The Journal of
Regional
Analysis
& Policy

JRAP 46(2): 202-216.

U.S. Shadow Economies, Corruption, and Entrepreneurship: State-level Spatial Relations

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Abstract: This paper offers a new theory of relationship between corruption and the shadow economy, one that defines it as either collusive – i.e., crony – or non-collusive. Using new estimates of state-level shadow economy size and data on corruption convictions of U.S. public officials for the 48 contiguous states, this study revisits this relationship empirically, controlling for spatial dependence. Additionally, the relationship between entrepreneurship and cronyism is investigated using productive entrepreneurship scores from Wiseman and Young (2014). Findings suggest that corruption and shadow economy size are positively related and both contagious and cross-contagious in the U.S. states. These results are fairly robust to several methods of spatial modeling. Results also reveal that productive entrepreneurship is contagious across states. Finally, this study attempts to draw a linkage among formal sector entrepreneurial outcomes, corruption, and the shadow economy using spatial GMM/IV modeling in an entrepreneurship regression.

1. Introduction

What is the link between shadow economy size and public official corruption? This question lacks a clear answer in the current literature. The existing evidence points to corruption and the shadow economy sometimes acting as complements and at other times substitutes. The shadow economy and corruption literatures are explored here to address previous findings and to highlight the absence of clarity in the corruption-shadow economy relationship. The designations "complement" and "substitute" often mask the underlying relationship between corrupt officials and shadow economy participants. The empirical analysis in this study focuses on corruption and shadow economy size across the U.S. states, but the theory presented might be applied more broadly. For example, in the U.S., like other high-income nations, a collusive relationship between corrupt public officials and firms is likely to result in more formal sector privileges for those firms party to the exchange (Dreher and Schneider, 2010). In this paper, such relationships are defined as *cronyism*. It is argued here that cronyism exists between public officials and firms primarily at two levels: highly visible officials with large firms and less visible officials with small firms. Additionally, cronyism creates barriers that drive otherwise legitimate firms, their workers, and entrepreneurs underground.

This is different than conventional arguments in the literature. Dreher and Schneider (2010), for example, suggest that collusion between firms and corrupt officials in high-income countries result in a negative — substitutive — relationship between corruption and shadow economy size. That is, according to Dreher and Schneider, firms *leave* the underground in order to collude with corrupt officials for formal sector work. (The substitution is not between corruption and shadow economy size in this case, but the formal and informal sectors). However, a cursory glance at the data (Figure 1 below) shows a positive corruption-shadow economy relationship in the United States. In what follows, a new theory is presented for the corruption-shadow economy relationship in high-income countries. In brief, the theory posits that large (more visible) firms will operate primarily in the formal sector to begin with; only brief crony transactions will take place off-the-books, contributing *positively*, if at all, to shadow economy size. Public officials who face a high degree of public scrutiny – e.g., politicians – will not likely engage in corrupt acts with small firms and entrepreneurs. As utility maximizers along political lines, corrupt political actors will want to engage in low-risk, high-reward cronyism. Therefore, corrupt officials who are more visible to the public will likely focus their solicitations on a small number of large firms. However, public officials who are less visible to the public eye – e.g., law enforcement – will probably have more luck shaking down smaller firms and sole proprietors. Again, however, the relationship between less visible corrupt officials and small firms should reveal a positive corruption-shadow economy relationship.

Moreover, some entrepreneurs and firms will flee all corruption and take their business underground. This, too, will be captured in a positive corruption-shadow economy relationship. Thus, the association between corrupt officials and shadow market participants addressed here is sometimes collusive, sometimes non-collusive. The importance of this realization is discussed further in the next section.

With this expectation in mind, both in-state and spatial aspects of the corruption and shadow economy relationship are investigated. First, the analysis looks at the association between corruption and shadow economy size within states' borders. Second, spatial contagion of both shadow economies and corruption are examined, followed by cross-contagion – the relationship between neighboring shadow economies (corruption) and home corruption (shadow economies). To anticipate the results, the U.S. corruption-shadow economy relationship, by all accounts, is positive. Both shadow economic activity and corruption appear to be contagious by themselves, but there also appears to be positive cross-contagion between shadow economies and corruption. These results support those of Goel and Saunoris (2014) and Goel and Nelson (2007) who find, respectively, corruption and shadow economy cross-contagion across countries and corruption contagion across U.S. states.

Additionally, the relationships among both in-state and border-state shadow economies (corruption) and formal sector entrepreneurial outcomes are explored.[1] If barriers erected by cronyism affect both small and large firms, and entrepreneurs, then it should be expected that some empirical relationship exists among corruption, shadow economy size, and formal sector entrepreneurial outcomes. Following the Wiseman (2015) study that first documents a link among these three variables, this paper explores the relationship in spatial analysis, using spatial GMM/IV modeling. Doing so provides two important results: first, support for the claim that the positive corruption-shadow economy relationship in the U.S. is at least partially non-collusive; and second, entrepreneurship is contagious across states.[2]

The remainder of the paper is organized in the following way: Section 2 discusses recent studies and attempts to clear up some of the ambiguity in the corruption-shadow economy relationship as it is explained in the literature. Section 3 provides theory for the corruption-shadow economy relationship in the United States. Section 4 presents data and methodology. Section 5 provides results. Finally, Section 6 concludes the study with some closing remarks.

2. Corruption and the shadow economy: an ambiguous duo

The relationship between corruption and shadow economy size is not made entirely clear in the literature. Competing arguments suggest plausible cases for both substitution (e.g., Dreher et al., 2009) and complementarity (e.g., Hindriks et al., 1999) – that is, for negative and positive corruption-shadow economy relations, respectively. Empirical studies find support for both cases (for a mix of results see, e.g., Johnson et al., 1997; Choi and Thum, 2005; Dreher et al., 2009; and Buehn and Schneider, 2012b). However, within each case there exist various possible story lines. These story lines may at times make empirical results difficult to interpret. An attempt is made here to make sense of the current literature, first by providing examples of past studies' theoretical considerations. The reader is also encouraged to

[1] The measure of entrepreneurship I use here captures large and small firm activity, as well as sole proprietorship, and innovative activities. Section 4 provides more detail.

[2] In a related study of productive entrepreneurship in U.S. metropolitan statistical areas, Bologna (2014) finds that positive, productive entrepreneurship spillovers result from improvements in neighboring institutional quality.

begin thinking about corruption and shadow economy participation in a new way: in terms of either collusive, i.e., crony, or non-collusive relationships between corrupt public officials and firms.

Past attempts to clear up this sometimes-positive-sometimes-negative relationship include, for example, Dreher and Schneider (2010), who in a cross-country study suggest that the relationship between corruption and the shadow economy – whether the two substitute or complement each other – hinges on income levels. But little has been done in one place to make sense of the details underlying either of these relationships, positive or negative.

This lack of clarity rests in part on the ambiguity that belies the very basic definitions of "complementary" and "substitute" in the literature. "Complementary" is most often defined as a *positive relationship between shadow economy size and corruption*. However, a positive relationship can represent various outcomes. Goel and Saunoris (2014), for example, use this definition in their assertion that "[m]ore corruption increases the size of the shadow economy when bribes facilitate setting up underground operations" (p. 123). Close inspection of this line is instructive, as it can be interpreted in a couple ways: first, corrupt officials and otherwise legitimate firms *work together* (indeed, complement each other, as the authors likely intend it) off the books, facilitating larger shadow economies (see also Hindriks et al., 1999); second, underground firms do not engage with corrupt officials, whatsoever. Instead, they either evade corrupt solicitations by going underground (Johnson et al., 1997) or possibly become a by-product of corrupt officials' interactions with other firms who have secured official sector privileges which establish higher barriers to market entry.

In each case, the corruption-shadow economy relationship is positive. The second case suggests the relationship may imply a *substitution* in the sense that firms substitute away from corruption to either avoid corrupt officials by hiding their activities underground or simply joining the shadow economy because they lack formal sector options.

Alternatively, "substitution" in the literature generally identifies a negative corruption-shadow economy relationship. Again, however, it is not clear whether such a relationship at present represents collusive or non-collusive relations among shadow participants and corrupt public officials. Choi and Thum (2005) construct a model wherein entrepreneurs' option to engage in shadow economic activity constrains (i.e., reduces) corruption among public officials – thus, the shadow economy serves as a complement to the *formal* sector, but a substitute to corruption. Dreher et al. (2009) provide some empirical support for the Choi and Thum hypothesis. Dreher and Schneider (2010) suggest that firms and corrupt officials engage in underground exchange for the purpose of securing more formal sector privileges, in which case firms and entrepreneurs leave the underground, effectively reducing its size. Though a collusive relationship, its present interpretation is substitutive.

Dreher and Schneider's hypotheses are informative: the authors argue that corruption and the shadow economy are substitutes in high income nations but complements in low-income nations. In the authors' words (pp. 218): "in high income countries corruption quite often takes place to bribe officials to get (huge) contracts from the public sector (e.g., in the construction sector), which are then handled in the official economy and not the shadow economy." Additionally, in low income countries "the shadow economy and corruption are likely to reinforce each other, as corruption is needed to expand shadow economy activities and – at the same time – underground activities require bribes and corruption." In other words, a collusive relationship exists among shadow participants and corrupt public officials in *both high- and low-income countries* according to Dreher and Schneider. However, the authors define the relationship as "substitutive" in the former and "complementary" in the latter case. It is argued here that both are *complementary* in the sense that both represent collusive – or crony – interactions.

Furthermore, if officials were granting formal sector contracts to firms operating primarily in the shadow economy to begin with, then one might expect Dreher and Schneider's high-income hypothesis to hold. However, the firms that Dreher and Schneider have in mind — those that acquire "huge" crony contracts — are likely to be larger firms operating primarily in the *formal* sector. The bribe itself will be captured in the shadow economy, adding to its size, but otherwise the transaction will do very little to reduce the shadow economy.

3. A theory for the corruption-shadow economy relation in the United States

Public choice theory suggests government officials are rational utility maximizers. Thus, it is expected that self-interested public officials will seek low-cost ways to maximize utility in line with their positions — e.g., politicians will maximize votes and budgets. In this paper it is argued that the costs associated with cronyism depend on both the official's visibility to the public and the visibility of the firm. For example, politicians may face more public scrutiny than law enforcement officers. Similarly, larger firms are more likely to operate entirely in the formal sector.

Intuitively, as utility maximizers along political lines, corrupt political actors will want to engage in low-risk, high-reward cronyism. Indeed, corrupt officials will want to reduce risk and increase reward in terms of the number of firms they effectively 'sell' privilege to. Since it is difficult for large firms to operate entirely off-the-books in rich countries, a corrupt official would necessarily have to deal with small firms and entrepreneurs if they were to engage full-time in the shadow economy. Thus, it makes sense that corrupt officials might benefit from colluding with a small number of large firms in the official sector, relative to a large number of small firms in the underground, which would arguably leave them more exposed to detection. This is particularly true for corrupt political actors' relationships with shadow economies in their own state, where their bribe solicitations will be levied on their constituents. This also suggests that if corrupt officials *were* to engage with small firms and entrepreneurs in the shadow economy, they would likely face less risk of detection across borders. (Border populations do not vote directly on their public positions). Alternatively, a less visible public official — such as a law enforcement officer — might be in a better position to solicit bribes from small, less visible firms, as smaller firms may find it more difficult to fend off corrupt officials through costly legal proceedings.

Additionally, corrupt officials may promise protection from local competition to firms from whom they solicit bribes; e.g., a law enforcement officer may harass and disrupt the small firms that do not pay or politicians may provide special breaks from regulation for the firms they favor. Cronyism will effectively restrict unfavored firms' ability to compete. Some unfavored entrepreneurs and firms will then be forced to either downsize (if a large firm) or go out of business, creating unemployed workers who themselves may turn to underground activities to maintain their livelihoods. Thus, in this paper it is predicted that public official corruption in the U.S. will be associated with larger shadow economies. In summary, for a high-income nation like the U.S.:

Hypothesis 1: *Highly visible public officials and large firms (operating primarily in the formal sector) will engage in crony underground transactions for the purpose of securing formal sector privileges. These transactions will increase shadow economy size and result in a positive corruption-shadow economy relationship.*

Hypothesis 2: *Corrupt officials and firms who are both less visible to the public will engage in crony transactions. These interactions will also contribute to a positive corruption-shadow economy relationship.*

Hypothesis 3: *All firms unfavored in crony transactions will transfer activity to the shadow economy. It is expected that this movement to the underground will be captured in a positive corruption-shadow economy relationship. This should also be revealed in a negative entrepreneurship-shadow economy relationship, as the entrepreneurship score used here measures productive formal sector activity.*

For a more formal expression of the cronyism-shadow economy relationship, this paper borrows from Cebula (1997), who models the effect of government policy — income tax rates, IRS audit probabilities, and IRS penalties — on the size of the U.S. underground economy. A similar cost-benefit model is presented here for a high-income country like the United States. Equation (1) represents the unfavored entrepreneur's decision, *Entrepreneur,* to engage in the formal sector as an increasing function of expected benefits, *EB*, and a decreasing function of expected costs, *EC*:

$$Entrepreneur = f(EB, EC), f_{EB} > 0,\ f_{EC} < 0 \qquad (1)$$

The expected benefit of formal sector entrepreneurial activity is an increasing function of institutional quality, for which "higher" quality implies that institutions secure property rights, personal choice, and voluntary exchange:

$$EB = g(EFNA),\ g_{EFNA} > 0 \qquad (2)$$

Expected cost is an increasing function of shadow economy development and indirectly an increasing function of public official corruption:

$$EC = h(Shadow\ (Corrupt)),\ h_{Shadow} > 0 \qquad (3)$$

Intuitively, the shadow economy becomes more attractive to politically unfavored firms and entrepreneurs as underground networks become better developed and as the unfavored actors, themselves, become more comfortable operating underground. Increasing corruption encourages underground development — e.g., Bitcoin, Silk Road, etc. — from entrepreneurs who are less likely to spend *any* time in the official sector, regardless of crony activity.[3] Hence, the shadow economy is an increasing function of public official corruption, *Corrupt,* that is constantly evolving to lower the cost of doing business underground.

Let *UGDP* be the unofficial value of gross domestic product – the value of all off-the-books transactions in an economy – and *GDP* represent the official measure of gross domestic product, such that:

$$UGDP + GDP = Total\ GDP \tag{4}$$

where *Total GDP* is an aggregate of *all* production in an economy. The ratio of unofficial-to-official GDP – or the value of the shadow economy as a percent of official sector gross domestic product – is represented in the following way:

$$Shadow = \frac{UGDP}{GDP} = l(Corrupt),\ l_{Corrupt} > 0 \tag{5}$$

Substituting (2), (3), and (5) into (1) yields:

$$Entrepreneur = F(EFNA, Shadow(Corrupt) \qquad f_{EFNA} > 0, f_{Shadow} < 0 \tag{6}$$

It is argued here that corruption affects formal sector entrepreneurship *through* its effect on shadow economy size. To support this claim, the relationship between corrupt public officials and shadow market participants is explored using both OLS and instrumental variable analysis in a GMM framework. Wiseman (2015) finds that corruption is a strong instrument for shadow economy size, one for which validity cannot be rejected, in regressions using entrepreneurship scores as a dependent variable. A strong and valid corruption instrument suggests that co-movements in corruption and productive entrepreneurship are likely the result of co-movements between corruption and shadow economy size. In other words, it is plausible that if corruption (cronyism) encourages larger shadow economies, it is because entrepreneurs are moving underground in response to developing shadow economies in the face of increased cronyism.

Using state-level data on shadow economy size from Wiseman (2013), productive entrepreneurship scores from Wiseman and Young (2014), and data on federal corruption convictions of U.S. public officials, this paper investigates the relationships among shadow economies, corruption, and entrepreneurship in regression analyses, with the above theory in mind.

4. Data and empirical methodology

4.1. Baseline model

The baseline models can be expressed in the following general form:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_k Z_i + \varepsilon_i \tag{7}$$

where $i = 1,\ldots,48$. Equation (7) is the basic model used to estimate relationships within state borders among each of the three variables of interest: average shadow economy size, average corruption convictions, and average entrepreneurial scores. Thus, each of these variables of interest will be examined as both a dependent variable and independent variable in the regressions that follow. Y_i will represent these variables on the left-hand side of the equation. X_i will represent the variables of interest when they are examined on the right-hand side. Z_i is a $(1,k)$ vector of control variables for which β_k is a $(k,1)$ vector of coefficients. β_1 is a coefficient for the determinant of interest; β_0 is a constant.

Data for shadow economy size come from MIMIC model estimates provided in Wiseman (2013). The size of the shadow economy is represented as a proportion of state-level GDP. Wiseman's estimates are founded on methodology that considers multiple indicators and multiple causes (MIMIC) of shadow economic activity in a system of equations designed to estimate unobserved phenomena by using covariance information from several observables. MIMIC estimation is a commonly used methodology with roots in shadow economy analysis dating back to Frey and Weck-Hanneman (1984). Wiseman's study period spans 1997 to 2008. This study covers the same period. The variable *Shadow* represents average shadow economy size for the *i*th state across the period.

[3] These entrepreneurs are of the lot who serve as a foundation for underground activity, as their participation in the underground likely depends more or less on much slower change in institutions (prohibitions, etc.).

Corruption data come from the U.S. Department of Justice's *Report to Congress on the Activities and Operations of the Public Integrity Section, 2010* and capture the annual number of corruption convictions of public officials in each state. Here, the number of corruption convictions is divided by each state's annual population to arrive at a measure of corruption convictions per 100,000 residents. Corruption crimes include convictions for election-related crimes (vote fraud and campaign-financing crimes, etc.), and various crimes related to bribery, embezzlement, unlawful insider deals with private vendors and other public officials, extortion, etc. Thus, corruption as it is captured in this data fits the more general definition of corruption often cited in the literature – that is, the abuse of public power for private gain (Dreher and Schneider, 2010). Additionally, this data differs from corruption data used in most other related studies in that it is *observed* (versus perceived) corruption. The *Corruption* variable represents average corruption convictions per capita for the *i*th state across the period 1997 to 2008.

Entrepreneurship data are scores that represent "productive entrepreneurship" (Baumol, 1990) in each of the 48 contiguous U.S. states. The data come from Wiseman and Young (2014) and are constructed based on Sobel's (2008) methodology. The scores (*Entrepreneur*) capture a wide range of entrepreneurial activity: per capita venture capital investments, patents per capita, the sole-proprietorship growth rate, total establishment birth rates, and large (500 employees or more) establishment birth rates. Development of a productive entrepreneurship score based on several indicators differentiates this analysis from the broader, more general body of entrepreneurship literature. Many studies focus on self-employment alone as a proxy for entrepreneurship. By focusing on multiple indicators of profit-seeking and innovative activity, a broad range of productive (formal sector) entrepreneurial activity is captured (Wiseman and Young, 2014).

When *Shadow* is the dependent variable, control variables include log of GDP per capita and *EFNA*, a measure of institutional quality from the *Economic Freedom of North America* index (Stansel and McMahon, 2013). Log of GDP per capita serves as a proxy for level of state development. The *EFNA* scores rank U.S. states on a scale of 1 to 10, separately, for three areas of economic freedom: size of government, takings and discriminatory taxes, and labor market freedom. A higher score indicates more freedom (i.e., respectively, smaller government, fewer and lower taxes, and less restricted labor markets). The comprehensive *EFNA* score is the average score across constituent areas. Intuitively, higher formal sector development, higher incomes, and better institutional quality will make doing business in the formal sector more attractive.

Following Goel and Nelson's (2007) estimation of corruption contagion in the U.S., when the dependent variable is *Corruption* the following controls are used: the unemployment rate; two measures of prosperity, income per capita and relative wages; three measures of government activity: state-level GDP per capita originating from the state-local public sector, federal civilian, and defense activities; police, corrections, and judicial employment as a percent of total state employment; and a dummy variable identifying states that share a border with the District of Columbia.

The expectations for the effect of many of these controls on *Corruption* are a bit ambiguous. Unemployed persons, for example, might be more willing to engage with corrupt officials; however, those officials might be reluctant to engage in corruption for fear of losing their own position in times of high unemployment. Government activity, too, might either serve as a deterrent to corruption or complement it by opening up opportunities for rent-seeking. The employment measures for police forces, corrections, and the judicial system might also serve as checks against corruption — that is, unless these forces themselves are corrupt (Goel and Nelson, 2007; see also Becker and Stigler, 1974). Concerning the dummy variable for D.C., states bordering D.C. might be more vulnerable to corruption contagion given the high concentration of public officials in the nation's capital. Alternatively, greater media scrutiny around the nation's capital might serve as a deterrent to corruption (Goel and Nelson, 2007).

Regressions of *Entrepreneur* on one of the other variables of interest (*Shadow* or *Corruption*) include a standard set of controls (see, e.g., Sobel, 2008; also Wiseman and Young, 2014): log of GDP per capita, EFNA, population density, median age, percent of the population with a bachelor's degree or more, and the percent of the population that is male. Summary statistics and sources for all variables used can be found in Table 1.

Table 1. Summary statistics and data sources.

Variable	Data Source	Mean	Std. Dev.	Min.	Max.
Shadow	Wiseman (2013); Shadow economy size (% GDP).	8.27	0.48	7.28	9.54
BorderShadow	Author's own calculation.	8.25	0.27	7.75	8.80
Corruption	U.S. Department of Justice's *Report to Congress on the Activities and Operations of the Public Integrity Section, 2010*; Corruption convictions per 100,000 state population.	0.31	0.14	0.09	0.64
BorderCorrupt	Author's own calculation.	0.34	0.10	0.12	0.56
Entrepreneur	Wiseman and Young (2014); Entrepreneurship score based Sobel (2008) methodology and is constructed using per capita measures of patents, and venture capital investment, as well as growth in sole proprietorship, total establishments, and large (500+ employee) establishments.	24.38	9.34	6.21	41.06
EFNA	Fraser Institute; Institutional quality on a scale of 1-10 (10=highest).	6.85	0.52	5.42	8.16
Ln GDP Per Capita	Bureau of Economic Analysis.	10.55	0.17	10.22	11.02
Unemployment	Bureau of Labor Statistics; Unemployment rate.	4.66	0.79	3.16	6.26
Federal	Bureau of Economic Analysis; State GDP originating from federal civilian activities per capita.	947.10	476.69	470.51	3209.0
Defense	Bureau of Economic Analysis; State GDP originating from defense activities per capita.	510.67	363.91	91.16	2050.4
StateLocal	Bureau of Economic Analysis; State GDP originating from state-local public sector activities per capita.	3724.6	485.44	2905.7	5101.8
Income	Bureau of Economic Analysis; Income per capita.	30543	4431.0	23186	43280
Wage	Goel and Nelson (2007); Census Bureau; Bureau of Economic Analysis; State-local March payroll divided by full-time-equivalent employment, expressed as a percent of state per capita personal income.	0.10	0.01	0.08	0.12
Corrections	Census Bureau; Corrections employment as a percent of total state-local employment.	4.52	1.15	2.40	7.02
Judicial	Census Bureau; Judicial employment as a percent of total state-local employment.	2.53	0.75	1.35	4.71
Police	Census Bureau; Police employment as a percent of total state-local employment.	4.28	0.86	2.61	6.62
D.C.	Dummy variable; 1=state shares a border with D.C.; 0 otherwise.	-	-	-	-
Population Density	Census Bureau.	192.51	260.42	5.45	1169.82
Median Age	Census Bureau.	36.59	2.07	28.01	40.63
%Bachelor's +	Census Bureau.	26.27	4.73	16.50	37.00
%Male Pop	Census Bureau.	49.25	0.65	48.35	50.89

Note: There are 48 observations for each variable in the cross-section – averaged across the period 1997 to 2008.

4.2. Spatial modeling: contagion and cross-contagion

Equation (8) is a very basic "spatial" approach to assessing contagion which adds to model (7) NS_j, a basic measure of neighboring states' shadow economy sizes or corruption convictions:

$$Y_i = \beta_0 + \beta_1 NS_j + \beta_k Z_i + \varepsilon_i \quad (8)$$

where i = 1,…,48. Following Goel and Nelson (2007), the *Shadow* and *Corruption* estimates, respectively, are averaged for the states j that share a border with home state i. These average estimates are defined as *BorderShadow* and *BorderCorrupt*.[4] Y_i, Z_i, and their respective parameters are the same as in equation (7). Again, β_1 is the parameter of interest.

Finally, in more formal spatial econometric analysis, both contagion and cross-contagion are examined in models designed to estimate spatial dependence – specifically, the spatial-autoregressive (SAR) model, spatial Durbin model (SDM), and a combined spatial-autoregressive model with spatial-autoregressive disturbances (SARAR). A general spatial model can be represented in the following way:

$$Y_i = \beta_i + \lambda \sum_{j=1}^{N} W_{ij} Y_j + \gamma \sum_{j=1}^{N} W_{ij} X_j + \beta_k Z_i + u_i, \quad (9)$$
$$u_i = \rho \sum_{j=1}^{N} W_{ij} u_j + \varepsilon_i$$

where i = 1,…,N; j = 1,…,N; N = 48 (states); and $j \neq i$. The variables Y, X, and Z are the same as before, W_{ij} represents a row-normalized spatial weight matrix. It is a 48 x 48 matrix in which non-zero elements define "neighbors" as states with shared borders — that is, an element in W_{ij} is "1" if i and j are "neighbors" and "0" otherwise. β_i is a state fixed effect (or constant).

Parameters λ, γ, and ρ represent spatial dependence in the dependent variable, explanatory variable, and error term, respectively. By restricting these parameters, the general model can be tailored to examine several special cases. A $\gamma = 0$ paired with a $\rho = 0$ restriction, for example, provides a model that measures spatial dependence in the dependent variable alone (i.e., shadow market or corruption contagion). This is the first formal spatial model considered here – the spatial autoregressive (SAR) model. Assigning the restriction $\rho = 0$ by itself results in the spatial Durbin model (SDM). This model allows for spatial dependence in both the dependent variable and an explanatory variable of interest (i.e., allows for measuring cross-contagion between shadow markets and corruption). The SDM is the second spatial model considered.

Following the recipe for these models in the literature (e.g., Lacombe and Ross, 2014; Anselin, 1988; LeSage and Pace, 2009) maximum likelihood estimation is applied to efficiently estimate the parameters.

Finally, a GMM/IV estimation strategy is imposed on the general model (9) using a $\gamma = 0$ restriction. This strategy and restriction result in the SARAR model — a combined spatial-autoregressive model with spatial-autoregressive disturbances (see Drukker *et al.*, 2001). This model helps test the claim that the shadow economy serves as a primary option productive entrepreneurs exploit in response to corruption (see Wiseman, 2015).

The analysis begins with a cursory glance at the cross-sectional data. Figure 1 illustrates a basic correlation between in-state shadow economy size and corruption. The slope is 1.37 and statistically significant at the one percent level. Intuitively, a one-unit increase in corruption convictions per capita is associated with a 1.37 percentage point increase in shadow economy size, on average. This basic relationship falls in line with the cronyism theory outlined above and is at odds with Dreher and Schneider's (2010) high-income hypothesis — which predicts a negative relationship between corruption and shadow economy size in high-income countries like the U.S.

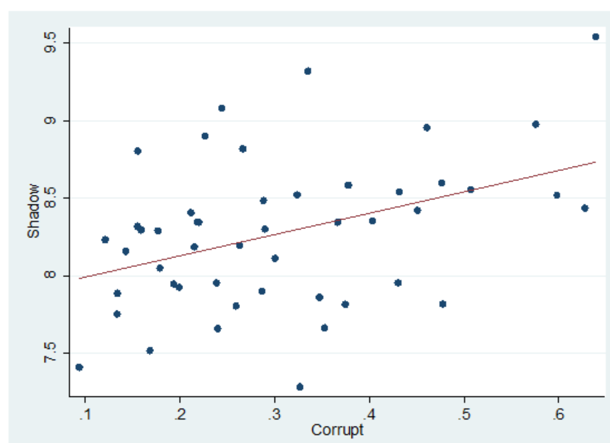

Figure 1. In-state shadow economy size and corruption.

[4] For example, for i = West Virginia, j = Virginia, Kentucky, Ohio, Pennsylvania, and Maryland. Therefore, $BorderShadow_j$ represents the average size of all states' shadow economies included in j; *BorderCorrupt* is the average of corruption convictions per capita across states included in j. This modeling technique is similar to using a first-order queen weight matrix in a mixed regressive-spatial autoregressive model (see, e.g., LeSage, 1999, pp. 63).

Figure 2 provides scatter plots between own state and border state shadow economies and between own state and border state corruption. Each of the correlations is positive, with slopes of 0.31 and 0.80, respectively, though only the corruption contagion correlation exhibits statistical significance (at the one percent level). Figure 3 illustrates a positive correlation with a slope of 1.40 (significant at the one percent level) between border state corruption and own state shadow economy size (cross-contagion). Results from more formal regression analysis are reported in the next section.

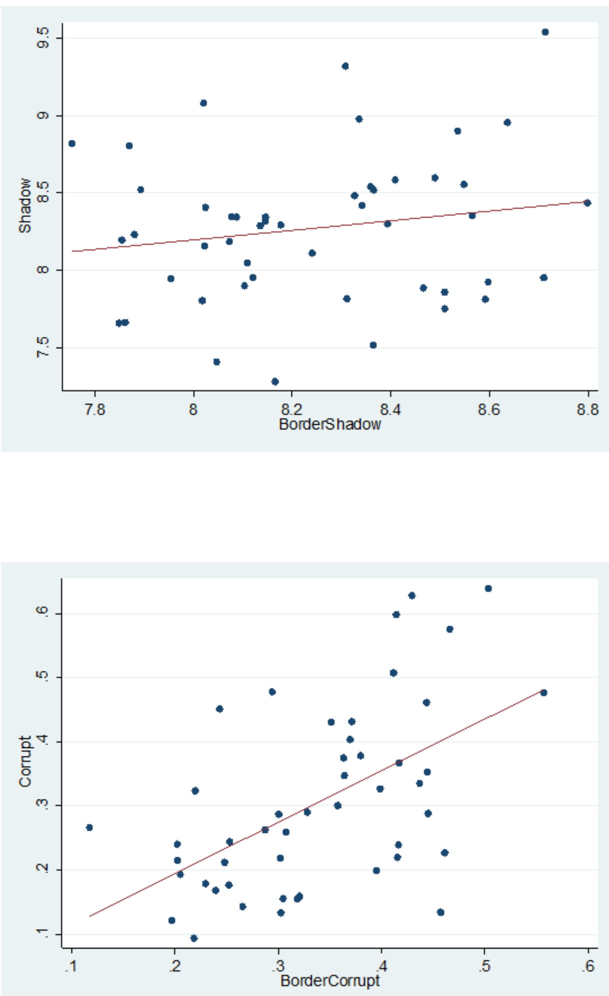

Figure 2. Shadow Economy Contagion and Corruption Contagion.

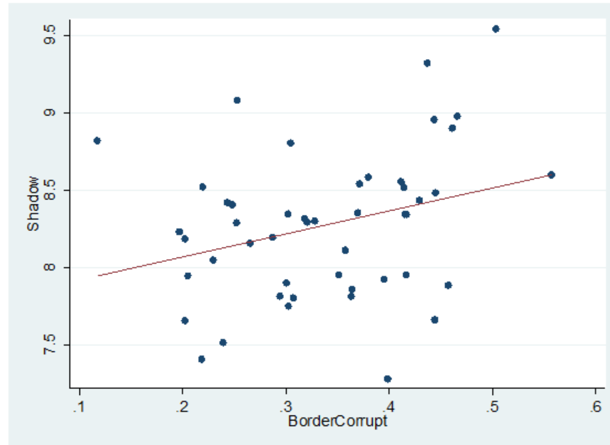

Figure 3. Shadow economy and corruption cross-contagion.

5. Results

5.1. Baseline results: shadow economy and corruption

Table 2 provides results for OLS regressions with *Shadow* as the dependent variable. Shadow economy contagion is examined first in specification 1. The *BorderShadow* coefficient is positively related with *Shadow* (slope of 0.291) and statistically significant at the 10 percent level. Intuitively, a 1 percent increase in the value of neighboring shadow economies (as a percent of GDP) is associated with a 0.291 percentage point increase in home shadow economy size, on average. Specification 2 examines the corruption-shadow economy relationship. Results suggest the *Corruption* coefficient is positive (0.760) and statistically significant at the 1 percent level. A 1 unit increase in own state corruption (per 100,000) is associated with a 0.760 percentage point increase in own state shadow economy size, on average. The third specification in Table 2 provides coefficient estimates for *Shadow* on *BorderCorrupt.* The coefficient is positive (0.921) and statistically significant at the 10 percent level.

Table 2. Regressions of shadow economy size on border shadow economy size, corruption, and border corruption.

	Specifications				
	1	2	3	4	5
BorderShadow	0.291*	-	-	0.074	-0.058
	(0.157)			(0.157)	(0.244)
Corruption	-	0.760***	-	0.684**	0.612**
		(0.281)		(0.304)	(0.274)
BorderCorrupt	-	-	0.921*	-	0.557
			(0.474)		(0.660)
EFNA	-0.456***	-0.341***	-0.377***	-0.363***	-0.330***
	(0.092)	(0.081)	(0.082)	(0.093)	(0.100)
Ln Real GDP Per Capita	-1.212***	-1.418***	-1.392***	-1.362***	-1.437***
	(0.258)	(0.258)	(0.251)	(0.265)	(0.282)
R^2	0.723	0.747	0.734	0.748	0.754
Observations	48	48	48	48	48

Notes: Robust standard errors are in parentheses. *, **, and *** denotes significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Constant included, but not reported.

One could argue, however, that the statistical significance of the parameters of interest, taken by themselves, in specifications 1-3 is driven by collinearity with the omitted variables in each regression. Table 3 provides a correlation matrix for the shadow economy and corruption variables. Specifications 4 and 5 in Table 2 address this concern. Results in specification 4 reveal that when own corruption and neighboring shadow economies are considered together, the *Corruption* coefficient maintains statistical significance (slope is 0.684, significant at the 5 percent level), but the *BorderShadow* coefficient does not. This suggests that perhaps the statistical significance of the *BorderShadow* parameter in specification 1 is driven by corruption. Specification 5 reveals that *BorderCorrupt* also loses statistical significance when *Corruption* and *BorderShadow* are included in the regression. While the relationship between own state shadow economy size and own corruption appears to be robust, the relationships between own state shadow economy size and neighboring shadow economies and corruption seem to be fairly weak.

Table 3. Correlation matrix of shadow economy and corruption variables.

	Shadow	*Border Shadow*	*Corruption*	*Border Corrupt*
Shadow	1.00	0.17	0.41	0.30
BorderShadow	0.17	1.00	0.49	0.66
Corruption	0.41	0.49	1.00	0.55
BorderCorrupt	0.30	0.66	0.55	1.00

Table 4 provides results for OLS regressions using *Corruption* as the dependent variable. Specification 1 investigates corruption contagion. The *BorderCorrupt* coefficient is positive (0.712) and statistically significant. Interestingly, the coefficient on states' own shadow economy size does not exhibit statistical significance when shadow economy size is used as an explanatory variable for states' own corruption in specification 2. This might suggest that causality runs the opposite direction — that is, corruption increases shadow economy size, but not the reverse. (Again, this relationship is positive and statistically significant when *Shadow* is used as the dependent variable in regressions illustrated in Table 2).

Results from specification 3 in Table 4 reveal a positive (0.212) and statistically significant (at the one percent level) *BorderShadow* coefficient. However, when more than one variable of interest is included as a regressor (specifications 4 and 5), each of their respective coefficients lose statistical significance, with the exception of the coefficient on neighboring corruption. This confirms Goel and Nelson's (2007) finding. Corruption appears to be contagious. The relationship between neighboring shadow economies and own state corruption appears weak.

Table 4. Regressions of corruption on border corruption, shadow economy size, and border shadow economy size

	Specifications				
	1	2	3	4	5
BorderCorrupt	0.712***	-	-	0.685***	0.564**
	(0.184)			(0.222)	(0.233)
Shadow	-	0.083	-	-	0.071
		(0.053)			(.045)
BorderShadow	-	-	0.212***	0.017	0.072
			(0.072)	(0.087)	(0.089)
R^2	0.600	0.441	0.510	0.600	0.616
Observations	48	48	48	48	48

Notes: Robust standard errors are in parentheses. *, **, and *** denotes significance at the 10, 5, and 1 percent levels, respectively. Constant and controls from Goel and Nelson (2007), including the dummy for D.C., are included in regressions, but not reported.

5.2. Spatial model results

To test the robustness of results in Tables 2 and 4, spatial dependence is considered next in spatial autoregressive (SAR) and spatial Durbin (SDM) models. Specifications 1 through 3 in Table 5 provide results from spatial regressions using *Shadow* as the dependent variable. The first equation considers only shadow economy contagion in an SAR model. The estimated coefficient for the shadow economy lag variable (0.251) suggests positive spatial dependence (statistically significant at the 10 percent level). Specification 2 models both own state corruption and spatial dependence in explaining shadow economy size. Only the *Corruption* coefficient (0.682) exhibits statistical significance in this regression. Specification 3 uses the SDM model. Regressors in this model include the spatial lags of both corruption and the shadow economy, as well as own state corruption levels. Results suggest positive spatial dependence (cross-contagion) in the corruption-shadow relationship (coefficient of 0.970, statistically significant at the 10 percent level), as well as a positive (0.547) and statistically significant (at the 10 percent level) coefficient on own state corruption. These results are similar to those reported in Table 2, with the exception that Table 5 provides better support for a statistically significant spatial cross-contagion between neighboring corruption and own state shadow economy size. Again, however, shadow economy contagion appears weak.

Specifications 4 through 6 provide results from spatial regressions using *Corruption* as the dependent variable. Specifications 4 and 5 test spatial dependence (contagion) in corruption with results that support those in Table 4: corruption appears contagious. Interestingly, specification 6 reveals that corruption may only be weakly contagious, as the coefficient estimate on neighboring corruption loses statistical significance when both neighboring shadow economy size and own shadow economy size are used as regressors. Both *Shadow* and the spatially lagged *Shadow* variable coefficients in this specification are positive and statistically significant. However, the coefficient estimate (0.230) on the lagged variable is both economically and statistically more significant than the coefficient on own state shadow economy size (0.107); they are significant at the 1 percent and 5 percent levels, respectively.

To summarize: results are fairly robust for corruption contagion, a positive own corruption-shadow economy relationship, and a positive cross-contagion between shadow economies and corruption. However, it is still difficult to determine direction of causality. Also, when considered by itself as a regressor in shadow economy regressions, neighboring shadow economy size is associated with own state shadow economies in a statistically significant way. However, the statistical significance of that result is lost whenever corruption (neighboring or own) is controlled for. Therefore, findings suggest only weak evidence of shadow economy contagion.

Table 5. Spatial dependence: shadow contagion, corruption contagion, and shadow-corruption cross-contagion.

	Specifications					
	1	2	3	4	5	6
	Shadow	*Shadow*	*Shadow*	*Corruption*	*Corruption*	*Corruption*
Shadow (lag)	0.251*	0.077	-0.071	-	-	0.230***
	(0.133)	(0.153)	(0.173)			(0.082)
Corruption (lag)	-	-	0.970*	0.429***	0.399***	-0.140
			(0.545)	(0.152)	(0.155)	(0.189)
Shadow	-	-	-	-	0.060	0.107**
					(0.050)	(0.051)
Corruption		0.682**	0.547*	-	-	-
		(0.296)	(0.298)			
R^2	0.725	0.749	0.760	0.515	0.524	0.576
Observations	48	48	48	48	48	48
Model	SAR	SAR	SDM	SAR	SAR	SDM
LR Statistic λ	3.352*	0.252	0.169	7.247***	6.620***	0.539
LR Statistic γ	-	-	3.170*	-	-	7.922***

Notes: Robust standard errors are in parentheses. *, **, and *** denotes significance at the 10, 5, and 1 percent levels, respectively. A constant and the standard controls for each dependent variable are included in regressions, but not reported. λ represents spatial dependence in the dependent variable, and γ represent spatial dependence in the explanatory variable of interest. For example, when Corruption is the dependent variable, λ represents the spatial lag of Corruption; and γ the spatial lag of Shadow.

5.3 *Entrepreneurship*

Next, an attempt is made to establish a link between corruption, the shadow economy, and formal sector entrepreneurial outcomes. Beginning with basic OLS regressions using *Entrepreneur* as the dependent variable and using the one-variable-at-a-time approach, specifications 1 through 4 in Table 6 examine the relationships between *Entrepreneur* and *Shadow, BorderShadow, Corruption,* and *BorderCorrupt.* Only the coefficient on in-state shadow economy size (-8.024) in specification 1 exhibits statistical significance (at the 10 percent level). The robustness of this result is tested by including on the right hand side of the equation both *Shadow* and *BorderShadow* in specification 5, and *Shadow* and *Corruption* in specification 6. The basic result from specification 1 does not change: the *Shadow* coefficient remains negative and statistically significant at the 10 percent level. Intuitively, the negative coefficient on *Shadow* in these regressions suggests the approximate point change in the productive entrepreneurship score given an increase in shadow economy size by a sample standard deviation (0.48). For example, in specification 1 a sample standard deviation increase in shadow economy size is associated with about an 8 point decrease in productive entrepreneurship, on average.

Wiseman (2015) suggests that the shadow economy likely serves as a conduit through which corruption affects entrepreneurship in the formal sector. That is, as corruption increases, entrepreneurs and firms leave the formal sector for shadow markets, resulting in lower formal sector participation. This claim is supported in the study by instrumental variable analysis using GMM specifications. Wiseman finds no evidence of a statistically significant relationship between corruption and formal sector entrepreneurial outcomes, the same result as reported here in Table 6. Interestingly, the Wiseman (2015) study shows that corruption is a strong instrument for shadow economy size, one for which validity cannot be rejected. Intuitively, it may be that co-movements in corruption and productive entrepreneurship are the result of co-movements between corruption and shadow economy size. In GMM regressions using corruption as an IV, results in the study demonstrate a negative, statistically significant effect on productive entrepreneurship. This finding suggests that the shadow economy is perhaps a primary option that productive entrepreneurs exploit in response to corruption.

Table 6. Regressions of productive entrepreneurship on shadow economy size, corruption, border shadow economy size, and border corruption.

	Specifications					
	1	2	3	4	5	6
Shadow	-8.024*				-7.999*	-7.333*
	(4.119)				(4.115)	(3.984)
BorderShadow	-	-1.592	-	-	-0.180	1.631
		(3.687)			(3.453)	(3.493)
Corruption	-	-	-9.569	-	-	-7.110
			(9.555)			(8.415)
BorderCorrupt	-	-	-	15.010	-	-
				(10.055)		
R^2	0.614	0.569	0.584	0.588	0.614	0620
Observations	48	48	48	48	48	48

Notes: Robust standard errors are in parentheses. *, **, and *** denotes significance at the 10, 5, and 1 percent levels, respectively. A constant and controls for median age, population density, percent of the population that is male, and EFNA are included in regressions, but not reported.

Based on Wiseman's findings, *Corruption* is used as an IV for *Shadow* here in a spatial-autoregressive model with spatial-autoregressive disturbances (SARAR). Table 7 provides results from a single GMM/IV regression using *Entrepreneur* as the dependent variable. Point estimates on the spatial lag of *Entrepreneur* suggest positive (0.290) and statistically significant (at the 10 percent level) spatial dependence. In other words, productive entrepreneurship in surrounding states affects productive entrepreneurship at home — i.e., entrepreneurship is contagious. The IV parameter is negative (-10.7) and statistically significant at the 1 percent level. Spatial error disturbances do not appear to be an important determinant of own-state productive entrepreneurship (ρ is -0.215, but not statistically significant).

6. Conclusions

The purpose of this paper is to help clarify the relationship between shadow economy size and corruption. At present, this relationship is a bit ambiguous in the literature. Thus, this paper steps away from recent "complement" and "substitute" designations and instead argues that the relationship might be better defined as either collusive or non-collusive — i.e., corrupt officials and shadow market participants either work together or they do not.

Here it is argued that in the U.S. large (more visible) firms will operate primarily in the formal sector to begin with; only brief crony (collusive) transactions will take place off-the-books, contributing positively, if at all, to shadow economy size. Additionally, officials who are less visible to the public (relative to, say, politicians) will be better able to engage with smaller firms in the shadow economy. Both of these scenarios add to a positive corruption-shadow economy relationship. Some portion of this positive relationship captures the value of transactions that entrepreneurs and firms, large and small, take to the underground in response to barriers erected by cronyism. This theory presents a challenge to Dreher and Schneider (2010), who predict a negative corruption-shadow economy size relationship in high-income countries.

Results from Wiseman (2015) support this theory while examining the relationships among corruption, shadow economy size, and entrepreneurship exclusively within states' borders. Additional support for the theory presented here is provided using U.S. state-level data to investigate spatial aspects of the relationships. First, a link is documented between own-state and border states' shadow economies (corruption), i.e., shadow economy (corruption) contagion. This paper also documents a link between shadow economies and corruption, both within and across borders (cross-contagion). Corruption and shadow economy size share a positive relationship within states' borders. In addition, there appears to be positive cross-contagion between shadow economies and corruption. These results are fairly robust to various model specifications.

Table 7. Spatial autoregressive model regression of productive entrepreneurship against shadow economy size with corruption IV.

	Specification
	1
Shadow (IV=Corrupt)	-10.713***
	(4.044)
Entrepreneur (Lag)	0.290*
	(0.168)
ρ	-0.215
	(0.253)
Pop. Density	0.001
	(0.005)
Median Age	-1.548***
	(0.451)
% Bachelor's +	0.559**
	(0.225)
% Male	-0.815
	(1.777)
EFNA	-1.277
	(3.061)
Model	SARAR-GMM/IV
Observations	48

Notes: Robust standard errors are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. A constant is included in the regression, but not reported.

OLS results reveal that corruption is not related to formal sector entrepreneurial outcomes in a statistically significant way. A positive shadow economy size coefficient, however, is supported by statistical significance in entrepreneurship regressions. A spatial GMM/IV entrepreneurship regression using *Corruption* as an instrument for *Shadow* results in a negative and statistically significant coefficient on *Shadow*. This result provides support for previous findings (Wiseman, 2015) that link corruption, entrepreneurship and the shadow economy. Intuitively, using *Corruption* as an instrument for *Shadow* tests for the possibility that the shadow economy works as a conduit through which corruption affects entrepreneurial outcomes in the formal sector (i.e., co-movements in *Corruption* and entrepreneurship are possibly explained by co-movements in *Shadow* and *Corruption*). This link appears to hold even when controlling for spatial disturbances.

Additionally, entrepreneurship itself appears contagious. One possibility is that entrepreneurs mimic the productive behavior of their neighbors. It is also plausible, however, that some portion of this entrepreneurial spatial dependence is driven by shadow economy contagion, which itself is likely a response to corruption (Table 2). When *Shadow* is the dependent variable, coefficients on neighboring shadow economy variables are only statistically significant when corruption controls are excluded from the regressions. It may be that home state shadow economy size is correlated with neighboring state shadow economy size through its relationship with home state corruption. Indeed, it follows from Section 3 that while corrupt officials face a high degree of public scrutiny in their home state, they may reduce risk of detection by interacting with corrupt officials and shadow economies in neighboring states, where they avoid direct contact with their constituents (Goel and Saunoris, 2014). This may explain some portion of the corruption-shadow economy cross-contagion found here and elsewhere, but, too, possible migration of productive entrepreneurs. However, migration in the face of cronyism is left for future research.

While the results presented here certainly do not provide the last word, they do provide some clarity for the corruption-shadow economy relationship in the case of a high-income country like the U.S.

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