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Abstract

This article analyses the exchange rate pass-through to domestic prices in Costa Rica during the current exchange rate flexibility period and tests whether there is evidence of asymmetry. To this end, we estimate structural distributed lag models that encompass symmetric and asymmetric data generating process in line with Kilian and Vigfusson (2011). We found evidence of sign asymmetry in the bivariate relationship between inflation and exchange rate and when controlling for interest rate differential and output gap.

Keywords: pass-through asymmetry, exchange rate, exchange rate flexibility.

JEL classification: E31, E37, E58.

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1. INTRODUCTION

An environment of free capital movement under an inflation targeting regime demands the monetary authority adopt exchange rate flexibility. Together with inflation commitments, said regime requires appropriate knowledge of the magnitude and time with which exchange rate (ER) movements are transmitted to domestic prices, i. e., the exchange rate pass-through (ERPT). Properly understanding ERPT requires determining whether it exhibits sign or magnitude asymmetries. Abstracting this type of nonlinearities can result in the estimation of pass-through levels different from those actually occurring.

This article analyzes ERPT to prices in Costa Rica from March 2006 to April 2017 and tests the hypothesis that it presents asymmetries. We estimate structural distributed lag models that encompass symmetric and asymmetric data generating process in line with Kilian and Vigfusson (2011), employing data exclusively for the exchange rate flexibility period.

The importance of knowing the magnitude of the ERPT to prices lies in the predictive capacity of such changes and the time it takes the economy to transmit them to domestic prices. Besides determining the magnitude and lag with which they appear, it is important to establish the presence of sign and magnitude asymmetries in said phenomenon. Positive asymmetry means domestic prices react more to domestic currency depreciations, while negative asymmetry would imply a stronger response to appreciations. On the other hand, if the ERPT shows magnitude asymmetries, the response of domestic prices to ER shocks would depend on the size of such shocks.

The amount of ERPT can be related to many factors, including an economy's level of openness, the organizational structure of import sectors, the level and volatility of inflation, the level of flexibility in the exchange rate regime, etc. The exchange rate regime in Costa Rica varied significantly towards the end of 2006 when the fixed rate regime (crawling peg exchange rate) was replaced by increasingly more flexible regimes. In light of the fact that the aforementioned factors upon which the magnitude of the ERPT could depend are not fixed over time, it is reasonable to propose a hypothesis that there are asymmetries in said phenomenon.

Although the ERPT in Costa Rica has been studied previously, in most cases the models employed have assumed that the magnitude of the ERPT is constant over time. Moreover, the data samples employed always include observations from two very different exchange rate regimes. Hence, quantifying and verifying the presence of asymmetries only using data extracted from the exchange rate flexibility period (last 11 years) is relevant given that it could provide estimates for the phenomenon more in line with the current economic situation. Furthermore, before 2006, when the period of exchange rate flexibility began, the exchange rate regime in force (crawling peg) fostered very few episodes of nominal appreciation, meaning the data were not optimal for studying sign asymmetries in the ERPT. Since the end of 2006 there has been a larger degree of freedom in exchange rate movements, there is a relatively greater number of appreciation periods and, therefore, more data for studying asymmetries.

The paper is organized as follows: after this introduction, Section 2 describes the most important background literature and the evolution of methodologies employed in its analysis. Section 3 details the conceptual framework of the methodological approximating used for testing the proposed hypothesis. Next, Section 4 examines methodological aspects, the data and the econometric approach used. Section 5 presents the main results and, finally, Section 6 lists the most important conclusions.

2. BACKGROUND

Empirical literature on the ERPT generally presents more evidence of symmetry for industrialized countries (see Taylor, 2000; Goldfang and Werlang, 2000; Choudhri and Hakamura, 2001; and Engel, 2002), while for emerging economies the linearity assumption does not seem appropriate [see Winkelried (2003), Wang and Guo (2016) and Mendoza (2012)].

Among recent studies that make flexible the linearity assumption, Przystupa and Wróbel (2011) analyze the case of Poland. The authors observe that pass-through varies according to the stage of the business cycle, identifying it as smaller during contractionary periods and larger during expansions. Moreover, for ER fluctuations below a certain magnitude (2%), the pass-through differs from the other observations. They also find that the ERPT is greater during periods of low volatility (understood as a standard deviation of the daily variation below 4.32%).

Pérez and Vega (2016), meanwhile, find evidence for sign asymmetry in the ERPT of Peru. The authors also provide evidence of a different behavior for each exchange rate regime in the period studied.

Lariau, El Said and Takebe (2016) review evidence for the cases of Angola and Nigeria. They find that the ERPT is higher over the long term for the less diversified more import-dependent economy (Angola). They also demonstrate that dedollarization in Angola led to a decline in the ERPT. Furthermore, over the short term the ERPT is not statistically different from zero, which according to the authors reveals distortions caused by protectionism afforded to certain industries. For Nigeria, they show that the food and drinks component of the CPI is not affected by changes on the ER given the large share of domestic production in that index grouping. The research reflects the importance of countries' domestic consumption structure for determining the ERPT. Angola and Nigeria are similar countries with regard to their dependence on crude oil exports and they also implement similar actions to offset possible price shocks in that commodity; despite this, the results reveal different ERPTs.

The Banco Central de Costa Rica has made significant research efforts to improve understanding of the ERPT. Such endeavors span from the fledgling estimations of León, Morera, and Ramos (2001) and León, Laverde, and Durán (2002), up to more recent papers such as those of Rodríguez (2009), Esquivel and Gómez (2010) and Orane (2016). Most of those studies employ the implicit assumption of linearity in the ERPT, estimating it with VAR models. The exception is Esquivel and Gómez (2010), who address the matter using an alternative methodology (LSTVAR) that considers the possibility of some variables inducing sign or magnitude asymmetries in the pass-through. The authors find that the lagged variation of oil prices is the variable most likely to induce asymmetries. Nevertheless, they conclude that there is little evidence of statistically significant sign or magnitude asymmetries.

Meanwhile, Esquivel and Gómez (2010) use a data sample between January 1991 and June 2009. In Costa Rica, the fixed exchange rate regime (crawling peg) was substituted in October 2006 by a flexible regime (exchange rate band), which was subsequently replaced by a managed float regime in February 2015. In view of this, there are at least three events to justify and make important a new study on the ERPT and its possible asymmetries.

First, the observations used in Esquivel and Gómez (2010) combine some (the majority) extracted from the period of fixed ER with others from the flexible phase. It should be taken into account that the crawling peg regime implied a systematic bias towards positive variations in the nominal ER (colones per US dollar). Only 15% of the observations used in that study are not affected by said bias. At present, the abundance of observations for the period after adoption of the flexible ER regime allows for considering estimations of the pass-through and statistical tests for asymmetry that use a sample with observations exclusively from the flexible regime.

Second, there is a large body of documented evidence that the series of variation of the CPI in Costa Rica underwent a structural change during 2009. It is possible that said structural change has influenced the magnitude and characteristics of the ERPT. The data set used in the paper of 2010 evidently does not allow for capturing said phenomenon.

Finally, to provide additional robustness to the test for asymmetries in the ERPT, it is wise to apply alternative estimation methodologies. A traditional approach for measuring asymmetries uses censored VAR models. Applied to the topic of ERPT, the aforementioned method would imply estimating a VAR model where ER variations with a negative sign are censored from the sample and another where positive variations are censored. Subsequently, the impulse response (IR) functions of both models would be compared in order to conclude whether they are statistically different or not.

It is well documented in the literature on static models that censoring explanatory variables causes ordinary least square estimators to be biased, as described in Rigobon and Stoker (2009) or Greene (2003).

Although the bias observed in those procedures is clear when the data generating process (DGP) is symmetric, asymptotic bias continues even when the DGP is asymmetric. Just as stated by Kilian and Vigfusson (2011), only when the DGP is such that it does not exercise an impact on the dependent variable when the explanatory variable decreases can one guarantee that the censored linear model is not biased. In their study, those authors demonstrate that censored VAR models generate asymptotic biases and propose a structural model to prevent them. Their model encompasses symmetric and asymmetric data generating processes as special cases. Combined with the proposal of Lee, Ni and Ratti (1995), in which shocks should be rescaled by a volatility measure before performing an estimation of the pass-through, it is not only possible to diagnose the presence of sign and magnitude asymmetries, but also to determine whether the pass-through is smaller in periods of high volatility. Álvarez and Esquivel (2016) apply this method to assess the presence of asymmetries in the pass-through of commodity prices to domestic prices in Costa Rica.

In the original work of Kilian and Vigfusson (2011), the authors estimate the impact of energy price shocks on economic growth, proposing two statistical tests for applying to the hypothesis of symmetry in the response of growth. One of them is conducted on regression coefficients and is a variation of that proposed by Mork (1989) but with higher statistical power. The other is applied directly to the IR functions. The latter is based on the fact that, as postulated in Koop, Pesaran and Potter (1996), in nonlinear VAR models the magnitude of shocks can influence the dynamic response of the variables. Moreover, under this same context, the dynamic response of a variable can exhibit asymmetries even if the coefficients do not exhibit departures from symmetry.

In addition to this problem, traditional empirical literature on censored VAR models also has the disadvantage of ignoring that, by being nonlinear models, IR functions depend on the history of observations [see Koop, Pesaran, and Potter (1996), and Gallant, Rossi, and Tauchen (1993)]. IR functions in this type of models require a Monte Carlo simulation in order to include possible data histories and different sizes of shocks.

3. CONCEPTUAL FRAMEWORK

Kilian and Vigfusson (2011) show that when the DGP is not symmetric it cannot be represented as a bivariate VAR model for x_t^+ and y_t. A DGP where only positive shocks to x_t have an impact on y_t can be denoted with the following system:

1
$$\begin{aligned} x_t &= a_1 + \rho x_{t-1} + e_{1t}, \\ y_t &= a_2 + \gamma x_t^+ + e_{2t}. \end{aligned}$$

The contemporaneous effect on y_t of a positive shock to x_t in System 1 is given by γ. The impact in the subsequent period would be $\rho\gamma$, and then $\rho^2\gamma$, and so on successively thereafter. Thus, estimation of coefficients γ and ρ of Model 1 would be unbiased. By using a censored VAR model such as Model 2, estimation of ρ would be asymptotically biased despite the fact that the estimation of γ would be unbiased. This would be reflected in the IR function.

2

$$x_t^+ = a_1 + \rho x_{t-1}^+ + \epsilon_{1t},$$
$$y_t = a_2 + \gamma x_{t-1}^+ + \epsilon_{2t}.$$

The problem with System 2 is that it is not a true representation of the DGP. Use of a full structural model would avoid that drawback. Kilian and Vigfusson (2011) propose the following model:

3

$$x_t = a_1 x_{t-1} + a_2 y_{t-1} + \ldots + \epsilon_{1t},$$
$$y_t = \beta_1 x_t^+ + \beta_2 x_{t-1}^+ + \beta_3 y_{t-1} + \ldots + \epsilon_{2t}.$$

System 3 is a structural model where, unlike Model 2, negative shocks to x_t can affect the future path of y_t if such shocks eventually lead to positive shocks in the future path of x_t.

System 4 is the reduced form of 3. The IR functions of a structural model such as 3 cannot be identified from a Cholesky decomposition of the variance-covariance matrix and its reduced version because such a composition does not discriminate between positive and negative shocks. Hence, applying Cholesky in 4 to $Var\left[\epsilon_{1t}, u_{2t}\right]$ is not appropriate given that u_{2t} should only reflect positive shocks.

4

$$x_t = a_1 x_{t-1} + a_2 y_{t-1} + \ldots + \epsilon_{1t},$$
$$y_t = \beta_1 x_{t-1}^+ + \beta_2 y_{t-1} + \ldots + u_{2t},$$

where $u_{2t} = \beta_1 \epsilon_{1t} + \epsilon_{2t}$.

Additional technical details on the conceptual proposal and tests for the absence of asymptotic bias in Model 3 can be consulted in the paper referred to (Kilian and Vigfusson, 2011). The points summarized here motivate the use of the methodology proposed by those authors to verify the presence of asymmetries in the exchange rate pass-through.

4. METHODOLOGY

4.1 Estimation of Impulse Response Functions in Asymmetric Structural Models

We propose a structural model where the endogenous variables in an equation system are used to allow exchange rate shocks to have a varied impact on prices in an economy depending on whether the currency is appreciating or depreciating.

In an initial approach using a bivariate model, the structure would be written as follows:

5
$$\begin{aligned} x_t &= a_1 x_{t-1} + a_2 y_{t-1} + \ldots + \epsilon_{1t}, \\ y_t &= \beta_1 x_t^{+} + \beta_2 x_{t-1}^{+} + \beta_3 y_{t-1} + \ldots + \epsilon_{2t}, \end{aligned}$$

where

- x_t is the level or variation of the ER in period t.
- y_t is the level or variation of the CPI in period t.
- $x_t^{+} = \begin{cases} x_t, \text{ si } x_t > 0 \\ 0, \text{ si } x_t \leq 0 \end{cases}.$

In contrast to a censored VAR, in which the endogenous variables correspond to x_t^{+} and y_t, in the proposed Model 5 negative shocks to x_t can affect the future path of y_t if they eventually lead to positive shocks in the future path of x_t. The authors of the reference study demonstrate that the estimators of this model are asymptotically unbiased, unlike those obtained using censored VAR models, regardless of whether the DGP is symmetric or not.

According to different studies (see Gallant, Rossi, and Tauchen, 1993; and Koop, Pesaran, and Potter, 1996), in nonlinear models such as 5, the dynamic response of y_t could be magnified or reduced by the accumulated effect of previous shocks. Hence, IR functions should be estimated as an average of the impulse responses generated based on a data set that is both diverse and representative of initial conditions. We estimate IR functions following the sequence of steps shown below:

1) Random selection of a *history* (Ω_i) composed of consecutive p values of x_t and y_t.[1]

2) Given Ω_i, simulate two-time paths for H data after the last observation available for x and y. That is, for x we generate $\left[x_{t+1}, x_{t+2}, \ldots, x_{t+H}\right]$ and $\left[x^*_{t+1}, x^*_{t+2}, \ldots, x^*_{t+H}\right]$, while for y we generate $\left[y_{t+1}, y_{t+2}, \ldots, y_{t+H}\right]$ and $\left[y^*_{t+1}, y^*_{t+2}, \ldots, y^*_{t+H}\right]$. For the first paths of de x and y, as well as the second of y, stochastic disturbances $\left[\epsilon_{1t}, \epsilon_{1t+1}, \ldots, \epsilon_{1t+H}\right]$ and $\left[\epsilon_{2t}, \epsilon_{2t+1}, \ldots, \epsilon_{2t+H}\right]$ are randomly selected from their respective marginal empirical distributions. Furthermore, for the second sequence of x, the value (δ) is assigned to the first component of the sequence of disturbances, $(\epsilon_{1t} = \delta)$, while the rest of the sequence is randomly extracted from its marginal empirical distribution.

3) Random sequences of ϵ_{1t} and ϵ_{2t} can be treated as independent given that they are obtained from the marginal distribution generated by estimated structural Model 5.

4) We proceed to obtain the difference between two paths of y for t=*1, 2,..., H*, defining each difference as y_i^{δ}, where i=*1, 2,..., H*.

5) Steps 2 and 4 are repeated (n_{boot}) times.

6) Steps 1 to 5 are repeated 1 to 5 (n_{hist}) times. We, therefore, obtain a number $n_{hist} * n_{hist}$ for different series y_i^{δ} that are then averaged.

[1] p corresponds to the number of lags used for each model estimated.

The result obtained from steps 2 to 5 is the response of y to a shock of size δ, over a horizon of H periods and conditional on Ω_i. Following the same nomenclature of Kilian and Vigfusson (2011), we can define this response as $I_y(\delta, H, \Omega_i)$. Repeating the exercise for all possible histories and averaging the responses, we obtain the response of y unconditional on Ω_i, that is, $I_y(\delta, H)$.

To more clearly differentiate the proposal of Kilian and Vigfusson (2011) regarding the traditional way of obtaining the IR functions, we define the response of y conditional on the historical paths of x and y (that is $x_{t-i} = y_{t-i} = 0$ for i=1, 2,...) as follows:

$$I_y(\delta, H, \underline{0}). \tag{6}$$

Relaxing the assumption of $x_{t-i} = y_{t-i} = 0$ and allowing a history (Ω_i) for x and y, besides inducing a shock of magnitude δ in the t-th observation of disturbance term ϵ_1, we can alternatively define the response:

$$I_y^*(\delta, H, \Omega_i) = E\left\{y_{t+h} \mid \Omega_i, \epsilon_{1t} = \delta, \left[\epsilon_{1t+j}\right]_{j=1}^{h}, \left[\epsilon_{2t+j}\right]_{j=0}^{h}\right\} - \\ -E\left\{y_{t+h} \mid \Omega_i, \left[\epsilon_{1t+j}\right]_{j=0}^{h}, \left[\epsilon_{2t+j}\right]_{j=0}^{h}\right\}. \tag{7}$$

As mentioned previously, by averaging 7 for all possible histories, we obtain the unconditional response in Ω_i, which corresponds to $I_y^*(\delta, H)$. The impulse response normally obtained in the literature corresponds to $I_y^*(\delta, H, \underline{0})$. This IR does not allow future shock dynamics (at least in disturbances) and does not condition history. In linear systems, this type of configuration for the calculations does not present any drawbacks. However, they do present them when computing IR in nonlinear systems: The response may not converge to zero even when the DGP is stationary (see Koop, Pesaran, and Potter, 1996). Moreover, Potter (2000) opts for considering future shocks as random rather than fixing them at zero when estimating nonlinear IRs. Finally, due to the lack of realism in conditioning an IR estimation at zero, this is not very useful.

In reduced-form VAR equations the errors are correlated. Based on this we use a method for orthogonalizing the impulses. The usual approach is to employ an inverse Cholesky factorization of the variance-covariance matrix of the estimation residuals. A structural model such as 5 used in this research becomes more attractive for estimating IR functions given that in $I_y\left(\delta, H, \Omega_i\right)$ and $I_y\left(\delta, H\right)$ calculations, an exchange rate shock $\left(x_t\right)$ is orthogonal to other shocks.

Kilian and Vigfusson (2011) show that, for small shocks, the difference between the IR estimated considering possible histories as well as the behavior of errors $\left[I_y^*\left(\delta, H\right)\right]$, and that estimated without considering those two items $\left[I_y^*\left(\delta, H, \underline{0}\right)\right]$, is substantial. Nonetheless, this difference declines as the size of the shock increases, i. e., the authors demonstrate that

$$\lim_{n \to \infty} \frac{1}{n} I_y\left(n\delta, H\right) = I_y^*\left(\delta, H, \underline{0}\right). \qquad (8)$$

For exchange rate shocks of a sufficiently large magnitude, we would expect that the importance of Ω_i and the randomness of ϵ_{1t} decrease until reaching the point at which the IR estimated using the traditional VAR approach is a good approximation to correct estimation. This is, therefore, the explanation of how the traditional VAR method can generate estimations for the response of domestic prices to exchange rate shocks that are very different from those correctly estimated through a nonlinear specification.

This inverse relationship between the size of shocks and the estimated response of domestic prices is important given that, for series where the variation (in this case of the exchange rate) exhibits a small standard deviation, the advantage of using $I_y\left(n\delta, H\right)$, in terms of reducing asymptotic bias in IR function measurement, is greater.

4.2 Symmetry Tests

Despite solving the problem of asymptotic bias with respect to a censured VAR, structural model 5 is asymptotically inefficient compared to a VAR when the DGP is symmetric. Hence, efficient ERPT estimation requires a prior statistical test to evaluate the hypothesis of symmetry in the DGP.

Those defined below as tests of symmetry in parameters assess the equality of the magnitude of coefficients associated with appreciations and depreciations.

Kilian and Vigfusson (2011) show that these tests are useful for reduced-form models to identify asymmetries in parameter responses. Nonetheless, they are not useful for identifying asymmetries in the IR functions of asymmetric structural models. This is due to the fact that they could obtain parameters associated with appreciations and depreciations that are not statistically different, while the IRs are indeed so. The latter because IR functions can be a nonlinear function of both the slope parameters and the variance of the innovations.

In light of this problem, Eldstein and Kilian (2007) suggest an alternative approximation based on the IR functions obtained according to the method explained in Section 4.1 to test the symmetry hypothesis. We refer to this second group of tests as tests of symmetry in the IRs.

4.2.1 Tests of Symmetry in Parameters

Tests for symmetry in parameters, or slope-based symmetry tests, are attractive given their simplicity and because they do not require the computation of IR functions. According to this method, after estimating the regression of y_t on its own lags as well as those on x_t^+ and x_t^-, we test the equality of the coefficients by means of Wald test statistics that, under the null hypothesis of symmetry, have distribution Ji^2 [see Mork (1989)].

Kilian and Vigfusson (2011) show that this approximation does not exploit all the restrictions implied by the null hypothesis of symmetry. They demonstrate that, by working with a reduced model, Mork (1989) omits the equality restriction of the contemporaneous terms of x_t^+ and x_t^-. The authors, therefore, propose, in terms of Model 5, working with the null hypothesis

$$H_0\colon \beta_1 = \beta_2 = 0.$$

The same authors argue that this hypothesis has higher statistical power than that of Mork (1989). They test this hypothesis in a model such as 5, and by means of parameter exclusion Wald tests seek to determine whether the fit of the model improves with the inclusion of regressors $x_t^+,\ x_{t-1}^+,\ldots,x_{t-p}^+$.

4.2.2 Tests of Symmetry in IR Functions

The proposal of Kilian and Vigfusson (2011), adapted for testing sign symmetry in IR functions for prices in the presence of exchange rate shocks to h over different horizons can be summarized in the following steps:

1) Estimate structural Model 5.

2) Calculate IR h periods ahead (in this case it was performed with a horizon of 24 periods) for both positive and negative shocks. That is, calculate $I_y^*(\delta,h)$ and $-I_y^*(-\delta,h)$.

3) Construct a Wald test of the joint null hypothesis of symmetry in positive and negative IRs up to a horizon of h periods in the future. The statistic, therefore, takes the form: $W = \sum_{i=0}^{h}\left[I_y^*(\delta,i) + I_y^*(-\delta,i)\right]^2 = 0.$

4) Estimate the variance-covariance matrix of the vector sum of response coefficients by bootstrap simulation.

The W statistic, therefore, has distribution Ji_{h+1}^2 given the asymptotic normality of the parameter estimators of the model.

4.3 Data

The database employed in the estimations corresponds to series published by the Banco Central de Costa Rica on its official online data portal.[2] Basic exchange rate data sets have a daily frequency, but a monthly series was constructed by taking the average between the purchase and sale references on every business day each month. Meanwhile, the series for the CPI are originally monthly.

As controls in the estimations, we included indicators on output gap and interest rate differentials. The base information for the output gap is the seasonally adjusted series of the monthly economic activity index (IMAE). We applied a Hodrick-Prescott filter to this with smoothing parameter $\lambda = 23.000$ in line with Segura and Vásquez (2011).

Finally, the series for interest rate differentials considers the United States Treasury federal funds effective rate[3] and the monetary policy rate of the Banco Central de Costa Rica. The sample period spans from January 2006 to March 2017.

5. RESULTS

5.1 Evaluation of Stationary Properties

The stationary properties of the series employed are determined in order to define the type of econometric method with which to perform the prior analysis. The results of the unit root tests applied are displayed in Table 1. It can be seen that both under the Dickey-Fuller (DF) test and that of Phillips-Perron (PP), it is not possible to reject the null hypothesis of a unit root for all the series at levels, except for the IMAE gap. In the case of the first difference, the null hypothesis of a unit root is

[2] <https://www.bccr.fi.cr/seccion-indicadores-economicos/indicadores-econ%C3%B3micos>.

[3] <https://fred.stlouisfed.org/series/FEDFUNDS>.

Table 1

***P* VALUES IN UNIT ROOT TESTS (H_0: X_T HAS UNIT ROOT)**

			Variable			
Variable in:	*Type of test*	*Specification*	*CPI*	*ER*	*Interest rate differential*	*IMAE gap*
Levels	ADF	Const	0.99	0.27	0.72	0.00
		Const and trend	0.99	0.55	0.91	0.00
	PP	Const	0.98	0.31	0.47	0.00
		Const and trend	1.00	0.60	0.77	0.00
First difference	ADF	Const	0.00	0.00	0.00	0.00
		Const and trend	0.00	0.00	0.00	0.00
	PP	Const	0.00	0.00	0.00	0.00
		Const and trend	0.00	0.00	0.00	0.00

Source: Authors' calculations.

rejected for all the series. Based on these results, all the variables in the estimations were used in first differences, except the IMAE gap, which was kept at levels.

5.2 Lag Order

We proceeded to determine the most appropriate lag order for estimating Model 5 in two ways. Firstly, based on VAR model lag selection criteria and secondly using goodness-of-fit criteria for the equation of y_t (price equation in the application of this paper) in asymmetric structural Model 5. The selection was made for three different model specifications: one bivariate model (consisting of the first difference of the CPI and the exchange rate); two models of three variables constructed based on the bivariate model adding the IMAE gap and interest rate differential, respectively. Table 2 displays the results for those models under five different criteria.

Table 2

OPTIMAL NUMBER OF LAGS ACCORDING TO DIFFERENT CRITERIA

		Model		
Specification	*Criteria*	*Bivariate*	*Bivariate + interest rate differentials*	*Bivariate + IMAE gap*
	LR	5	1	3
	FPE	1	1	1
VAR	AIC	1	1	1
	SC	1	1	1
	HQ	1	1	1
Asymmetric prices equation	AIC	5	5	5
	SC	1	1	1

Note: LR stands for likelihood ratio, FPE to final prediction error, AIC to Akaike information criterion, SC to Shwarz's criterion, and HQ to that of Hannan-Quinn.
Source: Authors' calculations.

In general, the specification that includes only one lag tends to dominate both in the criteria for the VAR model and for the equation of y_t in the asymmetric structural model, regardless of whether the model is bivariate or incorporates interest rate differentials or the IMAE gap. It should be emphasized, however, that based on the AIC, the model with five lags dominates all the cases for the equation of y_t in the asymmetric structural model.

The results presented here are useful for assessing the evidence on asymmetric effects shown in the following section, where tests of symmetry in parameters and in IR functions for models with up to 12 lags are revealed. Furthermore, the IR functions presented below for measuring the exchange rate pass-through correspond precisely to the specifications with lag order selection based on the evidence in Table 2.

Table 3

P VALUE IN TEST OF PARAMETER SYMMETRY
(H_0: SYMMETRIC PASS-THROUGH)

	Type of model		
Lags	*Bivariate*	*Trivariate with interest rate differentials*	*Trivariate with IMAE gap*
1	0.29	0.43	0.19
2	0.64	0.85	0.46
3	0.48	0.71	0.44
4	0.71	0.87	0.58
5	0.55	0.61	0.38
6	0.58	0.56	0.41
7	0.33	0.28	0.39
8	0.24	0.25	0.23
9	**0.07**	0.13	0.15
10	**0.07**	0.11	0.10
11	**0.10**	0.20	**0.08**
12	0.11	0.32	**0.07**

Note: Cases with the rejection of the H_0 at 10% are highlighted in bold.
Source: Authors' calculations.

5.3 Symmetry Tests

5.3.1 Test of Symmetry in Parameters

The results of the test of symmetry in the parameters, explained in Section 4.2.1, are shown in Table 3. As mentioned previously, they include the models that consider from 1 up to 12 lags. As can be seen, for models identified as having better goodness-of-fit (with 1 and 5 lags) there is not sufficient evidence to reject the null hypothesis of symmetric pass-through either in the bivariate case or trivariate ones. Nonetheless, it is interesting to see that the inclusión of additional lags (above 9) tends to increase the evidence against the hypothesis of symmetry, at least for the bivariate and trivariate models that include IMAE gap.

5.3.2 Test of Symmetry in Impulse Response Functions

The results from applying the test of symmetry on IR functions, the methodology for which was described in Section 4.2, can be seen in Table 4. The results were obtained by simulating 40,000 forecasts of structural Model 5 with a horizon of up to 24 months.[4] It is worth remembering that the variables involved are, alternatively, the first difference of the CPI and the first difference of the nominal ER (bivariate case), adding IMAE gap and interest rate differentials for the models denominated trivariate. In view of the fact that the nonlinearity of IR functions may appear on any horizon, the table contains p values for each forecasting horizon from 1 up to 24 months.

In general, the results do not lead to very different conclusions than those obtained from the tests of symmetry in parameters. For the models with better goodness-of-fit (those that include 1 and 5 lags), the evidence against the symmetry hypothesis is scarce in all models and for all horizons. Table 4 also displays the results for the model with most evidence against the symmetry hypothesis (the version that includes up to 12 lags). In this case, and at 10% significance, the bivariate model at horizons of between four and six months, and the trivariate model with interest rate differentials for horizons above ten months, exhibit some evidence in favor of the alternative hypothesis of an asymmetric response in domestic prices to exchange rate shocks. Nevertheless, it should be emphasized that goodness-of-fit criteria do not favor this specification.

The fact that the greatest evidence of asymmetric pass-through is found when the model estimated includes 12 lags (trivariate model with interest rates differentials) might be because the estimations do not take into account seasonal factors.

[4] See procedure explained in Section 4.1.

Table 4

_P_ VALUE IN TEST OF SYMMETRY IN IMPULSE RESPONSE FUNCTIONS (H_0: SYMMETRIC PASS-THROUGH)

	Model Specification								
	Bivariate			*Bivariate with interest rate differentials*			*Bivariate with* IMAE *gap*		
Horizon	*1 lags*	*5 lags*	*12 lags*	*1 lags*	*5 lags*	*12 lags*	*1 lags*	*5 lags*	*12 lags*
1	0.19	0.10	0.16	1.00	0.95	0.35	0.97	0.97	0.96
2	0.35	0.16	**0.10**	1.00	0.98	0.12	1.00	1.00	0.98
3	0.55	0.29	0.17	1.00	1.00	**0.07**	1.00	1.00	1.00
4	0.68	0.30	**0.04**	1.00	1.00	0.12	1.00	1.00	1.00
5	0.78	0.41	**0.03**	1.00	1.00	0.20	1.00	1.00	1.00
6	0.86	0.47	**0.05**	1.00	1.00	0.25	1.00	1.00	1.00
7	0.92	0.57	**0.08**	1.00	1.00	0.34	1.00	1.00	1.00
8	0.96	0.68	0.12	1.00	1.00	0.30	1.00	1.00	1.00
9	0.98	0.76	0.12	1.00	1.00	0.38	1.00	1.00	1.00
10	0.98	0.83	0.10	1.00	1.00	0.11	1.00	1.00	1.00

11	0.99	0.89	0.12	1.00	1.00	0.07	1.00	1.00	1.00
12	1.00	0.93	0.16	1.00	1.00	0.05	1.00	1.00	1.00
13	1.00	0.95	0.20	1.00	1.00	0.05	1.00	1.00	1.00
14	1.00	0.97	0.25	1.00	1.00	**0.07**	1.00	1.00	1.00
15	1.00	0.98	0.29	1.00	1.00	**0.08**	1.00	1.00	1.00
16	1.00	0.99	0.35	1.00	1.00	**0.08**	1.00	1.00	1.00
17	1.00	0.99	0.42	1.00	1.00	**0.04**	1.00	1.00	1.00
18	1.00	1.00	0.48	1.00	1.00	**0.05**	1.00	1.00	1.00
19	1.00	1.00	0.55	1.00	1.00	**0.02**	1.00	1.00	1.00
20	1.00	1.00	0.40	1.00	1.00	**0.03**	1.00	1.00	1.00
21	1.00	1.00	0.46	1.00	1.00	**0.01**	1.00	1.00	1.00
22	1.00	1.00	0.52	1.00	1.00	**0.01**	1.00	1.00	1.00
23	1.00	1.00	0.54	1.00	1.00	**0.02**	1.00	1.00	1.00
24	1.00	1.00	0.60	1.00	1.00	**0.02**	1.00	1.00	1.00

Note: Cases with rejection of the H_0 at 10% are highlighted in bold.
Source: Authors' calculations.

Nonetheless, visual examination of the correlograms, as well as simple tests in which the variables analyzed are regressed in fictitious seasonal variables, do not suggest the presence of this type of effects (see Figure A.1 and Table A.1 in the Annex).

5.4 Quantification of Exchange Rate Pass-through to Prices

In this section, we quantify the ERPT estimated using structural Model 5. For each model (bivariate and the two model variations with three endogenous) IR function estimations were performed following the procedure described in Section 4.1, fixing $n_{boot} = n_{hist} = 200$, i. e., averaging 40,000 estimations at each horizon from 1 up to 24 months. The magnitude of these functions is shown as a proportion of the size of the original shock. Moreover, those corresponding to negative exchange rate shocks are shown multiplied by –1 to allow their magnitude to be easily compared with those corresponding to positive shocks. The confidence bands shown are empirical and correspond to percentiles 5 and 95 of the distribution of the 40,000 forecast simulations performed for each horizon and for each model specification.

They also display IR functions for four different sizes of ER shock (1, 2, 4 and 10 standard deviations), in order to analyze whether sign asymmetry could be associated to the size of the shocks, a matter that would not be evident in the tables presented in the previous section.

Figure 1 displays the IR functions obtained from the bivariate model that includes only one lag. The first point that should be mentioned is that the proportional magnitude of the pass-through during positive shocks (appreciations) ends up being between 22% and 35%, which is consistent with the most recent estimations based on linear methods.[5] However,

[5] See Orane (2016).

the pass-through in negative shocks is estimated to be around 15% for small shocks and close to 0% for larger shocks.

Meanwhile, with respect to matters of asymmetry, it can be seen that, for the case of small shocks (one standard deviation), the evidence is consistent with that shown in Table 4 in the sense that the dynamic response of prices is not statistically different in positive or negative ER shocks. Furthermore, in accordance with the size of the shock confidence bands for the estimations cease to overlap. Thus, for mid-sized and large shocks the response of prices does appear statistically different.

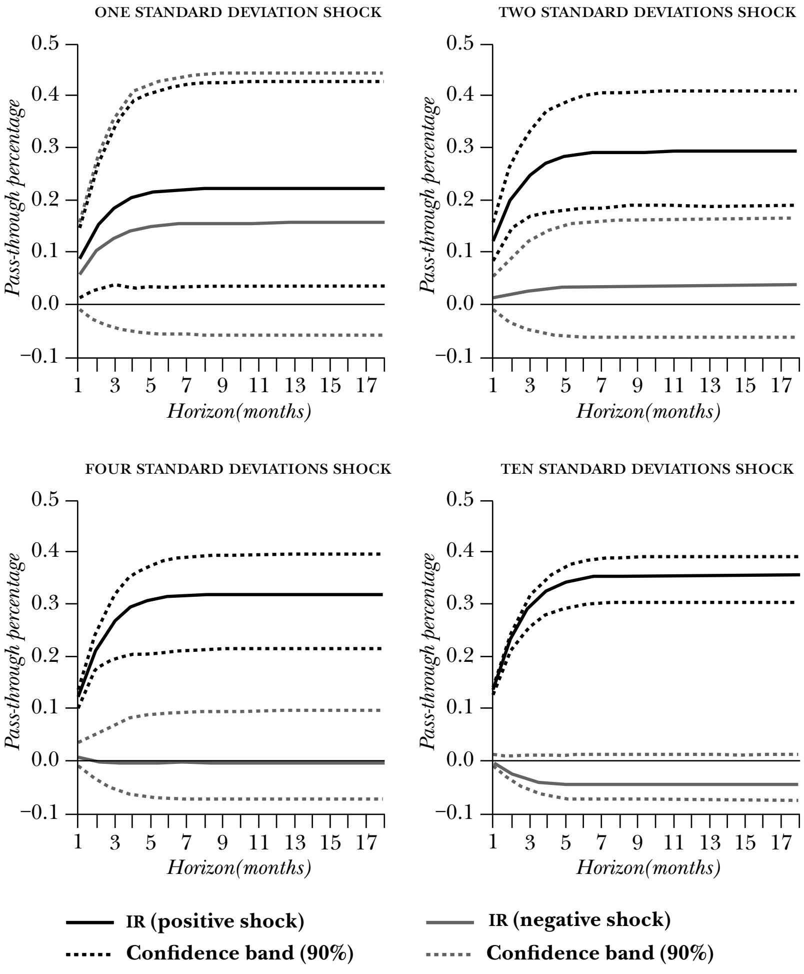
Figure 2 shows the IR functions obtained when the additional variable is incorporated into the model, specifically interest rate differentials. In terms of the proportional magnitude of the long-term pass-through we estimate, there is not much difference from the bivariate case. The pass-through is between 20% and 30% in depreciations, and between 0% (large shocks) and 15% (small shocks) in the case of appreciations.

Just as in the bivariate case, when the ER shock is small (one standard deviation), there is no significant difference in the dynamic response of domestic prices. Nonetheless, for larger shocks (four and ten standard deviations) the spaces between the confidence bands move apart during positive and negative shocks, indicating sign asymmetry in the response.

One pattern that can be extracted from the IR functions in Figure 1 and Figure 2 is that when ER shocks are small, the response of domestic prices is no different in the presence of appreciations or depreciations. However, when the shocks are mid-sized and large, the response during appreciations tends to decrease in proportional magnitude, eventually differing from the response during depreciations. One possible explanation for this behavior is that economic agents may interpret large appreciations as temporary phenomena that do not merit price adjustments. This could be caused by the historical trend (which has reverted during recent years) of inflation in Costa Rica being higher than in the country's main trading partners. The aforementioned meant the public became accustomed to

Figure 1

IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE
Bivariate model with a lag

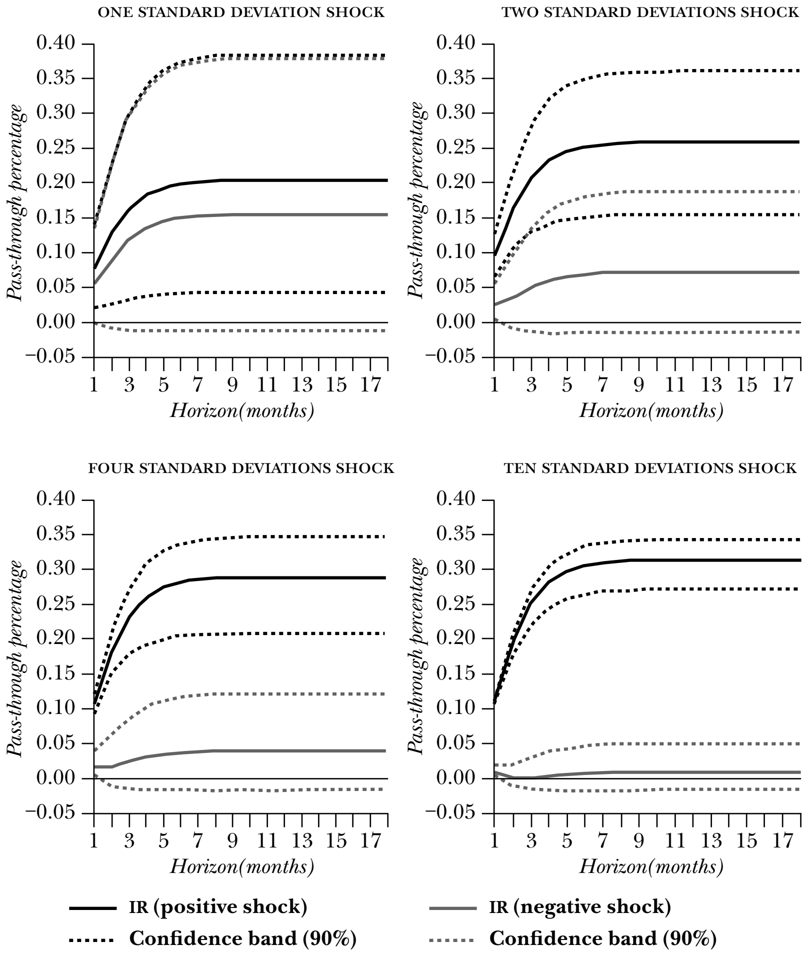


Source: Authors' calculations.

Figure 2

IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE

Trivariate model (rates differential) with a lag



Source: Authors' calculations.

increases in the nominal ER, and episodes of appreciations, particularly very large ones, tend to be seen as exceptions to the trend and therefore temporary.

Figures A.2 and A.3 in the Annex display the IR functions for the case of bivariate and trivariate models (with interest rate differentials) with five lags. Except for being necessary a horizon of over 18 months to illustrate convergence, the dynamic response pattern is similar to that observed in the figures mentioned here.

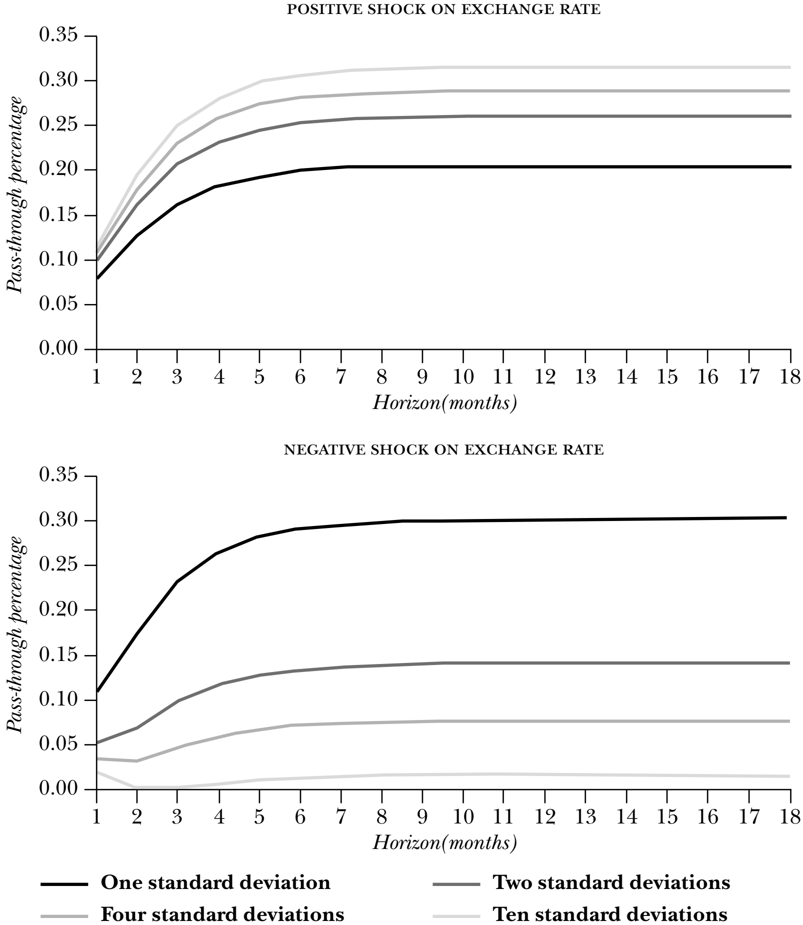
One item that can be extracted from the estimations performed, but that is not easily appreciable in Figure 1 or Figure 2, is that the magnitude of the pass-through is a growing function of the shocks when they are depreciations, but a decreasing function if they are appreciations. This is illustrated in Figure 3 corresponding to estimations using the trivariate model that includes interest rate differentials (the trend is the same in the case of the bivariate model). Note that for positive exchange rate shocks (upper panel of the figure) the dynamic response of domestic prices is larger than for smaller shocks. On the other hand, for negative shocks (lower panel of the figure), the smaller the shock, the larger the proportional response (in absolute value).[6]

As mentioned, this phenomenon could be explained by economic agents' expectations being rooted in considering episodes of appreciation in the domestic currency as unusual. If this were the case, negative exchange rate shocks, especially the largest ones, would be considered temporary and, possibly due to items such as menu costs, would not generate downward adjustments in prices in domestic currency.

[6] As shown, IR functions appear multiplied by −1 in the presence of appreciations.

Figure 3

IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE
Trivariate model (rates differential) with a lag



Source: Author's calculations.

6. CONCLUSIONS

In general, the magnitude of exchange rate pass-through to prices is calculated to be between 20% and 35% in the case of depreciations. This estimation is similar in size to the most recent ones obtained by the Banco Central de Costa Rica employing linear methods. Nevertheless, those linear methods assume sign symmetry in the estimation. In this paper, we calculate that in the case of appreciations the magnitude of the pass-through is between 0% and 15 percent.

The dynamic response of the CPI to exchange rate shocks exhibits evidence of sign asymmetry only when the shocks are mid-sized or large.

For more common unexpected appreciations or depreciations (of one standard deviation), tests for asymmetry in parameters and in IR functions do not find sufficient evidence to reject the hypothesis of symmetry. Meanwhile, the empirical confidence bands for IR functions indicate that when the size of the appreciation or depreciation is mid-sized or large (four or more standard deviations), the response of domestic prices is greater (in absolute value) during a depreciation. Hence, it is not correct to assume a response of similar magnitude in domestic prices to appreciations than to deprecations when these are relatively large.

The size of the shock influences the proportional magnitude of the pass-through

When it comes to unexpected depreciations in the domestic currency, those of greatest magnitude are transmitted to a larger extent than smaller ones. Moreover, during unexpected appreciations, the largest ones are transmitted less to domestic prices.

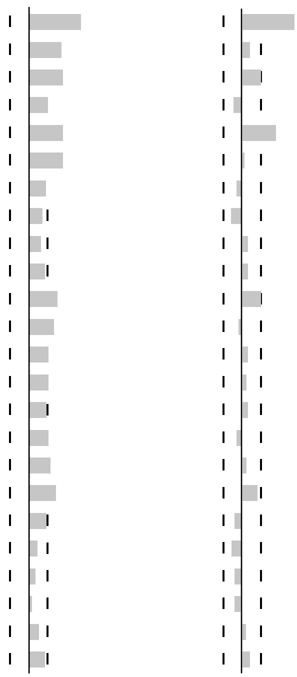
The evidence found in this research indicates that considering a constant pass-through regardless of the direction or magnitude of exchange rate shocks possibly leads to erroneous estimates for the impact of exchange rate variations on domestic prices.

ANNEX

Figure A.1

CORRELOGRAM AND PARTIAL CORRELOGRAM OF LOGARITHMIC FIRST DIFFERENCE OF THE CPI

Sample: 2006M1-2017M4
Observations: 13



	AC	*PAC*	*Q statistic*	*Prob.*
1	0.493	0.493	33.504	0.000
2	0.300	0.076	46.029	0.000
3	0.312	0.183	59.655	0.000
4	0.174	−0.071	63.926	0.000
5	0.332	0.312	79.605	0.000
6	0.316	0.020	93.880	0.000
7	0.167	−0.045	97.929	0.000
8	0.116	0.094	99.882	0.000
9	0.102	0.057	101.41	0.000
10	0.147	0.054	104.59	0.000
11	0.277	0.184	116.01	0.000
12	0.230	−0.014	123.95	0.000
13	0.172	0.050	128.45	0.000
14	0.180	0.026	133.40	0.000
15	0.156	0.044	137.16	0.000
16	0.174	−0.041	141.86	0.000
17	0.198	0.027	147.98	0.000
18	0.252	0.151	158.02	0.000
19	0.164	−0.058	162.33	0.000
20	0.074	−0.084	163.21	0.000
21	0.065	−0.056	163.89	0.000
22	0.023	−0.051	163.97	0.000
23	0.088	0.029	165.26	0.000
24	0.155	0.076	169.27	0.000

Source: Author’s calculations.

Table A.1

STATIONARITY TEST WITH DICHOTOMOUS VARIABLES

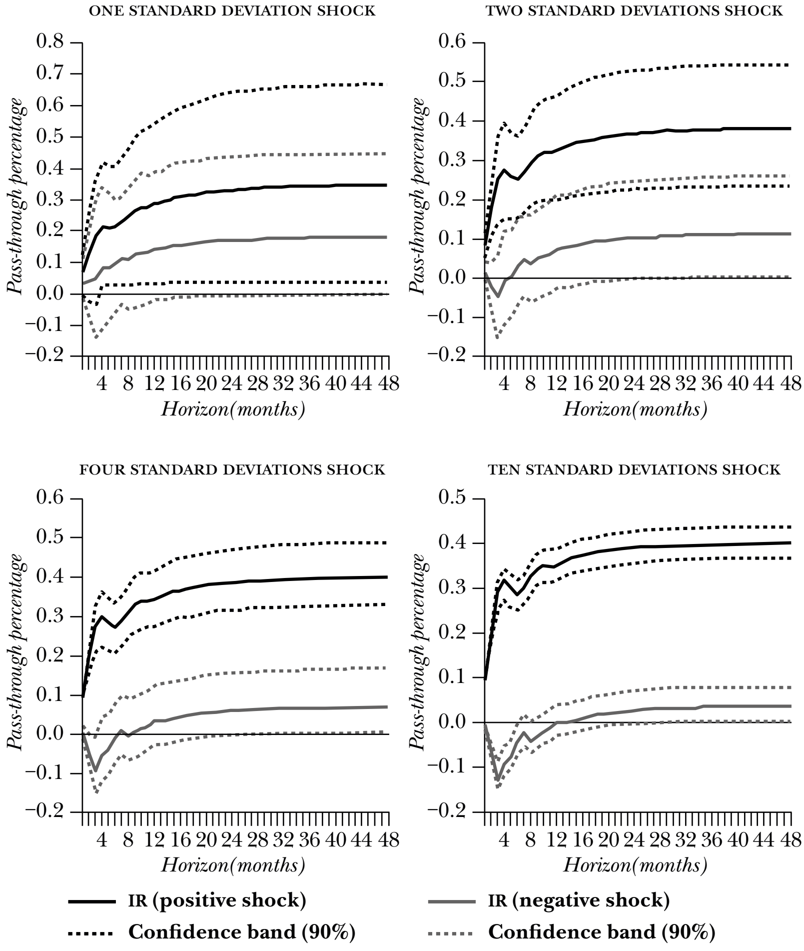
Dependent variable: DLOGIPC
Method: least squares
Sample (adjusted): 2006M2-2017M4
Included observations: 135, after adjustments

Variable	*Coefficient*	*Standard error*	*Statistical probability* t	*Probability*
C	0.5911	0.1250	4.7305	0.0000
DUMCE	0.6718	0.0818	8.2114	0.0000
@SEAS(2)	−0.2532	0.1718	−1.4732	0.1433
@SEAS(3)	−0.6152	0.1718	−3.5801	0.0005
@SEAS(4)	−0.3096	0.1718	−1.8018	0.0740
@SEAS(5)	−0.1398	0.1756	−0.7959	0.4276
@SEAS(6)	−0.3344	0.1756	−1.9041	0.0592
@SEAS(7)	−0.1404	0.1756	−0.7994	0.4256
@SEAS(8)	−0.2920	0.1756	−1.6627	0.0989
@SEAS(9)	−0.7188	0.1756	−4.0935	0.0001
@SEAS(10)	−0.6174	0.1756	−3.5159	0.0006
@SEAS(11)	−0.2678	0.1756	−1.5249	0.1299
@SEAS(12)	−0.1626	0.1755	−0.9267	0.3559
R^2		0.4498	Mean of the dependent variable	0.4377
Adjusted R^2		0.3956	Standard deviation of the dependent variable	0.5293
Standard error of the regression		0.4115	Akaike criteria	1.1532
Residual sum of squares		20.6554	Schwarz criteria	1.4329
Log likelihood		−64.8392	Hannan-Quinn criteria	1.2669
Statistical measure of F		8.3102	Durbin-Watson statistic	1.3304
Probability (statistical measure of F)		0.0000		

Source: Authors' calculations.

Figure A.2

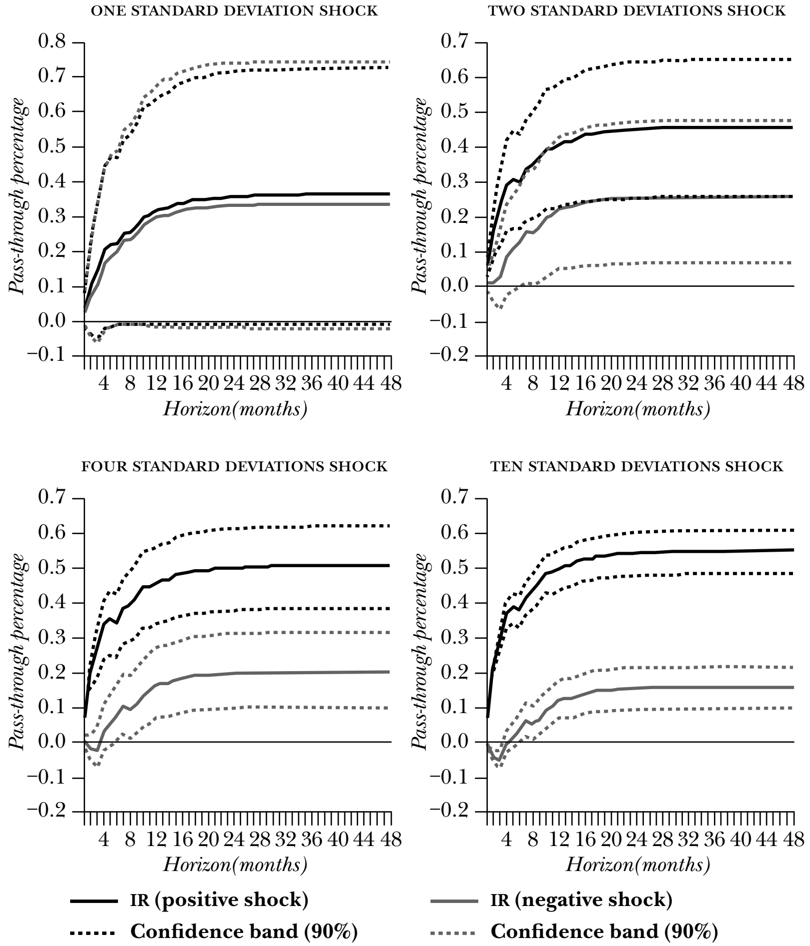
IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE
Bivariate model with five lag



Source: authors' calculations.

Figure A.3

IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE
Trivariate model (rates differential) with five lags



Source: Authors' calculations.

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Corporate Firms' Financial Conditions and Investment in Latin America: Determinants and Measurement

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Jonathan Barboza Pineda
Ignacio Garrón Vedia

Abstract

For our research, we used a large dataset of nonfinancial firms from ten Latin American countries to assess leverage determinants and their dynamics. The results seem to be consistent with elements of both the trade-off and pecking order views. Also, the regression results show the presence of significant adjustment costs. According to our results, a firm's leverage is significantly reduced in the face of rising interest rates, with feed-back effects. Furthermore, we observed that reducing tangible assets induces more volatility in the interest rates paid by firms in the future. Essentially, when we separate firms according to leverage level, it appears that these effects are stronger for the highly leveraged

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enterprises. Dynamically, in the case of increasing rates, there seems to be more risk associated with higher leverage. Our results show that this effect is manifested in higher volatility of interest rates and reduced collateral levels, potential asset liquidation and rapid deleveraging. The segments most likely affected are medium size firms and large firms with high costs of liquidation and high sunk costs, especially in the service sector. Firms operating in markets with unique products would also suffer. Traditional market-based indexes of financial conditions could be complemented by corporate indicators underlying the role of collateral, cash flows, and risk. Based on these findings we propose and calculate an index of corporate financial conditions for the region.

Keywords: corporate finance; Latin American firms, pecking order, trade-off theory, financial distress.

JEL classification: G3, G30, G31.

1. INTRODUCTION

Over the last decade, the patterns of financial intermediation have dramatically changed in emerging economies. First, there has been a change in the characteristics of financial intermediation between bank and market, the base source of corporate funding. This process happened after the global financial crisis and in tandem with the increase in global liquidity, which was a result of nonorthodox monetary policy in advanced economies. Also, many emerging economies (EMEs) shifted their source of funding to corporate deposits (a less stable form of funding that tends to emerge from debt issuance), which translates into a close relation between nonfinancial firms' leverage and banks' funding.

There has been substantial growth in the number of total debt securities, in particular those of foreign ownership. In parallel, emerging economies have become more financially integrated with the rest of the world, especially regarding global corporate debt markets. While this is seemingly a welcoming phenomenon, some market observers and researcher have warned about potential pitfalls in the process of monetary policy reversal. Easier access to funding may have distorted corporate investment decisions. Also, currency mismatches might be exposed. Even if firms are naturally or financially hedged, they might be still exposed to changes in global financial conditions, directly by interest-rate shocks or indirectly by falling commodity prices (Hattori and Takáts, 2015).

For example, Fuertes and Serena (2014) examined after-crisis financial vulnerabilities for 2,773 debt-issuer nonfinancial firms in 36 EMEs, for 2000-2014. They do not find in general issuers financial ratios to have dramatically worsened. However, they did find particular segments, high leveraged, low profitability, low interest coverage ratio (ICR), and low liquidity firms, to be worrisome. Latin American trends do not differ from these global trends. As a consequence, their potential exposure to some risks, related to profitability, currency mismatches, rollovers, and global markets conditions, might have had risen.

In this article, we examine these issues by modelling the possible determinants of nonfinancial firms leverage ratios, by using a firm-level dataset of ten Latin American economies and then assessing the influence of firm-level indicators reflective of market financial conditions. Further research on these patterns showed how this model could contribute to informing the creation of a better calibrated, higher frequency financial condition indexes, comprised of both financial and nonfinancial information. After this step, we evaluated leverage determinants in a panel data frame and estimate in a more dynamic framework the effects of financial factors proxies on a firm's leverage, using a panel VAR methodology (Abrigo and Love, 2016; Love and Zicchino, 2006).

Overall, our results show that Latin American nonfinancial firm's leverage determinants are stable across countries, coherent with the standard theory and other cross-sectional studies on the topic. Our more-dynamic approach give us preliminary evidence on the existence of significant and robust interactions between the fundamental determinants of nonfinancial firms' capital structure and the firm-level proxy indicators of financial conditions. These new findings support the fact that nonfinancial firm's indicators yield useful information to construct better calibrated, high-frequency indexes of financial conditions.

To that end, we calculate a simple index of financial conditions in the corporate sector. We also extend our dynamic analysis by including investment as an endogenous variable in our dynamic panel model. Implicit in our exercise is to representing financial variables in terms of their contribution to creating real investment impulses. By controlling for fundamental factors in the investment equation, we use the coefficients for the financial variables as factor loadings in the construction of a financial condition index for nonfinancial firms.

The rest of the paper is structured as follows. In Section 2, we review the related literature and present our research hypotheses. Section 3 explains the methodological aspects of the empirical exercise. The data elaborations are presented in Section 4. The empirical results are contained in Section 5, for the financial panel VAR, and 6, for our investment panel model. Section 7 concludes the research study.

2. LITERATURE REVIEW

According to Jensen and Meckling (1976), firm behavior should be seen as a conundrum of conflicting objectives in equilibrium, with a nexus of complex contractual relations as the outcome. The principal-agent problems are of primary importance in those equilibria in the context of pervasive asymmetric information environments. The literature on modelling nonfinancial debt ratio determinants has been done according to two prevailing approaches: *trade-off* and *pecking order* hypotheses.

Under the static version of the *trade-off* hypothesis, the optimal leverage reflects a single period trade-off between the benefits of debt tax shields and the deadweight costs of financial distress caused by an excessive debt ratio (DeAngelo and Masulis, 1980; Bradley et al., 1984). Meanwhile, under the dynamics *trade-off* view, firms exhibit dynamic target adjustment behavior, with the presence of short-term costs of adjustment, as deviations from individual target levels of leverage are gradually removed over time (Flannery and Rangan, 2006; Lemmon et al., 2008; Frank and Goyal, 2007, Huang and Ritten, 2007).

On the other hand, under the *pecking order* hypothesis, the costs of issuing risky debt or equity overwhelm the forces that determine optimal leverage in the trade-off model. To minimize asymmetric information costs and other financing costs, firms establish a hierarchy over their sources of funding: financing investments first with internal funds (i.e., retained earnings), then with safe debt, followed by risky debt, and finally equity (Myers, 1984; Myers and Majluf, 1984). Table 1 summarizes the implications for several leverage determinant variables, regarding the two competing views.

A very important implication of the pecking order view is that firms would prefer internal rather than external sources of funding. Regarding external funding, firms would prefer debt financing over equity financing. In this regard, the variable "Internal financing deficit" (IFD) is quite relevant, as it indicates the firm's needs for external funding. Thus, the equilibrium corporate financing mix for any firm, at any point in time, would depend critically on where the firm is located in the hierarchy of funding. Thus, cross-sectional estimates would be unable to capture funding optimal patterns. Indeed, we find evidence suggesting that the internal financing deficit is a critical determinant of leverage for forms in the region. In a final section, we use these findings to propose and calculate an index of financial conditions for the corporate sector in the region.

Table 1

LEVERAGE DETERMINANTS ACCORDING TO COMPETING HYPOTHESES

Variable	*Trade-off hypothesis*	*Pecking order hypothesis*
Tax rate	Since there is a debt tax shield, a positive relation is expected between corporate tax rates and leverage (Fama and French, 2002).	
Other nondebt tax shields	Considering this is a substitute for the debt tax shields, there is a negative relation between nondebt tax shields and leverage (DeAngelo and Masulis, 1980).	
Profitability	Given that highly profitable firms are likely more able to payback their debts, this justifies a positive relation between profitability and leverage (Fama and French, 2002). However, in a dynamic model, profitability could proxy growth opportunities, so in this context the relation is ambiguous.	Since firms may be constrained due to asymmetric information problems, and thus adopt a hierarchy in selecting sources of funding, using retained profits firstly, there is a negative relation between profitability and leverage.
Growth opportunities	Since firms with high expectations for growth opportunities tend to be likely more exposed to bankruptcy and agency costs, and therefore may not use higher amounts of debt, there is a negative relation between growth opportunities and leverage (Myers, 1977, 1984; Rajan and Zingales, 1995).	Firms with high growth opportunities must undertake major investment projects, so their need for funding is greater. When internal funding is exhausted, firms prefer financing through debt rather than equity. Therefore, a positive relation is forecasted between growth opportunities and leverage (Shyam-Sunder and Myers, 1999; Ramalho and Silva, 2009).

Collateral value (tangible or intangible fixed assets)	Tangible assets can be used as collaterals in the case of a firm's bankruptcy, so the firms with tangible assets tend to have easier access to external finance. Therefore, there is a positive relation expected between tangibility and leverage (Titman and Wessels, 1988; Michaelas et al., 1999).	On the one hand, tangible/intangible assets can be used as collaterals, which can help diminish asymmetric information problems between managers and creditors (Michaelas et al., 1999; Sogorb-Mira, 2005). In contrast, Harris and Raviv (1991) argue that this contributes to make equity less costly. Therefore, the relation between tangibility and leverage is ambiguous.
Size	Larger firms tend to increase their leverage and to take advantage of debt tax shields (Smith and Stulz, 1985) which results in a lower likelihood of bankruptcy (Titman and Wessels, 1988).	On the one hand, since larger firms tend to accumulate retained earnings, making debt less necessary (López-García and Sogorb-Mira, 2008). On the other hand, larger firms tend to have fewer problems with asymmetric information, and can obtain external funding on more favorable terms (Myers, 1984). Therefore, the relation between size and leverage is ambiguous.
Age	Older firms with better reputations tend to have lower costs of external funding. Therefore, there is a positive relation between age and debt (Ramalho and Silva, 2009).	Older firms with better reputation tend to have more capacity to retain and accumulate earnings. Therefore, a negative relation between age and leverage is expected (La Rocca et al., 2011).
Mean reversion	There is an optimal leverage ratio, where tax shield benefits are comparable to financial distress costs. Whenever firms deviate from their optimal ratios, the existence of adjustment costs prevents firms from making a total adjustment to that ratio. Therefore, firms make short-term partial adjustments of leverage towards the optimal ratio (López-García and Sogorb-Mira, 2008).	

Table 1 (cont.)

LEVERAGE DETERMINANTS ACCORDING TO COMPETING THEORIES

Variable	*Trade-off hypothesis*	*Pecking order hypothesis*
Internal financing deficit		Firms with high internal financing deficit tend to rely more heavily on external debt to finance their investment projects. Therefore, there is a positive relation between internal financing deficit and leverage.
Volatility of earnings	For *reasonable* parameter values, Bradley et al. (1984) state that a firm's optimal leverage is a decreasing function of the volatility of its earnings.	When net cash flows are low, firms with more volatile net cash flows are likely to have lower dividend payouts and less leverage (Fama and French, 2002).
Uniqueness	Customers, workers, and suppliers of firms that produce unique or specialized products probably suffer from relatively high costs (imposed by the firm) in the event of a firm's liquidation. This attribute may be negatively related to the observed debt since it is correlated with non-debt tax shields and collaterals.	
Industry classification	Firms manufacturing machines and equipment should be financed relatively less, since they will find liquidation relatively costly.	

Sources: Titman and Wessels (1988), Frank and Goyal (2007, 2008), and Serrasqueiro y Caetano (2012).

3. METHODOLOGY

3.1 Breaking Down the Debt Ratio Model

As suggested by the literature, we use a dynamic partial adjustment model to capture the cost of adjustments and other leverage determinants. The introduction of a lagged dependent variable among the right-hand side variables creates an endogeneity problem since the lagged dependent variable might be correlated with the disturbance term. To solve this problem, Arellano and Bond (1991) developed a difference GMM estimator for the coefficients in the equation mentioned above, where the lagged levels of the regressors are the instruments for the first differential equation. Further, Arellano and Bover (1995) and Blundell and Bond (1998) suggest differentiating the instruments instead of the regressors in order to make them exogenous from fixed effects. This leads to the differences between the GMM and the system GMM estimator, which is a joint estimation of the equation in levels and in first differences. Hence, we use the two-step system GMM estimators, with Windmeijer (2005) corrected standard error.

3.2 Examining How the Debt Ratio Model Is Influenced by Financial Conditions

Further, and considering the results from the previous partial adjustment model, we examine how equilibrium leverage ratios are impacted by financial conditions in a more dynamic setting. For doing so, we implement a panel vector autoregression (panel VAR) methodology. This approach treats all variables as endogenous (VAR) and incorporates the unobserved individual heterogeneity in the panel. We present the results of the panel VAR estimations as well as well as the corresponding impulse-response functions.

Following closely the instrumental variables system-GMM methodology suggested by Love and Zicchino (2006) and

Abrigo and Love (2015), we estimate a first order panel VAR as follows:

$$Y_{it} = \alpha + \theta Y_{it-1} + f_i + d_{ct} + e_{it},$$

where Y_{it} and Y_{it-1} are (5×1) vectors of variables (profitability, tangibility, leverage, tax shield and a proxy of financial conditions), for firm i, at a time t and $t-1$, respectively; θ is a (5×5) matrix of coefficients which are homogeneous for all firms; f_i denotes for firms' fixed effects and d_{ct} are country effects which are homogeneous for each firm in country c at time t. Finally, e_{it} is the vector of the respective white-noise disturbances.

Eliminating firms fixed effect f_i by differencing will create correlation with the lagged dependant variables, generating bias in the estimators. Also, the specification include country effects d_{ct} to account for country-specific macro shocks that affect all firms in country c at the same time, wich also would create estimators' bias. Thus, following Love and Zicchino (2006), we perform a two-way standardization of the variables used in the panel VAR, in order to eliminate f_i and d_{ct} effects. First, with regard to the country effects, we subtract the means of each variable for every country and year. Secondly, regarding the endogeneity of fixed effects and lagged dependent variables, we use the *Helmert procedure* for each variable by forward mean-differencing (Arellano and Bover, 1995). This method removes from the regressors the mean of all available future observations, thus preserving orthogonality between the resulting transformed variables and lagged regressors.

Also, following Abrigo and Love (2015), we also perform a Granger-causality Wald test for each equation of the panel VAR, to check for the empirical order of the VAR. As in a standard VAR model, we check for the presence of eigenvalues outside the unitary circle, thus assessing the stability of the panel VAR system. Also, we calculate and show Cholesky impulse-response functions and forecast-error variance decompositions. Then, we use the evidence from the Granger-Wald causality tests to inform the ordering of the variables in the Cholesky decompositions. The confidence intervals for the impulse-response exercises are generated by Monte-Carlo random generation of $\hat{\theta}$ and its corresponding estimated variance-covariance matrix. We present 90% confidence intervals, with 1,000 repetitions. Lastly, for the construction of a financial condition index in the final section of the paper, we extend our initial dynamic panel model, in order to incorporate investment dynamics and the role of financial conditions.[1]

4. DATA

The data we used in this study was Orbis BvD corporate dataset for ten Latin American countries: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico, Peru, Uruguay, and Venezuela. After checking the data for extreme outliers and inconsistencies, we obtained leverage information for 10,005 firms in 17 economic sectors, in the period 2006-2015. Next, we aggregated those sectors in manufacturing, services, primary sector, utilities, and public sector.[2] We counted, on average, approximately 2.03 years of observations of each of the 10,005 firms (20,315 observations). Figure 1 shows leverage distributions for the 17 sectors represented in our sample. Notably, and as reflected in our results, sectoral patterns are a clear determinant of leverage. For the panel VAR exercise, a data subset is used, comprised of 1,939 firms with information with an average period of 5.92 years. Depending on the variables used in the regression, N could be reduced. Tables A.1 and A.2 in Annex A, show descriptive statistics for the samples.

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[1] All calculations were perfomed using the following Stata's user-written comands *pvar*, *pvarsoc*, *pvargranger*, *pvarirf* and *pvfevd*, developed by Abrigo and Love (2015).

[2] We show table results only for the manufacturing, services, and primary sectors, the bulk of our sample.

Figure 1

LEVERAGE DISTRIBUTIONS BY SECTORS

Overall sample, 2006-2015

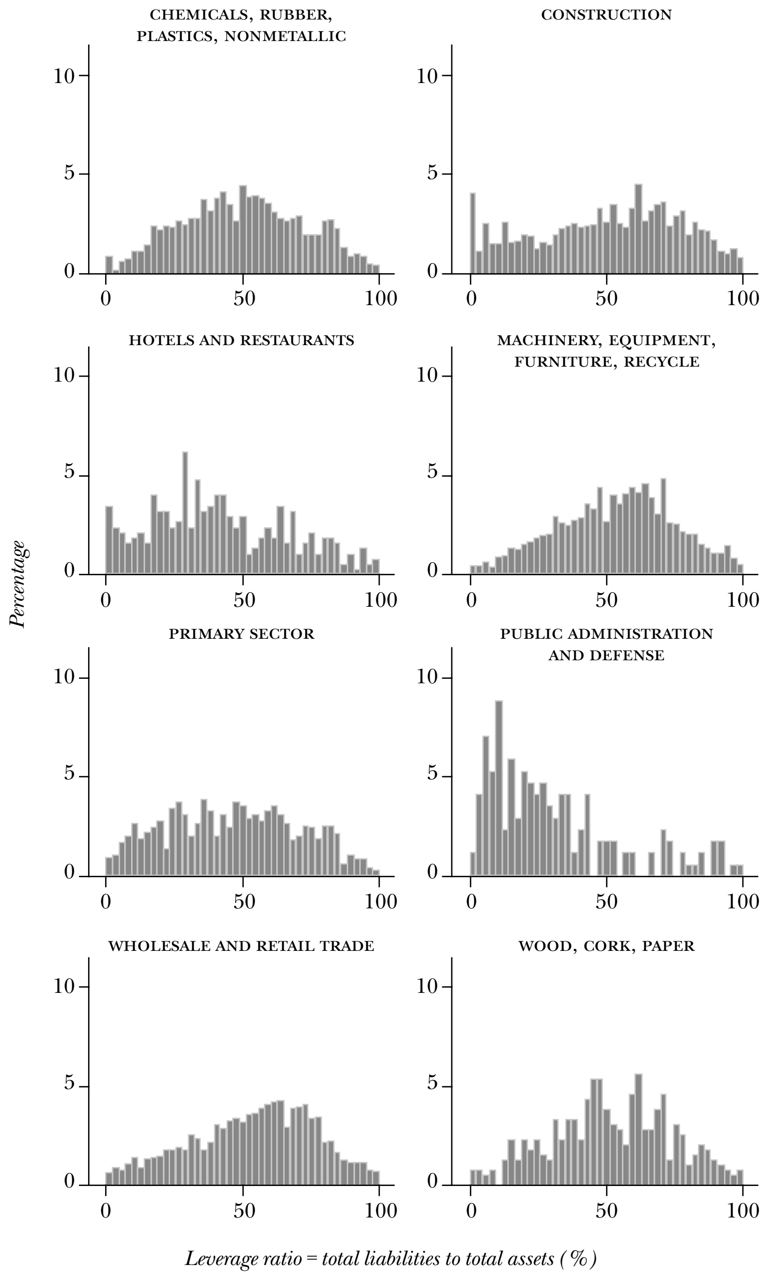
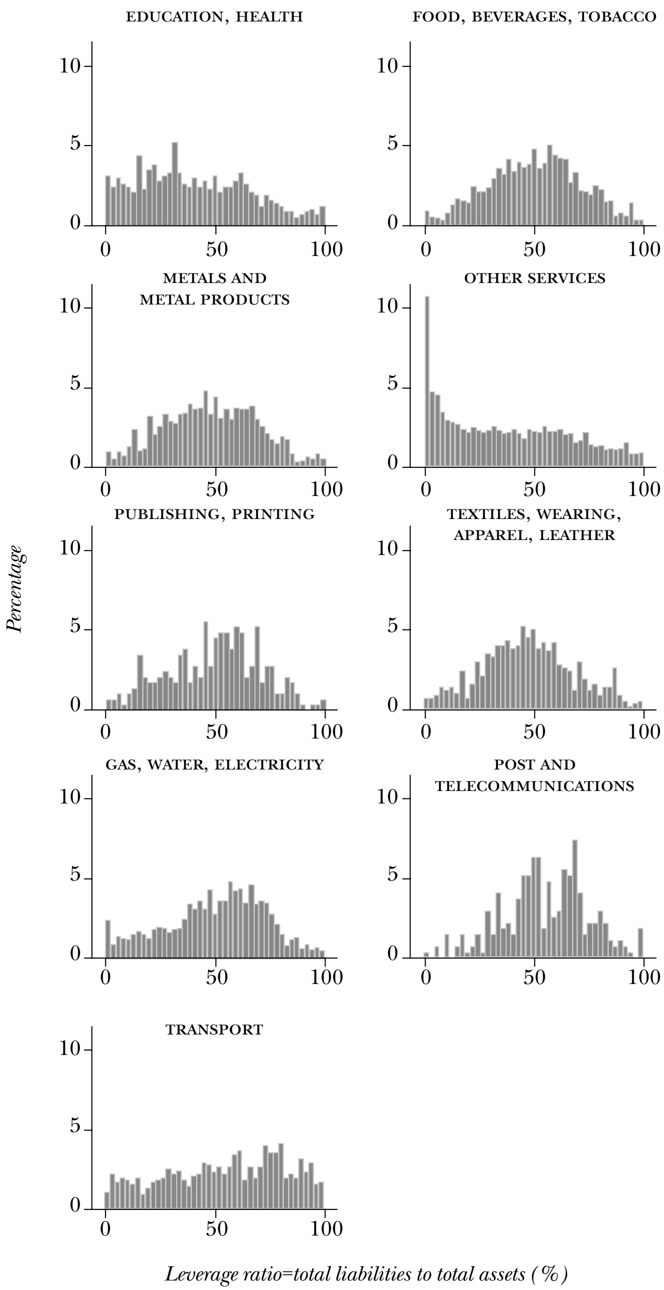


Figure 1

LEVERAGE DISTRIBUTIONS BY SECTORS

Overall sample, 2006-2015



5. RESULTS

Tables B.1 and B.2[3] show Blundell-Bond system-generalized moments method (GMM) estimation results for the determinants of leverage in manufacturing, services, and the primary sectors.[4] Similar to other corporate finance studies the results obtained seem to be consistent with the elements of the two main theories (Rajan and Zingales, 1995). Regression results show the presence of significant adjustment costs. To the extent that firms have unobservable target levels, firms face low speed of adjustment. This would be consistent with the trade-off dynamic theories. Additional evidence supporting the trade-off theory is provided by variable's tax shield results, which is positively correlated with leverage.

For manufacturing and service firms, the ratio of tangible assets to total assets is negatively correlated with leverage. Also, tangible assets are found to be correlated with growth opportunities.

On the other hand, these assets can be used as collateral. Thus, this piece of evidence seems to be supportive of both the *trade-off* and the *pecking order* hypotheses. Furthermore, our results suggest that medium-sized firms in manufacturing and services tend to be significantly more leveraged than the small firms in these sectors, while very large and large companies in the services sector are significantly more leveraged than their counterparts in the medium-sized-firms group (see Annex A.3 for variables description). This is in line with the trade-off hypothesis, as well as with Myers (1984). Regarding the uniqueness indicator,[5] we found that it affects leverage positively and

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[3] Henceforth, all the statistical tables not displayed in the body of this document can be located in the Annex B.

[4] In Table B.2 we use ROAA as measure of cash flow effects, instead of our IFD variable.

[5] Uniqueness, measured as costs of goods sold to operating revenue, is related to the extent to which the market for a good depends on retaining a significant customer base. To that regard,

significantly only for firms in the primary and service sectors, which is contrary to the trade-off hypothesis. Uniqueness, as pointed out by Gilchrist et al. (2016), is critical to understanding a firm's ability to increase prices; thus, it is connected to the financial distress during episodes of aggregated shocks. Firms that produce unique products are more vulnerable to interest rate shocks while being highly leveraged, since they tend to have less flexibility to increase prices.

Three variables' estimates are quite consistent with the pecking order hypothesis, namely the internal financing deficit,the dichotomic variable equal to one if the firm is listed (and zero otherwise), and the pofitability variable (return on average assets, or ROAA). Leverage is higher for firms with a larger financing deficit. On the one hand, listed firms or firms with higher profitability tend to have lower leverage ratios, likewise for smaller firms, so they are also consistent with this hypotheses.

In order to examine the possibility of multiple endogeneity of the regressors, our empirical strategy also includes estimating panel VARs and impulse-response functions for the subsample of firms with larger time series dimension.

In this regard, we reproduce previous specifications as much as possible, considering panel VAR stability conditions.[6] Then we augment the regressions in two variables to show the effects of financial conditions at the individual firm's level. In one case, we include the previous year's implicit interest rate paid on liabilities. In the other, we calculated the rate's previous 3-year rolling window standard deviation. Figures 2a and 2b show the evolution of median and inter-quartile ranges for the implicit interest rates and its standard deviation for the ten countries examined. Most countries have experienced episodes of high

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firms deploy marketing and sale forces resources to convey the special and unique nature of their product. In that regard, the customer base becomes a valuable asset in this kind of markets, with price competition playing a secondary role.

[6] We use instead tangibility in this set of results, calculated as the ratio of fixed to total assets.

Figure 2a

AVERAGE AND INTER-QUARTILE IMPLICIT INTEREST RATE EVOLUTION

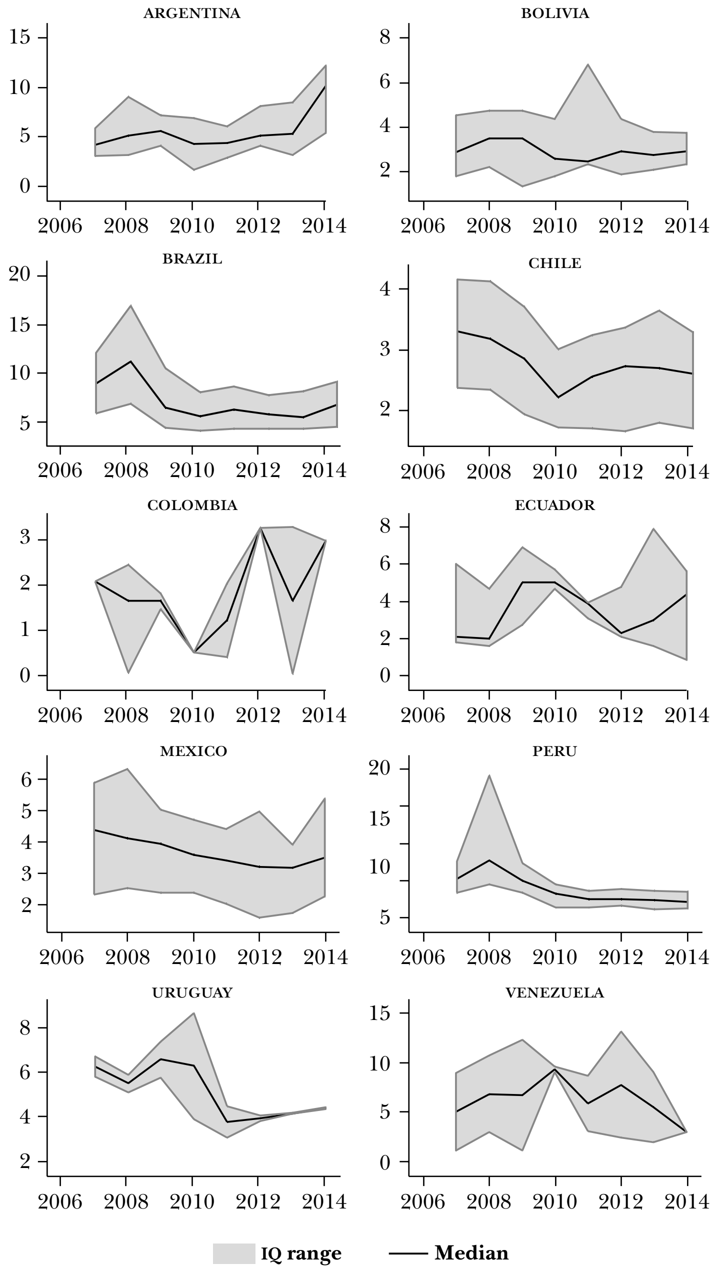
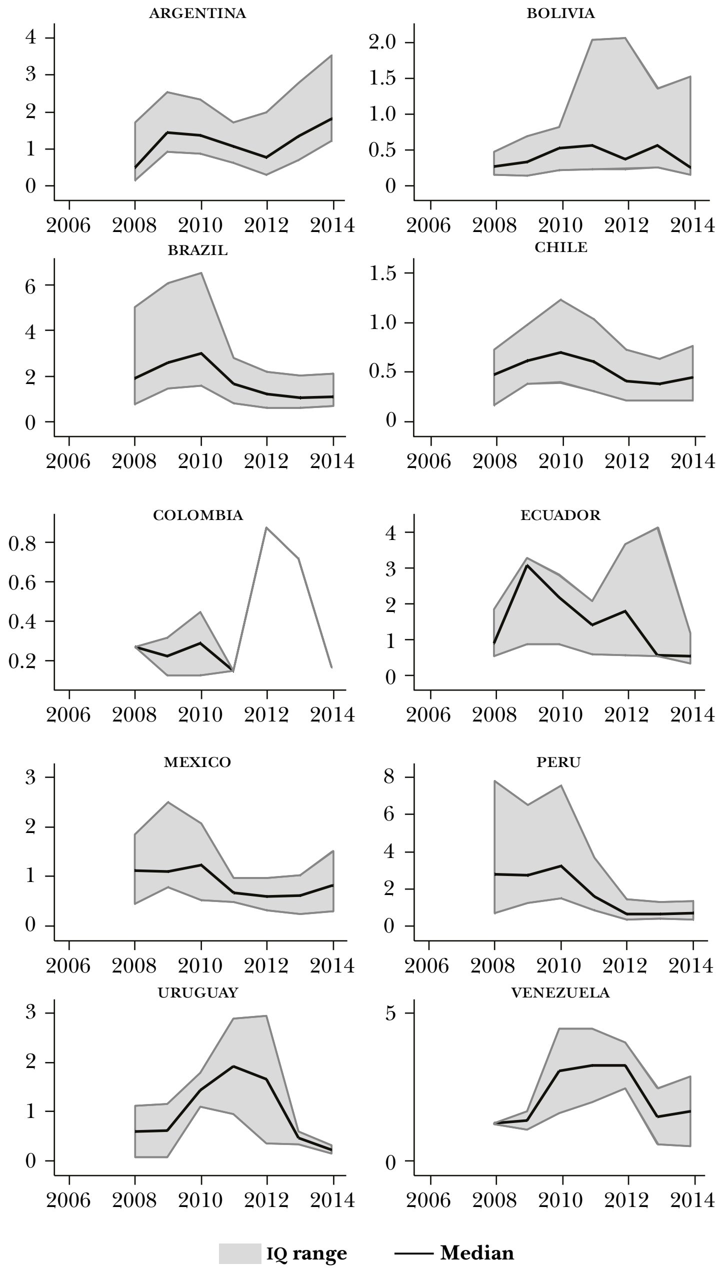


Figure 2b

AVERAGE AND INTER-QUARTILE VOLATILITY

3-Year Rolling SD of Implicit Interest Rate



interest rate volatility and level, especially in the immediate post global financial crisis.

Table 2 shows the panel VAR results for the interest rate variable. In Table 3 and Figure 4, the corresponding variance decomposition and impulse-responses are displayed. Our results suggest the presence of a bidirectional causality between interest rates and leverage. Previous year interest rates reduce leverage at a time *t*, whereas a rise in the previous year's leverage reduces the future rate charged on a firm's liabilities. The impulse-response functions (figure 4) shows that a shock increasing *Leverage* tend to have negative and significant effects over the future interest rate lasting about four years, while a shock increasing the implicit interest rate has negative and significant effects over *Leverage* lasting about five years.

When including the volatility (standard deviation) of the implicit interest rate as an endogenous component of the panel var (Table 4), we find that firms with larger collateral (tangible assets) face lower future interest rate volatility. Also, under this specification, higher previous leverage seems to be associated with higher future profitability (ROAA). As shown by impulse-response functions (Figure 5), a shock increasing leverage has an immediate negative effect on profitability, compensated onwards with a significant increase in the second year wich lasts for about the fifth year.

Overall, our results seem to indicate that leverage is affected by previous interest rates, an obvious result, but with feedback effects involved. Conversely, collateral values seem to be important determinants of the future interest rate volatility facing firms. As shown by variance-decomposition results (Table 3), around 10% of the implicit interest variance is explained by leverage. Also, the tangibility of assets explains about 45% of volatility-of-interest-rate variance. The impulse responses for the effect of previous interest rates on leverage last for at least five years. Of similar duration is the reverse causality effect. Also, the effect of the tangibility of the future volatility of interest rates lasts for five years Figure 5).

Table 2

PANEL VECTOR AUTOREGRESSIOM FOR DETERMINANTS OF CORPORATE FINANCING AND THE PREVIOUS IMPLICIT INTEREST RATE

	Response to				
Response of	*ROAA (t−1)*	*Leverage (t−1)*	*Tangibility (t−1)*	*Imp. int. rate (t−1)*	*Tax shield (t−1)*
ROA (t)	0.3744[c]	0.0609	−0.0417	0.0004	0.2178
	(0.0686)	(0.0379)	(0.0346)	(0.0331)	(0.1412)
Leverage (t)	−0.1891	0.8051[c]	−0.0135	−0.0857[a]	0.1794
	(0.0793)	(0.0644)	(0.0607)	(0.0459)	(0.2139)
Tangibility (t)	−0.1252	−0.0660	0.8286[c]	−0.0910	0.0068
	(0.0777)	(0.0769)	(0.0837)	(0.0587)	(0.2075)
Imp. int. rate (t)	0.0291	−0.1209[c]	−0.0005	0.2944[b]	−0.0557
	(0.0432)	(0.0378)	(0.0311)	(0.1157)	(0.0916)
Tax shield (t)	0.0601[b]	−0.0042	0.0126	−0.0034	0.3312[c]
	(0.0240)	(0.0156)	(0.0142)	(0.0103)	(0.0738)

Number of observations (N): 2,400

Number of firms (N): 669

Average number of years: 3.587

Final GMM criterion Q(b): 7.52e−34

Initial weight matrix: identity

GMM weight matrix: robust

[a] $p < 0.10$, [b] $p < 0.05$, [c] $p < 0.01$. Standard errors in parenthesis. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. This panel VAR satisfies the stability condition proposed by Hamilton (1994) and Lütkepohl (2005).

Table 3

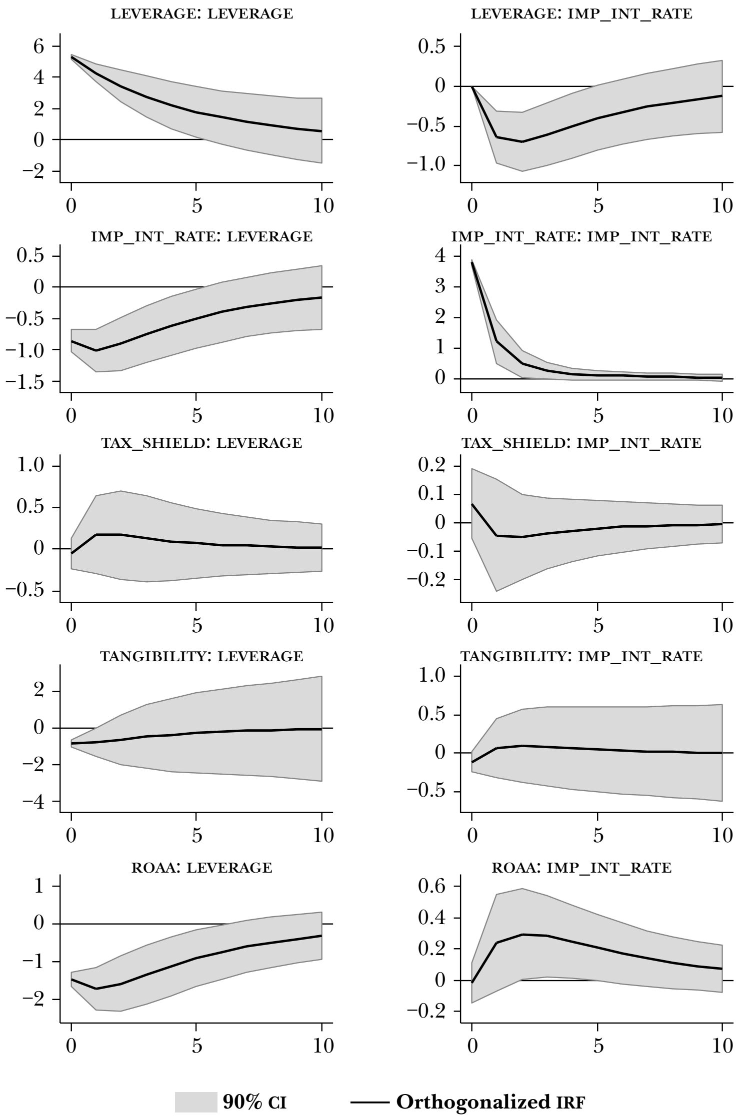
VARIANCE DECOMPOSITION OF THE PANEL VAR FOR DETERMINANTS OF CORPORATE FINANCING AND THE PREVIOUS IMPLICIT INTEREST RATE

	Impulse variable				
Response variable	ROAA	*Tangibility*	*Tax shield*	*Imp. int. rate*	*Leverage*
ROAA	0.8911	0.0508	0.0086	0.0017	0.0477
Tangibility	0.0271	0.9515	0.0001	0.0012	0.0201
Tax shield	0.2379	0.0160	0.7457	0.0002	0.0003
Imp. int. rate	0.0213	0.0023	0.0006	0.8721	0.1036
Leverage	0.1293	0.0239	0.0010	0.0427	0.8030

Percent of variation in the row variable (10 years ahead) explained by the column variable. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. The variables were sorted following Granger-Wald causality test criteria.

Figure 4

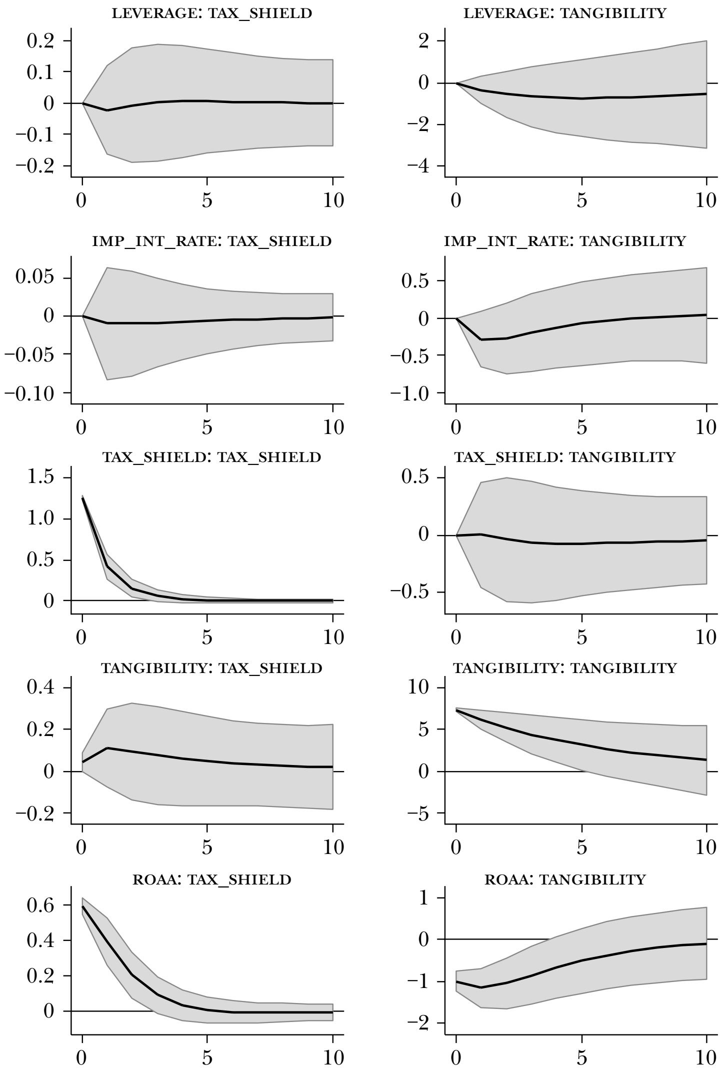
IMPULSE-RESPONSES OF THE PANEL VECTOR AUTOREGRESSION FOR DETERMINANTS OF CORPORATE FINANCING AND THE PREVIOUS IMPLICIT INTEREST RATE AS A PROXY OF FINANCIAL CONDITIONS



Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure 4 (cont.)

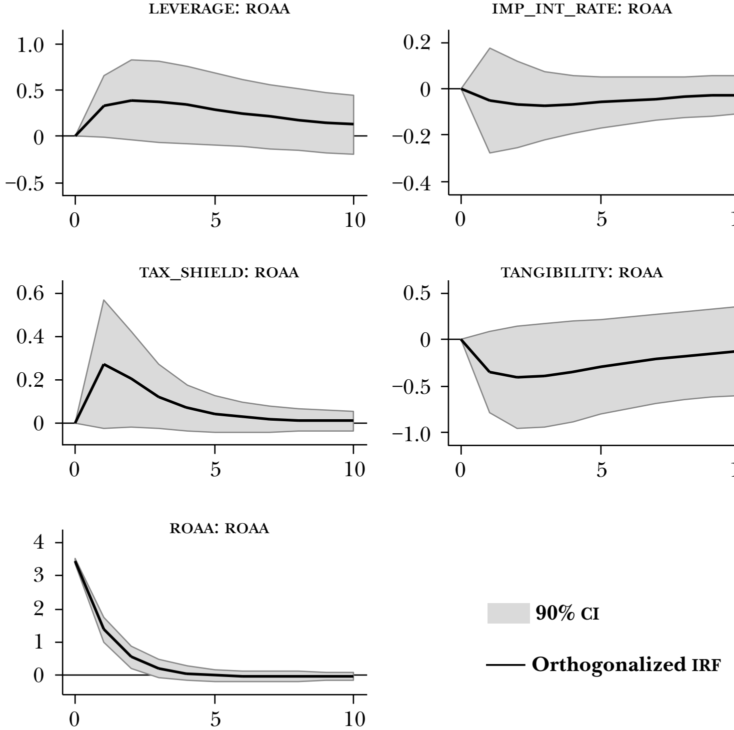
IMPULSE-RESPONSES OF THE PANEL VECTOR AUTOREGRESSION FOR DETERMINANTS OF CORPORATE FINANCING AND THE PREVIOUS IMPLICIT INTEREST RATE AS A PROXY OF FINANCIAL CONDITIONS



Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure 4 (cont.)

IMPULSE-RESPONSES OF THE PANEL VECTOR AUTOREGRESSION FOR DETERMINANTS OF CORPORATE FINANCING AND THE PREVIOUS IMPLICIT INTEREST RATE AS A PROXY OF FINANCIAL CONDITIONS



Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Table 4

PANEL VECTOR AUTOREGRESSION FOR DETERMINANTS OF CORPORATE FINANCING AND THE 3-YEAR ROLLING SD OF THE IMPLICIT INTEREST RATE

	Response to				
Response of	*ROAA (t−1)*	*Leverage (t−1)*	*Tangibility (t−1)*	*SD imp. int. rate (t−1)*	*Tax shield (t−1)*
ROAA (t)	0.3420[c]	0.1058[b]	−0.0330	−0.0006	−0.0398
	(0.0790)	(0.0457)	(0.0472)	(0.0675)	(0.2213)
Leverage (t)	−0.1181	0.7694[c]	−0.0470	−0.0662	−0.0626
	(0.1049)	(0.0775)	(0.0782)	(0.0906)	(0.3259)
Tangibility (t)	−0.1359	-0.0889	0.8497[c]	−0.0315	0.0724
	(0.1172)	(0.0890)	(0.1093)	(0.0938)	(0.3358)
SD. imp. int. rate (t)	0.0105	−0.0120	−0.0586[c]	0.8131[c]	0.0742
	(0.0293)	(0.0208)	(0.0224)	(0.0940)	(0.0680)
Tax shield (t)	0.0334	−0.0071	−0.0011	−0.0104	0.3727[c]
	(0.0321)	(0.0194)	(0.0214)	(0.0176)	(0.1208)

Number of observations (N): 1,745

Number of firms (N): 537

Average number of years: 3.25

Final GMM criterion Q(b): 4.24e−34

Initial weight matrix: identity

GMM weight matrix: robust

[a] $p < 0.10$, [b] $p < 0.05$, [c] $p < 0.01$. Standard errors in parenthesis. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. This panel VAR satisfies the stability condition proposed by Hamilton (1994) and Lütkepohl (2005).

Table 5

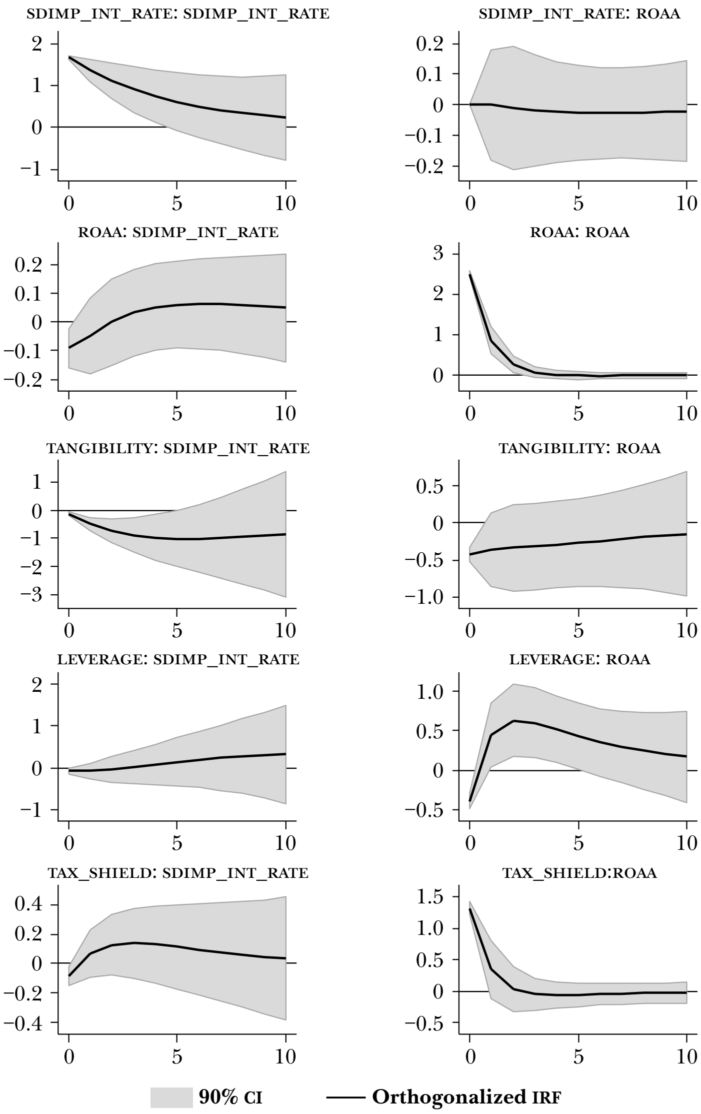
VARIANCE DECOMPOSITION OF THE PANEL VAR FOR DETERMINANTS OF CORPORATE FINANCING AND THE 3-YEAR ROLLING SD OF THE IMPLICIT INTEREST RATE

	Impulse variable				
Response variable	*Tax shield*	*Leverage*	*Tangibility*	ROAA	*SD imp. int. rate*
Tax shield	0.9912	0.0017	0.0005	0.0059	0.0008
Leverage	0.0240	0.9523	0.0156	0.0045	0.0036
Tangibility	0.0013	0.1063	0.8895	0.0027	0.0002
ROA	0.1607	0.1610	0.0737	0.6042	0.0004
SD imp. int. rate	0.0063	0.0190	0.4584	0.0020	0.5143

Percent of variation in the row variable (10 years ahead) explained by the column variable. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. The variables were sorted following Granger-Wald causality test criteria.

Figure 5

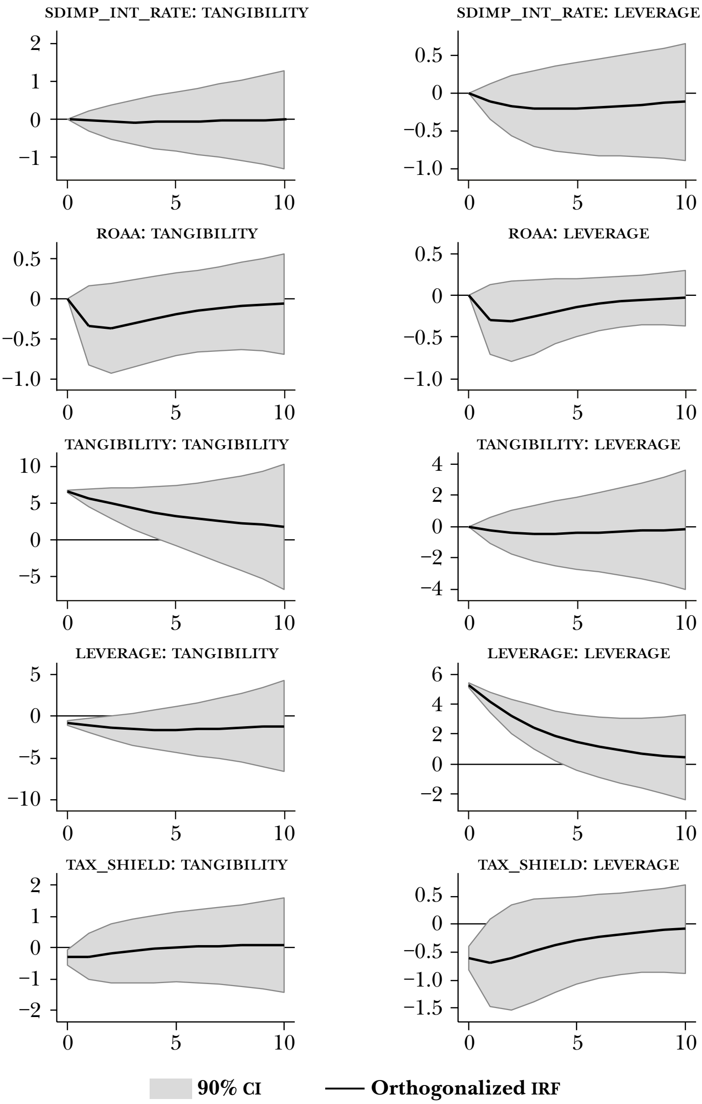
IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE 3-YEAR ROLLING SD OF THE IMPLICIT INTEREST RATE



Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure 5 (cont.)

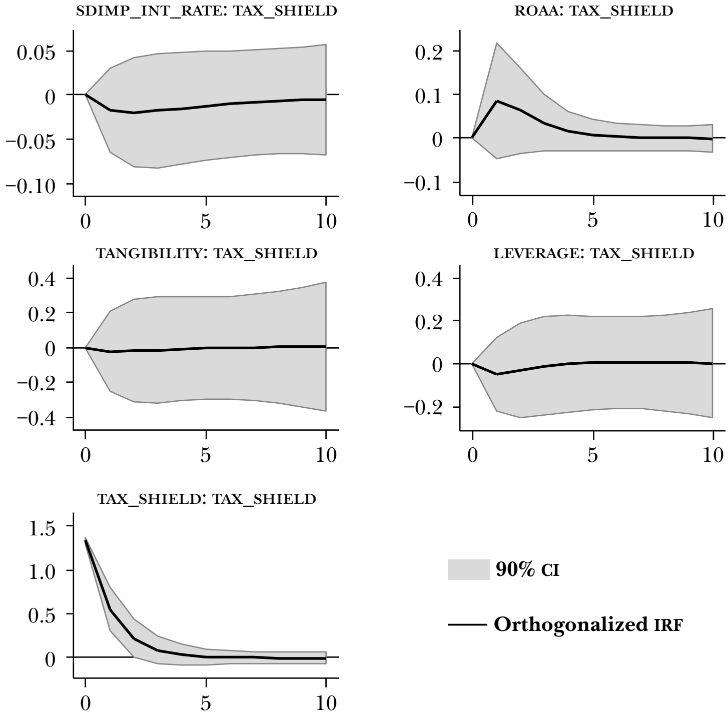
IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE 3-YEAR ROLLING SD OF THE IMPLICIT INTEREST RATE



Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure 5 (cont.)

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE 3-YEAR ROLLING SD OF THE IMPLICIT INTEREST RATE



Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

We further look at threshold effects in the leverage distribution by dividing firms into above and below median leverage. Results are shown in Tables B.3-B.4 and Figures B.1-B.2,[7] for previous implicit interest rates; and Tables and Figures B.5-B.6 and Figures B.3-B.4 show results for the volatility of implicit interest rates.

The first part of Table B.3 reports the panel VAR estimates for firms whose mean leverage ratio is lower than the median and where the bidirectional causal relation between leverage and implicit interest rate found in the baseline model is reproduced. Interchangeably, results for the highly leveraged group of firms are presented in the bottom part of Table B.3. As the opposite of low-leveraged firms, in the case of high-leveraged the feed-back effect between implicit interest rates is no longer held, since only the one-year lagged leverage impacts the implicit interest rate significantly and negatively. Also important is the fact that, for this group of firms, implicit interest rates are negatively associated with the future collateral measured by tangibility, which means that an increases in previous rates reduces significantly the tangible assets of the firm in the next five years (with regards to impulse-response functions presented in Figure B.2). We presume this result is driven by the fact that already highly leveraged firms tend to face relevant price effects in their balance sheets when interest rates increase, and additionally, they are induced to liquidate asset positions in the face of interest rate shocks.

Regarding the impulse-response functions for highly leveraged firms (Figure B.2), then the future profitability grows up significantly from the second year after the leverage increases, up to about to the fifth year (Figure B.2). In turn, a positive shock of the implicit interest rate at year t leads to a significant decrease of the future collateral values, while the collateral itself is found to cause an increase in the future volatility of

[7] Henceforth, all figures not displayed in the body of this document can be located in the Annex B.

rate (as shown at the bottom of Table B.5, for highly leveraged firms). This fact constitutes a negative spiral, in which financial conditions for firms are further deteriorated. The compensating mechanism to end up this harmful process seems to operate at lower leverage and profitability, as firms engage in a new leverage cycle. This is reflected in the negative and significant coefficient of the lagged profitability on future leverage.

6. AN AGGREGATED INDEX OF CORPORATE FINANCIAL CONDITIONS FOR TEN LATIN AMERICAN COUNTRIES

In this section, we extend our previous analysis by including investment as an endogenous variable in our dynamic panel model. Implicit in our exercise is representing of financial variables in terms of their contribution with the goal of creating real investment impulses. By controlling for fundamental factors in the investment equation, we use the coefficients for the financial variables, as factor loading in the construction of a corporate financial condition index.

We derive our intuition for our proposed index from the literature on micro-level real investment measuring. Investment dynamics within a PVAR firm-level have been estimated with the inclusion of financial variables (Love and Zicchino, 2006; Gilchrist and Himmelberg, 1998). Love and Zicchino (2006) estimated an investment PVAR using firm-level data from 36 countries. In their model, they included *fundamental factors* such as a measure of the marginal productivity of capital and Tobin's *q*. Their financial factors variable is represented by cash flows scaled by capital. Thus, their exercise is determining the dynamic function of investment that is augmented by a financial variable. They found the friction effect of the financial variable on investment to be larger for the group of countries with less developed financial systems. Also, a series of papers have looked at the elasticity of investment to cash flow and other financial variables, generally in a static or dynamic panel data context (Gomes, 2001; Balfoussia and Gibson, 2016; Hernando and Martínez-Carrascal, 2008) analyzed the impact of alternative measures of firms' financial conditions on investment and employment by using a large-scale panel dataset of Spanish firms over the period 1985-2001. They then used the estimated coefficients of the investment equation as factor loadings in the construction of a corporate financial conditions index. As Hernando and Martínez-Carrascal (2008), we estimate an error-correction investment model, as suggested by Bond et al. (1999). We follow this latest approach in the construction of our index of corporate financial conditions.

In this sense, we estimate a dynamic system-GMM panel model for fixed investment ratio at firm-level assuming the existence of additive year-specific effects, μ_t, country-specific effects, τ_k, and industry specific effects, γ_f, which could be expressed as follows:

$$\begin{aligned}\frac{I_{it}}{K_{i,t-1}} = \rho_1\left(\frac{I_{i,t-1}}{K_{i,t-2}}\right) + \omega_0 \Delta y_{it} + \omega_1 \Delta y_{i,t-1} + \theta(k-y)_{i,t-2} + \beta_0 Lev_{it} + \\ +\beta_1 Lev_{i,t-1} + \beta_2 IDB_{it} + \beta_3 IDB_{i,t-1} + \beta_4 (Zscore)_{it} + \beta_5 (Zscore)_{i,t-1} \\ +\beta_6 (IFD)_{it} + \beta_7 (IFD)_{i,t-1} + \beta_8 (Tangibility)_{i,t} + \\ +\beta_9 (Tangibility)_{i,t-1} + X_{i,t}\delta + \mu_t + \tau_k + \gamma_f + \varepsilon_{it}.\end{aligned}$$

We then construct indexes of financial conditions for our ten countries as follows. First, we estimate an error-correction investment model including lagged fixed investment, lagged and contemporaneous sales growth; the error-correction term, and other controls. Alternatively, we expand the investment model by including lagged and contemporaneous of several key financial variables from our previous analysis- Leverage, our internal financing deficit indicator (IFD), the interest debt burden, the tangibility of assets and the firms' Z-score, as a measure of risk. Results are shown in Table 7. A key aspect of the model is the inclusion of time and firm effects to capture capital replacement costs. Also, the model predicts the existence of significant and negative error correction component. We then use the results for the investment equation for the construction of our financial conditions index.

Notice that about the financial variables included, only the IFD, Z-score and tangibility coefficients were found to be significant. Consistent with previous results, we used specification 2 in Table B.7, as leverage was found in previous sections to be caused by both tangibility and IFD. Accordingly, in the specification 1, lagged leverage is found to significantly explain investment when excluding these two of its determinants. In specification 3, we use profitability (ROAA) instead of IFD, and get similar results. For the variables of interest, the contemporaneous effects are significantly positive, and the lagged effects are significantly negative. However, the sum of both coefficients is found to be significantly different from zero and positive for Z-score and the IFD, the variables with the largest effects, indicating a positive relation between the index loadings and investment financial conditions. Accordingly, we propose the following financial conditions index (FCI) for nonfinancial firms:

$$FCIit = \widehat{\beta_4}\left(Zscore\right)_{it} + \widehat{\beta_5}\left(Zscore\right)_{i,t-1} + \widehat{\beta_6}\left(IFD\right)_{it} + \widehat{\beta_7}\left(IFD\right)_{i,t-1} + \\ + \widehat{\beta_8}\left(Tangibility\right)_{it} + \widehat{\beta_9}\left(Tangibility\right)_{i,t-1}.$$

FCI can be interpreted as the predicted *financial* value of the investment. In order to have a country index, we aggregate at country-time level by calculating percentile 25, 50 and 75 statistics for the index. Figures B.5 and B.6 show the resulting lags of country-time FCI pair as compared to gross fixed capital formation and GDP growth.

The index is constructed so that increasing/decreasing values imply improving/deteriorating financial conditions for investment. The figures convey, at the simple examination, the potential for a positive correlation. We further explore these patterns as follows. First, we estimate a simple first order panel VAR model including FCI, gross fixed capital formation, and

GDP growth, for the ten countries in the sample. As an initial step, and test for Granger causality. The results are shown in Table B.8.

Granger causality Wald tests indicate IFC to Granger cause both gross fixed capital formation and GDP growth. The reverse causality is not found. Also, GDP growth Granger causes gross fixed capital formation. At a final exercise, we show in Figure 9, resulting impulse-response functions assuming a Cholesky variance decomposition with ordering given by the obtained Granger criteria. A one-standard deviation positive shock in FCI results in an increase in both gross fixed capital formation and GDP future growth, which is significant and lasting for about 12 months, with 90% confidence levels. Thus, these preliminary results, albeit restricted about its simplicity and extent of the series, provides some evidence on the potential explanatory relevance of the financial conditions index constructed thus far, using firm level data. It is also worth to notice that the financial shock implicit in the exercise is common across countries, given the nature of the exercise. Thus, the real impulses obtained must be interpreted accordingly, as the average national real effects to a common financial shock.

7. CONCLUSIONS

In this article, we use a large dataset of nonfinancial firms from ten Latin American countries to assess leverage determinants and their dynamics. We then use that information to inform the specification of a new index of corporate financial conditions.

With regard to the first set of issues, our results seem to be consistent with elements of the two main theories, the trade-off, and pecking order views. Regression results show the presence of significant adjustment costs. To the extent that firms have unobservable target levels, firms face low speed of adjustment. Furthermore, our results suggest that medium-sized firms in manufacturing and services tend to be significantly more leveraged than their small firms in these sectors, whereas very large and large companies in the services sector are significantly more leveraged than their counterparts in the medium-sized-firms group. Regarding the uniqueness indicator, we found that it affects leverage levels positively and significantly, only for firms in the primary and service sectors, which is evidence against the trade-off hypothesis. With regard to our dynamics determinants of leverage, we observe that a firm's leverage is significantly reduced in the face of rising interest rates, with feed-back effects. Also, firms' collateral resulted to be critical, as reductions in tangible assets bring about future volatility in the interest rates paid by the firms. When we separate firms according to the leverage level, it turns out that these effects are stronger for highly leveraged firms.

Dynamically, the risk seems to be associated with high leverage in the context of rate increases. It is manifested in higher rate volatility and reduced collateral levels, potential asset liquidation and rapid deleveraging. These dynamics are probably more likely in the context of policy rate changes and capital outflows. According to our results, segments most likely affected are medium size firms and large firms with high costs of liquidation as well as high sunk costs, especially in the service sector. Firms operating in markets with unique products would also suffer.

Our results ultimately suggest that traditional market-based indices of financial conditions could be complemented by corporate indicators. As mentioned, collateral levels, indicators of corporate distress and firms' cash flow positions are natural candidates for an index. To that end, we calculated a simple index of financial conditions in the corporate sector (FCI). Granger causality Wald tests indicate ICFC to Granger-cause both gross fixed capital formation and GDP growth. According to resulting impulse-response functions, a one-standard deviation positive shock in IFC results in an increase in both gross fixed capital formation and GDP future growths, which is significant and lasts for about 12 months. Thus, these preliminary evidence suggests the potential predictive relevance of the index proposed here.

Annex A

Table A.1

DESCRIPTIVE STATISTICS FOR THE INITIAL LEVERAGE DETERMINANTS EXERCISE

Variable	*Description*	*Type*	*Observations*	*Panels (firms)*	*Mean*	*Std. dev.*	*Min*	*Max*
Leverage	Total liabilities to total assets (%)	Firm-level	20,315	10,005	48.059	25.012	0.000	100.000
Intangibility	Intangible assets to total assets (%)	Firm-level	17,457	8,969	5.182	13.580	0.000	99.948
Tangibility	Tangible assets to total assets (%)	Firm-level	20,315	10,005	32.834	28.339	0.000	100.000
Internal financial déficit (IFD)	Operative expenditures (investment+working capital) minus the cash flow (which is assumed to be equal to 110% of the net income) to total assets (%)	Firm-level	20,315	10,005	−2.968	23.299	−99.885	99.819
Uniqueness	Costs of goods sold to operating revenue	Firm-level	13,359	3,960	65.389	22.346	0	199.633
Listed	(1): if the firm is publicly listed, (0): otherwise (source: Orbis and own calculations)	Firm-level	20,315	10,005	0.213	0.409	0	1
ROAA	Net income to average of total assets (%)	Firm-level	20,315	10,005	5.115	11.643	−96.000	98.425
Tax shield	Total taxes to total assets (%)	Firm-level	16,643	8,744	3.474	5.324	0.000	99.579

Source: Orbis and own calculations.

Table A.2

DESCRIPTIVE STATISTICS FOR THE PANEL VAR LEVERAGE DETERMINANTS EXERCISE

Variable	*Description*	*Type*	*Observations*	*Panels (firms)*	*Mean*	*Std. dev.*	*Min*	*Max*
Leverage	Total liabilities to total assets (%)	Firm-level	11,487	1,939	49.994	22.739	0.005	100.000
Tangibility	Tangible assets to total assets (%)	Firm-level	11,487	1,939	29.097	24.548	0.000	99.080
ROAA	Net income to average of total assets (%)	Firm-level	11,487	1,939	4.637	8.326	−92.576	85.797
Tax shield	Total taxes to total assets (%)	Firm-level	9,206	1,851	4.243	5.370	0.000	94.073
Imp. interest rate	Interest paid to total liabilities (%)	Firm-level, proxy of financial conditions	5,183	849	5.639	5.363	0.013	115.096
SD of imp. interest rate	3-year rolling standard devation of the implicit interest rate (with the exception of year 2008, in which we imputed a 2-year rolling standard deviation)	Firm-level, proxy of financial conditions	4,122	832	2.003	3.473	0.001	78.814

Source: Orbis and own calculations.

Table A.3

FIRM'S CLASSIFICATION

		Arellano-Bond GMM		*Panel VAR (only 849 firms with data for imp. interest rate)*	
Variable	*Description*	*Observations*	*Panels (firms)*	*Observations*	*panels (firms)*
By size (Orbis criteria):					
Very large and large	Firms that match at least one of the following conditions: operating revenue ⩾ USD 13 M; total assets ⩾ USD 26 M; employees ⩾ 150.	11,849	5,747	5,131	831
Medium	Firms that match at least one of the following conditions: operating revenue ⩾ USD 1.3 M; total assets ⩾ USD 2.6 M; employees ⩾ 15; not very large or large.	6,076	1,288	48	17
Small	Firms that are not included in any of the above categories.	2,390	2,970	4	1
By industrial qualification (Bureau Van-Dijk main sector criteria):					
Manufacturing	Firms classified in any of the following sectors: "Chemicals, rubber, plastics, non-metallic products," "Food, beverages, tobacco," "Machinery, equipment, furniture, recycling," "Metals and metal products," "Publishing, printing," "Textiles, wearing apparel, leather," "Wood, cork, paper."	6,110	2,568	2,170	336

Table A.3 (cont.)

FIRM'S CLASSIFICATION

		Arellano-Bond GMM		*Panel VAR (only 849 firms with data for imp. interest rate)*	
Variable	*Description*	*Observations*	*Panels (firms)*	*Observations*	*panels (firms)*
Services	Firms classified in any of the following sectors: "Construction," "Education, health," "Hotels and restaurants," "Post and telecommunications," "Transport," "Wholesale and retail trade."	11,368	6,290	1,701	302
Primary	Firms classified in the following sector: "Primary sector."	934	233	367	62
Public administration	Firms classified in the following sector: "Public administration and utilities."	170	69	11	2
Utilities	Firms classified in the following sector: "Gas, water, electricity."	1,733	845	934	147

Annex B

Table B.1

BASELINE GMM (BLUNDELL-BOND) REGRESSIONS FOR LEVERAGE

	Manufacturing	*Services*	*Primary sector*	*Manufacturing*	*Services*	*Primary sector*
Leverage (−1)	0.667[c]	0.644[c]	0.790[c]	0.664[c]	0.650[c]	0.761[c]
	(0.0417)	(0.0453)	(0.0924)	(0.0423)	(0.0437)	(0.0990)
Tangible assets	0.0375[b]	−0.0481[c]	0.0389	0.0377[b]	−0.0436[c]	0.0442
	(0.0164)	(0.0159)	(0.0379)	(0.0162)	(0.0159)	(0.0342)
IFD	0.0661[c]	0.0981[c]	0.0516[a]	0.0633[c]	0.0975[c]	0.0575[a]
	(0.0124)	(0.0123)	(0.0311)	(0.0126)	(0.0124)	(0.0321)
Listed	−2.061[b]	−2.157[b]	−3.435	−2.180[b]	−2.432[c]	−3.875[a]
	(0.882)	(0.888)	(2.262)	(0.908)	(0.933)	(2.027)
Tax shield	0.0524	0.0577	0.0768	0.107[a]	0.0903	0.183
	(0.0482)	(0.0662)	(0.0990)	(0.0568)	(0.0654)	(0.117)
Small	−1.499	−3.781[c]	−2.412	−1.012	−3.590[c]	−3.088
	(1.454)	(1.151)	(2.141)	(1.423)	(1.122)	(1.960)
Very large	0.931	2.230[c]	0.279	0.864	1.820[b]	−0.453
	(0.974)	(0.830)	(2.075)	(0.944)	(0.815)	(2.014)
Uniqueness				0.0703[c]	0.0438[c]	0.114[c]
				(0.0170)	(0.0152)	(0.0403)
Constant	18.81[c]	24.66[c]	12.31[a]	14.62[c]	22.46[c]	8.409
	(2.769)	(3.631)	(6.907)	(2.695)	(3.524)	(6.120)

Table B.1 (cont.)

BASELINE GMM (BLUNDELL-BOND) REGRESSIONS FOR LEVERAGE

	Manufacturing	*Services*	*Primary sector*	*Manufacturing*	*Services*	*Primary sector*
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	3697	3774	606	3622	3562	601
Firms	835	1127	167	799	1053	165
J	74	68	65	75	69	66
Hansen	57.42	42.34	37.78	57.46	38.96	38.12
Hansen-p	0.0696	0.289	0.571	0.0691	0.426	0.555
AR1	−8.117	−7.124	−3.711	−8.123	−7.059	−3.552
AR1-p	4.79e−16	1.05e−12	0.000206	4.55e−16	1.68e−12	0.000382
AR2	1.056	−0.452	1.940	1.134	−0.386	2.004
AR2-p	0.291	0.651	0.0524	0.257	0.700	0.0451

Standard errors in parentheses [a] $p < 0.10$, [b] $p < 0.05$, [c] $p < 0.01$. Columns 1, 2 and 3 represent the regressions for manufacturing, services, and primary industry conglomerates. The Hansen is a test of the over-identifying restrictions for the GMM estimators. AR1 and AR2 are tests for the first-order and second-order serial correlation. N denotes the number of observations and J number of instruments. Country, Year and Industry denote if their respective dummy variables were introduced in the regressions. Variables are listed as follows: Lending(-1) represents the lagged value of the firm's leverage ratio (%); Listed is dummy variable for firms that participate in the stock market; Tangible assets is the firm's tangible fixed assets to total assets(%); IFD is the firm's internal financing deficit to total assets (%); Tax shield is the firm's taxes to total assets(%); Small and Very large are dummies for small and very large firms according to Orbis disaggregation; and Uniqueness is the firm's cost of goods sold to operating revenue(%).

Table B.2

BASELINE REGRESSIONS FOR LEVERAGE

	Manufacturing	*Services*	*Primary sector*	*Manufacturing*	*Services*	*Primary sector*
Leverage(−1)	0.481^{c}	0.445^{c}	0.633^{c}	0.545^{c}	0.490^{c}	0.674^{c}
	(0.0469)	(0.0377)	(0.0720)	(0.0414)	(0.0411)	(0.0721)
Tangible assets	0.0638^{c}	−0.0153	0.0666^{a}	0.0416^{b}	-0.0404^{c}	0.0692^{a}
	(0.0186)	(0.0145)	(0.0349)	(0.0168)	(0.0146)	(0.0360)
ROAA	-0.365^{c}	-0.328^{c}	-0.206^{c}	-0.310^{c}	-0.366^{c}	-0.201^{c}
	(0.0381)	(0.0319)	(0.0671)	(0.0376)	(0.0393)	(0.0542)
Listed	-3.340^{c}	-4.915^{c}	-7.186^{c}	-3.406^{c}	-5.445^{c}	-5.740^{b}
	(1.155)	(1.083)	(2.479)	(1.000)	(1.123)	(2.379)
Tax shield	0.0846^{a}	0.0403	0.0270	0.0980^{b}	0.0269	0.174^{b}
	(0.0436)	(0.0373)	(0.0524)	(0.0494)	(0.0490)	(0.0813)
Small	-4.134^{c}	-5.705^{c}	-4.889^{b}	-3.018^{b}	-4.150^{c}	−3.277
	(1.340)	(1.007)	(2.294)	(1.305)	(1.020)	(2.311)
Very large	−0.0293	4.107^{c}	0.525	0.0209	3.072^{c}	−0.228
	(1.262)	(1.029)	(3.183)	(1.088)	(0.968)	(2.825)
Uniqueness				0.0315^{a}	0.0277^{b}	0.0847^{c}
				(0.0183)	(0.0128)	(0.0245)
Constant	29.23^{c}	38.56^{c}	24.23^{c}	25.17^{c}	37.47^{c}	15.59^{c}
	(3.806)	(3.981)	(6.756)	(3.185)	(3.915)	(5.887)

Table B.2 (cont.)

BASELINE REGRESSIONS FOR LEVERAGE

	Manufacturing	*Services*	*Primary sector*	*Manufacturing*	*Services*	*Primary sector*
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	4,851	6,765	923	4,396	5,434	835
Firms	1,134	1,964	232	1,004	1,614	212
J	74	72	66	75	72	67
Hansen	60.94	57.24	32.86	64.62	42.21	30.72
Hansen-p	0.0370	0.0586	0.814	0.0181	0.418	0.879
AR1	−7.604	−9.476	−4.180	−8.370	−8.285	−4.278
AR1-p	2.88e−14	2.63e−21	0.0000292	5.74e−17	1.18e−16	0.0000189
AR2	0.863	0.824	0.332	1.300	0.335	1.279
AR2-p	0.388	0.410	0.740	0.194	0.738	0.201

Standard errors in parentheses [a] $p < 0.10$, [b] $p < 0.05$, [c] $p < 0.01$. Columns 1, 2 and 3 represent the regressions for manufacturing, services, and primary industry conglomerates. The Hansen is a test of the over-identifying restrictions for the GMM estimators. AR1 and AR2 are tests for the first-order and second-order serial correlation. N denotes the number of observations and J number of instruments. Country, Year and Industry denote if their respective dummy variables were introduced in the regressions. Variables are listed as follows: Leverage (−1) represents the lagged value of the firm's leverage ratio (%); Listed is dummy variable for firms that participate in the stock market; ROA is firm's return on assets (%); Tangible assets is the firm's tangible fixed assets to total assets (%); Tax shield is the firm's taxes to total assets (%); Small and Very large are dummies for small and very large firms according to Orbis disaggregation; and Uniqueness is the firm's cost of goods sold to operating revenue (%).

Table B.3

PANEL VECTOR AUTOREGRESSION (GMM ESTIMATION) FOR DETERMINANTS OF CORPORATE FINANCING AND THE IMPLICIT INTEREST RATE AS A PROXY OF FINANCIAL CONDITIONS–BY GROUPS OF FIRMS REGARDING LEVERAGE RATIO (TOTAL LIABILITIES TO TOTAL ASSETS)

	Response to				
Response of	*ROAA (t–1)*	*Leverage (t–1)*	*Tangibility (t–1)*	*Imp. int. rate (t–1)*	*Tax shield (t–1)*
a) Firms with a mean leverage ratio lower than the median (<51.02%)					
ROAA (t)	0.3944[c]	–0.0149	–0.0201	0.0199	0.2484
	(0.0974)	(0.0650)	(0.0526)	(0.0326)	(0.1946)
Leverage (t)	–0.0975	0.9575[c]	–0.1012	–0.1698[c]	0.2877
	(0.1111)	(0.1104)	(0.0994)	(0.0394)	(0.2705)
Tangibility (t)	–0.0656	–0.0237	0.8316[c]	–0.0288	–0.1909
	(0.1021)	(0.1531)	(0.1202)	(0.0572)	(0.2430)
Imp. int. rate (t)	0.0353	–0.1505[a]	–0.0575	0.307[b]	–0.135
	(0.0831)	(0.0779)	(0.0588)	(0.1503)	(0.1705)
Tax shield (t)	0.0872[c]	–0.0323	0.0068	–0.0022	0.1519[a]
	(0.0285)	(0.0242)	(0.0169)	(0.0115)	(0.0806)

Number of observations (N): 1,106

Number of firms (N): 291

Average number of years: 3.801

Final GMM criterion Q(b): 4.45e–34

Table B.3 (cont.)

	Response to				
Response of	*ROAA (t−1)*	*Leverage (t−1)*	*Tangibility (t−1)*	*Imp. int. rate (t−1)*	*Tax shield (t−1)*
ROAA (t)	0.3704[c]	0.1111[b]	−0.0573	−0.0228	0.1477
	(0.0991)	(0.0478)	(0.0457)	(0.0888)	(0.2037)
Leverage (t)	−0.2754[b]	0.7171[c]	0.0527	0.1084	0.1586
	(0.1175)	(0.0813)	(0.0800)	(0.1474)	(0.3218)
Tangibility (t)	−0.1999[a]	−0.1131	0.7985[c]	−0.3252[b]	0.1733
	(0.1125)	(0.0766)	(0.1139)	(0.1376)	(0.3237)
Imp. int. rate (t)	0.0166	−0.0926[c]	0.0513[a]	0.2717[c]	0.0205
	(0.0401)	(0.0297)	(0.0312)	(0.0600)	(0.1033)
Tax shield (t)	0.0418	0.0129	0.0176	0.0034	0.4610[c]
	(0.0348)	(0.0209)	(0.0223)	(0.0272)	(0.1131)

Number of observations (N): 1,294

Number of firms (N): 378

Average number of years: 3.423

Final GMM criterion Q(b): 3.25e−34

Initial weight matrix: identity

GMM weight matrix: robust

[a] $p < 0.10$, [b] $p < 0.05$, [c] $p < 0.01$. Standard errors in parenthesis. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. This panel VAR satisfies the stability condition proposed by Hamilton (1994) and Lütkepohl (2005).

Table B.4

P-VAR VARIANCE DECOMPOSITION FOR DETERMINANTS OF CORPORATE FINANCING AND THE IMPLICIT INTEREST RATE AS A PROXY OF FINANCIAL CONDITIONS– BY GROUPS OF FIRMS REGARDING LEVERAGE RATIO (TOTAL LIABILITIES TO TOTAL ASSETS)

a) Firms with a Mean Leverage Ratio Lower than the Median (<51.02%)

Response Variable	*Impulse variable*				
	ROAA	*Tangibility*	*Imp. int. rate*	*Leverage*	*Tax shield*
ROAA	0.9498	0.0039	0.0073	0.0306	0.0084
Tangibility	0.0351	0.9611	0.0003	0.0016	0.0019
Imp. int. rate	0.0221	0.0302	0.7027	0.2429	0.0021
Leverage	0.0247	0.1939	0.0925	0.6845	0.0045
Tax shield	0.2340	0.0507	0.0215	0.1517	0.5421

b) Firms with a mean leverage ratio higher than the median or equal to the median (>51.02%)

Response Variable	*Impulse variable*				
	Tax shield	*Leverage*	*ROAA*	*Tangibility*	*Imp. int. rate*
Tax shield	0.9533	0.0066	0.0066	0.0331	0.0004
Leverage	0.0247	0.7952	0.0703	0.1076	0.0022
ROAA	0.1584	0.1454	0.6583	0.0363	0.0016
Tangibility	0.0007	0.0365	0.0524	0.8926	0.0178
Imp. int. rate	0.0063	0.1539	0.0226	0.0438	0.7734

Percent of variation in the row variable (10 years ahead) explained by the column variable. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. The variables were sorted following Granger-Wald causality test criteria.

Table B.5

PANEL VECTOR AUTOREGRESSION (GMM ESTIMATION) FOR DETERMINANTS OF CORPORATE FINANCING AND THE 3-YEAR ROLLING SD. OF IMPLICIT INTEREST RATE AS A PROXY OF FINANCIAL CONDITIONS–BY GROUPS OF FIRMS REGARDING LEVERAGE RATIO (TOTAL LIABILITIES TO TOTAL ASSETS)

	Response to				
Response of	*ROAA (t–1)*	*Leverage (t–1))*	*Tangibility (t–1)*	*SD imp. int. rate (t–1)*	*Tax shield (t–1)*
a) Firms with a mean leverage ratio lower than the median (<51.02%)					
ROAA (t)	0.4022[c]	0.0319	–0.0092	–0.0091	0.0779
	(0.1161)	(0.0619)	(0.0651)	(0.0844)	(0.3005)
Leverage (t)	–0.1334	0.9129[c]	–0.1269	–0.084	0.4354
	(0.1526)	(0.1216)	(0.1071)	(0.1146)	(0.4123)
Tangibility (t)	–0.1752	–0.0101	0.7109[c]	–0.1038	0.0702
	(0.1646)	(0.1480)	(0.1326)	(0.1015)	(0.3314)
SD imp. int. rate (t)	0.0595	–0.0198	–0.0371	0.8741[c]	–0.0267
	(0.0656)	(0.0403)	(0.0278)	(0.1137)	(0.1305)
Tax shield (t)	0.0793[a]	–0.0446[a]	0.0074	0.0052	0.1797
	(0.0425)	(0.0258)	(0.0248)	(0.0188)	(0.1205)

Number of observations (N): 829

Number of firms (N): 243

Average number of years: 3.412

Final GMM criterion Q(b): 1.96e–33

Table B.5 (cont.)

PANEL VECTOR AUTOREGRESSION (GMM ESTIMATION) FOR DETERMINANTS OF CORPORATE FINANCING AND THE 3-YEAR ROLLING SD. OF IMPLICIT INTEREST RATE AS A PROXY OF FINANCIAL CONDITIONS–BY GROUPS OF FIRMS REGARDING LEVERAGE RATIO (TOTAL LIABILITIES TO TOTAL ASSETS)

	Response to				
Response of	*ROAA (t−1)*	*Leverage (t−1))*	*Tangibility (t−1)*	*SD imp. int. rate (t−1)*	*Tax shield (t−1)*
b) Firms with a mean leverage ratio higher than the median or equal to the median (>51.02%)					
ROAA (t)	0.3408[c]	0.1812[b]	−0.0602	−0.0259	−0.3205
	(0.1135)	(0.0729)	(0.0676)	(0.1260)	(0.3636)
Leverage (t)	−0.1628	0.6629[c]	0.0587	−0.067	−0.2643
	(0.1523)	(0.1035)	(0.1129)	(0.2171)	(0.5654)
Tangibility (t)	−0.1585	−0.12	0.9836[c]	0.2273	0.2578
	(0.1810)	(0.1177)	(0.1691)	(0.2232)	(0.6302)
SD imp. int. rate (t)	−0.034	−0.0275	−0.0556[b]	0.606[c]	0.1205
	(0.0290)	(0.0201)	(0.0250)	(0.0978)	(0.0880)
Tax shield (t)	0.0068	0.0179	−0.0068	−0.0535	0.4555[b]
	(0.0446)	(0.0289)	(0.0338)	(0.0530)	(0.2131)

Number of observations (N): 916

Number of firms (N): 294

Average number of years: 3.116

Final GMM criterion Q(b): 7.13e−34

Initial weight matrix: identity

GMM weight matrix: robust

[a] $p < 0.10$, [b] $p < 0.05$, [c] $p < 0.01$. Standard errors in parenthesis. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. This panel VAR satisfies the stability condition proposed by Hamilton (1994) and Lütkepohl (2005).

Table B.6

P-VAR VARIANCE DECOMPOSITION FOR DETERMINANTS OF CORPORATE FINANCING AND THE 3-YEAR ROLLING SD OF IMPLICIT INTEREST RATE AS A PROXY OF FINANCIAL CONDITIONS–BY GROUPS OF FIRMS REGARDING LEVERAGE RATIO (TOTAL LIABILITIES TO TOTAL ASSETS)

a) Firms with a Mean Leverage Ratio Lower than the Median (<51.02%)

Response variable	*Impulse variable*				
	ROAA	*Leverage*	*Tangibility*	*SD imp. int. rate*	*Tax shield*
ROAA	0.9594	0.0328	0.0056	0.0006	0.0016
Leverage	0.0066	0.8939	0.0868	0.0053	0.0074
Tangibility	0.0310	0.0437	0.9130	0.0122	0.0001
SD imp. int. rate	0.0180	0.0313	0.0900	0.8599	0.0008
Tax shield	0.2751	0.1762	0.0232	0.0017	0.5238

b) Firms with a Mean Leverage Ratio Higher than the Median or Equal to the Median (>51.02%)

Response variable	*Impulse variable*				
	Leverage	*Tangibility*	*Tax shield*	*SD imp. int. rate*	*ROAA*
Leverage	0.7852	0.1904	0.0113	0.0010	0.0121
Tangibility	0.0681	0.9095	0.0118	0.0069	0.0038
Tax shield	0.0294	0.0198	0.9435	0.0071	0.0003
SD imp. int. rate	0.0330	0.6676	0.0085	0.2872	0.0037
ROAA	0.2300	0.0991	0.0943	0.0059	0.5708

Percent of variation in the row variable (10 years ahead) explained by the column variable. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. The variables were sorted following Granger-Wald causality test criteria.

Table B.7

GMM (BLUNDELL-BOND) REGRESSIONS FOR INVESTMENT

Percent of the change in fixed assets

	(1)	*(2)*	*(3)*
Investment (–1)	–0.0285	0.0734[a]	–0.0524[a]
	(0.0303)	(0.0390)	(0.0292)
Sales growth	27.89[c]	9.304[c]	32.68[c]
	(3.110)	(1.875)	(3.704)
Sales growth (–1)	13.59[b]	10.88[a]	15.42[b]
	(6.929)	(6.554)	(6.674)
Leverage	0.205		
	(0.134)		
Leverage (–1)	–0.292[b]		
	(0.139)		
(k–y) (–2)	–6.999[c]	–5.957[c]	–7.913[c]
	(1.411)	(1.227)	(1.679)
Interest debt burden	0.374[c]	–0.00290	0.385[c]
	(0.0979)	(0.0619)	(0.113)
Interest debt burden (–1)	–0.0316	–0.0228	–0.152
	(0.105)	(0.0517)	(0.111)
Z-score	0.487	10.53[c]	
	(2.335)	(1.266)	
Z-score (–1)	0.418	–8.515[c]	
	(2.351)	(1.260)	
Listed	1.271	1.112	1.786[a]
	(0.994)	(0.709)	(1.022)

Table B.7 (cont.)

GMM (BLUNDELL-BOND) REGRESSIONS FOR INVESTMENT

Percent of the change in fixed assets

	(1)	*(2)*	*(3)*
Small	–9.489	0.242	–12.08
	(8.215)	(6.393)	(10.70)
Very large	0.492	–0.454	–3.940
	(4.020)	(6.046)	(4.352)
IFD		1.074[c]	
		(0.0289)	
IFD (–1)		–0.175[c]	
		(0.0409)	
Tangibility		0.278[c]	0.251[c]
		(0.0488)	(0.0650)
Tangibility (–1)		–0.258[c]	–0.226[c]
		(0.0425)	(0.0591)
Uniqueness		–0.0605[b]	–0.0169
		(0.0305)	(0.0587)
Uniqueness (–1)		–0.115[c]	–0.131[b]
		(0.0249)	(0.0545)
ROAA			–0.228[b]
			(0.103)
ROAA (–1)			0.288[c]
			(0.103)
Constant	22.03[b]	31.28[c]	34.89[c]
	(8.651)	(8.158)	(10.07)

Table B.7 (cont.)

GMM (BLUNDELL-BOND) REGRESSIONS FOR INVESTMENT

Percent of the change in fixed assets

	(1)	(2)	(3)
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	5443	3990	5172
N_g	1219	893	1080
J	74	78	76
Hansen	44.90	38.01	42.18
Hansen-p	0.0810	0.252	0.131
AR1	−9.738	−7.643	−9.547
AR1-p	2.07e−22	2.12e−14	1.33e−21
AR2	−0.989	0.751	−1.330
AR2-p	0.323	0.453	0.183

Standard errors in parentheses [a] $p < 0.10$, [b] $p < 0.05$, [c] $p < 0.01$. Columns 1, 2 and 3 represent the regressions for manufacturing, services, and primary industry conglomerates. The Hansen is a test of the over-identifying restrictions for the GMM estimators. AR1 and AR2 are tests for the first-order and second-order serial correlation. N denotes the number of observations and J number of instruments. Country, Year and Industry denote if their respective dummy variables were introduced in the regressions. Variables are listed as follows: Investment represents the lagged value of the firm's fixed investment; Leverage is the firm's indebtness ratio; Interest debt burden is the ratio of interest paid to operating revenue (%); Sales growth is the annual variation of operating revenue; Listed is a dummy variable for firms that participate in the stock market; ROA is firm's return on assets (%); Z-score is the firm profitability deviation from its capital ratio divided by ROAA's standard deviation, this indicator is expressed in log-transformation ; Tangibility assets is the firm's tangible fixed assets to total assets (%); IFD is the firm's internal financing deficit to total assets (%); k-y is the error correction term that reflects how firms adjust their capital towards a target; Small and very large are dummies for small and very large firms according to Orbis disaggregation; and Uniqueness is the firm's cost of goods sold to operating revenue (%).

Table B.8

PANEL VECTOR AUTOREGRESSION FOR FINANCIAL CONDITIONS INDEX AND MACROECONOMIC VARIABLES

Response of	*Response to*		
	Gross fixed investment growth (t–1)	*FC index (t–1)*	*GDP growth (t–1)*
Gross fixed investment growth(t)	–0.861[b]	0.421[b]	3.108[b]
	(0.350)	(0.194)	(1.497)
FC index–country median (t)	0.196	–0.150	–0.536
	(0.377)	(0.229)	(1.622)
GDP growth (t)	–0.145	0.130[b]	0.447
	(0.0976)	(0.0551)	(0.403)
Number of observations (N):	53		
Number of countries (N):	10		
Average number of years:	5.30		
Final GMM criterion Q(b): 3.04e–32			
Initial weight matrix: identity			
GMM weight matrix: robust			

[a] $p < 0.10$, [b] $p < 0.05$, [c] $p < 0.01$. Standard errors in parenthesis. This panel VAR satisfies the stability condition proposed by Hamilton (1994) and Lütkepohl (2005).

Panel VAR-Granger causality Wald test
Ho: Excluded variable does not Granger-cause equation variable
Ha: Excluded variable Granger-causes equation variable

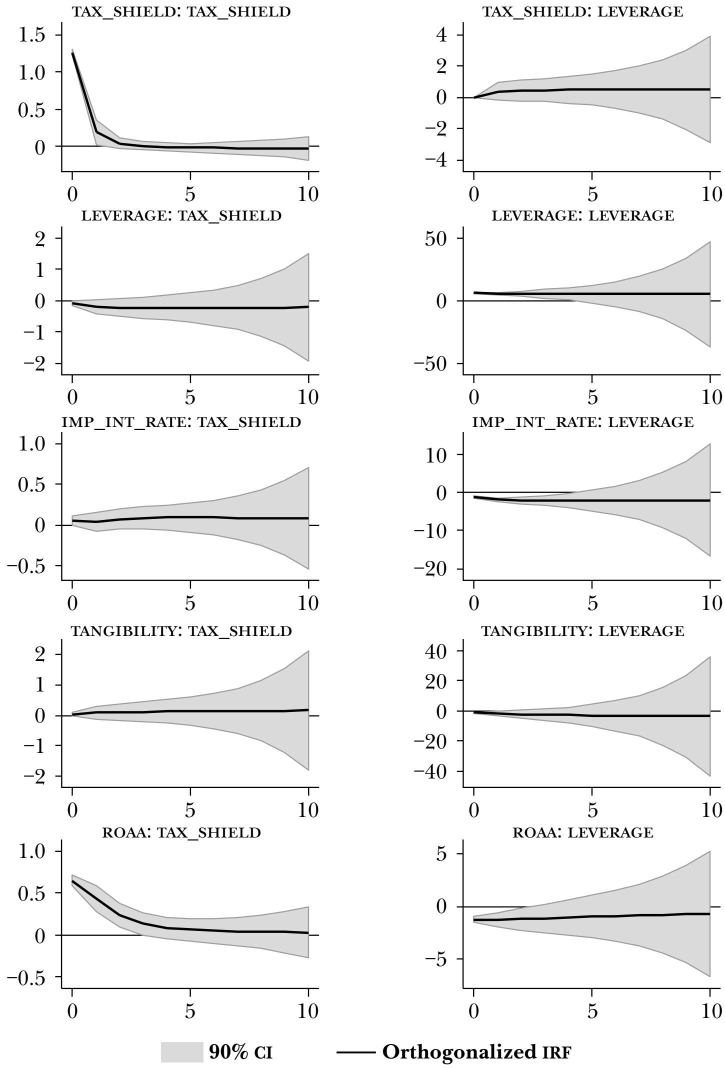
Equation	*Excluded*	*Chi-sq*	*df*	*Prob > Chi-sq*
Gross fixed investment growth (%)	FC index–country median	4.714	1	0.030
	GDP growth (%)	4.310	1	0.038
	All	7.135	2	0.028
FC index–country median	Gross fixed investment growth (%)	0.270	1	0.603
	GDP growth (%)	0.109	1	0.741
	All	0.359	2	0.836
GDP growth (%)	Gross fixed investment growth (%)	2.217	1	0.136
	FC index–country median	5.578	1	0.018
	All	6.721	2	0.035

Figure B.1

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio lower than the median (<51.02%)



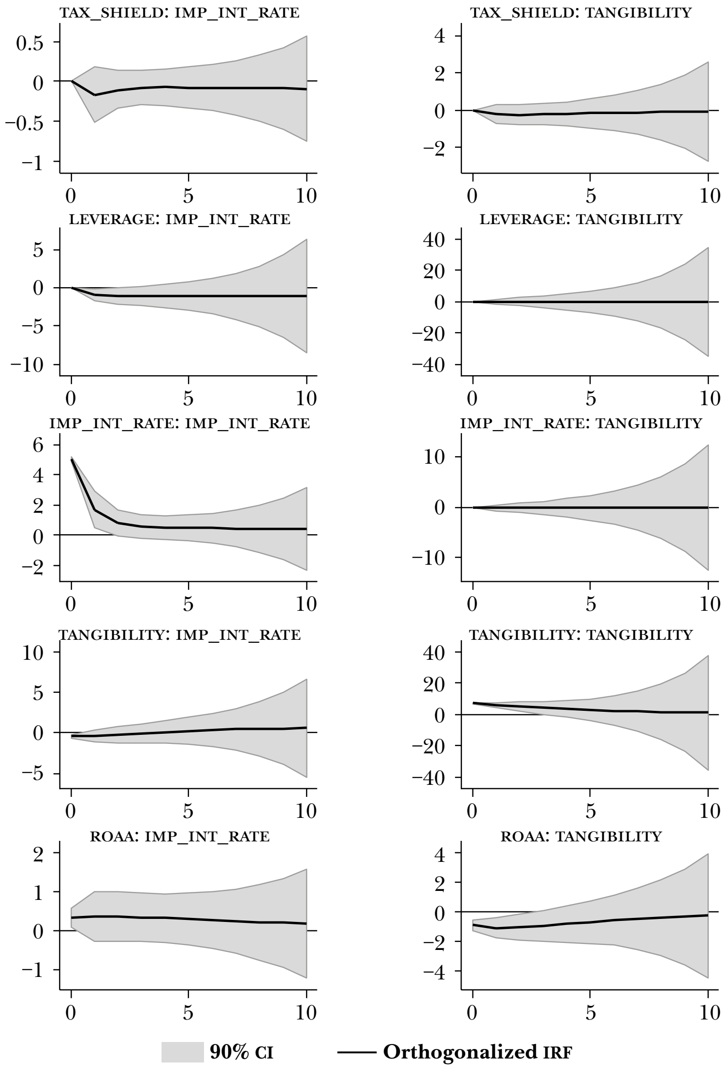
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.1 (cont.)

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio lower than the median (<51.02%)



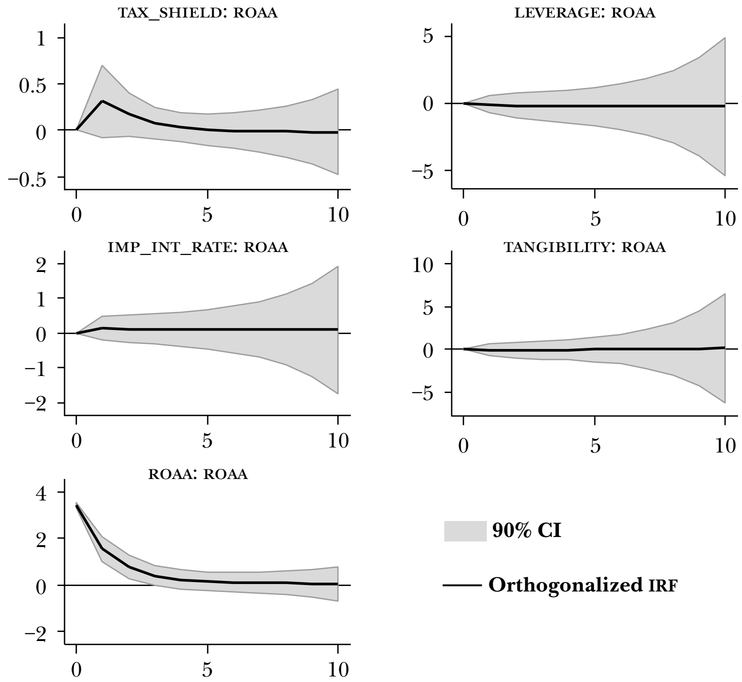
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.2 (cont.)

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio lower than the median (<51.02%)



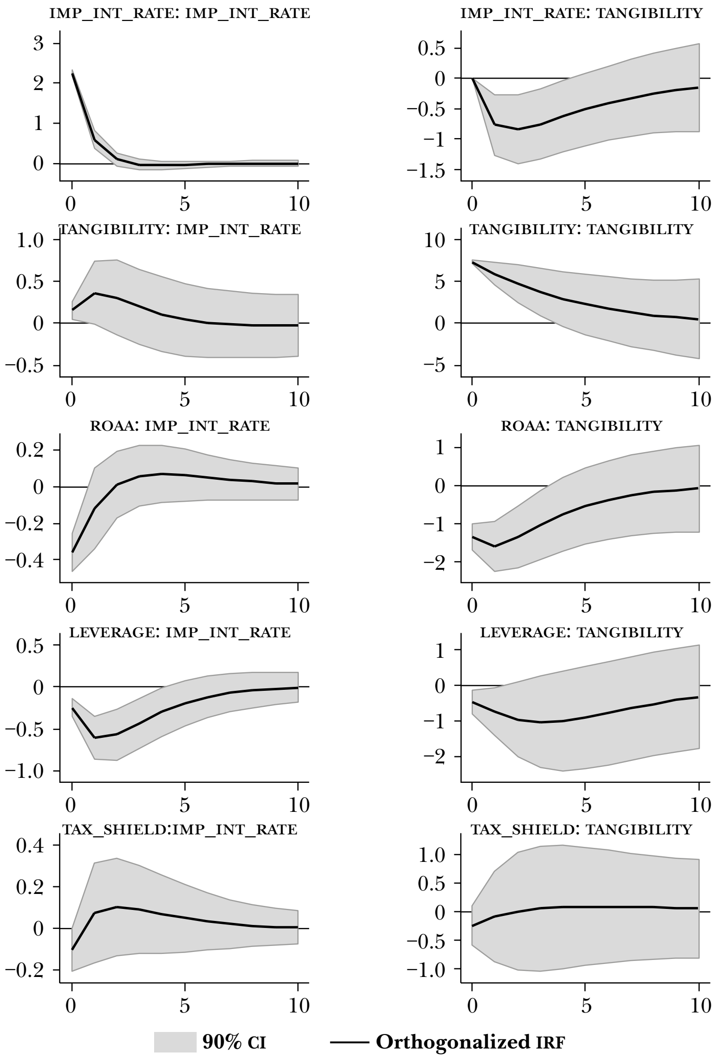
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.2

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio higher than the median or equal to the median (>51.02%)



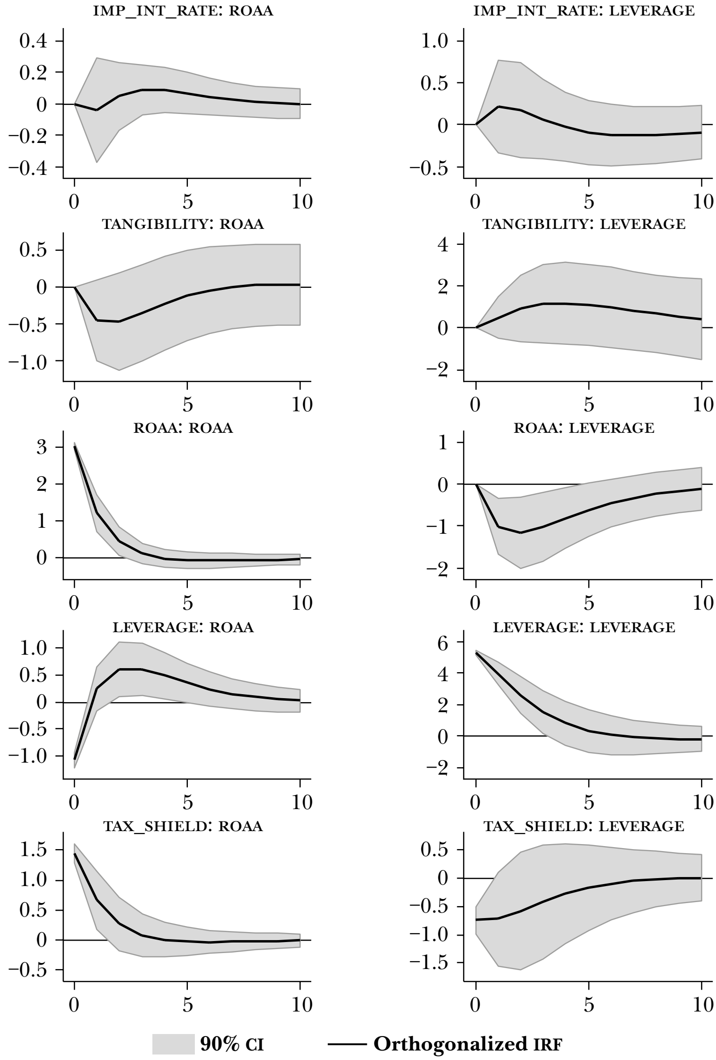
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.2 (cont.)

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio higher than the median or equal to the median (>51.02%)



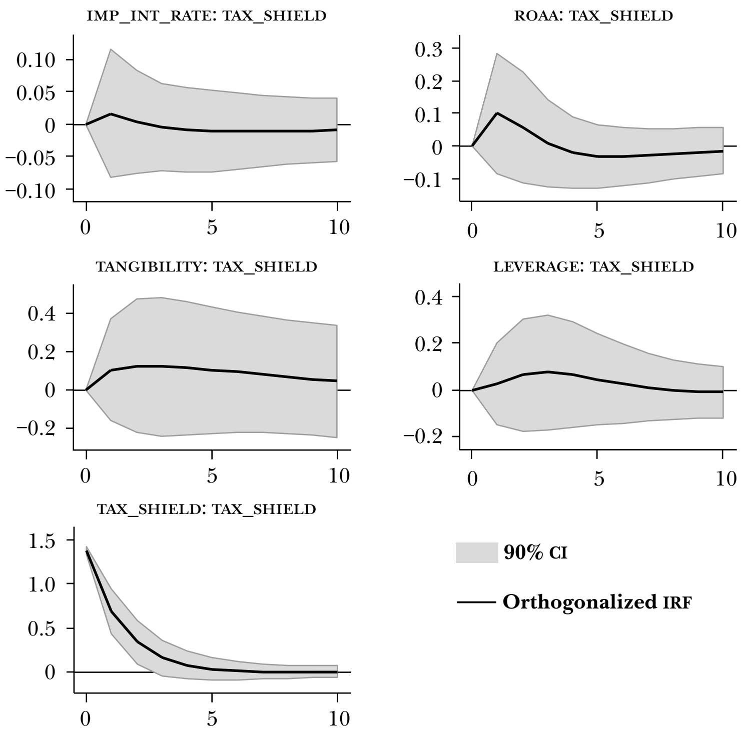
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.2 (cont.)

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio higher than the median or equal to the median (>51.02%)



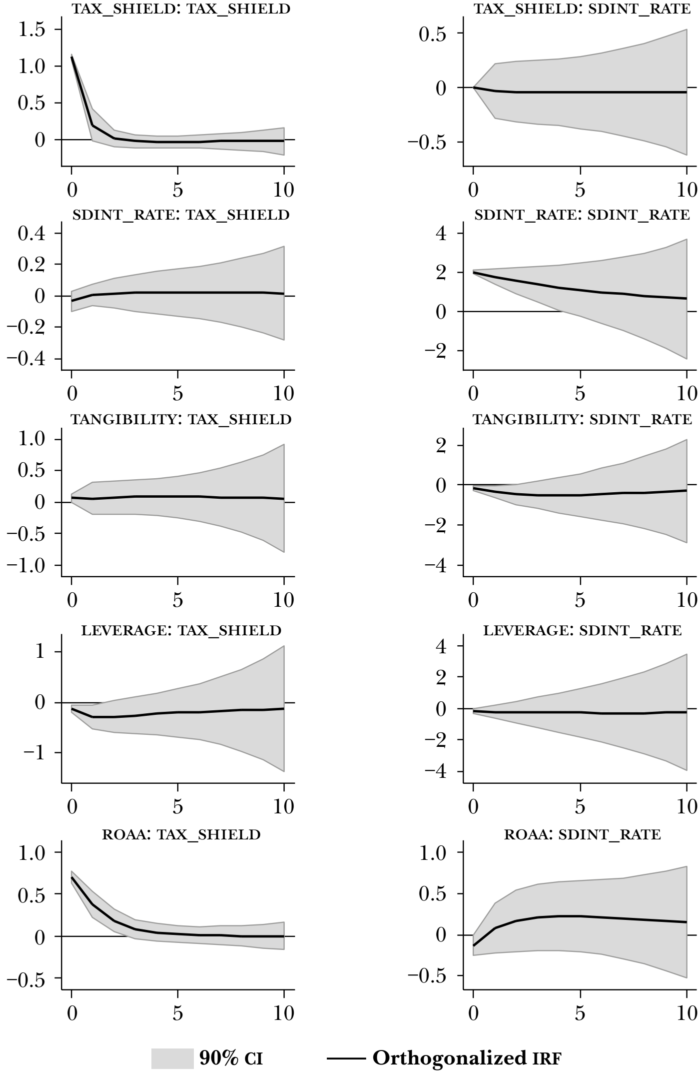
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.3

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE SD OF IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio lower than the median (<51.02%)



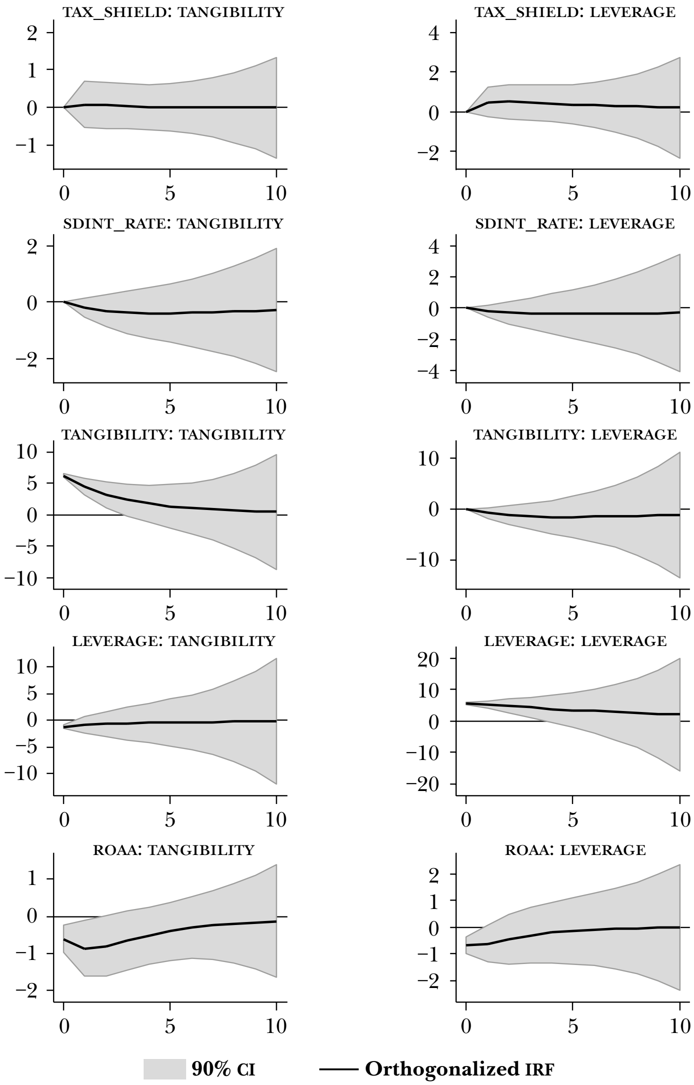
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.3 (cont.)

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE SD OF IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio lower than the median (<51.02%)



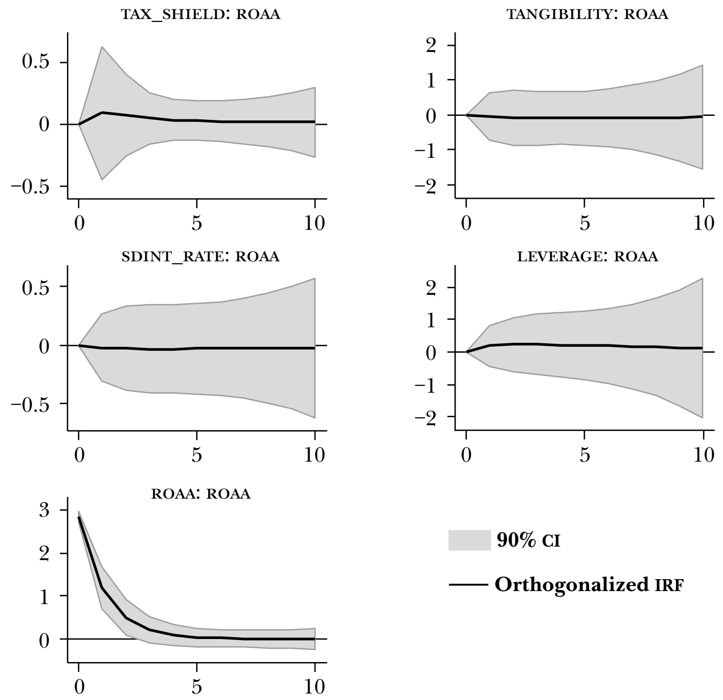
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.3 (cont.)

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE SD OF IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio lower than the median (<51.02%)



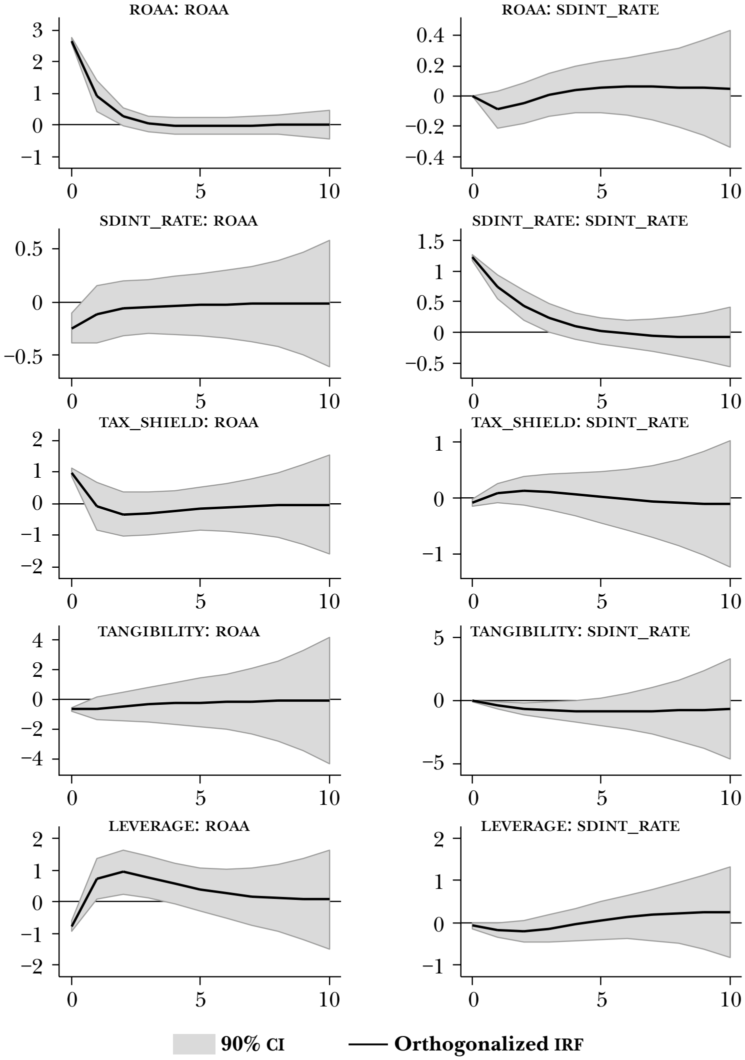
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.4

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE SD OF IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio higher than the median or equal to the median (>51.02%)



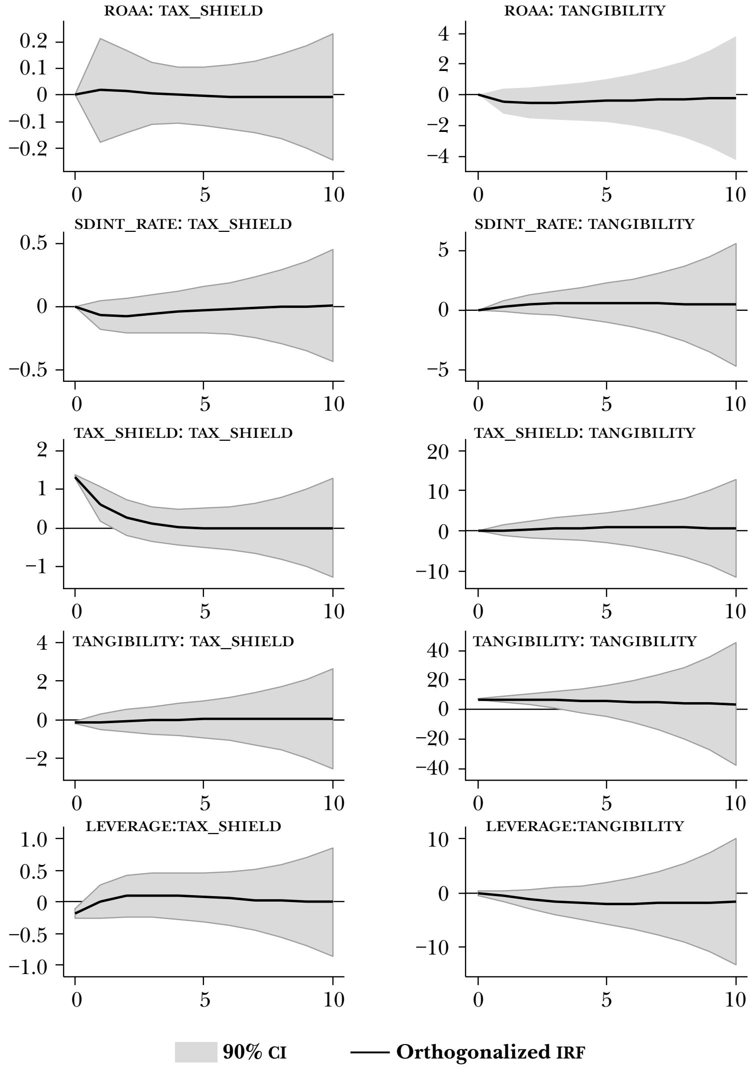
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.4 (cont.)

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE SD OF IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio higher than the median or equal to the median (>51.02%)



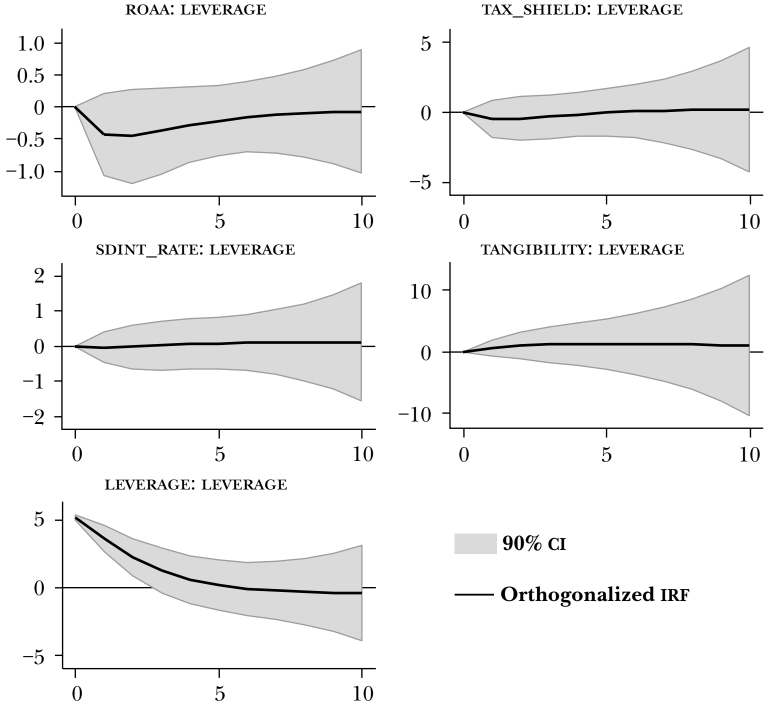
Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.4 (cont.)

IMPULSE-RESPONSE FUNCTIONS FOR DETERMINANTS OF CORPORATE FINANCING AND THE SD OF IMPLICIT INTEREST RATE

Total liabilities to total assets

Firms with a mean leverage ratio higher than the median or equal to the median (>51.02%)



Impulse-response functions derived by Cholesky's variance decomposition. All variables were transformed using forward orthogonalization suggested by Arellano and Bover (1995), through the Helmert procedure. All country effects were included by subtracting the means of each variable calculated for each country-year. Variables were sorted following Granger-Wald causality test criteria. Confidence intervals were generated by a Monte-Carlo simulation with 1,000 repetitions.

Figure B.5

LAGGED INDEX OF CORPORATE FINANCIAL CONDITIONS AND GROSS FIXED CAPITAL GROWTH

Selected ICFC quantiles for the ten sample countries, own calculations and WB-WDI

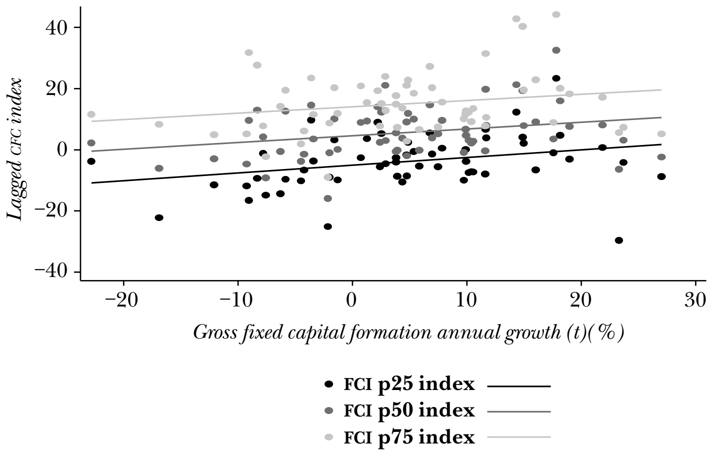


Figure B.6

LAGGED INDEX OF CORPORATE FINANCIAL CONDITIONS AND GDP GROWTH

Selected ICFC quantiles for the ten sample countries, own calculations and WB-WDI

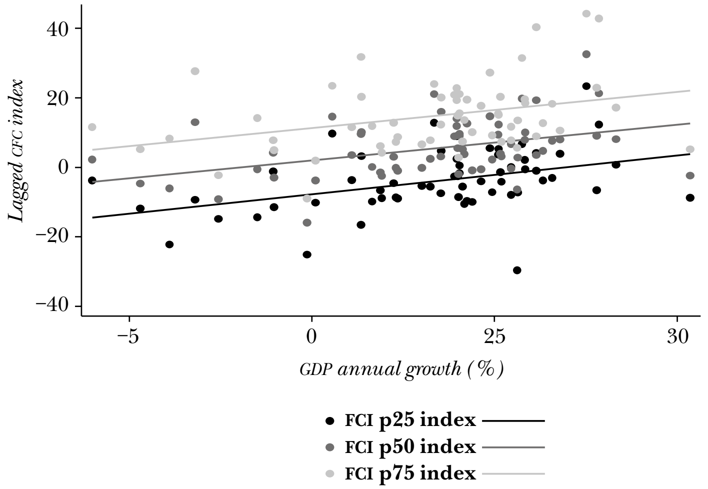
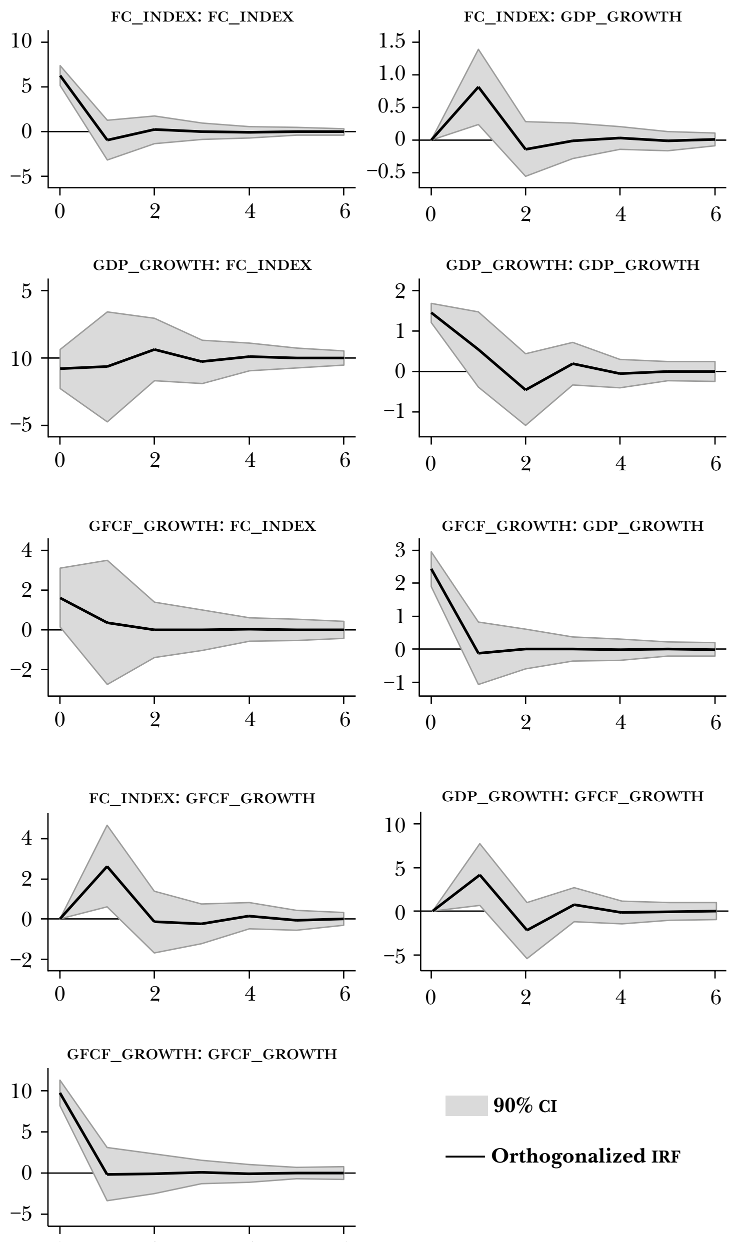


Figure B.7

IMPULSE-RESPONSES OF THE PANEL VECTOR AUTOREGRESSION FOR FINANCIAL CONDITIONS INDEX AND MACROECONOMIC VARIABLES



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The Demand for Credit at the Individual Level: The Credit Registry (RCC) Meets the National Household Survey (ENAHO)

Nikita Céspedes Reynaga

Abstract

This article examines the demand for credit at the individual level in Peru. It uses a unique database resulting from merging the Credit Registry (RCC) and the National Household Survey (ENAHO). The data allows for ideally identifying the amount of credit and the interest rate as well as the characteristics of each credit granted in the Peruvian banking system. It also includes indicators of the supply of each credit, which is key for the identification of demand. The elasticity of the demand for credit relative to the interest rate is estimated using a two-step procedure proposed by Heckman (1979) and is approximately –0.29. This value means that a rise in the market interest rate by 1% implies a reduction in the demand for credit by 0.29%. This elasticity is slightly lower than the one provided by international evidence and is highly heterogeneous throughout credit types and features of individual debtors.

Keywords: demand for credit, balance sheet effect, heterogeneity.

JEL classification: E21, E44, E51, E52.

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1. INTRODUCTION

Credit as a funding mechanism for firms and households is crucial to a country's economic development. Study of the fundamentals influencing borrowing by households and firms has received considerable attention from academics and economic policymakers during the years following the international financial crisis that broke out in 2008. The reason behind such increased interest has been the growing participation of individuals in the credit market, allowing them to receive the benefits of said market, and at the same time exposing them to financial fluctuations. This is the case, for instance, of the 2008 financial crisis, the effects of which have spread beyond the business sector, extending to the household segment. [1] This paper examines the characteristics of credit at the individual level in Peru while also estimating the demand for debt in this segment of economic agents. We believe the study is justified by the growing participation of households in Peru's formal credit market. Moreover, the Peruvian economy and its credit market have institutional and idiosyncratic characteristics, such as the dollarization of loans, its inflation targeting scheme and the economy's high level of exposure to external crises that make it different from others.

With respect to aggregate trends, household credit at the international level has been growing during recent decades (IMF, 2012), and Peru has seen a similar behavior.[2] Hence, between

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1 There is a large body of international literature on this subject suggesting business credit has positive effects on economic growth through higher investment and the resulting increased accumulation of physical capital. Meanwhile credit to households has a less clear impact on growth, functioning more as a mechanism that can improve households' wellbeing by the intertemporal smoothing of consumption during any adverse shocks they face (Hall, 1978).

2 Diverse factors have contributed to the expansion of credit, among which stand out: low inflation and interest rates, higher income and wages within a context of strong economic growth,

2001 and 2016 consumer credit grew at an average annual rate of 19%, increasing as a percentage of GDP from 4.2% in 2001 to 14.8% in 2016 (Figure 1). This significant growth in credit has been enough to change the composition of credit between consumers and firms. Thus, in 2001 consumer loans accounted for 18% of total credit and in 2016 this figure had increased to 37%. In this regard, international evidence suggests that the significant growth of consumer loans as a proportion of total credit could represent a source of vulnerability for this segment of the population during adverse events, both for the financial system and households themselves (BIS, 2006; IMF, 2016). The latter point is another reason to study and understand the characteristics of the determinants of household debt in Peru.

Another useful aspect of this study is an estimation of the elasticity of demand for credit, which under stable financial conditions allows for measuring the necessary adjustments in monetary policy rates aimed at correcting deviations in inflation with respect to price stability levels through the credit transmission channel in line with Bernanke and Blinder (1988). In general terms, this elasticity captures the transmission to households of shifts in the financial system (credit supply shocks) as a result, for instance, of changes in Reserva Federal's monetary policy and external financial crises propagated through international credit restrictions. The latter being the case of the 2008-2009 global financial crisis that marked the beginning of higher financing costs for small economies like Peru.

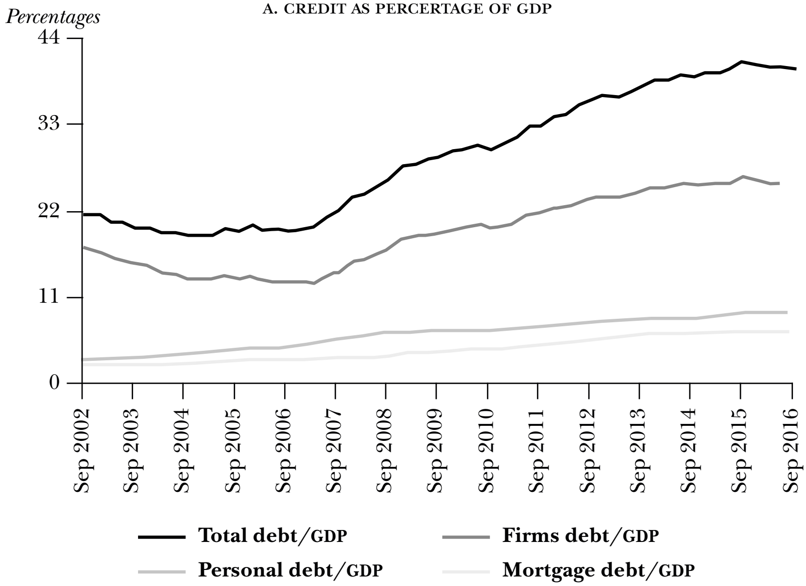
This paper reveals new evidence regarding the importance of dollarization in Peru's debt market. It should be remembered that dollarization has been one of the (greatest) vulnerabilities in the Peruvian economy since the beginning of the nineties. Dollarization of credit reached historically high levels in December 1999 when loans in dollars represented 81.7% of total

opening of capital markets, larger capital flows and improved credit offerings under an environment of positive macroeconomic performance reflected in low country-risk levels, etcetera.

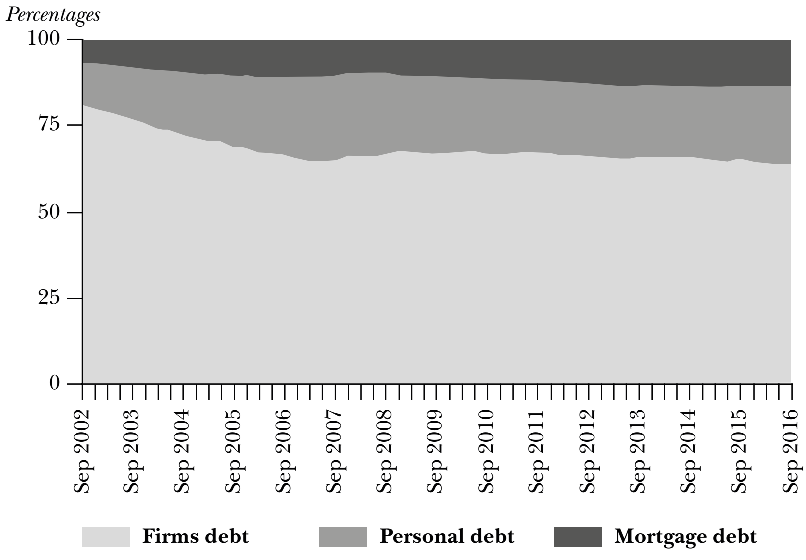
Figure 1

PERU: CREDIT EVOLUTION

A. CREDIT AS PERCERTAGE OF GDP



B. CREDIT COMPOSITION



Note: Credit (balances) of deposit entities to private is shown, by type of credit.
Source: Banco Central de Reserva del Perú.

credit.[3] Towards the end of 2015, and after a prolonged struggle in economic policy and macroeconomic stability terms, dollarization has fallen to around 30% of total credit. Given that dollarization is a phenomenon affecting only a small number of countries, empirical studies on foreign currency borrowing has been limited to a few particular cases [4] and no studies have been carried out for Perú.[5]

Literature examining credit dollarization at the individual level is very limited internationally, and in the case of Peru, nonexistent. For instance, Beer et al. (2010) analyze the borrowing behavior of Austrian households and estimate the influence of household characteristics, which are divided into subjective factors (e.g. risk perception, financial literacy and level of education) and objective factors (e.g., sociodemographic).

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[3] Corresponds to the dollarization ratio (%) of deposits firms to private banks (end of period).

[4] Internationally, there are several authors who study foreign currency borrowing at the aggregate level, while a smaller number of papers characterize the demand for credit among firms. For instance, Brown et al. (2011) and Cowan et al. (2005) include enterprise level features in a theoretical model examining the borrowing behavior of small firms. Those models emphasize the role of institutional infrastructure and compliance, imperfect bank information and the monetary composition of income. Brown et al. (2011) consider various micro-level determinants of borrowing among firms in Bulgaria (employing enterprise level data for loans between 2003 and 2007). Their model includes supply features (bank characteristics) and demand determinants (firm characteristics) of loans in foreign currency. Their findings demonstrate that comparatively larger and older firms, as well as those with lower bailout costs in case of default, demand more loans in foreign currency. Moreover, banks grant loans in foreign currency mainly for fixed investments and long-term projects.

[5] Data employed correspond to periods of high dollarization, even at the household credit level, meaning estimates from the study could be used to characterize the potential effects of external shocks on households' standards of living through the credit channel in domestic as well as foreign currencies.

According to their results, foreign currency borrowers tend to be risk seeking, older, financially literate and more affluent. Pellényi and Bilek (2009) present a study of survey data on foreign currency borrowing among households in Eastern Europe. They analyzed survey data collected in 2008 for Hungarian households and find that foreign currency borrowers tend to be less risk-loving and better aware of exchange rate risks.[6]

This paper studies the demand for loans among individuals using data disaggregated to the level of each loan. This procedure represents an advance in the literature on the credit market, especially in the case of Peru, for which no published papers are to be found on the subject.[7]

The study employs a unique database resulting from a merging of the National Household Survey (ENAHO) and the Credit Registry (RCC), which because it is an administrative registry allows for identifying without measurement errors the amount and interest rate of each individual bank loan by type of credit and currency, as well as the features of individual debtors. This consideration makes it possible to characterize the heterogeneity of credit according to the observable characteristics of individual debtors by currency type, age, income levels, region of residence, employment and informality, among others. After characterizing credit, we estimate the demand for credit at the individual level. This demand allows for identifying the sensitivity of credit to changes in interest rates after

6 There is also some recent literature that examines credit demand using data at the individual level, such as that of Fidrmuc et al. (2013) which studies the determinants of foreign currency borrowing in nine Eastern European countries and finds that a lack of confidence in local currency stability among households is an important consideration when taking out loans in foreign currency.

7 Papers on household credit in Peru include those of Cámara et al. (2013) and Alfageme and Ramírez-Rondán (2016), who use the ENAHO to perform a general study of the determinants of participation in the mortgage market.

controlling for the observable characteristics of demand and institutional features of credit supply. The estimation method consists of a two-step process (Heckman, 1979). In the first step, we estimate an equation for credit market participation and in the second an equation for credit demand that relates credit with interest rates and a group of relevant controls.

The results highlight a significant degree of heterogeneity of credit according to the observable features of individuals. One level of heterogeneity that stands out concerns an individual's income. Those with access to formal credit have high incomes. In line with the latter, credit in Lima is concentrated among middle-aged and better educated individuals, while informal workers are also seen to have access to formal credit. As for the elasticity of demand for credit relative to the interest rate, the estimation reveals that this is -0.29, figure heterogeneous according to several observable features of individuals such as the type of credit, the currency in which it is granted, geographic region and informality. Moreover, the average elasticity found is lower than those estimated by the literature employing similar quality administrative data, which is consistent with the existence of an inelastic and uncompetitive credit market.

The rest of the paper is organized as follows. Section 2 presents data sources and explains the methodology for constructing the data. Section 3 discusses the heterogeneity of credit according to different categories of individuals, and Section 4 presents the model that justifies the credit demand equation. Section 5 shows the econometric estimation and Section 6 summarizes the main findings.

2. DATA

Data is taken from two sources. Firstly, there is administrative data for each loan granted to individuals by financial entities registered in the Credit Registry (RCC). This information is collected each month by the Superintendence of Banking and

Insurance and the number of registries represents the whole population with loan obligations in the banking system. Information from the RCC corresponds to the credit balance of each individual by the banking institution. It is worth pointing out that this information discloses all loans held by an individual, identifying credit type and currency. The number of loans registered varies according to the month studied. Thus, in December 2014, for instance, 12.4 million loans were included, corresponding to a total of 5.7 million individuals with loans in the formal banking system.

The other source of information is the National Household Survey (ENAHO) conducted every year by the National Institute of Statistics and Information (INEI). This database collects information on diverse aspects, such as an individual's employment and personal data, that allow for identifying credit demand characteristics. The two databases are merged using the National Identity Document (DNI) and the names and surnames of each individual for data between 2008 and 2014 as common links, obtaining a total of 95 037 individuals in both databases. Considering that around 500 thousand individuals are registered in the ENAHO, the number with loans in the final sample during those years represents everyone in Peru that accessed formal credit in said period.

The credit sample in the final database is representative at the national level. This assertion is substantiated by comparing credit indicators estimated in the final database with those estimated in the RCC and the ENAHO. Hence, there is a similarity between the proportion of individuals reported in the final database and the corresponding value reported by the original data in the RCC (see Table 1). The RCC is used to estimate the share of individuals in the banking system with credit. As expected, the latter value is lower than the total share of individuals with credit in the banking system as well as other institutions (informal).

Table 1

CHARACTERISTICS OF CREDIT IN THE SAMPLE
Percentages

	RCC	*ENAHO and RCC*
Mortgage dollarization (no. of loans)	32.0	35.0
Mortgage dollarization (balances)	34.6	38.1
Consumer credit dollarization (no. of loans)	4.2	3.3
Consumer credit dollarization (balances)	7.7	5.9

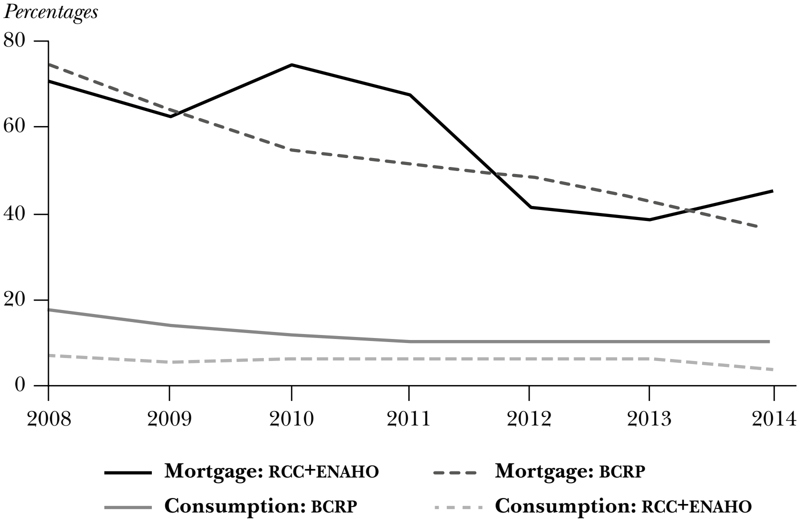
Notes: the second column (RCC) corresponds to 2014.
Sources: ENAHO, RCC, 2008-2014.

Another useful indicator for controlling the quality of data employed is aggregate credit dollarization information. The latter makes it possible to verify that household debt dollarization trends reported by the BCR are similar to those reported in the final database obtained by merging the ENAHO and the RCC (Figure 2).

Estimating the demand for credit requires indicators regarding the interest rates on each loan. Although no direct measure of interest rates is available, in this paper we estimate the implicit interest rate on each credit using the yields of the loans, which in practice correspond to the monthly interest charged (accrued) by financial institutions on the loans they grant. The indicator for average interest rates calculated in this way is closely related to the interest rates published by the SBS, thereby upholding the known stylized facts for said indicator, such as, for instance, mortgage rates are lower, consumer loans have lower rates and average interest rates during the study period have followed a downward trend.

Figure 2

DOLLARIZATION OF CREDIT FROM BCRP AND RCC–ENAHO DATA



Note: Percentage of credit balances in foreign currency to total of credit.
Sources: SBS, BCRP, ENAHO, and RCC, 2008-2014.

3. CHARACTERISTICS OF CREDIT AT THE HOUSEHOLD LEVEL

3.1 Descriptive Statistics

Credit and interest rates should be expressed in logs in the empirical model. This is particularly useful here because in order to guarantee the efficiency of model estimators. The first and second moments of the series employed must be well-defined. A casual inspection of the series suggests that these have a normal log distribution. The reason is that there is a considerable number of individuals with micro loans and a very small proportion with very large ones. Estimates for interest rates behave similarly, the use of logs, therefore, normalizes the series and guarantees stability in the variance of the estimators.[8] With this taken into consideration, the descriptive statistics correspond to the log series.

Credit heterogeneity is noteworthy at the level of its principle moments, meaning the estimation should control for those average effects. Average mortgage credit is larger than credit to small firms and consumer credit. Moreover, there are differences in terms of loans denominated in domestic currency and those in foreign currency. The data in Table 2 also reveal that there is heterogeneity with respect to the observable characteristics of individuals such as age, income, and region of residence, among others. This heterogeneity found regarding loan size is also seen in terms of estimated implicit interest rates as shown in Table 3. These two stylized facts suggest that the regression estimated to measure the elasticity of the demand for credit should be controlled for the heterogeneity of demand.

3.2 Correlation between Interest Rates and Credit

Aggregate data suggest the likelihood of a negative correlation between credit and interest rates as illustrated in Figure 3 for data between 1992 and 2016. Nevertheless, this aggregate correlation might not be correct in all the study periods. The correlation is positive, for instance, in the years between 2004 and 2008. Estimation of aggregate demand for credit should also be corrected for the influence of macroeconomic type variables. Furthermore, although it is not documented, estimation of the demand for credit might be susceptible to aggregation biases. With these considerations in mind, we take into account that estimation of the demand for credit among agents can properly identify the elasticity we aim to calculate.

[8] A comparison of the distribution of credit in levels as well as logs reveals that the log series has an approximately normal distribution as illustrated in Figures A.1 to A.4 in the Annex.

Table 2

CHARACTERISTICS OF CREDIT BY INDIVIDUAL ACCORDING TO CREDIT TYPE AND CURRENCY

Size of credit in logs

	Type of Credit											
	Consumption				*Small firm*				*Mortgage*			
	DC		*FC*		*DC*		*FC*		*DC*		*FC*	
	$\bar{X}$	*SD*	$\bar{X}$	*SD*	$\bar{X}$	*SD*	$\bar{X}$	*SD*	$\bar{X}$	*SD*	$\bar{X}$	*SD*
Average	7.91	2.36	7.33	3.10	8.54	2.23	12.06	2.51	11.57	1.45	11.48	1.96
Quintiles												
I	8.07	2.43	7.02	2.87	8.38	2.30	13.26	1.79	12.15	2.12	11.67	1.59
II	8.20	2.51	9.14	3.65	8.50	2.28	12.22	2.74	10.78	1.56	13.42	2.59
III	7.99	2.43	7.52	3.87	8.53	2.22	11.76	2.35	11.01	1.06	12.44	2.15
IV	7.85	2.31	6.96	3.38	8.53	2.16	11.45	2.23	11.42	1.54	11.22	2.04
V	7.88	2.32	7.36	2.90	8.79	2.18	12.12	2.52	11.71	1.46	11.47	1.88
Age												
17 to 24	7.56	2.07	7.21	3.10	8.19	2.26	13.1	2.35	11.26	1.46	10.91	1.16
25 to 34	7.60	2.24	6.78	2.91	8.49	2.24	12.56	2.30	11.71	1.13	12.73	2.01
35 to 44	7.94	2.37	7.60	3.10	8.54	2.22	11.04	2.47	11.57	1.50	11.27	1.73

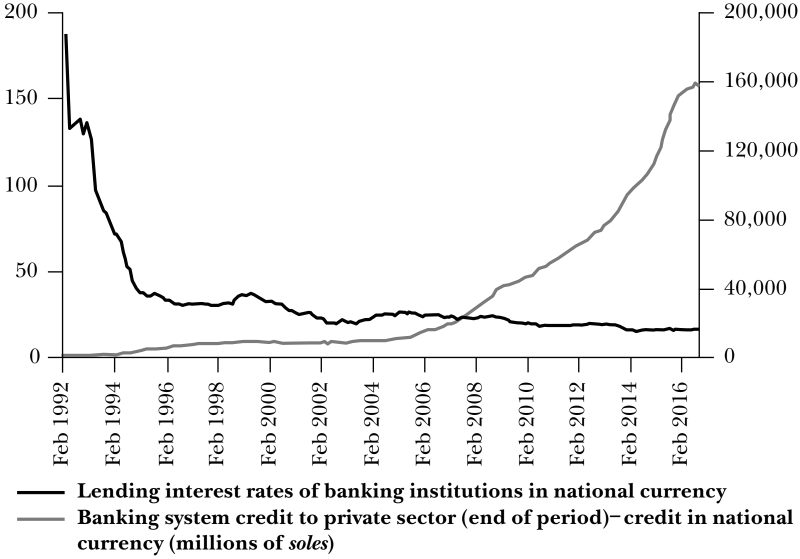
45 to 54	8.15	2.40	7.26	3.20	8.59	2.22	12.51	2.40	11.47	1.64	11.36	1.85
55 to 100	8.11	2.47	7.90	3.13	8.72	2.23	11.78	2.53	11.59	1.39	11.46	2.31
Region												
North Coast	7.80	2.25	7.04	3.49	8.18	2.12	11.09	1.91	11.26	1.31	11.41	1.78
Central Coast	7.73	1.99	6.68	3.24	8.29	2.03	10.97	3.00	10.39	0.88	10.93	1.77
South Coast	8.11	2.22	7.22	2.75	8.69	2.25	11.34	2.55	11.38	1.66	11.04	2.02
North Mountain Range	8.40	2.43	8.39	3.16	8.26	2.12	11.31	1.84	11.26	1.39	10.59	2.53
Central Mountain Range	8.13	2.15	7.81	3.99	8.34	2.17	12.04	1.97	11.54	1.33	11.98	2.01
South Mountain Range	8.18	2.47	7.08	2.96	8.78	2.29	12.03	2.54	11.31	1.41	12.18	2.20
Jungle	8.55	2.28	7.57	3.56	8.57	2.19	13.69	2.26	11.30	1.17	12.00	2.34
Lima metropolitan area	7.71	2.45	7.34	2.99	8.80	2.35	12.64	2.34	12.14	1.49	11.46	1.88
Without remittances	7.91	2.36	7.33	3.10	8.54	2.23	12.07	2.51	11.57	1.45	11.44	1.93
With remittances	8.07	2.45	6.74	3.22	8.92	2.40	10.85	–	–	–	15.44	0.29

Note: Shows the average $\overline{X}$ and standard deviation (SD) of credit per individual. DC denotes domestic currency and FC foreign currency. Note that the log average of credit is shown given that the distribution of credit is lognormal and in this case the use of logs better characterizes the series under consideration.
Source: ENAHO, RCC, 2008-2014.

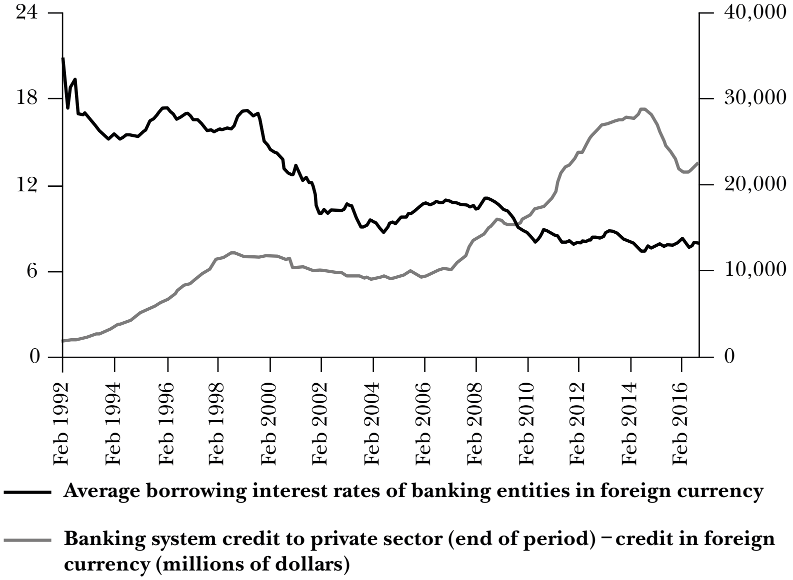
Figure 3

CREDIT AND INTEREST RATE AT AGGREGATED LEVEL

A. CREDIT AND INTEREST RATE IN NATIONAL CURRENCY



B. CREDIT AND INTEREST RATE IN FOREIGN CURRENCY



Note: Identify the credit demand requires credit supply indicators. This identification is not possible at macro level.
Source: Banco Central de Reserva del Perú.

The correlation between credit and interest rates is difficult to identify using a scatter plot between credit and interest rates as seen in Figure 4. The latter shows the correlations for all loans considered (consumer, small business, mortgage), differentiating between the loan denomination currency. These five figures, together with the descriptive statistics presented, help to suggest that an estimation of the demand for credit requires the inclusion of additional controls on the supply as well as the demand side.

4. THE DEMAND FOR CREDIT MODEL

Credit demand compares the size of the loan with the interest rate through a reduced form that can be deduced from a household optimization equation. This equation is the simplest case where households decide the amount of credit based on their fundamentals with respect to sources of income and different preferences represented by an aversion indicator, their level of impatience, and the interest rate they face. Formally, we follow the representation of the consumption-savings intertemporal choice model of Hall (1978), whose household optimization equation is as follows:

$$\max \sum_{t=1}^{\infty} \beta^{t-1} U\left(c_t\right), \tag{1}$$

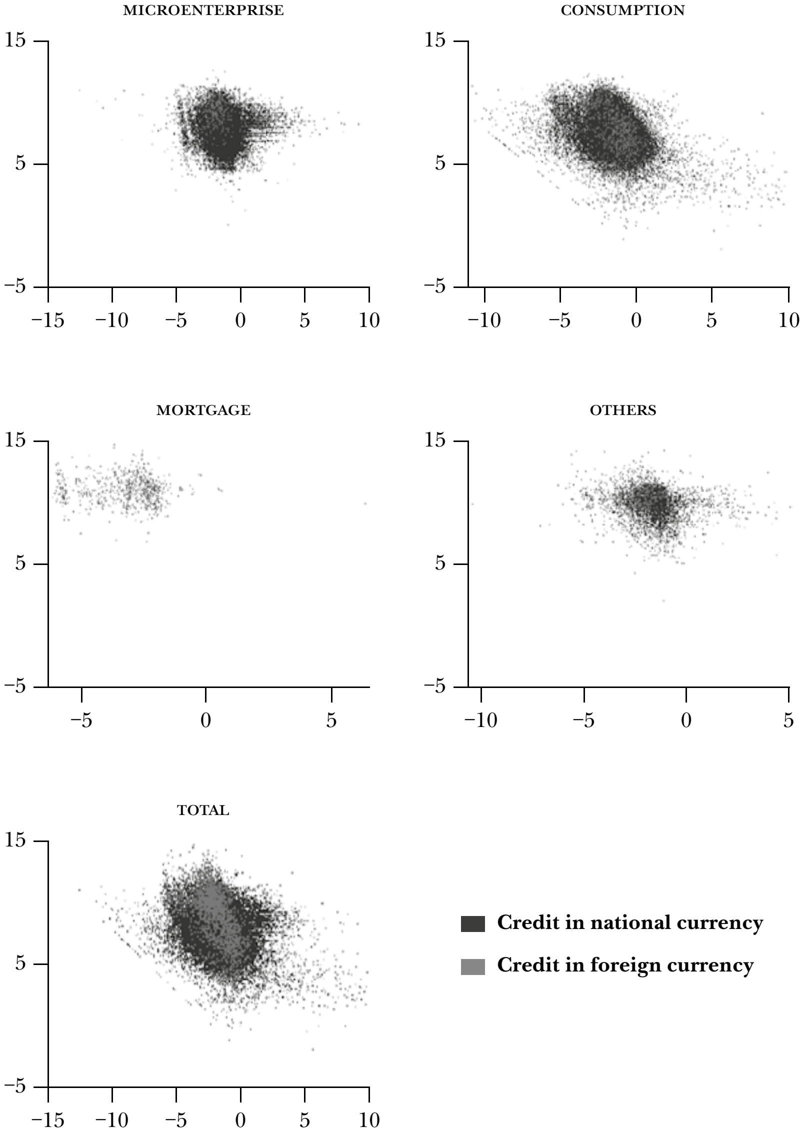
subject to:

$$c_t + b_t = y_t + \left(1 + r_t\right) b_{t-1}; \quad \forall t = 1, 2, \ldots \tag{2}$$

$$c_t \geq 0 \tag{3}$$

Figure 4

CORRELATION BETWEEN CREDIT AND INTEREST RATE



Note: Credit is on the y-axis, and the interest rate is on the x-axis. Variables are in logs.
Sources: RCC and ENAHO, 2008-2014.

4 $$\lim_{t\to\infty}\left[\frac{1}{1+r_t}\right]^{t+1} b_t \to 0,$$

where c_t is consumption and b_t a household's bond holdings in period t, with $b_t < 0$ representing the size of a household's credit. The preferences of each household at every moment, which for simplicity sake we assume has only one member, are described by the following utility function $u_t = \frac{c_t^{1-\sigma}}{1-\sigma}$. We include the usual assumptions $u_c(\cdot) > 0$, i.e., consumption generates positive utility in the individuals. The budget constraints families face in each period capture the equivalence between resource funds and uses, $c_t + b_t = y_t + (1+r_t)b_{t-1}$. Household income is y_t, r_t the interest rate, β the subjective discount factor, and σ the risk aversion parameter. The last two equations (3 and 4) represent the positive consumption constraint and the trasversality condition, respectively.

The solution to this problem is a set of optimum values for consumption and the amount of credit for every value of t=1, 2, ..., which take the following values after considering a constant interest rate over time and an initial amount of debt (b_0):

5 $$c_t = \{\beta(1+r)\}^{\frac{t}{\sigma}} \frac{\sum_{t=1}^{\infty}\left[\frac{1}{1+r_t}\right]^{t-1} y_t}{\sum_{t=1}^{\infty}\left[\frac{1}{1+r_t}\right]^{t-1} \beta^{\frac{t}{\sigma}}(1+r)^{\frac{t}{\sigma}-t+1}},$$

6 $$b_t = (1+r)^t b_0 + \sum_{j=1}^{t-1}(1+r)^{t-j}\{y_j - c_j\}.$$

In the equation above, credit corresponds to a representative individual and is defined by the measure of household risk aversion, level of impatience, interest rate and income. Nevertheless, the empirical section uses a reduced form for credit demand with different degrees of heterogeneity, which can be better justified if the heterogeneity of credit is explicit in the derivation of credit demand. To generate credit heterogeneity in the aforementioned equation it is only necessary to include the existence of different individuals with varying income levels. This idea can also be strengthened by including heterogeneity in the values for risk aversion and level of impatience, parameters that are considered heterogeneous by a large body of literature. Another item that can be used to generate heterogeneity is the interest rate.[9] The data employed suggest that individuals access the credit market at heterogenous rates that change over time, which captures risk profiles at the individual level from the perspective of credit granting institutions. The econometric estimation considers these different levels of heterogeneity by including observable features for individuals, their income and interest rates.

4.1 Reduced Form of the Demand for Credit

The previous expression represents the solution for each household under ideal credit conditions. It is easy to deduce from this sequence that credit depends negatively on interest rates for all individuals whose current income levels are below their corresponding consumption $\left(y_j > c_j\right)$. It can also be seen that said dependence is non-linear. Another characteristic that can be inferred from the equation is that other determinants of credit are present, such as risk aversion and level of impatience. We, therefore, summarize the equation into a reduced form that linearly relates the log of credit and the interest rate.

Empirical estimation of this reduced form requires prior consideration of some specific features of Peru's credit market. One such consideration is participation in the credit market. In

[9] Among the first papers to estimate preference heterogeneity and risk aversion in particular are: Barsky et al. (1997), Kimball et al. (2008) and Kimball et al. (2009).

practical terms the sample of individuals who access the credit market might be different from those who do not. If this is the case, the estimated parameters of the demand for credit equation might contain so-called sample selection bias. This problem is solved by including a Heckman correction, which basically suggests that the demand for credit should be estimated using a two-step approach. The first step consists of estimating the credit market participation equation using the whole sample, while the second corresponds to estimating the intensive demand for credit considering only the sample of individuals with credit.

Credit Market Participation

Participation in the credit market is only observed for those who manage to obtain a loan, and this only takes place after a credit assessment process that is not observed in the data. The data only shows individuals who participate in the credit market, which is denoted by $I_{ijt}=1$. This event is related to a continuous and latent variable I^{*} that is determined by a set of variables, grouped in x, that identify participation in the credit market through the equation

$$I_{ijt}^{*}=\delta x_{ijt}+\varepsilon_{ijt}.$$

We can see that the data registers credit market participation $\left(I_{ijt}=1\right)$ only if the latent variable is positive $\left(I_{ijt}^{*}>0\right)$, where i denotes each individual and t the period. With this in mind, and assuming a normal distribution of random component ε_{ijt}, the probability of participation in the credit market is expressed as follows:

7 $$Pr\left(I_{ijt}=1\right)=Prob(\delta x_{ijt}+\varepsilon_{ijt}>0)=\Phi(\delta x_{ijt}),$$

where as usual Φ represents the normal distribution characterizing the probit model.

Intensive Demand for Credit

In the second stage, we define the amount of credit (b), that depends on a set of variables divided into demand-side and supply-side. The equation to be estimated is as follows:

8 $$b_{ijt}^{n} = \alpha + \beta_r R_{ijt} + \beta x_{ijt} + \theta z_{jt} + \delta T_t + \gamma \lambda_{ijt} + \nu_{ijt},$$

where b_{ijt} is the demand for credit in period t for household i in bank j, and R_{ijt} is the interest rate. x_{ijt} are the controls representing different levels of heterogeneity among individuals and z_{ijt} are the controls per bank (j), and T_t captures aggregate variables that are known to affect the credit market. ν is the error term that captures the determinants of credit that are not considered. The aforementioned specification includes the inverse Mills ratio λ_{ijt}, to correct the sample selection problem and also connect intensive demand with the estimation of extensive demand from the first stage.

The types of heterogeneity considered include observable features of individuals in terms of the level of education, age, and geographical region. We also include other less structural indicators for individuals captured in the type of employment (formal and informal) and by the shocks they experience, among which stand out employment, demographics, etc. Although there is only a small amount of literature on the subject, we believe the levels of heterogeneity employed capture probable differences in preferences (risk aversion, impatience, etc.) among households with respect to borrowing. This differentiation can be made according to the type of credit (consumer, mortgage) or the currency in which a loan is taken out, i.e. domestic or foreign. The latter separation allows for studying differences in the determinants of credit by type of currency.

One important aspect of the estimation is identifying the demand for debt achieved by including credit supply related variables measured for each credit granting institution in the estimation. The estimation contains identifiers of formal financial institutions using binary variables.[10]

It is also important to mention that, in the case of Peru, credit supply characteristics should include the potential role of exchange rate variations and their influence on the interest rates at which financial institutions offer loans. By including a binary variable at the level of the main banks and their interaction with time and loan currency, we are implicitly controlling for the expected devaluation such institutions incorporate into their loans. Besides expected changes in the exchange rate, this interaction effect also captures the institutional characteristics of Peru's banking system. Among the latter stand out, for instance, the high interest rates charged by small financial entities, while larger institutions report lower rates as mentioned in Céspedes and Orrego (2014).

5. RESULTS OF THE ESTIMATIONS

5.1 Credit Market Participation

Participation in the credit market is represented using a discrete choice probit model where the explanatory variable takes a value of one if an individual has a loan and zero if not. Among the variables that determine access to credit, we have a set of indicators commonly used in the literature to capture different aspects of participation. Hence, we consider the following.

- Property rentals: Individuals with property rentals have a regular flow of income they can use to ensure loan repayments. This variable identifies credit market participation in the data as illustrated in Panel A of Figure 5. The latter figure shows that access to credit for individuals with property rentals is clearly higher than that of individuals without such income, a fact sustained on average for all age groups considered.

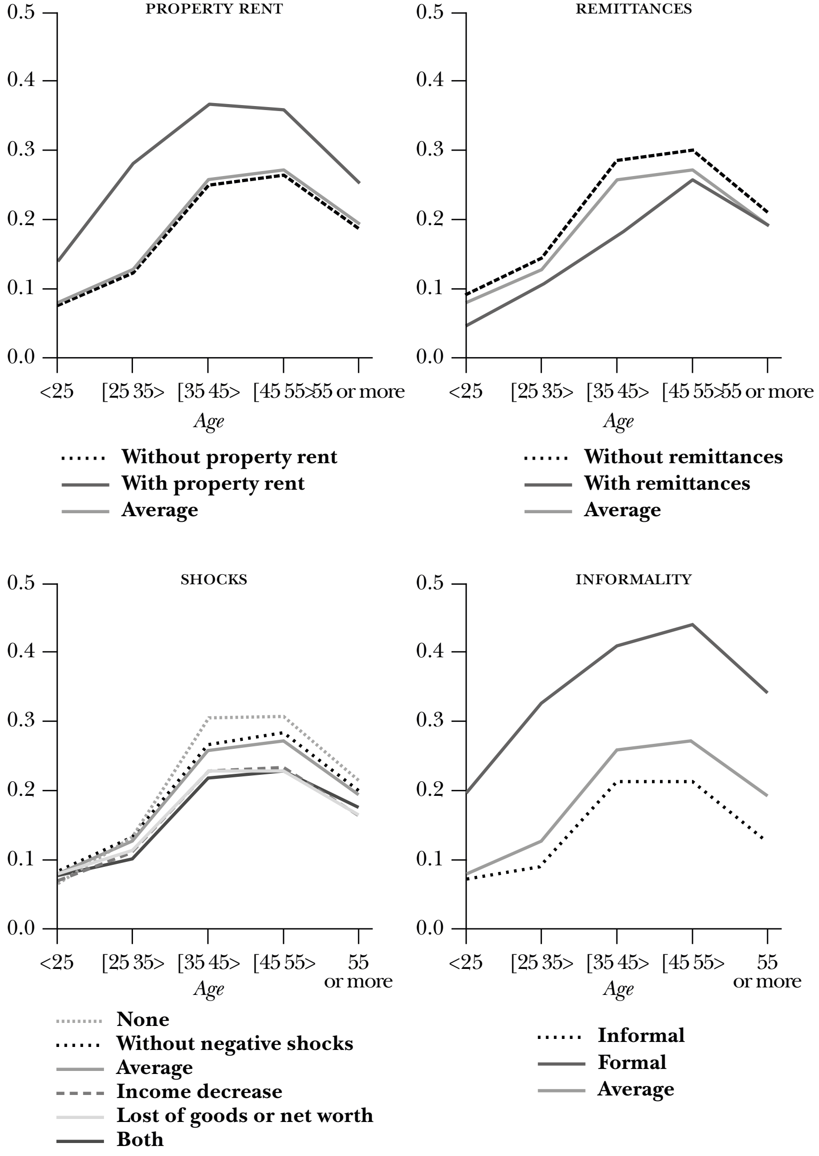
[10] It includes 26 artificial variables. The first 25 correspond to the largest financial institutions, while the remaining financial entities (small ones) are grouped into variable 26.

- Remittances: External remittances received by workers constitute a source of income that could be used as a mechanism for hedging loans, particularly those in foreign currency. This variable has been widely used in the literature on foreign currency borrowing, for instance: Fidrmuc et al. (2013) show the importance of external remittances in the demand for loans in Eastern European countries.
- Age and age-squared: The use of an individual's age as a variable to identify their participation in the credit market obeys the shape of inverted U of the age of participation in the credit market. Along the same lines, age-squared captures lower credit market participation among young and old-aged people, while the middle-aged participate more in said market.
- Shocks faced by households: This variable captures one characteristic of the credit theory as an insurance mechanism for responding to the shocks a household faces. According to this argument, households smooth consumption by using the credit market to face adverse events at the expense of future income. A set of shocks faced by households are considered such as, for instance: demographic shocks, employment shocks, natural disasters, etc. The reported index takes into account that an individual has been exposed to one of the shocks during the last 12 months.
- Informality: We consider that formal employment among workers identifies credit market participation basically using the characteristics of the credit database, which is limited to formal bank credit. In our data, formal workers access the credit market, while those in informal employment exhibit a much smaller access as shown in Panel D of Figure 5.

The participation equation estimated includes an additional set of controls such as gender, marital status, and region of residence. The estimation results provide a good fit in econometric terms as displayed in Table 3. Note that the variables identifying the selection are significant and also have signs consistent with that shown in Figure 3. These results are comparable to the estimates of Alfageme and Ramírez-Rondán (2016), and Cámara et al. (2013), although the size of the differences could be related to

Figure 5

PERSONS WHO HAVE A CREDIT
Percentage of the total population



Note: Participation in the credit market (percentage of persons with credit in each category).
Source: ENAHO and RCC, 2008-2014.

the inclusion of a set of variables identifying credit market participation, such as age, remittances, shocks and property rentals.

5.2 The Demand for Credit

The estimated elasticity of the demand for credit in Peru is −0.29. This figure is obtained after controlling for credit supply variables and Peruvian institutional characteristics as presented in Table 4. The latter table also presents estimated elasticities of the demand for credit using different specifications and estimation methods. This procedure highlights that the ordinary least squares estimator is not much different from the value estimated using Heckman's two-step method. The result that stands out is the fact that the elasticity of demand for credit is small, making it possible to conclude there is low credit market sensitivity among individuals during shocks channeled through interest rates. One of these events that occur relatively often are changes in Peruvian or US monetary policy. According to the results of this study, such changes would have had a modest impact on the demand for credit among individuals. International evidence on the value of this elasticity is mixed. On the one hand, Gross and Souleles (2002) use credit card records in the USA to find an elasticity of demand for credit of −1.3, which indicates a substantial reaction in credit demand (cards) to the interest rate. Meanwhile, another commonly referred to paper is that of Alessie et al. (2005), who use administrative data from a leading institution in Italy to find an elasticity of credit (instalment, revolving, personal loan) relative to the interest rate of −1.2 between 1995 and 1999. Nevertheless, this stance does not command full consensus because there is also literature suggesting a low elasticity of demand for credit. For instance, Ausubel (1991) includes one of the stylized facts most used for credit demand. This author employs administrative records and reveals that the demand for credit in the USA is rigid with respect to the interest rate and suggests that credit card holders rarely react to interest rate changes.

Table 3

CREDIT MARKET PARTICIPATION EQUATION

	Heckman selection equation	
	Coefficients	*z test*
Remittance (=0)	−0.0689[b]	(−2.68)
Property rentals	0.213[c]	(23.58)
Age	0.0842[c]	(101.10)
Age x age	−0.000870[c]	(−100.48)
Informal (=1)	−0.673[c]	(−138.24)
Married	−0.0320[c]	(−5.29)
Widowed	−0.171[c]	(−13.47)
Divorced	0.0150	(0.51)
Separated	−0.0378[c]	(−4.25)
Single	−0.178[c]	(−24.01)
Effect of shocks		
Reduced income	−0.0801[c]	(−13.09)
Loss of assets/wealth	−0.0374[b]	(−2.88)
Both	−0.0437[c]	(−3.59)
None	0.0127	(0.70)
Central Coast	−0.192[c]	(−20.58)
South Coast	0.0212[a]	(2.05)
North Mountain Range	−0.376[c]	(−31.63)
Central Mountain Range	−0.390[c]	(−47.53)
South Mountain Range	−0.0990[c]	(−12.14)
Jungle	−0.210[c]	(−27.77)
Lima metropolitan area	−0.249[c]	(−30.50)
Constant	−2.102[c]	(−101.87)
Mills (lambda)	−0.135[c]	(−5.97)
Rho	−0.10507	
Sigma	1.2845615	

Notes: corresponds to probit model estimates described in Equation 7. z statistic in parenthesis. [a] $p<0.05$, [b] $p<0.01$ and [c] $p<0.01$.
Source: ENAHO and RCC, 2008-2014.

The low elasticity of demand for credit could also be related to Peru's banking structure, which is characterized by being concentrated in a small number of financial entities (Céspedes and Orrego, 2014; and Jopen, 2013). In this regard, some literature suggests that the elasticity of demand for credit with respect to the interest rate should be high in a competitive market.

Table 4

CREDIT DEMAND ESTIMATES

	Dependent variable: log(credit)			
	MCO (1)	*MCO (2)*	*Heckman (3)*	*Heckman (4)*
Interest rate (log)	−0.362[a] (0.0066)	−0.295[a] (0.0057)	−0.307[a] (0.0034)	−0.294[a] (0.0035)
Demand characteristics				
Gender		✓	✓	✓
Age		✓	✓	✓
Age^2		✓	✓	✓
Education		✓	✓	✓
Parentage		✓	✓	✓
Marital status		✓	✓	✓
Economic sector		✓	✓	✓
Geographic region		✓	✓	✓
Supply characteristics				
Type of credit		✓	✓	✓
Type of currency		✓	✓	✓
Type of bank		✓	✓	✓
Year		✓	✓	✓
Type of bank×year×currency		✓		✓
Mills (lambda)			−0.233[a]	−0.135[a]
R^2	0.05	0.66		
Number of observations	84,394	78,889	543,358	543,353
Prob > F	0.0	0.0		
Prob > χ^2			0.0	0.0

Note: standard error in parenthesis.
Source: ENAHO and RCC, 2008-2014.

The elasticity of demand for credit could be an indicator of competition in Peru's market. The reasoning behind this lies in the capacity banks have to pass the shocks they face on to households by changing interest rates, and this capability depends on the elasticity of the interest rate. Under such interpretation, financial institutions maintain high rates because lowering them does not significantly increase the demand for credit.

The recent strong economic growth experienced by Peru could be important in explaining the low elasticity of credit with respect to the interest rate. The significant expansion of household credit seen between 2001 and 2014 mostly reflects the aggressive placement policies of financial institutions in an environment of higher employment and wages. The growth of placements basically takes place on the extension side, i.e., the number of new loans granted rather than average loan size. Such facts are consistent with the greater financial inclusion experienced by the economy in those years, with a larger amount of institutions offering credit such as rural savings banks and cooperatives, among others, that enabled previously unattended sectors to participate. These new loans are potentially riskier and reflect the participation of high-risk individuals with credit profiles that accept the high interest rates offered by the banks. In this context, banks have few incentives to lower (the high) interest rates on their products because this would not substantially increase the demand for credit given the corresponding low elasticity.

Another factor considered as possibly explaining the low elasticity is the greater financial inclusion being seen in the Peruvian economy (arriving at economic sectors that did not previously have access to credit). This phenomenon has been observed, for instance, in the marginalized areas of Lima, and generally in different regions of Peru where there were practically no banks in previous decades. However, the scenario has changed considerably and nowadays the network of agencies and agents offering loans (rural savings banks, municipal savings banks, savings, and credit cooperatives, major bank branches, etc.) has widened along with access to credit (new loans), which has followed a similar path.

5.3 Heterogeneity of the Demand for Credit

The demand for credit is heterogeneous and depends on the credit market supply and demand side characteristics. Moreover, the literature has found that heterogeneity is also present in the elasticity of demand for credit with respect to the interest rate. In this section, we consider several levels of heterogeneity basically related to the institutional order of Peru's economy that could sustain the heterogeneity of the transmission of interest rate shocks to household credit. This heterogeneity takes place according to the type of currency in which loans are granted, according to the region where they are granted and type of loan. We also consider the possibility that the elasticity of demand for credit changes over time.

Formally, Equation 8 is modified by including the effects of interaction between the interest rate and a set of artificial variables $\left(D_{ijt}^{l}\right)$ that take a value of one at each level of heterogeneity considered, the resulting equation is written as follows:

9 $$b_{ijt}^{n} = \alpha + \sum_{l=1}^{Q} \beta_r^l D_{ijt}^{l} \times R_{ijt} + \beta x_{ijt} + \theta z_{jt} + \delta T_t + \gamma \lambda_{ijt} + \nu_{ijt},$$

where Q levels of heterogeneity are considered. In this specification, indexes associated with interaction $\left(\beta_r^l\right)$ are the elasticities for each level of heterogeneity.

5.3.1 Heterogeneity by Type of Loan

The demand for credit is particularly heterogeneous according to the type of credit. The data allow for disaggregating up to three types of credit: consumer loans, mortgages, and credit to small and micro enterprises. The estimates suggest that the elasticity of the demand for credit differs according to the type of credit; consumer loans being the most elastic with an elasticity of close to −0.40, while mortgage loans are the least elastic.

5.3.2 Dollarization and Credit Demand

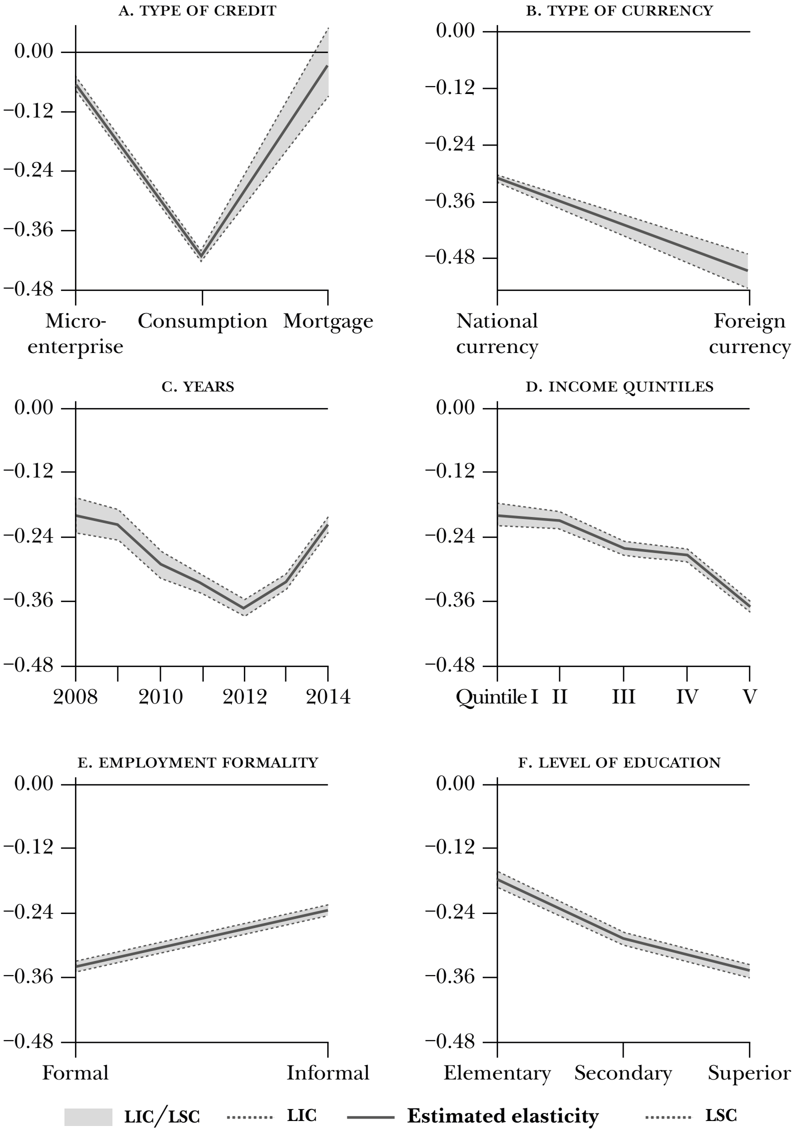
The type of currency can play an important role in the transmission of interest rate changes to credit. In this respect, dollarization of household credit in Peru's economy is around 30% and very heterogenous according to different observable categories among individuals such as income, age, and region of residence, among others, as documented in Céspedes (2017). The estimations in this section suggest that the elasticity of demand for credit is heterogeneous according to loan currency, those denominated in foreign currency being more elastic, while those in domestic currency are less so (Figure 6, Panel B).

The higher sensitivity of foreign currency borrowing could respond to a greater exposure of personal loans to interest rate movements. For instance, changes in international rates originating from, among other reasons, adverse global events could have a larger pass-through to households' foreign currency denominated credit, while such effects would be smaller in the case of loans in domestic currency.

However, the estimation methodology that has been implemented in this study might overestimate the sensitivity of interest rates to credit. This could be the case, for instance, of the exchange rate and the registration method used in the RCC by the SBS. In this regard, the RCC expresses loans in domestic currency using, in the case of loans in foreign currency, the official exchange rate at any given day (end-of-month for accounting purposes) for all loans and all financial institutions. Nevertheless, each financial entity uses a specific exchange rate that captures the expected exchange rate devaluation and is included in the interest rate they charge on loans, especially for individuals whose income is in domestic currency and have loans in foreign currency. The suggested overestimation would take place because the interest rate series employed has a lower variance by considering an average exchange rate and

Figure 6

ESTIMATED ELASTICITY OF CREDIT DEMAND BY DIFFERENT CATEGORIES



Note: The estimates of β_r^l from equation 9 are showed. There are also showed the confidence intervals. LIC is the lower limit of confidence of the credit demand elasticity, while LSC is the upper limit.
Source: ENAHO and RCC, 2008-2014.

a specific date, while interest rate variance would be larger if, ideally, it was possible to include the exchange rate used by each institution on the date loans are paid. Given that this volatility is not controlled in the regressions this would result in a larger elasticity of loans in foreign currency.

5.3.3 Changes in the Demand for Credit

By estimating the elasticity of demand for credit over time we find that this parameter increased in absolute value between 2008 and 2012 and exhibited a downward trend in 2013 and 2014 (Figure 6, Panel C). This result could be evidence that the pass-through of interest rate changes to credit has been related to the credit cycle, recalling that credit expanded at the highest rates between 2008 and 2012, and has slowed since 2012.

5.3.4 Credit Demand and Income

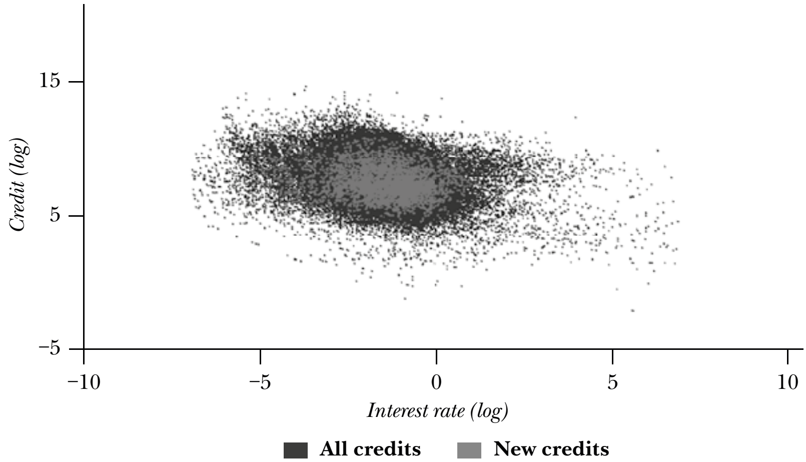
Participation in the credit market depends on the position in the income distribution. In this section, we have also found that the elasticity of the interest rate is lower in high income and better educated households, as well as among those with formal employment. These elasticities are statistically significant as illustrated in panels D, E, and F of Figure 6.

5.4 New and Old Loans

The demand for credit estimated in the previous section encompasses all loans registered in the RCC, while loan size corresponds to their balances. From the viewpoint of monetary policy, the loans that capture the transmission of changes in monetary policy would be new ones. We identify new loans using the credit panel in consecutive periods. To be specific, we distinguish the new loans in each month, identifying individuals with credit who did not have loans or were not registered in the RCC during the immediately preceding month. Note that individuals identified as having new loans might have had some type of credit in the past. We find that the new loans identified maintain a negative correlation with the corresponding interest rates, similar to that shown in Figure 4. Moreover, the new loans sample is small compared to the total sample, and said sample becomes even smaller if the different types of loan and individuals' characteristics are included, meaning the elasticity of demand for credit estimated for the previously mentioned categories (loan type, an individual's age, etc.) would only have high standard errors and be inaccurate with new loans. In light of the aforementioned considerations, the elasticity of credit is estimated with new loans and compared with the elasticities estimated using the full sample.

Figure 7

CREDIT AND INTEREST RATE OF NEW AND OLD CREDITS



Note: Credit is on the y-axis and the interest rate on the x-axis. Variables are expressed in logs.
Source: ENAHO and RCC, 2008-2014.

Credit demand for new loans is estimated using the same procedure described in the previous section, i.e., employing a binary variable that identifies new and old loans. As a result of this procedure, we find that the elasticity of demand for new loans is lower in absolute value (−0.17) than the elasticity reported for old loans (−0.30). This gap between the elasticity of new and old loans is similar using different methods (ordinary leas squares, Heckman). Furthermore, the elasticity increases when medium length loans and the oldest ones are included. The rationale of these outcomes lies in the particular characteristics of Peru's credit market, where interest rates on loans change over time even after being stipulated in a contract. Furthermore, there is a secondary market for purchasing debt, and each repo transaction qualifies as a new loan, although it would be difficult to identify them from RCC data. In sum, an important percentage of loans deemed to be old are in fact new ones and, therefore, the elasticity of demand for such loans in the secondary market should be higher.

6. CONCLUSIONS

Demand for credit at the individual level is an equation seldom estimated for an economy. The reason for this is that it is necessary to know credit and interest rates along with credit demand and supply features, but databases with this type of indicators are scarce at the international level. In this paper, we construct a new database that allows for observing the aforementioned variables by merging the National Household Survey with the Credit Registry for the period 2008-2014. The resulting database enabled us to examine 73,000 individual debtors.

Households' demand for credit is estimated using a two-step procedure proposed by Heckman (1979). The first step estimates extensive credit demand and the second intensive credit demand. The results highlight that participation in the credit market is determined by the number of property rentals households have, the remittances they receive, the size of the shocks they face, and their informality status. The latter characteristic is particularly important because it reveals a significant participation of informal individuals in formal bank credit. On this point, it is interesting to delve deeper into the reasons why informal workers participate in the formal credit market.

With respect to intensive demand for credit, it stands out that there is an elasticity of demand of approximately −0.29, figure slightly lower than that reported by the small number of international studies related to this paper.

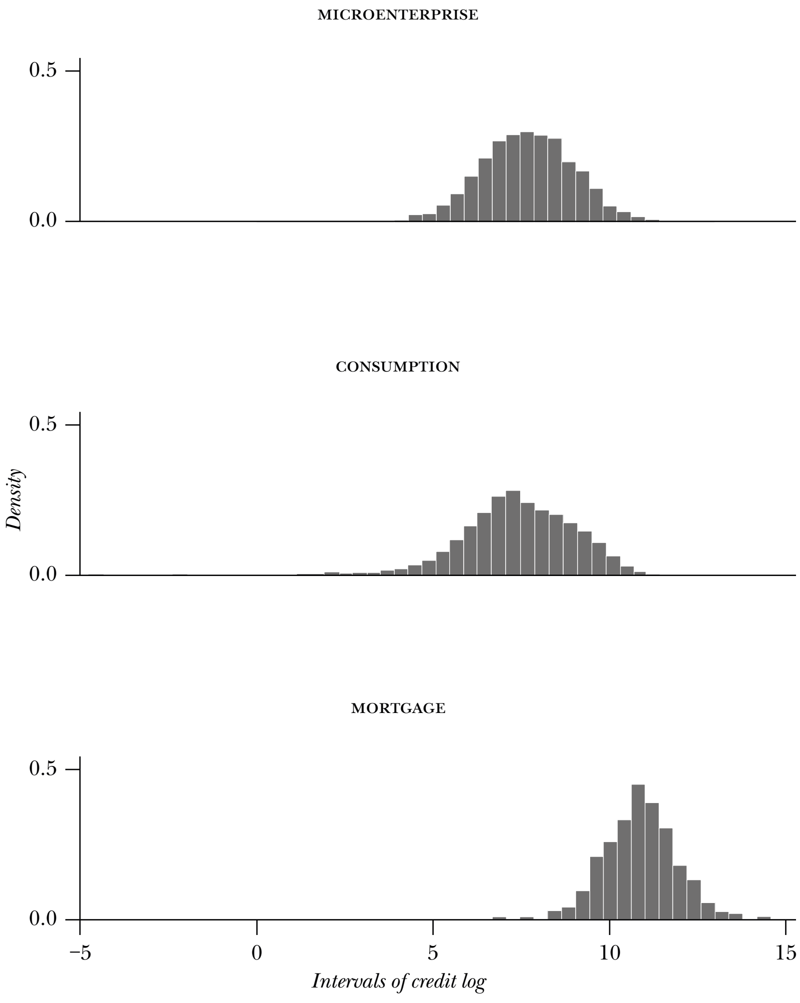
The elasticity of demand for credit is found to be heterogeneous in the estimation after controlling for the heterogeneity of credit demanders (individuals) and the heterogeneity of credit suppliers (banks). This evidence suggests that fixed effects at the individual and bank level not only impact average credit but also the elasticity of demand for credit. This heterogeneity is found according to loan type, currency denomination (domestic or foreign), individuals' income and level of education, among others.

Finally, it is important to highlight that the findings provide a first look at the heterogeneity of the demand for credit at the individual level in Peru. In general, the results of the study could be useful for assessing the transmission of the effects of the variables determining interest rates on individuals' credit and through the same channel on their consumption and standard of living. In particular, and considering the high and persistent dollarization in Peru's economy, the data shown in this article should be taken into account as arguments for explaining the pass-through of exchange rate shocks to credit at the individual level.

ANNEX

Figure A.1

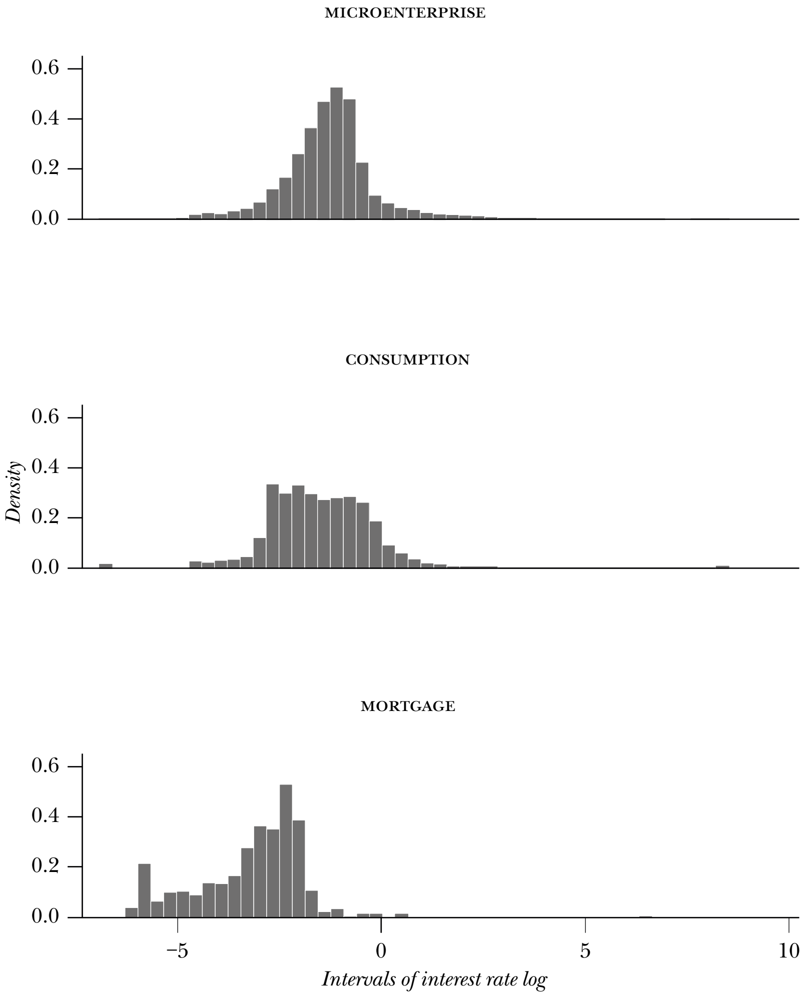
FREQUENCIES OF REAL CREDIT BY TYPE OF CREDIT



Source: ENAHO and RCC, 2008-2014.

Figure A.2

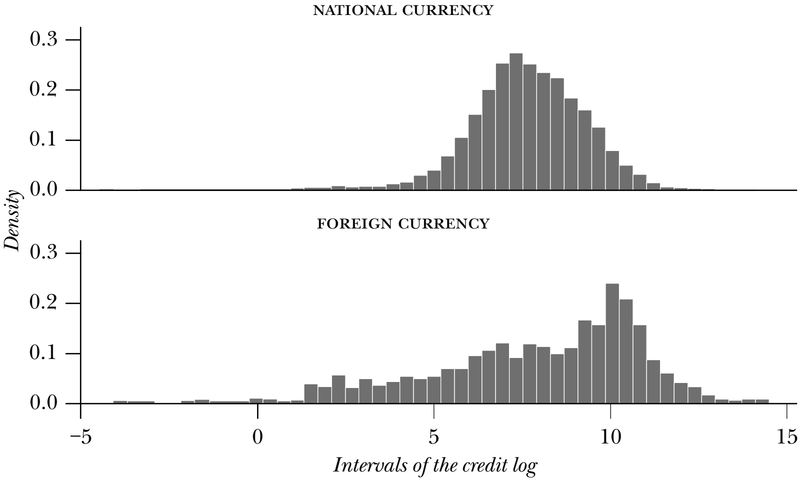
FREQUENCY OF INTEREST RATE BY TYPE OF CREDIT



Source: ENAHO and RCC, 2008-2014.

Figure A.3

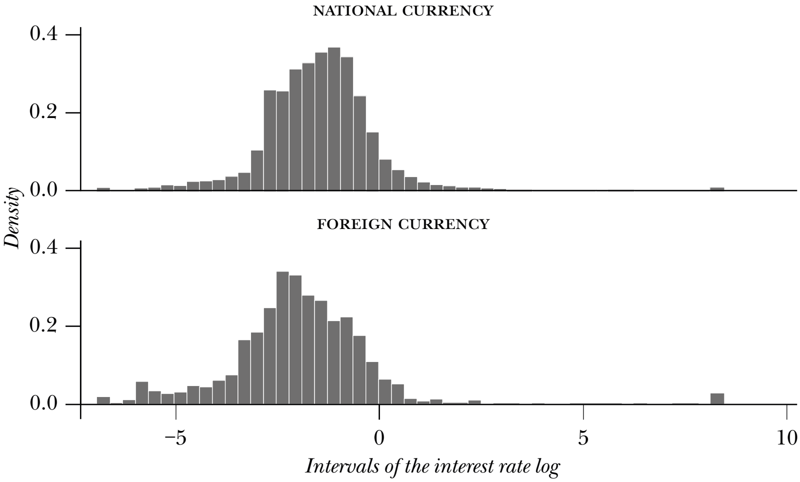
FREQUENCIES OF REAL CREDIT BY CURRENCY



Source: ENAHO and RCC, 2008-2014.

Figure A.4

FREQUENCY OF INTEREST RATE BY CURRENCY



Source: ENAHO and RCC, 2008-2014.

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Inventory Adjustments to Demand Shocks under Flexible Specifications

Carlos R. Barrera Chaupis

Abstract

The relations among growth rates in GDP *and four aggregate demand components associated with inventory management are approximated by a neural* VAR *model with* t-*Student disturbances and an* ARCH *covariance matrix. The estimation sample corresponds to Peru's market-based growth experience (1993Q1-2010Q1). The main finding is that a positive shock to private demand growth will contemporaneously generate a more than proportional increase in production growth. This amplifier impact effect is consistent with the cycle of inventories and the average incidence of the inventory investment growth inside the production growth during the last four recessions.*

Keywords: time series models, neural networks, inventories, production smoothing, business fluctuations.

JEL *classification: C32, C45, E22, E23, E32.*

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1. INTRODUCTION

Since the 1940s the *inventory cycles* of Metzler (1941) have been recognized as a predominant characteristic of economic cycles (Blinder and Maccini, 1991). Their importance has been confirmed as lengthier expansions observed recently in the world economy came to an end with the United States (US) financial crisis (2007-2008) and the temporary collapse of international trade (see Alessandria et al., 2010), which also impacted the demand associated to commodity exports.

The sustained expansions seen since the start of the 1990s, particularly in the developed world, fostered growth in emerging economies due to greater commercial and financial openness. In general terms, this expansion was characterized by *1)* a decreasing and eventually low world inflation, an environment that had not been observed since the 1960s; and *2)* a reduction in the GDP growth volatility.

The literature on inventories have justifiably become relevant because they provide an explanation for the observed phenomenon of sustained and stable expansions, also known as the *Great Moderation*. According to this *explanatory history*, the continuous development of information technologies, communications, and sales forecasting techniques have fostered improvements in inventory management accompanied by a consequent reduction in the volatility of *inventory variation* (in other words, inventory investment or flow of inventory balances), which explains the reduction in the volatility of United States GDP and its corresponding growth rates (see, for instance, Kahn et al., 2002).

The prolonged economic expansion in US that started in 1991 was followed by a very short recession during the first few months of 2001, in which massive inventory liquidation was in contrast to the smooth movements observed previously, even before the prolonged expansion. For Kahn and McConnell (2002), this massive liquidation did not show that improvements in inventory management had been tenuous, but that firms had predicted falling sales long before they appeared, wich allow them to drastically reduce their inventories and thereby avoid excessive accumulation. Predicting the fall in sales allowed them to reduce their production in advance and then ration inventories according to demand, maintaining inventory-to-sales-ratios close to desired values.[1]

To characterize the stabilization observed in the US durable goods sector, Kahn (2008) points to two key facts: *1)* a significant reduction in the volatility of output growth and *2)* a more modest reduction in the volatility of sales growth. To characterize the stabilization of aggregate output in Australia, Simon (2001) also highlights two key facts: *1)* changes in the inventories cycle, and *2)* declines in *underlying output* volatility. By dismissing an increase in structural stability (the previously mentioned explanatory history), Simon (2001) explains the second key fact through a decline in the volatility of *productivity shocks* (supply shocks) that hit the economy, but leaves the source of such shocks as an open question.[2] In any case, the sectoral decomposition (by productive sectors) provides an explanation for the Great Moderation, which is complementary to that based on a decomposition of GDP growth by type of expenditure,[3] and both lines of work emphasize the unconditional variance of GDP.

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1 The objectives of predicting sales and remaining close to the desired ratio imply that movements in inventories amplify business cycle fluctuations. Despite this, the *average* contribution of inventories to the volatility of GDP growth in the USA (its *average incidence*) is smaller. The model in the following section encompasses those contributions.

2 Later in this paper it will be seen that Simon's underlying output (2001) is actually an *aggregate demand excluding inventories*, meaning it is inappropriate to decompose it with an output function in order to estimate *productivity shocks*.

3 Eggers and Ioannides (2006) point to a decline in the importance within GDP of relatively more volatile sectors (agriculture and manufacturing) in favor of other less volatile ones (financial and services) as *the* explanation for the Great Moderation. Davis

The recent financial crisis in USA (2007-2008) affected demand associated with exports as part of the inventory cycle in the economic cycle, generating an unparalleled collapse and recovery of international trade. The literature has highlighted the role of private domestic demand and the inventories mechanism (Alessandria et al., 2010), as well as the private domestic demand of a country's main trading partner (Eaton et al., 2011), the latter being the most important determinant of external demand for exports.

In this context, although towards the start of 2010 it was too early to outline a general description of the turning point stemming from the US crisis in 2007-2008, the experience of Peru up until then might be illustrative of the inventory cycle in an emerging economy, despite having only a few business cycles, i.e., recorded under market conditions (Barrera, 2009). Moreover, economic relations between inventory growth during GDP growth shocks and three aggregate demand components (public domestic demand, private domestic demand and external demand for exports) stand out as being the least studied in Peru.

Table 1 quantifies the importance of inventory change as a percentage of GDP variation in the four recessions observed in Peru prior to that generated as a consequence of the US crisis in 2007-2008.[4]

The average of these coefficients is 230.4%, with a variation range of [100.9, 466.6]. As a reference, the average for the USA is 87%, with a variation range of [2, 232] according to the calculations made by Blinder and Maccini (1991) with the eight recessions recorded during 1948-1982. Firstly, this confirms that shifts in inventory investment have contributed by amplifying the recessive phases of the Peruvian economy since the start of the 1990s, especially the most recent one. Secondly,

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and Kahn (2008) seek a more complete explanatory theory, with several interacting factors.

[4] The units employed are peak to trough changes in the *four-quarter average percentage variations* (percentage variations in four-quarter moving averages expressed in millions of 1994 nuevos soles).

Table 1

AVERAGE INCIDENCE OF INVENTORY CHANGES
Inventory investment and recessions since 1990

Reference variable: nonprimary GDP (peak-trough dates)	*Change in four-quarter average percentage variations (peak-trough)* Real GDP (1)	Inventory investment (2)	*Inventory investment to real GDP (2/1)*
Sample: 1992M12-2007M12[a]			
(1) 1995M7-1996M10	−2.4	−2.4	100.9
(2) 1997M12-1999M8	−1.7	−3.5	212.1
(3) 2000M8-2001M8	−1.8	−2.6	141.9
(4) 2003M3-2004M6	−0.7	−3.3	466.6
Average (1-4)	−1.6	−2.9	230.4
Memo: 2008Q2-2009Q2	−3.3	−12.2	373.9

[a] Four-quarter average percentage variations were the units employed to identify business cycles in Peru's economy using the Bry-Boschan approach (see Barrera, 2009).
Source: Author's calculations using data at levels from the Banco Central de Reserva del Perú.

and in contrast to the Great Moderation observed in US business cycles, Peru has seen a phenomenon of *demoderation*, at least since the third recession recorded.[5]

This paper aims to explain why the *demoderation* phenomenon takes place in Peru. To that end we quantitatively approximate the dynamic relations (potentially asymmetric) between inventory growth, GDP growth and three aggregate demand components (domestic public demand, domestic private demand and, especially, external demand for exports) during

[5] Note that the coefficients for USA are calculated using peak to trough flows in billions of 1982 dollars, making them indirectly comparable with coefficients for Peru.

Peru's market-based growth experience between the first quarter of 1993 and the first quarter of 2010 (1993Q1-2010Q1).

The second section describes the data that will be used to obtain empirical results. These data allow us to outline what we tentatively and temporarily call the *stylized facts* regarding the use of inventories. In principle, inventories serve to buffer the effect of demand shocks on manufacturing operations, although they can also be used for *other objectives* that would explain the demoderation phenomenon in Peru. The third section presents a conceptual framework with respect to production and inventory decisions to provide a qualitative explanation for the demoderation phenomenon. The fourth section proposes a flexible nonstructural model to approximate the dynamic asymmetric relations among GDP and inventories and three aggregate demand sources, as well as a structural model to decompose the covariance matrices of the last period in the sample (final period T= 2010Q1). The fifth section describes the results in terms of conditional covariance and impulse responses in an attempt to provide an explanation for the demoderation phenomenon in Peru. The sixth section gives the conclusions.

2. DATA AND STYLIZED FACTS: AGGREGATE FLOW OF INVENTORIES IN PERU

Data used in this study are taken from the Banco Central de Reserva del Perú and are available on its website under the title "Economic Statistics" at the following links: All Sets, Economic Activity and GDP expenditure, at <https://estadisticas.bcrp.gob.pe/estadisticas/series/trimestrales/pbi-gasto>. Figures are originally expressed in real 2007 soles.

2.1 Aggregate Data of Inventory, Production, and Demand

Aggregate production and inventories of firms in an economy will obviously respond to different types of demand shocks.

Thus, aggregate demand excluding inventory investment (*AgDem*) can be decomposed into:

1) real exports, goods and nonfinancial services (*XDem*);

2) public sector: real consumption and investment, goods and nonfinancial services (*PuDem*); and

3) private sector: real consumption and investment, goods and nonfinancial services (*PrDem*).

Figure 1 illustrates the *four-quarter average percentage variations* of those three components, and this *data transformation* will be used throughout the study.[6] To represent the scenario it was not sufficient to use the variance of the aggregate *AgDem:* fluctuations in *PuDem* were aimed at offsetting those in *PrDem* on several occasions (anticyclical policies) since the start of the 1990s (with a weak quantitative impact though), and since 1996 aimed to offset short term fluctuation in *XDem* (partially and at their discretion). Only since 2001, as comprehensive financial *constraints* on the public sector imposed during the economic stabilization were lifted, the frequency of these more focused countercyclical policies increased. These constraints consisted of continuous fiscal efforts to build public revenues to enable more effective medium-term anticyclical policies, which fostered a larger quantitative impact of fluctuations in *PuDem* during the sharp fluctuation in *XDem* caused by the crisis in the USA in 2007-2008.

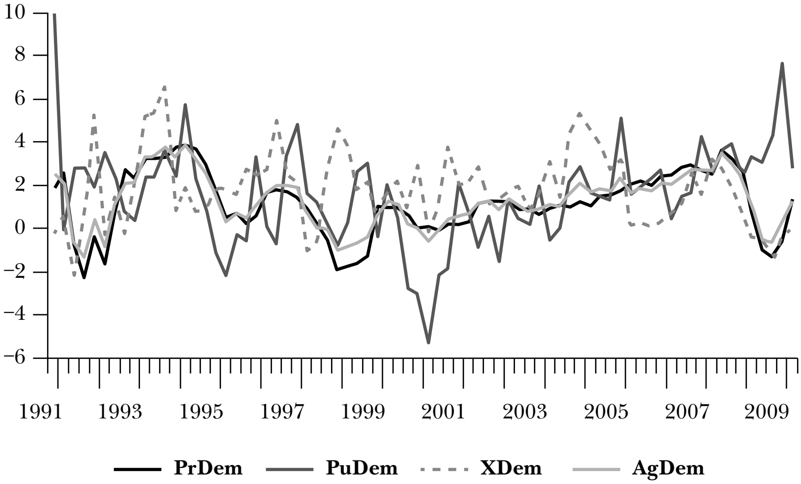
It is also important to consider two other endogenous variables: *1)* real calibrated balance of inventories (*BInv*), and *2)* real gross domestic product (GDP).

[6] One reason for not following the rules established in the literature for real cycles is due to the fact that data at levels contains a significant measurement error component, while these variations have a very low signal-noise ratio. Thus, Section 3 only provides a qualitative explanation that allows for structurally interpreting the empirical results in Section 5.

Figure 1

AGGREGATE DEMAND AND COMPONENTS

Four-quarter average percentage variations, 1991Q1-2010Q1



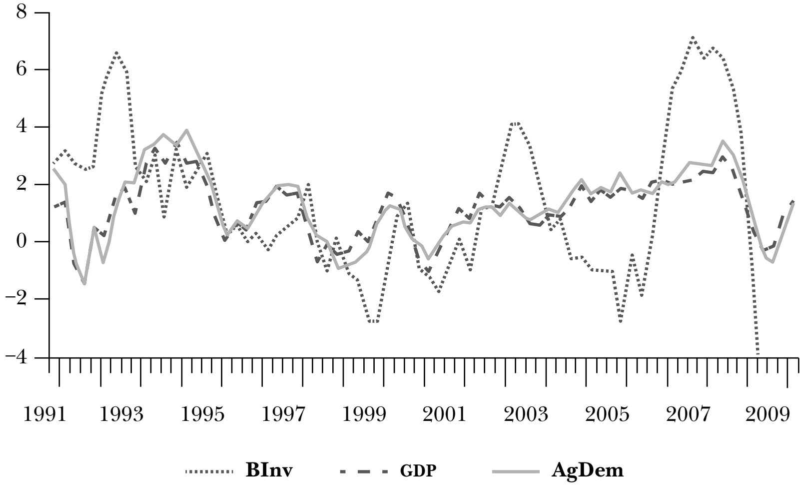
Source: author's calculations, using data at levels from the Banco Central de Reserva del Perú.

Figure 2 shows the same type of variations for these two variables, together with those of *AgDem*. It can be seen that *AgDem* and GDP grow at very similar rates. Meanwhile, the growth of *BInv* remained relatively close to aggregate demand since the reversal of the period of inventory overaccumulation at the end of 1994[7] and until the end of 1998. Later, three overaccumulations of growing magnitude are observed, the first ending

7 This episode of overaccumulation reflected, at first, the recovery of production recorded by the success of the stabilization program (inflation decreased drastically, although still at double-digit levels), as well as the optimistic outlook for the economy before the end of the internal war, in the second half of 1992.

Figure 2

INVENTORY STOCK, PRODUCTION AND AGGREGATE DEMAND
Four-quarter average percentage variations
1991Q1-2010Q1



Source: author's calculations, using data at levels from the Banco Central de Reserva del Perú.

at the peak of 2000Q2; the second at that of 2003Q2; and the third at that of 2008Q1.[8]

Although only aggregate data is available for inventory investment, *DInv*, the increasing amplitude of *BInv* growth cycles might be explained by the growing participation of goods-in-process inventories in the whole *DInv*, particularly in traditional export sectors.

2.2 Stylized Facts for Aggregate Inventory Flows

The stylized facts on the relation between inventory investment, sales and production in Peru are presented similarly to

[8] The third reversal reaches negative rates of around 12% between 2009Q4 and 2010Q1.

in the literature on US inventories. We attempt to explain two stylized facts: *1)* why is production more or less volatile than sales? and *2)* why are inventory investment and sales not negatively correlated?[9]

One approach to these stylized facts comes from the unconditional sample moments of *four-quarter average percentage variations*, with quarterly frequency, of different GDP components by type of expenditure (one subaggregate of which is aggregate demand excluding inventory investment, *AgDem*). Table 2 presents the mean and standard deviation of these changes, as well as their correlations with inventory investment variation (*DInv*) and calibrated inventory stocks (*BInv*)[10] for two sample subperiods: before and during the period following the international financial crisis arising from the US crisis in 2007-2008.

In terms of standard deviations, production in Peru is *less* variable than sales (demand) for all *AgDem* components except private consumption (in both subperiods). Might there be incentives to use inventories as a buffer against positive demand shocks and maintain smooth production growth?

Given the extreme values in the means and standard deviations of *DInv* variation, the changes of calibrated inventory stocks, *BInv*, is a more stable indicator. This is confirmed in its correlations with the variance of all expenditure components.

Correlations with *DInv* variation reveal that variance in inventory investment and sales (demand) are positively correlated

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9 A third stylized fact emerges from recent improvements in the quality of inventory investment statistics for developed countries: The most volatile components of inventory investment are not finished goods inventories of the manufacturing sector, but rather its commodity inventories, as well as retail trade inventories (see Blinder and Maccini, 1991).

10 High levels of volatility in inventory investment growth rates in Table 2 justify such calibration (see Annex A) and explain emphasis on the relations between growth rates of aggregate production, aggregate demand and a *calibrated* sequence of inventory stocks.

Table 2

GDP BY TYPE OF EXPENDITURE (GOODS AND SERVICES)

Four-quarter average percentage variations

	Mean (M)				*Standard deviation (S)*				*Corr with D(Inv) (R1)*				*Corr with B(Inv) (R2)*			
	1995-2007		*2008-2010*		*1995-2007*		*2008-2010*		*1995-2007*		*2008-2010*		*1995-2007*		*2008-2010*	
	m()	*%m(GDP)*	*m()*	*%m(GDP)*	*s()*	*%s(GDP)*	*s()*	*%s(GDP)*	*r()*	*%r(GDP)*	*r()*	*%r(GDP)*	*r()*	*%r(GDP)*	*r()*	*%r(GDP)*
I. Global demand (1+2)	5.0	108.2	6.1	96.7	4.3	124.2	6.4	156.6	0.11	120.4	−0.02	−124.5	0.53	111.5	0.97	100.9
Ib. Global demand (1b+2)	5.0	107.3	7.3	117.1	4.1	118.4	5.3	128.7	0.11	120.8	−0.11	−613.8	0.50	104.5	0.98	101.9
1. Domestic demand with *D(Inv)*	4.5	97.5	6.4	102.3	4.9	144.3	6.6	161.6	0.14	154.9	−0.02	−103.9	0.58	121.5	0.97	100.8
1b. Domestic demand without *D(Inv)*	4.5	96.2	7.9	126.8	4.7	136.0	5.3	128.8	0.14	157.9	−0.13	−686.9	0.55	116.0	0.98	101.6
a. Private consumption	4.1	87.5	6.2	99.4	3.0	88.3	2.8	69.3	0.08	94.4	−0.15	−836.6	0.58	121.8	0.99	102.7
b. Public consumption	4.9	104.6	7.7	123.1	5.0	146.5	5.4	130.8	0.13	147.8	0.27	1,437.7	0.11	23.6	−0.95	−98.8
c. Gross domestic investment	6.3	136.2	7.6	121.0	13.0	380.1	20.5	500.8	0.17	186.9	0.00	20.7	0.57	120.6	0.97	100.3
Gross fixed investment (GFI)	6.0	129.5	13.8	221.0	11.8	344.1	15.9	388.8	0.18	201.7	−0.12	−638.0	0.52	109.5	0.98	101.6

Table 2 (cont.)

	Mean (M)				*Standard deviation (S)*				*Corr with D(Inv) (R1)*				*Corr with S(Inv) (R2)*			
	1995-2007		*2008-2010*		*1995-2007*		*2008-2010*		*1995-2007*		*2008-2010*		*1995-2007*		*2008-2010*	
	m()	*%m(GDP)*	*m()*	*%m(GDP)*	*s()*	*%s(GDP)*	*s()*	*%s(GDP)*	*r()*	*%r(GDP)*	*r()*	*%r(GDP)*	*r()*	*%r(GDP)*	*r()*	*%r(GDP)*
– Private	7.3	156.4	10.5	166.9	13.4	391.6	17.7	431.6	0.16	183.8	−0.13	−678.1	0.54	113.2	0.98	102.1
– Public	1.6	35.4	32.5	519.5	11.6	338.5	9.2	225.1	0.15	173.4	−0.06	−340.0	0.15	31.0	0.77	79.5
Stocks variance *(D(Inv))*	−83.3	−1,792.2	0.8	12.9	583.3	17,036.7	319.7	7,804.7	1.00	1,122.8	1.00	5,408.0	0.16	34.5	−0.23	−23.5
Memo: inventory stocks *(S(Inv))*	2.7	57.7	6.1	96.9	7.6	220.6	24.4	595.5	0.16	184.0	−0.23	−1227.3	1.00	210.5	1.00	103.8
2. Exports	8.4	181.2	4.3	68.4	4.3	125.4	5.4	132.6	−0.13	−142.9	−0.05	−258.9	−0.32	−67.9	0.97	100.8
II. Global supply (3+4)	5.0	108.2	6.1	96.7	4.3	124.2	6.4	156.6	0.11	120.4	−0.02	−124.5	0.53	111.5	0.97	100.9
3. GDP	4.7	100.0	6.3	100.0	3.4	100.0	4.1	100.0	0.09	100.0	−0.02	−100.0	0.48	100.0	0.96	100.0
– Goods	5.0	107.7	5.2	83.7	3.8	110.5	5.1	124.0	0.03	34.1	−0.01	−58.0	0.37	77.2	0.96	99.9
– Services	4.5	96.0	6.8	108.9	3.4	98.8	3.6	86.9	0.12	136.0	−0.03	−136.1	0.52	109.5	0.96	100.1
4. Imports	7.4	159.6	5.6	89.5	10.3	299.7	17.0	415.8	0.13	145.3	−0.03	−163.1	0.55	116.4	0.98	101.4

Source: Author's calculations using data at levels from the Banco Central de Reserva del Perú.

in the period 1995-2007 for all components of *AgDem* except exports. In period 2008-2010, they are negatively correlated, except public consumption. The size of all the correlations with *DInv* variation is close to zero due to the large proportion of noise present in *DInv*.

Correlations with the variation of *BInv* are more informative: changes in calibrated inventory stocks and sales (demand) are positively correlated in period 1995-2007 for all components of *AgDem* except exports. They are also positively correlated in period 2008-2010 except for public consumption. The magnitudes of this second group of correlations take values far from zero due to a clearer sign in calibrated stocks *BInv* (a small proportion of noise).

Why are variations of *BInv* and that of demand not negatively correlated? Could there be additional incentives for accumulating inventories at a *higher* rate than the minimum needed to cover positive shocks in demand growth and thereby slow or stabilize production growth?

If firms' main incentive for holding inventories is to meet positive shocks in demand growth and thereby smooth the evolution of production in order to leverage complementary opportunities such as, for instance, low input prices, firms are said to be producing to build stocks. In this case, changes in *BInv* allow them to control supply in response to demand fluctuations. Nevertheless, successive periods with higher than expected demand growth rates lead to increased production to meet part of the unanticipated demand and even achieve additional growth in *BInv*. This extra incentive for larger *BInv* growth stems from a need to increase a nonfinancial asset that offsets higher short-term borrowing incurred to cover production when demand is growing just in case this demand growth reverts (successive periods with lower expectations regarding demand growth could have symmetric effects). Hence, *BInv* and production operate in a coordinated manner, but with different periods, where *BInv* can be more than just the main instrument for offsetting demand shocks over the short-term.

Finally, although the stylized facts favor these hypotheses, it is worth questioning their suitability. Should we consider the description of those *unconditional* moments as a correct description of the stylized facts for the relations between aggregate demand growth, on the one hand, and growth in *BInv* and GDP, on the other? According to the variance decomposition theorem, the conditional variance of an available data set is less than unconditional variance. A more general theory sets forth that conditional covariance is different to unconditional covariance (which is also valid for the correlations). Therefore, the unconditional moments can only provide a preliminary description. In this regard, this paper aims to determine whether the conditional moments of the data provide evidence for the presence of the demoderation phenomenon in Peru.

3. GENERAL THEORETICAL MODEL WITH HETEROSCEDASTICITY

Sensier (2003) presents a model that encompasses those of Blanchard (1983), Blinder (1986), Eichenbaum (1989), Kahn (1987), and Ramey (1991) based on the model of Callen et al. (1990) and Cuthbertson and Gasparro (1993). Being I_t a vector of M levels of inventories held by a representative firm by type of good k, for instance, if $M=3$, $k=1$ (finished goods); $k=2$ (work-in-progress) and $k=3$ (raw materials), denominated in units of some finished consumer good that serves as a numeral. Moreover, the vector of functions for its corresponding desired levels is defined as

1 $$I_t^* = I^*\left(\underbrace{S_t}_{+}, \underbrace{z_t^I}_{-}, \underbrace{h_t^S}_{+}, \underbrace{r_t^H}_{-}\right),$$

where S_t is the vector of sales in period t[11] of M types of goods (to the market and to the firm's transfer pricing area), z_t^I is a

[11] It is feasible to interpret this function for desired inventory levels in period t as dependent on sales in period t, whatever this level

vector of technological change factors in period t for inventory control procedures for M types of goods, r_t^H is the financial-tax benefit of holding inventories as an asset[12] in period t and h_t^S is a vector of M standard deviations in period t of the prediction error (one period ahead) of each component of vector of sales S_t, conditional to all data available up to current period t. The signs under each variable suggest the direction of dependence in comparative statics (Callen et al., 1990, and Cuthbertson and Gasparro, 1993). The costs or losses incurred for moving away from desired levels are defined as the function

2 $$C_t^A = C^A(I_t - I_t^*),$$

that has been named *accelerator* in the literature.[13] The physical cost of holding inventories, which includes renting warehouse space, maintaining a suitable environment for preserving the qualities of the goods (for instance, refrigeration), transport equipment upkeep and man-hours for operating it, among others, is defined as the vector of functions

3 $$C_t^m = C^m(I_t, \delta),$$

where δ is the vector with M rates of depreciation (maximum effective decrease allowed) of each good k held in the firm's inventories (for instance, δ^f is the component corresponding

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may be (including a predicted or expected level and elaborated with data available in any previous period $t-s$, where $s > 0$). The literature has typically considered it as dependent on expected sales for period t (see, for instance, Sensier, 2003; Cuthbertson and Gasparro, 1993; Blinder and Maccini, 1991).

12 See Sensier (1993). Callen et al. (1990) treat it as a unitary financial cost for holding inventories.

13 For instance, the sum of quadratic terms corresponding to each good k, multiplying each one by a coefficient $b_k/2$.

to finished goods).[14] The cost of producing finished goods is defined as the function

$$C_t^P = C^P(v_t, P_t), \quad (4)$$

where v_t is the marginal cost term that varies over time[15] and P_t is the level of production.[16] To simplify, from now on we assume that a firm only holds inventories of finished goods $\left(I_t = I_t^f\right)$, meaning all the vectors mentioned previously in this section are scalar.

The *inventories restriction* establishes a relation between production, sales, and finished goods inventory flows

$$P_t = S_t + \Delta I_t^f, \quad (5)$$

---

[14] In Blinder (1982, 1986a, 1986b) and Sensier (2003), C_t^m is a quadratic function in I_t^f without a constant and with coefficient $e_2/2$ for the quadratic term. Eichenbaum (1989) use a quadratic function, but with coefficient e_{1t} for the linear term (that varies over time). Here the physical holding costs depend on depreciation rates (that can vary over time).

[15] In Eichenbaum (1989) it is a stochastic shock to the marginal cost of producing P_t in order for the model to encompass the motive for production cost smoothing of Blanchard (1983) and West (1990), such as for instance a shock to relative factor prices. In general, it can be any variable that affects a firm's intertemporal production decisions, such as financial or liquidity position (Cuthbertson and Gasparro, 1993; Sensier, 2003) or a one step ahead sales forecast error (Sensier, 2003 also uses production forecasts in her estimates).

[16] In Blanchard (1983), Eichenbaum (1989), Sensier (2003) and West (1990), C_t^P is a quadratic function in P_t without a constant and with coefficients v_t for the linear terms and $a/2$ for the quadratic term. If a is positive, marginal production costs are rising and the model encompasses the production smoothing motive of Blinder (1986a); if a is negative, the model includes the case considered by Ramey (1991).

that is normally used to obtain total flows (billed and unbilled) of finished goods sales. The historic sequence of inventory flows can be used to obtain inventory stocks, for instance, of finished goods,

$$I_t^f = \left(1-\delta^f\right) I_{t-1}^f + \quad I_t^f, \tag{6}$$

i.e., an equation of perpetual inventories where δ^f is the depreciation rate of finished goods inventories.

Under these assumptions, the firm maximizes the conditional expectation of the present value of real benefit at time t, Π_t, with respect to the decision variable sequence, $\left\{I_{t+j}^f\right\}_{j=0}^{\infty}$, given predetermined variables I_{t+j-1}^f and sequences of the best forecasts of $\left\{S_{t+j}, z_{t+j}^I, r_{t+j}, h_{t+j}^S, v_{t+j}\right\}_{j=0}^{\infty}$ for the whole period considered in the present value, $\left[t, t+1, \cdots, \infty\right)$.

$$E_t\left[\Pi_t\right] \equiv \Big[\Sigma_{J=0}^{\infty} \beta^j \Big\{S_{t+j} - C^A\left(I_{t+j}^f - I^*\left(S_{t+j}, z_{t+j}^I, r_{t+j}, h_{t+j}^S\right)\right) - C^m\left(I_{t+j}^f, \delta^f\right) - C^P\left(c_{t+j}, S_{t+j} + \Delta I_{t+j}^f\right)\Big\}\Big], \tag{7}$$

where β is the discount factor and $E_t[.] \equiv E_t\left[.\,|\,\Omega_t\right]$ is the conditional expectation operator for full relevant data set Ω_t available for a firm at time t when it is going to determine the optimal sequence $\left\{\tilde{I}_{t+j}^f\right\}_{j=0}^{\infty}$. We have assumed that the sales income function is concave and that cost functions are all convex, meaning the first order condition (Euler equation) is the necessary and sufficient condition for an optimal.[17]

Eichenbaum (1989) solves this problem for a set of specific parameters where the first order condition gives a necessary

[17] This formula should include benefits stemming from all production and financial operations conducted by a firm, or at least those associated to different types of inventories. For in-

and sufficient condition. After appropriate algebraic manipulation, he obtains the condition for the optimal plan of inventory stocks $\left\{\tilde{I}^f_{t+j}\right\}^{\infty}_{j=0}$, according to which:

1) I^f_t depends positively on expected future sales $\left\{S^f_{t+j}\right\}^{\infty}_{j=0}$: Inventories are held for production smoothing;

2) I^f_t depends negatively on current sales S^f_t: Because marginal production costs are increasing, there is a margin above which firms would rather cover their sales with inventories than increase production;

3) I^f_t depends negatively on a current stochastic shock to marginal production costs v_t : When marginal production costs are high, firms would rather meet current sales with current inventories than increase production;

4) I^f_t depends positively on future shocks to marginal productions costs $\left\{v_{t+j}\right\}^{\infty}_{j=1}$: Firms would rather build up inventories with current production when current marginal production costs are low compared to future ones, and therefore meet future sales out of those stocks of inventories instead of future production; and

5) I^f_t depends negatively on the linear coefficients (present and future) of inventory holding costs, $\left\{e_{1t+j}\right\}^{\infty}_{j=0}$ (see note 14).

Formulating the problem of a representative firm assumes that the variables are stationary. Given that production and aggregate sales are not stationary, the problem must be rewritten

---

stance, costs associated to the factors of production for work in progress separated from finished goods, net benefits resulting from production operations for work-in-progress as well as financial operations such as purchases-sales of raw materials (the *inventories restriction* would be modified accordingly). The simple specification in terms of real benefits avoids considering the possibility for accounting part of the financial-speculative activities the corporate sector may perform with different types of inventories it holds.

through an appropriate normalization or alternatively by using a two-step approach proposed by Callen et al. (1990): *1)* propose a linear cointegration relationship between the *nonstationary* level of inventories and the determinants of a desired level of inventories; and *2)* use the cointegration error sequence to minimize total costs $C_t^T = C_t^m + C_t^P$ for each period as a function of inventory stocks.

The theoretical framework provides a qualitative explanation for the relation between the level of inventories and its determinants, although as mentioned previously, we will only use average percentage variations $(var\%)$ in the following sections.[18]

4. PROPOSED VARNN-ARCH MODELS

A family of dynamic models are immune to heteroskedasticity problems and are appropriate for both the conceptual model of the previous section and most models used in macroeconomics, where the aim is for the conditional means to be correctly calculated despite the presence of outliers and high variance episodes (Hamilton, 2008).

4.1 Conditional Means

First, we describe the models to be estimated for the conditional means. The first model for those moments is a typical linear multivalued function of VAR(K, p) models,

8
$$y_t = A_0 + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \varepsilon_t = A_0 + \Sigma_{j=1}^{p} A_j y_{t-j} + \varepsilon_t,$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N\left(0, \Sigma_t\right),$$

[18] Another justification for this can be found in the properties of elasticities ε_i of a scalar function that depends on n variables, $z_t = z\left(x_t^1, \ldots, x_t^n\right)$, or $var\%z_t = \sum_{i=1}^{n}\left(var\%x_t^i\right)\varepsilon_i$. The property is applicable to any of the functions used under this theoretical framework (including Euler conditions).

where $y_t' \equiv \{y_{1t}, y_{2t}, \ldots, y_{Kt}\}$ and $\varepsilon_t' \equiv \{\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{Kt}\}$ are vectors of K stationary variables, $\Omega_{t-1} \equiv \{y_{t-1}', y_{t-2}', \ldots, y_{t-p}'\}$ is the relevant data set and $\Sigma_t \equiv \left[\sigma_t^{ij}\right]$ is matrix $K \times K$ of conditional covariances of period t ($\sigma_t^{ij} = \sigma^{ij}$ for VAR(K,p) models).

The second group of nonlinear VAR models generalizes the model of Equation 8:

9 $$y_t = A_0 + g\left(\Omega_{t-1}\right) + \varepsilon_t \quad \varepsilon_t \mid \Omega_{t-1} \sim N\left(0, \Sigma_t\right),$$

where it is usual to postulate a specific nonlinear multivalued function $g(.)$, for instance, choosing (somewhat arbitrarily) the smooth transition function, VSTVAR, or the self-excited threshold function SETVAR (see Granger and Teräsvirta, 1993).

Instead of assuming a priori the knowledge of function $g(.)$, a hypothesis that is taken as a premise in modern macroeconomics, here we employ a more general assumption: the existence of unknown nonlinear patterns in the data. Hence, we propose using flexible dynamic models (neural networks) whose main property is precisely a high capacity for approximating those patterns in the data. In this context, we choose a network architecture named *multilayer perceptron* (MLP).[19] Its dynamic version (VARNN-perceptron or VARMLP) will be used to obtain an approximation (global) of the nonlinear multivalued $g(.)$, the one that best adjusts to nonlinear patterns in the data.[20] According to that architecture, this is made possible by combining a finite number of basic structured nonlinear H functions in a multilayer graph,

[19] See Dorffner (1996). This architecture of *artificial neural networks* (ANN) are used in temporal series (also known as *feedforward* ANN; see Kuan and Liu, 1995).

[20] A Taylor approximation requires a specific function and an approximation point.

$$g\left(\Omega_{t-1}\right) \approx \beta_0 + \Sigma_{i=1}^{H} \beta_i h_i\left(\Omega_{t-1}\right) = \Sigma_{i=1}^{H} \beta_i \Psi_i\left(\Delta_{0,i} + \Sigma_{j=1}^{p} \Delta_i\left(j\right) y_{t-j}\right), \tag{10}$$

where H units h_i are denoted *hidden units*, each one of which is a multivalued linear function Ψ_i whose components are bounded functions.[21]

4.2 Conditional Covariances

Second, we describe the family of models for the conditional covariance matrices of the model we will finally estimate. This is the family of multivariate ARCH models, of which the most well-known are VECH, BEKK and exponential. The VECH model is the most general,

$$vech\left(\Sigma_t\right) = c + \Sigma_{h=1}^{p} C_h vech\left(\varepsilon_{t-h}\varepsilon'_{t-h}\right) + \Sigma_{k=1}^{q} B_k vech\left(\Sigma_{t-k}\right), \tag{11}$$

where using a *vech* operator (that stacks elements above and below the square matrix diagonal) gives c as a vector of order $\left[K\left(K+1\right)/2\right]\times 1$ and $\{C_h\}$, $\{B_k\}$ are matrices of order $\left[K\left(K+1\right)/2\right]\times\left[K\left(K+1\right)/2\right]$. As mentioned in Ding and Engle (2001), their generality goes hand in hand with their reduced parsimony and the difficulty of imposing restrictions that ensure a sequence of positively defined matrices $\{\Sigma_t\}$ (except when imposing $\{C_h\}$ and $\{B_k\}$ diagonals).

The BEKK model is a restricted version of the VECH model that generates a sequence of positively defined $\{\Sigma_t\}$ matrices by imposing a quadratic parameter structure,

[21] Shachmurove (2002) mentions that a major advantage of ANNs is their ability to analyze complex patters quickly with a high degree of accuracy and without making assumptions about the distribution of the data. Among the disadvantages are the fact they tend to over-fit data and lack a standard structured method for choosing, developing, training and evaluating an ANN.

12 $$\Sigma_t = CC' + \Sigma_{h=1}^{p} D_h \left(\varepsilon_{t-h}\varepsilon'_{t-h}\right) D'_h + \Sigma_{k=1}^{q} E_k \Sigma_{t-k} E'_k,$$

where C, $\{D_h\}$ and $\{E_k\}$ are matrices $K\times K$ and only C is a lower triangle. Engle and Kroner (1995) provide the conditions by which a BEKK model encompasses all diagonal VECH models with a sequence of positively defined matrices $\{\Sigma_t\}$ and almost all VECH models with a set of positively defined matrices $\{\Sigma_t\}$. These conditions eliminate all redundant representations (that are observed as equivalent).

The possibility of asymmetries in conditional covariances has been taken into account through two strategies. The first imposes specific restrictions not necessarily substantiated by the data (for instance, those proposed in Ebrahim, 2000; see Annex B in Barrera, 2010) while the second, proposed by Kawakatsu (2006), uses specific unrestricted parameterization, which we will use to adapt the model for this study.

Kawakatsu (2006) proposes a generalization of the asymmetric model of Nelson (1991) to the multivariate case that manages to maintain the generality of the VECH representation through an innovative parametric structure that generates a sequence of positively defined $\{\Sigma_t\}$ matrices without the sensitive simplifications of Ebrahim (2000). Using a VECH representation, Kawakatsu (2006) proposes

13 $$\begin{aligned} vech\left(log(\Sigma_t)\right) - c_0 &= \Sigma_{h=1}^{p} C_t^{*} \varepsilon_{t-h} + \Sigma_{h=1}^{p} C_t^{**} \left(\left|\varepsilon_{t-h}\right| - E\left\{\left|\varepsilon_{t-h}\right|\right\}\right) \\ &+ \Sigma_{k=1}^{q} B_k \left(vech\left(log(\Sigma_{t-k})\right) - c_0\right), \end{aligned}$$

where $log(\Sigma_t)$ is the *matrix logarithm* of Σ_t, $vech\left(log(\Sigma_t)\right)$ and $c_0 \equiv vech(C)$ are vectors $\left[K(K+1)/2\right]\times 1$, C is a symmetrical matrix $K\times K$ and matrices $\left\{C_h^{*}\right\}$, $\left\{C_h^{**}\right\}$ and $\{B_k\}$ have dimensions $\left[K(K+1)/2\right]\times K$, $\left[K(K+1)/2\right]\times K$ and

$\left[K(K+1)/2\right]\times\left[K(K+1)/2\right]$, respectively. Matrices $\left\{C_h^{**}\right\}$ capture the *leverage effects* in the conditional covariance process.

Using the matrix logarithm transformation of the covariance matrix (symmetrical) means it is not necessary for $log(\Sigma_t)$ to be positively defined (or to impose any condition). Applying the exponential matrix (inverse) operation to that transformed space gives a covariance matrix that is symmetric and therefore positively defined. This allows any dynamic to be specified for this matrix, always generating a positively defined sequence of $\{\Sigma_t\}$ matrices.

If T is the number of observations, where $y_t' \equiv \{y_{1t}, y_{2t}, \ldots, y_{Kt}\}$ is the transposed vector of K variables and Θ is the column vector of all the parameters, the normal multivariate conditional density of $y_t \mid \Omega_{t-1}$ can be written as:

14 $$f\left(y_t \mid \Omega_{t-1};\Theta\right) = (2\pi)^{-\frac{K}{2}} \left|\Sigma_t\right|^{-\frac{1}{2}} exp\left(-\frac{1}{2}\left(\varepsilon_t'\Sigma_t^{-1}\varepsilon_t\right)\right);$$

and log-likelihood function $l_Q = \Sigma_{t=1}^{T} l_t$, is obtained, where $l_t \equiv log\left(y_t \mid \Omega_{t-1};\Theta\right)$. For comparison purposes, the contribution of observation t to this log-likelihood function is

15 $$l_t = -\frac{1}{2}\left(Klog(2\pi) + log\left(\left|\Sigma_t\right|\right) + \varepsilon_t'\Sigma_t^{-1}\varepsilon_t\right).$$

In the case of the exponential matrix model of Kawakatsu (2006), this expression can be written as

16 $$l_t = -\frac{1}{2}\left(Klog(2\pi) + logm\left(\left|e^{logm(\Sigma_t)}\right|\right) + \varepsilon_t'\left(e^{logm(\Sigma_t)}\right)\varepsilon_t\right).$$

Using the following exponential matrix and matrix logarithm properties:

1) For all square matrix A, $\left(e^{A}\right)^{-1} = e^{-A}$.

2) For all symmetrical matrix S, $logm\left(\left|e^{S}\right|\right) = traza(S)$.

We obtain

17 $$l_t = -\frac{1}{2}\left(Klog(2\pi) + traza\left(logm(\Sigma_t)\right) + \varepsilon_t'\left(e^{-logm(\Sigma_t)}\right)\varepsilon_t\right).$$

By adding the exponential matrix of Kawakatsu (2006) to the proposed nonstructural modelling, which includes a multivariate Student's *t* distribution, all the parameters are robust to the presence of atypical observations without imposing specific restrictions not necessarily substantiated by the data. This model is estimated for the case of Peru with 65 quarterly data for the period 1994Q1-2010Q1.[22] Al the variables are expressed as *four-quarter average percentage variations.*

Estimation of the dynamic flexible econometric model is feasible, despite computing restrictions, if the over-parameterization problem is addressed. The latter is common in neural network models and can reduce their usefulness for predictive purposes. Annex B describes the *maximum penalized likelihood* method for solving this problem and the associated reduced number of degrees of freedom.

4.3 A Contemporaneous Structure

We proposed a structural model for covariance matrix decomposition for the final period $t = T$ of the nonstructural VARNN-ARCH model estimated (although the following discussion is applicable to the covariance matrix of any period t). Using decomposition *AB*, matrix $(I-A)$ is triangular and matrix B is dimension diagonal $k = 5$. Ordering of the structural model $y_t \equiv \left\{XDem_t, PuDem_t, PrDem_t, BInv_t, GDP_t\right\}$ should be taken into account for interpreting its coefficients: The most

[22] The possibility of including the period of high inflation and its subsequent stabilization was rejected due to considerable fluctuations in relative prices. With the lags in conditional means and lags in conditional covariances, the estimated sample of conditional covariances includes 41 observations (2000Q1-2010Q1).

exogeneous shocks correspond to those of the growth rates of $\left\{XDem_t, PuDem_t, PrDem_t\right\}$, in response to which follows the compensatory action of the shock to the growth rate of $\left\{BInv_t\right\}$ (according to prevailing incentives), all of which finally determines the shock in the growth rate of $\left\{GDP_t\right\}$.

Expected values or signs of coefficients a_{ij} in the matrix (*I–A*) come from the theoretical model described in Section 3. We postulate that there are contemporaneous relations among shocks to the three aggregate demand components: It is anticipated that $\left\{PuDem_t\right\}$ fulfills some type of compensatory function in response to shocks in $\left\{PrDem_t\right\}$ and $\left\{XDem_t\right\}$ (*inverse* relations reflected in *positive* coefficients immediately below the main diagonal of the submatrix (1:3,1:3) of (*I–A*); see Table 3). Moreover, shocks in all three components affect firms' inventory and production decisions. If a firm's only incentive for holding inventories was production smoothing, the contemporaneous relations between $\left\{BInv_t\right\}$ and the three aggregate demand components would be *inverse* and reflected in *positive* coefficients in the fourth row of (*I–A*). However, if there are additional incentives for increasing $\left\{BInv_t\right\}$, these relations might be *direct* (*negative* coefficients in said row). Furthermore, while production smoothing, $\left\{GDP_t\right\}$, would free it from demand shocks (coefficients in the fifth row would be null), *additional incentives* would generate *direct* relations between supply shocks[23] and all the rest (*negative* coefficients in that row).[24]

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[23] As mentioned in Section 3, production shocks encompass marginal costs shocks (for instance, in the relative prices of factors of production) and technology shocks (investments that improve capital assets), but also include shocks to production processes (problems of logistics such as, for instance, cuts in energy supplies for manufacturing or mining, or shortages in inputs such as water for agricultural production, etc.).

[24] Section 2 does not mention that growth of $\left\{AgDem_t\right\}$ is a weighted average of the growth of the first three components of the vector

Table 3

MATRIX (I–A)

Affect a structural shock in:	*Structural shocks of*				
	XDem	*PuDem*	*PrDem*	*BInv*	*GDP*
XDem	1	0	0	0	0
PuDem	a_{21}	1	0	0	0
PrDem	a_{31}	a_{32}	1	0	0
Binv	a_{41}	a_{42}	a_{43}	1	0
GDP	a_{51}	a_{52}	a_{53}	a_{54}	1

5. RESULTS

From an econometric and statistical standpoint, it is worth questioning the relevance of using such general assumptions, performing statistical tests to validate the need for them, either individually or jointly. The answer, however, should consider the need to nest simpler hypotheses within the proposed model, a consideration that has proved hard to find in the literature consulted on the penalized likelihood (see Annex B).

The results of the proposed general observation tool that imposes a minimum number of maintained assumptions (with the additional cost associated with their estimation) are shown below. Another significant product of this tool is the availability of conditional covariances estimates (conditional variances indicate periods of greater uncertainty for each variable in the model).

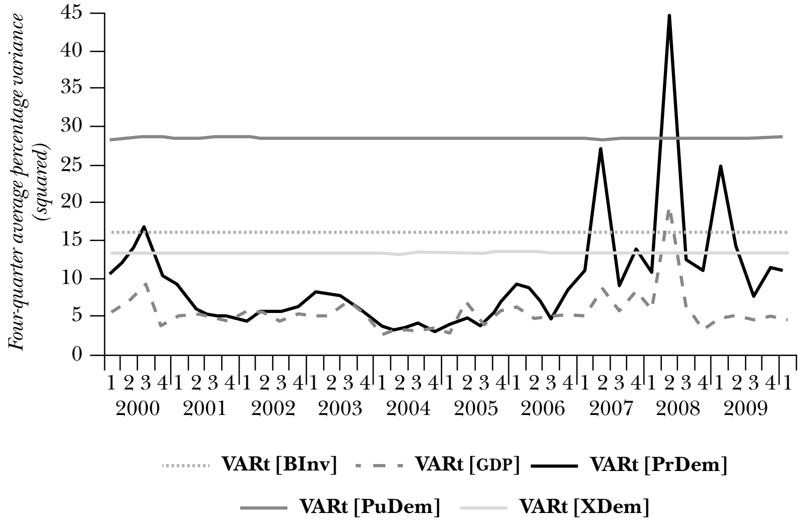
5.1 Nonstructural VARNN-ARCH Model

Figure 3 shows the conditional variance of four-quarter average percentage variations for each of the three aggregate

of endogenous variables.

Figure 3

CONDITIONAL VARIANCES OF THE AGGREGATE DEMAND COMPONENTS, INVENTORIES, AND PRODUCTION
2000Q1-2010Q1



demand components, inventories, and production (i.e., units are squared variations).

It can be seen that the conditional variances of *PrDem* and GDP change over time, while that of *BInv*, *PuDem,* and *XDem* appear as pseudo-constants due to the variation range of conditional variances that clearly change over time.[25]

Conditional variances of *PrDem* and GDP tend to rise contemporaneously, standing out the more recent jumps in uncertainty. Meanwhile, the sequence of conditional variances for GDP tends to be smaller than the sequence corresponding

[25] These two wide ranges of variation could reflect the need to separate *quanta* from relative prices inherent to original units (1994 nuevos soles) for including them in larger sized models (and difficult to estimate). In any case, all conditional moments of the model estimated are so with respect to the small number of included variables.

to *PrDem*, which reflects the existence of a degree of production stabilization with respect to *PrDem* that is attributable to inventory management and is more noteworthy in the event of jumps in the uncertainty of *PrDem*. As for pseudo constant conditional variances over time, that of the *PuDem* is greater than that of *BInv*, and that one is in turn larger than that of *XDem*. Given that these pseudo constants tend to be larger than the variances that change over time (*PrDem* and GDP), production stabilization is performed for each of those aggregate demand components.

With respect to the estimated conditional variance sequence for *AgDem*, which has been added to the previous figures, we calculated it based on the conditional covariances submatrix of its three components (*PrDem*, *PuDem*, and *XDem*).

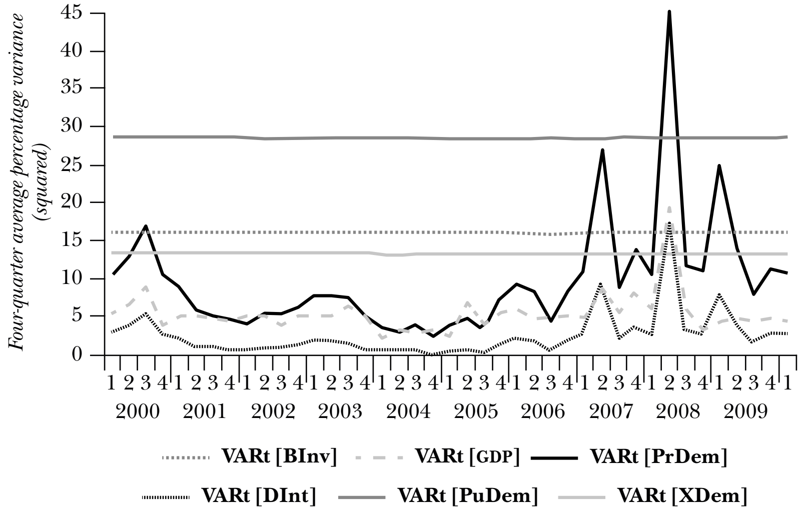
The conditional variance of *AgDem* confirms the possibility that motivated this study: That it is smaller than the conditional variance of GDP (except in one quarter subsequent to the recent period of maximum uncertainty) and with a relative magnitude of around one to four (during the period of low lower uncertainty). This result is in contrast to results obtained with unconditional variances (see Table 2), explained by the impact of conditional covariances among their three components.

To conclude, aggregate management of inventories leads to production stabilization through mechanisms that are reflected in the conditional covariances of variances in all three components of *AgDem* (*PrDem*, *PuDem,* and *XDem*). The evolution of all 15 different entries in the conditional covariance matrix (standardized) is presented in Annex C. Two out of the three covariances that intervene in calculating *AgDem* variance are negative, (*PrDem*, *XDem*) and (*PuDem*, *XDem*), which contributes to the sequence of the variance of *AgDem* being closer to abscissa (see Figure 4).

Covariances (*BInv*, *PuDem*) and (*BInv*, *XDem*) are negative, reflecting expected inverse relations when there are no other incentives for holding inventories except GDP smoothing. Covariance (*PrDem*, *BInv*) is the only positive one, reflecting the expected direct relations when there are additional incentives for *BInv* growth.

Figure 4

CONDITIONAL VARIANCES OF THE AGGREGATE DEMAND COMPONENTS, INVENTORIES, PRODUCTION, AND INVENTORY INVESTMENT
2000Q1-2010Q1



5.2 Structural VARNN-ARCH Model: Contemporaneous Structure

Table 4 displays the coefficients estimated for the matrices of *AB* decomposition of the conditional covariance matrix estimated for the last sample period (T=2010Q1). Note that items below the diagonal in ($I-A$) have the opposite sign to those of the corresponding items of A, while items different to zero in matrix B (its diagonal) are shown as a column vector.

All the parameters estimated in the matrix ($I-A$) for period T of the sample are statistically equal to zero, except the parameter that measures the *positive* impact of the *PrDem* structural shock on GDP (−1.207 in the table). Estimates in period T of the sample reveal that the contemporaneous relations between *BInv* and *AgDem* components are statistically equal to zero. Therefore, GDP growth smoothing is not the only incentive

Table 4

ESTIMATED CONTEMPORANEOUS RELATIONS
SpVARNN-ARCH with five variables

			I−A				
			1	*2*	*3*	*4*	*5*
		B	*XDem*	*PuDem*	*PrDem*	*BInv*	GDP
1	*XDem*	3.671	1.000				
		(1.985)					
2	*PuDem*	5.361	0.053	1.000			
		(1.679)	(0.123)				
3	*PrDem*	3.332	0.059	(0.047)	1.000		
		(1.112)	(0.074)	(0.118)			
4	*BInv*	4.040	0.044	0.172	(0.076)	1.000	
		(0.521)	(0.117)	(0.188)	(0.115)		
5	GDP	1.822	(0.013)	(0.002)	(1.207)	(0.008)	1.000
		(1.335)	(0.016)	(0.026)	(0.016)	(0.033)	

for increasing *BInv* in that period, meaning there are possibly *additional incentives* for it. The only parameter statistically different from zero is consistent with the presence of additional incentives, which according to the macroeconomic context of that period means that negative shocks in *PrDem* growth are reflected in decreases in production growth measured in GDP.

On the basis of these contemporaneous relations we obtain the response functions for any variable i after a 1% change in any variable j (*impulse response functions*), denoted as $FRI\left[j \rightarrow i\right]$. Impulse response functions (IRF) were calculated as the difference between two projections that are not based on a stationary state: a projection with the structural shock from period T, the last period of the sample, and a projection without this shock (see Koop et al., 1996).

The IRFs do not generally show asymmetries in the sign or magnitude of shocks, although the scale of contemporaneous impacts (responses in period T) dominate the scale of the rest of the sequence (responses in periods $T+h$, $h \neq 0$). For this reason, IRFs are presented in 2×2 subgraph matrices: IRFs in the first row include contemporaneous impacts, while those in the second row exclude them.[26]

5.3 Impulse Responses in the *PrDem*

Figure 5 displays IRFs for estimated increases in *BInv* and GDP after a shock of 1% in *PrDem* growth. This positive structural shock in *PrDem* causes GDP growth to increase at the time of impact, it falls soon after and then continues to decline slowly towards zero. Meanwhile, *BInv* growth increases upon impact, continues increasing very slowly and then falls 10 quarters ahead.

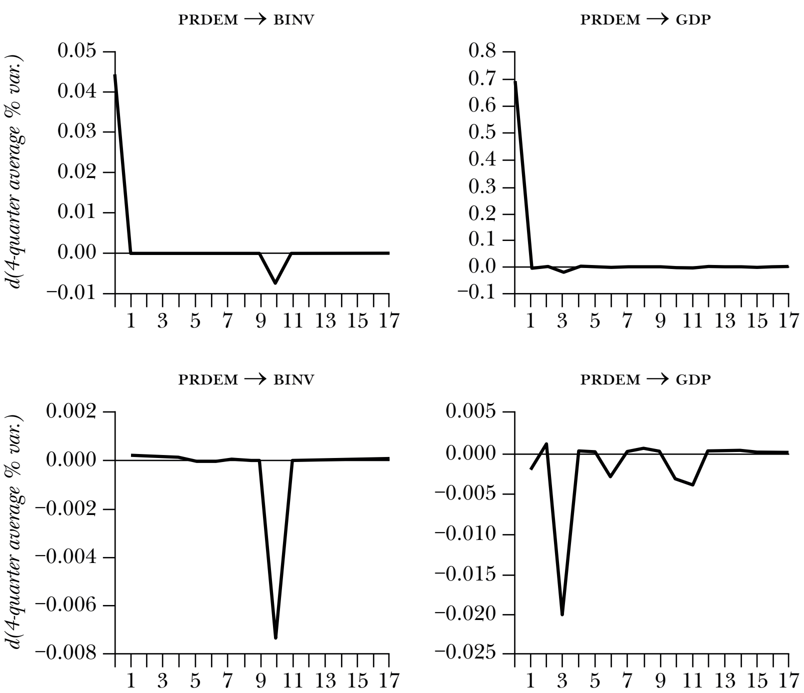
Considering the relative magnitudes, a positive structural shock in *PrDem* growth is initially absorbed by a sharp increase in the GDP growth and a slight increase in *BInv* growth (which is followed by a delayed smaller decrease 10 quarters ahead). This behavior is in disagreement with simple intuitive inventory management, but consistent with *additional incentives* for raising the growth of *BInv*, such as lags in the adjustment of the aggregate production process and induced price changes that maximize private profits (high current prices with respect to the marginal production costs of stocked goods, not necessarily finished goods).

The model estimated captures here the episodes where inventory investment amplifies the response of GDP to large negative demand shocks (during the recessive phases of Peru's

[26] The first row of graphs includes the value of the coefficient corresponding to the estimated contemporaneous impact in matrix A (Table 4), which is typically greater (in absolute value) than the contemporaneous impact in the corresponding IRF due to the way it was calculated.

Figure 5

IMPULSE-RESPONSE FUNCTIONS FOR ESTIMATED INCREASES IN BINV AND GDP AFTER A SHOCK OF 1% IN PRDEM GROWTH



economy since the start of the 1990s, particularly the most recent one), the *demoderation* phenomenon mentioned in Section 1.

Limitations to inventory statistics in Peru[27] make it necessary to postpone a strict comparison of a new hypothesis

[27] Barrera (2009) employs 12-month average percentage changes to date the phases of business cycles in Peru's economy with monthly periodicity. Using those units avoids problems for measuring real monthly levels, making the monthly dates for peaks

expounded in the literature that the recent international crises explain most of the recent fluctuations in the inventory cycle (especially in exportable primary products) and therefore in the activity of an increasingly globalized economy such as Peru's (see Alessandria et al., 2010).[28] This paper provides indirect evidence to support this hypothesis.

5.4 Impulse Responses in *PuDem*

Figure 6 displays IRFs for the estimated growth in *BInv* and GDP after a shock of 1% in *PuDem* growth. In response to a positive structural shock in *PuDem* growth, *BInv* growth falls upon impact and subsequently remains unchanged until it increases 10 quarters ahead. On the other hand, GDP growth increases upon impact, then rises very slightly and falls lightly after which it exhibits a series of small falls and rebounds with the zero line as a ceiling.

Given the relative magnitudes, an increase in *PuDem* growth is absorbed by a significant fall in *BInv* growth and a small increase in GDP growth. The tendering process associated with government expenditure, very different on aggregate from the private expenditure process, can explain this behavior more in line with intuitive inventory management, but opposite to that resulting from a shock in *PrDem* (of the same sign).

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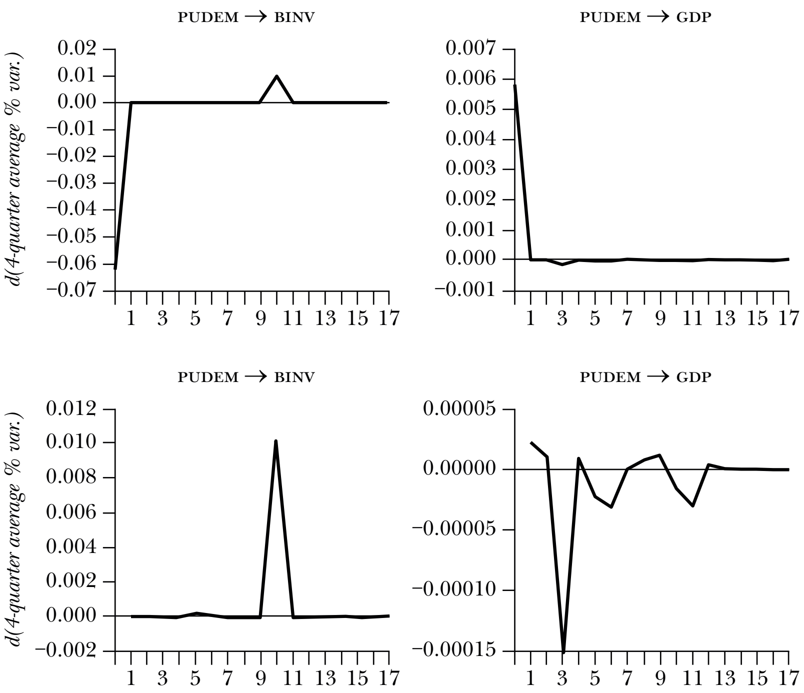
and troughs more robust. Given those dates, if the coefficients (inventory investment) / GDP of recessionary phases in Peru are calculated using real quarterly flows in millions of 1994 soles, only the coefficient corresponding to the recession between December 1997 and August 1999 (1997M12-1999M8) will be valid.

[28] Disaggregating inventory investment into its typical components (inputs, work-in-progress and finished goods) is not feasible with data for Peru, and even less so with its external trade components (exports, imports and nontradeable goods). The latter disaggregation is used by Alessandria et al. (2010) for USA.

Figure 6

IMPULSE-RESPONSE FUNCTIONS FOR ESTIMATED INCREASES IN BINV AND GDP AFTER A SHOCK OF 1% IN PUDEM GROWTH

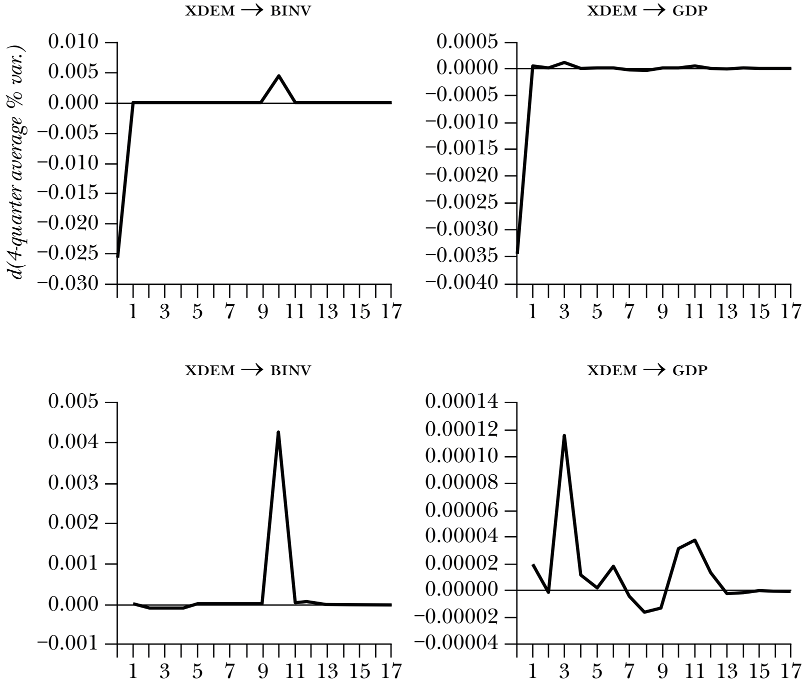


5.5 Impulse Responses in XDem

Figure 7 displays IRFs for the estimated growth in *BInv* and GDP after a shock of 1% in *XDem* growth. In response to a positive structural shock in *XDem* growth, *BInv* growth falls upon impact and then remains unchanged until it increases marginally 10 quarters ahead. Meanwhile, GDP growth decreases almost unnoticeably and subsequently posts a series of modest increases and decreases.

Figure 7

IMPULSE-RESPONSE FUNCTIONS FOR ESTIMATED INCREASES IN BINV AND GDP AFTER A SHOCK OF 1% IN XDEM GROWTH



Given the relative magnitudes, an increase in *XDem* growth is absorbed by a fall in *BInv* growth as well as an imperceptible drop in GDP growth. With respect *BInv* growth, the response is qualitatively similar to the response to a positive structural shock in *PuDem*, meaning it is not possible to reject that the way sales of goods and services are conducted abroad has similar effects to those that stem from the way sales are made to the federal government on aggregate inventory management. In both cases, the magnitude of responses in GDP growth reflects the fact that GDP growth is not the main adjustment channel. Nonetheless, decreases in GDP growth in response to the shock in *XDem* can be understood as the impact of mining production dynamics (where production is reduced when external prices are high).

5.6 Observations

IRF calculations employ a projection without a shock that is not based on a stationary state. A comparison of this projection with the recent execution of aggregate demand components for the 2010Q2-2010Q4 (out of sample) was not encouraging, reflecting that the propagation of shocks during the last two years point to a scenario of an economic slowdown in the medium term.

IRF patterns do not follow a smooth transition as in the over-parameterized linear VAR models. For instance, those for *BInv* are reflected upon impact as well as 10 quarters after the shock to any component of *AgDem* (although with different signs), which is explained by different ways for contracting or demanding goods and services.[29] This lack of a smooth transition is normally obtained when exclusion restrictions are imposed (parsimony) on the parameters of a linear VAR model (see Lütkepohl, 2005). It could also result from the penalized log-likelihood (see Annex B) used when parsimoniously estimating a VARNN-ARCH model.

[29] Another explanation is that mechanisms associated to aggregate inventory management are not reflected so much in their conditional means (that serves to quantify them) as in their conditional second moments. In structural terms, more comprehensive inventory management includes risk factors associated to profits and losses. In econometric terms, it is possible that maximization of the penalized log-likelihood reflects the dominance of changes in the conditional covariance matrix over the quadratic errors of the conditional mean vector.

Finally, the absence of asymmetries in shock response with different signs or magnitudes might be a preliminary but robust result. Optimization of the penalized log-likelihood of a neural network model (see Annex B) is equivalent to a learning process, and this could be lengthy. Due to computing time restrictions, the optimization must be truncated after a large number of iterations, without the network having detected asymmetries. However, the *t*-Student distribution allows for discarding spurious asymmetries in conditional means, making it possible to state that the neural network has still not detected asymmetries in the data because they are not evident.

6. CONCLUSIONS AND OUTLOOKS

This paper econometrically approximates the potentially significant nonlinear effects (asymmetries) that inventory management exerts on production dynamics considering that its volatility varies over time. To that end, we decompose aggregate demand into three components (domestic public, domestic private and external).

The most important results are shown in terms of conditional covariances. Covariances (*BInv*, *PuDem*) and (*BInv*, *XDem*) are negative, reflecting the expected inverse relations when there are no incentives for holding inventories except production smoothing. Covariance (*BInv*, *PrDem*) is the only positive one, reflecting the expected direct relation when there are additional incentives besides smoothing GDP growth. In terms of contemporaneous relations, the only parameter statistically different from zero is consistent with the presence of such additional incentives. This parameter indicates that a positive shock in *PrDem* will be mainly absorbed by *a more than proportional increase* in the production rate shock, meaning there is an amplifier effect (demoderating) of demand shocks on the evolution of production that is explained by the inventory cycle. In fact, some of this faster production rate will be used for increased inventory accumulation, which will probably allow for maximizing profits when current prices are high with respect to the marginal production costs of stocked goods.

Another incentive for holding inventories stems from the need to have a nonfinancial asset that allows for offsetting short-term borrowing incurred to cover production when demand is growing in the event such increased demand reverts. Precisely, given the symmetry found in IRFs, a negative shock in *PrDem* will be offset mainly by a slower rate of production, as well by decreases in the growth of inventory stocks (although to a lesser extent). This result might be consistent with inventory management that takes into account lags in the adjustment of the aggregate production process, as well as changes induced in prices that maximize private profits, particularly when current prices are high compared to the marginal production costs of stocked goods (not necessarily finished goods). In this regard, there are indications that the amplifier effect (demoderating) could be explained by the inventory cycle of raw materials or work-in-progress (although we do not have the data to prove this more specific hypothesis).

The model estimated partly captures episodes around the turning points of GDP in which inventory investment amplifies the response of GDP to large demand shocks. This paper, therefore, provides indirect evidence to support the hypothesis that recent international crises mostly explain recent fluctuations in the inventory cycle (especially for commodity exports) and therefore in the activity of an increasingly globalized economy such as Peru's (see Alessandria et al., 2010). This would provisionally explain the demoderation described in Section 1, particularly in the average incidence of inventory investment growth on real GDP growth during four recently observed recessions in Peru (before that generated as a consequence of the US crisis in 2007-2008; see Table 1).

There is clearly a need to include other potentially relevant variables (some of which are not available for Peru's economy, such as disaggregated inventory investment in raw materials, work-in-progress and finished goods). Given the absence of such disaggregated data, the results of this inventory investment model with aggregate data regarding production *stabilization* could represent a reference for more complete models that manage to include inventories of work-in-progress and raw materials (separate from finished goods) in conditional covariance index modelling. This would provide more appropriate evaluation of production stabilization in terms of conditional second moments, as well as an improvement in the capability of representing the structure of relationships in conditional means and, therefore, in the model's predictive capacity.

ANNEX

Annex A. Aggregate Stock of Inventories according to the Perpetual Inventory Method

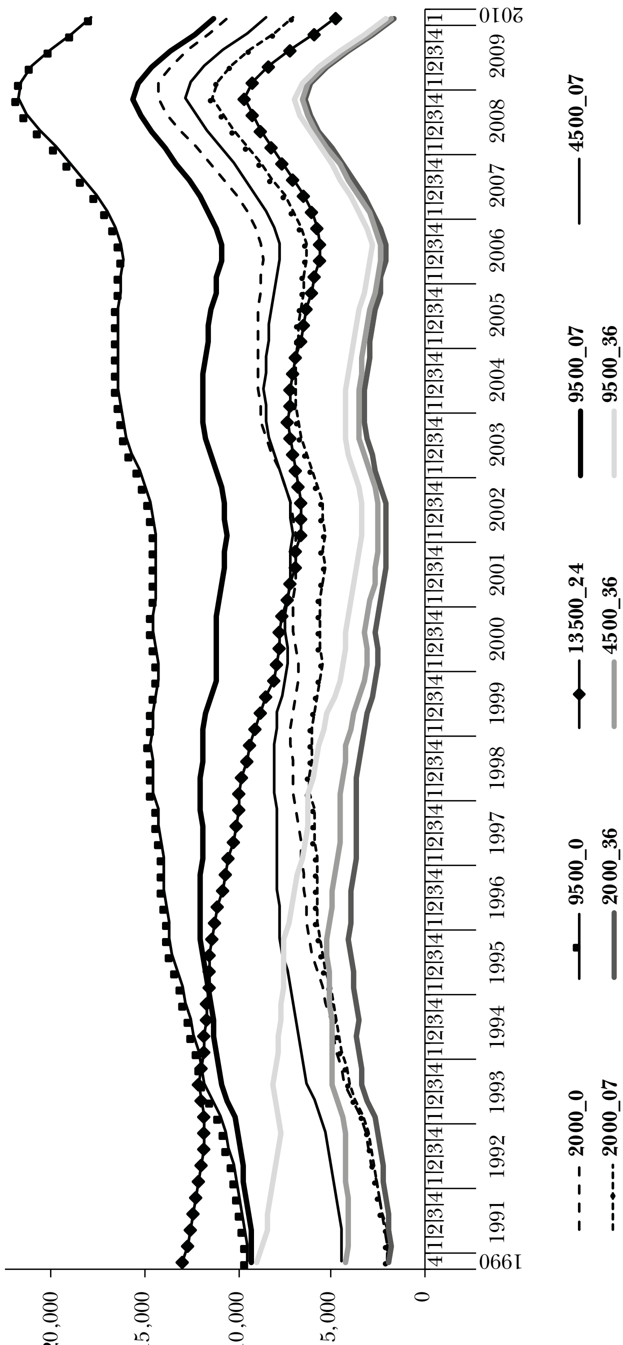
In Peru's experience, shifts in inventory investment have contributed (amplified) recessionary phases since the start of the 1990s. With the US financial crisis (2007-2008), this amplification is more noteworthy, unfolding a demoderation phenomenon in contrast to the Great Moderation observed in the business cycles of the US economy (see introductory discussion). In any case, highly volatile inventory investment growth rates in Peru (see Table 2 in the main text) reveals the need for using a calibrated series of aggregate inventory stocks instead of a series of changes in inventory.

This annex explains the assumptions employed for calibrating a series for the aggregate stock of inventories. This is obtained based on inventory changes data through two quantitative assumptions: *1)* initial inventory stocks and *2)* the depreciation rate. Figure A.1 presents a set of alternative sequences with initial stocks of between 2,000 million and 13,500 million 1994 soles for the first quarter of 1990, as well as quarterly depreciation rates of between 0.0% and 3.6% (a rate of 2.4% corresponds to that of physical capital that depreciates in 10 years).

Figure A.1

ALTERNATIVE SEQUENCES FOR THE BALANCE OF INVENTORIES IN MILLIONS OF 1994 SOLES

1990Q4-2010Q1



All these inventory stock sequences indicate that, before the international crisis of 2008 affected most economies in the region (2008Q3), Peru had been registering significant inventory accumulation that reached a peak in 2008Q4, just after the initial impact of the crisis was perceived in financial variables such as the exchange rate and interest rates (August 2008). In terms of inventory stocks, the impact of the crisis is evident since the start of 2009 in the form of an unprecedented deaccumulation in the available sample (1990Q4-2010Q1).

All deaccumulations associated to the financial crises of 1995, 1998-1999 and 2001 appear small in size and generally affect the evolution of inventory stocks cumulatively, for instance, when assuming a depreciation rate higher than that for physical capital (for instance, with a quarterly rate of 3.6%) and 2,000 million or 4,500 million of initial stock. If we wish to reduce the preponderance of the sharp accumulation and later deaccumulation of inventories associated to the international crisis of 2008 in the sample, the initial stock can be raised slightly to above 5,000 million, which would be qualitatively compatible with high inventory levels expected to be registered at the start of the 1990s.[30] This paper explicitly addresses the conditionality of all the results with respect to these two quantitative assumptions: *1)* initial inventory stock and *2)* depreciation rate.[31]

[30] Fujino (1960) refers to high levels of inventory stocks of finished goods as a percentage of demand in some Japanese industries in 1950 or 1951 due to speculation under the setting of the Korean war (June 1950 to July 1951). Japan provided military, logistical and medical support to the allied forces led by USA.

[31] The results shown use a calibrated sequence of inventory stocks that assumes an initial balance of 2,000 million 1994 nuevos soles and a null depreciation rate (perpetual inventories).

Annex B. Estimation via Penalized Maximum Likelihood

Estimation of multiple time series models typically finds the problem of over parameterization unsurmountable. The usual strategies for tackling this problem have been elimination algorithms with stepwise and a data criteria sequence, thereby achieving parsimonious models.

Based on statistical applications to penalized regression problems in chemistry and biology (molecule and genotype structures), the literature on parameter shrinkage has re(emerged); in it a penalization function in them, is included which is added to the function that typically optimized in parameter estimation (GLS, GMM or MV).[32]

In the case of MV estimation, the loss function minimized is the negative of log-likelihood, which we denote as $L(\theta)$, where θ is a parameter vector. In a system with multiple variables, this vector θ can be decomposed into two blocks: interceptors α and all other parameters β, to define the penalized loss function as

B.1 $$g(\theta) \equiv L(\theta) + P_{\lambda}(\beta),$$

where $P_{\lambda}(\beta)$ is one of the three penalized functions available in the literature (see McCann and Welsch, 2006, and Ulbricht and Tutz, 2007) that depend on tuning parameters λ_i (positive):

[32] The typical MCO estimator minimizes $SSE(\tilde{\beta}) \equiv (y - x\tilde{\beta})'(y - x\tilde{\beta})$. To avoid a potential problem of multicollinearity, the ridge estimator $\tilde{\beta} \equiv [x'x + \lambda Q]^{-1} x'y$ was devised to minimize $SSER(\tilde{\beta}) \equiv SSE(\tilde{\beta}) + \lambda \tilde{\beta}' Q \tilde{\beta}$, where Q should be a positively defined arbitrary matrix and $\lambda > 0$ so the MCO estimator *regularizes* (see Firinguetti and Rubio, 2000, for references and a generalization). Returning to our context, a parsimonious estimator belongs to this same family of estimators because $Q = I$ obtains the penalized version of $SSE(\tilde{\beta})$.

1) Lasso or *L1* (strong zeros; Tibshirani, 1996),
$P_\lambda(\beta) \equiv \lambda \sum_{i=1}^{q} |\beta_i|$.

2) Ridge or *L2* (against over-parameterization),
$P_\lambda(\beta) \equiv \lambda \sum_{i=1}^{q} \beta_i^2$.

3) Elastic network (*L1* and *L2*), $P_\lambda(\beta) \equiv \lambda_1 \sum_{i=1}^{q} |\beta_i| + \lambda_2 \sum_{i=1}^{q} \beta_i^2$.

The most direct reason for optimizing this new loss function is clearly that of estimating the parameters at the same time as selecting the specification (Fan and Li, 1999). This model selection is apparently more direct than the alternative of performing a series of hypothesis tests. Nonetheless, the main motivation is to reduce the mean squared error (MSE) of the sample. One well-known econometric result is that the MV estimator over-estimates the length of the true parameter vector when the regressors are not orthogonal amongst each other, causing significant bias in the MV estimator. Minimizing this bias led to the family of *ridge* estimators (see Fomby et al., 1984, pp. 300-302 and references), specifically an MV estimator with restrictions or penalties.

However, similarly to the *ridge* family of estimators (see note 29), it is necessary to determine tuning parameters $\lambda > 0$ through a set of estimations for different values of λ. [33]

B.1 Tuning λ Parameters in VARNN-ARCH Models

We define the estimator we will use as

$$\theta(\lambda) \equiv \arg\min\{g(\theta)\}. \tag{B.2}$$

[33] The complexity of the resulting optimization problem for each fixed value of λ is considerably greater, meaning addressing it various times to fill a grid and thereby select the tuning parameters (and associated β parameters) is extremely costly in computational terms. For the simple case of a *lasso* regression, a group of algorithms has been proposed (see Wu and Lange, 2008).

Tuning parameters λ are basically Lagrange multipliers and are usually determined in such way that the asymptotic mean squared error (MSE) of estimator $\theta(\lambda \neq 0)$ is less than the asymptotic variance of the estimator of MV, $\theta(\lambda = 0)$. This determination is direct in a simple problem such as a linear regression, but generally requires, in the case of the *elastic network*, a search algorithm in an $\mathbb{R}^2_{++}$ mesh with simulation at each point of it, a procedure too computationally costly for a VARNN-ARCH model.

The alternative is to define its optimization as a *weak apprentice*, i.e., (λ_1, λ_2) with large values to force small changes in each maximum likelihood iteration and thereby obtain more stable estimates (Ulbricht and Tutz, 2007).[34] The advantage of this likelihood penalization is that neural network training and pruning is performed in parallel, meaning the neural network can adapt for minimizing errors associated with pruning (see Reed, 1993). This alternative was the first to be used for a VARNN-ARCH model, without managing to converge after a large number of iterations.

After forcing very small changes with large values for (λ_1, λ_2), we used ad hoc values based on the proposals of Fan and Li (1999), i.e.,

B.3 $$\lambda_i = \sqrt{2\log(nparam)},$$

where *nparam* is the total number of θ parameters in the model. This strategy did not manage convergence for an even higher number of iterations (three million). The results reported in this version of the paper use nonstructural parameters of the VARNN-ARCH estimated using this strategy.

[34] In fact, the nonlinear classification problems that are typical applications of neural networks, optimization of the objective function $L(\theta)$ is established around a set of desirable values, defining these regularization penalties and fixing parameters (λ_1, λ_2) through other criteria. See Jaakkola (2006).

B.2 Alternative to a Single Tuning Parameter

Finally, results were obtained with the truncated maximum (reaching the maximum number of iterations without converging) of the penalized likelihood function for a lasso function using the value of the previous equation for the single tuning parameter. These results have allowed for estimating the proposed contemporaneous structure and performing *provisional* tests on it (they would not be provisional if the required convergence had been achieved), which has been reflected in a lack of accuracy of the projections generated. Although convergence has not been produced after a prohibitive number of iterations, in this subsection we present an alternative tuning strategy proposed by Wang et al. (2007).

Wang et al. (2007) propose discarding the lasso penalty with a single tuning parameter due to the potentially significant bias it generates and using multiple tuning parameters, in fact, one for each parameter of the unpenalized likelihood function.

B.4
$$\lambda_i = \frac{\log(nparam)}{nparam\lambda_i}.$$

Greater parametric complexity in the penalization function proposed in Wang et al. (2007) is addressed through a profitable strategy for estimating in a first stage all the tuning parameters for optimizing the unpenalized likelihood, and then using said estimates in a second stage of penalized likelihood optimization. Another advantage of this strategy is that it solves the problem of a lack of asymptotic characteristics required for performing statistical tests when there is only one tuning parameter.

Annex C. Evolution of Conditional Covariances (Standardized)

Figure C.1

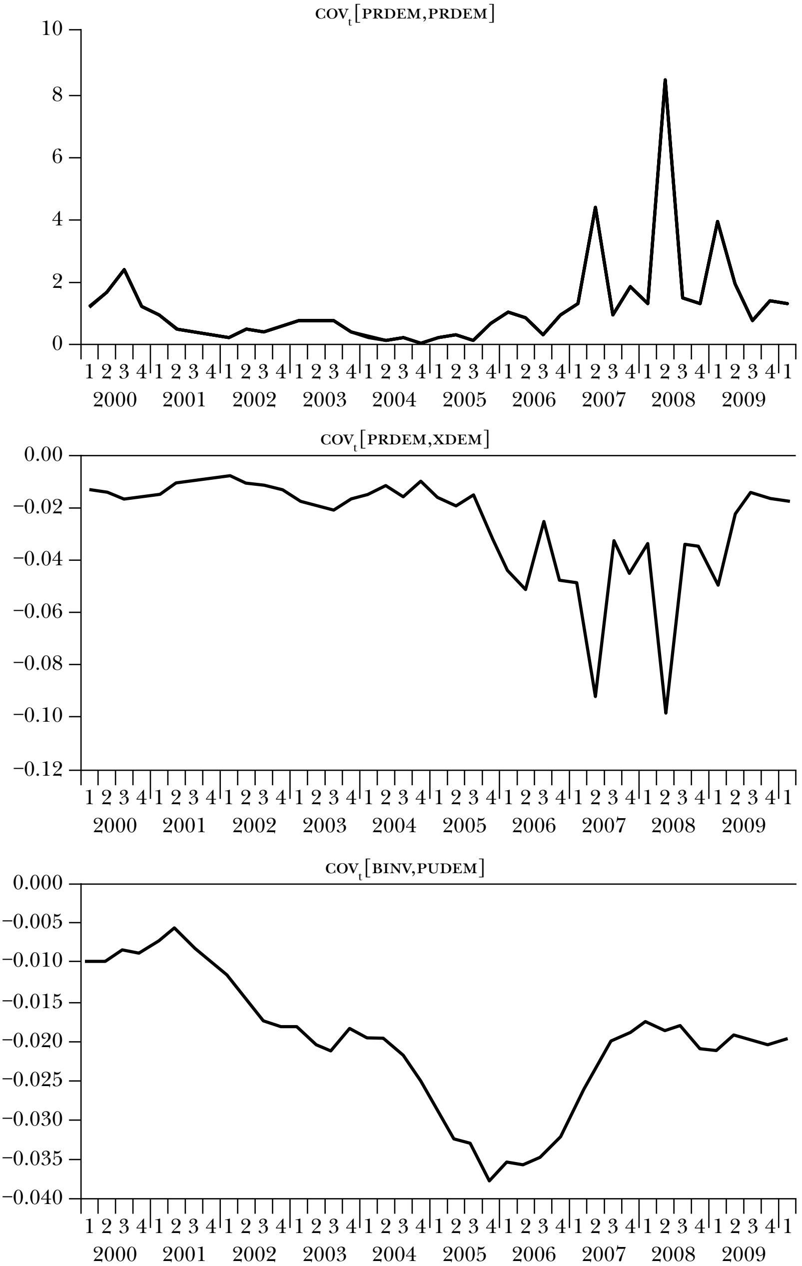


Figure C.1 (cont.)

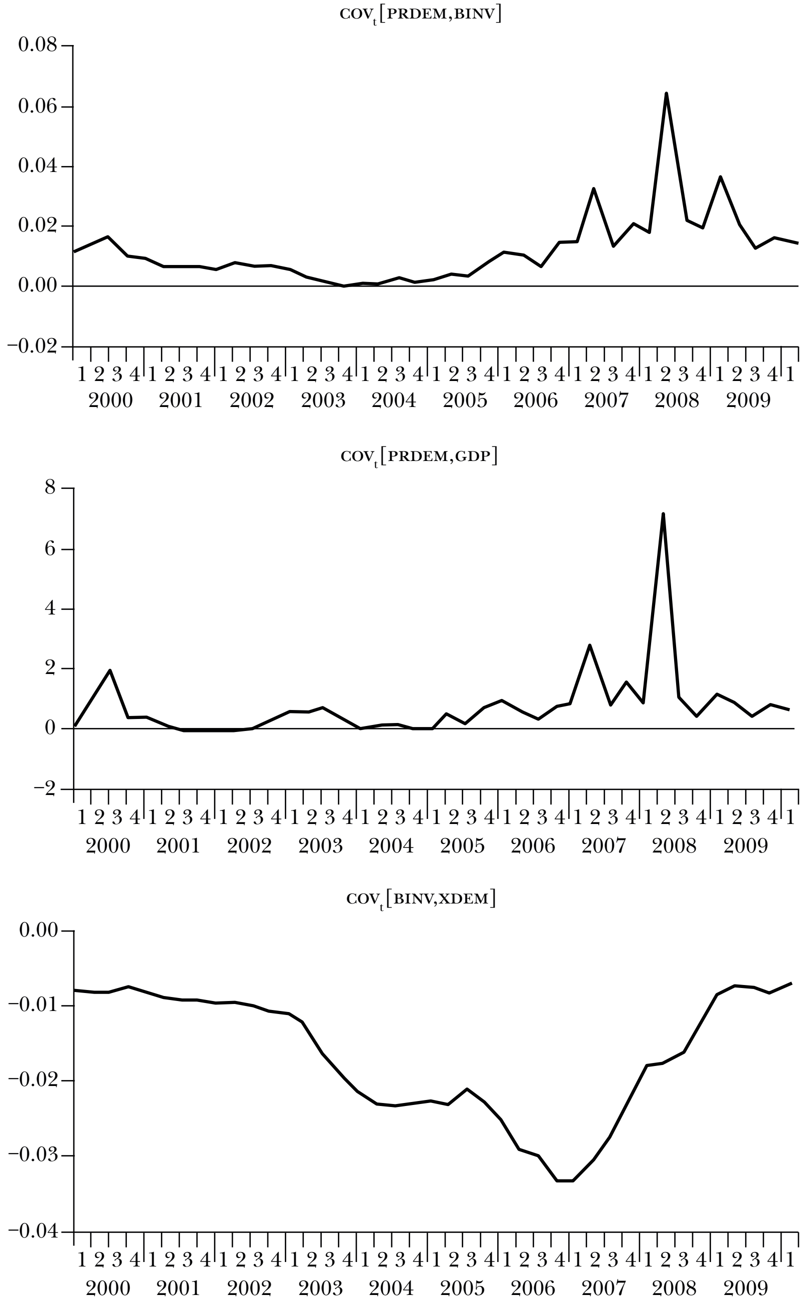


Figure C.1 (cont.)

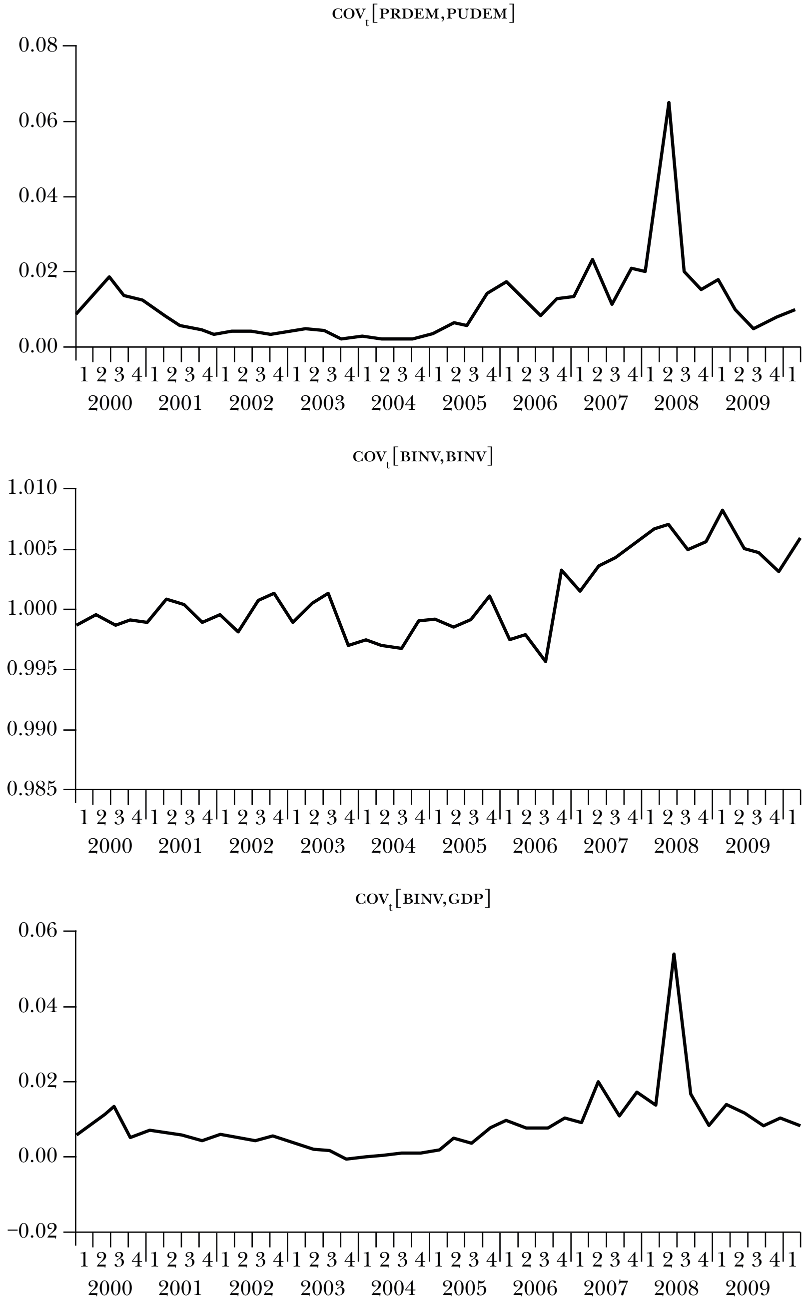


Figure C.2

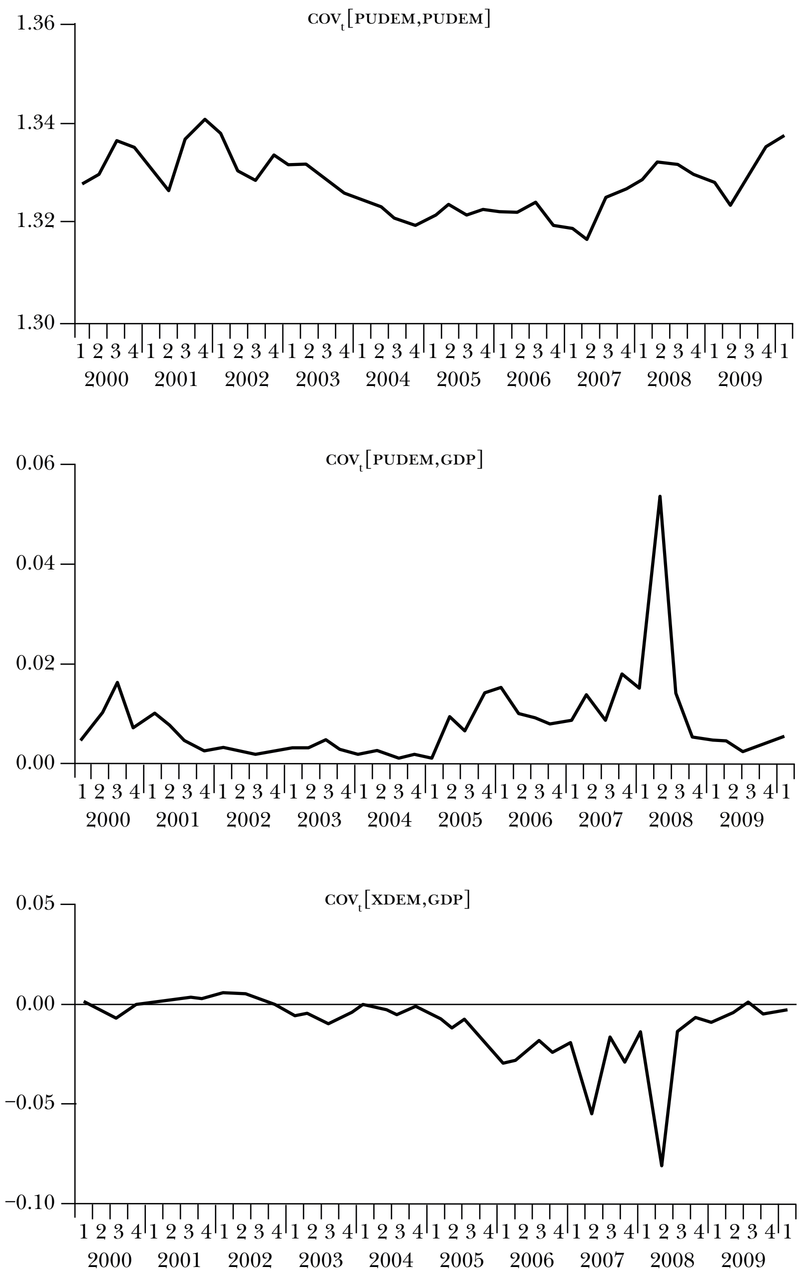
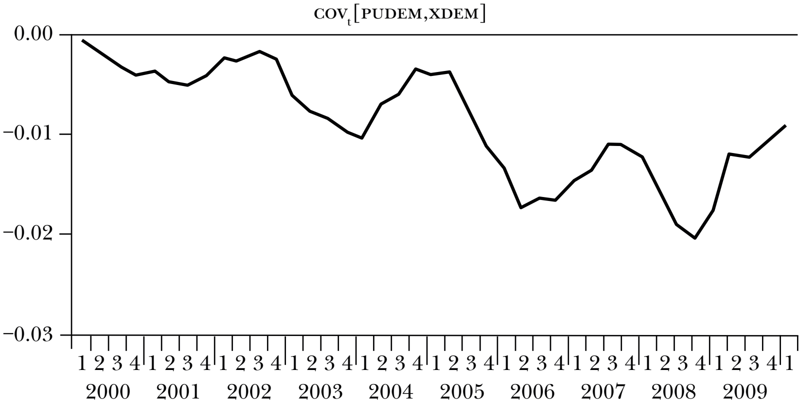
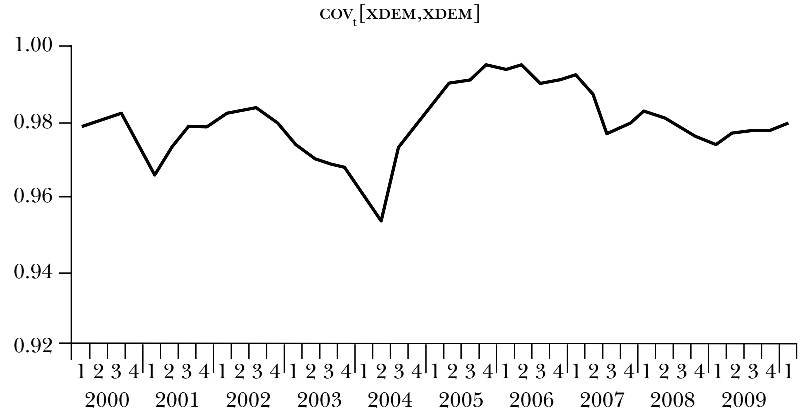
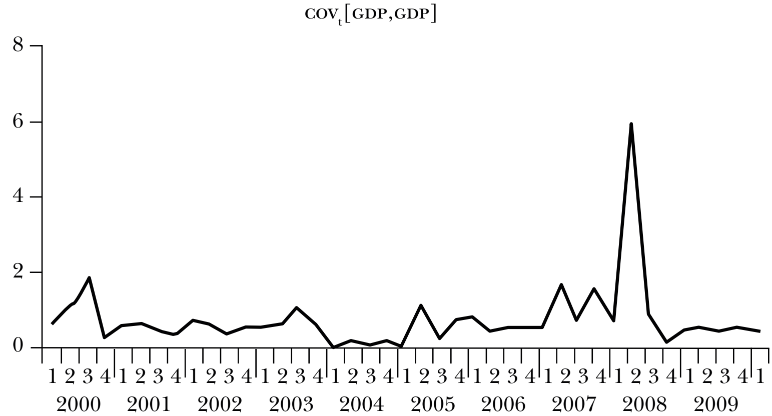

cov$_t$[PUDEM,PUDEM]
1.36
1.34
1.32
1.30
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009
cov$_t$[PUDEM,GDP]
0.06
0.04
0.02
0.00
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009
cov$_t$[XDEM,GDP]
0.05
0.00
−0.05
−0.10
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

Figure C.2 (cont.)







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