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Catching the mirage: The shadow impact of financial crises

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Abstract

This paper examines the dynamics of the shadow economy in times of financial crises. First, we estimate the size of the shadow economy in nine developing countries using energy consumption as a proxy for total economic activity. We show that our proposed proxy performs better than the conventional proxy of electricity consumption. In addition, given that financial crises usually overlap; a fact that is overlooked by existing literature, we construct a zero-one index to measure the intensity of a given shock. To explain the shadow economy impact of financial crises, we employ a set of country-specific VAR models and exploit their impulse responses. To this end, the paper finds empirical evidence of the countercyclical behaviour of the shadow economy, which suggests its buffering role in time financial crises. We show that our results are not sensitive to the method used to measure the size of the shadow economy. Finally, we build on these results to draw some policy recommendations.

Keywords: Financial Crisis, Shadow Economy, Developing Countries
JEL code:

1. Introduction

Many development economists believe that a considerable portion of economic activities in developing countries is taking place off records (Schneider and Enste, 2000; Eilat and Zinnes, 2002; Macias and Cazzavillan, 2009; Lesica, 2011)[1]. However, their claims

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[1] Figures reported in Pratap and Quintin (2006), for instance, show that although the size of the shadow economy varies greatly among nations, it represents 25 to 80 percent of official GDP in developing countries, compared to 10 to 15 percent in most developed nations. Shadow economic activities include, but are not limited to, house production, street vendors and even illegal activities such as drug dealing.

have never been rigorously proven, mainly due to a failure to measure what is meant to remain in the shadow (Arby et al., 2010)[2]. Despite this, researchers and policy makers have shown a great deal of interest in understanding the unseen part of the economy, claiming that it has a distorting impact from a policy standpoint (Georgiou, 2007). This interest has increased significantly since the eruption of the recent financial and economic crises. More particularly, these crises have put forward questions such as how both sides of the economy interact over business cycles, and what would be the appropriate policy response in times of financial turbulence. There is ample evidence of the fact that financial crises have a negative impact on official output. In times of crisis, unemployment rises and workers may be forced to move to the informal sector. Also, restricted access to bank credit during financial crises may push more firms into the informal sector than in normal times (Thomas, 1992; Colombo et al., 2012). Therefore, this paper investigates the dynamics of the shadow economy in times of financial crisis. More particularly, it examines whether the shadow economy acts as a transmission channel for financial shocks, or it can play a buffering role in times of crisis.

Thus, our objective in this paper is twofold. Firstly, the size of the shadow economy in a number of developing countries is estimated for a forty year period (1971-2011). We employ an augmented version of the modified total activity MTA method introduced by Eilat and Zinnes (2002). In response to critiques facing studies using electricity consumption as a proxy for total economic activity, we show that energy consumption might be a better proxy. Our second objective is to investigate the underground response to financial shocks. To proxy for financial shocks, we construct an index that takes the value of zero if there is no crisis, and the value of one if the crisis is very severe. For estimation purposes, we employ a *VAR* model for each country separately and exploit its impulse response function.

To this end, the current study makes a genuine contribution to the literature from several aspects. First, using an improved methodology, this study contributes to the literature on measuring the shadow economy by providing updated estimates as they pertain to a number of developing countries. Second, we introduce an in-depth analysis of the shadow economy dynamics in times of financial crisis, suggesting a channel of transmission that has been, so far, overlooked in the existing literature. Finally, this study contributes to the limited, however growing, literature studying the dynamics of the shadow economy over business cycles. This contribution to the literature is based on the fact that only very few studies have examined the effect of financial crises on the size of the shadow economy, especially after the incidence of the global financial crisis.

This study is important to policy makers in developing countries for at least the following reasons: While policy makers design strategies intended to repress the shadow economy in order to mitigate its distortion to development policies, these strategies may '*unintentionally*' play a destructive role in time of crises, if the expansion of the shadow economy is temporary and therefore can act as a buffer to the shock. In the latter case, policies that repress the shadow economy may hinder one of the mechanisms by which

[2]The unrecorded economy has appeared in the literature under various names. In this paper, we will use the terms shadow economy and underground economy interchangeably to refer to the same thing.

the economy has a chance to absorb the shock[3]. In contrast, if the shadow economy response to financial crises is procyclical or if it expands persistently, then it would not be advisable to relax the anti-shadow regulations in times of financial crisis. Therefore, it is imperative and informative to examine whether the shadow economy response is procyclical or countercyclical and if this response persists over time, or is short-lived.

The remainder of this study consists of the following sections: Section 2 reviews the literature. Section 3 discusses our empirical strategy and the dataset. Finally, the empirical results and conclusion are presented in sections 4 and 5, respectively.

2. Literature review

A relevant strand of literature is concerned with the cyclical behaviour of the shadow economy; i.e., whether it is procyclical or countercyclical. The former concept refers to a larger shadow economy in times of boom, while in times of bust a smaller shadow economy will exist. However, the latter suggests the opposite, while the shadow size flourishes in recessions, it shrinks in peak times. In fact, economic theory explains the business cycles properties of the shadow economy as the final outcome of *income effect* and *substitution effect* (Bajada, 1999, 2003; Elgin, 2012). While *income effect* implies that negative shocks to an economy will affect both sides of that economy, and hence lends support to the procyclicality behaviour of the shadow economy, the *substitution effect* indicates that laid-off formal workers in response to the shock- will be enticed to go underground, which legitimises the countercyclicality assumption[4].

Although, theoretically speaking, it may appear unclear whether the shadow economy is procyclical or countercyclical, empirical research suggests that it tends to display a countercyclical adjustment, i.e. backing the *substitution hypothesis*. Using a VAR modelling approach, Fiess et al. (2010) have reported similar patterns in Argentina, Brazil, Colombia and Mexico. Loayza and Rigolini (2011) find that shadow employment plays a temporary safety net role when it negatively co-moves over the business cycle. Elgin (2012) uses the shadow economy estimates from Schneider et al. (2010) to examine the informal sector behaviour over the business cycles. The author finds evidence towards the countercyclical nature of the underground economy, where the presence and volatility of the underground sector amplifies the magnitude of the business cycles. Using this finding, the paper interprets the higher amplitude of business cycles in developing countries with a large shadow economy. Çiçek and Elgin (2011) build their empirical analysis on the idea that the shadow economy exhibits a countercyclical pattern[5]. Work by Bajada and Schneider (2005); Schneider and Enste (2000); Feld and Schneider (2010) supports

[3]We understand that the movement from the official economy to the shadow economy may have adverse implications on total productivity. However, holding other things equal, when official economy becomes incapable to produce productive jobs, less productive jobs may be more preferred from policy point of view compared to no jobs at all.

[4]Another way to interpret the procylcicality behaviour of the shadow economy is suggested by Elgin (2012), who states that in times of negative shock, while less productive businesses which operate in the shadow are perfect candidates to shut down, those businesses in the official economy are more likely to survive thanks to their relatively higher level of productivity.

[5]In Australia, the findings of Bajada (1999, 2003) support the procyclicality of the underground economy.

the expansion of the shadow economy in times of recession. Roca et al. (2001) conclude that lower wage premium in the official economy triggers expansion in the underground economy, which leads to larger fluctuations in the official economy. In addition, Vaillant et al. (2014) and Lee and Ofreneo (2014) examine the underground adjustments in tough times. Vaillant et al. (2014) find that after growth was hit hard by a political crisis in Madagascar in 2004, the informal sector has proved to be a *labour-absorbing* function. Lee and Ofreneo (2014) study the Asian labour markets adjustments in two crisis times; Asian crises and global financial crises. They find that labour markets continue to be characterised by informal, vulnerable and precarious employment, even in recovery times.

None of the extant literature has explicitly investigated the effect of financial crises on the size of the underground economy as we do in this study. The only exception is Colombo et al. (2016), who study the impact of two different types of financial crisis; banking and currency crises, measured as a dummy variable to identify periods of shocks. However, our study differs from theirs in the way we model financial crises. More particularly, while we construct a zero-one index to proxy for the intense of the shock, they merely rely on the incidence of a shock using a dummy variable ignoring the fact that financial crises usually overlap. Keeping this in mind, what type of financial crisis should one be interested in? Even if one decides to compare the shadow response to each crisis, there is no way to explain the overlapping of two or more crises. In addition, while they use electricity consumption to proxy for total economic activity which is heavily criticised, we employ energy consumption in an attempt to respond to those critiques.

To this end, this review of the literature shows that, apart from the study by Colombo et al. (2016) which we deviate from, there is a strong need for more empirical evidence on the shadow economy adjustments of financial crises, the main objective of this study.

3. Methodology and Data

The underground economy is a phenomenon that could be, and in fact has been, studied under plenty of names, including the 'shadow', 'unrecorded', or 'informal' economy; the list is endless. So far, the present study has intentionally made no attempt to engaging the long lasting debate on defining what the term 'underground' actually means. The reason is that we do not wish to get bogged down in a discussion on how legitimate these definitions are, which will certainly distract our attention away from the main focus of this study. In addition, the existence of fine surveys of literature defining the shadow, such as Schneider (2012), obviates the need for a comprehensive review here. Yet, measuring the underground economic activities has to start with a satisfactory identification of what is being under the spotlight. For this purpose, we define the underground economy as all economic activities which contribute to the economy but with no means of being detected under the official GDP umbrella. Thus, it encompasses

They show that negative shocks in the official economy have a greater effect on the underground economy than do positive shocks, which implies that the underground economy may deepen economic downturns and increase the volatility of the business cycle. A similar pattern is found by Giles (1997) in New Zealand.

not only legitimate but also unlawful activities, such as the production and distribution of drugs. The precedent definition has been adopted by a number of studies, see for example Feige (1989) and Lubell et al. (1991). According to this definition, the shadow economy includes monetary and non-monetary transactions. What is more, available estimates of the shadow economy do not usually disentangle legal from illegal activities, and thus we follow their foot steps. In part, this is so as not to fall into a '*quantitative nightmare*' as described by Gomis-Porqueras et al. (2014). Rather, we prefer to focus on a broader definition of the underground economy, which goes hand in hand with our aim of contributing to the literature on the underground impact of financial shocks, which has so far overlooked the effects of such events on the dynamics of the shadow economy. Bearing this in mind, we first elucidate the modified total economic activity method MTA proposed by Eilat and Zinnes (2002) to estimate the size of the underground economy. Then, we lay out the framework by which this study is bounded, and introduce our empirical strategy.

3.1. Modified total economic activity MTA approach

As is the case with all known methods of measuring the shadow economy, the physical input method of measuring the size of the shadow economy is not immune to criticism. The major issue with the latter method is the empirical stability of the energy-consumption to GDP ratio, which may cause a downward bias on the ground of energy-saving technological changes. To counter this problem, Eilat and Zinnes (2002) suggest running a regression of electricity consumption against several possible influence variables. These variables include demand changes due to percentage change in electricity prices to capture price changes and percentage-point change in industry share of GDP to capture changes in the structure of output. We follow their modified total economic activity MTA method to estimate the size of the shadow economy in the countries of interest. However, we go against their assumption of electricity consumption being the best single measure of economic activity, and accept that not all of the underground activities rely on electricity. Thus, rather than using electricity consumption as a proxy of total economic activity, we use energy consumption which in fact includes besides electricity consumption all other sources of energy. To explain the MTA method, we start off with the following equation.

$$\Delta enc_{i,t} = \alpha_i + \beta_1 \Delta enp_{i,t} + \beta_2 \Delta ind_{i,t} + \epsilon_{i,t} \tag{1}$$

where $t = 1972, 1974, \ldots, 2011$ and $i = 1, 2, \ldots, 9$ which are time and country indexes, Δenc is the annual percentage changes in energy consumption, Δenp is the real price of energy and Δind is the industrial value added to GDP. The main idea here is to filter out the energy consumption data by removing the effects of other factors beside the changes in total economic activity that could explain changes in energy use. To do so, the MTA exploits the residuals obtained from Eq.1. Given the relatively long time dimension of our dataset, the panel co-integration techniques are used to estimate Eq. 1. Section 3.2 provides more details about the estimation technique. After estimating Eq. 1 and obtaining the residuals Δenc^{resid}, we compute the predicted percentage changes in total economic activity ΔTEA_t by multiplying the Δ_t^{resid} values by an appropriate output elasticity ($\eta = 0.90$). Finally, we use theses figures converted into a decimal to compute the TEA_t series relative to its 1972 value by chain-multiplication.

3.2. *Panel cointegration*

To estimate Eq.1, we first test for the stationarity of our panels using Hardi LM (Hadri, 2000). Then, we test for the presence of cointegrating relationships using two tests of panel cointegration, namely Pedroni (1999, 2004) and Westerlund (2007) tests. Finally, if found cointegrated, we estimate Eq. 1 using the group-mean panel fully modified ordinary least squares (GM-FMOLS) method proposed by Pedroni (2001). The GM-FMOLS estimator allows for the heterogeneity of the panel, adjusts for the effects of autocorrelation of the errors, and adjusts for the potential long-term endogeneity of the regressors. In this estimator, the impact of the cross-section dependence is captured through common time effects. It provides a consistent and efficient estimation of the cointegrating vector, in particular where non-stationarity, endogeneity and serial correlation problems are suspected.

3.3. *VAR model*

This study utilises a multivariate *VAR* model to study the dynamics of the shadow economy in response to financial shocks. Our selection of empirical method is justified on the basis of two reasons. First, when studying the shadow economy and its dynamics, endogeneity biases may emerge (Gomis-Porqueras et al., 2014), which makes the *VAR* modelling approach a reasonable choice as it does not assume exogeneity of the regressors. Thus, each variable is treated symmetrically and feedback is allowed for among all variables. Second, the *VAR* modelling approach is known to be superior to a single-equation modelling in capturing the long-run dynamics of the variables. Our m-variate *VAR(p)* model can be represented as follows.

$$\mathbf{Y_t} = \boldsymbol{\beta}_0 + \sum_{i=1}^{p} \boldsymbol{\beta}_i \mathbf{Y}_{t-p} + \mathbf{u_t} \tag{2}$$

where $\mathbf{Y_t}$ are $(m \times 1)$ victor of endogenous variables, namely the size of the shadow economy, GDP and *crisis* index. $\boldsymbol{\beta}_0$ is a $(m \times 1)$ vector of the deterministic component, i.e., intercept. $\boldsymbol{\beta}_i$ is an $(m \times m)$ matrix and p is the lag order. Finally, $\mathbf{u}_t$ are $(m \times 1)$ of the white noise errors. The choice of the number of lags is made on the basis of AIC and SIC information criteria. The number of lags is set to 1 or 2 whichever provides serially uncorrelated residuals, according to the autocorrelation function of the VAR residuals. The Augmented Dickey-Fuller test is used to detect for the presence of unit roots. Also, we test for the stability of the model by making sure that all AR roots lie within the unit circle. Finally, we employ the impulse response innovation to stimulate a 1SD shock to the *crisis* variable and report the responses of GDP and the size of the shadow economy.

3.4. *Data*

Our dataset includes data for nine middle income countries over the period 1971-2011. These countries are Argentina, Brazil, China, Ecuador, Malaysia, Mexico, the Philippines, Thailand and Turkey. We first estimate the size of the underground economy in this set of countries using the MTA method explained in section 3.1. To obtain the size of the underground economy according the MTA method, we have used the following data:

Energy consumption enc is the kilogram of oil equivalent of energy use per constant PPP GDP. This includes electricity consumption as well as other sources of energy. The data comes from the International Energy Agency. The *enc* accounts for the domestic production of energy, stock changes and international trade. *Energy price enp* was constructed for individual countries by deflating the world index of energy by the country specific consumer price indexes. *World index of energy* is the relative energy prices were proxied by this global index of real energy prices. The data for this index comes from the World Bank- Commodity Price Data. *Consumer price index CPI* is individual country CPI series are extracted from Datastream (Hits: AGYCP009F, BRY..NECE, CHRP...., EDWD0O8IF, MYWD0O8IF, MXWD0O8IF, PHWD0O8IF, THWD0O8IF, TKWD0O8IF). *Industry share of GDP ind* is the industrial value added as a percentage of the country's GDP. Data are extracted from the World Bank-World Development Indicators database. *Official GDP:* data comes from the World Bank World Development Indicators in current value of the PPP US dollar. For our purpose of calculating the size of the underground economy, these were transformed to their constant values using 1972 as the base year. In order to obtain the series of the size of the underground economy as a percentage of the country GDP, it was essential to rely on a base year of the underground economy. These figures were obtained from the model based estimates available in Elgin and Oztunali (2012). Although it is important the credibility of the base year estimate, we do not think it should present much concern for us, because we use the growth rate in our empirical strategy. We follow in this Colombo et al. (2016) who state that using any estimation for the base year would not cause any issues as long as we use the growth rate to examine the dynamics of the shadow economy.

To obtain the empirical results presented in section 4, we have used the following data: *Underground size* y_t*:* which is based on our estimates according to the MTA method. In section 4, we briefly present our estimates of the size of the underground economy. GDP_t data come from the World Bank WDI database, measured in real terms of 2005 prices and is log-transformed. *Financial crisis index* $crisis_t$*:* is an index that takes the value of zero if there is no crisis, and takes the value of one if the crisis was very severe. This index is constructed based on a simple unweighted average of the 0-1 identification of different types of financial crisis which is published in the popular Reinhart and Rogoff (2010) dataset. They document six types financial crises. These are currency crises, inflation crises, stock market crash, sovereign debt crises (domestic and external), and banking crises. In fact, their crisis identification shows that financial crises are more likely to overlap. Argentina and Brazil, for example, experienced five financial crises (all the above crises except a stock market crash) in 2002 and 1990, respectively. This highlights the fact that relying on a single financial shock might be misleading as it will be mixed with the effect of other financial crises that happened in the same time. For this reason, we believe that our constructed index will be more successful at capturing the intensity of the shock rather than merely the shock incidence. However, it should be noted that our index should be treated as an ordinal measure in which data on the intensity of the shock can be sorted with no indication of the relative degree of difference between them. For example, an index score of 0.66 indicates a shock that is more intense compared to another shock with a score of 0.33, without necessarily being twice as severe as the second case. This means that a crisis which is both a banking and a currency crisis should not be considered twice as severe as a banking crisis only. However, the overlapping between both crises is expected to result in a more severe shock compared to the incidence of only one shock, which is captured by our proposed index. As a robustness check, we will use the 0-1 dummy of Reinhart and Rogoff (2010) dataset for banking crises (see section 4.3). Table 1 shows the descriptive statistics for our dataset.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Shadow	369	39.8746	13.0234	23.1407	78.0900
Crisis	369	0.2387	0.2472	0.0000	1.0000
GDP	369	25.8262	1.2493	23.1493	29.0652
Bank	369	0.2195	0.4145	0.0000	1.0000

Shadow is our estimated size of the shadow economy using the MTA method based on energy consumption. Crisis is our 0-1 proposed index that capture the severity of a financial shock. GDP is the log of GDP. Bank is a dummy variable for banking crises as published in Reinhart and Rogoff (2010) dataset which we use as part of our robustness checks in section 4.3.

4. Empirical Results

As shown in section 3, our empirical strategy comprises estimating the size of the shadow economy using an augmented version of the MTA method. For this reason, we employed panel cointegration technique to estimate Eq. 1 in order to filter out the energy consumption. Then, we employ a *VAR* model to examine the response of the shadow economy to financial crises in each country in our dataset. Thus, in what follows we first discuss the estimation of the shadow economy, then we discuss the impulse response functions from our *VAR* models.

4.1. Estimating the shadow economy

4.1.1. Panel stationarity results

Table 2 reports the results of Hadri (2000) panel root test, which is designed for testing for stationarity in heterogeneous panels. The results shown in Table 2 reject the null hypothesis [6]. Therefore, we proceed to examine the cointegrating relations among our variables.

4.1.2. Panel cointegration results

With non-stationary pooled time series, the application of the OLS estimator may result in biased and inconsistent estimates (Granger and Newbold, 1974; Engle and Granger, 1987). Thus, to decide on an appropriate estimator for Eq. 1, it is important to test for cointegration among the variables. We test for the presence of cointegration relationships between Δenc, Δenp and Δind using the residual-based procedure developed by Pedroni (1999, 2004) as well as a set of panel cointegration tests developed by Westerlund (2007). The null hypothesis for both tests is that there is no cointegration. The results for the cointegration tests are reported in Tables 3 and 4. These results show that we strongly reject the null hypothesis of no cointegration, which implies that it is important to use the panel cointegration techniques to estimate Eq. 1.

[6] We also applied the ADF unit root test to individual series and found that a significant portion of series has unit root. Results are not sown here but available upon request.

Table 2: Hadri panel stationarity test

	assumption	$Z\mu$	$Z\tau$
enc	*Homo*	2.971***	2.535***
enc	*Hetero*	3.887***	2.535***
enc	*SerDep*	1.847**	3.185***
enp	*Homo*	3.71***	5.313***
enp	*Hetero*	3.910 ***	3.433***
enp	*SerDep*	0.069	1.178
ind	*Homo*	-0.123	0.437
ind	*Hetero*	0.584	0.801
ind	*SerDep*	0.186	1.93**

; H_0: All 9 time series in the panel are stationary processes; Lag selection: fixed at 1; τ individual linear trend; The statistics are asymptotically distributed as a standard normal with left hand side rejection area; $***$.

Table 3: Pedroni residual-based cointegration test

Statistics	intercept	time trend
	Within	
panel-v	0.629	-1.569
panel-ρ	-11.855***	-9.752***
panel-PP	-12.769***	-14.403***
panel-ADF	-6.293***	-6.664***
	Between	
group-ρ	-9.723***	-7.242***
group-pp	-13.732***	-13.966***
group-ADF	-5.967***	-5.231***

; H_0: No cointegration; Trend assumption: heterogeneous intercepts; Lag selection: fixed at 1. Not that all reported values are asymptotically distributed as standard normal. Panel statistics are weighted by long variances. The Pedroni tests are left-sided. A $^{*}**$ indicates the rejection of the null hypothesis of no cointegration at the 1 per cent level of significance.

Table 4: Error-correction based cointegration tests

Statistic	Value	Z-value	P-value
G_t	-3.561	-3.685	0.000
G_a	-20.644	-2.869	0.002
$P-t$	-10.403	-3.925	0.000
$P-a$	-20.867	-4.607	0.000

H_0: no cointegration; Lag selection: fixed at 1; individual linear trend included.

4.1.3. Panel estimation

Since the panel cointegration tests suggest the presence of cointegrating relations among our variables, we employ the MG-FMOLS estimation of Pedroni (2001) for cointegrated panels. The results presented in Table 5 show that estimated coefficients are significant and with the expected sign. This suggests that our approach has successfully filtered out the effect of price and technology changes. Thus, we obtain the residuals and follow the procedure described in section 3 to obtain the estimates of the shadow economy.

Table 5: Cointegrated panel estimation MG-FMOLS

	No trend	with trend
Δenp	-0.045***	-0.055**
Δind	0.323***	0.255***

Mean group fully modified OLS estimator of Pedroni (2001) for cointegrated panels. Estimation includes a constant and one lag

First, to show that the newly proposed proxy, namely overall energy use, for estimating the size of the underground economy, is superior over the incumbent, namely electricity use, we do the following: (i) establish that the proposed proxy is econometrically better than the existing one, by showing that its elasticity with respect to national income is closer to one than that of the existing proxy; (ii) estimating the size of the informal sector by using the existing proxy and comparing the results obtained by each of the proxies; the latter should give some sense of the importance of distinguishing between the two proxies. Therefore, we first estimate energy and electricity elasticities with respect to the national income using the MG-FMOLS estimator. The dependent variable is GNI, while the independent variable is the underlying proxy, both expressed in the logarithmic form. Results reported in Table 6 show that our proposed proxy entertains a closer to one elasticity when compared to the conventional electricity consumption proxy. Moreover, Figure 1 shows the estimation for the size of the shadow economy according to using both proxies, energy consumption and electricity consumption. This evidence supports the importance of distinguishing between the two proxies. More specifically, the electricity consumption proxy tends to overestimate the size of the shadow economy.

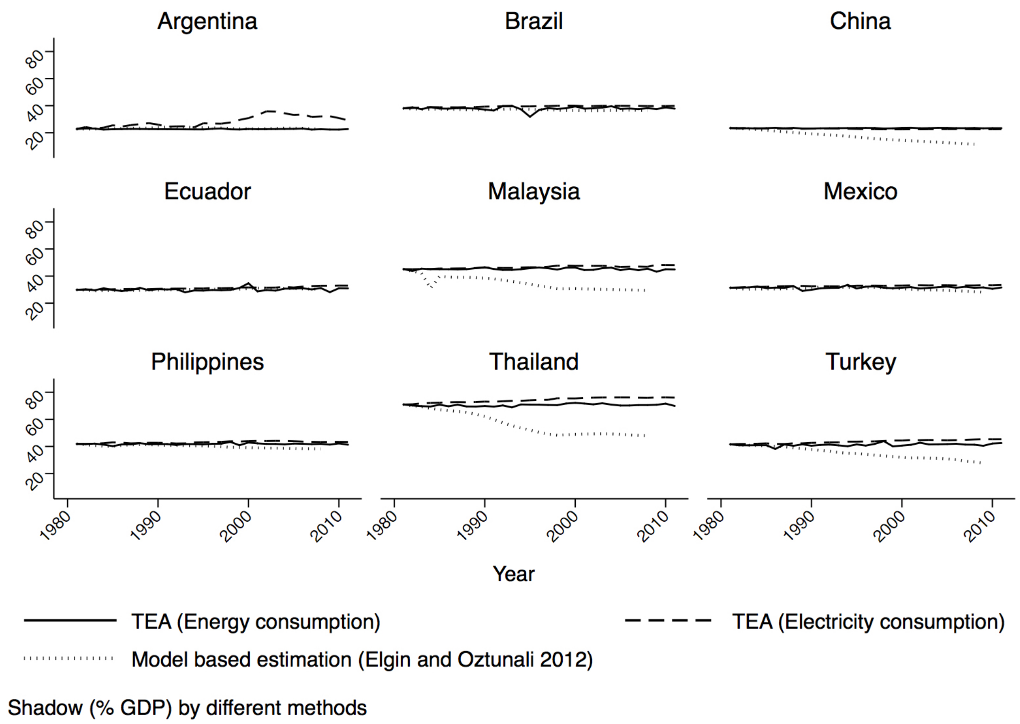
Table 6: Energy and electricity consumption elasticities

	constant	constant and trend
energy	1.107***	0.639***
electricity	0.728***	0.464***

Mean group fully modified OLS estimator of Pedroni (2001) for cointegrated panels. Estimation includes a constant and one lag

Second, to gauge the relevance of our filtering approach, we compare our estimates of the size of the underground economy with those of Elgin and Oztunali (2012), who use a two-sector dynamic general equilibrium model to estimate the shadow economy, see Fig. 1. As can be seen from the graph, using the Elgin and Oztunali (2012) estimation as a base year, both estimates show a downward tendency of the shadow size. As explained

Figure 1: Shadow economy estimation by different methods



earlier, using a base year should not cause much concern as we use the growth rate when empirically examining the dynamics of the shadow economy. However, the use of a base year here was merely for comparison purposes.

4.2. Shadow response to financial shocks

4.2.1. Estimating VAR model

First, we test the unit root properties of our variables in level using the ADF test. Results reported in Table 7 show that we failed to reject the ADF null hypothesis of unit root for most of our series. Thus, we performed the test on the data in the first difference. Results reported in Table 8 show that we reject the null hypothesis of unit root for all series. Thus, we estimate a *VAR* model with the variables entering in their first difference. The appropriate lag length is chosen such that the AIC and SIC information criteria are minimized. In addition, the stability of the *VAR* model is confirmed by having all the inverse roots of the *AR* process inside the unit circle. To ensure such stability, using one lag was enough for all countries except in Malaysia where two lags were necessary.

Table 7: ADF unit root test - level

	No trend			trend		
	shadow	gdp	crisis	shadow	gdp	**crisis**
Argentina	0.423	2.197	-2.511	-3.955**	-0.641	-2.751
Brazil	-2.598	-2.091	-2.423	-2.280	-2.906*	-2.693
China	-1.613	1.117	-3.379**	-0.729	-4.752***	-3.386**
Ecuador	-2.048	-2.443	-2.101	-2.210	-3.910**	-1.995
Malaysia	-3.613***	-1.880	-4.036***	-2.165	-1.512	-3.962***
Mexico	-1.855	-2.707*	-2.845*	-2.282	-2.833	-3.068
Philippines	-2.769*	0.129	-1.971	-2.753	-2.472	-3.344*
Thailand	-3.101**	-1.965	-2.057	-0.462	-1.048	-3.046
Turkey	-0.852	-0.431	-2.495	-0.181	-3.189	-2.500

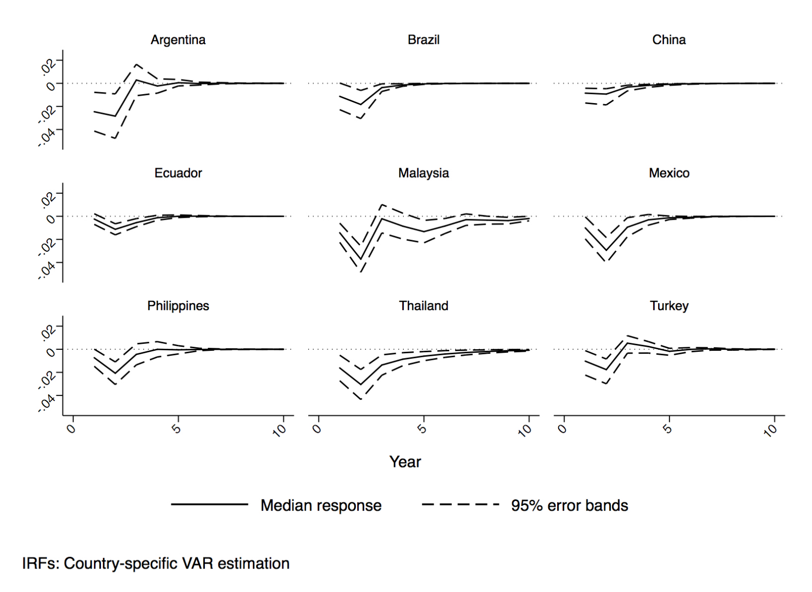
Table 8: ADF unit root test - first difference

	No trend			trend		
	shadow	gdp	crisis	shadow	gdp	crisis
Argentina	-4.461***	-4.841***	-7.441***	-4.970***	-4.986***	-7.394***
Brazil	-5.292***	-3.801***	-7.789***	-5.377***	-4.989***	-7.795***
China	-4.175***	-4.405***	-7.853***	-4.342***	-4.062***	-7.785***
Ecuador	-6.628***	-3.972***	-5.217***	-6.556***	-4.060***	-5.305***
Malaysia	-5.078***	-5.298***	-7.434***	-5.801***	-5.528***	-7.433***
Mexico	-5.975***	-4.656***	-7.561***	-5.899***	-4.859***	-7.555***
Philippines	-5.140***	-3.567**	-8.317***	-5.409***	-3.501*	-8.246***
Thailand	-4.530***	-3.620***	-6.313***	-4.609***	-4.103***	-6.346***
Turkey	-5.450***	-6.199***	-6.096***	-6.696***	-6.100***	-6.370***

4.2.2. GDP response to financial shocks

We stimulate a 1SD shock to the '*crisis*' variable and report the impulse responses of the GDP in each country in our dataset. Figure 2 presents the GDP response to financial shocks. Two observations can be drawn from figure 2. First, GDP response to financial shocks is negative and statistically significant in all countries. Second, the GDP takes at least two years to recover after a financial shock. For example, in Argentina, GDP falls by 2.5% and 2.8% in the first and second years after the shock, and the shock response becomes statistically insignificant after the third year. The shock response dies out in year 4. A similar response is reported for Brazil, where the GDP falls by 1.1% and 1.8% in years 1 and 2, respectively. In China, the GDP response to financial shocks is less than it is in Argentina and Brazil, where the Chinese output falls by only 0.8% and 1% in year 1 and 2. However, the Chinese GDP takes about 4 years to achieve recovery. In fact, Ecuador experiences a similar response to that of the Chinese GDP to financial shocks, where the response is really low, however, it exists for a longer period of a time. In particular, the GDP in Ecuador falls by much less than it does in China, 0.2% in the first year but however it takes almost four years to recover. In Malaysia, the GDP is found to be much more sensitive to financial shocks as it falls by 1.4% and 3.7% in years 1 and 2, respectively. However, this response is only significant till year 2. In Mexico, the GDP falls by 1% and 2.9% in years 1 and 2, and the shock takes about three years to become statistically insignificant. In the Philippines, the GDP falls by 0.7% and 2% in the first two years, then it becomes insignificant from the third year onwards. In Thailand, the GDP falls by 1.6% and 3% in the first two years, and this fall continues to be significant till year 6. Finally, in Turkey, the GDP falls by 1% and 1.7% in the first two years, however, this response becomes statistically insignificant three years after the shock.

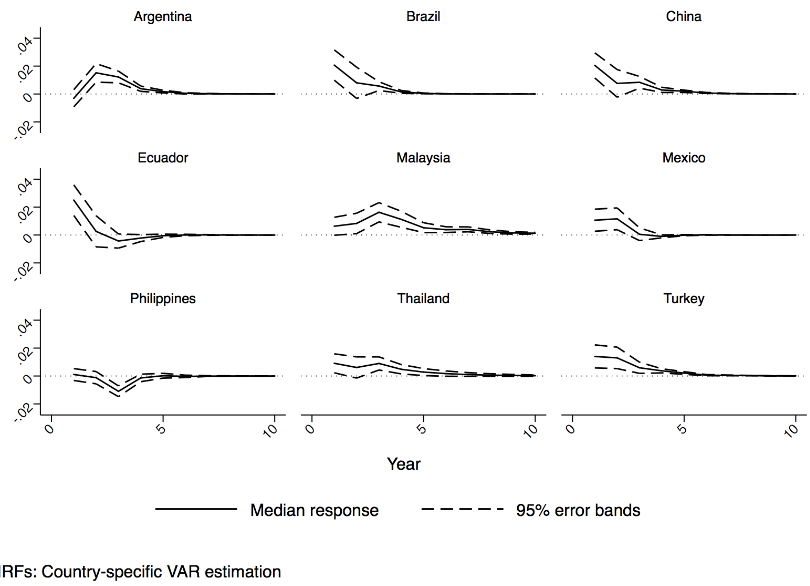
Figure 2: IRFs - GDP response to financial shocks



4.2.3. Shadow response to financial shocks

Figure 3 presents the shadow economy response to financial shocks. As expected, the size of the shadow economy seems to responds positively to financial shocks. Although this expansion in the shadow economy appears to be statistically significant, it does not seem to be persistent over time. However, the period of time needed for this expansion in the shadow economy to die out differs from one country to another. For Argentina, the shadow economy increases by 0.15% in the first year after the shock and this response takes about five years to die out. For Brazil, the shadow economy increases by 1% in the first year, and becomes statistically insignificant after the second year. A similar response is found for China, where the size of the shadow economy increases by 2% in the first year, and this expansion is found to be statistically insignificant after the second year. In Ecuador, the size of the shadow economy increases by 2.5% in the first year and this response becomes insignificant after the second year. In Malaysia, it seems that the response of the shadow economy persists for a longer period of time, where the shock response is not very high (i.e., 0.6%) in the first year. However, it continues to be significant for at least nine years after the shock. For Mexico, the expansion of the shadow economy in response to a financial shock is found to be 0.5% in the first two years and this response becomes statistically insignificant after the second year. In the Philippines, the shadow economy increases by 0.05% in the first year, however this increase is not statistically significant. Surprisingly, the response of the shadow economy to financial shocks seems to be negative in the Philippines where the size of the shadow economy falls in the second and third years by 0.06% and 0.5, respectively. This drop in the size of the shadow economy in the Philippines is statistically significant. Despite this, the shock response becomes insignificant after the third year. In Thailand, the size of the shadow economy increases by 0.2% in the firs year. The magnitude of this expansion after a financial shock drops after the first year to become 0.15% and 0.022% in the second and third years, respectively. This falling trend continues till the fifth year when the shock response becomes very close to zero and statistically insignificant. Finally, for Turkey, the shock response of the shadow economy is positive and statistically significant, which continues till six years after the shock. The expansion in the Turkish shadow economy after a financial shock is found to be 0.7%, 0.6% in the first two years. This declining trend continues until the sixth year when the response becomes almost zero.

Figure 3: IRFs - shadow response to financial shocks



4.3. Robustness checks

So far, we have estimated the size of the shadow economy using the MTA method based on the energy consumption. Then, utilising the IRFs from a set of country-specific VAR models, we showed that the shadow economy expands in times of financial crisis. However, our results may be driven by the estimation of the shadow economy and/or our measure of financial crises. Therefore, to check the robustness of our findings as follows. First, we estimate the size of the shadow economy using the MTA method based on electricity consumption instead of energy consumption and report the IRFs. Results reported in Fig. 4 confirm our findings wherein the shadow economy tends to increase in size as a response to a financial shock [7]. Second, to make sure that our results are not influenced by our proposed index of financial crises, we re-estimate the individual country models using data on banking crises provided by Reinhart and Rogoff (2010). The estimated IRFs of a one-off shock to the size of the shadow economy show that it expands after the incidence of a banking crisis, see Fig. 5. Finally, as a further robustness check, we estimate a panel VAR model of all of the nine countries together instead of the individual country-specific VAR models (see Fig. 6). Again, the estimated IRF from our panel VAR model shows that the shadow economy is likely to expand in response to a financial shock and this expansion does not seem to be persistence over time.

[7] In addition, we use data on the size of the shadow economy estimated by Elgin and Oztunali (2012) to produce the IRFs and it confirms our results. Results are note reported here but are available upon request.

Figure 4: IRFs for the shadow economy (based on electricity consumption)

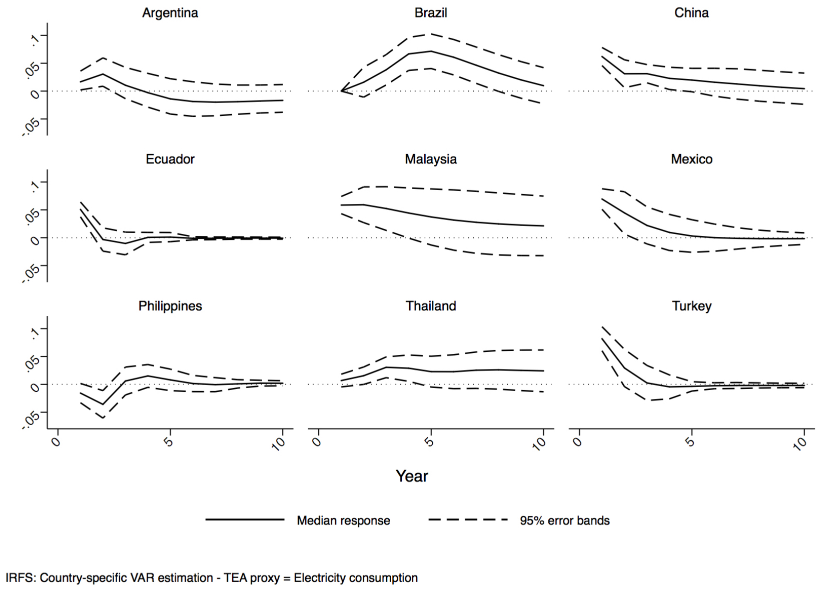


Figure 5: IRFs for the shadow economy (banking crisis)

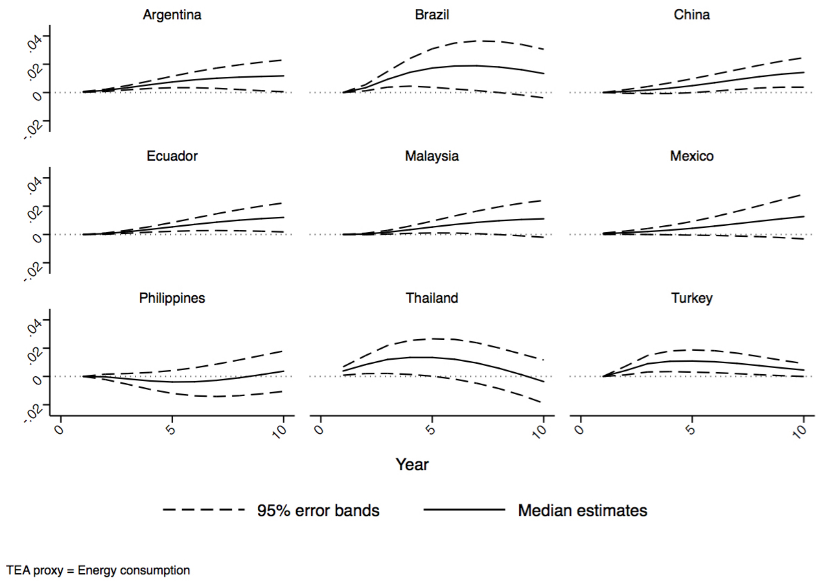
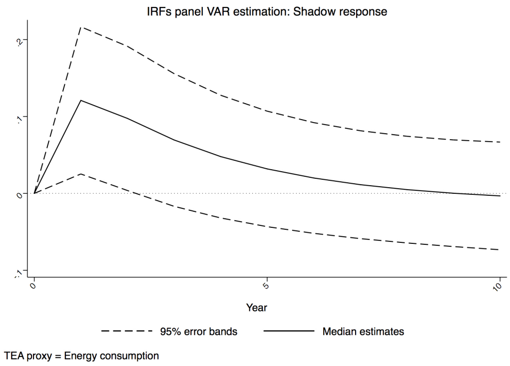


Figure 6: IRFs - Panel VAR estimation



5. Conclusions

This study makes a genuine contribution to the limited literature studying the dynamics of the shadow economy in times of financial crisis, a topic that is still poorly understood but important from the policy perspective. To do so, we set out two key objectives. Firstly, the size of the underground economy in a number of developing countries is estimated for the period 1971-2011. Secondly, a set of individual country *VAR* models is built and their impulse response functions are exploited to address our key question: how does the shadow economy respond to financial shocks? We use an improved methodology that is independent from theoretical assumptions and avoids the *ad-hoc* assumptions that plague the applications of other methods; i.e, an augmented version of the modified total activity MTA method. In particular, to proxy for total economic activity, we use energy consumption in a response to the critiques facing the use of electricity consumption. We show that our proposed proxy of energy consumption performs better than the conventional proxy of electricity consumption. In addition, to account for the fact that financial crises usually overlap, we construct a zero-one index to capture the intensity of a financial shock. Applying a number of robustness checks, we show that our results are not sensitive to the method used in measuring the size of the shadow economy or to our proposed index of financial crises. Our results show that financial shocks have negative impacts on GDP in all countries. Moreover, in most countries, the shadow economy appears to behave countercyclically, which implies that it expands in times of financial crisis. This finding suggests that the shadow economy may play a buffering role in harsh times. Furthermore, since the expansion of the shadow economy does not seem to be persistent over time, an important policy implication can be drawn based upon our empirical results. In particular, we go against the conventional wisdom by suggesting a lax enforcement of anti-shadow regulations in times of financial crisis.

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References

Arby, M. F., Malik, M. J. and Hanif, M. N. (2010), 'The size of informal economy in pakistan'.

Bajada, C. (1999), 'Estimates of the underground economy in australia', *Economic Record* **75**(4), 369–384.

Bajada, C. (2003), 'Business cycle properties of the legitimate and underground economy in australia', *Economic Record* **79**(247), 397–411.

Bajada, C. and Schneider, F. (2005), 'The shadow economies of the asia-pacific', *Pacific Economic Review* **10**(3), 379–401.

Çiçek, D. and Elgin, C. (2011), 'Cyclicality of fiscal policy and the shadow economy', *Empirical Economics* **41**(3), 725–737.

Colombo, E., Onnis, L. and Tirelli, P. (2012), 'The shadow side of financial crises'.

Colombo, E., Onnis, L. and Tirelli, P. (2016), 'Shadow economies at times of banking crises: empirics and theory', *Journal of Banking & Finance* .

Eilat, Y. and Zinnes, C. (2002), 'The shadow economy in transition countries: Friend or foe? a policy perspective', *World Development* **30**(7), 1233–1254.

Elgin, C. (2012), 'Cyclicality of shadow economy', *Economic Papers: A journal of applied economics and policy* **31**(4), 478–490.

Elgin, C. and Oztunali, O. (2012), 'Shadow economies around the world: model based estimates', *Bogazici University Department of Economics Working Papers* **5**.

Engle, R. F. and Granger, C. W. (1987), 'Co-integration and error correction: representation, estimation, and testing', *Econometrica: journal of the Econometric Society* pp. 251–276.

Feige, E. L. (1989), *The meaning and measurement of the underground economy*, Edgar L. Feige, Cambridge University Press.

Feld, L. P. and Schneider, F. (2010), 'Survey on the shadow economy and undeclared earnings in oecd countries', *German Economic Review* **11**(2), 109–149.

Fiess, N. M., Fugazza, M. and Maloney, W. F. (2010), 'Informal self-employment and macroeconomic fluctuations', *Journal of Development Economics* **91**(2), 211–226.

Georgiou, G. M. (2007), 'Measuring the size of the informal economy: a critical review', *Occasional Paper in Economics* **7**(01).

Giles, D. E. (1997), 'Causality between the measured and underground economies in new zealand', *Applied Economics Letters* **4**(1), 63–67.

Gomis-Porqueras, P., Peralta-Alva, A. and Waller, C. (2014), 'The shadow economy as an equilibrium outcome', *Journal of Economic Dynamics and Control* **41**, 1–19.

Granger, C. W. and Newbold, P. (1974), 'Spurious regressions in econometrics', *Journal of econometrics* **2**(2), 111–120.

Hadri, K. (2000), 'Testing for stationarity in heterogeneous panel data', *The Econometrics Journal* **3**(2), 148–161.

Lee, H.-A. and Ofreneo, R. E. (2014), 'From asian to global financial crisis: Recovery amidst expanding labour precarity', *Journal of Contemporary Asia* **44**(4), 688–710.

Lesica, G. T. (2011), Estimating the size of the informal sector in Latin America, PhD thesis, Eastern Illinois University, Illinois.

Loayza, N. V. and Rigolini, J. (2011), 'Informal employment: safety net or growth engine?', *World Development* **39**(9), 1503–1515.

Lubell, H. et al. (1991), *The informal sector in the 1980s and 1990s*, Development Centre Studies: OECD, Paris.

Macias, J. B. and Cazzavillan, G. (2009), 'The dynamics of parallel economies. measuring the informal sector in mexico', *Research in Economics* **63**(3), 189–199.

Pedroni, P. (1999), 'Critical values for cointegration tests in heterogeneous panels with multiple regressors', *Oxford Bulletin of Economics and statistics* **61**(S1), 653–670.

Pedroni, P. (2001), 'Fully modified ols for heterogeneous cointegrated panels', *Advances in econometrics* **15**, 93–130.

Pedroni, P. (2004), 'Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the ppp hypothesis', *Econometric theory* **20**(03), 597–625.

Pratap, S. and Quintin, E. (2006), *The informal sector in developing countries: Output, assets and employment*, number 2006/130, Research Paper, UNU-WIDER, United Nations University (UNU).

Reinhart, C. M. and Rogoff, K. S. (2010), From financial crash to debt crisis, Technical report, National Bureau of Economic Research.

Roca, J. C. C., Moreno, C. D. and Sánchez, J. E. G. (2001), 'Underground economy and aggregate fluctuations', *Spanish Economic Review* **3**(1), 41–53.

Schneider, F. (2012), 'The shadow economy and work in the shadow: What do we (not) know?'.

Schneider, F., Buehn, A. and Montenegro, C. E. (2010), 'New estimates for the shadow economies all over the world', *International Economic Journal* **24**(4), 443–461.

Schneider, F. and Enste, D. (2000), *Shadow economies around the world-size, Causes, and Consequences*, International Monetary Fund.

Thomas, J. J. (1992), *Informal economic activity*, Harvester Wheatsheaf Hemel Hempstead.

Vaillant, J., Grimm, M., Lay, J. and Roubaud, F. (2014), 'Informal sector dynamics in times of fragile growth: The case of madagascar', *European Journal of Development Research* **26**(4), 437–455.

Westerlund, J. (2007), 'Testing for error correction in panel data*', *Oxford Bulletin of Economics and Statistics* **69**(6), 709–748.