Economic and crime cycles synchronization across states in México: A dynamic factor model approach

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Crime deterrence is of significant importance in public policy in México due to high and sustained levels of insecurity. Traditionally, public policies, including training programs for security enforcement agents and increasing the police force, have been implemented under an implicit understanding that economic stress and fluctuations have comparable effects across all territories. However, if the synchronization of the economy and crime has a geographically determined rate, policymakers need to consider these differences to increase policy efficiency. This study determines whether business cycles correlate with robbery cycles among states in México. To analyse these correlations, we implement a General Dynamic Factor Model, as proposed by Forni et al. (2000), which extracts each cyclical component from robberies in the states and from permanent and temporary employment measures. The results reveal the synchronization of a heterogeneous cyclical component among states and between both types of employment, which strongly suggests public security policies should incorporate a regional perspective. Additionally, the monitoring of economic performance should keep pace with public security actions, as this will improve the effectiveness of crime-deterrence actions.

Keywords:
crime trends,
economic cycles,
robbery,
employment,
synchronization,
dynamic factor models,
México

Introduction

During the last 15 years, criminal activity in México has intensified significantly, which has raised serious concerns for Mexican authorities and scholars regarding what public policy actions on security could more effectively ameliorate criminality and the effects on the country's social and economic functioning. Previous economic research has focused on investigating the long-term effects of crime on the economy, with empirical findings showing that criminal activity, particularly violent crime measured by homicide rates, hinders economic progress (Feliz 2012, González 2014 Torres-Preciado et al. 2017). While studies addressing the Mexican context have helped elucidate the potential economic costs of crime, notably, most have been concerned with the long-term economic performance in México while neglecting the effect of crime on the country's short-term economic performance.

In this respect, Torres-Preciado et al. (2017) have suggested some crimes follow a countercyclical behaviour with respect to per capita gross domestic product (GDP), although without systematically approaching such analysis. However, Muriel Torrero and Cortez (2019) advanced the relationship between the economy's short-term performance and crime at the state level in México. Based on Cantor and Land (1985), Muriel Torrero and Cortez (2019) estimated the effect of economic cycles on several measures of crime, including those related to property and people. While the authors improved the analysis by explicitly considering spatial effects, some aspects of their work remain subject to the same previous criticism of Cantor and Land's (1985) work, particularly their use of a contemporaneous and lagged unemployment rate to approximate economic cycle fluctuations. This then makes room for research into alternative methodologies.

Beyond merely complementing previous long-term economic performance findings on the relationship between crime and economic activity cyclical fluctuations in México, further research can elucidate the extent of the impact and, furthermore, whether criminal behaviour aligns with episodes of economic prosperity or hardship. These findings can provide a useful understanding about the crime – economy link to enhance the effectiveness of public security policy decisions. However, in the case of México, violent drug-related crimes have attracted most of the attention of public security authorities and scholars because of their proliferation, visibility, and continued increase. However, other crimes can inflict significant economic harm, especially robberies, which appropriate others' income and wealth possessions and potentially lead to lowering individuals' economic conditions, discouraging private investment in hot-spot zones, and even increasing closures of small and medium sized enterprises. In this respect, national surveys of individuals in México show that 94% of crime-related monetary economic losses are attributed to non-health expenditures, and 70% of these monetary losses are due to robbery (INEGI 2017). Moreover, about 34% of the establishments surveyed declared they had been victims of crime, with 19.4% of this victimized group cancelling investments, stopping commercialization activities, or even ceasing to do business with other enterprises (INEGI 2018). Similar to victimized individuals, robbery is a significant burden on enterprises in México, as 57% of the total crime rate within this sector is attributed to robberies.

Additionally, the statistics show that robbery follows a fluctuating dynamic behaviour over time, with some years reaching an annual growth variation of 12% nationally, while some states register even higher annual growth rates, demonstrating heterogeneous dynamic behaviour. These findings posit relevant implications for the robbery–economy link in México, suggesting a correlation between a state's robbery cyclical movements and some variables measuring economic cyclical behaviour.

Previous literature analysing the cyclical relationship between crime and the economy have used unemployment rates as the variable to approximate economic performance (Cantor–Land 1985, Torres-Preciado et al. 2017) because unemployment measures resource utilization and the functioning of labour markets; hence, it is suitable for investigating whether unemployment can lead to an increase in crime. However, the significant caveat of unemployment as a reference variable for the economy is that unemployed individuals do not necessarily turn to illegal activities. Additionally, unemployment measures suffer from undervaluation bias because classification technicalities might cause inaccuracies in the analysis of cyclical fluctuations.

However, using employment measures to investigate the economy's cyclical movements could be a fairly good alternative to unemployment rates for several reasons. First, employment closely follows the general economic performance of a country, both in the short- and long-term. Moreover, employment represents a labour market's outcome, which is promising for the economic analysis of crime. Second, employment measures can be decomposed into additional labour market dimensions, such as permanent, temporary, and other kinds of labour market components, which could enrich the analysis.

Recently, the Mexican economy has engaged in a process of labour market flexibilization which has, presumably, created a competitive environment to attract foreign direct investment, promote macroeconomic stability, and foster employment creation through contractual relationships based on temporary labour arrangements. While the actual economic effects of such labour market policy reforms is still a matter of academic discussion in Mexico with no consensus yet, recent statistics show that temporary employment has grown faster than permanent employment, with an annual average growth of 9% and 2.6%, respectively. This trend has reduced permanent employment from 95% to 86% of total employment, indicating that non-standard employment is gradually gaining ground among employers in México. This growing preference for temporary employment may carry implications for the robbery–economy link in México because, as hiring and firing temporary workers is less costly, such employment is more susceptible to variations in economic prosperity or hardship. Therefore, both labour dimensions may display differentiated relationships with robbery activity. However, the relationship between temporary and permanent employment and robbery fluctuations in México is an issue yet to be explored.

In this context, this study investigates whether business cycles movements, as measured by employment fluctuations, correlate with robbery cycles in Mexican states, characterizing the main correlation features. Specifically, we answer the following research questions: Are the common cyclical movements between employment, both permanent and temporary, synchronized to robbery cyclical fluctuations in states in México? Do state robbery cyclical fluctuations follow a countercyclical or procyclical pattern with respect to employment cyclical movements? Is the correlation between business and state robbery cyclical fluctuations a contemporaneous, leading, or lagging behaviour?

To answer these questions, we follow the methodology of Forni et al. (2000) and Forni and Lippi (2001) to identify and extract latent common cyclical components from variables and, subsequently, examine their correlation features. This modelling strategy is advantageous as it helps overcome using a static common cyclical component by incorporating a dynamic structure. In addition, the non-parametric nature of this approach avoids potential over-parametrization problems.

The remainder of this manuscript is structured as follows. The following section reviews the relevant literature on the relationship between crime and business cycles, both internationally and in México. The subsequent section offers an exploratory analysis of employment and robbery in México. The next section details the methodological aspects of the generalized dynamic factor approach and the collected dataset; and in the following section, we discuss the empirical findings. The final section presents our conclusions.

Literature review

Criminal activity and its relation to economic activity have been of increasing interest in economic and econometric studies. Beginning with the seminal work of Becker (1968), which approaches criminal activity using the framework of rational decision making under uncertainty and explains it in terms of expected utility, a large body of literature has emerged on the topic. Ehrlich (1973), Baldry (1974), Wolpin (1978), and Schmidt and Witte (1984) extend Becker's findings and generalize the economic model of crime. Recent studies on economic theories on crime include Fielding, Clarke, and Witt (2000) and Eide, Rubin, and Shepherd (2006). While these models give rise to comparatively static results that tend to agree on fundamental facts about the determinants of crime, the empirical research has corroborated theories and related crime to the real economy.

The study of the relation between criminal activity and the real economy is not a new endeavour. Bonger (1916) observed an association between economic booms and an increase in property crime, such as theft and robbery, and a slightly larger increase in violent crime. Thomas (1925) found a negative correlation between economic indicators of prosperity and property crime. Several explanations have been proposed to account for the relationship between economic prosperity and upsurges in delinquent behaviour that take advantage of opportunity, motivation, or both. Opportunity theorists argue that with economic booms come an increased availability of goods susceptible to theft, which has a positive effect on property crimes. Furthermore, increased economic activity implies increased mobility patterns, which creates vulnerability to property and personal crimes. When it comes to economic busts, motivation is an important part of the explanation. Specifically, the continued needs of unemployed or precariously employed economic agents create enough stress that they may become involved in criminal activity. Paradoxically, higher unemployment rates can be negatively correlated or simply uncorrelated, empirically, with the rate of property crimes. In a classical work on the subject, Chiricos (1987) analyses the results of 63 studies on the empirical relation between crime and unemployment and suggests 'a consensus of doubt' around this relation, questioning its strength, significance, and direction.

To explain these variations, Cantor and Land (1985) suggest that the empirical instability of the estimates of the causal relation between unemployment and crime can be attributed to a combination of an opportunity and a motivation effect acting in opposing directions and on different time scales. Later studies, including Cantor and Land (1991), Land, Cantor and Russel (1995), and Greenberg (2001), discuss the relation between the two variables unemployment and crime in more depth. However, summarizing the economic landscape in aggregate unemployment is limited, and the economic cycle should be considered related to criminal activity. The moving average, including up to five years of the unemployment rate, is used first by Cook and Zarkin (1985) and later by Paternoster and Bushway (2001), arguing that using only the contemporaneous and lagged unemployment rate is not a sufficient measure of the economic cycle. Similarly, Arvantines and Defina (2006) use a broader measure of the economic cycle; specifically, they use the business cycle component of real GDP per capita as estimated from a log-linear regression of GDP to a polynomial in time. From a different perspective, Mocan and Bali (2010) argue that the increase in property crime during economic hardships exceeds its decrease during periods of economic welfare, thus providing evidence of asymmetry in this relationship, which may have policy implications. Detotto and Otranto (2012) use a nonparametric version of the Dynamic Factor Model to identify common factors underlying the dynamics of the economic and criminal cycles.

Only recently has the relationship between crime and the economic cycle in México been studied. Using panel data from the state level, Verdugo-Yepes, Pedrioni, and Hu (2015) study the transmission of shocks in criminal activity, represented by measures of organized crime, on the economy in terms of real GDP and foreign direct investment. Analysing different causal theories on criminal activity and to determine which economic variables are key determinants of crime, Ramírez de Garay (2014) formalize four specifications of the crime–economy relationship and apply them to the case of violent personal crimes, specifically, homicide. As in other studies, the results are geographically heterogenous. Considering this geographical heterogeneity, Torres-Preciado et al. (2017) use a spatial panel data model to conclude that delinquency, particularly property and person crime, exerts a negative total effect on economic growth in México, which is reinforced by spatial significant spill-overs. The geographical spatial aspect of the relationship between crime and the economy is not only due to criminal activity being dependent on space. As noted by Alpek, Tésits, and Hoványi (2018), the fluctuations inherent in economic cycles may have different consequences or affect at different rates depending on location. In the study of criminal activity in México, we need to bear in mind that demographic dynamics may vary by region. Urban areas tend to be more heterogeneously populated, while rural areas exhibit more homogeneous population dynamics and overall structure, which may comprise, as studied by Salvati (2020), different population growth rates. Some studies, like Muriel Torrero and Cortez (2019), control for some regional heterogeneity in the panel setting.

Using time series econometrics, Quiroz, Castillo, Ocegueda, and Varela (2015) establish that crime and economic activities share a common tendency but have different short-run dynamics, which can explain the apparent persistence in criminal activity even when the economy is recovering. Similarly, but with a technically different approach, Cortez and Islas-Camargo (2017) use a Markov switching model to show that the partial effect of crime on economic growth is regime-dependent and, thus, asymmetric. Finally, Muriel Torrero and Cortez (2019) study the relationship between the economic cycle and crime using a spatial panel model at the state level. The partial effect of the economic cycle on crime is estimated for different forms of property and people crimes and, in accordance with past studies, an asymmetric, location-dependent impact is found.

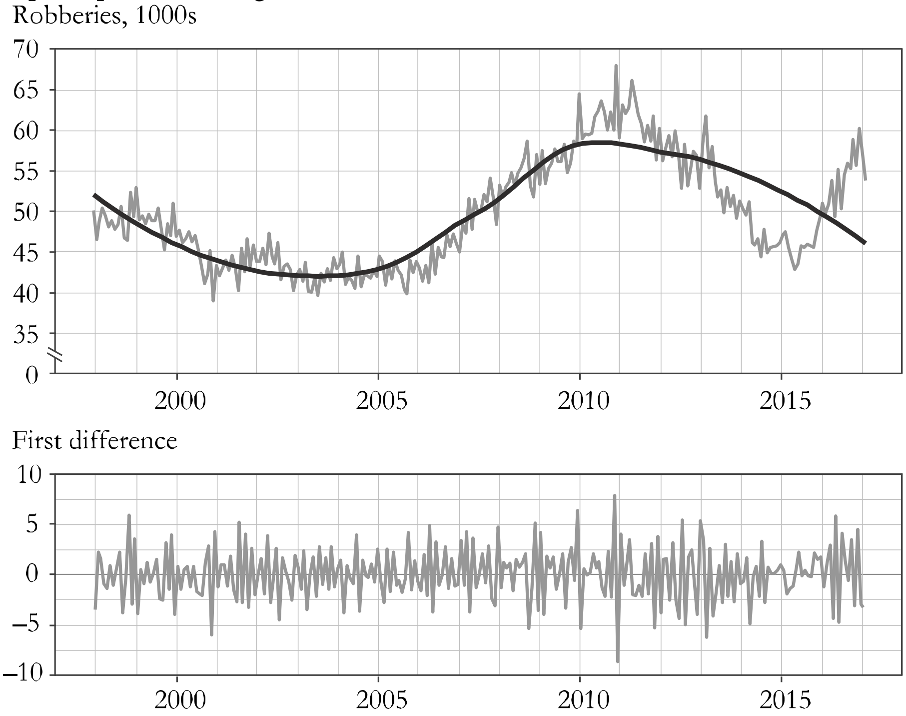
Overall, the studies on the relationship between crime and the economic cycle in México suggest the existence of a correlation that may be explained causally, in either direction, or by the existence of a latent factor. Most studies have focused on the first scenario, causality, and have studied both directions systematically. The other explanation, the existence of common latent factors, has yet to be investigated.

Basic facts of robbery in México at the state level

In this study, we use data generated by the Executive Secretariat of the Public Security National System (SESNSP, in Spanish), which gathers information from the investigation files opened in Public Prosecutor Offices after crimes have been reported by an alleged victim. While not all of these investigation files correspond to an actual crime, the proportional participation of spurious reports in the aggregate series is negligible and does not affect the conclusions of our study. In this study, we define robbery as the sum total of reported burglary, business robbery, street robbery, car robbery, and robberies classified as 'other' or 'without data' by SESNP. The dataset spans the period from January 1997 to December 2017 and has a monthly frequency. On a national scale, robbery behaves much like a random walk with an apparent random trend and cycle, as can be seen in Figure 1.

Figure 1

Total robberies in México from January 1997 to December 2017 with superimposed local regression (above) and first difference of the series (below)

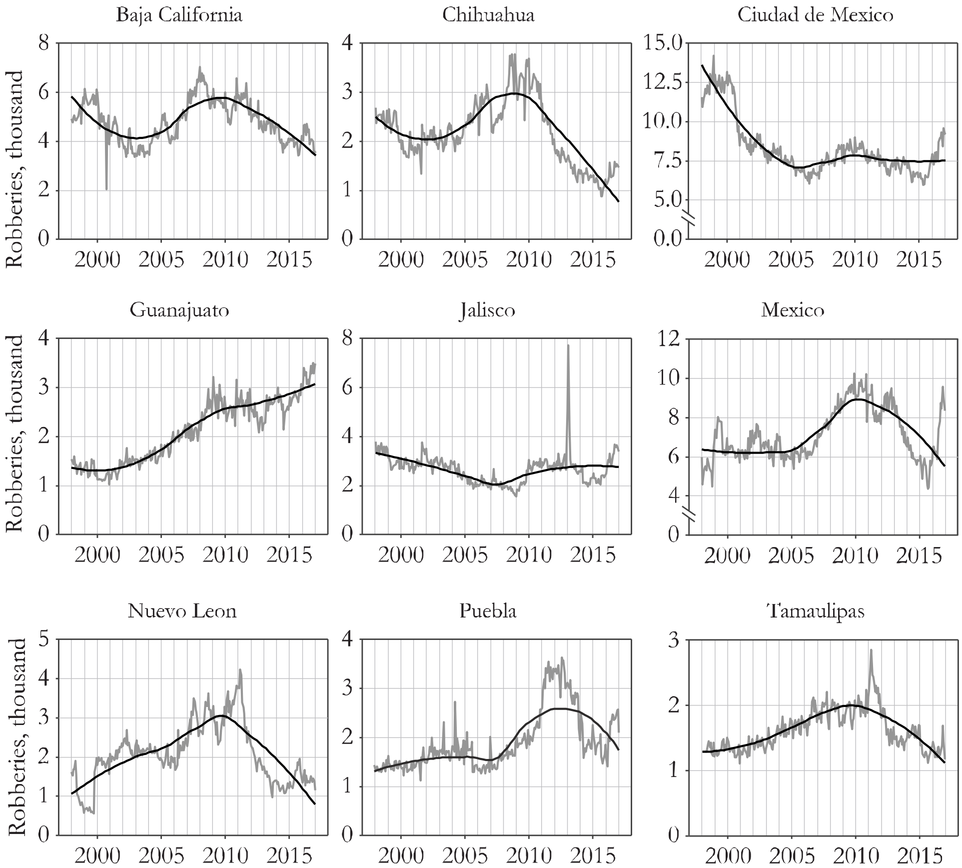


Source: Authors' elaboration with information from SESNSP.

The local behaviours of the nine cities most afflicted by robbery are illustrated in Figure 2, and Figure 3 displays the map of México at state level. These cities are responsible for large variations in the overall total. As expected, the dynamics of robbery have a local character, showing decreasing trends (Chihuahua, Nuevo León, Tamaulipas), relapses into insecurity (México), or pronounced and continued increases in robbery (Guanajuato and, lately, Jalisco and México). We expect the synchronization of crime and the labour market cycles to be local too, meaning that it may be leading in some states and time periods while lagging in other states; it may even be unrelated to other states in the same time periods. Recognizing these differences may prove important in determining when to implement local social assistance programs or reducing criminal activity (property crime) through temporal employment paradigms. Additionally, the non-stationarity[1] of the series has methodological consequences common in macro-econometrics, namely, the need to work with differences of some order rather than the level of the series. We use the first-differenced series to examine the cyclical relations between robberies and employment in each state.

Figure 2

Total robberies in each of the nine states most afflicted by the crime



Source: Authors' elaboration with information from SESNSP.

[1] Non-stationarity is a common property of macroeconomic time series, which implies that a raw series cannot be accurately predicted as a function of its past. Additionally, contemporaneous innovations are exogenous, and the series is highly variable. This feature, which complicates statistical analysis, can be corrected by using first differences, which is a widespread practice in applied econometric analysis.

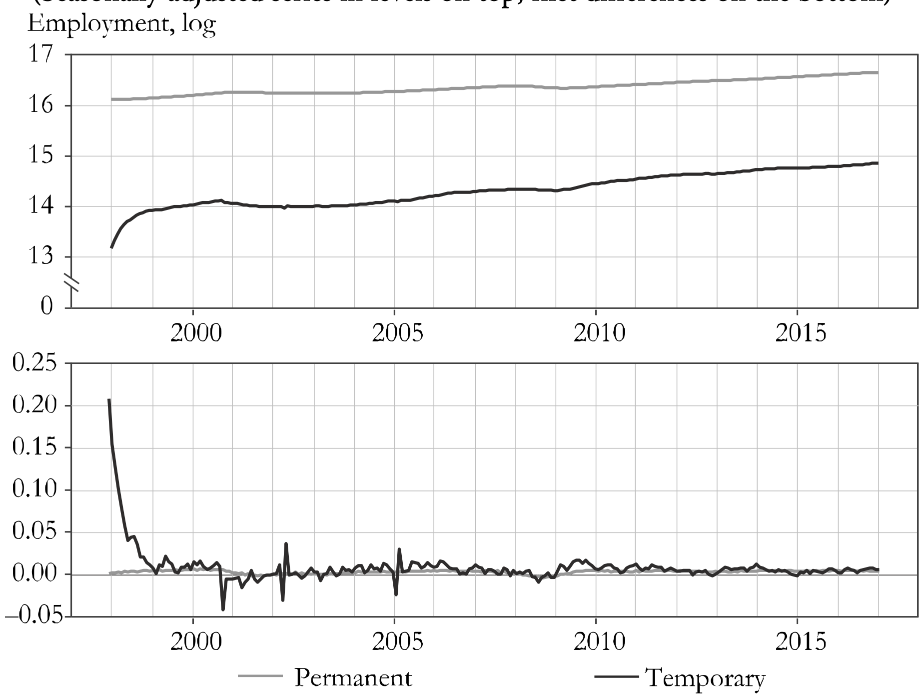
Figure 3

Map of México with territorial divisions and names at state level

Source: National Institute of Statistics and Geography (INEGI).

Figure 4

Permanent and temporary employment
(Seasonally adjusted series in levels on top, first differences on the bottom)



Source: Authors' elaboration with information from SESNSP.

We consider two types of employment: permanent and temporary. To understand employment dynamics, we adjust the series seasonally using the X-13-ARIMA filters. Figure 4 shows the logarithms of the seasonally adjusted series and the first differences in these series (millions of workers). The growth rate of temporary employment displays a more pronounced variability, which suggests that the two types of employment will have different synchronization dynamics with property crime.

Methodological aspects, procedure of estimation, database and series stochastic behaviour

We investigate whether national employment and state-robbery cyclical components in México are synchronized and the main correlation features by implementing a dynamic factor model (DFM) in its nonparametric version, as developed by Forni et al. (2000). In the DFM, all variables of interest are driven by a common set of non-observable factors that can be extracted so that each variable can be decomposed into a specific common component and an idiosyncratic component.

In the equation, z_t, a vector of n observable variables, has q orthogonal and unobserved common factors represented by a vector, $y_t=(y_{1t}, \ldots, y_{qt})$. Specifically, each of the observed variables within the z_t vector can be decomposed as in equation (1):

$$z_t = \chi_t^q + \varsigma_t \tag{1}$$

where χ_t^q represents the common component that linearly projects the observed variables in z_t onto the space of the unobserved common factors within y_t as in equation (2):

$$\chi_t^q = C_q(L)y_t \tag{2}$$

The common component χ_t^q can thus be estimated by dynamic principal components, which stands as an extension of its static counterpart (Forni et al. 2000), (Detotto and Otranto, 2012). Hence, a consistent estimator of the common component χ_t^q can be obtained as the projection of z_t on the first q eigenvalues and eigenvectors of the spectral density matrix $\sum(\omega)$, where ω is a frequency parameter. The associated general estimation procedure requires computing the spectral density matrix $\sum(\omega)$ at different frequencies and obtaining the eigenvalues and eigenvectors for each computed matrix, which are combined to compute the q unobserved common factors in y_t. These common factors are linearly combined along their lagged, coincident, and leading dynamic structure to estimate a common component for each of the n observables belonging to z_t, as in equation (3):

$$\chi_t^{qj} = \sum_{i=-m}^{m} c_{1,i}^j \, y_{1,t-i} + \sum_{i=-m}^{m} c_{2,i}^j \, y_{2,t-i} + \sum_{i=-m}^{m} c_{q,i}^j \, y_{q,t-i} \tag{3}$$

Accordingly, the χ_t^{qj} common component for the *jth* variable is loaded with $c_{q,i}^{j}$, which are the weights associated with each q unobserved common factor. In our investigation, the common component represents the cyclical component, which, in concordance with the previously described general procedure of estimation, will deliver the common cyclical behaviour for each of the variables to further analyse their correlation properties.

Another common method for estimating in the DFM setting is from Chamberlain and Rothschild (1983) and further developed by Stock and Watson (2002). Under this method, the factors can be estimated as the first r principal components, but restrictions need to be imposed on the model. To avoid these restrictions, we estimate the DFM following Forni et al. (2000). A mid-ground could arise from analysing estimators based on nonparametric, non-linear principal components as proposed by Egidi et al. (2021); however, this is outside the scope of our study.

To estimate the specific cyclical component for the observed variables within the z_t vector and to characterize their correlation, we implement the following empirical procedure. First, we define the z_t vector of observed variables as composed of 32 core variables, measuring the total number of robberies for an equal number of Mexican states, and two reference variables, corresponding to the types of employment: permanent and temporary. Second, the core and reference variables are seasonally adjusted, if necessary, and tested for the null of a stationary process to identify the order of integration underlying the stochastic process within each variable. For the common component to represent specific cyclical movements among the variables, these variables must be stationary. Third, based on the common component variance over series variance ratio, a statistic measuring the degree of correlation between the variables, we choose the number of q unobserved common factors to be linearly combined as described in equation (3). We follow Detotto and Otranto (2012) and use a 60% ratio of correlation as a minimal empirical threshold.

Based on the economic literature highlighting the relevance of labour market conditions in explaining robbery, we choose employment as the variable measuring the economic conditions, from which the cyclical component is extracted to approximate business cycles. However, instead of using unemployment rates, we use employment as the reference variable based on the following: (1) Although labour market outcomes closely follow general economic activity performance, they are linked to crime motivation. (2) For México, the methodology used to measure unemployment rates tends to underestimate the number of unemployed individuals,[2] which occurs in several other countries as well (Samba 2013).

In addition, the use of permanent and temporary employment dimensions as reference variables will account for changes in the functioning of the labour market in México, which has been characterized by relatively stable growth in permanent contractual relationships, whereas temporary labour relationships show pronounced fluctuations. Hence, the role of employment in the functioning of the economy, in times of both economic prosperity and hardship, may display differentiated synchronization features with robbery. The statistical data for permanent and temporary employment were obtained from the Mexican Institute for Social Security (IMSS, in Spanish) and were measured by the number of employees under a monthly frequency from 1997 to 2017. The core variable statistical data, measuring the total number of robberies among Mexican states, were obtained from the SESNSP and are available on a monthly basis spanning the same time period. Additional transformations and stationarity tests were performed to extract the cyclical components. Some series were seasonally adjusted, when necessary, by implementing X13-ARIMA, and then, all series were subjected to logarithmic transformations.

According to Forni et al. (2000), implementation of the generalized DFM for cycle correlation analysis requires that the series be covariance stationary. Therefore, the stationarity test of Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) was applied to all the series to test for the null of stationarity. The results in Table A1 in the Appendix show the null rejected for the series' level in 27 of 32 series, accounting for the total number of robberies, but not rejected for the series' first difference, strongly suggesting that they can be described as order one integrated, I(1), stochastic processes. The null was not rejected for the remaining five series; thus, they can be characterized as I(0) processes. In Table A2, the stationarity test results show that both permanent and temporary employment can be regarded as I(1).

[2] Underestimation of unemployment rates in México is, in part, a matter of classification. According to the current methodology (INEGI 2020), people who lose their jobs can be classified as part of the inactive economic population (PNEA, in Spanish) and not as unemployed because the former is defined as a person who chose unemployment within a reference period and has not been actively seeking reintegration into the labor market but is willing to accept a job. In this case, the key conceptual technicality defining people's final classification rests in assuming whether they are actively seeking to reintegrate into the labor market, which hides unemployment and leads to its underestimation. Cortez and Islas-Camargo (2009) offer detailed explanations about several factors causing unemployment rate measures to be underestimated in México: consider people who work an hour or less without remuneration of any sort as employed; classify people under temporary unemployment situations as actually employed; include informal work posts, which do not offer social security benefits, as part of the employment component, which may bias the unemployment rate downwards. The authors suggest that emigration to foreign countries and the low weight attributed to rural zones within the calculation of unemployment rates may contribute to underestimation.

Characterization of employment and crime cycles synchronization

Empirical implementation of the generalized DFM, based on a 70% ratio of the common component variance over series variance, calculated eight common factors, which were linearly combined to estimate the common cyclical component for each of the state-level robbery and employment variables (Table A1 in Appendix). Displaying the ratio of the common component variance over series variance for each of the variables, Table 1 shows that cyclical components of 30 states conform with the 60% empirical threshold when both permanent and temporary employment are considered as the reference variable. As the latter is a helpful criterion to choose the number of common factors to be calculated, and the ratio is a measure of correlation degree; hence, the results in Table 1 suggest that the series share a high degree of cyclical correlation. Broadly, Tabasco's specific ratio of cyclical correlation degree is 0.70 (70%), which is in the lower limit. However, the states displaying higher synchronization are Quintana Roo, Querétaro, and Guanajuato, with the topmost cyclical correlation degree at 0.93 (93%). Regarding permanent and temporary employment cyclical correlations, they both show synchronization with states' cyclical movements in terms of total number of robberies, with the permanent employment ratio slightly higher.

Having established that permanent and temporary employment cyclical components and each states' cyclical movements in terms of total number of robberies share a significant degree of correlation, we investigate salient correlation features. We characterize cyclical synchronization between reference series' and core series' cyclical components through phase classification and their lagged, coincident, and leading dynamic structure. Phase classification requires identifying whether core series' cyclical components achieve a peak (or trough) when the reference series' cyclical components achieve a peak (or trough). When the latter occurs, both cyclical components follow a procyclical behaviour, while the opposite occurs as a countercyclical behaviour. Because permanent and temporary employment cyclical components represent our reference series and the states' robbery cyclical components the core series, a procyclical relationship means robbery may increase as employment increases. While the opposite behaviour may be more commonly expected (i.e., robbery increases when employment decreases), this may not always be the case. According to the theoretical and empirical literature, a procyclical relationship may elicit criminal opportunistic behaviour related to economic prosperity, while a countercyclical behaviour would elicit criminal behaviour related to economic hardship.

Table 1

Ratio common component variance over series variance

Series name	Ratio	Series name	Ratio
Permanent employment	0.79	Temporary employment	0.74
Robbery		Robbery	
Aguascalientes	0.85	Aguascalientes	0.84
Baja California	0.77	Baja California	0.77
Baja California Sur	0.81	Baja California Sur	0.82
Campeche	0.76	Campeche	0.71
Chiapas	0.79	Chiapas	0.78
Chihuahua	0.79	Chihuahua	0.84
Coahuila	0.77	Coahuila	0.79
Colima	0.89	Colima	0.89
México City	0.84	México City	0.85
Durango	0.84	Durango	0.83
Guanajuato	0.93	Guanajuato	0.97
Guerrero	0.72	Guerrero	0.72
Hidalgo	0.86	Hidalgo	0.87
Jalisco	0.80	Jalisco	0.88
México	0.80	México	0.81
Michoacán	0.76	Michoacán	0.80
Morelos	0.74	Morelos	0.72
Nayarit	0.84	Nayarit	0.88
Nuevo León	0.89	Nuevo León	0.89
Puebla	0.73	Puebla	0.83
Quintana Roo	0.90	Quintana Roo	0.92
Querétaro	0.91	Querétaro	0.89
Sinaloa	0.76	Sinaloa	0.76
Sonora	0.88	Sonora	0.87
Tabasco	0.70	Tabasco	0.78
Tamaulipas	0.75	Tamaulipas	0.81
Tlaxcala	0.84	Tlaxcala	0.85
Veracruz	0.85	Veracruz	0.85
Yucatán	0.84	Yucatán	0.82
Zacatecas	0.77	Zacatecas	0.76

Source: Authors' estimations.

Similarly, characterization of the underlined lagged, coincident, and leading structure between the reference and core cyclical components illustrates procyclical or countercyclical dynamic behaviour. In particular, a state's robbery cyclical component following a procyclical (or countercyclical) and lagged behaviour with regard to employment's cyclical component depicts a dynamic relationship where criminal activity may increase (or decrease) with employment, but later in time. A leading behaviour would show criminal activity fluctuations occur before employment fluctuations, while a coincident behaviour describes contemporaneous synchronization between the reference and core cyclical movements.

In this regard, Table A4 in the Appendix shows a correlation matrix between contemporaneous permanent employment's and each state's cyclical components for the total number of robberies and for the seven positive (leading) and negative (lagged) lags. States' cycle components display a heterogenous synchronization with regard to permanent employment cyclical movements. Specifically, only 11 of the 30 states show a countercyclical phase between robbery and employment fluctuations. These states are Campeche, Chihuahua, Mexico City, Guanajuato, Hidalgo, México, Michoacán, Morelos, Nayarit, Querétaro, and Tabasco. Of these, Nayarit, Querétaro, and Tabasco demonstrate a lagging behaviour, which means that they show a decline in the number of robberies in times of economic prosperity when total employment increases. However, given their predominant lagged behaviour, the countercyclical response in these three states occurs later within the first months. The remaining eight states demonstrate a leading behaviour with respect to permanent employment cyclical movements. As a leading behaviour over the reference series means the cyclical movements continue, this implies that robbery activity may hinder economic performance as measured by permanent employment in these states. In this respect, both phase and lag analyses, as elucidated by means of correlation statistics, do not imply causal relationships, but at most help characterize the cyclical correlation association. Hence, while the countercyclical and leading behaviour observed among those eight states cannot provide sufficient evidence of a causal relationship, they suggest an underlying influence on the interaction between robbery and permanent employment common cyclical movements.

The remaining 19 states display a procyclical behaviour with respect to permanent employment common cyclical movements, which means opportunistic criminal behaviour is predominant in these states. However, as occurred in countercyclical-behaving states, these states demonstrate a differentiated dynamic synchronization. Among these 19 states, only Baja California, Baja California Sur, Coahuila, Durango, Nuevo León, Quintana Roo, Tamaulipas, and Tlaxcala show a coincident behaviour, indicating that robbery may contemporaneously intensify when employment increases within these states. Additionally, the states of Aguascalientes, Colima, Guerrero, Puebla, and Sinaloa show a procyclical lagged behaviour, suggesting that permanent employment and robbery jointly increase or decrease, but the latter would do so later. The remaining six states show a procyclical leading behaviour with respect to permanent employment cyclical movements (Table A4).

While both permanent and temporary employment show a significant common cyclical correlation, as measured by the correlation ratio, temporary employment represents a more flexible type of contractual labour relationship, which makes it prone to more accentuated fluctuations than permanent employment (Figure 3). This may render different synchronization features with each state's robbery cyclical component. Table A5 shows that 13 of the 30 states have a countercyclical phase between the temporary employment's and state robbery's cyclical components, that is, two more cases than those with permanent employment. However, only five states (Campeche, Guanajuato, Hidalgo, Michoacán, and Morelos) consistently feature the same countercyclical leading synchronization pattern regarding both types of employment, although clearly showing a higher correlation with respect to permanent employment cyclical components. The remaining eight states (Aguascalientes, Baja California Sur, Coahuila, Guerrero, Jalisco, Nuevo León, Puebla, and Quintana Roo) show a countercyclical leading behaviour with respect to temporary employment cyclical components, which otherwise feature a procyclical pattern with respect to permanent employment cyclical components, indicating that accounting for the functioning of labour markets through relevant dimensions may help elucidate different types of criminal inducements. Hence, a motivational criminal behaviour seems to be associated with temporary employment cyclical components within this latter group of states. In addition, most of the remaining 17 states have procyclical behaviour as with permanent employment, with only Nayarit, Querétaro, Chihuahua, Mexico City, Tabasco, and México featuring a change from the countercyclical pattern. An inspection of dynamic behaviour shows that coincident synchronization predominates over leading or lagging synchronization, so opportunistic criminal inducements may be predominant in these states.

The observed lack of homogeneity in the synchronization between employment and state–robbery cyclical components clearly indicates that individuals, and even regions, behave differently in relation to prevalent economic conditions. This suggests that it is a mistake to believe that individuals and regions would react similarly to crime-deterrent actions. Economic actions based on common beliefs that criminal activity, such as robbery, would diminish if employment increases might lead to counterproductive results. While widely accepted as a good economic action, in some cases, pursuing expansionary economic policies might expand criminal activity. This is particularly true when procyclical relationships are predominant. Implementation of public security actions without recognizing the heterogeneous synchronization between employment and robberies in the states may render less-effective results. In this respect, public security institutions would benefit from economic monitoring from a geographical perspective. Use of public security deterrence actions along with economic monitoring of prevalent conditions and expected economic policy effects would render a specific geographical and timely use of public security resources, such as police force and equipment, and could improve the effectiveness of crime-deterrence actions.

Conclusions

The relation between crime and the economic cycle has been the focus of a considerable amount of research in recent decades. Common sense suggests that this relation should be causal and that the economic cycle causes criminal activity, at least in some form. This conclusion may seem accurate when applied to a state where law enforcement tends to be inefficient due to low and, at times, inappropriate government expenditures, and when applied to widespread corruption, since this implies the ineffectiveness of one of the classical deterrents to crime. Moreover, this causal relationship seems applicable to property crime, since this activity is susceptible to being interpreted, within the framework of Becker (1968), as a labour market phenomenon. This interpretation states that property crime may be either a substitute or a complementary means of income and, thus, is expected to closely follow the economic cycle. During economic hardships, rational agents are inclined toward criminal activity and aggregated measures of crime demonstrate this increase. However, when the economy thrives, rational economic agents return to legitimate avenues of income, which reduces criminal activity. Econometric research on criminal activity bears witness that such intuition is neither completely correct nor universally applicable.

An alternative to thinking of economic activity as a causal factor for criminal activity is searching for a common, latent factor that drives both. This common factor, which summarizes the dynamics and variability of all the series under study, is especially useful when the problem becomes highly dimensional, and provides a way of representing specific common cycles, to further analyse pro- and counter-cyclical behaviours, either leading, lagging, or coincident. Upon this latter approach we were able to identify a cycle in criminal activity, and moreover, we found that this cycle shares dynamics with the business cycle in a nontrivial way. The synchronization between these two cycles is regional and dependent upon the type of employment. Hence, in some states, such as Chihuahua, robberies are immediately countercyclical to permanent employment. In other states, such as Nayarit, this countercyclical nature is lagging. Furthermore, in yet other states, such as Nuevo Leon, the relation is procyclical, and this procyclicality can be lagging, as it is in Puebla. Additionally, robberies have contradicting cyclical relations with the two types of employment, as is the case of Chihuahua, where crimes are procyclical with respect to temporary employment. These findings indicate that policies to reduce criminal activity should be regionally conceived and evaluated. For instance, some states will benefit from promoting temporary employment in the short run, while other states may benefit from procuring long-term contracts for workers. In both cases, the delay between the implementation of the policy and its fruits may vary among states, suggesting that coordination between local government and the federal administration is crucial in reducing the negative economic effects of criminal activity.

Providing a causal or theoretical explanation of our results is difficult. From the point of view of Cantor and Land (1985), we note that the relation is countercyclical when the motivation effect surpasses the opportunity effect such that the better opportunities for crime that come with economic welfare are not consequential. When this countercyclical relation is lagging, we conclude that the diminishing motivational effects lead rational agents to cease criminal activity and return to legitimate wage-earning activities. Similarly, procyclical relations are a consequence of the opportunity effect outweighing the motivation effect, a feature that illuminates specialization of criminals, where even if the economy is rising and employment opportunities are better, some agents prefer to earn from illegitimate sources. This relation may lag because, even if employment increases in these regions, wages do not. Hence, the apparently better economic landscape hides an implicit impoverishment of the working class, a fact that is a source of social frustration, which itself leads to (lagged) criminal activity. This interpretation is dependent upon the variables chosen to represent and measure the economic cycle. Here, we chose permanent and temporary employment to depict the economic landscape and, in a sense, overall social distress. In this way, the common factor between the economic and criminal cycle encompasses a measure of social discontent, which may be an amenable interpretation.

Appendix

Table A1

KPSS stationarity test for robbery among Mexican states

States	KPSS test statistic (levels)	KPSS test statistic (First difference)	1% critical value	5% critical value	Integration order
Aguascalientes	1.775	0.360	0.739	0.463	I(1)
Baja California	0.228	0.103	0.739	0.463	I(0)
B. California Sur	1.611	0.084	0.739	0.463	I(1)
Campeche	0.896	0.428	0.739	0.463	I(1)
Chiapas	0.518	0.079	0.739	0.463	I(1)
Chihuahua	0.485	0.120	0.739	0.463	I(1)
Coahuila	0.998	0.197	0.739	0.463	I(1)
Colima	1.008	0.138	0.739	0.463	I(1)
Mexico City	1.023	0.360	0.739	0.463	I(1)
Durango	1.209	0.052	0.739	0.463	I(1)
Guanajuato	1.908	0.181	0.739	0.463	I(1)
Guerrero	0.771	0.097	0.739	0.463	I(1)
Hidalgo	1.626	0.077	0.739	0.463	I(1)
Jalisco	0.303	0.170	0.739	0.463	I(0)
México	0.545	0.060	0.739	0.463	I(1)
Michoacán	1.554	0.097	0.739	0.463	I(1)
Morelos	1.800	0.153	0.739	0.463	I(1)
Nayarit	0.504	0.054	0.739	0.463	I(1)
Nuevo León	0.369	0.123	0.739	0.463	I(0)
Oaxaca	1.727	0.106	0.739	0.463	I(1)
Puebla	1.042	0.064	0.739	0.463	I(1)
Quintana Roo	1.124	0.049	0.739	0.463	I(1)
Querétaro	1.595	0.776	0.739	0.463	I(1)
Sinaloa	0.588	0.120	0.739	0.463	I(1)
San Luis P.	0.221	0.053	0.739	0.463	I(0)
Sonora	0.179	0.050	0.739	0.463	I(0)
Tabasco	1.556	0.236	0.739	0.463	I(1)
Tamaulipas	0.588	0.227	0.739	0.463	I(1)
Tlaxcala	1.681	0.182	0.739	0.463	I(1)
Veracruz	0.653	0.132	0.739	0.463	I(1)
Yucatán	0.785	0.288	0.739	0.463	I(1)
Zacatecas	1.816	0.096	0.739	0.463	I(1)

Source: Authors' estimations.

Table A2

KPSS stationarity test for permanent and temporary employment among Mexican states

	KPSS test statistic (Levels)	KPSS test statistic (First difference)	1% critical value	5% critical value	Integration order
Permanent employment	1.872	0.449	0.739	0.463	I(1)
Temporary employment	1.942	0.159	0.739	0.463	I(1)

Source: Authors' estimations.

Table A3

Parameters used as inputs in the generalized dynamic factor model

Number of common factors	8
Ratio of minimal variance proportion	0.6
Number of cross correlations lags	7
Common sample length	246
Common frequency	12

Source: Authors' estimations.

Table A4

Correlation between cyclical common components of states' robbery and permanent employment in Mexico

Serie name	Negative lags							0	Positive lags							Sum
	–7	–6	–5	–4	–3	–2	–1		1	2	3	4	5	6	7	
Permanent employment	0.01	0.11	0.24	0.39	0.56	0.71	0.86	1.00	0.86	0.71	0.56	0.39	0.24	0.11	0.01	6.78
Aguascalientes	0.06	0.10	0.14	0.16	0.16	0.15	0.12	0.08	0.03	0.01	0.00	0.00	0.01	0.01	0.01	1.06
Baja California	–0.03	0.00	0.02	0.05	0.08	0.10	0.13	0.15	0.12	0.08	0.05	0.01	–0.02	–0.05	–0.05	0.63
Baja California Sur	0.10	0.19	0.30	0.41	0.51	0.58	0.64	0.68	0.55	0.42	0.31	0.22	0.14	0.08	0.04	5.15
Campeche	–0.04	–0.05	–0.05	–0.06	–0.07	–0.09	–0.13	–0.17	–0.17	–0.16	–0.15	–0.13	–0.10	–0.08	–0.05	–1.49
Chiapas	0.01	0.00	0.01	0.02	0.04	0.07	0.12	0.17	0.20	0.20	0.20	0.19	0.16	0.12	0.07	1.57
Chihuahua	0.01	0.04	0.07	0.09	0.09	0.06	0.01	–0.07	–0.14	–0.19	–0.22	–0.23	–0.22	–0.17	–0.10	–0.95
Coahuila	0.03	0.05	0.07	0.09	0.11	0.13	0.15	0.17	0.14	0.10	0.06	0.03	0.00	–0.01	–0.01	1.07
Colima	0.04	0.06	0.07	0.08	0.08	0.08	0.07	0.07	0.06	0.04	0.03	0.02	0.02	0.02	0.02	0.75
Mexico City	–0.01	–0.05	–0.11	–0.18	–0.27	–0.35	–0.45	–0.54	–0.50	–0.44	–0.37	–0.28	–0.20	–0.11	–0.04	–3.90
Durango	–0.01	0.03	0.10	0.17	0.25	0.33	0.39	0.42	0.33	0.24	0.15	0.07	0.00	–0.04	–0.05	2.40
Guanajuato	0.04	0.07	0.08	0.05	–0.01	–0.10	–0.21	–0.35	–0.38	–0.39	–0.37	–0.32	–0.26	–0.18	–0.10	–2.42
Guerrero	0.13	0.19	0.24	0.29	0.32	0.33	0.34	0.35	0.29	0.23	0.20	0.17	0.14	0.11	0.08	3.39
Hidalgo	–0.02	–0.02	0.00	0.02	0.03	0.05	0.05	0.03	–0.02	–0.06	–0.10	–0.12	–0.12	–0.10	–0.06	–0.45
Jalisco	0.02	0.01	0.01	0.02	0.05	0.09	0.13	0.19	0.20	0.19	0.18	0.16	0.14	0.11	0.08	1.59
Edo. México	0.06	0.05	0.02	–0.02	–0.07	–0.13	–0.19	–0.27	–0.27	–0.26	–0.22	–0.18	–0.11	–0.05	0.01	–1.63
Michoacán	0.00	0.02	0.02	–0.01	–0.05	–0.10	–0.17	–0.24	–0.25	–0.23	–0.21	–0.18	–0.14	–0.11	–0.08	–1.72
Morelos	0.02	0.00	–0.04	–0.10	–.15	–0.21	–0.26	–0.30	–0.26	–0.21	–0.15	–0.10	–0.05	–0.01	0.02	–1.80
Nayarit	–0.01	–0.01	–0.02	–0.03	–0.05	–0.06	–0.06	–0.06	–0.03	–0.01	0.00	0.02	0.02	0.02	0.01	–0.28
Nuevo León	0.04	0.08	0.12	0.15	0.19	0.21	0.23	0.24	0.21	0.18	0.16	0.14	0.11	0.08	0.05	2.18
Puebla	0.11	0.14	0.15	0.14	0.11	0.08	0.04	–0.01	–0.04	–0.06	–0.05	–0.04	–0.01	0.02	0.05	0.64
Qquintana Roo	0.05	0.06	0.08	0.11	0.13	0.16	0.18	0.20	0.17	0.14	0.12	0.10	0.09	0.07	0.05	1.70
Querétaro	–0.01	–0.02	–0.03	–0.04	–0.04	–0.05	–0.05	–0.04	–0.03	–0.02	–0.01	0.00	0.00	0.00	0.00	–0.32
Sinaloa	0.06	0.09	0.13	0.16	0.18	0.19	0.18	0.16	0.10	0.06	0.02	0.01	0.00	0.01	0.03	1.37
Sonora	0.00	0.00	0.00	0.01	0.02	0.03	0.05	0.08	0.09	0.09	0.08	0.07	0.06	0.04	0.03	0.64
Tabasco	–0.04	–0.06	–0.09	–0.11	–0.13	–0.14	–0.15	–0.15	–0.12	–0.09	–0.06	–0.04	–0.03	–0.02	–0.02	–1.26
Tamaulipas	–0.01	0.00	0.01	0.03	0.04	0.05	0.06	0.07	0.07	0.07	0.06	0.05	0.03	0.01	–0.01	0.53
Tlaxcala	0.02	0.05	0.09	0.14	0.20	0.25	0.29	0.33	0.29	0.24	0.18	0.12	0.07	0.03	0.01	2.29
Veracruz	–0.02	–0.01	0.04	0.11	0.20	0.31	0.44	0.57	0.55	0.50	0.43	0.34	0.24	0.15	0.06	3.89
Yucatán	–0.01	–0.03	–0.05	–0.05	–0.04	–0.02	0.01	0.04	0.06	0.07	0.07	0.07	0.06	0.06	0.04	0.29
Zacatecas	–12	–0.16	–0.17	–0.14	–0.09	0.00	0.12	0.25	0.30	0.30	0.28	0.22	0.15	0.08	0.01	1.02

Source: Authors' estimations. High cross-correlations at positive (negative) lags indicates a leading (lagging) behavior of the variable with respect to the reference series.

Table A5

Correlation between cyclical common components of states' robbery and temporary employment in Mexico

Serie name	Negative lags							0	Positive lags							Sum
	–7	–6	–5	–4	–3	–2	–1		1	2	3	4	5	6	7	
Temporary emp.	0.01	0.01	0.01	0.17	0.36	0.57	0.79	**1.00**	0.79	0.57	0.36	0.17	0.01	0.01	0.01	4.84
Aguascalientes	0.00	0.00	0.01	0.04	0.02	–0.05	–0.16	–0.32	**–0.33**	–0.30	–0.22	–0.11	0.01	0.01	0.01	–1.41
Baja California	0.01	0.01	0.00	0.08	0.16	0.23	0.29	**0.33**	0.24	0.16	0.10	0.05	0.01	0.01	0.01	1.70
Baja California Sur	0.01	0.02	0.02	0.03	0.02	–0.02	–0.07	–0.13	**–0.13**	–0.12	–0.10	–0.06	–0.02	–0.02	–0.01	–0.57
Campeche	–0.01	0.00	0.00	0.02	0.04	0.03	0.01	–0.02	–0.05	**–0.06**	–0.05	–0.04	–0.03	–0.02	–0.02	–0.19
Chiapas	–0.01	–0.02	–0.03	–0.06	–0.03	0.06	0.21	0.38	**0.39**	0.33	0.23	0.11	–0.01	0.00	–0.01	1.55
Chihuahua	0.01	0.01	0.02	0.05	0.08	0.13	0.16	**0.18**	0.13	0.07	0.02	–0.01	–0.02	–0.01	0.00	0.82
Coahuila	0.01	0.00	–0.01	–0.13	–0.24	–0.34	–0.44	**–0.55**	–0.44	–0.32	–0.21	–0.09	0.03	0.03	0.02	–2.70
Colima	0.00	0.00	0.00	0.02	0.07	0.15	0.25	**0.36**	0.32	0.25	0.17	0.09	0.02	0.01	0.00	1.71
Mexico City	–0.02	–0.01	0.00	0.02	0.03	0.02	0.02	0.04	0.06	**0.07**	0.06	0.04	–0.02	–0.03	–0.03	0.27
Durango	0.02	0.01	0.00	0.01	0.04	0.07	0.10	**0.12**	0.08	0.04	0.00	-0.01	-0.01	0.01	0.02	0.47
Guanajuato	–0.01	0.00	0.01	–0.01	–0.02	–0.04	–0.06	**–0.08**	–0.07	–0.06	–0.04	–0.02	0.00	–0.01	–0.01	–0.42
Guerrero	0.01	0.01	0.00	–0.04	–0.06	–0.08	–0.10	**–0.11**	–0.09	–0.08	–0.06	–0.04	–0.01	0.00	0.00	–0.66
Hidalgo	0.01	0.01	0.01	–0.02	–0.05	–0.06	–0.09	**–0.12**	–0.11	–0.09	–0.06	–0.02	0.02	0.02	0.02	–0.54
Jalisco	0.00	–0.01	–0.01	–0.04	–0.07	–0.11	–0.14	**–0.16**	–0.12	–0.08	–0.05	–0.02	–0.01	–0.01	0.00	–0.82
Edo. México	0.00	0.01	0.02	0.07	0.13	0.20	0.27	**0.34**	0.27	0.19	0.11	0.04	–0.01	–0.02	–0.01	1.62
Michoacán	–0.02	–0.02	–0.02	0.00	0.01	0.01	0.01	0.00	–0.02	–0.03	**–0.03**	–0.02	–0.01	–0.02	–0.02	–0.17
Morelos	0.02	0.02	0.03	0.04	0.01	–0.05	–0.17	–0.32	**–0.34**	–0.30	–0.23	–0.11	0.02	0.01	0.01	–1.36
Nayarit	–0.01	–0.01	–0.01	–0.01	–0.01	0.00	0.02	0.05	**0.06**	0.06	0.05	0.03	0.01	0.00	0.00	0.22
Nuevo León	0.00	0.00	0.00	–0.04	–0.14	–0.29	–0.47	**–0.68**	–0.60	–0.47	–0.32	–0.16	0.00	0.00	0.00	–3.17
Puebla	0.00	0.01	0.01	0.01	0.01	–0.01	–0.02	–0.04	–0.05	**–0.05**	–0.05	-0.04	–0.03	–0.03	–0.02	–0.31
Q. Roo	0.00	0.00	0.00	–0.08	–0.21	–0.36	–0.52	**–0.68**	–0.56	–0.42	–0.28	–0.14	–0.02	–0.02	–0.01	–3.29
Querétaro	–0.01	–0.01	–0.01	–0.02	–0.03	0.00	0.05	0.12	0.15	**0.16**	0.14	0.09	0.02	0.01	–0.01	0.65
Sinaloa	0.01	0.02	0.03	0.05	0.06	**0.07**	0.07	0.06	0.03	0.00	–0.01	–0.02	–0.01	–0.01	0.00	0.37
Sonora	–0.01	–0.01	0.00	–0.01	0.04	0.13	0.28	**0.46**	0.46	0.39	0.29	0.15	–0.01	–0.01	–0.01	2.13
Tabasco	0.02	0.02	0.02	0.12	0.20	**0.24**	0.23	0.16	0.02	–0.06	–0.07	–0.04	0.04	0.04	0.03	0.97
Tamaulipas	0.00	0.00	0.00	0.07	0.13	0.18	0.21	**0.24**	0.18	0.13	0.09	0.05	0.01	0.01	0.01	1.30
Tlaxcala	0.02	0.02	0.03	0.07	0.13	0.21	0.28	**0.35**	0.27	0.20	0.12	0.06	0.01	0.00	0.01	1.77
Veracruz	0.02	0.01	0.01	0.05	0.10	0.12	**0.13**	0.10	0.03	–0.01	–0.03	–0.01	0.02	0.03	0.02	0.59
Yucatán	0.00	0.00	0.01	0.10	0.22	0.35	0.49	**0.64**	0.53	0.41	0.28	0.15	0.02	0.01	0.01	3.21
Zacatecas	0.00	–0.01	–0.02	–0.05	–0.04	0.00	0.09	0.20	**0.22**	0.21	0.17	0.10	0.02	0.02	0.01	0.93

Source: Authors' estimations. High cross-correlations at positive (negative) lags indicates a leading (lagging) behavior of the variable with respect to the reference series.

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