Spatial Nexus in Crime and Unemployment in Times of Crisis*

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Abstract

Space is important. In this paper we use the global financial crisis as an exogenous shock to the German labor market to elucidate the spatial nexus between crime and unemployment. Our contribution is twofold: first, we lay down a parsimonious spatial labor market model with search frictions, criminal opportunities, and, unlike earlier analyses, productivity shocks which link criminal engagement with employment status. Second, we seek empirical support using data on the 402 German regions and years $2009-2010$, in a setting that not only allows for crime spatial multipliers but also circumvents reverse causality by exploiting exogenous changes in unemployment due to the crisis. As predicted by our theory, the destruction of the lowest productivity matches, measured by increases in unemployment rates, has a significant impact on pure property crime (housing burglary and theft of/from motor vehicles) and street crime. The analysis offers important implications for local government policy.

JEL Classification: C31, J64, K42, R10

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1 Introduction

"Poverty is the parent of revolution and crime," *Aristotle*

The nexus between income and crime is recognized from Aristotle's time. In this paper we study how spatial attributes of the labor markets become intertwined with socio-economic aspects such as criminal activities in times of crisis. In our attempt to establish a causal and spatial link between unemployment – or income effects – and crime we exploit the 2008 global financial crisis as an experiment: the crisis hit German export-oriented manufacturing firms mainly in the west as well as the relevant manpower, namely young, male, short- and part-time workers (BfA, 2009). Although Germany's economy demonstrated resilience during the whirl of the 2008 economic crisis with a decline in employment much smaller than expected ("Germany's jobs miracle"),[1] the short deterioration of the German labor market during $2008-2009$ was driven by a trade shock with origins in the U.S. banking sector. These labor market adjustments were not a result of an increase in crime, unlike normal times when the two may reinforce each other and reverse causality threatens identification. The fact that crime was decreasing around the crisis period (see Figure 8.1) adds more credibility to our identification strategy: changes in the (un)employment of the crisis-hit sector and its relevant manpower could have a one-way, direct effect on crime only in the immediate aftermath of the shock. Therefore, we focus on $2009-2010$ as Germany returns to a growth path after this period.

Our contribution is twofold: first, we build theory based on the studies of Burdett et al. (2003), Boeri (2011) and Patacchini and Zenou (2007). We introduce a new economic mechanism as to why income affects crime: through shocks in match productivity and adjustments in labor market tightness originating from both home and neighboring regions. More specifically, we assume that agents who are willing to commute to work are also willing to commit crime in regions other than their domicile. The link between criminal activity and labor markets is a shock in agents' productivity. When a shock occurs productivity at which firms are willing to employ an agent changes. Agents whose productivity falls below the new threshold productivity level lose their jobs. An agent decides to commit crime after weighing expected gains and losses. By allowing for in- and outmigration in job seekers we allow for changes in domestic labor market tightness as well as in reservation wages. In turn, these changes shape steady states of crime and unemployment: it is always the low-productive and unemployed agents who have the incentive to commit property crime. We demonstrate that regional crime depends on crime in neighboring regions as well as unemployment, labor market tightness, average productivity, crime wages both in home and neighboring regions and deterrence. Second, we operationalize the theoretical model using the global financial crisis as the shock responsible for the link between property crime and unemployment in the 402 German administrative regions and years $2009-2010$. We carefully map our main theoretical crime equation into a spatial autoregressive econometric equation which models crime spatial multipliers and circumvents reverse causality by exploiting exogenous changes in unemployment due to the crisis. Our model performs well for property-related crime as intended originally, pinpoints the importance of unemployment and clearance rates as well as the share of subsistence benefits recipients for explaining crime rates, and, finally, offers implications for local government policy.

The remainder of this paper is organized as follows. We review related literature in Section 2. We motivate our work and outline the chain of events that underlie our empirical strategy in Section

[1] Indeed, as Moeller (2010) argues, the specific type of German flexibility does not stem from high labor turnover rates (hiring and firing) but through an unprecedented level of buffer capacity within firms. Avoidance of mass firing during the $2008-2009$ crisis can be ascribed to the so-called "Kurzarbeit" program of reduced working hours in Germany (OECD, 2010). A more recent approach can be found in Burda and Hunt (2011). Faia et al. (2013) confirm that unlike standard demand stimuli "Kurzarbeit" policies yield large fiscal multipliers, as they stimulate job creation and employment.

3. Section 4 is devoted to the model outline and main theoretical results. We translate theory into a spatial autoregressive type model and conduct some data exploratory analysis in Section 5. In Section 6 we present empirical findings and impacts that incorporate spatial multipliers. Section 7 is devoted to policy implications. Finally, Section 8 concludes, whereas the separate Online Appendix collects proofs, derivations and supporting material.

2 Literature Review

The strategy to use exogenous variation in economic activity to establish a link with crime has been gaining more popularity. For instance, Dix-Carneiro et al. (2016) use the 1990s trade liberalization in Brazil as a shock to construct exogenous variation in local labor demand and find a link with crime in the medium run. Deiana (2016) also employs local labor market conditions (earnings), identified by the exposure to Chinese imports, on crime for the U.S. commuting zones (722) panel (1990 − 2007). Andrews and Deza (2016) exploit shocks in the value of reserves in oil fields in Texas, U.S.A., to link income effects to crime. They find that oil shocks can explain crime, particularly through the influx of young males. Notably, this finding is in line with ours, despite differences in reasoning, spatio-temporal coverage of data, and identification strategy.

From a theoretical perspective, the seminal studies by Becker (1968), Ehrlich (1973) and Block and Heineke (1975) constitute early contributions to modeling criminal activity and linking them to economic decline. Freeman et al. (1996) recognize the spatial concentration of crime and model the decision between working and stealing. The number of criminals in a neighborhood increases returns to crime initially, which can explain why theft might flourish in one and not another – albeit similar in every aspect – neighborhood. In more recent advances, Burdett et al. (2003) develop a search equilibrium framework and incorporate interrelations between crime, unemployment, and inequality. Although the framework does not deal with space directly, the model points to spatial patterns: otherwise similar cities or neighborhoods can end up with very different crime rates, which points to multiple equilibria. One possible source for multiplicity is that people living in high-crime neighborhoods either get encouraged to engage in criminal activities because relative returns to legitimate activity are low, or can get discouraged because crime is more competitive. The strength of a particular effect is an empirical question. Burdett et al. (2004) extend the model by incorporating on-the-job search.

From an empirical perspective, Entorf and Spengler (2000) verify the positive effect of youth unemployment on crime rates with panel data on the German States. Entorf and Sieger (2014) find no effect of unemployment on violent crime through the mean but they establish a link through quantile regression.[2] Raphael and Winter-Ember (2001) focus on possible omitted variable bias and the direction of causation. Unemployment rates are suspected to be endogenous, first, because offenders get stigmatized, which in turn reduces the probability of legal employment; second, because companies find areas with high crime rates unattractive for business (reverse causality). Gould et al. (2002) empirically analyze the links between U.S. labor markets and crime prevalence. They are also careful at addressing potential endogeneity between crime and labor market outcomes. The wages and unemployment of unskilled men seem to be the most associated with crime, with the trend in wages being the main determinant.

Regarding the regional dimension, Edmark (2005) exploits significant increases in unemployment during the early nineties in Sweden to identify effects on crime with county panel data. The author finds a positive effect for burglary, car and bike theft. Öster and Agell (2007) also focus on Sweden and with a short panel on municipalities and instrumental variables estimation verify a positive effect

[2]For the case of Germany there exists literature, first, with data on the German Federal States such as Entorf and Spengler (2000) on socioeconomic and demographic factors of crime, Entorf and Spengler (2008) on the effectiveness of criminal prosecution, Entorf and Winker (2008) on the drug-crime relationship, and second, on individual inmate data such as Entorf (2009) on the link between job prospects and expected recidivism.

of unemployment on specific property crime categories and drug possession. The effect remains robust only for burglary after controlling for unemployment in neighboring municipalities. Kelly (2000) confirms that property and violent crime are quite different, and the latter is better explained by strain and social disorganization theories than economic reasoning. Lin (2008) with U.S. panel data resorts to instrumentation of unemployment rates and finds that the Two Stage Least Squares (2SLS) estimates are larger than the respective Ordinary Least Squares (OLS) verifying the existence of bias for property crime. With panel data on the French département level, Fougère et al. (2009) uncover the causal effect of youth unemployment on certain categories of property crime and drug offenses using again 2SLS. Buonanno and Montolio (2008) proceed differently, i.e., they model lagged crime rates in a Generalized Method of Moments (GMM) procedure that unveils the effect youth unemployment has on property crime for panel data on Spanish provinces. Bennett and Ouazad (2016) exploit Danish employer-employee data and focus on men, born between 1945 and 1960, to study the impact of job displacement on an individual's propensity to commit crime.

McIntyre and Lacombe (2012) explore spatial effects by introducing personal indebtedness as an explanatory variable in a crime equation. Using data from the city of London, the authors confirm the existence of spatial autocorrelation and the role of indebtedness on robberies and theft from a person. In a similar vein, Hooghe et al. (2011) demonstrate using both a spatial lag and a spatial error model the existence of a significant spillover effect for property crime and the strong impact of unemployment rates for Belgian municipalities, although they do not instrument the latter.[3]

Following studies that confirm a link between recessions and property crime (Cook and Zarkin, 1985 and Bushway et al., 2012), we examine the role of the geographical distributions of unemployment and crime rates by incorporating possible spillovers among neighboring German communities. We emphasize the neglected spatial aspect both in theory and empirics.[4] Our paper contributes to the emerging facts that recessions are causally intertwined with crime, and may have not only transitory but also more long-run effects, as established by Bell et al. (2015). In what follows, we describe how the global financial crisis affected local labor markets, and, therefore, crime in Germany.

3 The Global Financial Crisis in Germany: Crime and the Labor Markets

The aftermath of the global financial crisis was initially felt in the German labor markets in autumn 2008, culminated in the beginning of 2009 with a steep increase of the unemployment rates and stabilized thereafter (BfA, 2009). More specifically, employment started falling in autumn 2008 and continued until spring 2009. After that it stabilized and in September 2009 employment actually increased. The areas where employment was particularly hit are Baden-Wuerttemberg, Bavaria, north Rhine-Westphalia, Saarland and Thuringia. The reason lies in the worker concentration in

[3]Obviously, herein we lean towards papers that explicitly consider the unemployment-crime channel, therefore omitted thorough mentioning of studies that consider work and crime, e.g., Witte and Tauchen (1994), and wages and crime, e.g., Grogger (1998) or Machin and Meghir (2004), although the latter do not find an association between unemployment and crime. Other strands include deterrence factors and crime, e.g., Witte (1980), Cornwell and Trumbull (1994) or Levitt (1997), inequality and crime, e.g., Fajnzylber et al. (2002), education and crime, e.g., Lochner and Moretti (2004) or Machin et al. (2011, 2012), immigration and crime, e.g., Bianchi et al. (2012), criminal networks, e.g., Lee et al. (2012), or the effect of growing up in a high crime neighborhood as in Damm and Dustmann (2014), just to name a few.

[4]Anselin et al. (2000) discuss the role of space for crime and misspecification as aftermath of ignoring spatial dependence. Exceptions are Bianchi et al. (2012) who tested for the presence of spatial dependence in Italian regions before choosing aspatial specifications, Öster and Agell (2007) who specify unemployment spillovers but not spatial multiplier effects, and Hooghe et al. (2011) who, nevertheless, do not aim at reverse causality of unemployment rates. Gibbons and Overman (2012) underpin the lack of spatial economic theory and causality in spatial econometric models.

these German States: the crisis mainly affected short-time ("Kurzarbeit") employment in export-driven oriented manufacturing firms, e.g., metal and engineering, car and electrical industries, which are concentrated in western and southern Germany. Regarding unemployment, there was a sharp increase from January to April 2009, i.e., a bit later than the decline in employment. Again, unemployment was mainly hit in export-driven manufacturing firms as well as western and southern Germany (although eastern Germany's labor market has a deeper problem than western or southern Germany, it was affected far less by the crisis). The unemployment victims were predominantly males as is the manpower in the relevant industries affected by the crisis. Youth unemployment and, more specifically, youth male unemployment, has also increased since February 2009 and continued until October the same year. In 2010 Germany was completely out of the crisis. The short-time and part-time working policies in Germany are responsible for the mild impact on the labor markets, both in employment and unemployment.

The chain of events takes place at the end of 2008 until the end of 2009 for employment and at the beginning until the end of 2009 for unemployment. In our attempt to elucidate the spatial nexus between crime and unemployment, the global financial crisis constitutes an excellent laboratory because German employment and unemployment were exogenously shocked: changes in employment between $2008-2009$ and between $2009-2010$ and changes in unemployment between $2009-2010$ are driven by a global shock originating from a banking crisis in the U.S.A., totally orthogonal to regional crime in Germany. Therefore, we identify spatial dynamics (as opposed to time dynamics) and circumvent reverse causality in the relationship between crime and unemployment by focusing on changes between years 2009 and 2010.

In the upper graph of Figure 8.1 we plot the yearly evolution of unemployment around the crisis period. The unemployment rate increased from 7.8% in 2008 to 8.2% in 2009 amounting to a percentage change of 5.13%. A year later, the unemployment rate was back to precrisis levels, i.e., 7.7% with a percentage change of -6.10% from the previous year (2009). Starting 2009 we have information on the unemployment rates of different demographic categories, namely age $15-25$, male, female and foreign unemployment. Although the precrisis rates cannot be tracked, we observe that all categories of unemployment rates decrease after 2009, especially the foreign and youth demographic categories which experience the sharpest declines. We encounter the highest rates among foreigners followed by males and, finally, although female unemployment was lower than male in 2009, by 2011 the gender differential vanishes.

In the lower graph of Figure 8.1 we present the temporal evolution for available crime categories. The total offenses rate decreased very slightly in 2009 (-0.72%) while it experienced a further decrease in 2010 (-2.20%). Damage to property, drug-related offenses and street crime rates follow the overall criminal offenses pattern, meaning a declining path with a smaller percentage change for 2009 than 2010 (from-2.67% to -9.60%, from -1.36% to -2.42% and from -3.41% to -5.70% respectively). For crime categories that lead to immediate monetary gains, first, we note a substantial increase in thefts by burglary of a dwelling after 2009 (139 cases per $100,000$ inhabitants and 5.30% percentage increase from 2008), which not only lingers but further increases in 2010 (148 cases per $100,000$ inhabitants and 6.48% percentage increase from 2009). Second, we observe that theft of property in/from motor vehicles continues a diminishing paths but with a progressively slower pace (from -12.71% percentage change in 2009 to -6.15% in 2010).

We observe that, first, variations after the 2008 crisis are greater for specific crime categories than overall crime rates and, therefore, empirical analysis merits from separate treatment of crime categories instead of overall crime. Second, the crisis has not affected all crimes in the same fashion, meaning direction and magnitude of change. A plausible explanation as well as a hypothesis formulated theoretically and tested empirically is whether pecuniary motives hide behind distinct crime categories, as some of the latter are more likely to be committed by economically deprived individuals, whose adverse situation clearly aggravates in times of recession.

Economic variables, and especially those we treat herein, can be characterized not only by their temporal evolution as shown in Figure 8.1 but also by their propagation through space. In Figures 8.2 and 8.3 we map unemployment rates and rates for various criminal offenses respectively across Germany for years $2009 - 2010$ on the regional level, which corresponds to the European Union's NUTS 3. Germany is divided into 402 administrative districts, 295 of which are rural (Landkreise), while the rest are the densely populated independent cities (Stadtkreise) forming the 107 urban districts with more than $100,000$ inhabitants. Darker colors on the map signify higher rates of unemployment or crime. We can see in any graph of Figures 8.2 and 8.3 that neighboring districts tend to have the same color, i.e., similar occurrence of unemployment or crime rates respectively. Obviously, unemployment rates are higher at the New States of Germany and the western urban districts in north Rhine-Westphalia – known for its industrialization and urban agglomeration. All unemployment categories follow similar spatial patterns but there is quite some heterogeneity in the magnitude of the rates with the highest observed for foreign unemployment and the lowest for the youth unemployment share.

The emerging geographical patterns are quite distinct for the criminal offenses of Figure 8.3. Drug-related offenses do not seem to be heavily concentrated in specific parts of Germany. Damage to property occurs at a higher degree to the New States or the (western) urban districts just as unemployment does. Theft by burglary of a dwelling occurs more frequently in districts belonging to north Rhine-Westphalia, Berlin and its surroundings or Schleswig-Holstein and the Hamburg area. Finally, theft of/from motor vehicles and street crime are recorded largely in northern Germany, with higher concentrations in the north-eastern parts and north Rhine-Westphalia. For most categories/maps we discern that the darkest colors coincide with urban districts whose polygon area is quite small. Our interpretation is that criminal activity is a predominant trait of large cities (Glaeser and Sacerdote, 1999), where illegal opportunities are abound.

We include Figures 8.2 and 8.3 to stimulate visually the interest for spatial distributions. Merely by looking at the maps we expect all unemployment rates and the youth unemployment share to display positive spatial dependence. Regarding crime rates, we expect to uncover decreasing positive spatial dependence as we move from theft by burglary of a dwelling to theft of/from motor vehicles and then to street crime as low (high) crime incidence concentrates systematically in the south, the west and the north of Germany. Finally, we expect smaller spatial dependence for overall crime rate, damage to property and drug-related offenses because these maps are characterized by the systematic alternation of low-high crime incidence. As our dependent variable is crime rates, the crime spatial effect has the potential to generate a spatial multiplier meaning a dying-out wave of effects, which can explain how the crisis reached out areas not initially affected by the exogenous trade shock (although the global economic shock has encompassed not only real but also financial sectors, our example draws from a production sector, which is critical for the German economy).

To illustrate, think of an export-oriented manufacturing firm A in region N_1 and a production firm B in the neighboring region N_2. Production firm B in region N_2 does not export and, therefore, is not directly hit by the crisis as the export-oriented firm A in region N_1. Nevertheless, let us assume that production firm B provides raw materials to firm A and, is therefore, *indirectly* hit by the crisis because firm A lowers its orders and purchases from firm B during the crisis period. This example illustrates how spatial proximity and interaction between regions results in contagion of the crisis in areas and firms not initially affected by the shock. We can also think of how a third firm C in region N_3 sharing borders with region N_2 – but not N_1 – and interacting with firm B – but not with firm A – is affected by the trade shock through the neighbor (firm A in region N_1) of its neighbor (firm B in region N_2). Keeping in mind that firms respond to lower demand by decreasing the number of hours for the short-time workers and by laying off employees, the crisis results in adjustments in the labor markets, first, through employment and then through unemployment. Consequently, crime rates increase as a respond to the labor market adjustments and not vice versa; Figure 8.1 shows that crime and unemployment follow different time paths around the crisis period. What is more, any initial effect of unemployment on crime gets multiplied through this circle of interdependence so that aggregate effects are greater than the sum of individual regional effects.

4 Conceptual Framework

To explore empirical regularities in a more structured and rigorous fashion, we develop a parsimonious conceptual framework, which underlies our empirical exercise, and may prove to be a useful building block for future empirical work at the regional level. We build on Burdett et al. (2003), Boeri (2011) and Patacchini and Zenou (2007) to describe dynamics in a search model and derive the equilibrium. The steady states of endogenous variables enable us to perform local comparative statics and draw testable implications. In contrast to earlier analyses, we include productivity shocks, which are important in explaining empirical regularity of criminal engagement among young, low-educated and unemployed males (see, for example, Chapman et al., 2002). Our framework also explicitly accounts for spatial effects, allows to generate inherent endogeneity of crime and unemployment, and yields a number of testable implications that find empirical support in Section 6. Most importantly, we emphasize the importance of an adverse shock that makes agents self-select into crime; therefore, it is not simply an income effect that matters but an uncertain environment within which agents act. The global financial crisis provides a laboratory to test this implication since regional crime in Germany can be excluded from explaining the global financial crisis.

4.1 Labor Market Flows

In the simplest framework that deals explicitly with space, we need to introduce at least two areas $i = 1, 2$ and $j = 1, 2$. Each unemployed worker can look for a job in the two areas $i = 1, 2$ despite of her residence (there are no frictions to search, move or engage in an activity in either of the regions). Firms provide vacancies in each of the two locations $j = 1, 2$. Note that for any variable the first subscript denotes where the agent lives and the second where the agent undertakes an action. For example, u_{ij} refers to the number of unemployed workers residing in i and searching for a job in j. We normalize the total population to one, so that the unemployment level in area i is equal to the unemployment rate in the same area.[5] Moreover,

$$E_{ii} + E_{ij} + u_{ii} + u_{ij} + n_{ii} + n_{ji} = 1,$$

in which E_{ij} denotes the number of employed workers residing in i and working in j, while n_{ji} stands for the number of enjailed criminals from region j who committed a crime in region i. Hence, population in i includes criminals of both regions' descent. Note that uncaught criminals may be both employed or unemployed with the precise conditions for belonging to either category determined below. Workers are free to search for work in both locations and commute to work if employment is found outside their domicile. Notice that we define unemployed workers u_i as those who originate from both, region i and j, as long as they search for a job in region i,[6]

$$u_i = u_{ii} + u_{ji} \text{ and } u_j = u_{jj} + u_{ij}.$$

The total labor force residing in i and working and searching in j is $u_{ij} + E_{ij}$, which implies that the total labor force in region j is equal to $u_{1j} + E_{1j} + u_{2j} + E_{2j}$. The vacancy rate in region j is defined as a fraction of the total mass of workers, i.e., $v_j/(u_{1j} + E_{1j} + u_{2j} + E_{2j})$. Clearly, spatial interactions matter: an increase in the number of employed or unemployed agents, working or searching for a job at the home region, decreases the home vacancy rate.

[5] An agent can end up in one region only – either i or j – although she can compare payoffs in both regions and instantaneously converge to the best option. Patacchini and Zenou (2007) apply the same normalization.

[6] An alternative is to separate job seekers from unemployed agents, as in the working paper version (see Lastauskas and Tatsi, 2013) but the current choice makes exposition more transparent without compromising generality.

Consistently with much of the empirical literature estimating matching functions (Petrongolo and Pissarides, 2001), we assume that matching occurs at constant returns to scale. The job finding (vacancy filling) rate depends uniquely on the ratio of the number of vacancies, v_i, to the level of unemployment, u_i, that is, on the degree of labor market tightness, $\theta_i \equiv v_i/u_i = v_i/\left(u_{ii} + u_{ji}\right)$. Denoting the aggregate matching function as $m_i = m\left(v_i,\, u_i\right)$, the unconditional probability that a vacancy is matched to an unemployed worker (instantaneous meeting probability for vacancies) is then

$$\frac{m\left(v_i,\, u_i\right)}{v_i} = m\left(1,\, \frac{u_i}{v_i}\right) = m\left(1,\, \frac{1}{\theta_i}\right) = q\left(\theta_i\right),$$

with $q'\left(\theta_i\right) < 0$, $q''\left(\theta_i\right) > 0$ and $\lim_{\theta_i \to 0} q\left(\theta_i\right) = \infty$ while the probability that an unemployed worker meets a vacancy is $p\left(\theta_i\right) = m\left(v_i,\, u_i\right)/u_i = \theta_i m\left(v_i,\, u_i\right)/v_i = \theta_i q\left(1/\theta_i\right)$. Space manifests through labor flows: labor market tightness changes through vacancy and unemployment rates in both regions.

Turning to the firm's side, production occurs when a worker is matched to a job. All newly-formed matches (filled jobs) generate a productivity φ with $\varphi \in (0,\, 1]$. Following Miyamoto and Takahashi (2011), we interpret φ as the firm's efficiency to implement a new project. Since labor is the only factor in our environment, we relate matches to productivity and subject them to exogenous shocks, e.g., innovations unknown at the time of match formation or external shocks occurring at a frequency λ. When a shock occurs, productivity is a random draw with a fixed, known cumulative distribution $F\left(\varphi\right)$. These shocks are persistent in the sense that productivity remains at this level until a new shock occurs. When productivity falls below a threshold level, $\tilde{\varphi}$, endogenously determined in the model, it is no longer profitable to continue production in the existing match so the job is destroyed.

Due to the presence of search frictions, any realized job match yields a rent. Wages share this rent between workers and firms according to a Nash bargaining rule and are instantaneously renegotiated whenever a new shock arrives. At the equilibrium, labor market flows depend on gross job creation (matching of vacancies to unemployed workers) and gross job destruction (dissolution of matches) when match productivity falls below the threshold level. More precisely, there are three states – employed, unemployed and enjailed – and six possible transitions:

$$\begin{array}{ccccccc}
\text{Employed} & \to & \text{Unemployed} & \lambda F\left(\tilde{\varphi}_j\right)\left(1 - u_j - n_j\right); & \text{Unemployed} & \to & \text{Enjailed} & \pi\phi_j^U u_j; \\
\text{Employed} & \to & \text{Enjailed} & \pi\phi^W\left(\varphi_j^C\right)\left(1 - u_j - n_j\right); & \text{Enjailed} & \to & \text{Unemployed} & \rho n_j; \\
\text{Unemployed} & \to & \text{Employed} & \theta_j q\left(\theta_j\right) u_j; & \text{Enjailed} & \to & \text{Employed} & 0,
\end{array}$$

in which we denote the probabilities that employed and unemployed workers from region i commit a crime in region j as $\phi_{ij}^W\left(\varphi\right)$ and ϕ_{ij}^U, respectively. We have already introduced $\tilde{\varphi}_j$ as the threshold productivity deciding which matches are kept and which are destroyed. We further introduce φ_j^C, i.e., the crime-preventing productivity for employed agents, which is also endogenously determined by the model. We assume that the probability of getting caught when committing a crime is the same for employed and unemployed agents and regions i or j, and equal to π. Finally, we denote the net rate of release from jail and transition into unemployment as ρ. Notice that $1 - u_j - n_j$ denotes employment in region E_j because we normalized the total population to one. In words:

1. The flow of employed agents into unemployment are $\lambda F\left(\tilde{\varphi}_j\right)\left(1 - u_j - n_j\right)$: after a shock occurs with frequency λ, the matches $F\left(\cdot\right)$ of the employed agents $\left(1 - u_j - n_j\right)$, whose productivity falls below the threshold level $\tilde{\varphi}_j$, are destroyed.

2. The flow of employed agents into imprisonment is $\pi\phi^W\left(\varphi_j^C\right)\left(1 - u_j - n_j\right)$: the number of employed agents $\left(1 - u_j - n_j\right)$ with crime-preventing productivity φ_j^C who commit a crime (with probability ϕ^W) and are caught (with probability π).

3. The flow of unemployment into employment is $\theta_j q(\theta_j) u_j$: the number of vacancies matched to unemployed agents (u_j) (with probability $\theta_j q(\theta_j)$) given the prevailing labor market tightness θ_j.
4. The flow of unemployment into imprisonment is $\pi \phi_j^U u_j$: the number of unemployed agents (u_j) who commit a crime (with probability ϕ_j^U) and are caught (with probability π).
5. The flow of the enjailed criminals into unemployment is ρn_j: the number of enjailed criminals (n_j) who get released into unemployment (with rate ρ).
6. The flow of the enjailed criminals into employment is zero: enjailed agents (n_j) need to transit via unemployment into either employment or imprisonment reflecting the fact that integration back into the society is usually noninstantaneous.

The evolution of unemployment is, therefore, governed by

$$\triangle u_j = \lambda F(\tilde{\varphi}_j)(1 - u_j - n_j) + \rho n_j - \left(\theta_j q(\theta_j) + \pi \phi_j^U\right) u_j, \tag{4.1}$$

in which the population is constant. Unemployment increases when a shock occurs and matches below the threshold productivity are destroyed or when criminals get released from prison while unemployment decreases when a vacancy is filled or when an agent is caught committing a crime.

It is obvious from equation (4.1) that gross flows in the labor market occur even if unemployment is constant. Indeed, by equating (4.1) to zero and solving for unemployment, we obtain the steady state for unemployment:

$$u_j = \frac{\lambda F(\tilde{\varphi}_j) + (\rho - \lambda F(\tilde{\varphi}_j)) n_j}{\lambda F(\tilde{\varphi}_j) + \theta_j q(\theta_j) + \pi \phi_j^U}. \tag{4.2}$$

The key endogenous variables determining the evolution of gross flows in the labor market are market tightness, θ_j, which affects the job creation margin, and the threshold productivity level, $\tilde{\varphi}_j$, which affects the job destruction margin. Equation (4.2) illustrates the first simple population-counting relationship between unemployed and enjailed criminals n_i, yet to be endogenized. We now turn to agents' decisions.

4.2 Agents' Decisions

We focus on crime that can be understood as property crime or, more generally, one that leads to an immediate financial gain embodied in a monetary value g_j. This specification allows for adding the income effect on crime in a very parsimonious way. Note that modeling a probability of being caught instantly and sent to jail, equal to π, generates differential effects on employed and unemployed agents. The expected payoff from committing crime in region j for an unemployed (employed) worker from i is

$$\begin{aligned} K_{ij}^U &= g_j + \pi J_{ij} + (1 - \pi) U_{ij}, \\ K_{ij}^W(\varphi) &= g_j + \pi J_{ij} + (1 - \pi) W_{ij}(\varphi), \end{aligned} \tag{4.3}$$

in which J_{ij} stands for the value function of an agent from i and enjailed in j while U_{ij} and $W_{ij}(\varphi)$ stand for the value functions for an unemployed agent and an employed agent with match-specific productivity φ, respectively. The expected payoff from crime for an unemployed (employed) agent depends on the immediate financial gain, the value function of imprisonment given the agent is caught and the value function of unemployment (employment with match productivity φ) given the agent is not caught. The payoffs are Bellman equations (value functions) as in the standard search model. The decision space for engaging in criminal activity is then

$$\phi_{ij}^U = \begin{cases} 1 & \text{if } U_{ij} - J_{ij} < \frac{g_j}{\pi}, \\ 0 & \text{if } U_{ij} - J_{ij} > \frac{g_j}{\pi}, \end{cases} \text{ and } \phi_{ij}^W(\varphi) = \begin{cases} 1 & \text{if } W_{ij}(\varphi) - J_{ij} < \frac{g_j}{\pi}, \\ 0 & \text{if } W_{ij}(\varphi) - J_{ij} > \frac{g_j}{\pi}. \end{cases} \tag{4.4}$$

These conditions state that criminal activity is deterred once a difference in value functions exceeds the expected gain from criminal activity, g_j/π. Notice that the financial gain from crime refers to region j where the action is undertaken. Hence, ϕ_{jj}^U and $\phi_{jj}^W(\varphi)$ follow trivially. Moreover, it is reasonable to assume that the value of enjailed agents, J_{ij}, never exceeds that of unemployed U_{ij} or employed W_{ij} agents. Note that we generate the decision space having in mind that an unemployed agent commits crime if and only if the expected payoff is larger than the unemployment value (i.e., $K_{ij}^U > U_{ij}$) whereas a worker with productivity φ engages in criminal activity if and only if $K_{ij}^W(\varphi) > W_{ij}(\varphi)$.[7]

Ruling out the possibility of crime and employment happening simultaneously yields

$$rU_{ij} = b_j + \phi_{ij}^U\left(K_{ij}^U - U_{ij}\right) + \theta_j q(\theta_j)\left(W_{ij}(\varphi) - U_{ij}\right), \tag{4.5}$$

in which b_j stands for the unemployment benefits in area j and r for the rate of time preference. In words, the flow return from unemployment rU_{ij} equals the instantaneous net income plus the expected value of receiving either a crime or job opportunity, i.e., a transit in states from unemployment to either crime or work. Again, the value functions for the residents of region j acting in j face the same labor market conditions, i.e., θ_j, $q(\theta_j)$ and b_j. Note that the probability of finding a job depends on region j's labor market tightness which, from the discussion above, entails flows from both regions, $\theta_j \equiv v_j/(u_{jj}+u_{ij})$. In a similar vein, the flow return from employment is

$$\begin{aligned} rW_{ij}(\varphi) &= w_{ij}(\varphi) + \lambda\int_{\tilde{\varphi}}^{1}\left(W_{ij}(z) - W_{ij}(\varphi)\right)dF(z) \\ &-\lambda F(\tilde{\varphi})\left(W_{ij}(\varphi) - U_{ij}\right) + \phi_{ij}^W(\varphi)\left(K_{ij}^W(\varphi) - W_{ij}(\varphi)\right), \end{aligned} \tag{4.6}$$

which demonstrates that the value of employment in a job-worker match with current productivity φ is equal to the current wage $w_{ij}(\varphi)$ plus the expected capital gain on the employment relationship and a criminal opportunity.[8] Finally, the flow return from imprisonment is described by the following simple Bellman's equation,

$$rJ_{ij} = z_j + \rho\left(U_{ij} - J_{ij}\right), \tag{4.7}$$

in which z denotes consumption by enjailed workers (meaning subsistence in prison, e.g., residence or nutrition). The flow return from imprisonment depends on consumption in prison and the difference in values from unemployment and imprisonment if the agent gets released.

This rather basic structure leads to a partitioning of wage rates which, in turn, determines equilibrium outcomes. There are two levels of wages that change agents' behavior: the so-called reservation wage $w(\tilde{\varphi})$ for reservation productivity $\tilde{\varphi}$ and the crime-preventing wage $w\left(\varphi^C\right)$. Then, an unemployed worker will accept any wage $w_{ij}(\varphi) \geq w_{ij}(\tilde{\varphi})$ where $\tilde{\varphi}$ is the solution to $W_{ij}(\tilde{\varphi}) = U_{ij}$[9], i.e., the threshold productivity that makes an agent indifferent between employment and unemployment. The reservation wage is homogeneous across agents due to the constant productivity threshold $\tilde{\varphi}$.[10] As a result:

Lemma 4.1. *Agents are less likely to commit crime when their wage incomes are higher; unemployed agents engage in criminal activity if and only if agents employed at the reservation wage $w(\tilde{\varphi})$ do.*

Proof. See Online Appendix. □

[7]For further details on job search and crime, see Burdett et al. (2004).

[8]We abstract from victimization costs which, as long as assumed exogenous, would not change the model apart from making the environment less transparent (see Burdett et al., 2003, for the ways to deal and interpret victimization for employed and unemployed agents).

[9]Change conditions for an agent from region j by switching i to j; to ease exposition, we omit the subscript for productivity when the subscript of the function makes it clear.

[10]We can infer wage symmetry also from the symmetric hiring costs across all firms.

The immediate implication of Lemma 4.1 states that, given an unemployed agent does not commit crime ($\phi_{ij}^{U}=0$) then neither does an employed agent ($\phi_{ij}^{W}(\varphi)=0$) for all wage incomes $w_{ij}(\varphi)$.[11] Intuitively, if an unemployed agent in i has no incentives to commit crime in j, then the employed one does not have such incentives either for any given wage. Similarly, given an unemployed agent decides to engage in crime ($\phi_{ij}^{U}=1$) then $\phi_{ij}^{W}(\varphi)=1$ for wages that are lower than the crime-preventing wage ($w_{ij}(\varphi)<w_{ij}\left(\varphi^{C}\right)$) and $\phi_{ij}^{W}(\varphi)=0$ for $w_{ij}(\varphi)\geq w_{ij}\left(\varphi^{C}\right)$. Notice that φ^{C} is constrained so that $\varphi^{C}>\tilde{\varphi}$ and is defined as the solution to $K_{ij}^{W}\left(\varphi^{C}\right)=W_{ij}\left(\varphi^{C}\right)$, i.e., the productivity for which an employed agent is indifferent between committing crime or working.

Clearly, if the unemployed actor commits crime, the employed one engages in criminal activity if and only if she earns less than the crime-preventing wage $w_{j}\left(\varphi^{C}\right)$ (where $w_{j}\left(\varphi^{C}\right)$ exceeds the reservation wage, $w_{j}(\tilde{\varphi})$). Therefore, if the wage an employed agent earns is larger than $w_{j}\left(\varphi^{C}\right)$, then the expected losses from committing crime are larger than the expected gains. This follows from equation (4.3) implying that the stolen amount equals the expected cost of crime, $g_{j}=\pi\left(W_{ij}\left(\varphi^{C}\right)-J_{ij}\right)$.

4.3 Wages and Firms' Decisions

To finalize the description of the theoretical motivation, we need to establish the cutoffs in the wage space by describing the firms' decisions. Let the continuation valuation by firms of an open vacancy (V) versus a job ($J(\varphi)$) be

$$rV_{ij}=-c_{j}+q(\theta_{j})\left(\mathcal{J}_{ij}(\varphi)-V_{ij}\right), \tag{4.8}$$

in which $\mathcal{J}_{ij}(\varphi)$ is the asset value condition for filled jobs with a productivity φ and c_{j} denotes the vacancy posting costs. The firm's valuation of a filled job in equation (4.9), given the current realization of φ, is

$$r\mathcal{J}_{ij}(\varphi)=\varphi-w(\varphi)+\lambda\int_{\tilde{\varphi}}^{1}\left(\mathcal{J}_{ij}(z)-\mathcal{J}_{ij}(\varphi)\right)dF(z)+\lambda F(\tilde{\varphi})\left(V_{ij}-\mathcal{J}_{ij}(\varphi)\right). \tag{4.9}$$

We solve for the reservation wage (and thus the cutoff productivity) and the crime-preventing wage using a free entry condition, $V=0$, along with a Nash bargaining game where the relative bargaining weights are β and $1-\beta$ for workers and firms, respectively (see Online Appendix for details). For the former, we obtain

$$w_{ij}(\tilde{\varphi})=\beta\tilde{\varphi}+(1-\beta)\left(b_{j}+\frac{(r+\lambda)\beta}{(1-\beta)\left(r+\lambda+\phi_{ij}^{U}\pi\right)}\theta_{j}c_{j}\right). \tag{4.10}$$

The wage clearly accounts for the outside option (unemployment benefits), the cutoff productivity needed to keep the job as well as to commit crime (decision to engage in crime, ϕ_{ij}^{U}, and probability of getting caught, π) and labor market components (labor market tightness, θ_{j}, and vacancy posting costs, c_{j}). In obtaining equation (4.10) we used the result from equation (4.3): by definition, the reservation productivity is such that the agent is indifferent between the value of employment and the value of unemployment, i.e., $W_{ij}(\tilde{\varphi})=U_{ij}$. Thus, the value from engaging in crime for an actor with the reservation productivity must coincide with the value that an unemployed agent receives

[11] In our model, if the expected value of criminal engagement exceeds the expected value of unemployment, then an unemployed agent chooses to commit crime. Since we abstain from modeling criminal productivity, its distribution is degenerate at either no crime (0) or crime (1). We could have introduced criminal "efficiency" or a reduced-form measure for the opportunities to engage in crime, which may differ for different agents. The first one does not differ conceptually from the literature on workers' ability (see, for instance, Helpman et al. (2010) who consider Pareto distributed abilities, screening technology for workers, and interactions with international trade), and would have generated one more endogenous object, i.e., an average or threshold level of criminal "efficiency". However, we abstract from this extension since we do not observe agent level data and rather concentrate on aggregate crime rates.

from criminal activity, $K_{ij}^{W}(\tilde{\varphi}_j) = g_j + \pi J_{ij} + (1-\pi) U_{ij} = K_{ij}^{U}$. Intuitively, the threshold match productivity equates the value from employment and unemployment and thus leads to the same payoffs from crime. Moreover, $\phi_{ij}^{U} = \phi_{ij}^{W}(\tilde{\varphi}_j)$ since $W_{ij}(\tilde{\varphi}_j) = U_{ij}$, and the decision rules coincide (see equation (4.4)). Notice that the reservation wage depends on productivity: the higher the productivity of a match is, the higher the reservation wage is required.

As for the crime-preventing wage, we obtain

$$\begin{aligned} w_{ij}\left(\varphi^{C}\right) &= \beta\left(\varphi^{C} + \theta_j c_j\right) \\ &+ (1-\beta)\frac{r}{r+\phi_{ij}^{U}\pi\left(\frac{r}{r+\rho}\right)}\left(b_j + \phi_{ij}^{U}\left(g_j + \frac{\pi}{r+\rho} z_j\right)\right). \end{aligned} \tag{4.11}$$

To gain more intuition, we explore the link between reservation and crime-preventing productivities. One can show that, given $\phi_{ij}^{U} = 1$ (unemployed agents engage in crime),

$$\begin{aligned} (1-\beta)\left(\varphi^{C} - \tilde{\varphi}\right) &= \frac{c_j}{q(\theta_j)}\left(r + \lambda + \beta\frac{\theta_j}{q(\theta_j)}\left(\frac{r}{r+\pi\left(\frac{r}{r+\rho}\right)} - \frac{r+\lambda}{r+\lambda+\pi}\right)\right) \\ &+ (1-\beta)\left(\frac{r}{r+\pi\left(\frac{r}{r+\rho}\right)}\right)\left(g_j + \frac{\pi}{r+\rho}(z_j - b_j)\right). \end{aligned}$$

The difference between the reservation and the crime-preventing productivities is driven, first, by the relative magnitudes of the rate of release from jail, ρ, and the probability of getting caught when committing a crime, π, and, second, by relative outside options such as consumption once in jail, z_j, and benefits once unemployed, b_j. If the unemployed agent does not commit crime ($\phi_{ij}^{U} = 0$), the value of the job is zero, and $\varphi^{C} = \tilde{\varphi}$ (see Online Appendix).

Remark. As mentioned earlier, following Burdett et al. (2003) we assume that the value of unemployment is never lower than that of imprisonment, $U_{ij} \geq J_{ij}$, as otherwise all unemployed agents would volunteer to go to jail. As a conclusion, there is no crime in an environment where monetary gains are absent: in that case, $\phi_{ij}^{U} = \phi_{ij}^{W}(\varphi) = 0$ as it is never worthwhile to engage in crime. Notice that this assumption is compatible with previous analyses. The monetary gain g_j creates a wedge between the value functions: it is possible to have $0 \leq U_{ij} - J_{ij} < \frac{g_j}{\pi}$ and $0 \leq W_{ij}(\varphi) - J_{ij} < \frac{g_j}{\pi}$ for $g_j > 0$. Obviously, the larger the monetary gain, the easier these conditions are satisfied and the higher the crime rate observed. Hence, the model applies to crime categories that entail income effects.

4.4 Testable Implications

Having gained economic rationale about the mechanisms that might be at work between crime, unemployment and income effects, we turn into testable implications. Since our empirical analysis concerns cross-sections, we will not cover transitional dynamics and consider steady states only. This approach is consistent with our empirical strategy to explore the effects of a shock that hits variables at equilibrium. We will partition the entire population into four segments: employees E_{ij}^{L}, E_{jj}^{L} with a wage $w_{ij}(\varphi) < w_{ij}\left(\varphi^{C}\right)$ ($w_{jj}(\varphi) < w_{jj}\left(\varphi^{C}\right)$), employees E_{ij}^{H}, E_{jj}^{H} with a wage $w_{ij}(\varphi) \geq w_{ij}\left(\varphi^{C}\right)$ ($w_{jj}(\varphi) \geq w_{jj}\left(\varphi^{C}\right)$), unemployed agents u_j and enjailed criminals n_j.[12]

Following our previous analysis of decision partitioning and letting $\phi_{ij}^{U} = 1$ for j denoting both j and i (for the general case refer to Online Appendix), we obtain the steady-state values of the following measures:

[12] Equivalently, we could work with the match-specific productivities as wages and productivities are isomorphic to each other. Notably, the larger the match-specific productivity is, the larger the wage. See equation (4.10) and Online Appendix for derivations.

$$\begin{aligned} u_j &= \frac{\rho\lambda F(\tilde{\varphi}_j)\left(\theta_j q(\theta_j)\left(1-F\left(\varphi_j^C\right)\right)+\lambda F(\tilde{\varphi}_j)+\pi\right)}{\Omega_j\left(\varphi_j^C,\tilde{\varphi}_j\right)}, \\ E_j^L = E_{jj}^L + E_{ij}^L &= \frac{\rho\lambda F(\tilde{\varphi}_j)\theta_j q(\theta_j)F\left(\varphi_j^C\right)}{\Omega_j\left(\varphi_j^C,\tilde{\varphi}_j\right)}, \\ E_j^H = E_{jj}^H + E_{ij}^H &= \frac{\rho\left(1-F\left(\varphi_j^C\right)\right)\theta_j q(\theta_j)(\theta_j q(\theta_j)+\lambda F(\tilde{\varphi}_j)+\pi)}{\Omega_j\left(\varphi_j^C,\tilde{\varphi}_j\right)}, \\ n_j &= \frac{\lambda F(\tilde{\varphi}_j)\pi(\theta_j q(\theta_j)+\lambda F(\tilde{\varphi}_j)+\pi)}{\Omega_j\left(\varphi_j^C,\tilde{\varphi}_j\right)}, \end{aligned} \tag{4.12}$$

in which $\Omega_j\left(\varphi_j^C,\tilde{\varphi}_j\right) \equiv \left(\theta_j q\left(\theta_j\right)+\lambda F\left(\tilde{\varphi}_j\right)+\pi\right)\left(\rho\theta_j q\left(\theta_j\right)\left(1-F\left(\varphi_j^C\right)\right)+(\rho+\pi)\lambda F\left(\tilde{\varphi}_j\right)\right)$ consists of model's parameters and endogenous productivities that are, in turn, functions of agents' flows in both regions (see Online Appendix for detailed expressions). The subscript for the productivities in (4.12) is used to emphasize the region-specific relationship. Using the expression for the unemployment, one can show that

$$E_j^L = \frac{\theta_j q\left(\theta_j\right)F\left(\varphi_j^C\right)}{\theta_j q\left(\theta_j\right)\left(1-F\left(\varphi_j^C\right)\right)+\lambda F\left(\tilde{\varphi}_j\right)+\pi}u_j.$$

The crime rate, under the condition $\phi_j^U = 1$, calculated over the nonimprisoned population is given by

$$\begin{aligned} \mathsf{c}_j &= \frac{E_{jj}^L+E_{ij}^L+u_j}{1-n_j} \\ &= \frac{\rho\lambda F(\tilde{\varphi}_j)}{\theta_j q(\theta_j)\left(1-F\left(\varphi_j^C\right)\right)+\lambda F(\tilde{\varphi}_j)}, \end{aligned} \tag{4.13}$$

in which reservation and cutoff productivities, $\tilde{\varphi}_j$ and φ_j^C, as well labor market tightness, θ_j, account for agents' flows from both i and j regions. An attentive reader notes that the crime rate does not depend on the probability to be caught directly; this is because the probability is constant and affects everyone the same way, so it gets canceled when we consider a ratio. It is, however, featured for the levels, as is obvious in equations (4.12).[13]

To see this effect more clearly, as it is somewhat hidden in the aggregate variables of labor market tightness and productivity, use the expressions for employees E_j^L and enjailed criminals n_j, which lead to the crime rate as a function of unemployment,

$$\mathsf{c}_j = \frac{\theta_j q\left(\theta_j\right)\left(1-F\left(\varphi_j^C\right)\right)+\left(1+\frac{\pi}{\rho}\right)\lambda F\left(\tilde{\varphi}_j\right)}{\theta_j q\left(\theta_j\right)\left(1-F\left(\varphi_j^C\right)\right)+\lambda F\left(\tilde{\varphi}_j\right)}\frac{\theta_j q\left(\theta_j\right)+\lambda F\left(\tilde{\varphi}_j\right)+\pi}{\theta_j q\left(\theta_j\right)\left(1-F\left(\varphi_j^C\right)\right)+\lambda F\left(\tilde{\varphi}_j\right)+\pi}u_j.$$

This expression is useful for building intuition. The crime rate is driven by adjustments in the labor market; most importantly, labor market tightness, reservation and crime-preventing productivities, which are functions of job seekers from home and elsewhere, shocks (release rate ρ, a match shock λ, a chance of being caught π), and the current unemployment rate. Further, consider steady states in (4.12) and the crime rate in (4.13) before substituting for the enjailed population, then evaluate the relative crime rate as the two are intertwined through threshold productivities and labor market

[13] The solely unemployment-driven crime rate is given by $\mathsf{c}_j^u = \frac{u_j}{1-n_j} = \frac{\left(\theta_j q\left(\theta_j\right)\left(1-F\left(\varphi_j^C\right)\right)+\lambda F\left(\tilde{\varphi}_j\right)+\pi\right)}{\left(\theta_j q\left(\theta_j\right)+\lambda F\left(\tilde{\varphi}_j\right)+\pi\right)}\mathsf{c}_j$. Since $1 \geq F\left(\varphi_j^C\right) \geq 0$, the overall crime rate is clearly larger than the one that would have been generated had only the unemployed agents engaged in criminal activities, $\mathsf{c}_j^u \leq \mathsf{c}_j$.

tightness,

$$
\begin{aligned}
\frac{\mathsf{c}_i}{\mathsf{c}_j} &\equiv \frac{E_{ii}^L+E_{ji}^L+u_i}{E_{jj}^L+E_{ij}^L+u_j}\frac{1-n_j}{1-n_i} \\
&= \left(\frac{\theta_i q(\theta_i)\big(1-F\big(\varphi_i^C\big)\big)+\big(1+\frac{\pi}{\rho}\big)\lambda F(\tilde{\varphi}_i)}{\theta_j q(\theta_j)\big(1-F\big(\varphi_j^C\big)\big)+\big(1+\frac{\pi}{\rho}\big)\lambda F(\tilde{\varphi}_j)}\right)\left(\frac{\rho\theta_j q(\theta_j)\big(1-F\big(\varphi_j^C\big)\big)+\rho\lambda F(\tilde{\varphi}_j)}{\rho\theta_i q(\theta_i)\big(1-F\big(\varphi_i^C\big)\big)+\rho\lambda F(\tilde{\varphi}_i)}\right)\left(\frac{\theta_i q(\theta_i)+\lambda F(\tilde{\varphi}_i)+\pi}{\theta_j q(\theta_j)+\lambda F(\tilde{\varphi}_j)+\pi}\right) \\
&\quad\times\left(\frac{\theta_j q(\theta_j)\big(1-F\big(\varphi_j^C\big)\big)+\lambda F(\tilde{\varphi}_j)+\pi}{\theta_i q(\theta_i)\big(1-F\big(\varphi_i^C\big)\big)+\lambda F(\tilde{\varphi}_i)+\pi}\right)\frac{u_i}{u_j} \\
&= \left(\frac{\theta_i q(\theta_i)+\lambda F(\tilde{\varphi}_i)+\pi}{\theta_j q(\theta_j)+\lambda F(\tilde{\varphi}_j)+\pi}\right)\left(\frac{\theta_j q(\theta_j)\big(1-F\big(\varphi_j^C\big)\big)+\lambda F(\tilde{\varphi}_j)+\pi}{\theta_i q(\theta_i)\big(1-F\big(\varphi_i^C\big)\big)+\lambda F(\tilde{\varphi}_i)+\pi}\right)\left(\frac{u_i}{u_j}\right)\left(\frac{1-n_j}{1-n_i}\right).
\end{aligned}
$$

The interdependence is captured by aggregate variables as well as by the direct effect of the crime rate in region j. Taking logs of the relative crime rate, and rearranging, lead to

$$
\begin{aligned}
\ln c_i = \ln c_j + \ln u_i - \ln u_j + \ln\left(\frac{\theta_i q(\theta_i)+\lambda F(\tilde{\varphi}_i)+\pi}{\big(\theta_i q(\theta_i)\big(1-F(\varphi_i^C)\big)+\lambda F(\tilde{\varphi}_i)+\pi\big)}\right) \\
- \ln\left(\frac{\theta_j q(\theta_j)+\lambda F(\tilde{\varphi}_j)+\pi}{\big(\theta_j q(\theta_j)\big(1-F(\varphi_j^C)\big)+\lambda F(\tilde{\varphi}_j)+\pi\big)}\right) + \ln(1-n_j) - \ln(1-n_i).
\end{aligned} \tag{4.14}
$$

Thus, the relative crime rate depends on: (1) the unemployment rate in regions i and j, (2) the nonimprisoned population in regions i and j, (3) a function that – ceteris paribus – increases with the probability of filling a vacancy (market tightness) in regions i and j, the average productivity in regions i and j, crime wages in regions i and j as well as the probability of being caught committing a crime and sent to jail, π.

Let's consider the equilibrium behavior of the crime equation in (4.13). It elucidates the relationship between crime and unemployment and leads to a cross-sectional proposition which underlies our empirical inquiry:

Proposition 4.2. *Regional unemployment and crime depend on average productivity in the region, labor market tightness, crime wage and exogenous variables (probability of catching a criminal, the rate of release into unemployment, and a match-specific shock). Then, ceteris paribus, the following statements hold true:*

1. *An increase in the frequency of match-specific shocks tends to increase the crime rate.*
2. *An increase in the exogenous variables that drive the cutoff productivity $\tilde{\varphi}$ (e.g. subsistence income) increases the crime rate.*
3. *An exogenous shock to labor market tightness changes the crime rate at the home region. Hence, a slacker labor market (e.g., due to an increase in job-seekers from other regions) is associated with a higher crime rate (given the elasticity of the instantaneous meeting probability for vacancies is less than one).*
4. *The crime rate increases if the productivity of matches of the unemployed agents from i in region j increases. Hence, an influx of more productive employees from i to j who raise the productivity of a match in j leads to an increase in crime in j.*

Proof. See Online Appendix. □

We just note that Part 1 refers to an increase in the frequency of match-specific shocks which can be interpreted as an increase in the volatility of the economic environment. Hence, an increase in uncertainty because of, for instance, a shock during the global crisis should lead to an increase in crime rates.[14] Part 2 states that any exogenous increase in the cutoff wage decreases the number

[14] Note that the exogenous shock is analyzed cross-sectionally in our empirical part, i.e., the *same* shock affects districts in a *different* way. Unlike our approach, Bushway et al. (2012) analyze the dynamic aspect of criminal activities where business cycles affect crime differentially across time. A long time series would open vistas to explore both spatial and factor structures of crime which we leave for future research.

of firms which afford paying such a wage, increases unemployment and this is how the number of criminals increases. Part 3 clarifies that any exogenous shock that increases the number of unemployed agents in the other region increases the crime rate. The rationale for this statement is such that the more the unemployed agents from the other region are, the smaller the labor market tightness is, ceteris paribus. This makes the local labor market slacker and encourages agents to consider engaging in criminal activities, something that entails lower opportunity costs compared to the situation before a shock. The claim requires a qualification of convexity of probability $q\left(\theta_i\right)$ (and that the elasticity of the instantaneous meeting probability for vacancies being larger than negative one), both assumed to hold in the literature (refer to Section 4.1 and Online Appendix for details). Intuitively, Part 4 states that more productive unemployed agents, ceteris paribus, induce an increase in the reservation wage (productivity), which leads to an increase in unemployment and the crime rate. This effect dominates since fewer home agents can take up job positions (higher competition from the other region) and higher wages are paid to foreign rather than domestic agents, which reduces the outside option and increases crime domestically.

Clearly, spatial competition manifests through labor market tightness in the domestic market in our partial equilibrium setting. We do not model full feedback effects among counties, yet allow for changes in unemployed agents through – among other things – an influx of migrants causing changes in threshold and crime wages. These, in turn, shape steady states of crime and unemployment. This partial account points to spatial competition: adjustments in the domestic labor market depend on the elasticity of labor market tightness whereas productivity of incomers affect the equilibrium in the home market through reservation and crime wages.[15]

In reality, of course, home region i has $j = 1, 2, ..., k$ neighboring regions. Therefore, we introduce weights w_j for each neighbor $j \neq i$ such that $\sum_j w_j = 1$. Taking the weighted sum of equation (4.14) yields

$$\begin{aligned}\ln c_i = \textstyle\sum_j w_j \ln c_j + \ln u_i - \sum_j w_j \ln u_j + \ln\left(\frac{\theta_i q(\theta_i)+\lambda F(\tilde{\varphi}_i)+\pi}{\left(\theta_i q(\theta_i)\left(1-F(\varphi_i^C)\right)+\lambda F(\tilde{\varphi}_i)+\pi\right)}\right) \\ - \textstyle\sum_j w_j \ln\left(\frac{\theta_j q(\theta_j)+\lambda F(\tilde{\varphi}_j)+\pi}{\left(\theta_j q(\theta_j)\left(1-F(\varphi_j^C)\right)+\lambda F(\tilde{\varphi}_i)+\pi\right)}\right) + \sum_j w_j \ln\left(1-n_j\right) - \ln\left(1-n_i\right).\end{aligned} \tag{4.15}$$

Note that unemployment and the nonimprisoned population, as reported in (4.12), are endogenous functions of productivities. After introducing stochastic shocks, we bear this aspect in mind for the econometric treatment of the spatial crime rate. We, therefore, turn to discussing the empirical implementation of the model and data.

5 Econometric Model and Data

5.1 Econometric model

We map the theoretical equation (4.15) with a spatial autoregressive econometric model:

$$Y_{nt} = \lambda \boldsymbol{W}_n Y_{nt} + Z_{nt}\delta_1 + \boldsymbol{W}_n Z_{nt}\delta_2 + \boldsymbol{X}_{nt}\beta_1 + \boldsymbol{W}_n \boldsymbol{X}_{nt}\beta_2 + \alpha_n + \theta_t \iota_n + \varepsilon_{nt},\ t = 1,\ 2 \tag{5.1}$$

in which $Y_{nt} = \left(y_{1t},\ y_{2t}, ...,\ y_{nt}\right)'$ is the $n \times 1$ vector of observations on the dependent variable, i.e., crime rates on $n = 402$ regions and $T = 2$, with λ denoting the spatial autoregressive coefficient and $\boldsymbol{W}_n$ the nonstochastic and time-invariant $n \times n$ spatial weights matrix that generates spatial dependence in the cross-sectional dimension. As neighbors we consider regions that share immediate geographical proximity. Elements w_{ii} on the main diagonal of the 402×402 contiguity matrix $\boldsymbol{W}_n$

[15] Ideally, of course, it would be desirable to have accounted for aggregate variables which require a general equilibrium approach.

take value zero, as no region is a neighbor to itself. Element w_{ij} takes value one if districts i and j share common borders and zero otherwise. The theoretical model in (4.15) dictates $\sum_j w_j = 1$ so we row-normalize $\boldsymbol{W}_n$. One implication is that a spatial effect captures the average effect of the neighbors; a second implication is that the parameter space of λ is $(-1, 1)$. Values of λ very close to 1 signify positive cross-sectional dependence or similarity in neighboring crime rates and vice versa while values very close to 0 signify lack of dependence in neighboring crime rates. Z_{nt} and $\boldsymbol{W}_n Z_{nt}$ denote the $n \times 1$ vectors of unemployment rates and their spatial effect with scalar coefficients δ_1 and δ_2 respectively. $\boldsymbol{X}_{nt}$ is the $n \times k$ matrix of observations on time-varying explanatory variables and their spatial effect $\boldsymbol{W}_n \boldsymbol{X}_{nt}$ with respective $k \times 1$ vector coefficients β_1 and β_2. The $n \times 1$ vector of error terms, $\boldsymbol{\varepsilon}_{nt}$, is *i.i.d.* across i and t with mean zero and variance σ_ε^2. Notice that we allow for fixed effects at the regional level, denoted by the $n \times 1$ vector α_n as well as a time fixed effect, θ_t (ι_n denotes the $n \times 1$ vector of ones). While regional fixed effects shall be eliminated by a within-transformation of the model, time fixed effects can be captured by the inclusion of a single time dummy whose parameter is estimated along with λ, δ_1, δ_2, β_1 and β_2. The short time span – effectively a cross-section – excludes the possibility of structural changes in the labor markets; hence, we consider modeling additive fixed effects as more appropriate than interactive fixed effects.

To circumvent reverse causality of unemployment rates and its spatial effect we use the global financial crisis as an experiment: from the period 2009 to 2010 changes in unemployment rates and their spatial effect are due to an exogenous shock in the export-oriented German manufacturing industry and its relevant manpower, namely short-time workers, younger persons and males (BfA, 2009). Still, in equation (5.1) the spatial effect of the crime rate, $\boldsymbol{W}_n Y_{nt}$, is endogenous by construction of the model.[16] Therefore, we estimate the model in equation (5.1) with Quasi Maximum Likelihood (QML) on the reduced form (Lee and Yu, 2010). Notice that when $T = 2$ the fixed effects and the first difference estimators are identical so that estimated coefficients capture the change from the previous year. To comply with the theoretical model in (4.15) all variables are in natural logarithms.

When $\lambda = 0$ in equation (5.1), coefficients translate into marginal effects – elasticities here – meaning the partial derivative of the crime rate with respect to an explanatory variable. If $\lambda \neq 0$, then the data are no longer independent; λ introduces a decaying feedback ($|\lambda| < 1$) among neighboring regions: a change in any explanatory variable for region i will affect not only region i but also the crime rate of other neighboring regions j. To illustrate, the expected value of the reduced form for model (5.1) is:

$$E(Y_{nt}) = (\boldsymbol{I}_n - \lambda \boldsymbol{W}_n)^{-1} (Z_{nt}\delta_1 + \boldsymbol{W}_n Z_{nt}\delta_2 + \boldsymbol{X}_{nt}\beta_1 + \boldsymbol{W}_n \boldsymbol{X}_{nt}\beta_2) \tag{5.2}$$

in which we assumed without loss of generality that the mean of the fixed effects is zero. The spatial multiplier matrix $(\boldsymbol{I}_n - \lambda \boldsymbol{W}_n)^{-1}$ exists because $|\lambda| < 1$ from row-normalization of $\boldsymbol{W}_n$. We can rewrite the expected value of the reduced form as:

$$E(Y_{nt}) = \left(\boldsymbol{I}_n + \lambda \boldsymbol{W}_n + \lambda^2 \boldsymbol{W}_n^2 + \lambda^3 \boldsymbol{W}_n^3 + \cdots\right) (Z_{nt}\delta_1 + \boldsymbol{W}_n Z_{nt}\delta_2 + \boldsymbol{X}_{nt}\beta_1 + \boldsymbol{W}_n \boldsymbol{X}_{nt}\beta_2) \tag{5.3}$$

from which it becomes obvious that the partial derivative with respect to any explanatory variable is a nonlinear function of the cross-sectional dependence parameter λ. $\boldsymbol{W}_n^2$ represents the neighbors of region i's neighbors while $\boldsymbol{W}_n^3$ the neighbors of the neighbors of region i's neighbors and so on. The latter illustrates the spatial dynamics (as opposed to time dynamics) embedded in model (5.1). We discern two effects: one from a change in an explanatory variable stemming from region i (average direct impact - ADI) and another stemming from region i's neighbors (average indirect impact - AII). The average (in)direct impact is comparable to δ_1 and β_1 (δ_2 and β_2) in a model with $\lambda = 0$.

[16] Suppressing fixed effects, it is trivial to show that $E(\boldsymbol{W}_n Y_{nt} \varepsilon_{nt}^{'}) = \sigma_\varepsilon^2 \boldsymbol{W}_n (I_n - \lambda \boldsymbol{W}_n)^{-1} \neq 0$.

In what follows, when $\widehat{\lambda} = 0$ we report estimated coefficients and when $\widehat{\lambda} \neq 0$ we report the estimated average direct and indirect impacts. Notice that $\widehat{\lambda}$ always denotes the strength of the spatial dependence in crime rates.

5.2 Data

We use offenses rates from the 2009 and 2010 yearly publications of the German Federal Criminal Police Office as a measure for crime rates (see Table 8.1 for variables and sources). Offenses rates are defined as the number of crimes reported to the police per $100,000$ inhabitants. The German Federal Criminal Police Office offers crime rates on the 402 regions for overall crime, theft by burglary of a dwelling, theft of/from motor vehicles, street crime, damage to property and drug-related offenses (see Online Appendix for a list of crime categories).

We downloaded regional data on unemployment rates from the German Regional Database. As in Öster and Agell (2007) and Fougère et al. (2009) we deploy two different definitions of unemployment for the youth, i.e., the rate calculated over the labor force and the share calculated over the total subpopulation; the distinction has been attested empirically, since rates and shares do not treat evenly a ceteris paribus increase in students. The German Regional Database reports the overall unemployment rate, the number of unemployed and the unemployment rate for those between 15 and 25 years old, male and female unemployment rates as well as the unemployment rate of the foreign population. The theoretical framework in Section 4 predicts that the effect of unemployment on crime in region i is positive but the sign of the spatial effect from neighboring regions j depends on the elasticity of the market tightness. We obtained the latter by contacting the Federal Employment Agency Statistics in Germany. Market tightness is defined as the number of vacancies over the number of unemployed. The labor market becomes tighter if the number of vacancies outpace the number of unemployed because it becomes harder for an employer to find an employee. To avoid reverse causality, we include the time-lagged market tightness by adding year 2008.

The probability of catching a criminal serves as the deterrence factor in an individual's decision to commit crime. We proxy deterrence with clearance rates from the 2009 and 2010 yearly publications of the German Federal Criminal Police Office, defined as the percent of solved cases in the number of reported or known to the police cases. The deterrence hypothesis is verified if the effect of clearance rates on crime rates is negative. Relevant literature, nevertheless, documents that the influence of clearance rates on crime rates can also work in the opposite direction, because policy makers may respond to rising crime rates in ways that affect clearance rates (see, for instance, Entorf and Spengler, 2000). In order to circumvent possible simultaneity we include the time-lagged clearance rates by adding year 2008.[17]

Average productivity in the region is one of the main channels that connects crime and unemployment. We proxy productivity heterogeneity, first, with the gross domestic product per working hour in euro and, second, with the share of graduates without secondary education qualification (GSEQ) and with general higher education entrance qualification (GGHEEQ). The former reflects the fraction of the young population that is low-skilled because of leaving school early on and not even obtaining vocational training, while the latter the future high-skilled or those keen to invest in human capital and pursue university education. From another point of view, the share of these graduates proxies the fraction of the future low and high-skilled young population who are released currently into unemployment. Furthermore, we use the share of employees in insolvent firms to proxy those facing uncertainty regarding their future employment status and, therefore, the rate of release into unemployment.

Crime wages or expected gains from committing a crime and wages represent illegal and legal

[17] The strategy to include time-lagged variables instead of contemporary ones is good if there is high serial correlation.

income opportunities, respectively. As the former are unobserved, we proxy those receiving the reservation wage with the share of the population in the region receiving subsistence benefits. On the other hand, we measure legal income opportunities with the disposable income of private households per capita in euro. As disposable income includes any benefits, capital gains and other earnings that a household receives and excludes paid taxes, we find it is a better measure of legally obtained income than gross domestic product per capita or per worker because disposable income reflects the money that a private household actually holds in its pockets. As both might be affected by criminal engagement, we include the time-lagged variables by adding year 2008.

In order to to accommodate a possible influx of migrants and changes in the nonimprisoned population we include interregional migration. In our model a foreigner is defined as an agent who acts in the home region but resides elsewhere. Therefore, we include information on the share of arrivals and departures in and from a region. As an agent's decision to migrate might depend on regional crime rates we use the time-lagged share of arrivals and departures by adding year 2008. Finally, we note that all of the aforementioned variables were obtained from the German Regional Database (see Table 8.1 for variables and sources).

In order to construct the weights matrix, W_n, we downloaded the shapefile for Germany from the German Federal Office of Cartography and Geodesy. We consider as neighbors regions that share immediate geographical proximity. This specification suffices to capture plausible commuting times in Germany and the possibility that, for instance, an agent lives in Offenbach or Bad Vilbel and works in Frankfurt, as proposed in the theoretical spatial setting of Section 4. Construction of the weights matrix based on commuting times as in Patacchini and Zenou (2007) or Patacchini and Zenou (2012) entails calculation between the centroids of the polygons or – put more simply – the centers of the regions, which does not necessarily reflect actual commuting times. Furthermore, since the German Regional Database provides information on commuters at a lower geographical level than ours – i.e. the "Gemeinden" comprised of urban regions ("Stadtkreise") and subdivisions of the rural regions ("Landkreise") – modeling influences beyond the region's immediate borders obviously represents implausible commuting times.

In Table 8.1 we present basic summary statistics. On average during the period $2009-2010$ there were $6,528$ reported offenses per $100,000$ inhabitants from which around 60% have been solved. Among the five crime categories, street crime has the highest mean rate for the same period, which can be safely attributed to its broad definition (see Online Appendix), followed by damage to property, drug-related offenses and then, pure property crime, namely theft of/from motor vehicles and by burglary of a dwelling. On average, drug-related crime cases are most successfully solved, around 96%, whereas all other categories have much lower average clearance rates, from 17% for theft of/from motor vehicles to about 27% for damage to property.

Turning to average unemployment for the period $2009-2010$, the foreign unemployment rate is on average double than the rest of the categories. The latter are around 7% with similar dispersions. The youth unemployment share is much lower and close to 4% since the denominator is the whole population with age $15-25$ and not just the respective labor force. Market tightness for the $2008-2009$ period is approximately 12 meaning that the number of vacant positions surpass the number of unemployed. Regarding average productivity measures for the period $2009-2010$, the value produced by an hour of work corresponds to about 40 euro while the share of school dropouts around 7% and the share of academic-path high school graduates around 29%. The fraction of the population receiving subsistence benefits reflects those in extreme poverty and is on average very low: only 0.4% for years 2008 and 2009. Also very low is the share of employees working in insolvent firms in $2009-2010$, namely 0.6%. The mean of the time-lagged disposable income is approximately $19,000$ euro with a standard deviation of about $2,000$ euro. The time-lag of interregional migration corresponds to 5% of the regional population for both arrivals and departures. Finally, on average a German "Kreis" shares borders with 5 regions.

6 Estimation Results

In Tables 8.2-8.7 we present the QML estimation results for the 6 crime and unemployment categories. From the 6 crime categories, overall crime, damage to property and drug-related crime do not depend on the respective neighboring crime rate; the estimated coefficient on spatial crime not only lacks statistical significance but also is very close to zero. For pure property crime, namely theft by burglary of a dwelling and theft of/from motor vehicles, as well as street crime we uncover spatial dependence in the respective neighboring crime rates. Theft by burglary of a dwelling has the largest spatial dependence with an estimated coefficient of around 0.23, followed by theft of/from motor vehicles ($0.14 - 0.16$) and by street crime ($0.10 - 0.13$). Thus, the empirical exercise verifies that the theoretical model of Section 4 correctly predicts spatial dependence in crime yielding direct monetary gains and not other types such as violent crime (damage to property) or drug usage (although the 7300 crime category includes trafficking and importing of narcotic substances; see Online Appendix).

Apart from drug-related offenses and the youth unemployment share, an increase in unemployment rates in the home region leads to an increase in crime rates. The effect is the largest for overall unemployment except for theft of/from motor vehicles in which the effect of male unemployment surpasses that of overall unemployment. Although foreign unemployment is the highest among the rates, its effect is absent for theft by burglary of a dwelling, statistically insignificant for theft of/from motor vehicles and the smallest compared to other rates for overall crime and street crime. This empirical finding verifies our story: the global financial crisis hit the manpower of export-oriented manufacturing firms, short-time workers, younger persons and males - not foreigners.[18] We find the largest effect for theft of/from motor vehicles and the male unemployment rate: a 1% increase in male unemployment in the home region leads to a 0.69% increase in the rate of theft of/from motor vehicles in the home region. Also, the magnitude of the youth unemployment rate is smaller than that of the overall, male and female unemployment while we cannot establish an effect for the youth unemployment share. What is striking to see is the large and significant effect for the female unemployment rate as the global financial crisis hit sectors of the German economy predominantly employing male workers (metal industry, production industry of vehicles and electrical equipment). Also, property crime is widely known as a male-dominated type of criminal activity. A plausible explanation lies in household economics as women drive men to criminal engagement by becoming unemployed. When the female loses her job, the male is now the sole responsible for the financial balance of the household. In times of crisis, the male cannot compensate the lost labor income of his partner through working more hours or getting a second job and, therefore, has incentive to gain income illegally.

Regarding the unemployment effect of the neighboring regions, it is always negative and sometimes larger than the effect of domestic unemployment, although not present in all crime and unemployment categories. A negative effect of neighboring unemployment is consistent with a slacker labor market: a shock that increases the number of unemployed agents in the neighboring regions means that there are more job seekers in the home region ceteris paribus, i.e., keeping the number of vacancies and the number of unemployed agents fixed in the home region. Hence, market tightness decreases (or the market becomes slacker) which according to Part 3 of Proposition 4.2 leads to an increase of crime in the home region. The latter is true when market tightness in the home region has a negative sign, which is verified for overall crime, theft by burglary of a dwelling and street crime.

The deterrence hypothesis in the home region is verified for overall crime, pure property crime and street crime but not for violent crime (damage to property) and drug-related offenses. For pure property crime and street crime the magnitude is on average 0.08: a 1% increase in clearance

[18] According to the German Federal Criminal Police Office, in 2009 and 2010 the percent of foreign suspects for overall crime was 21.1% and 21.9% respectively.

rates in the home region (last year) leads to a 0.08% decrease in the crime rates (this year). The neighboring effect of clearance rates is absent except for theft of/from motor vehicles and drug-related crime. Regarding theft of/from motor vehicles, the positive effect from neighboring clearance rates means that more effective deterrence in the neighboring regions (last year) increases crime in the home region (this year) because criminals find the home region more attractive in terms of a lower probability of getting caught. The absence of neighboring effects in other categories points to the lack of a spatial component in clearance rates, perhaps because of the definition of neighbors. As discussed in Section 5.2, the "Kreise" as a level of aggregation might be too large for clearance rates to display spatial dependence.

Turning to regional productivity, the estimated coefficient of the gross domestic product per working hour in the home region is always negative apart from damage to property. Also, it is statistically and economically significant for overall and drug-related crime. The neighboring labor productivity has a positive effect only for overall crime. The share of graduates with general higher education entrance qualification (the future high-skilled labor force) in the home region seems to have better explanatory power in our crime equation: a higher percentage of graduates starting the university lowers overall crime, theft by burglary of a dwelling and drug-related crime. The effect is quite large for theft by burglary of a dwelling and drug-related crime and for the former it is actually about 3.5 times larger than the deterrence effect. Apart from street crime we cannot establish the relevance of a neighboring effect for the share of graduates. From another viewpoint, the youth who invest in university education postpone their release into unemployment for a later date when they will be high-skilled employees. The share of employees working in insolvent firms and facing employment uncertainty matters for property crime: through a positive own effect for theft by burglary of a dwelling and through a positive neighboring effect for theft of/from motor vehicles.

Disposable income per capita (time-lag) has an own and neighboring effect for overall crime, an own effect for street crime and a very large own and neighboring effect for drug-related offenses. For overall and drug-related crime, disposable income or a pure income effect is actually the most important factor for explaining relevant crime rates. The estimated coefficient is also very high in the theft-by-burglary-of-a-dwelling equation but lacks statistical significance. The share of those receiving subsistence benefits (time-lag) has a positive effect on the rate of theft by burglary of dwelling (own effect), theft of/from motor vehicles (neighbors' effect), street crime (own and neighbors' effect) as well as damage to property (own and neighbors' effect). This empirical finding verifies Part 2 of Proposition 4.2: an increase in the exogenous variables that drive cutoff productivity, e.g. subsistence income, increases the crime rate.

Finally, the time-lags of interregional migration have an effect on crime rates except for theft of/from motor vehicles and damage to property. Part 4 of Proposition 4.2 predicts that an influx of more productive workers increases crime rates by pushing up the threshold productivity in the home region. Empirically, although we cannot discern the productivity of in- and outmigrants, we can at least verify that population movements do matter for crime rates.

Summing up, in this Section we test empirically the implications of the theoretical model laid out in Section 4 and Proposition 4.2 and conclude that our spatial theory indeed fits best pure property crime and street crime as intended.[19] Own unemployment and some of the neighboring categories have an effect for crime committed by damage to property and so do the (time-lag of) own and neighboring share of those receiving subsistence benefits. Therefore, although damage to property is not directly related to monetary gains (but can be combined with committing property crime), it responds to changes in domestic unemployment and poverty in the broader neighborhood. Hence, our empirical results provide an explanation for phenomena of riots and looting with protagonists young, low-educated and unemployed males. The model fails to predict drug-related crime as

[19]Results treating reverse causality of unemployment and its spatial effect are available upon request for a log-levels model estimated with 2SLS.

major theoretical and spatial implications are not verified. Finally, crime lacks a regional/spatial dimension for overall crime, damage to property and drug-related crime. For the last two categories, it is possible that our choice of regions is too aggregated for spatial dependence to show up as they might take place in hot-spots of urban districts.

7 Policy Implications

The 402 German "Kreise" constitute regional administrative units that stand between the Federal States ("Bundesländer") and the municipalities ("Gemeinden"). The "Kreis" council is elected every 5 years (6 in Bavaria) and is – among other things – responsible for social, old-age and youth welfare and implementation of labor market policies (Hartz policies), the maintenance of hospitals and state schools, the provision of savings banks, public transport and natural parks as well as the accommodation and integration of foreign refugees.[20]

If local governments aim at lowering overall crime rates domestically, the most effective way is through increasing clearance rates because the (absolute value of the) magnitude of own clearance rates (time-lag) surpasses the magnitude of own unemployment rates/share (see Table 8.2). The lack of a neighboring effect means that the "Kreis" council cannot improve the policy's efficiency by taking into consideration related policies of the neighbors. The increase in clearance rates can be achieved with hiring more police officers or investing in forensic technology. Nevertheless, Section 6 provides evidence on differentiating the analysis according to the crime type: for theft by burglary of a dwelling, theft of/from motor vehicles, street crime, and damage to property, reduction of domestic unemployment is the most effective way to combat crime. In fact, damage to property is a type of crime that cannot be deterred with higher clearance rates (see Table 8.6).

In Tables 8.2-8.6, the repeatedly positive sign of home unemployment and a negative sign of neighboring unemployment suggest that if local governments aim at lowering crime rates they should provide incentives to unemployed agents to outmigrate and employed agents to inmigrate: crime rates decrease directly from a decrease in home unemployment and indirectly from an increase in neighboring unemployment. In principle, the policy tool could take the form of spatial competition in unemployment benefits: offer 1 euro less than the neighboring regions. In Germany, setting the level of unemployment benefits at the regional level is not possible because Hartz benefits are uniformly decided at the country level.[21] Therefore, local governments could improve the efficiency of the jobcenters or increase their number.[22] Furthemore, unemployment-reduction policies should be both gender and nationality neutral because, although the culprits are young low-skilled males, both male and female unemployment rates have an effect on crime while the effect of foreign unemployment is rather weak.

Along with unemployment and clearance rates, the share of those living in extreme poverty in a region is an important factor in explaining crime rates. But unlike unemployment, the sign of the share receiving subsistence benefits is positive for changes stemming both from home and neighboring regions. Therefore, in- and outmigration policies in the fashion of unemployment do not make sense in the case of subsistence benefits. Reduction of crime rates through a decrease in the share of subsistence benefits recipients happens either directly through the home region or indirectly through neighbors. Thus, the home region can "free-ride" on policies in the neighborhood: spend 0 euro and enjoy a decrease in crime because neighbors reduce poverty. Also, for pure property crime and street crime, the crime spatial multiplier due to $\widehat{\lambda} > 0$ propagates any decreasing effect so that a poverty-reduction policy is doomed to be more efficient than initially intended.

[20] http://www.landkreistag.de/ueber-den-dlt/aufgaben-der-kreise.html?showall=&limitstart=.
[21] http://www.hartziv.org/hartz-iv-rechner.html.
[22] http://www.jobcenter-ge.de/DE/Home/home_node.html.

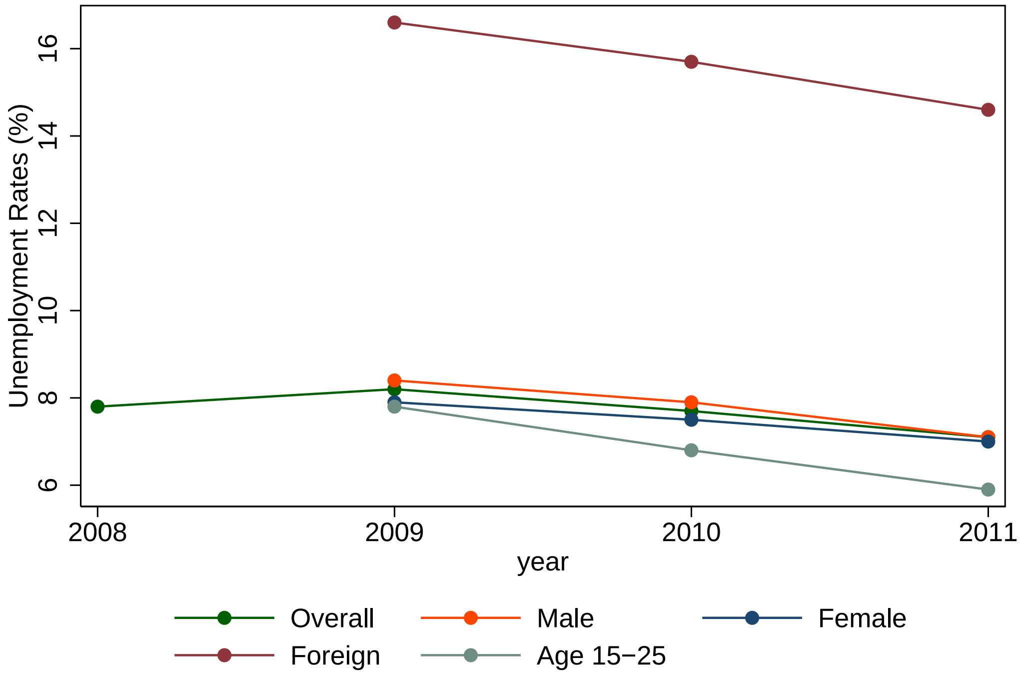
8 Conclusions

The case of Germany in studying spatial aspects of the labor markets such as the nexus between unemployment and crime rates is unarguably interesting, first, because evidently the German economy has survived the 2008 financial crisis, and, second, because Germany is Europe's economic powerhouse. The concept of our theory is simple: agents commute for work or crime and what links criminal activity and labor markets is an agent's productivity. The introduction of shocks in match productivities can provide an explanation to the aftermath of the global financial crisis in Germany. The global crisis was felt primarily as a trade shock with exports falling sharply in automotives, other vehicles, electrical equipment and the metal industry. The industries responded to lower demand either by decreasing employment hours (low-productivity matches look for outside options to increase income) or by laying off younger, male and unskilled employees (destruction of the low-productivity matches). This is exactly how a banking crisis in the U.S. ended up affecting regional crime in Germany: through adjustments in match productivities.

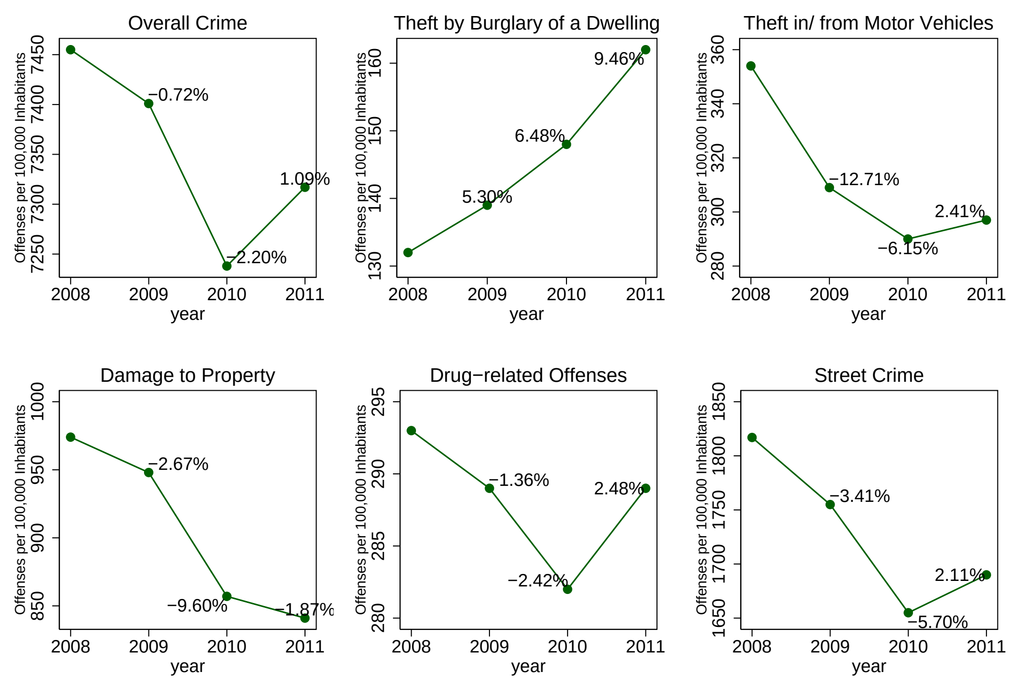
In order to test theory we translate our main crime equation into a spatial autoregressive model and use the global financial crisis as a laboratory: we exploit exogenous changes in unemployment to circumvent reverse causality. We uncover the existence of spatial multipliers for theft by burglary of a dwelling, theft of/from motor vehicles and street crime. These categories are most linked to crime that delivers monetary gains. Spatial multipliers are important in explaining why local crime rates are higher than they would be in the absence of a dying-out feedback effect transferred through neighboring regions. The most important determinants of crime happen to be unemployment, deterrence and the share of subsistence benefits recipients.[23] From a policy perspective, one of the most effective ways to combat crime is to tackle unemployment or labor market conditions instead of police expenditures and deterrence. One of the potential ways is to engage in a strategic budget design by incorporating decisions of neighboring local governments. In our example, crime in the home region will decrease first, by incentivizing unemployed agents to migrate to neighboring regions, and, second, by free-riding on poverty-reduction policies of the neighbors.

We consider that the literature would benefit from applying the space-embedded model of our type to countries that undergo increasing unemployment rates and reduction in welfare benefits, for instance, Greece, Portugal, Spain and Italy due to the ongoing fiscal debt crisis in Europe. The interplay can be considered not only within but also among European Union countries, which enjoy freedom of mobility especially with regards to employment. Furthermore, our model has the potential to explain the increasing crime rates after 2010 shown in Figure 8.1: one channel is through the influx of high productivity workers in Germany that period and, second, through the role of low-productivity workers in the economy (focus on the employment-crime link as unemployment decreases). Accordingly, one can exploit our model and identification strategy to link labor markets and crime rates in Europe after the war in Syria, which resulted in an exogenous influx of refugees for many countries. However, we do not delve fully into these mechanisms and leave such explorations for future research.

[23] The latter is a crucial component of the economic reasoning. There are, of course, many directions that can fruitfully expand or augment our theoretical framework. The literature on trade and unemployment (see, for example, Helpman and Itskhoki, 2010, Helpman et al., 2010, Felbermayr et al., 2011, and Felbermayr et al., 2013) can benefit from introducing effects on criminal activities from trade shocks on labor markets. Another unexploited track concerns the dual labor markets literature (see, for example, Saint-Paul, 1996, Bentolila et al., 2012, and Boeri, 2011), which lacks analysis on the costs of duality. The latter are mainly driven by large unemployment among young and less educated people, which in turn affects crime.

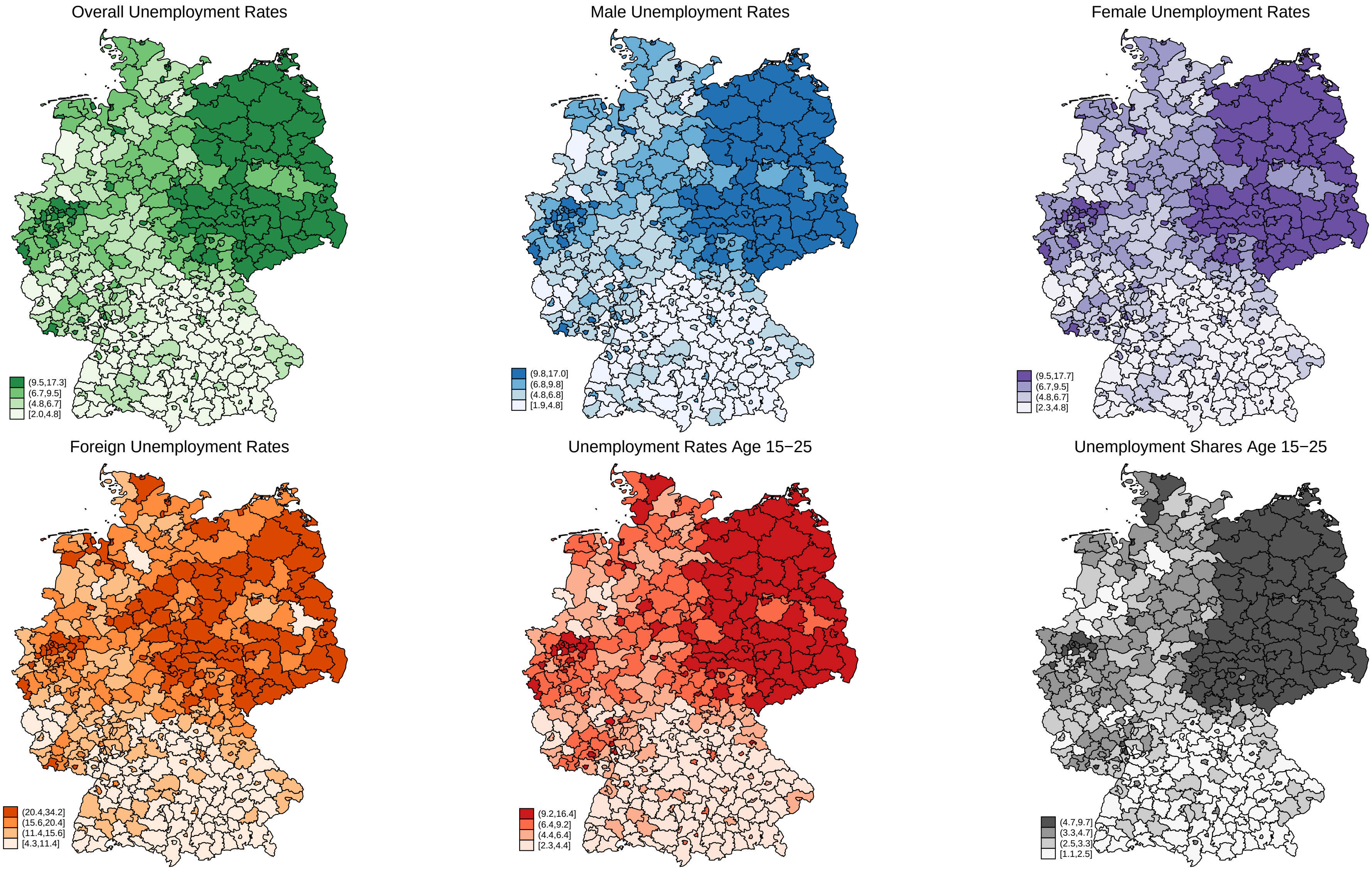


Source: German Regional Database



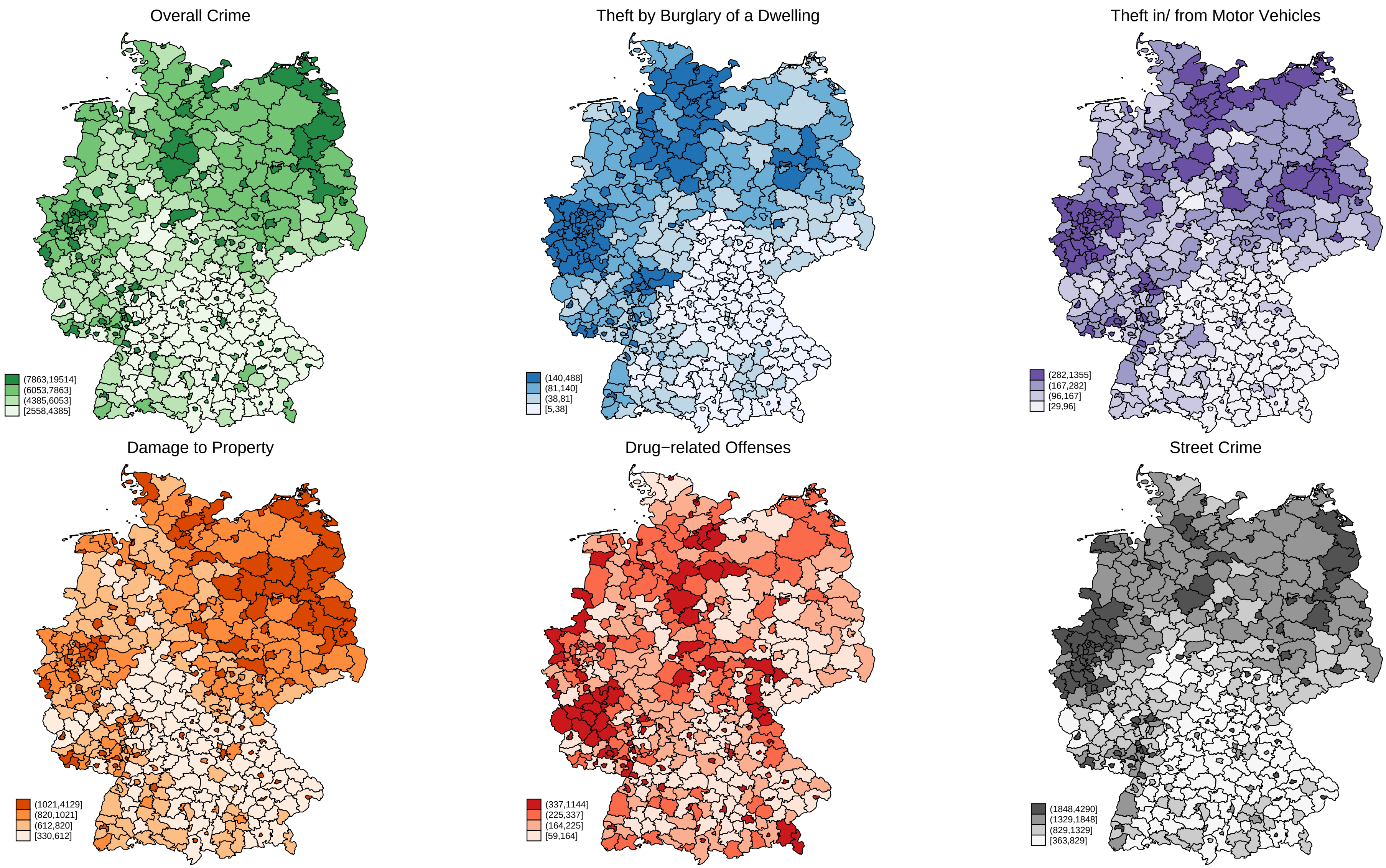
Source: German Federal Criminal Police Office

Figure 8.1: Unemployment Rates, Crime Rates and Crime Percentage Changes, 2008-2011, Germany.



Sources: German Regional Database

Figure 8.2: Spatial distribution of Unemployment Rates (%), 2009-2010, Germany.



Sources: German Federal Criminal Police Office

Figure 8.3: Spatial distribution of Crime Rates (Offenses per 100,000 Inhabitants), 2009-2010, Germany.

Table 8.1: Summary Statistics and Data Sources

Variable	Mean	Standard Deviation	Source	Date Obtained	Time Period
Overall Crime Rate	6,528	2,805	(1)	30.09.2011	2009, 2010
Clearance Rate (lag)	60.093	6.715	(1)	30.09.2011	2008, 2009
Theft By Burglary of a Dwelling Rate	106	94	(1)	30.09.2011	2009, 2010
Clearance Rate (lag)	23.659	13.439	(1)	30.09.2011	2008, 2009
Theft in/ from Motor Vehicles Rate	221	190	(1)	30.09.2011	2009, 2010
Clearance Rate (lag)	16.967	11.375	(1)	30.09.2011	2008, 2009
Street Crime Rate	1,452	775	(1)	30.09.2011	2009, 2010
Clearance Rate (lag)	22.127	5.736	(1)	30.09.2011	2008, 2009
Damage to Property Rate	854	358	(1)	30.09.2011	2009, 2010
Clearance Rate (lag)	26.919	6.618	(1)	30.09.2011	2008, 2009
Drug-related Offenses Rate	278	173	(1)	30.09.2011	2009, 2010
Clearance Rate (lag)	95.727	4.003	(1)	30.09.2011	2008, 2009
Unemployment Rate	7.521	3.354	(2)	28.06.2013 / 12:48:04	2009, 2010
Unemployment Rate Age 15-25	7.078	3.233	(2)	28.06.2013 / 12:48:04	2009, 2010
Unemployment Share Age 15-25	3.824	1.886	(2)	28.06.2013 / 12:48:04	2009, 2010
Male Unemployment Rate	7.648	3.478	(2)	28.06.2013 / 12:48:04	2009, 2010
Female Unemployment Rate	7.391	3.272	(2)	28.06.2013 / 12:48:04	2009, 2010
Foreign Unemployment Rate	16.361	6.247	(2)	28.06.2013 / 12:48:04	2009, 2010
Market Tightness (lag)	12.301	8.497	(3)	04.11.2015 / 14:56	2008, 2009
Gross Domestic Product per Working Hour	40.599	7.097	(2)	01.10.2015 / 15:58:28	2009, 2010
Disposable Income per Capita (lag)	18,653	2,274	(2)	01.10.2015 / 14:10:39	2008, 2009
Share Subsistence Benefits Recipients (lag)	0.358	0.177	(2)	01.10.2015 / 16:03:59	2008, 2009
Share Employees in Insolvent Firms	0.613	1.260	(2)	01.10.2015 / 15:04:22	2009, 2010
Share GSEQ[a]	6.861	2.125	(2)	28.06.2013 / 13:24:50	2009, 2010
Share GGHEQ[b]	28.670	10.356	(2)	28.06.2013 / 13:24:50	2009, 2010
Share of Arrivals (lag)	5.333	1.298	(2)	28.06.2013 / 12:56:37	2008, 2009
Share of Departures (lag)	5.445	1.096	(2)	28.06.2013 / 12:56:37	2008, 2009
Weights Matrix	5	-	(4)	28.06.2013 / 10:52	-

Note: [a] Graduates without Secondary Education Qualification.
[b] Graduates with General Higher Education Entrance Qualification.
(1) German Federal Criminal Police Office, www.bka.de/DE/AktuelleInformationen/StatistikenLagebilder/PolizeilicheKriminalstatistik/AeltereAusgaben/aeltere Ausgaben__node.html.
(2) German Regional Database, German Federal Statistical Office and Statistical Offices of the Länder, www.regionalstatistik.de.
(3) German Federal Employment Agency Statistics, www.statistik.arbeitsagentur.de.
(4) German Federal Office of Cartography and Geodesy, www.bkg.bund.de/DE/Home/home.html.

Table 8.2: Spatial Model - Overall Crime

	UR		UR15-25		US15-25		URMale		URFemale		URForeign	
Spatial Dependence	0.063		0.026		0.023		0.065		0.047		0.038	
in Crime	(0.057)		(0.058)		(0.058)		(0.057)		(0.058)		(0.058)	
	Own	W	Own	W	Own	W	Own	W	Own	W	Own	W
Unemployment (U)	0.413***	-0.209*	0.164***	0.018	0.003	0.128*	0.394***	-0.281***	0.365***	-0.089	0.164***	-0.147**
Rate (R)/Share(S)	(0.054)	(0.110)	(0.036)	(0.071)	(0.040)	(0.074)	(0.053)	(0.106)	(0.053)	(0.106)	(0.037)	(0.070)
Clearance Rate	-0.466***	-0.076	-0.491***	-0.174	-0.476***	-0.169	-0.459***	-0.060	-0.464***	-0.123	-0.433***	-0.063
(lag)	(0.068)	(0.162)	(0.070)	(0.166)	(0.071)	(0.170)	(0.068)	(0.162)	(0.068)	(0.162)	(0.070)	(0.161)
Market Tightness	-0.013	-0.021	-0.028*	-0.028	-0.028*	-0.022	-0.016	-0.020	-0.012	-0.017	-0.018	-0.008
(lag)	(0.014)	(0.025)	(0.014)	(0.026)	(0.014)	(0.027)	(0.014)	(0.025)	(0.014)	(0.025)	(0.014)	(0.025)
GDP per Working	-0.211***	0.371**	-0.165**	0.444***	-0.175**	0.414**	-0.188**	0.330**	-0.213***	0.402***	-0.196**	0.364**
Hour	(0.075)	(0.154)	(0.077)	(0.164)	(0.078)	(0.164)	(0.075)	(0.155)	(0.076)	(0.155)	(0.077)	(0.158)
Disposable Income	0.796***	-0.891**	0.618**	-0.721	0.645**	-0.865*	0.791***	-0.932**	0.777**	-0.841*	0.768**	-1.047**
per Capita (lag)	(0.306)	(0.431)	(0.312)	(0.438)	(0.316)	(0.443)	(0.307)	(0.432)	(0.308)	(0.431)	(0.314)	(0.435)
Sh. Subsist. Ben.	-0.000	0.019	-0.001	0.006	-0.001	0.018	-0.000	0.021	-0.001	0.022	0.000	0.025
Recipients (lag)	(0.015)	(0.024)	(0.015)	(0.024)	(0.015)	(0.025)	(0.015)	(0.024)	(0.015)	(0.024)	(0.015)	(0.024)
Sh. Employees in	0.003	-0.002	0.001	0.000	0.001	0.000	0.003	-0.003	0.003	-0.000	0.002	-0.003
Insolvent Firms	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)
Sh. Grad. w/o	-0.025	-0.012	-0.028*	-0.005	-0.034**	-0.007	-0.024	-0.015	-0.025	-0.012	-0.030*	-0.026
Educ. Qualific.	(0.016)	(0.032)	(0.016)	(0.033)	(0.016)	(0.033)	(0.016)	(0.032)	(0.016)	(0.033)	(0.016)	(0.033)
Sh. Grad. with HE	-0.089***	-0.029	-0.081**	-0.028	-0.088**	-0.021	-0.087***	-0.028	-0.089***	-0.036	-0.090***	-0.035
Entrance Qualific.	(0.034)	(0.049)	(0.034)	(0.051)	(0.035)	(0.052)	(0.034)	(0.050)	(0.034)	(0.050)	(0.034)	(0.051)
Sh. Arrivals (lag)	0.201**	0.556***	0.216**	0.501**	0.268***	0.499**	0.205**	0.526***	0.222**	0.601***	0.250***	0.519**
	(0.090)	(0.198)	(0.093)	(0.203)	(0.093)	(0.206)	(0.090)	(0.199)	(0.091)	(0.199)	(0.092)	(0.203)
Sh. Departures	-0.101	-0.036	-0.133	0.002	-0.148*	0.005	-0.092	0.028	-0.121	-0.091	-0.109	0.045
(lag)	(0.084)	(0.191)	(0.085)	(0.194)	(0.086)	(0.197)	(0.084)	(0.189)	(0.084)	(0.192)	(0.085)	(0.191)

Note: 804 observations (402 regions for years 2009, 2010). Estimation with QML including regional and time fixed effects. All variables are in logarithms. *, **, *** denote significance at 10%, 5% and 1% respectively. Reported coefficients are the estimated coefficients due to lack of spatial dependence in crime. W denotes neighboring effects.

Table 8.3: Spatial Model - Theft by Burglary of a Dwelling

	UR		UR15-25		US15-25		URMale		URFemale		URForeign	
Spatial Dependence	0.227***		0.232***		0.230***		0.232***		0.224***		0.229***	
in Crime	(0.051)		(0.051)		(0.051)		(0.051)		(0.051)		(0.051)	
	ADI	AII	ADI	AII	ADI	AII	ADI	AII	ADI	AII	ADI	AII
Unemployment (U)	0.472***	-0.309	0.291***	-0.518**	0.121	-0.519**	0.425***	-0.493	0.400**	0.160	0.007	-0.457*
Rate (R)/Share(S)	(0.168)	(0.370)	(0.110)	(0.234)	(0.121)	(0.238)	(0.163)	(0.352)	(0.166)	(0.355)	(0.115)	(0.240)
Clearance Rate	-0.078***	-0.008	-0.080***	0.005	-0.080***	0.001	-0.077***	-0.002	-0.079***	-0.018	-0.079***	-0.003
(lag)	(0.015)	(0.039)	(0.015)	(0.039)	(0.015)	(0.039)	(0.015)	(0.039)	(0.015)	(0.039)	(0.015)	(0.039)
Market Tightness	-0.034	0.030	-0.038	0.062	-0.039	0.101	-0.036	0.037	-0.035	0.040	-0.046	0.048
(lag)	(0.048)	(0.101)	(0.048)	(0.100)	(0.048)	(0.101)	(0.048)	(0.101)	(0.049)	(0.102)	(0.048)	(0.102)
GDP per Working	-0.004	-0.032	0.012	-0.253	-0.010	-0.254	0.026	-0.088	-0.003	0.018	-0.014	-0.117
Hour	(0.257)	(0.633)	(0.261)	(0.644)	(0.260)	(0.642)	(0.258)	(0.636)	(0.258)	(0.632)	(0.260)	(0.639)
Disposable Income	2.109*	-1.376	1.919*	-1.420	1.975*	-1.513	2.089*	-1.500	2.079*	-1.155	2.000*	-1.611
per Capita (lag)	(1.093)	(1.455)	(0.044)	(1.461)	(1.101)	(1.468)	(1.092)	(1.457)	(1.095)	(1.450)	(1.096)	(1.458)
Sh. Subsist. Ben.	0.100**	-0.138	0.112**	-0.132	0.115***	-0.118	0.102**	-0.134	0.097**	-0.144	0.107**	-0.113
Recipients (lag)	(0.044)	(0.096)	(0.044)	(0.098)	(0.044)	(0.098)	(0.044)	(0.096)	(0.044)	(0.096)	(0.044)	(0.096)
Sh. Employees in	0.018**	-0.032	0.018**	-0.034	0.017*	-0.035	0.018**	-0.035	0.019**	-0.027	0.016*	-0.038
Insolvent Firms	(0.009)	(0.023)	(0.009)	(0.023)	(0.009)	(0.023)	(0.009)	(0.023)	(0.009)	(0.023)	(0.009)	(0.023)
Sh. Grad. w/o	0.084*	0.078	0.076*	0.036	0.070	0.036	0.083*	0.070	0.086*	0.097	0.069	0.042
Educ. Qualific.	(0.045)	(0.136)	(0.045)	(0.137)	(0.045)	(0.137)	(0.045)	(0.136)	(0.045)	(0.136)	(0.045)	(0.136)
Sh. Grad. with HE	-0.284***	0.199	-0.278***	0.157	-0.297***	0.162	-0.284***	0.198	-0.285***	0.195	-0.299***	0.174
Entrance Qualific.	(0.106)	(0.180)	(0.106)	(0.182)	(0.106)	(0.183)	(0.106)	(0.181)	(0.106)	(0.179)	(0.106)	(0.182)
Sh. Arrivals (lag)	0.176	0.020	0.187	0.077	0.273	0.139	0.190	0.015	0.202	0.091	0.269	0.124
	(0.306)	(0.755)	(0.309)	(0.772)	(0.309)	(0.777)	(0.307)	(0.769)	(0.306)	(0.747)	(0.307)	(0.774)
Sh. Departures	0.712**	0.676	0.741***	1.032	0.724**	1.085	0.728**	0.807	0.655**	0.467	0.714**	0.844
(lag)	(0.284)	(0.805)	(0.283)	(0.812)	(0.284)	(0.815)	(0.283)	(0.806)	(0.285)	(0.799)	(0.284)	(0.794)

Note: 804 observations (402 regions for years 2009, 2010). Estimation with QML including regional and time fixed effects. All variables are in logarithms. *, **, *** denote significance at 10%, 5% and 1% respectively. Reported coefficients are the estimated average direct (ADI) and average indirect (AII) impacts taking into account the positive spatial dependence in crime.

Table 8.4: Spatial Model - Theft of/from Motor Vehicles

	UR		UR15-25		US15-25		URMale		URFemale		URForeign	
Spatial Dependence	0.167***		0.149***		0.142***		0.164***		0.160***		0.140***	
in Crime	(0.053)		(0.053)		(0.053)		(0.053)		(0.053)		(0.054)	
	ADI	AII	ADI	AII	ADI	AII	ADI	AII	ADI	AII	ADI	AII
Unemployment (U)	0.654***	-1.191***	0.330***	-0.124	0.093	0.098	0.687***	-1.285***	0.571***	-0.776**	0.190*	-1.151***
Rate (R)/Share(S)	(0.157)	(0.328)	(0.105)	(0.204)	(0.116)	(0.207)	(0.152)	(0.310)	(0.155)	(0.314)	(0.106)	(0.211)
Clearance Rate	-0.094***	0.061**	-0.091***	0.057*	-0.092***	0.057*	-0.093***	0.060**	-0.093***	0.059**	-0.092***	0.045
(lag)	(0.011)	(0.029)	(0.011)	(0.029)	(0.011)	(0.029)	(0.011)	(0.029)	(0.011)	(0.029)	(0.011)	(0.029)
Market Tightness	0.083*	-0.131	0.057	-0.138	0.053	-0.130	0.081*	-0.115	0.082*	-0.141	0.069	-0.113
(lag)	(0.045)	(0.088)	(0.045)	(0.087)	(0.045)	(0.088)	(0.045)	(0.087)	(0.046)	(0.090)	(0.045)	(0.086)
GDP per Working	-0.151	-0.855	-0.065	-0.745	-0.076	-0.724	-0.094	-0.953*	-0.151	-0.794	-0.184	-0.899*
Hour	(0.240)	(0.555)	(0.244)	(0.557)	(0.245)	(0.554)	(0.239)	(0.552)	(0.241)	(0.555)	(0.240)	(0.541)
Disposable Income	-1.051	0.203	-1.338	0.835	-1.309	0.671	-1.076	0.187	-1.100	0.468	-1.045	0.006
per Capita (lag)	(1.033)	(1.345)	(1.050)	(1.348)	(1.057)	(1.354)	(1.031)	(1.339)	(1.039)	(1.344)	(1.034)	(1.323)
Sh. Subsist. Ben.	0.025	0.155*	0.020	0.123	0.020	0.137	0.024	0.156*	0.023	0.168**	0.029	0.193**
Recipients (lag)	(0.042)	(0.083)	(0.043)	(0.085)	(0.043)	(0.085)	(0.042)	(0.083)	(0.042)	(0.083)	(0.042)	(0.081)
Sh. Employees in	0.002	0.044**	0.002	0.053***	0.001	0.054***	0.003	0.042**	0.002	0.048**	0.001	0.033*
Insolvent Firms	(0.008)	(0.021)	(0.008)	(0.021)	(0.008)	(0.020)	(0.008)	(0.021)	(0.008)	(0.021)	(0.008)	(0.020)
Sh. Grad. w/o	-0.022	0.086	-0.017	0.139	-0.025	0.146	-0.018	0.087	-0.020	0.092	-0.028	0.039
Educ. Qualific.	(0.042)	(0.121)	(0.042)	(0.121)	(0.043)	(0.120)	(0.042)	(0.120)	(0.042)	(0.121)	(0.042)	(0.117)
Sh. Grad. with HE	-0.048	-0.025	-0.036	-0.027	-0.046	-0.006	-0.050	-0.031	-0.043	-0.036	-0.074	-0.068
Entrance Qualific.	(0.100)	(0.161)	(0.101)	(0.161)	(0.102)	(0.162)	(0.100)	(0.160)	(0.101)	(0.160)	(0.100)	(0.158)
Sh. Arrivals (lag)	-0.249	-0.483	-0.257	-0.635	-0.176	-0.652	-0.232	-0.434	-0.228	-0.495	-0.137	-0.292
	(0.287)	(0.676)	(0.291)	(0.680)	(0.292)	(0.682)	(0.287)	(0.680)	(0.288)	(0.668)	(0.285)	(0.667)
Sh. Departures	0.308	0.884	0.189	0.682	0.146	0.642	0.308	0.911	0.252	0.687	0.296	0.750
(lag)	(0.266)	(0.708)	(0.266)	(0.698)	(0.268)	(0.697)	(0.264)	(0.700)	(0.267)	(0.702)	(0.263)	(0.672)

Note: 804 observations (402 regions for years 2009, 2010). Estimation with QML including regional and time fixed effects. All variables are in logarithms. *, **, *** denote significance at 10%, 5% and 1% respectively. Reported coefficients are the estimated average direct (ADI) and average indirect (AII) impacts taking into account the positive spatial dependence in crime.

Table 8.5: Spatial Model - Street Crime

	UR		UR15-25		US15-25		URMale		URFemale		URForeign	
Spatial Dependence	0.134***		0.095*		0.090*		0.126**		0.126**		0.106**	
in Crime	(0.050)		(0.051)		(0.052)		(0.051)		(0.051)		(0.051)	
	ADI	AII	ADI	AII	ADI	AII	ADI	AII	ADI	AII	ADI	AII
Unemployment (U)	0.456***	-0.497***	0.206***	-0.075	0.008	0.056	0.423***	-0.478***	0.426***	-0.361***	0.196***	-0.345***
Rate (R)/Share(S)	(0.061)	(0.125)	(0.041)	(0.078)	(0.047)	(0.081)	(0.060)	(0.119)	(0.060)	(0.120)	(0.042)	(0.079)
Clearance Rate	-0.065***	0.029	-0.075***	0.012	-0.073***	0.014	-0.066***	0.034	-0.067***	0.023	-0.064***	0.029
(lag)	(0.014)	(0.035)	(0.014)	(0.035)	(0.014)	(0.035)	(0.014)	(0.035)	(0.014)	(0.035)	(0.014)	(0.035)
Market Tightness	-0.001	0.052	-0.017	0.051	-0.018	0.062*	-0.005	0.057*	0.001	0.050	-0.008	0.064*
(lag)	(0.018)	(0.033)	(0.018)	(0.032)	(0.018)	(0.033)	(0.018)	(0.033)	(0.018)	(0.034)	(0.018)	(0.033)
GDP per Working	-0.065	-0.113	-0.015	-0.049	-0.026	-0.069	-0.033	-0.161	-0.070	-0.073	-0.055	-0.103
Hour	(0.094)	(0.209)	(0.097)	(0.208)	(0.098)	(0.209)	(0.094)	(0.208)	(0.094)	(0.208)	(0.096)	(0.207)
Disposable Income	-0.734*	0.071	-0.928**	0.331	-0.893**	0.178	-0.752*	0.083	-0.756*	0.165	-0.739*	-0.003
per Capita (lag)	(0.402)	(0.508)	(0.415)	(0.513)	(0.422)	(0.521)	(0.404)	(0.507)	(0.405)	(0.508)	(0.410)	(0.508)
Sh. Subsist. Ben.	0.039**	0.149***	0.038**	0.130***	0.038**	0.144***	0.038**	0.149***	0.038**	0.156***	0.039**	0.157***
Recipients (lag)	(0.016)	(0.031)	(0.017)	(0.031)	(0.017)	(0.032)	(0.016)	(0.031)	(0.016)	(0.031)	(0.016)	(0.031)
Sh. Employees in	0.002	-0.004	0.001	0.001	0.000	0.001	0.002	-0.004	0.002	-0.002	0.002	-0.005
Insolvent Firms	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)
Sh. Grad. w/o	-0.028*	0.013	-0.031*	0.025	-0.038**	0.026	-0.027	0.016	-0.028*	0.009	-0.032*	-0.002
Educ. Qualific.	(0.016)	(0.046)	(0.017)	(0.045)	(0.017)	(0.046)	(0.017)	(0.046)	(0.016)	(0.046)	(0.017)	(0.045)
Sh. Grad. with HE	-0.000	-0.128**	0.009	-0.133**	-0.002	-0.124**	0.000	-0.129**	0.002	-0.137**	-0.004	-0.138**
Entrance Qualific.	(0.039)	(0.061)	(0.040)	(0.061)	(0.041)	(0.062)	(0.039)	(0.061)	(0.039)	(0.061)	(0.040)	(0.061)
Sh. Arrivals (lag)	0.122	-0.581**	0.132	-0.635**	0.198*	-0.625**	0.133	-0.596**	0.136	-0.551**	0.174	-0.586**
	(0.112)	(0.250)	(0.115)	(0.250)	(0.116)	(0.253)	(0.112)	(0.252)	(0.112)	(0.247)	(0.113)	(0.250)
Sh. Departures	0.244**	0.491*	0.190*	0.480*	0.169	0.481*	0.238**	0.525**	0.221**	0.403	0.221**	0.493**
(lag)	(0.103)	(0.258)	(0.104)	(0.253)	(0.106)	(0.256)	(0.103)	(0.256)	(0.103)	(0.256)	(0.103)	(0.250)

Note: 804 observations (402 regions for years 2009, 2010). Estimation with QML including regional and time fixed effects. All variables are in logarithms. *, **, *** denote significance at 10%, 5% and 1% respectively. Reported coefficients are the estimated average direct (ADI) and average indirect (AII) impacts taking into account the positive spatial dependence in crime.

Table 8.6: Spatial Model - Damage to Property

	UR		UR15-25		US15-25		URMale		URFemale		URForeign	
Spatial Dependence	0.068		0.060		0.048		0.069		0.061		0.053	
in Crime	(0.054)		(0.054)		(0.055)		(0.054)		(0.054)		(0.054)	
	Own	W	Own	W	Own	W	Own	W	Own	W	Own	W
Unemployment (U)	0.431***	-0.297**	0.184***	-0.216**	0.010	-0.098	0.404***	-0.345**	0.397***	-0.222	0.228***	-0.104
Rate (R)/Share(S)	(0.074)	(0.145)	(0.049)	(0.093)	(0.055)	(0.097)	(0.073)	(0.141)	(0.073)	(0.139)	(0.050)	(0.093)
Clearance Rate	-0.015	-0.020	-0.016	-0.014	-0.016	-0.016	-0.016	-0.013	-0.019	-0.026	-0.015	-0.028
(lag)	(0.024)	(0.049)	(0.024)	(0.050)	(0.025)	(0.051)	(0.024)	(0.050)	(0.024)	(0.049)	(0.024)	(0.049)
Market Tightness	0.054***	-0.040	0.044**	-0.027	0.043**	-0.014	0.051***	-0.038	0.056***	-0.039	0.050***	-0.028
(lag)	(0.019)	(0.034)	(0.020)	(0.035)	(0.020)	(0.036)	(0.019)	(0.034)	(0.020)	(0.035)	(0.020)	(0.034)
GDP per Working	0.172*	0.168	0.193*	0.099	0.184*	0.107	0.197*	0.125	0.164	0.199	0.199*	0.209
Hour	(0.103)	(0.211)	(0.105)	(0.221)	(0.106)	(0.220)	(0.103)	(0.212)	(0.104)	(0.212)	(0.105)	(0.214)
Disposable Income	0.248	-0.416	0.079	-0.358	0.122	-0.466	0.237	-0.440	0.227	-0.378	0.244	-0.496
per Capita (lag)	(0.422)	(0.586)	(0.427)	(0.591)	(0.431)	(0.596)	(0.423)	(0.587)	(0.423)	(0.585)	(0.426)	(0.587)
Sh. Subsist. Ben.	0.050**	0.072**	0.055***	0.070**	0.055***	0.081**	0.050**	0.073**	0.050**	0.077**	0.049**	0.074**
Recipients (lag)	(0.020)	(0.033)	(0.021)	(0.034)	(0.021)	(0.034)	(0.020)	(0.033)	(0.020)	(0.033)	(0.020)	(0.033)
Sh. Employees in	0.001	0.009	0.000	0.009	-0.001	0.009	0.001	0.008	0.001	0.010	0.001	0.010
Insolvent Firms	(0.004)	(0.008)	(0.004)	(0.008)	(0.004)	(0.009)	(0.004)	(0.008)	(0.004)	(0.008)	(0.004)	(0.009)
Sh. Grad. w/o	-0.036	-0.025	-0.042*	-0.038	-0.047**	-0.035	-0.035	-0.026	-0.036*	-0.030	-0.037*	-0.032
Educ. Qualific.	(0.022)	(0.045)	(0.022)	(0.046)	(0.022)	(0.046)	(0.022)	(0.045)	(0.022)	(0.045)	(0.022)	(0.045)
Sh. Grad. with HE	-0.026	-0.073	-0.021	-0.090	-0.033	-0.084	-0.024	-0.073	-0.024	-0.081	-0.021	-0.071
Entrance Qualific.	(0.046)	(0.068)	(0.047)	(0.069)	(0.047)	(0.070)	(0.046)	(0.068)	(0.046)	(0.068)	(0.047)	(0.068)
Sh. Arrivals (lag)	0.173	-0.382	0.195	-0.381	0.258**	-0.373	0.181	-0.409	0.187	-0.339	0.214*	-0.450
	(0.124)	(0.273)	(0.126)	(0.277)	(0.127)	(0.280)	(0.124)	(0.274)	(0.124)	(0.274)	(0.124)	(0.276)
Sh. Departures	0.120	0.148	0.114	0.298	0.094	0.307	0.124	0.209	0.106	0.098	0.096	0.181
(lag)	(0.116)	(0.268)	(0.117)	(0.270)	(0.117)	(0.273)	(0.116)	(0.266)	(0.116)	(0.269)	(0.116)	(0.264)

Note: 804 observations (402 regions for years 2009, 2010). Estimation with QML including regional and time fixed effects. All variables are in logarithms. *, **, *** denote significance at 10%, 5% and 1% respectively. Reported coefficients are the estimated coefficients due to lack of spatial dependence in crime. W denotes neighboring effects.

Table 8.7: Spatial Model - Drug-Related Crime

	UR		UR15-25		US15-25		URMale		URFemale		URForeign	
Spatial Dependence	0.039		0.050		0.052		0.045		0.032		0.052	
in Crime	(0.053)		(0.053)		(0.053)		(0.053)		(0.053)		(0.053)	
	Own	W	Own	W	Own	W	Own	W	Own	W	Own	W
Unemployment (U)	-0.075	-0.762***	-0.169**	-0.047	-0.174*	0.015	0.071	-0.792***	-0.206	-0.708***	-0.028	-0.331**
Rate (R)/Share(S)	(0.130)	(0.250)	(0.085)	(0.158)	(0.094)	(0.163)	(0.126)	(0.240)	(0.127)	(0.239)	(0.088)	(0.160)
Clearance Rate	0.027	-0.914**	0.021	-0.799**	0.024	-0.775**	0.039	-0.875**	0.022	-0.880**	0.039	-0.877**
(lag)	(0.117)	(0.375)	(0.118)	(0.376)	(0.118)	(0.377)	(0.117)	(0.374)	(0.117)	(0.374)	(0.118)	(0.377)
Market Tightness	0.028	-0.019	0.026	0.003	0.028	-0.003	0.033	-0.010	0.020	-0.036	0.022	-0.026
(lag)	(0.034)	(0.060)	(0.034)	(0.062)	(0.034)	(0.063)	(0.034)	(0.060)	(0.034)	(0.060)	(0.034)	(0.060)
GDP per Working	-0.383**	0.356	-0.382**	0.316	-0.366**	0.354	-0.364**	0.335	-0.373**	0.316	-0.392**	0.373
Hour	(0.180)	(0.370)	(0.182)	(0.383)	(0.181)	(0.379)	(0.180)	(0.371)	(0.180)	(0.370)	(0.182)	(0.373)
Disposable Income	-1.804**	2.201**	-1.755**	2.402**	-1.750**	2.441**	-1.809**	2.237**	-1.846**	2.273**	-1.791**	2.516**
per Capita (lag)	(0.740)	(1.031)	(0.742)	(1.034)	(0.743)	(1.034)	(0.740)	(1.031)	(0.738)	(1.026)	(0.744)	(1.029)
Sh. Subsist. Ben.	-0.035	0.097*	-0.037	0.109*	-0.041	0.105*	-0.037	0.094	-0.035	0.108*	-0.037	0.101*
Recipients (lag)	(0.035)	(0.057)	(0.036)	(0.058)	(0.036)	(0.058)	(0.035)	(0.057)	(0.035)	(0.057)	(0.035)	(0.058)
Sh. Employees in	-0.006	-0.006	-0.006	-0.000	-0.006	0.000	-0.006	-0.006	-0.007	-0.007	-0.005	-0.004
Insolvent Firms	(0.007)	(0.015)	(0.007)	(0.015)	(0.007)	(0.015)	(0.007)	(0.015)	(0.007)	(0.015)	(0.007)	(0.015)
Sh. Grad. w/o	-0.021	0.067	-0.017	0.097	-0.015	0.104	-0.016	0.070	-0.023	0.060	-0.013	0.088
Educ. Qualific.	(0.038)	(0.078)	(0.038)	(0.079)	(0.038)	(0.079)	(0.038)	(0.078)	(0.038)	(0.078)	(0.038)	(0.078)
Sh. Grad. with HE	-0.208**	-0.042	-0.221***	-0.039	-0.220***	-0.044	-0.212***	-0.048	-0.204**	-0.041	-0.219***	-0.050
Entrance Qualific.	(0.081)	(0.117)	(0.082)	(0.118)	(0.082)	(0.118)	(0.081)	(0.117)	(0.081)	(0.117)	(0.082)	(0.118)
Sh. Arrivals (lag)	0.420*	-0.491	0.481**	-0.462	0.465**	-0.456	0.419*	-0.378	0.430**	-0.608	0.417*	-0.427
	(0.217)	(0.491)	(0.219)	(0.496)	(0.219)	(0.497)	(0.217)	(0.493)	(0.216)	(0.490)	(0.217)	(0.495)
Sh. Departures	-0.431**	0.746	-0.520**	0.535	-0.517**	0.495	-0.439**	0.651	-0.432**	0.796*	-0.488**	0.475
(lag)	(0.203)	(0.460)	(0.202)	(0.460)	(0.202)	(0.460)	(0.202)	(0.456)	(0.202)	(0.459)	(0.202)	(0.453)

Note: 804 observations (402 regions for years 2009, 2010). Estimation with QML including regional and time fixed effects. All variables are in logarithms. *, **, *** denote significance at 10%, 5% and 1% respectively. Reported coefficients are the estimated coefficients due to lack of spatial dependence in crime. W denotes neighboring effects.

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