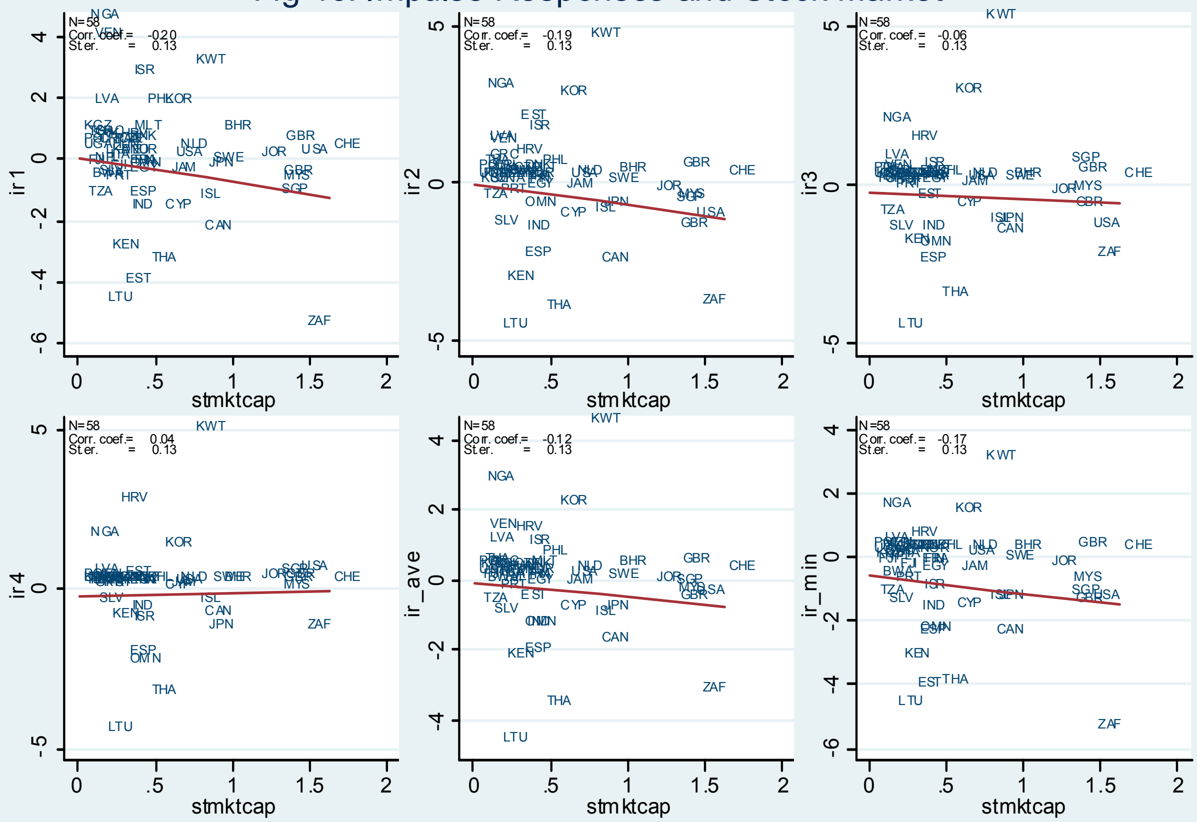
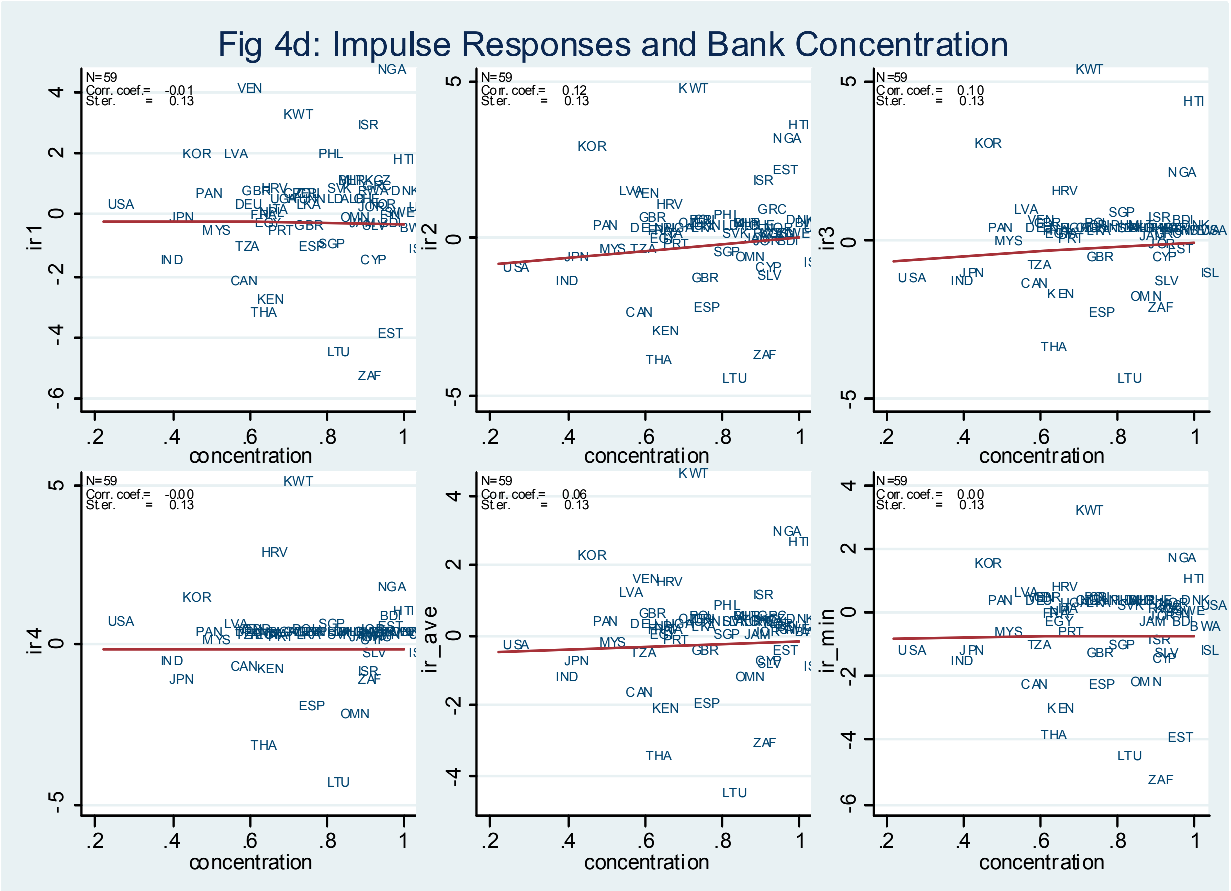


Fig 4c: Impulse Responses and Stock Market





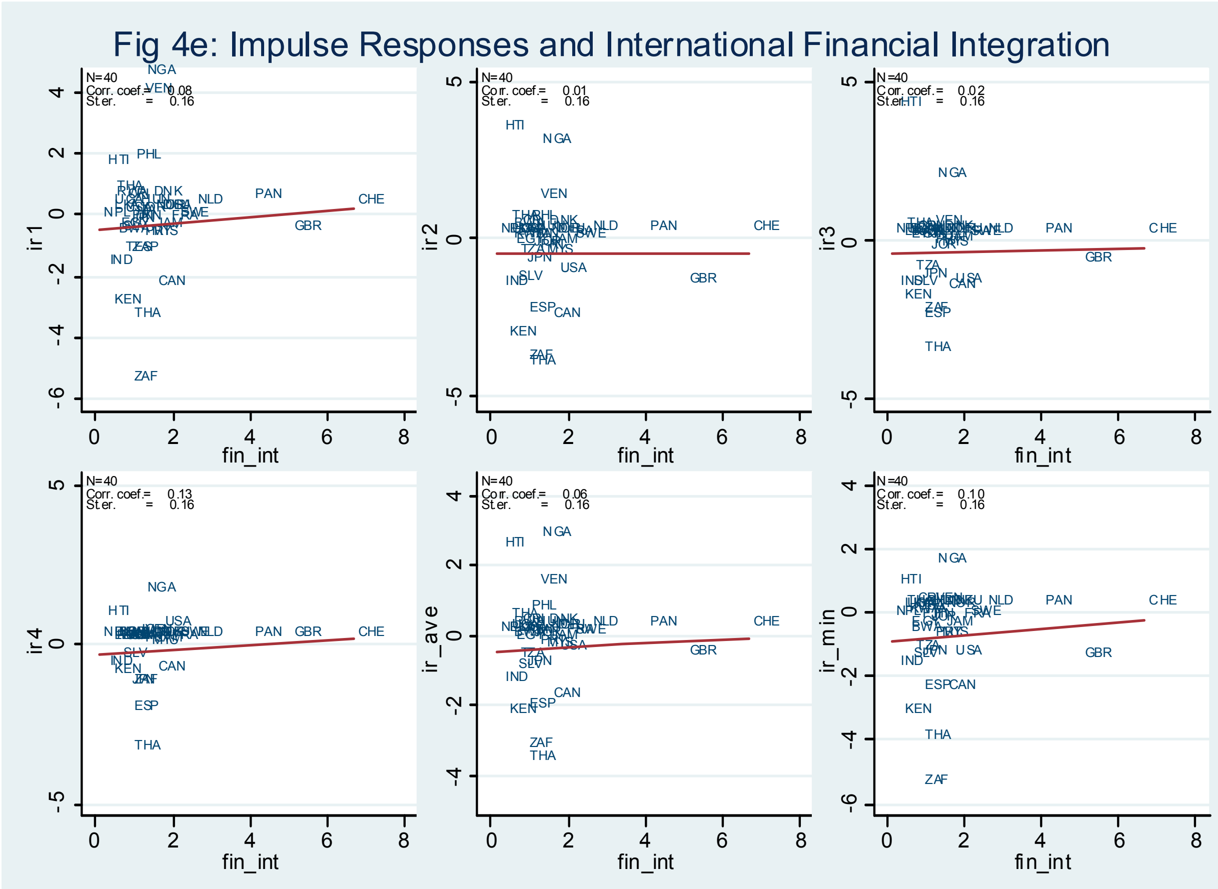
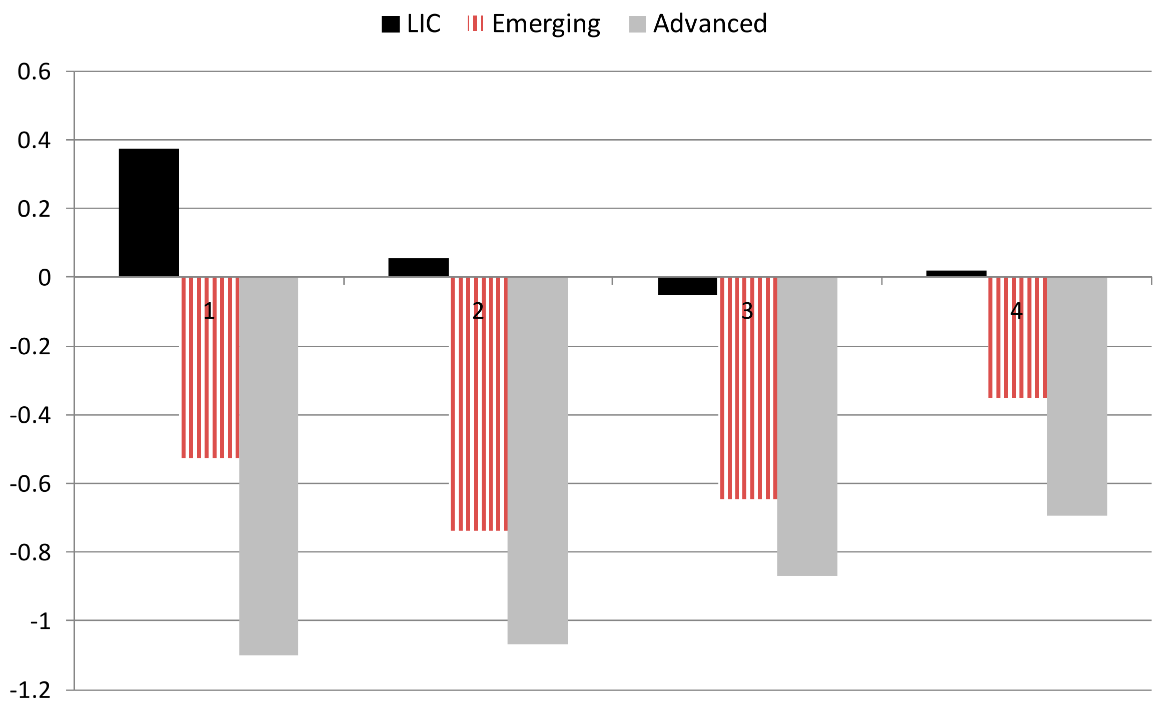


Fig 4e: Impulse Responses and International Financial Integration
N=40
Corr. coef.= 0.08
St.er. = 0.16
ir1
fin_int
N=40
Corr. coef.= 0.01
St.er. = 0.16
ir2
fin_int
N=40
Corr. coef.= 0.02
St.er. = 0.16
ir3
fin_int
N=40
Corr. coef.= 0.13
St.er. = 0.16
ir4
fin_int
N=40
Corr. coef.= 0.06
St.er. = 0.16
ir_ave
fin_int
N=40
Corr. coef.= 0.10
St.er. = 0.16
ir_min
fin_int

Figure 5. Predicted Four-Quarter Impulse Responses Conditional on Country Specific Characteristics



Notes. The predicted responses are based on the coefficient estimates in Table 1 (including the constant) and country-group means shown in Table 2.

Table 1. Impulse response of log(lending rate) to nominal shocks: Correlates

	1st quarter	2nd quarter	3rd quarter	4th quarter	Average	Minimum
Regulatory quality	-0.465	-0.226	-0.109	0.063	-0.184	0.006
	[0.409]	[0.326]	[0.245]	[0.196]	[0.278]	[0.325]
Deposit money bank assets/ GDP	-0.219	-0.279	-0.397	-1.135**	-0.507	-0.24
	[0.876]	[0.700]	[0.526]	[0.419]	[0.596]	[0.696]
Stock market capitalization / GDP	-1.532*	-1.311**	-0.807*	-0.054	-0.926*	-1.569**
	[0.756]	[0.604]	[0.454]	[0.362]	[0.514]	[0.601]
Bank concentration	0.919	1.508	1.406	0.167	1.0000	0.987
	[1.541]	[1.231]	[0.926]	[0.738]	[1.048]	[1.224]
International Financial Integration	0.623**	0.455**	0.366**	0.295**	0.435**	0.493**
	[0.255]	[0.204]	[0.153]	[0.122]	[0.173]	[0.202]
Number of observations	36	36	36	36	36	36
R-squared	0.26	0.28	0.30	0.31	0.28	0.29
p-value for the F-stat	0.09	0.06	0.05	0.04	0.07	0.06

Notes. Regulatory quality is for 2008, and is taken from Kaufman, Kraay and Mastruzzi (2009). All other explanatory variables are long-term averages. Deposit money bank assets, stock market capitalization, and bank concentration are from Beck, Demirguc-Kunt and Levine (2009). The first two are averages over 1980-2007, the third is averaged over 1987-2007. The financial integration measure is from Dhungana (2008), and is averaged over 1980, 85, 90, 95, and 2000.

Table 2. Country-Group Characteristics

	Advanced	Emerging	Low-income
Institutional quality	1.36	0.60	0.06
Deposit money banks/GDP	1.02	0.67	0.35
Stock market capitalization/GDP	0.64	0.50	0.18
Bank concentration	0.73	0.65	0.76

Notes. Institutional quality is for 2008, and is taken from Kaufman, Kraay and Mastruzzi (2009). All other explanatory variables are long-term averages. Deposit money bank assets, stock market capitalization, and bank concentration are from Beck, Demirguc-Kunt and Levine (2009). The first two are averages over 1980-2007, the third is averaged over 1987-2007. The financial integration measure is from Dhungana (2008), and is averaged over 1980, 85, 90, 95, and 2000.

Table A1. Sample Coverage

Country name	WB code	Start time	End time
ADVANCED			
Canada	CAN	1980q3	2006q2
Cyprus	CYP	2001q1	2007q4
Denmark	DNK	1980q3	1990q1
Finland	FIN	1980q3	1998q4
France	FRA	1988q3	1997q4
Germany	DEU	1991q1	1998q4
Greece	GRC	1987q2	1994q4
Iceland	ISL	1983q1	2008q1
Italy	ITA	1983q3	1998q4
Japan	JPN	1980q3	2008q4
Kuwait	KWT	1992q1	2005q2
Malta	MLT	1995q1	2007q4
Netherlands	NLD	1980q3	1997q3
Norway	NOR	1985q4	2004q4
Portugal	PRT	1985q3	1998q4
Spain	ESP	1982q1	1998q4
Sweden	SWE	1980q3	2006q3
Switzerland	CHE	1986q2	2003q3
UK	GBR	1990q4	2008q4
US	USA	1980q3	2003q2
EMERGING COUNTRIES			
Czech Rep	CZE	1993q1	2008q4
Egypt	EGY	1991q2	2007q3
Hungary	HUN	1988q3	2008q4
India	IND	1994q4	2001q1
Israel	ISR	1980q3	1996q2
Jordan	JOR	1996q1	2008q4
Korea	KOR	1996q2	2008q4
Malaysia	MYS	1981q3	2008q4
Philippines	PHL	1986q4	2008q4
Poland	POL	1988q1	2008q4
Singapore	SGP	1980q3	1995q3
South Africa	ZAF	1981q1	1999q4
Thailand	THA	1980q3	2003q2
Venezuela	VEN	1984q1	2008q4

Country name	WB code	Start time	End time
LOW INCOME COUNTRIES			
Albania	ALB	1999q1	2008q4
Bahrain	BHR	1996q1	2001q3
Botswana	BWA	1988q1	1995q1
Bulgaria	BGR	1995q1	2008q4
Burundi	BDI	1990q3	2008q4
Costa Rica	CRI	1986q3	2008q4
Croatia	HRV	1993q1	2008q4
Dominica	DMA	1998q4	2006q3
El Salvador	SLV	1989q3	2000q4
Estonia	EST	1994q1	2008q4
Fiji	FJI	1988q1	2008q4
Haiti	HTI	1999q1	2003q4
Jamaica	JAM	1980q3	2008q4
Kenya	KEN	1992q4	2008q4
Kyrgyz Rep	KGZ	2002q1	2008q4
Latvia	LVA	1995q1	2008q4
Lithuania	LTU	1994q1	2008q4
Nepal	NPL	1997q4	2005q2
Nigeria	NGA	1980q3	1993q1
Oman	OMN	2003q1	2008q4
Panama	PAN	1990q2	2008q4
Rwanda	RWA	1996q1	2006q4
Samoa	WSM	2000q3	2008q4
Slovak Rep	SVK	1993q1	2008q4
Sri Lanka	LKA	1989q4	2008q4
St Vincent Gr	VCT	1994q2	2006q3
Tanzania	TZA	1995q2	2008q4
Tonga	TON	1993q1	2002q2
Uganda	UGA	1994q2	2008q4

Table A2. Data Sources

Variable	Data Source
Money base	IFS line 14
Bank lending rate	IFS line 60
Deposit money bank assets/GDP	Beck, Demirguc-Kunt and Levine (2009)
Bank concentration	Beck, Demirguc-Kunt and Levine (2009)
Stock market capitalization / GDP	Beck, Demirguc-Kunt and Levine (2009)
Regulatory Quality	Kaufman, Kraay and Mastruzzi (2009)
International Financial Integration	Dhungana (2008)

Figure A1. Impulse Responses from a Structural VAR Model

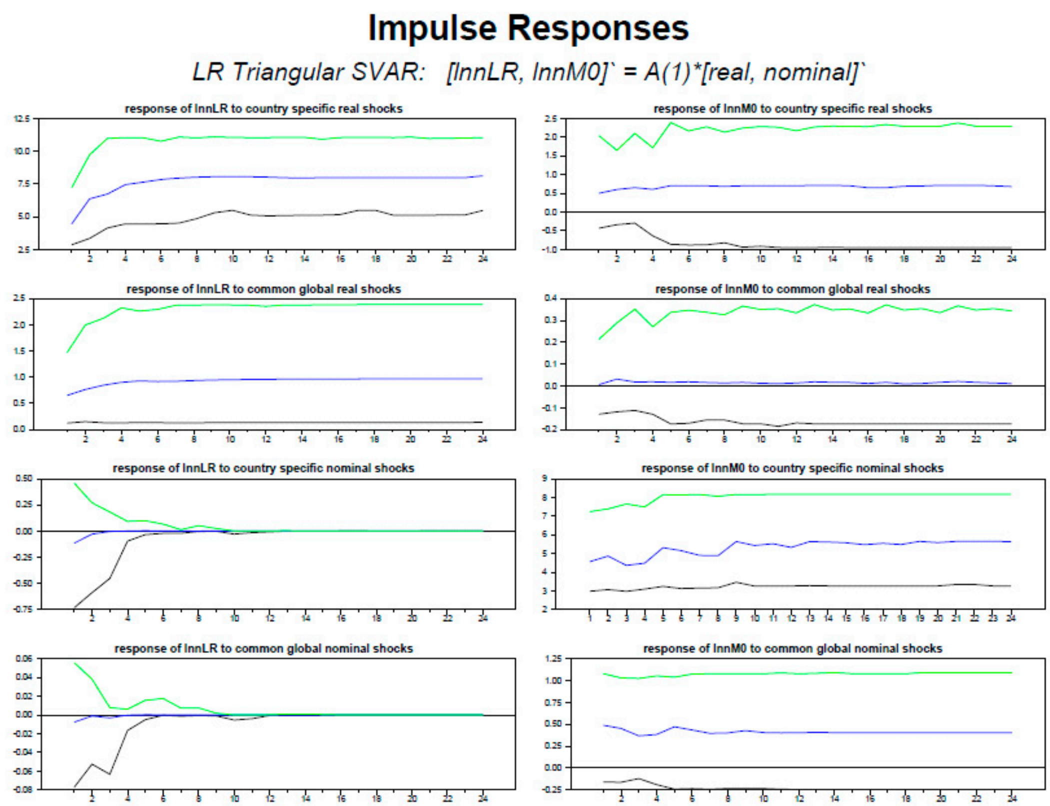


Figure A2. Variance Decomposition from a Structural VAR model