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Times of Crisis: Evidence from Germany

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Space is important.¹ The recent global financial crisis has vividly pointed to spatial patterns in economies' reactions to the global economic shocks. This paper focuses on labor market responses and its interactions with criminal activities in a causal and spatial framework. We study the case of Germany as evidently this country's economy has demonstrated resilience during the whirl of economic crisis. Our contribution is twofold: first, we lay down a parsimonious labor market model with search frictions, criminal opportunities, and, unlike earlier analyzes, productivity shocks which are important in explaining empirical regularity of criminal engagement. Second, we seek empirical support using data on the 402 German districts for 2009-2010, the years following the global financial crisis, in a setting that allows not only crime spatial multipliers but also inherent endogeneity of unemployment. Adverse income shocks clearly unfold a spatial nexus between unemployment and crime rates. More specifically, we find that youth unemployment plays a prominent role in explaining property crime, namely housing burglary. Our results are in line with previous research: neglecting endogeneity of unemployment understates its impact and employing the youth unemployment *share* instead of *rate* points to distinctive effects. The analysis offers important implications for countries that are currently undergoing fiscal consolidation and are experiencing high unemployment rates.

JEL Classification: C31, J64, K42, R10

Keywords: Crime, Unemployment, Spatial Econometrics, Economic Crisis

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¹This is the first sentence in Ingmar Prucha's notes distributed during the Spatial Econometrics Advanced Institute (SEAI) in Rome, 2011.

1 Introduction

The recent global financial crisis has vividly pointed to spatial patterns in economies' reactions to the global economic shocks. Some countries, especially European, have entered fiscal consolidation and faced employment deterioration even contemporarily, while others experienced fast recovery in the form of a temporary increase in unemployment rates acting as spatial outliers. Even within a country, geographical dependencies are prevalent and may refer both to positive and negative correlations, depicting - respectively - resemblance or dissimilarity of regional economic traits. In this paper we are interested in how spatial attributes and conditions of the labor markets become intertwined with other socio-economic aspects such as criminal activities, by examining the role of the geographical distribution of unemployment and crime rates at the regional level incorporating possible spillovers among neighboring German communities.

Cook and Zarkin (1985) and even more recently Bushway, Cook, and Phillips (2012) analyze the association between recessions and crime for the U.S. and confirm a link for property crime (burglary, robbery and motor vehicle theft) but none for violent (homicide). Thus, contemporaneous socio-economic developments render the study of the causal nexus between unemployment and crime rates felicitous: provided we observe severe changes in unemployment rates, especially sharp increases as aftermath of the global financial crisis, are we also faced with similar comovements in crime? Understanding the nexus between labor markets and crime incidence can have immense public policy implications on (local) government budget decisions regarding the allocation of resources in order to minimize social and economic costs stemming from the incidence of crime. If the findings point to this direction, then we are readily provided with an effective policy tool to combat crime, i.e. adjusting labor market conditions as opposed to deterrence factors or penology.

For our undertaking we choose to concentrate on the social-shock absorbers in Germany as evidently the country's economy has demonstrated resilience during the whirl of economic crisis. Germany survived the crisis with a decline in employment that was much smaller than had been expected - coined as "Germany's jobs miracle". The decline itself affected mainly export-oriented manufacturing firms,² younger persons and males especially in Western Germany and lasted for the year 2009, that is the year following the global financial crisis (BfA, 2009). In essence, Germany's case allows us to exploit a single-year deterioration of the labor market conditions in order to explore effects on various crime-rate categories in a spatial, yet conceptually simple framework. Our contribution to the related literature can be summarized as follows: first, we intertwine theory and empirics by laying down a labor market model and testing its theoretical predictions with data at a more disaggregate level than that of the Federal States. Second, as the processes of unemployment and crime unfold not only with the passage of time but also in natural space, we deploy spatial notions in both theoretical and econometric models. Third, we manage to verify the importance of youth unemployment as a major determinant of property crime, namely theft by burglary of a dwelling. Fourth, and most importantly, for the first time we address not only plausible biases stemming from the simultaneity of unemployment in a crime equation, but also misspecification

²Indeed, 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" recession program of reduced working hours in Germany (OECD, 2010). A more recent approach can be found in Burda and Hunt (2011). Faia, Lechthaler, and Merkl (2013) confirm that unlike standard demand stimuli "Kurzarbeit" policies yield large fiscal multipliers, as they stimulate job creation and employment.

attributed to the presence of the spatially lagged dependent variable.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and lays down a motivation of our work. Section 3 is devoted to the model outline and main theoretical results. We conduct some data exploratory analysis in Section 4 and translate theory into a spatial autoregressive type model. In Section 5 we present empirical findings and calculate impacts incorporating spatial multipliers. Finally, Section 6 concludes, whereas Appendices collect all the proofs and supporting material.

2 Literature Review and Motivation

The work of [Becker \(1968\)](#), [Ehrlich \(1973\)](#) and refinements in [Block and Heineke \(1975\)](#) formulated a framework to model criminal activities from an economic theory perspective. The implications commenced a series of studies with the aim to uncover crime-deterrence factors and the causal relationship between economic decline - e.g. increasing income inequality or unemployment - and crime rates. In the decades to follow various data structures such as pure time series or longitudinal data sets and diverse statistical and econometric techniques have been deployed. [Chiricos \(1987\)](#) and later on [Levitt \(2001\)](#) cast doubts on the appropriateness of aggregate data, e.g. time series, as means to examine the link between unemployment and crime; national-level data ignore much of the variation realized at more disaggregate levels. [Rupp \(2008\)](#) provided a comprehensive review of the issue at hand and emphasized that results depend on the time horizon distinguishing between short-run or long-run effects as well as subgroups of unemployed considered according to skills and education, race and age. Overall, the relevant empirical literature remained inconclusive on the existence of a relationship between unemployment rates and criminal activity (see [Gould, Weinberg, and Mustard, 2002](#)). Indeed, for the case of Germany [Entorf and Spengler \(2000\)](#) verify the existence of an ambiguous effect with regards to unemployment but a positive effect of youth unemployment on crime rates. [Raphael and Winter-Ember \(2001\)](#) provided insight from an econometric point of view focusing on possible omitted variable bias and the direction of causation. Hence, since unemployment rates are suspected to be endogenous as offenders are stigmatized facing reduced probability of legal employment or as companies find areas with high crime rates unattractive for business (reverse causality), estimates based on studies failing to address the endogeneity/simultaneity problems will be plagued with bias.

[Edmark \(2005\)](#) uses Swedish county panel data and exploits significant increases in unemployment during the early nineties to identify effects on crime. Indeed, the author verifies a positive effect for certain property type categories (burglary, car and bike theft). [Öster and Agell \(2007\)](#) also focused on the case of Sweden and with a short panel on municipalities verify a positive effect of unemployment on specific property crime categories and drug possession. The effect remains robust only for burglary after controlling for unemployment in neighboring municipalities. Furthermore, instrumental variables estimation based on regional employment composition as well as interaction terms between the share of manufacturing employment with exchange rates uncovers coefficients larger than Ordinary Least Squares (OLS) counterparts. [Lin \(2008\)](#) in a similar fashion resorts to Two Stage Least Squares (2SLS) and instrumentation of unemployment rates with interaction terms of changes in the real exchange rate and oil prices with the percent employed and GDP in the manufacturing industry for U.S. panel data. The author also finds that the 2SLS estimates are larger than the respective OLS verifying the existence of bias for property crime. [Fougère, Kramarz,](#)

and Pouget (2009) instrument unemployment with predicted industrial structure on the regional level (département) and find a causal effect of youth unemployment on certain categories of property crime and drug offenses for France. Buonanno and Montolio (2008) proceed differently, i.e. they model lagged crime rates in a GMM procedure that unveils the effect youth unemployment has on property crime for panel data on Spanish provinces. From a spatial econometrics perspective, recently Hooghe, Vanhoutte, Hardyns, and Bircan (2011) demonstrate for Belgian municipalities through 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, although they do not instrument the latter.³

Turning to theory, Freeman, Grogger, and Sonstelie (1996) recognize the spatial concentration of crime and model the decision between work and steal. The authors demonstrate that the number of criminals in a neighborhood increases returns to crime initially and use this as an explanation as to why theft might flourish in one and not another - albeit similar in every aspect - neighborhood. In more recent advances, Burdett, Lagos, and Wright (2003) develop a search equilibrium framework which incorporates the interrelations between crime, unemployment, and inequality. Though space is not dealt with directly, the model has spatial implications. Multiple equilibria are relevant given that otherwise similar cities or neighborhoods can end up with very different crime rates. One of the channels for multiplicity is simply an encouragement of criminal activity if one lives in a neighborhood with high crime rates because the relative returns to legitimate activity are low.⁴ Moreover, when local labor market conditions are good the incentive for crime is reduced, and this makes it relatively easy to maintain good labor market conditions. Burdett, Lagos, and Wright (2004) extend the model and allow for crime, unemployment and inequality, at the same time incorporating on-the-job search. Their model also yields a multiplicity of equilibria with different unemployment and crime rates.

In light of the literature review, our first motivation stems from the observation that for the majority of relevant studies theoretical and empirical literatures remain separate. As recently proved, a further understanding of casual relationships between unemployment and crime across both time and space is indispensable for policy matters (e.g., timely reaction and prevention or reduction of adverse effects). Our contention is that theory and empirics should inform and reinforce each other, and see our paper as a building block in that direction. Our second motivation follows the line of Edmark (2005) and Öster and Agell (2007), meaning we exploit turbulent times - the most recent recession - responsible for variations in order to identify the unemployment-crime nexus. What induces a third motivation for our work is the fact that “geography matters”⁵ when it comes to understanding and explaining economic processes. Most of the aforementioned studies do not model

³Obviously, the literature review leans 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. Kelly (2000) or Fajnzylber, Lederman, and Loayza (2002), education and crime, e.g. Lochner and Moretti (2004) or Machin, Marie, and Vujić (2011, 2012), or immigration and crime, e.g. Bianchi, Buonanno, and Pinotti (2012), or criminal networks, e.g. Liu, Patacchini, Zenou, and Lee (2012) just to name a few.

⁴This example manifests in a spatial dimension but is by no means the only possible source for multiplicity. Other sources include wage setting that affects inclination to criminal activity, congestion in law enforcement, etc. Moreover, it can be that crime is more competitive in high crime neighborhoods and this discourages pursuing illegal actions. It nevertheless points to spatial patterns; the strength of a particular effect is an empirical question.

⁵Enrico Moretti, Keynote Speech, European Association for Labour Economists, Bonn, 2012.

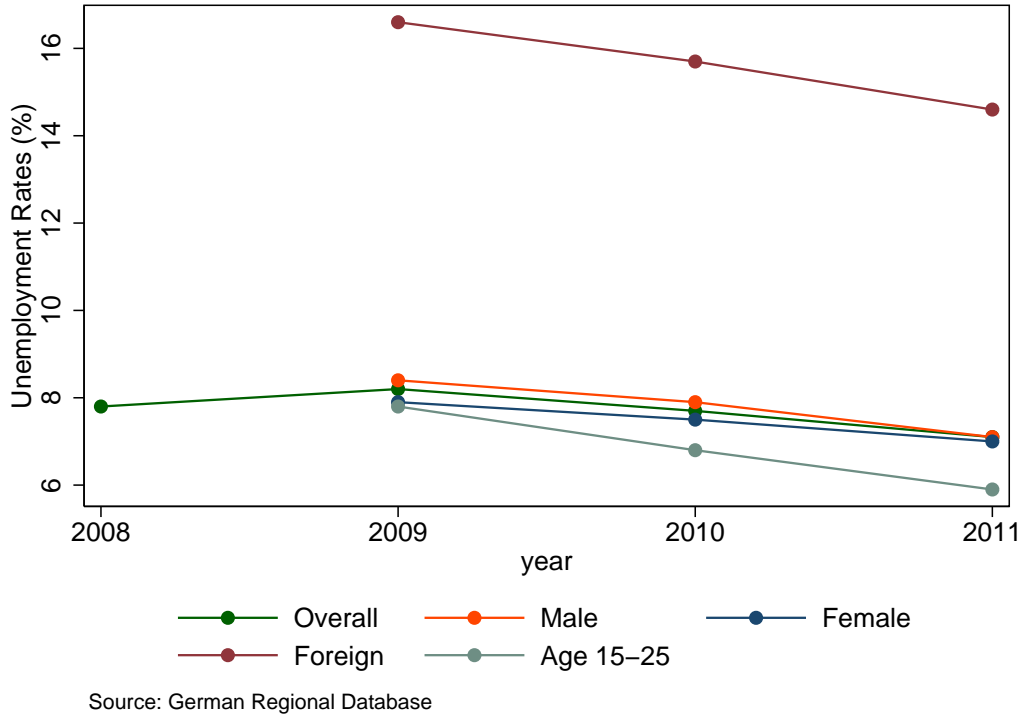


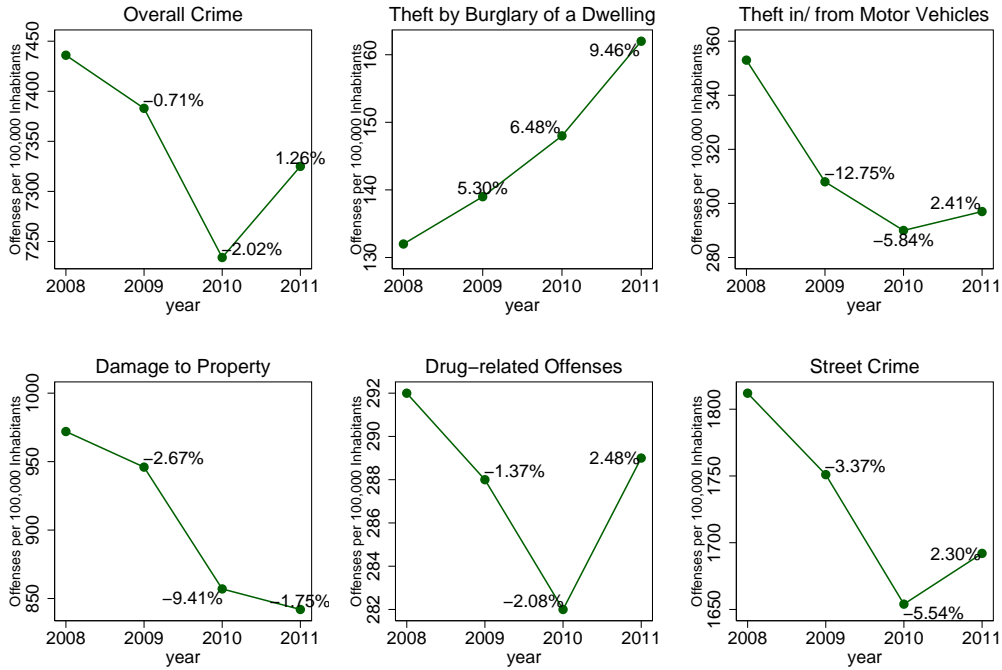
Figure 2.1: Unemployment Rates, 2008-2011, Germany.

the presence of spatial patterns prevalent in crime and unemployment rates, which are inherent in regional analyzes and in principle constitute an additional statistical impediment. [Anselin, Cohen, Cook, Gorr, and Tita \(2000\)](#) discuss the role of space for crime and misspecification as aftermath of ignoring spatial dependence. [Öster and Agell \(2007\)](#) is one exception, but restrict the specification to unemployment spillovers ignoring a possible spatial multiplier effect. [Hooghe, Vanhoutte, Hardyns, and Bircan \(2011\)](#) is another but do not provide evidence to substantiate a more causal interpretation of the results by instrumenting unemployment rates. In what follows we attempt to reconcile spatial with causal frameworks both in theory and empirics.⁶

With reference to our second motivation, 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](#)). In conjunction with [Figure 2.1](#) and yearly information, 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 pre-crisis 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 pre-crisis 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 [Figure 2.2](#) we present the temporal evolution for specific crime categories. These include

⁶Admittedly, [Bianchi, Buonanno, and Pinotti \(2012\)](#) tested for the presence of spatial dependence in Italian regions before choosing aspatial specifications.



Source: German Federal Criminal Police Office

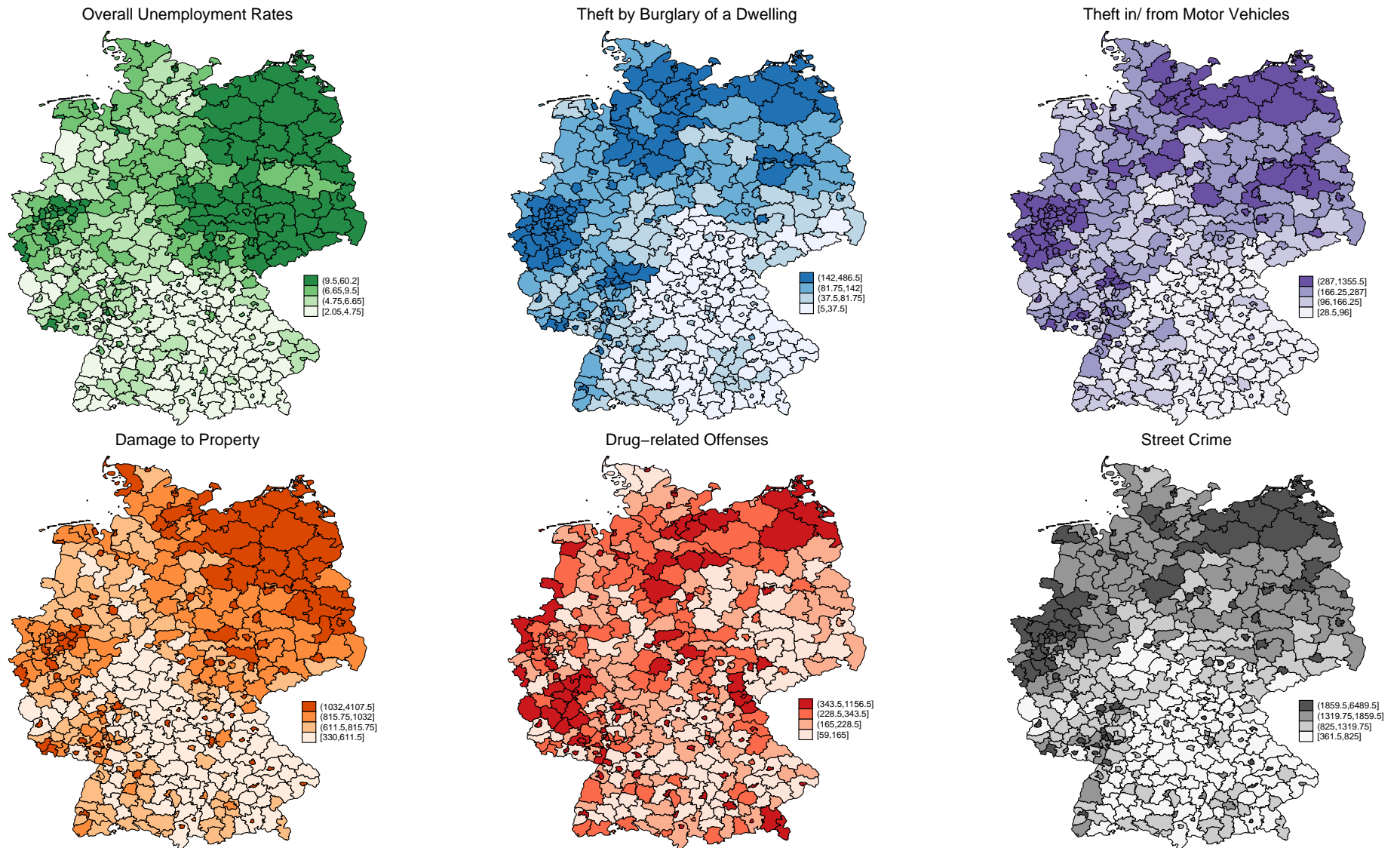
Figure 2.2: Crime Rates and Percentage Changes, 2008-2011, Germany.

violent crime such as damage to property, purely property-related crime such as theft by burglary of a dwelling or theft in/ from motor vehicles as well as categories that may embody both, e.g. street crime, and finally drug-related offenses.⁷ As obvious from Figure 2.2, damage to property, slightly declined in 2009 and in 2010 decreased even more. 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 6.47% percentage increase from 2009). Second, we observe that theft of property in/ from motor vehicles continues a diminishing path, but with a progressively slower pace after 2008 (from -16.94% percentage change to -12.75% in 2009 and -5.84% in 2010). Drug-related offenses and street crime rates follow the overall criminal offenses pattern, meaning a declining path with a smaller percentage change for 2009 (-1.37% and -3.37% respectively).

Clearly, 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 and discriminative 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 in this paper, can be characterized not only by their temporal evolution as shown in Figures 2.1 and 2.2, but also by their propagation through space

⁷The Appendix provides thorough definitions of the crime categories used throughout this paper. We dropped bodily injury due to the fact that the Federal Criminal Police Office reports different categories at the district level for years 2009 and 2010.



Sources: German Regional Database and German Federal Criminal Police Office

Figure 2.3: Spatial distribution of Unemployment Rates (%) and Crime Rates (Offenses per 100,000 Inhabitants), 2009-2010, Germany.

that manifests in differences in local variations. Data analysis confirms our preliminary inklings. In Figure 2.3 we map unemployment rates and rates for various criminal offenses respectively across Germany for years 2009-2010 on the district level, which corresponds to the European Union’s NUTS 3 classification. Germany is divided into 402 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. It is readily seen from any graph of Figure 2.3 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 (Brandenburg, Mecklenburg-Vorpommern, Saxony-Anhalt, Saxony and Thuringia) and the western urban districts in North Rhine-Westphalia, which is known for its industrialization and urban agglomeration. We note that geographical patterns among unemployment rates calculated overall or for specific subgroups of the population such as age 15 to 25, male, female or foreign unemployment, convey a similar picture; therefore, we omitted the maps. In what follows, we seek augmenting our analysis to include different unemployment rate categories in order to shed light on whether and to what extent overall, male, female, foreign and *especially* youth unemployment affected crime in Germany after the passage of the global financial crisis.

With reference to the criminal offenses of Figure 2.3 the emerging geographical patterns are quite distinct as we plot rates for the five available crime categories. 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 is more frequently occurring in districts belonging to north Rhine-Westphalia, Berlin and its surroundings or Schleswig-Holstein and the Hamburg area. Finally, theft of property in/ from motor vehicles and street crime are recorded predominantly 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. One possible interpretation lies in the fact that criminal activity is a predominant trait of large cities (Glaeser and Sacerdote, 1999), where illegal opportunities are affluent. Thus, we would expect urbanization in the form of urban versus rural districts to play a role in explaining crime in the dawn of crisis.⁸ In Section 4 we formally test for spatial autocorrelation for each year separately, i.e. 2009 and 2010.

Finally, it is worth mentioning that this work is motivated by the (relatively) recent availability of disaggregate data (Kreise) on crime in Germany released by the German Federal Criminal Police Office. We are quoting Entorf and Spengler (2002), who wrote a decade ago that “Evidence on crime in Europe is rare” (p.1). Fortunately, as the review above reveals studies pertaining to European countries are no longer seldom; specifically for Germany there is a bulk of notable exceptions, 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. Although individual data would seem more appropriate in order to elucidate the channel between crime and labor markets (see Durlauf, Navarro, and Rivers, 2010, on aggregate crime regressions),

⁸Unfortunately, this information is swept out by the within transformation as it doesn’t vary over time.

still the current paper is the first one to examine crime and unemployment at a more disaggregate level than the German Federal States, namely the 402 districts.

3 Conceptual Framework

We develop a parsimonious conceptual framework which underlies our empirical exercise. We build on [Burdett, Lagos, and Wright \(2003\)](#), [Boeri \(2011\)](#) and [Patacchini and Zenou \(2007\)](#). An equilibrium search model, though describes the dynamics, can be fruitfully applied for cross-sectional analysis. The constancy of endogenous variables in steady states enables performing local comparative statics exercises and drawing testable implications. Unlike earlier analyzes, we also include productivity shocks which are important in explaining empirical regularity of criminal engagement among young, low-educated and unemployed males (see, for example, [Chapman, Kapuscinski, Chilver, and Roussel, 2002](#)). Our framework also explicitly accounts for spatial effects, allows generating inherent endogeneity of crime and unemployment, and yields a number of empirically confirmed results. We find that youth unemployment plays a prominent role in explaining theft by burglary of a dwelling, i.e. property crime, and moreover, that neglecting endogeneity of unemployment understates its effect. Calculation of average direct impacts (ADI) reveals that the effect is larger and significant for the youth unemployment share. For the rest of the crime categories, results are inconclusive either regarding spatial dependencies or the effect of unemployment per se.

In the simplest framework where space is explicitly dealt with, 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 $i = 1, 2$ in spite of her residence. Firms provide vacancies in each of two locations $j = 1, 2$. Note that for any variable the first subscript will denote where an agent is living and the second one refers to where an action is undertaken. For example, u_{ij} refers to the number of unemployed workers residing in i and searching in j . We normalize total population to 1, so that the unemployment level in area i is equal to the unemployment rate in the same area.⁹ Moreover,

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

where E_{ij} denotes the number of employed workers residing in i and working in j , and n_{ji} stands for a number of enjailed criminals from 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, the precise conditions for belonging to either of the category to be determined below. Workers are free to search for work in both locations and commute to work if employment is found outside their domicile. Notice a difference between job seekers S_i and unemployed workers u_i , namely

$$S_i = u_{ii} + u_{ji} \text{ and } S_j = u_{jj} + u_{ij},$$

while

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

⁹Agent can end up in one region only - either i or j - though she can compare payoffs in both regions and instantaneously converge to the best option. The same normalization as ours was applied by [Patacchini and Zenou \(2007\)](#).

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 j is defined as a fraction of the total mass of workers: $v_j / (u_{1j} + E_{1j} + u_{2j} + E_{2j})$.

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

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

with $q'(\theta_i) < 0$, $q''(\theta_i) > 0$ and $\lim_{\theta_i \rightarrow 0} q(\theta_i) = \infty$, whilst the probability of an unemployed worker meeting a vacancy is $p(\theta_i) = m(v_i, S_i) / S_i = \theta_i m(v_i, S_i) / v_i = \theta_i q(1/\theta_i)$.

For production to occur, a worker must be matched with a job. All newly-formed matches (i.e., filled jobs) generate a periodic productivity φ where $\varphi \in (0, 1]$. This match-specific productivity is subject to shocks, e.g., innovations unknown at the time of match formation, occurring at a (Poisson) frequency λ . When a shock occurs, productivity is a random draw with a fixed, known cumulative distribution $F(\varphi)$. These shocks are *persistent*: productivity remains at this level until a new shock occurs. And when productivity falls below a threshold level, $\tilde{\varphi}$, endogenously determined in this model, it is no longer profitable to continue to produce in the existing match and 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 shock occurs. Insofar as $\tilde{\varphi}$, the reservation productivity threshold, is strictly smaller than one, a nondegenerate distribution of wages is obtained at the equilibrium. The labor market flows prevailing at the equilibrium are given by the matching of unemployed workers to vacancies (gross job creation) and by the dissolution of matches (gross job destruction) when their productivity falls below this threshold level. The evolution of unemployment is governed by

$$\Delta u_i = \lambda F(\tilde{\varphi})(1 - u_i - n_i) + \rho n_i - (\theta_i q(\theta_i) + \pi) u_i = 0, \quad (3.1)$$

where the constant population has been normalized to one, so that $(1 - u_i - n_i)$ denotes employment E_i , ρ is the release rate to unemployment of the enjoined criminals n . Moreover, unemployment is diminished by those who manage to meet a vacancy with probability $\theta_i q(\theta_i)$ and are caught committing a crime with probability π . As the above makes clear, gross flows in the labor market occurs also when unemployment is constant. Indeed, equating (3.1) to zero and solving for the steady state, constant unemployment level obtains

$$u_i = \frac{\lambda F(\tilde{\varphi}) + (\rho - \lambda F(\tilde{\varphi})) n_i}{\lambda F(\tilde{\varphi}) + \theta_i q(\theta_i) + \pi}. \quad (3.2)$$

Moreover, the two key (endogenous) variables determining the evolution of gross flows in the labor market are market tightness (affecting the job creation margin) and the threshold productivity level (affecting the job destruction margin). Equation (3.2) illustrates the first simple population-counting

relationship between unemployed and enjailed criminals n_i , to be endogenized.

Both employed and unemployed workers from region i commit a crime in region j with probabilities, respectively, $\phi_{ij}^W(\varphi)$ and ϕ_{ij}^U . Crime is understood as a property crime or, more generally, the one that leads to an immediate financial gain, embodied by a monetary value g . This specification allows adding the income effect on crime in a very parsimonious way. Finally, note that including a probability of being caught instantly and sent to jail, equal to π , will generate differential effects on employed and unemployed agents. The expected payoff from crime in region j for an unemployed (employed) worker from i is

$$\begin{aligned} K_{ij}^U &= g_j + \pi J_{ij} + (1 - \pi) U_{ij} \\ K_{ij}^W(\varphi) &= g_j + \pi J_{ij} + (1 - \pi) W_{ij}(\varphi), \end{aligned} \quad (3.3)$$

where J_{ij} stands for the value function of an agent from i and enjailed in j , similarly U_{ij} and $W_{ij}(\varphi)$ are value functions for unemployed agent and employed with match-specific productivity φ , respectively. The decision space for engaging in criminal activity is simply

$$\phi_{ij}^U = \begin{cases} 1 & \text{if } U_{ij} - J_{ij} < \frac{g_j}{\pi} \\ 0 & \text{if } U_{ij} - J_{ij} > \frac{g_j}{\pi} \end{cases} \quad \text{and} \quad \phi_{ij}^W(\varphi) = \begin{cases} 1 & \text{if } W_{ij}(\varphi) - J_{ij} < \frac{g_j}{\pi} \\ 0 & \text{if } W_{ij}(\varphi) - J_{ij} > \frac{g_j}{\pi} \end{cases}. \quad (3.4)$$

These conditions state that criminal activities are deterred once a difference in value functions exceed the expected gain from criminal activity, g_j/π . It is reasonable to assume that the value of enjailed J_{ij} never exceeds that of unemployed U_{ij} or employed W_{ij} . Given disjointness of two or more events happening simultaneously, we have

$$rU_{ij} = b_j + \phi_{ij}^U (K_{ij}^U - U_{ij}) + \theta_j q(\theta_j) (W_{ij}(\varphi) - U_{ij}), \quad (3.5)$$

where b_j is an unemployment benefit in area j and r is the rate of time preference. In words, the flow return to being unemployed rU_{ij} equals instantaneous net income plus the expected value of receiving either a crime or job opportunity, i.e. a transit in states from unemployed to either a crime or work. Note that the probability of finding a job depends on the region j 's labor market tightness. In a similar vein,

$$\begin{aligned} rW_{ij}(\varphi) &= w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\varphi)) dF(z) \\ &- \lambda F(\tilde{\varphi}) (W_{ij}(\varphi) - U_{ij}) + \phi_{ij}^W(\varphi) (K_{ij}^W(\varphi) - W_{ij}(\varphi)), \end{aligned} \quad (3.6)$$

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 crime opportunity. Finally, the enjailed is described by the following Bellman's equation,

$$rJ_{ij} = z_j + \rho (U_{ij} - J_{ij}), \quad (3.7)$$

where z is the consumption of the enjailed workers and ρ is the rate of release into unemployment. There exists a partitioning of wage rates which determines the equilibrium outcomes:

1. Employed worker: accept any outside offer above her current wage;
2. Unemployed worker: accept any wage $w_{ij}(\varphi) \geq R_{ij}$, where R_{ij} is the reservation wage defined by $W_{ij}(w_{ij}^{-1}(R_{ij})) = U_{ij}$.

The partitioning leads to a result which links criminal activities to earnings:

Lemma 3.1. *Workers are less likely to commit crimes when their wage incomes are higher; unemployed agents engage in criminal activities if and only if the workers employed at the reservation wage R do.*

Proof. The result trivially follows from the above environment (also see [Burdett, Lagos, and Wright, 2003](#)). Note that (3.3) implies $K_{ij}^W(\varphi) - W_{ij}(\varphi) = g_j + \pi(J_{ij} - W_{ij}(\varphi))$ which is decreasing in $w_{ij}(\varphi)$ as can be traced from (3.6)-(3.7): hence, the first statement. Further, $K_{ij}^U - U_{ij} = K_{ij}^W(w_{ij}^{-1}(R_{ij})) - W_{ij}(w_{ij}^{-1}(R_{ij})) = g_j + \pi(J_{ij} - W_{ij}(w_{ij}^{-1}(R_{ij}))) = g_j + \pi(J_{ij} - U_{ij})$ since by definition $W_{ij}(w_{ij}^{-1}(R_{ij})) = U_{ij}$. \square

This result immediately leads to the following corollary:

Corollary 3.2. *Given $\phi_{ij}^U = 0$, then $\phi_{ij}^W(\varphi) = 0$ for all wage incomes $w_{ij}(\varphi)$. In words, if unemployed in i has no incentives to commit a crime in j , then employed does not have such incentives either for any given wage.*

Given $\phi_{ij}^U = 1$, then $\phi_{ij}^W(\varphi) = 1$ for wages $w_{ij}(\varphi) < C$ and $\phi_{ij}^W(\varphi) = 0$ for wages $w_{ij}(\varphi) \geq C$ where C stands for the crime wage, constrained so that $C > R$, and defined as a solution to $K_{ij}^W(w_{ij}^{-1}(C)) = W_{ij}(w_{ij}^{-1}(C))$. In words, even if unemployed commits a crime, it is sufficient for employed to engage in criminal activities only if her wage is lower than the crime wage. Yet, if the wage she earns is larger than C , the expected losses from a crime are larger than the expected gains. This follows from the fact that equation (3.3) implies that the stolen amount equals the expected cost of a crime, $g_j = \pi(W_{ij}(w_{ij}^{-1}(C)) - J_{ij})$.

To finalize the description of the proposed framework, we need to establish the cutoffs in the wage space. First, we equate (3.5) to (3.6) to obtain

$$w_{ij}(\tilde{\varphi}) = b_j + \lambda\beta \left[\int_{\tilde{\varphi}}^{\varphi^c} \frac{(1-F(z))dz}{r+\lambda(1-F(z))+\lambda F(\tilde{\varphi})+\pi} + \int_{\varphi^c}^1 \frac{(1-F(z))dz}{r+\lambda(1-F(z))+\lambda F(\tilde{\varphi})} \right], \quad (3.8)$$

where $\varphi_{ij}^c = w_{ij}^{-1}(C)$ and β measures the relative bargaining strength of workers vis-a-vis employers (see Appendix).

We used the result from equation (3.3): by definition, the cutoff productivity is such that $W_{ij}(\tilde{\varphi}) = U_{ij}$. Thus, $K_{ij}^W(\tilde{\varphi}) = g_j + \pi J_{ij} + (1 - \pi)U_{ij} = K_{ij}^U$. In words, the threshold match productivity equates value from employment and unemployment and thus leads to the same payoffs from crime. Moreover, $\phi_{ij}^U = \phi_{ij}^W(\tilde{\varphi})$ since $W_{ij}(\tilde{\varphi}) = U_{ij}$ and decision rules coincide (see equation (3.4)). Notice that the reservation wage is productivity-dependent: the higher the productivity of a match, the higher the reservation wage.

To obtain the crime wage, we need to equate (3.3) to (3.6). If we employ the assumption that $\lambda F(\tilde{\varphi}) = \rho$,¹⁰ this leads to

$$w_{ij}(\varphi^c) = (\lambda F(\tilde{\varphi}) + r) \frac{g_j}{\pi} + z_j + \lambda\beta \int_{\varphi^c}^1 \frac{(1-F(z))dz}{r+\lambda(1-F(z))+\lambda F(\tilde{\varphi})}, \quad (3.9)$$

where by definition, $K_{ij}^W(\varphi^c) = W_{ij}(\varphi^c) = (g_j + \pi J_{ij})/\pi$ and equation (3.3) yields a difference in payoffs of a crime and unemployment, $g_j + \pi(J_{ij} - U_{ij}) = K_{ij}^U - U_{ij}$. Agents forgo crime when

¹⁰Though an assumption of equal probabilities of going to unemployment both from a job and from a jail is *ad hoc*, it helps eliciting the channels which interest us.

$w_{ij} = C$, and $\phi_{ij}^W(\varphi^c) = 0$. As before, productivity heterogeneity is reflected in the last term which requires higher crime wage for more productive matches.¹¹

Remark. As mentioned earlier, we assume, as in [Burdett, Lagos, and Wright \(2003\)](#), that unemployed generates no lower value than criminals, $U_{ij} \geq J_{ij}$, as otherwise unemployed would volunteer for jail. This leads to the conclusion that there is no crime in such an environment if monetary gain is absent: in that case, $\phi_{ij}^U = \phi_{ij}^W(\varphi) = 0$ as it is never worthwhile to engage in crime. Note that $K_{ij}^W(\varphi^c) = W_{ij}(\varphi^c) = J_{ij}$.

Notice that this assumption is compatible with previous analysis. The monetary gain g_j creates a wedge between 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 it is to satisfy these conditions and the higher crime rate is to be observed.

Since our empirical analysis concerns cross-sections, we will not cover transitional dynamics and consider steady states only. We will partition the entire population into four segments: employees E_{ji}^L with a wage $w_{ij}(\varphi) < C_{ij}$, employees E_{ji}^H with a wage $w_{ij}(\varphi) \geq C_{ij}$, unemployed u and enjailed criminals n .¹²

Following our previous analysis of decision partitioning and letting $\phi_{ij}^U = 1$, we obtain the steady-state values of the following measures:

$$\begin{aligned} u_i &= \frac{\rho\lambda F(\bar{\varphi}_i)(\theta_i q(\theta_i)(1-F(\varphi_{ij}^C)) + \lambda F(\bar{\varphi}) + \pi)}{\Omega_i}, \\ E_{ji}^L &= \frac{\rho\lambda F(\bar{\varphi}_i)\theta_i q(\theta_i)F(\varphi_{ij}^C)}{\Omega_i}, \\ E_{ji}^H &= \frac{\rho(1-F(\varphi_{ij}^C))\theta_i q(\theta_i)(\theta_i q(\theta_i) + \lambda F(\bar{\varphi}) + \pi)}{\Omega_i}, \\ n_i &= \frac{\lambda F(\bar{\varphi}_i)\pi(\theta_i q(\theta_i) + \lambda F(\bar{\varphi}) + \pi)}{\Omega_i}, \end{aligned} \quad (3.11)$$

where Ω_i consists of model's parameters (see [Appendix 6](#) for detailed expressions). The crime rate calculated over the population which has not committed a crime is given by

$$\begin{aligned} c_i &= \frac{E_{ji}^L + u_i}{1 - n_i} \\ &= \frac{\rho\lambda F(\bar{\varphi}_i)}{\theta_i q(\theta_i)(1-F(\varphi_{ij}^C)) + \lambda F(\bar{\varphi})}. \end{aligned} \quad (3.12)$$

These expressions elucidate the relationship between crime and unemployment and lead to a cross-sectional proposition which underlies our empirical inquiry:

¹¹We do not concentrate on bargaining or producer's side. Yet, it is shown in the [Appendix 6](#) that the match-specific wage obeys the Nash bargaining rule

$$w_j(\varphi) = \beta\varphi + \frac{(r + \rho)\beta c_j \theta_j + (1 - \beta)b_j + (1 - \beta)\left(g_j + \frac{\pi}{r + \rho} z_j\right)}{r + \rho + \pi}, \quad (3.10)$$

where $0 \leq \beta < 1$ measures the relative bargaining strength of workers vis-a-vis employers. This wage corresponds to the situation when unemployed commit a crime and employed do not ("honest equilibrium" with no crime for earners with $w_{ij} \geq C$). Equation (3.10) shows that wages are increasing in match specific productivity φ , match frictions c_j and market tightness θ_j at a rate which is increasing in the bargaining power of workers. Moreover, it also demonstrates a dependence on unemployment benefits b_j , financial gain from a crime, g_j , a probability of being caught and sent to a jail, π , the consumption of the enjailed workers z_j and ρ which is the rate of release into unemployment. The more powerful are workers, the more they appropriate of the match surplus. It is bargaining power and frictions that allow workers to obtain a markup over their reservation wage.

¹²Equivalently, 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 (3.10) and [Appendix 6](#) for derivations.

Proposition 3.3. *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 the following hold:*

1. *An increase in a frequency of match-specific shocks tends to increase the crime rate;*
2. *An increase in the cutoff productivity $\tilde{\varphi}_i$ increases the crime rate;*
3. *An increase in job seekers in the other region increases the crime rate if the elasticity of the instantaneous meeting probability for vacancies is larger than one in absolute value and there is no effect on cutoff productivities of matches and the crime wage;*
4. *The crime rate increases if the productivity of matches of the job seekers 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 if criminals are more sensitive to changes in match-specific productivity than wage-earners whose earnings are above a crime wage.*

Proof. See Appendix 6. □

We just note that part 1 refers to the increase in a frequency of match-specific shocks which can be interpreted as an increase in a volatility of economic environment. Hence, an increase in uncertainty because of, for instance, trade shock during a global crisis should lead to an increase in crime rate.¹³ Part 2 states the fact that an increase in a cutoff wage decreases a number of firms which afford paying such a wage, increases unemployment and this how it increases a number of criminals. Finally, an increase in job seekers in the other region increases the crime rate given the elasticity of the labor market tightness is larger than one in absolute value. The rationale for part 3 is such that the more there are the job seekers from the other region, the smaller is the labor market tightness, ceteris paribus. Then, for the crime rate to increase, we require a more than proportional drop in the instantaneous meeting probability for vacancies than there is an increase in new job seekers. Intuitively, part 4 tells that more productive job seekers, ceteris paribus, induce an increase in the reservation wage (productivity). This 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 other region) and higher wages are paid to foreign rather than home agent which reduces the outside option and increases crime domestically. More precisely, we can employ the following corollary:

Corollary 3.4. *The positive effect of threshold on crime productivity holds if and only if $\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i} > -\frac{r(\tilde{\varphi}_i)}{\lambda(\varphi_{ij}^C)}$ where $\lambda(\varphi_{ij}^C) \equiv f(\varphi_{ij}^C) / (1 - F(\varphi_{ij}^C))$ is the hazard function and $r(\tilde{\varphi}_i) \equiv f(\tilde{\varphi}_i) / F(\tilde{\varphi}_i)$ is the reverse hazard function. Using the wage expressions stemming from agent's choice and production side, and ruling out complex solutions, we can confirm that the effect is always non-negative.*

Proof. See discussion in Appendix 6. □

As is clear, spatial competition manifests through labor market tightness in a domestic market in our partial equilibrium setting. We do not model full feedback effects among counties, yet allow for changes in job seekers through, among others, influx of migrants to cause changes in threshold and

¹³Trade or income shock is analyzed cross-sectionally in our empirical part, i.e., the same shock affects districts in a different way. A dynamic aspect of criminal activities where business cycles affect crime differentially across time is analyzed by [Bushway, Cook, and Phillips \(2012\)](#).

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 depends on the elasticity of labor market tightness whereas productivity of incomers affect the equilibrium in home market through reservation and crime wages.

4 Econometric Model and Data

Having provided insight into the theoretical nexus of the propensity to engage in criminal activities and unemployment in a spatial framework, we now seek to operationalize the crime rate equation given in (3.12) and find empirical support of its implications as described in the previous section and the cross-sectional Proposition 3.3. Our empirical exercise is designed to fit the aftermath of the global financial crisis in Germany, which affected mainly *export-oriented manufacturing firms, younger persons and males especially in Western Germany* (BfA, 2009). First, we need to accommodate the theoretical notion that agents reside in one region but act in another, where the set of actions/ decisions consists of unemployed or low-wage employed agents committing a crime and employed agents working in a region other than their domicile.¹⁴ For this purpose we will employ an econometric model that incorporates cross-sectional dependencies. Our short time span, i.e. 2 years, excludes the possibility of testing for weak against strong cross-sectional dependence as in Pesaran (2012). Therefore, we assume weak dependence and proceed by translating our spatial theory into a spatial autoregressive type model. Moreover, since the steady states of the key variables, i.e. crime and unemployment rates, are generated by a common mechanism in equations (3.11) and (3.12), it is our contention that optimally one should model a spatial simultaneous equation system to jointly explain crime and unemployment rates in the fashion of Kelejian and Prucha (2004) and exploit foreseeable efficiency gains. Since parameters on paramount aspects of the unemployment process cannot be estimated due to data considerations (e.g. vacancy rates or unemployment benefits) at the district level (Kreise), we focus on estimating determinants of crime. The single equation econometric model should treat the unemployment rate and its spatial effect as endogenous; for the former we expect a positive effect on crime as seen from equation (3.12) and for the latter the effect on crime will depend on the elasticity of the labor market tightness as stated in part 3 of Proposition 3.3.

Second, regarding measurement for our key endogenous variables, we note that the crime rate was calculated over the population which has not committed a crime. Lack of data on the district-level regarding the number of (released) prisoners prohibits the usage of such definitions. In what follows we will utilize the German Federal Criminal Police Office’s calculation for offenses rates. In district i :

$$OR_i \equiv \frac{\text{number of offenses reported to the police}}{\text{number of inhabitants}} \times 100,000.$$

The German Federal Criminal Police Office uses the district population in the beginning of the year as a denominator to calculate the offenses rate OR_i , e.g. the number of offenses reported to the police for 2009 are divided by the number of inhabitants in 2008. We have re-calculated offenses rates with the population at the end of the year, as the latter is used by the German Regional

¹⁴More specifically, $c_i = c_{ii} + c_{ji}$ reveals that crime in region i stems from criminals who live in region i or j , and $u_i = u_{ii} + u_{ij}$ that the unemployed in region i live in region i but search work in region i or j .

Database. Obviously, standard measurement issues apply, since the number of known to the police cases may not coincide with the true number of committed crimes. To partially address this we work with the log of crime rates, $\ln(OR_i)$ (see [Bianchi, Buonanno, and Pinotti, 2012](#)). The extent of measurement error will also depend on the crime category, since, for instance, murder or breaking and entering are more likely to be reported to the police than theft of a mobile phone from a motor vehicle. Regarding unemployment, we will deploy two different definitions of unemployment for the young, i.e. unemployment rate calculated over the labor force and unemployment share calculated over the total subpopulation. This distinction has been attested empirically when examining the effect of youth unemployment, since rates and shares do not treat evenly a ceteris paribus increase in students (see [Öster and Agell, 2007](#), and [Fougère, Kramarz, and Pouget, 2009](#)). As far as sources are concerned, we extracted district offenses rates from the 2009-2010 yearly publications of the German Federal Criminal Police Office¹⁵ and unemployment rates from the German Regional Database.¹⁶ Herein, we focus our analysis on the 2009-2010 period, i.e. the years following the global financial crisis, because it can be perceived as the period that Germany experienced a productivity shock and the economic environment was more volatile. Proposition 3.3 predicts that the crime rate will increase either through part 1 or through an increase in unemployment as in part 2.

Next, we need to translate other parameters underlying the theoretical setup into an estimable relationship. The probability of catching a criminal (π) serves as the deterrence factor in an individual's decision to commit crime and constitutes on its own a subject of interest in criminometrics.¹⁷ Police expenditures, the number of policemen, the probability of arrest/ conviction/ imprisonment, the severity of punishment as well as the average sentence length are common options for the crime empiricist. In our case, we will proxy deterrence with clearance rates from the German Federal Criminal Police Office, defined as the percent of solved cases in the number of reported or known to the police cases. For the deterrence hypothesis to be verified we require clearance rates to impact crime rates negatively. 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 [Entorf and Spengler, 2000](#)). Lack of a natural instrument prohibits us from adopting a more causal approach in this perspective. One strategy towards circumventing simultaneity is the inclusion of (spatial) time lags.

Crime wage (C_{ij}) or expected gains from committing a crime (g_j) and wages ($w_{ij}(\cdot)$) represent illegal and legal income opportunities, respectively. As the former are unobserved and the latter are unavailable for our time span, we proxy (il)legal income opportunities with the log of per worker income in the region. Per capita measures have also been proposed in the relevant literature, but we find that the per worker proxy is more appropriate for measuring wages.¹⁸ Accordingly, we expect a positive effect on crime if this measure captures crime wage and a negative effect if it represents income from legal opportunities and especially employment. At this point it seems apposite to repeat that crime is perceived herein as the one that offers monetary returns. We therefore anticipate our

¹⁵http://www.bka.de/nm_233820/DE/Publikationen/PolizeilicheKriminalstatistik/AeltereAusgaben/PksJahrbuecher/pksJahrbuecher__node.html?__nnn=true

¹⁶<https://www.regionalstatistik.de>

¹⁷[Cornwell and Trumbull \(1994\)](#) use county level U.S. panel data and explore the role of various deterrence factors on crime rates. [Levitt \(1997\)](#) studies the causal impact of police on crime for 59 U.S. city panel data. More recently, see [Durlauf, Fu, and Navarro \(2012\)](#) for deterrence effects under model uncertainty.

¹⁸We note that adopting per capita or per worker measures does not affect main conclusions. We have also estimated specifications with deviations from the national mean as relative income indicator (see [Entorf and Spengler, 2000](#)). Results are available upon request.

model to explain pecuniary criminal motives alone. Nonetheless and for the sake of completion, we will provide empirical evidence on all available crime categories in order to test our assumption.

Average productivity in the district $\left(\int_{\bar{\varphi}}^1 z dF(z)\right)$ is one of the main channels that connects crime and unemployment. Productivity heterogeneity will be accommodated by the inclusion of key demographic variables, such as the proportion of young males at the age of 15-25 in the population. Including the proportion of males among the youth is driven by the empirical regularity that describes young males as more prone to crime than respective females. Furthermore, as discussed in Section 2, urbanization is a part of demographics that plays a well-documented role. Important information on whether the district is urban or rural is swept out by the within transformation; therefore, we adopt a time-varying measure, i.e. population density defined as population in the district per square kilometer.¹⁹

Equation (3.12) dictates that apart from the unemployed, it is the low-productivity/ wage partition $\left(E_{ji}^L\right)$ living in district j and working in district i who decide to commit crime, since the legal wage is smaller than the crime wage. Although E^L can be proxied by the proportion of unskilled labor in the district, we abstain from its inclusion, first, because we choose to place emphasis upon the unemployment of the labor markets, and second, because the steady states of the theoretical setting imply treating unskilled labor as endogenous.²⁰ Instead, in order to fit the profile of those who experienced the unemployment shock during the 2009 crisis according to the German Federal Employment Service, we model the proportion of graduates without secondary education qualification and with general higher education entrance qualification. The proportion of dropouts reflects the fraction of the young population that is low-skilled because of leaving school early on, while the proportion of those qualified to enter higher education reflects those keen to invest in human capital.

The theoretical setup requires us to accommodate interregional migration, whose presence affects endogenous variables through labor market tightness. In our model a foreigner is defined as an agent who acts in the home region but resides elsewhere. Therefore, we are not strictly interested in foreigners with non-German passports per se, but in regional migrants regardless of their country of origin. Employing the proportion of the net influx of migrants in the district (arrivals minus departures), which might also embody foreigners in the conventional sense, may be problematic since this measure might be affected by crime rates in the district. To avoid reverse causality issues we will deploy information on the proportion of foreigners. Our theory, and more specifically part 4 of Proposition 3.3, predicts that an influx of more productive employees will increase crime in the home region. Unfortunately, none of the two measures, namely interregional migration or proportion of foreigners, provides information on incomers' productivity. Nevertheless, the foreign proportion measure, first, comprises a more convincing fit to the influx of EU workers in Germany starting 2010, especially from EU countries faced with sovereign debt crisis, and, second, can be considered more impervious to changes in crime rates.²¹ Finally, we note that all of the aforementioned variables were obtained from the German Regional Database.

¹⁹Employment or labor force density is perhaps more in concordance with our attempt to connect crime and labor market outcomes. Inclusion of the various measures does not affect main conclusions. Results are available upon request.

²⁰Corman, Dave, and Reichman (2013) is an example that sheds light on the female employment - property crime channel.

²¹Results with the net influx of interregional migrants are available upon request. We note that the inclusion of one or the other measure does not affect main conclusions on the effect of youth unemployment on crime rates.

Since our theoretical design refers to cross-sectional analysis, we model dynamics over space but not time with a short panel for years 2009 and 2010 instead of a single cross-section in order to address possible omitted variable bias attributable to district specific unobserved factors.²² Another issue pertains to which spatial components to include. [Fingleton and Le Gallo \(2008\)](#), [Drukker, Prucha, and Raciborski \(2011\)](#) and [Drukker, Egger, and Prucha \(2013\)](#) discuss spatial autoregressive models with spatial autoregressive errors and additional endogenous variables, whereas [Liu and Lee \(2013\)](#) focus on a model without autoregressive disturbances and additional endogenous variables. We are inclined to advocate the Spatial Durbin model, first, because the spatial lag of the dependent variable can generate a multiplier effect, so that the econometric setup follows as the equilibrium solution of a reaction function that includes the decision variable of other agents in the determination of the decision variable of an agent (see [Manski, 2000](#), and [Brueckner, 2003](#)), and, second, the spatial lags of the explanatory variables ensure mitigation of biases for both the spatial-endogenous and own-exogenous parameters.

The static spatial Durbin model with additional endogenous variables can be written as:

$$Y_{nt} = \lambda W_n Y_{nt} + Z_{nt} \delta_1 + W_n Z_{nt} \delta_2 + X_{nt} \beta_1 + W_n X_{nt} \beta_2 + \alpha_n + \theta_t \iota_n + \varepsilon_{nt}, \quad t = 1, 2, \dots, T \quad (4.1)$$

where $Y_{nt} = (y_{1t}, y_{2t}, \dots, y_{nt})'$ is the $n \times 1$ vector of observations on the dependent variable, i.e. crime rates on $n = 402$ districts and $T = 2$, with λ denoting the spatial autoregressive coefficient and W_n the nonstochastic and constant-over-time $n \times n$ spatial weights matrix that generates spatial dependence in the cross-sectional dimension. Z_{nt} and $W_n Z_{nt}$ denote the $n \times p$ matrices of additional endogenous covariates and their spatial effect respectively, with the corresponding $p \times 1$ parameter vectors δ_1 and δ_2 , which in our case reduce to the $n \times 1$ vector of unemployment rates and its spatial effect with scalar coefficients. X_{nt} is the $n \times k$ matrix of observations on time-varying explanatory variables and their spatial effect $W_n X_{nt}$ with respective $k \times 1$ vector coefficients β_1 and β_2 . The $n \times 1$ vector of error terms, ε_{nt} , is typically assumed to be *i.i.d.* across i and t with mean zero and variance σ_ε^2 . Notice that we allow for fixed effects at the district 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, as usual). Due to the small time span, time fixed effects can be captured by the inclusion of time dummies whose parameters will be estimated along with λ , δ_1 , δ_2 , β_1 and β_2 .

The spatial autoregressive model in equation (4.1) is characterized by inherent endogeneity: the spatial lag of the crime rates, $W_n Y_{nt}$, by construction and unemployment rates, Z_{nt} , as well as their spatial lag, $W_n Z_{nt}$, by formulation of the theoretical setup.²³ Due to the additional endogenous variable we will proceed with method-of-moments estimation instead of maximum likelihood. To achieve identification, Two Stage Least Squares (2SLS) or Generalized Method of Moments (GMM) procedures require at least three valid instruments - the same as the number of endogenous variables. [Drukker, Egger, and Prucha \(2013\)](#) allow some of the vectors of X_{nt} to be spatial lags of the exogenous variables and use their higher order spatial lags along with other valid instruments for

²²Alternatively, one may use a single cross-section of data, i.e. focus on the year of the crisis 2009, and allow for fixed effects at the Federal State level. This approach possibly addresses unobserved factors regarding crime, since - for instance - important determinants of crime such as police expenditures are determined at the Federal State level, but not unemployment aspects.

²³One can trivially show that $E(W_n Y_{nt} \varepsilon_{nt}') = \sigma^2 W_n (I_n - \lambda W_n)^{-1} \neq 0$. Also, if $E(Z_{nt} \varepsilon_{nt}') \neq 0$, then one can show that $E(W_n Z_{nt} \varepsilon_{nt}') \neq 0$.

the additional endogenous variables as the set of excluded instruments. [Liu and Lee \(2013\)](#) further assume the presence of many valid instruments, the number of which grows with the sample size, and propose a bias-correction procedure for the 2SLS estimator. Our number of instruments does not increase with the sample size, but with the number of explanatory variables; for instance, k regressors translates into at least k excluded instruments, so that using higher order spatial lags as excluded instruments may induce bias to the 2SLS estimator, the severeness of which will depend on the order of the spatial lags - the first order being the neighbors, $W_n X_{nt}$, the second the neighbors of the neighbors, $W_n^2 X_{nt}$, and so on. We suspect that the higher is the order of the spatial lags, the less will their explanatory power and relevance in the first stages be, so that we might be confronted with a weak-instruments problem. Estimation with three endogenous variables can be quite demanding in terms of identification; therefore, initially we focus on a spatial lag model, meaning $\delta_2 = \beta_2 = 0$ in equation (4.1), which reduces the number of endogenous variables to two, i.e. $W_n Y_{nt}$ and Z_{nt} :

$$Y_{nt} = \lambda W_n Y_{nt} + Z_{nt} \delta_1 + X_{nt} \beta_1 + \alpha_n + \theta_t \iota_n + \varepsilon_{nt}, \quad t = 1, 2, \dots, T \quad (4.2)$$

If the spatial lags do not have a direct effect on Y_{nt} , then $W_n X_{nt}$ qualifies as a matrix of valid excluded instruments. Nevertheless, since the data generating process is unknown, we avoid using higher spatial orders of the exogenous variables as instruments and resort to additional excluded instruments stemming from the labor demand side to achieve identification (see below). Then, we can include $W_n Z_{nt}$ and $W_n X_{nt}$ as explanatory variables and compare results between the spatial lag and spatial Durbin models. We follow [Drukker, Egger, and Prucha \(2013\)](#) and estimate the model with a two-step GMM procedure allowing for arbitrary heteroscedasticity.²⁴ The within transformation matrix that will sweep out the district fixed effects is $J_T = I_T - \frac{1}{T} \iota_T \iota_T'$. Because the weights matrix, W_n , does not vary over time, the within-transformed model keeps its spatial autoregressive interpretation (see [Lee and Yu, 2010](#)). Multiplying equation (4.1) with J_T yields the estimable model:

$$\tilde{Y}_{nt} = \lambda W_n \tilde{Y}_{nt} + \tilde{Z}_{nt} \delta_1 + W_n \tilde{Z}_{nt} \delta_2 + \tilde{X}_{nt} \beta_1 + W_n \tilde{X}_{nt} \beta_2 + \tilde{\theta}_{nt} \iota_n + \tilde{\varepsilon}_{nt}, \quad t = 1, 2, \dots, T \quad (4.3)$$

where $\tilde{Y}_{nt} = Y_{nt} - \bar{Y}_{nT}$ for $t = 1, 2$ with $\bar{Y}_{nT} = \frac{1}{T} \sum_{t=1}^T Y_{nt}$ etc.

Before proceeding with statistical exploration of the variables we describe the excluded instruments. The idea comes initially from [Bartik \(1991\)](#) and [Blanchard and Katz \(1992\)](#) and was later on adapted by [Gould, Weinberg, and Mustard \(2002\)](#) as well as [Fougère, Kramarz, and Pouget \(2009\)](#).

“The instrument is obtained by constructing for each district i the growth of employment in group g that would have occurred given the sectoral group composition of employment in the district had each group grown at the national growth rate.”

Denote the change in group g 's share of employment between date 0 and t in district i as:

²⁴2SLS with clustered standard errors, where the district constitutes a cluster, is a commonly used alternative option with panel data in this setting. We have a preference for GMM due to its expected efficiency gains. Moreover, deployment of a spatial autoregressive type model already acknowledges that observations are not independent, but clustered at the neighborhood, and captures this dependence with the spatial weights matrix. Consequently, further clustering at the unobservable part seems redundant.

$$f_{git} - f_{gi0}.$$

We then replace the actual end of period f_{git} with its prediction using national measures and initial district level shares:

$$\hat{f}_{git} = f_{gi0} \frac{f_{gt}}{f_{g0}}$$

which implies that the change in group g 's share between time 0 and t is the difference between the prediction and the initial district level share:

$$\hat{f}_{git} - f_{gi0} = f_{gi0} \frac{f_{gt}}{f_{g0}} - f_{gi0}$$

or

$$\Delta \hat{f}_{git0} = f_{gi0} \left(\frac{f_{gt}}{f_{g0}} - 1 \right)$$

where $(f_{gt}/f_{g0} - 1)$ denotes the national growth in group g 's share of employment between time 0 and t . The definition per se of the constructed instruments guarantees their validity as each district i - 402 of them - is considered too small to affect national trends.²⁵

The German Regional Database provides information on the district level regarding employees subject to social security contributions according to age and scope of employment. We constructed instruments following the aforementioned procedure on the predicted change in the share of employment for agents below 20 years of age and between 20 and 25 years old as well as for agents with full-time or part-time employment contract. As shown below, these are relevant in explaining German labor markets during the global financial crisis, which affected young males and culminated quickly due to the part-time employment contracts ("Kurzarbeit" policies). In carrying out our empirical exercise we have also concluded that spatial lags of the constructed instruments - especially the first order - can serve as relevant instruments.

In Tables 4.1, 4.2 and 4.3 we explore some basic statistical properties of the variables utilized. Table 4.1 presents basic summary statistics. Among the five crime categories street crime has the highest mean rate for years 2009-2010, which can be safely attributed to its broad definition (see the Appendix), followed by damage to property, drug-related offenses and then, property crime, namely theft in/ from motor vehicles and by burglary of a dwelling. The latter has the minimum number of cases reported per 100,000 inhabitants - only 4 - for Hildburghausen (State of Thuringia) in year 2009. On the opposite direction, the highest housing burglaries rate was met in Aachen for 2009 in western Germany (State of North Rhine-Westphalia). Theft in/ from motor vehicles is happening more frequently than housing burglaries, with minimum reported cases per 100,000 inhabitants in Oberallgäu (Bavaria) and maximum in Bremen for 2009. For the rest of the categories, we find that damage to property was soaring in Brandenburg a.d.Havel (Brandenburg) in 2010, drug-related offenses in Frankfurt am Main (Hesse) during 2009, and street crime in Aachen - again - for 2009. Further districts that can be characterized as crime-free are the rural Nienburg (Weser) in Lower Saxony for 2009 (damage to property), the rural Rheingau-Taunus in Hesse (drugs) for 2010, and rural Bayreuth for 2010 in Bavaria (street crime). On average, drug-related crime cases

²⁵See Blanchard and Katz (1992) p.49 for an explanation on the validity and relevance of instruments built in the same spirit.

are most successfully solved, around 96%, whereas all other categories have much lower average clearance rates, from 17% for theft in/ from motor vehicles to about 27% for damage to property. Interestingly, we can see that for theft by burglary of a dwelling and theft in/ from motor vehicles the clearance rates are above 100%. The German Federal Criminal Police Office reports that this can be the case if unsolved offenses from previous years are transferred and solved during the current year.

Table 4.1: Summary Statistics

Variable	Mean	Std.Dev.	Min	Max
Theft By Burglary of a Dwelling Rate	106.345	94.548	4.046	680.601
Clearance Rate	23.659	13.440	0.000	113.300
Theft in/ from Motor Vehicles Rate	221.542	189.746	26.058	1543.084
Clearance Rate	16.967	11.375	0.000	115.200
Damage to Property Rate	854.518	358.413	221.596	4203.269
Clearance Rate	26.920	6.618	12.100	90.800
Drug-related Offenses Rate	278.019	173.527	49.048	1163.593
Clearance Rate	95.727	4.003	31.900	100
Street Crime Rate	1452.143	775.440	347.259	5100.495
Clearance Rate	22.127	5.736	9.900	63.900
Unemployment Rate	7.521	3.354	1.900	19.800
Age 15-25	7.078	3.233	1.800	17.600
Unemployment Share	3.824	1.886	1.060	10.046
Male	7.648	3.478	1.700	20.200
Female	7.391	3.272	2.200	19.300
Foreign	16.361	6.247	3.500	45.800
Per Worker Income	56110.770	9333.646	38805	110301
Proportion Graduates without Secondary Education Qualification	6.543	2.367	1.879	17.781
Proportion Graduates with General Higher Education Entrance Qualification	29.672	9.668	5.737	64.234
Proportion Males Age 15-25	5.810	0.526	4.353	7.469
Proportion Foreigners	7.240	4.476	0.745	25.770
Population Density	521.054	676.925	38.624	4505.954

Note: 804 observations for years 2009 and 2010.

Turning to unemployment rates, foreign unemployment is on average double than the rest of the categories. It is striking to see that in the district of Oder-Spree in the State of Brandenburg foreign unemployment was as high as 45.8% in 2009. Furthermore, we find Aachen (overall, youth, male, and female unemployment) to have the highest unemployment rates for 2009. The list of low-unemployment rates districts includes the rural district of Eichstätt in Bavaria for 2010 (overall, youth, male and female unemployment) and the rural district Dingolfing-Landau - again in Bavaria - for the same year (foreign unemployment). The general impression from summary statistics on our key variables, i.e. crime and unemployment rates, directs to an association of high property crime and unemployment in Aachen and low crime-unemployment in Bavaria.

The average income per worker is around 56,000 euros with large dispersions: about 39,000 in the urban district of Eisenach in Thuringia in 2009, while more than 110,000 euros in the rural district of Munich in Bavaria for 2010. In 2010 the rural district of Unterallgäu in Bavaria had a proportion

of graduates without secondary education qualification as low as 1.9%, whereas during 2009 the urban district of Potsdam in Brandenburg had a proportion of graduates with higher education entrance qualification as high as 64%. On average, around 6% of the population is males of age 15 to 25, while foreigners amount to about 7% of the population. At the extremes, the most vivid presence of foreigners can be found in the urban district of Offenbach in 2010 (State of Hesse), i.e. approximately 26%, and the most disperse in the rural district of Sömmerda for the same year (State of Thuringia). Finally, the most sparsely populated district was the rural Prignitz in Brandenburg for 2010 - only 39 inhabitants per square kilometer - and the most densely populated was the city of Munich for the same year.

The weight matrix, W_n , parametrizes spatial dependencies. For our empirical exercise we consider as neighbors districts 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 3.²⁶ Construction of the weights matrix requires a shapefile, which can be downloaded from the German Federal Office of Cartography and Geodesy.²⁷ Elements w_{ii} on the main diagonal of the 402×402 contiguity matrix W_n take value zero, as no district is a neighbor to itself. Element w_{ij} takes value one if districts i and j share common borders and zero otherwise. Although not dictated by the theoretical model, we apply row-normalization so that a spatial effect can be interpreted as the average effect of the neighbors just as in the linear-in-means model. Table 4.2 below provides summary statistics for the weights matrix.

Table 4.2: Weights Matrix Summary Statistics

<i>Links</i>		<i>Values</i>	
Total	2106	Min	0
Min	1	Min>0	0.083
Mean	5.239	Mean	0.002
Max	12	Max	1

In total there exist 2,106 links. At the extremes, only one district has 12 neighbors,²⁸ whereas 27 districts have only one neighbor,²⁹ all urban districts surrounded by a rural district. On average, a district has approximately 5 neighbors. The minimum positive value of the matrix is 0.083 corresponding to the single district with 12 links and the maximum 1 corresponding to the 27 districts with one neighboring district.

As mentioned above, [Anselin, Cohen, Cook, Gorr, and Tita \(2000\)](#) discuss the role of space for crime and misspecification as aftermath of ignoring spatial dependence. Along their line of argument, we test with Moran's I spatial correlation in the variables as well as in the residuals from

²⁶We have considered construction of the weight matrix based on commuting times as in [Patacchini and Zenou \(2007\)](#) or [Patacchini and Zenou \(2012\)](#). This entails calculation between the centroids of the polygons or - put more simply - the centers of the districts. Our choice adheres to the German reality, since it is rather uncommon to commute daily from districts not immediately adjacent. Even if this is the case, our specification is simply more primitive and a commuting time based weight matrix is expected to only improve our empirical findings.

²⁷http://www.bkg.bund.de/EN/Home/homepage__node.html__nnn=true

²⁸LK Ludwigshafen.

²⁹SK Flensburg, SK Wilhelmshaven, SK Trier, SK Pirmasens, SK Heilbronn, SK Baden-Baden, SK Rosenheim, LK Berchtesgadener Land, SK Landshut, SK Passau, SK Straubing, SK Amberg, SK Regensburg, SK Weiden i.d.OPf., SK Bamberg, SK Bayreuth, SK Coburg, SK Hof, SK Ansbach, SK Schweinfurt, SK Würzburg, SK Kaufbeuren, SK Kempten, SK Cottbus, SK Rostock-Hansestadt, SK Halle (Salle) and SK Weimar.

the regression of the aspatial model for each year, i.e. 2009 and 2010, using the row-normalized matrix W_n described in Table 4.2. Rejection of the null hypothesis of uncorrelation between the variable and its spatial lag renders misleading any results from aspatial specifications (see [Arbia, 2014](#), for details) and dictates addressing the cross-sectional dependence. In Table 4.3 we present Moran's I statistic for testing spatial correlation.

Table 4.3: Moran I's Tests for Spatial Correlation

Variable	year	2009			2010		
		I	Z-Score	P-value	I	Z-Score	P-value
Theft by Burglary of a Dwelling Rate		0.638	19.370	0.000	0.705	21.318	0.000
Clearance Rate		0.376	11.405	0.000	0.365	11.110	0.000
OLS Residuals		0.625	18.841	0.000	0.505	15.245	0.000
Theft in/ from Motor Vehicles Rate		0.406	12.413	0.000	0.434	13.209	0.000
Clearance Rate		0.050	1.568	0.058	0.185	5.726	0.000
OLS Residuals		0.443	13.378	0.000	0.343	10.378	0.000
Damage to Property Rate		0.264	8.135	0.000	0.238	7.45	0.000
Clearance Rate		0.313	9.683	0.000	0.425	12.846	0.000
OLS Residuals		0.262	7.959	0.000	0.218	6.653	0.000
Drug-related Offenses Rate		0.090	2.799	0.003	0.079	2.450	0.007
Clearance Rate		0.100	3.429	0.000	0.304	9.254	0.000
OLS Residuals		0.228	6.919	0.000	0.213	6.475	0.000
Street Crime Rate		0.406	12.291	0.000	0.411	12.451	0.000
Clearance Rate		0.318	9.705	0.000	0.393	11.873	0.000
OLS Residuals		0.539	16.272	0.000	0.432	13.063	0.000
Unemployment Rate		0.701	21.120	0.000	0.701	21.124	0.000
Age 15-25		0.700	21.102	0.000	0.708	21.336	0.000
Unemployment Share		0.760	22.906	0.000	0.765	23.079	0.000
Male		0.696	20.986	0.000	0.702	21.162	0.000
Female		0.693	20.904	0.000	0.687	20.702	0.000
Foreign		0.653	19.693	0.000	0.670	20.172	0.000
Per Worker Income		0.388	11.819	0.000	0.358	10.893	0.000
Proportion Graduates without Secondary Education Qualification		0.384	11.621	0.000	0.530	16.028	0.000
Proportion Graduates with General Higher Education Entrance Qualification		0.451	13.613	0.000	0.246	7.478	0.000
Proportion Males Age 15-25		0.507	15.319	0.000	0.621	18.726	0.000
Proportion Foreigners		0.534	16.130	0.000	0.536	16.203	0.000
Population Density		0.292	8.905	0.000	0.284	8.683	0.000

Note: OLS residuals from the regression of (log) crime rates on clearance rates, unemployment rate age 15-25, (log) income per worker, proportion of graduates without secondary education qualification, proportion of graduates with general higher education entrance qualification, proportion males age 15-25, proportion foreigners and population density - standard errors clustered at the district.

The Z-score determines whether we can reject the null hypothesis and when it's statistically significant, Moran I's values close to 1 signify spatial clustering, while values close to -1 dispersion.³⁰ Values close to 0 indicate random spatial patterns. Apart from clearance rates for theft in/from motor vehicles for year 2009, there is affluent statistical evidence of positive spatial correlation

³⁰An example of perfect negative spatial correlation is the chessboard.

in the variables as well as the OLS residuals of an aspatial model with youth unemployment.³¹ Theft by burglary of a dwelling displays the highest spatial clustering among the crime categories, while drug-related offenses the lowest. One of our key set of variables, unemployment rates, are also highly positively correlated in space, something that brings more confidence to spatial specifications in estimation.

5 Estimation Results

We start exploring the effect of unemployment on crime by means of a spatial lag model with both district and time fixed effects as in equation (4.2). Table 5.1 below collects for each crime category (theft by burglary of a dwelling, theft in/ from motor vehicles, damage to property, drug-related crime and street crime) estimates on the endogenous spatial crime effect (λ) as well as unemployment categories (unemployment rate, unemployment rate age 15 to 25, unemployment share 15 to 25, male/ female / foreign unemployment) treating the latter as exogenous. This specification enjoys simplicity as it assumes a single endogenous variable, i.e. neighbors' crime rates. We consecutively endogenize unemployment rates and display results under Table 5.2, where we compare and quantify possible biases from ignoring reverse causality; the latter specification entails two endogenous parameters, i.e. neighbors' crime rates and own unemployment rates. Finally, we turn to estimation of the full spatial model under equation (4.1) and gather raw estimates under Table (5.3). In this case, the spatial Durbin model considers three endogenous variables, namely neighbors' crime rates, own and neighbors' unemployment rates. Following LeSage and Pace (2009), we incorporate the time-invariant spatial multiplier matrix $(I_n - \lambda W_n)^{-1}$ in order to capture the propagation of spatial spillovers for the estimated model of Table 5.3 and present these impacts in Table 5.4. As mentioned above, results are obtained by the two-step GMM estimator. In all cases, we provide three test statistics that ensure the quality of the estimator: first, a test for underidentification, meaning testing whether the matrix of reduced-form coefficients on excluded instruments has full column rank. Second, a test for weak identification, which in a broad sense corresponds to obtaining a first-stage F-statistic on excluded instruments greater than 10 in the presence of a single endogenous variable. Third, a test for overidentifying restrictions to verify that excluded instruments are correctly excluded from the equation.³² For subsequent estimation and interpretation we consider models that pass all three tests.

At the first rows of Table 5.1 we display estimates for the endogenous spatial crime effect (λ) as well as the various unemployment categories for property crime.³³ The first stages can be found under Table 6.1 of the Appendix 6, where we deploy five excluded instruments based on predicted growths in employees, first, under age 20 and its spatial lag, second, age 20 to 25, third, under part-time contract and, fourth, under full-time contract. For theft by burglary of a dwelling we uncover a positive and statistically significant autoregressive parameter ranging from 0.765 in male unemployment to 0.804 in foreign unemployment rate. The share of unemployed age 15 to 25 and the foreign unemployment rate do not have a significant effect on the (log) of theft by burglary of a dwelling rate, but the rest of the unemployment categories are highly statistically significant with a magnitude around 5%. All six specifications are identified, since the test statistic for the

³¹The findings are similar for the other unemployment categories.

³²For details see Baum, Schaffer, and Stillman (2007).

³³Estimates on the rest of the variables are available upon request.

underidentification test is large and with a p-value of 0.000 we reject the null hypothesis that the equation is underidentified. Although the latter ensures that correlations between excluded instruments and the endogenous variable are nonzero, it does not ensure that these correlations are large enough, i.e. lack of a weak instruments problem. Therefore, we exploit the weak identification test, whose test statistic allows to reject 5% maximal IV relative bias, the rejection meaning that there is improvement in terms of incurred bias comparing with the OLS bias counterpart. Lastly, the failure to reject the null hypothesis of the overidentification test signifies that excluded instruments are valid and appropriately exogenous. In general, we note that a p-value of at least 0.05 is required to be comfortable with validity of excluded instruments. Turning to theft in/ from motor vehicles, we observe that the spatial autoregressive parameter is less significant and lower in magnitude - around 0.5 - than in theft by burglary of a dwelling, apart from foreign unemployment. Results on the share age 15 to 25 and foreign unemployment linger and for the rest of the unemployment categories are slightly higher. Although this crime category enjoys very strong first stages except for the foreign unemployment rate, and exogeneity of excluded instruments, we fail to reject the null of underidentification. In this case one or more of the correlations between the excluded instruments and the single endogenous variable is zero, which suggests possible re-examination of instruments for theft in/ from motor vehicles.

Damage to property estimation suffers from both weak instruments and rejection of excluded instruments exogeneity, although the equation is in all cases identified. Therefore, we consider performance of the spatial lag econometric model poor and do not comment further as it seems our excluded instruments merit from revision for damage to property. For drug-related offenses the equations are underidentified, but excluded instruments seem strong and exogenous. As expected from Moran's I test in Table 4.3, the spatial autoregressive parameter is positive but insignificant, which implies that drug-related offenses is a crime category whose specification can be safely formulated as aspatial with respect to neighboring crime, but spatial with reference to the rest of the exogenous variables. Finally, we see that our estimator performs poorly also for street crime, since the autoregressive parameter is in all cases greater than one. This result signals misspecification, because the parameter space for the autoregressive parameter can be taken as $(-1, 1)$ due to the row-normalization of the weights matrix. As a conclusion, although in Table 4.3 we have established the presence of significant spatial correlation for damage to property and street crime as well as for the set of explanatory variables, estimation of the spatial lag model as in equation (4.2) does not perform satisfactorily for the three non-property crime categories. One possible solution is considering specifications that exclude the endogenous crime spatial component and focus on spatial spillovers on the rest of the regressors as proposed for drug-related offenses.³⁴ Notwithstanding, the latter econometric model is not interesting per se as it does not explicitly capture simultaneity and spatial dependence in crime rates as dictated by the theoretical setup.

In Table 5.2 we turn to more causal approaches regarding property crime, that is we instrument unemployment rate categories and the unemployment share age 15 to 25. Again, details on the first stages for the spatial lag of (log) crime rates and unemployment can be found in Appendix 6. As we increase the number of endogenous variables from one to two, the weak identification test statistic decreases in comparison with Table 5.1. The least biased estimates - rejection of at least 10% maximal IV relative bias - belong to the share age 15 to 25, male and foreign unemployment for theft

³⁴Results are available upon request.

Table 5.1: Endogenous Crime Spatial Effects with Exogenous Unemployment

(log) Crime Rate	CSL	UR	CSL	UR 15-25	CSL	US 15-25	CSL	Male UR	CSL	Female UR	CSL	Foreign UR
Theft by Burglary of a Dwelling	0.773*** (0.207)	0.057*** (0.014)	0.767*** (0.206)	0.049*** (0.015)	0.779*** (0.207)	0.037 (0.028)	0.765*** (0.207)	0.051*** (0.016)	0.791*** (0.207)	0.059*** (0.015)	0.804*** (0.209)	0.001 (0.011)
<i>Test for:</i>												
Underidentification	82.632 [0.000]		82.262 [0.000]		81.749 [0.000]		82.487 [0.000]		82.814 [0.000]		82.577 [0.000]	
Weak Identification	22.848		22.772		22.679		22.874		22.758		22.988	
Overidentification	6.675 [0.1541]		5.718 [0.221]		6.931 [0.140]		6.574 [0.160]		7.024 [0.135]		7.750 [0.101]	
Theft in/ From Motor Vehicles	0.522** (0.226)	0.080*** (0.019)	0.486** (0.233)	0.051** (0.020)	0.462** (0.193)	0.038 (0.028)	0.592** (0.250)	0.084*** (0.019)	0.412** (0.205)	0.073*** (0.019)	0.837* (0.430)	0.023* (0.013)
<i>Test for:</i>												
Underidentification	6.725 [0.242]		6.813 [0.235]		7.288 [0.200]		6.513 [0.259]		7.030 [0.218]		6.226 [0.285]	
Weak Identification	34.161		33.642		34.005		31.760		37.499		14.748	
Overidentification	3.324 [0.505]		4.490 [0.344]		4.548 [0.337]		3.499 [0.478]		3.188 [0.527]		3.409 [0.492]	
Damage to Property	0.956** (0.401)	0.046*** (0.014)	0.917** (0.396)	0.033*** (0.013)	0.807** (0.399)	0.022 (0.014)	0.924** (0.396)	0.044*** (0.013)	0.972** (0.406)	0.045*** (0.015)	0.964** (0.412)	0.011* (0.006)
<i>Test for:</i>												
Underidentification	34.026 [0.000]		33.740 [0.000]		35.337 [0.000]		33.769 [0.000]		34.351 [0.000]		30.554 [0.000]	
Weak Identification	5.764		5.800		6.075		5.838		5.720		5.654	
Overidentification	10.391 [0.034]		11.198 [0.024]		10.153 [0.038]		11.012 [0.026]		9.579 [0.048]		9.967 [0.0410]	
Drug-related Offenses	0.342 (0.692)	0.001 (0.009)	0.203 (0.667)	-0.005 (0.009)	0.064 (0.671)	-0.033 (0.022)	0.333 (0.687)	0.008 (0.008)	0.303 (0.684)	-0.009 (0.013)	0.225 (0.658)	0.003 (0.004)
<i>Test for:</i>												
Underidentification	6.392 [0.270]		6.324 [0.276]		5.912 [0.315]		6.447 [0.265]		6.312 [0.277]		6.499 [0.261]	
Weak Identification	26.366		26.518		25.415		25.828		27.298		22.074	
Overidentification	7.164 [0.127]		7.582 [0.108]		7.389 [0.117]		6.789 [0.147]		7.506 [0.111]		7.156 [0.128]	
Street Crime	-	0.061*** (0.015)	-	0.039*** (0.015)	-	0.014 (0.013)	-	0.056*** (0.015)	-	0.061*** (0.018)	-	0.015** (0.006)
<i>Test for:</i>												
Underidentification	80.275 [0.000]		82.493 [0.000]		83.612 [0.000]		80.372 [0.000]		80.741 [0.000]		82.543 [0.000]	
Weak Identification	43.495		43.751		45.400		42.056		45.588		33.138	
Overidentification	8.175 [0.085]		6.981 [0.137]		3.321 [0.506]		10.130 [0.038]		6.272 [0.180]		6.642 [0.156]	

Note: 804 observations for years 2009 and 2010. CSL denotes the crime spatial lag, UR the unemployment rate, US the unemployment share and “-” a value greater than 1. Results with district fixed effects and time fixed effects further including (time-lagged) clearance rates, (log) income per worker, proportion of graduates without secondary education qualification, proportion of graduates with general higher education entrance qualification, proportion males age 15-25, proportion foreigners and population density. Excluded instruments are the predicted growth in employees under age 20 and its spatial lag, predicted growth in employees age 20 to 25, predicted growth in part/ full-time employees. Standard errors robust to heteroscedasticity in parentheses and p-values in brackets. *, **, *** denote significance at 10%, 5% and 1% respectively. Critical values for weak identification test: 18.37 for 5% maximal IV relative bias, 10.83 for 10% maximal IV relative bias.

by burglary of a dwelling and the share age 15 to 25 for theft in/ from motor vehicles. In all cases except for foreign unemployment in theft by burglary of a dwelling we appropriately cannot reject the null of excluded instruments' validity. Theft in/ from motor vehicles continues to suffer from underidentification and none of the autoregressive parameter - unemployment estimates is statistically significant. Empirical findings for theft by burglary of a dwelling are more convincing. The test of underidentification fails to reject the null only for female and foreign unemployment rates. For the rest of the categories the autoregressive parameter estimates slightly decrease in comparison to the respective estimates from Table 5.1, whereas the unemployment magnitude increases substantially and is significant for the rate age 15 to 25. These estimates may not represent the true impact of unemployment on property crime for two reasons: first, because they do not take into account the spatial multiplier effect, $(I_n - \lambda W_n)^{-1}$, and second, they neglect possible spatial effects for variables other than the dependent, the magnitude and direction of which is not necessarily the same as the own effects. Regarding the former, since the crime spatial effect is positive we expect the impact of unemployment to be higher than the estimate of Table 5.2. We explore the calculation of the exact expressions below.

In Table 5.3 we present estimation results corresponding to model under equation (4.1) for theft by burglary of a dwelling. We show estimates on parameters for the full set of explanatory variables to shed light on the difference in effects coming from the observation i itself (own effect) and from other observations $j \neq i$ on i (neighbors' or spatial effect). Starting from the tests, we cannot reject the null of overidentification for all unemployment categories verifying that our excluded instruments are exogenous in the sense that they are uncorrelated with the residuals. Next we see that the only specifications identified are the unemployment rate and share age 15 to 25 with p-values 0.020 and 0.000 respectively. For the same categories we detect no weak instruments problem with less bias for the share of youth unemployment. For these two categories the autoregressive parameter is statistically significant, with magnitude just below 0.8 and higher than the specification without exogenous spatial effects of Table 5.2. Moreover, not only is the effect of own youth unemployment rate and share positive and more prominent than in Table 5.2, but also we verify the existence of a negative and highly significant spatial unemployment effect, meaning an effect stemming from neighboring districts and affecting theft by burglary of a dwelling in the opposite direction than unemployment in the district itself. This is in line with our main theoretical model, which predicted that the effect on crime will depend on the elasticity of the labor market tightness as stated formally in part 3 of Proposition 3.3.

Table 5.2: Endogenous Crime Spatial Effects with Endogenous Unemployment

(log) Crime Rate	CSL	UR	CSL	UR 15-25	CSL	US 15-25	CSL	Male UR	CSL	Female UR	CSL	Foreign UR
Theft by Burglary of a Dwelling	0.705*** (0.218)	0.244 (0.154)	0.694*** (0.215)	0.189** (0.093)	0.692*** (0.213)	0.184* (0.112)	0.687*** (0.220)	0.173 (0.114)	0.786*** (0.230)	0.455 (0.287)	0.848*** (0.219)	-0.023 (0.043)
<i>Test for:</i>												
Underidentification	10.017 [0.040]		22.461 [0.000]		33.383 [0.000]		14.213 [0.007]		3.516 [0.475]		6.357 [0.174]	
Weak Identification	6.607		6.749		8.908		13.070		0.683		19.866	
Overidentification	4.465 [0.215]		2.491 [0.477]		4.614 [0.202]		4.852 [0.183]		3.773 [0.287]		8.606 [0.035]	
Theft in/ From Motor Vehicles	0.508* (0.277)	0.067 (0.150)	0.325 (0.280)	-0.054 (0.079)	0.266 (0.350)	-0.101 (0.097)	0.510 (0.324)	0.040 (0.119)	0.390* (0.221)	0.142 (0.202)	0.658 (1.116)	0.015 (0.060)
<i>Test for:</i>												
Underidentification	6.287 [0.170]		6.495 [0.165]		6.086 [0.193]		6.247 [0.181]		3.674 [0.452]		2.331 [0.675]	
Weak Identification	2.259		8.338		16.183		4.370		0.714		0.468	
Overidentification	3.363 [0.339]		3.540 [0.316]		3.006 [0.391]		3.512 [0.319]		2.851 [0.415]		2.995 [0.392]	

Note: 804 observations for years 2009 and 2010. CSL denotes the crime spatial lag, UR the unemployment rate and US the unemployment share. Results with district fixed effects and time fixed effects further including (time-lagged) clearance rates, (log) income per worker, proportion of graduates without secondary education qualification, proportion of graduates with general higher education entrance qualification, proportion males age 15-25, proportion foreigners and population density. Excluded instruments are the predicted growth in employees under age 20 and its spatial lag, predicted growth in employees age 20 to 25, predicted growth in part/ full-time employees. Standard errors robust to heteroscedasticity in parentheses and p-values in brackets. *, **, *** denote significance at 10%, 5% and 1% respectively. Critical values for weak identification test: 13.97 for 5% maximal IV relative bias, 8.78 for 10% maximal IV relative bias.

Table 5.3: Theft by Burglary of a Dwelling: Endogenous and Exogenous Spatial Effects

	UR	UR 15-25	US 15-25	Male UR	Female UR	Foreign UR
Own Unemployment	0.151 (0.177)	0.286*** (0.098)	0.525*** (0.147)	0.047 (0.122)	0.579 (0.370)	0.254 (0.449)
Spatial Unemployment	-1.335*** (0.270)	-0.472*** (0.131)	-0.785*** (0.160)	-1.379*** (0.342)	-0.871*** (0.193)	-1.654 (2.106)
Crime Spatial Lag	0.800** (0.335)	0.765** (0.300)	0.785*** (0.302)	-	0.835** (0.351)	-
(lag) Clearance Rate	-0.003** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003* (0.001)	-0.003** (0.001)	0.001 (0.007)
Per Worker Income	0.167 (0.327)	0.000 (0.262)	0.042 (0.267)	0.421 (0.334)	-0.449 (0.480)	-0.823 (1.355)
Proportion Graduates without SEQ	0.009 (0.015)	0.020* (0.011)	0.013 (0.011)	0.001 (0.013)	0.023 (0.017)	0.064 (0.091)
Proportion Graduates with GHEEQ	-0.009* (0.005)	-0.006 (0.005)	-0.008 (0.005)	-0.012** (0.005)	-0.008 (0.005)	0.001 (0.032)
Proportion Males Age 15-25	0.076 (0.208)	-0.312* (0.178)	-0.463** (0.190)	0.171 (0.180)	-0.596 (0.523)	-0.439 (0.884)
Proportion Foreigners	-0.244** (0.114)	-0.098 (0.093)	-0.155* (0.094)	-0.235** (0.103)	-0.198 (0.130)	-0.776 (0.805)
Population Density	-0.002*** (0.001)	-0.001** (0.001)	-0.001** (0.001)	-0.002*** (0.001)	-0.002** (0.001)	-0.002 (0.002)
<i>Spatial Effects</i>						
(lag) Clearance Rate	0.008*** (0.003)	0.004 (0.003)	0.004 (0.003)	0.010*** (0.003)	0.004 (0.003)	0.020 (0.022)
Per Worker Income	1.416** (0.672)	-0.447 (0.568)	-0.363 (0.537)	1.393** (0.686)	0.531 (0.814)	7.769 (10.030)
Proportion Graduates without SEQ	-0.098*** (0.021)	-0.066*** (0.021)	-0.061*** (0.018)	-0.097*** (0.024)	-0.067*** (0.024)	-0.056 (0.138)
Proportion Graduates with GHEEQ	0.010 (0.008)	0.013* (0.007)	0.015** (0.007)	0.013 (0.008)	0.011 (0.008)	-0.089 (0.142)
Proportion Males Age 15-25	2.035*** (0.578)	0.362 (0.295)	0.367 (0.271)	1.922*** (0.613)	0.974 (0.735)	7.177 (8.605)
Proportion Foreigners	0.498* (0.273)	0.554** (0.255)	0.540** (0.248)	0.522** (0.256)	0.654* (0.351)	-1.437 (2.692)
Population Density	0.006*** (0.002)	0.003 (0.002)	0.004** (0.002)	0.003 (0.002)	0.004 (0.004)	0.007 (0.011)
<i>Test for:</i>						
Underidentification	2.300 [0.512]	9.878 [0.020]	19.929 [0.000]	2.463 [0.482]	3.557 [0.313]	0.456 [0.928]
Weak Identification	6.264	8.392	12.239	4.475	1.334	0.089
Overidentification	2.938 [0.230]	1.442 [0.486]	0.761 [0.684]	3.589 [0.166]	1.236 [0.539]	0.309 [0.857]

Note: 804 observations for years 2009 and 2010. UR denotes the unemployment rate, US the unemployment share, “-” a value greater than 1, SEQ secondary education qualification, and GHEEQ general higher education qualification. Theft by burglary of a dwelling is in logs. Results with district fixed effects and time fixed effects further including (time-lagged) clearance rates, (log) income per worker, proportion of graduates without secondary education qualification, proportion of graduates with general higher education entrance qualification, proportion males age 15 to 25, proportion foreigners and population density. Excluded instruments are the predicted growth in employees under age 20 and its spatial lag, predicted growth in employees age 20 to 25, predicted growth in part/ full-time employees. Standard errors robust to heteroscedasticity in parentheses and p-values in brackets. *, **, *** denote significance at 10%, 5% and 1% respectively. Critical values for weak identification test: 9.53 for 5% maximal IV relative bias, 6.61 for 10% maximal IV relative bias.

With reference to other own effects, we note that the lag of the clearance rate affects negatively and in a significant manner both the rate and share of youth unemployment, but the extent of the effect is negligible especially with comparison to the unemployment estimate. An increase of per worker income in the home region does not seem to affect crime rates, since the magnitude is (very close to) zero and lacks statistical significance. The same holds for the next two variables, i.e. the proportion of graduates without secondary education qualification and with general higher education entrance qualification. Nevertheless, the first enters with a positive sign and the second with a negative, roughly meaning that had these effects been of larger magnitude and of statistical significance, an increase of unskilled labor in the home region would be associated with an increase in crime rates while an increase in the prospective high-skilled youth population with a decrease in housing burglary rates. Interestingly, the proportion of young males in the home district has a negative sign and is significant for the share of youth unemployment. Even more interestingly, we find that the proportion of foreigners in the home population cannot be associated with crime rates. Last, although population density in the home region is significant at 5%, the estimated coefficient is very close to zero.

Turning to the spatial effects of Table 5.3, we see that for the youth unemployment rate the proportion of graduates without secondary education qualification as well as the proportion of foreigners in districts other than the domicile have a significant effect on theft by burglary of a dwelling, while this extends to the proportion of graduates with general higher education entrance qualification and population density for the share of unemployment among the young. Combining the latter empirical findings with the noticeable change in both autoregressive and unemployment estimated parameters of Table 5.3 as compared to Table 5.2, reveals the virtue of employing equation (4.1) instead of neglecting spatial effects other than the crime rate as in (4.2). Further advantages of the full spatial specification become clear as we translate the estimated unemployment coefficients for the youth rate and share into marginal effects. The impact from changing unemployment in the home district embodies not only the own effect but also any possible indirect feedbacks from neighboring districts through the spatial multiplier matrix $(I_n - \lambda W_n)^{-1}$. Since own and neighboring effects move to opposite directions, we expect the impact from a change in unemployment in district i on (log) theft by burglary of a dwelling in district i - coined as an average direct impact (ADI) - to be smaller than the estimated coefficient, i.e. 0.286 for the rate and 0.525 for the share. Furthermore, we anticipate the impact from a change in unemployment in district j on (log) theft by burglary of a dwelling in district i - coined as the average indirect impact (AII) - to have a negative sign, just as the estimated coefficients, i.e. -0.472 and -0.785 for the rate and share respectively. The overall impact from a change in unemployment stemming either from the domicile or foreign districts - the average total impact (ATI) will crucially depend on the magnitudes of the ADI and AII, as those affect crime rates in opposite directions and will tend to cancel each other out.

Indeed, as obvious from Table 5.4, our initial expectations with respect to unemployment are confirmed. First, the ADI of the spatial lag model in equation (4.2) is slightly higher than the respective estimates for the rate and share, namely 0.189 and 0.184 respectively as seen from Table 5.2. This increase is attributable to the feedback loop induced by the presence of a positive spatial autoregressive parameter (0.694 and 0.692 for the rate and share respectively). Although the ADI is almost the same between the rate and share of youth unemployment, it is statistically significant only for the rate. The AII and ATI are positive, i.e. bear the same sign as the ADI, but are not

statistically significance - not even at 10%. Hence, we conclude that the spatial autoregressive model treating unemployment as endogenous and excluding spatial effects from the rest of the explanatory variables provides evidence that an increase in youth unemployment rates at the home district results in an increase in theft by burglary of a dwelling. Second, as we turn to the more complete specification of the spatial Durbin model under equation (4.1), we verify that the inclusion of spatial effects other than crime rates reduces the impact from an increase in unemployment in the home district, since the ADI for both rates and shares is smaller than the estimate of Table 5.3 (compare 0.219 with 0.286 and 0.420 with 0.525). Again, none of the AII and ATI are significant, so that we cannot associate changes in neighboring districts' unemployment rates/ shares with changes in theft by burglary of a dwelling in the home district. Notwithstanding, the spatial autoregressive model treating unemployment and its spatial lag as endogenous while including spatial effects for the rest of the variables, is capable of predicting a positive and highly significant - both economically and statistically - effect of the youth unemployment share on housing burglaries for the crisis period in Germany.

Table 5.4: Theft by Burglary of a Dwelling: Impacts for Unemployment Rate and Share Age 15-25

	Spatial Lag of Table 5.2			Spatial Durbin of Table 5.3		
	ADI	AII	ATI	ADI	AII	ATI
Unemployment Rate Age 15 to 25	0.217** (0.105)	0.401 (0.419)	0.618 (0.048)	0.219* (0.123)	-1.009 (1.157)	-0.790 (1.150)
Unemployment Share Age 15 to 25	0.211* (0.123)	0.387 (0.393)	0.598 (0.467)	0.420** (0.180)	-1.628 (1.890)	-1.208 (1.881)

Note: Standard errors in parentheses. * denotes significance at 10% and ** at 5%.

These results are in accordance with findings in other countries, e.g. France (see Fougère, Kra-marz, and Pouget, 2009), where, first, the distinction between rate and share of youth unemployment points to different directions regarding the causal impact on crime, and second, where the effect pertains to youth as opposed to overall unemployment; as mentioned above, the aftermath of the global financial crisis in Germany has reportedly affected mainly younger persons.³⁵ Moreover, our empirical exercise not only fits the main predictions of the conceptual framework unfolded in Section 3 regarding property as opposed to violent crime, but also the empirical regularity that housing burglaries increase in time of recessions along with unemployment, whereas motor vehicle theft is counter-cyclical. Here, let us repeat the distinction on motor vehicle theft and theft from motor vehicles, the latter being the category we explore with regional data. The fact that the ADI of youth unemployment share is positive and significant has interesting policy implications at the district level, since it reveals that such interplays among districts can be exploited when designing unemployment-related policy, for instance deciding on unemployment benefits (in connection to our theory, unemployment benefits increase threshold productivity which, in turn, positively affects crime rate, see decision choices (3.4) and crime wage (3.9)).

The region approach allows emphasizing a need for national or federal level decisions. This is because labor movements affect not only labor market but also criminal activities. This is particularly crucial when the composition of labor force starts changing - as is the case with European labor markets whose youth find very hard time in securing a job while at the same time low turnover for

³⁵We have calculated impacts for West and East Germany separately, but found no important differences.

permanent positions is occupied by older generation (see [Cahuc, Carcillo, Rinne, and Zimmermann, 2013](#), for a comparison between France and Germany). This two-tier (or dual) market creates externalities on crime, a point not emphasized by theorists or practitioners. As illustrated, youth unemployment is crucial, and spatial dimension matters significantly, therefore, national decisions are necessary.

6 Conclusions

The case of Germany in studying spatial aspects of the labor markets such as the nexus between unemployment and crime rates is undoubtedly interesting, because evidently the country's economy has survived the 2008 financial crisis. In tackling this case, we allow for changes in job seekers through, among others, influx of migrants to cause changes in threshold and crime wages. These, in turn, shape steady states of crime and unemployment. This emphasizes spatial competition: adjustments in the domestic labor market depends on the elasticity of labor market tightness whereas productivity of incomers affects the equilibrium in home market through reservation and crime wages. Moreover, our introduction of match productivities allows shedding some light on witnessing phenomena of riots and looting with protagonists young, low-educated and unemployed males.

Perfectly, since the processes under consideration are dynamic and effects manifest with the elapse of time, the model should expand time horizon and include not only spatial but also time spillovers.³⁶ Furthermore, in a system setting one can accommodate policy competition spillovers among administrative districts regarding welfare benefits or police expenditures, which are also suspected to be correlated with unemployment and criminal activity.³⁷ As mentioned above, operationalizing our theoretical setup with a spatial Durbin model entails three endogenous variables, although causality pertains to a single variable, i.e. unemployment. As an alternative we suggest modeling not the reaction function, but the time-lagged adjustment to neighbors' crime rates. The learning component, $W_n Y_{n,t-1}$, incorporates the spatio-temporal dynamic effect of crime instead of the simultaneous interplay. At the same time, it captures spatial interaction in the dependent variable and is - perhaps - more pragmatic in terms of policy implementation, since it assumes the passage of time between observing a neighbor's outcome and deciding own outcome.³⁸

Theoretically, we foresee a number of important research directions. The literature on trade and unemployment (see, for example, [Helpman, Itskhoki, and Redding, 2010](#), [Helpman and Itskhoki, 2010](#), [Felbermayr, Prat, and Schmerer, 2011](#), and [Felbermayr, Larch, and Lechthaler, 2013](#)) can benefit from introducing effects on criminal activities after labor market adjustments, due to changes

³⁶Our preliminary analysis shows the usefulness of the Common Correlated Effects (CCE) estimators, that can be computed by running standard panel regressions augmented with the cross-section averages of the dependent and independent variables. This is an approach advanced by [Pesaran \(2006\)](#) and applicable to panels with a single factor or multiple unobserved factors. Moreover, as shown by [Kapetanios, Pesaran, and Yamagata \(2011\)](#), the main results of the CCE approach continue to hold even for the unobservable common factors which follow unit root processes.

³⁷For large (multi-country or multi-region) systems, dimensionality might be a real obstacle. One of the solutions is to define the neighborhood effects with a fixed number of dominant regions that have non-negligible effects on all other areas. [Pesaran and Chudik \(2010\)](#) and [Chudik and Pesaran \(2011\)](#) demonstrate that the asymptotic normality of the augmented least squares (ALS) estimator holds once the individual auxiliary regressions are correctly specified. However, this requires to conduct additional analysis for specifying the dominant unit(s), the number of the unobserved common factors (if any), and the nature of spatial contemporaneous dependencies.

³⁸In the taxonomy of spatial panel models this specification is referred to as the *pure space recursive* model ([Anselin, Gallo, and Jayet, 2008](#)). We have estimated this class of models but chose not to report the results as they fail to pass the overidentification test.

in trade, have taken place. Another unexploited track concerns the dual labor markets literature (see, for example, [Saint-Paul, 1996](#), [Bentolila, Cahuc, Dolado, and Le Barbanchon, 2012](#), and [Boeri, 2011](#)), which lacks analysis on the costs of duality, mainly being driven by large unemployment among young and less educated people, thereby affecting crime, as demonstrated in our paper. Finally, we still lack understanding about transitional dynamics which is partly because of data constraints to confront theoretical results.

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 in an attempt to shed light on the link of economic decline and inclination to criminal activity explicitly dealing at the same time with the spatio-temporal spillovers. The interplay can be considered not only within but also among European Union countries, which enjoy freedom of mobility especially with regards to employment.

Appendix

Reservation wage

First, we equate (3.5) to (3.6) to obtain

$$b_j = w_{ij}(\tilde{\varphi}) - \lambda \int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\tilde{\varphi})) dF(z),$$

where integration by parts yields

$$\lambda \int_{\tilde{\varphi}}^1 (W(z) - W(\tilde{\varphi})) dF(z) = -\lambda \int_{\tilde{\varphi}}^1 W'(z) (1 - F(z)) dz.$$

Differentiating equation (3.6) gives

$$\begin{aligned} rW'_{ij}(\varphi) &= w'_{ij}(\varphi) - \lambda W'_{ij}(\varphi) (1 - F(\varphi)) - \lambda F(\tilde{\varphi}) W'_{ij}(\varphi) + \phi_{ij}^{W'}(\varphi) K_{ij}^W(\varphi) \\ &+ \phi_{ij}^W \left(K_{ij}^{W'} - W'_{ij}(\varphi) \right) \left(r + \lambda(1 - F(\varphi)) + \lambda F(\tilde{\varphi}) + \phi_{ij}^W \pi \right) W'_{ij}(\varphi) = w'_{ij}(\varphi) = \beta, \end{aligned}$$

where the last equality follows from equation (3.10). We also used equation (3.3) to arrive at $K_{ij}^{W'} = (1 - \pi) W'_{ij}(\varphi)$. Therefore,

$$W'_{ij}(\varphi) = \frac{\beta}{r + \lambda(1 - F(\varphi)) + \lambda F(\tilde{\varphi}) - \phi_{ij}^W (1 - \pi)},$$

which we can plug back in

$$\begin{aligned} &\int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\tilde{\varphi})) dF(z) = \\ &-\beta \left[\int_{\tilde{\varphi}}^{\varphi^c} \frac{(1 - F(z)) dz}{r + \lambda(1 - F(z)) + \lambda F(\tilde{\varphi}) + \pi} + \int_{\varphi^c}^1 \frac{(1 - F(z)) dz}{r + \lambda(1 - F(z)) + \lambda F(\tilde{\varphi})} \right], \end{aligned}$$

and finally obtain the reservation wage

$$w_{ij}(\tilde{\varphi}) = b_j + \lambda\beta \left[\int_{\tilde{\varphi}}^{\varphi^c} \frac{(1 - F(z)) dz}{r + \lambda(1 - F(z)) + \lambda F(\tilde{\varphi}) + \pi} + \int_{\varphi^c}^1 \frac{(1 - F(z)) dz}{r + \lambda(1 - F(z)) + \lambda F(\tilde{\varphi})} \right].$$

Crime wage

Start with the function $W_{ij}(\varphi)$ in equation (6.3) which returns the value of employment in a job-worker match with current productivity φ . The implicit rate of return on the asset of working in a job at productivity φ is equal to the current wage $w(\varphi)$ plus the expected capital gain on the employment relationship. The lower bound of the definite integral, $\tilde{\varphi}$, is the cutoff or threshold value of match productivity, which is determined endogenously in the model. If idiosyncratic productivity φ falls below $\tilde{\varphi}$, the match is no longer profitable and the job/ worker pair is destroyed. Introduce a new cutoff level φ^c , recall that $\phi_{ij}^W(\varphi^c) = 0$ and evaluate this function at it, $\varphi = \varphi^c$,

$$(r + \lambda F(\tilde{\varphi})) W_{ij}(\varphi^c) = w_{ij}(\varphi^c) + \lambda F(\tilde{\varphi}) U_{ij} + \lambda \int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\varphi^c)) dF(z),$$

rearranging for wage yields

$$\begin{aligned}
w_{ij}(\varphi^c) &= \lambda F(\tilde{\varphi})(W_{ij}(\varphi^c) - U_{ij}) + rW_{ij}(\varphi^c) - \lambda \int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\varphi^c)) dF(z) \\
&= \lambda F(\tilde{\varphi})(W_{ij}(\varphi^c) - U_{ij}) + \frac{r}{\pi}(g_j + \pi J_{ij}) - \lambda \int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\varphi^c)) dF(z) \\
&= (\lambda F(\tilde{\varphi}) + r) \left(\frac{g_j + \pi J_{ij}}{\pi} \right) - \lambda F(\tilde{\varphi}) U_{ij} - \lambda \int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\varphi^c)) dF(z) \\
&= (\lambda F(\tilde{\varphi}) + r) \frac{g_j}{\pi} + rJ_{ij} - \lambda F(\tilde{\varphi})(U_{ij} - J_{ij}) - \lambda \int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\varphi^c)) dF(z),
\end{aligned}$$

since $rJ_{ij}(\varphi) - \rho(U_{ij} - J_{ij}(\varphi)) = z_j$ and given $\rho = \lambda F(\tilde{\varphi})$, we end up with

$$w_{ij}(\varphi^c) = (\lambda F(\tilde{\varphi}) + r) \frac{g_j}{\pi} + z_j + \lambda \beta \int_{\varphi^c}^1 \frac{(1-F(z))dz}{r + \lambda(1-F(z)) + \lambda F(\tilde{\varphi})}.$$

Notice that we are effectively dealing with the fixed point problem - the wage at crime productivity depends on the term which is also dependent on φ^c .

Wage income: Nash bargaining

Let us first evaluate the steady-state, equilibrium valuations of states. Given our assumptions, the continuation valuation by workers of unemployment (U), and employment ($W(\varphi)$), and by firms of an open vacancy (V) versus a job ($J(\varphi)$) must solve the following functional equations that equate normal returns on capitalized valuations of labor market states to their expected periodic payouts

$$rU_{ij} = b_j + \phi_{ij}^U (K_{ij}^U - U_{ij}) + \theta_j q(\theta_j) (W_{ij}(\varphi) - U_{ij}). \quad (6.1)$$

In equation (6.1), the flow yield from the valuation of the state of unemployment U at interest rate r is equated to an expected ‘‘capital gain’’ stemming from finding new employment at φ . Further,

$$rV_{ij} = -c_j + q(\theta_j) [J_{ij}(\varphi) - V_{ij}]. \quad (6.2)$$

Equation (6.2) governs the valuation of an unfilled vacancy. Moreover,

$$\begin{aligned}
rW_{ij}(\varphi) &= w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\varphi)) dF(z) - \lambda F(\tilde{\varphi})(W_{ij}(\varphi) - U_{ij}) \\
&\quad + \phi_{ij}^W(\varphi) (K_{ij}^W(\varphi) - W_{ij}(\varphi)).
\end{aligned} \quad (6.3)$$

The function $W_{ij}(\varphi)$ in equation (6.3) returns the value of employment in a job-worker match with current productivity φ . The implicit rate of return on the asset of working in a job at productivity φ is equal to the current wage $w_{ij}(\varphi)$ plus the expected capital gain on the employment relationship. The lower bound of the definite integral, $\tilde{\varphi}$ is the cutoff or threshold value of match productivity, determined endogenously in the model. If idiosyncratic productivity φ falls below $\tilde{\varphi}$, the match is no longer profitable and the job/ worker pair is destroyed. Finally,

$$rJ_{ij}(\varphi) = \varphi - w(\varphi) + \lambda \int_{\tilde{\varphi}}^1 (J_{ij}(z) - J_{ij}(\varphi)) dF(z) + \lambda F(\tilde{\varphi})(V_{ij} - J_{ij}(\varphi)). \quad (6.4)$$

A similar arbitrage argument determines the valuation to a firm of a filled job in equation (6.4), given the current realization of φ .

Use now $V = 0$ and rewrite the two asset value conditions (for jobs)³⁹

$$\begin{aligned}
r\mathcal{J}_{ij}(\varphi) &= \varphi - w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 (\mathcal{J}_{ij}(z) - \mathcal{J}_{ij}(\varphi)) dF(z) - \lambda F(\tilde{\varphi}) \mathcal{J}_{ij}(\varphi) \\
&= \varphi - w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 \mathcal{J}_{ij}(z) dF(z) - \lambda (\mathcal{J}_{ij}(\varphi) (1 - F(\tilde{\varphi})) + F(\tilde{\varphi}) \mathcal{J}_{ij}(\varphi)) \\
&= \varphi - w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 \mathcal{J}_{ij}(z) dF(z) - \lambda \mathcal{J}_{ij}(\varphi), \\
\mathcal{J}_{ij}(\varphi) &= \frac{\varphi - w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 \mathcal{J}_{ij}(z) dF(z)}{r + \lambda}.
\end{aligned}$$

Similarly with the asset value conditions for employment

$$\begin{aligned}
rW_{ij}(\varphi) &= w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 (W_{ij}(z) - W_{ij}(\varphi)) dF(z) - \lambda F(\tilde{\varphi}) (W_{ij}(\varphi) - U_{ij}) \\
&\quad + \phi_{ij}^W(\varphi) (K_{ij}^W(\varphi) - W_{ij}(\varphi)) \\
&= w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 W_{ij}(z) dF(z) + \lambda F(\tilde{\varphi}) U_{ij} + \phi_{ij}^W(\varphi) g_j + \phi_{ij}^W(\varphi) \pi J_{ij} - (\lambda + \phi_{ij}^W(\varphi) \pi) W_{ij}(\varphi), \\
W(\varphi) &= \frac{w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 W_{ij}(z) dF(z) + \lambda F(\tilde{\varphi}) U_{ij} + \phi_{ij}^W(\varphi) g_j + \phi_{ij}^W(\varphi) \pi J_{ij}}{r + \phi_{ij}^W(\varphi) \pi + \lambda}.
\end{aligned}$$

Wage equation under the Nash bargaining rule should solve the following,

$$\begin{aligned}
w(\varphi) &= \arg \max (W_{ij}(\varphi) - U_{ij})^\beta (\mathcal{J}_{ij}(\varphi) - V_{ij})^{1-\beta} \\
&= \arg \max \left(\frac{w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 W_{ij}(z) dF(z) - (\lambda(1-F(\tilde{\varphi})) + r + \phi_{ij}^W(\varphi) \pi) U_{ij} + \phi_{ij}^W(\varphi) g_j + \phi_{ij}^W(\varphi) \pi J_{ij}}{r + \phi_{ij}^W(\varphi) \pi + \lambda} \right)^\beta \\
&\quad \times \left(\frac{\varphi - w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 \mathcal{J}_{ij}(z) dF(z) - (r + \lambda) V_{ij}}{r + \lambda} \right)^{1-\beta}, \tag{6.5}
\end{aligned}$$

with the first-order necessary condition

$$\begin{aligned}
\beta \frac{dW_{ij}(\varphi)}{dw(\varphi)} (W_{ij}(\varphi) - U_{ij})^{\beta-1} (\mathcal{J}_{ij}(\varphi) - V_{ij})^{1-\beta} + (1 - \beta) \frac{d\mathcal{J}_{ij}(\varphi)}{dw(\varphi)} (W_{ij}(\varphi) - U_{ij})^\beta (\mathcal{J}_{ij}(\varphi) - V_{ij})^{-\beta} &= 0 \\
(W_{ij}(\varphi) - U_{ij})^\beta (\mathcal{J}_{ij}(\varphi) - V_{ij})^{1-\beta} \left(\beta \frac{dW_{ij}(\varphi)}{dw(\varphi)} (W_{ij}(\varphi) - U_{ij})^{-1} + (1 - \beta) \frac{d\mathcal{J}_{ij}(\varphi)}{dw(\varphi)} (\mathcal{J}_{ij}(\varphi) - V_{ij})^{-1} \right) &= 0 \\
\beta \frac{dW_{ij}(\varphi)}{dw(\varphi)} (W_{ij}(\varphi) - U_{ij})^{-1} &= - (1 - \beta) \frac{d\mathcal{J}_{ij}(\varphi)}{dw(\varphi)} (\mathcal{J}_{ij}(\varphi) - V_{ij})^{-1} \\
W_{ij}(\varphi) - U_{ij} &= \frac{\beta (\mathcal{J}_{ij}(\varphi) - V_{ij})}{(1 - \beta)} \\
W_{ij}(\varphi) - U_{ij} &= \beta (\mathcal{J}_{ij}(\varphi) + W_{ij}(\varphi) - V_{ij} - U_{ij}).
\end{aligned}$$

Now we can use the above with $V_{ij} = 0$ and the FOC in equation (6.5) to obtain

$$\begin{aligned}
(1 - \beta) (W_{ij}(\varphi) - U_{ij}) &= \beta \mathcal{J}_{ij}(\varphi) \\
(1 - \beta) \left(\frac{w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 W_{ij}(z) dF(z) - (\lambda(1-F(\tilde{\varphi})) + r + \phi_{ij}^W(\varphi) \pi) U_{ij} + \phi_{ij}^W(\varphi) g_j + \phi_{ij}^W(\varphi) \pi J_{ij}}{r + \phi_{ij}^W(\varphi) \pi + \lambda} \right) & \\
&= \beta \frac{\varphi - w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 \mathcal{J}_{ij}(z) dF(z)}{r + \lambda}. \tag{6.6}
\end{aligned}$$

If we are interested in an honest equilibrium when working employees do not commit a crime,

³⁹Using the fundamental theorem of calculus, $\int_{\tilde{\varphi}}^1 dF(z) = F(z) \big|_{\tilde{\varphi}}^1 = F(1) - F(\tilde{\varphi}) = 1 - F(\tilde{\varphi})$.

$\phi_{ij}^W(\varphi) = 0$ or $w_{ij} > C$, we have

$$\begin{aligned} (1 - \beta) \left(w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 W_{ij}(z) dF(z) - (\lambda(1 - F(\tilde{\varphi})) + r) U_{ij} \right) \\ = \beta \left(\varphi - w_{ij}(\varphi) + \lambda \int_{\tilde{\varphi}}^1 \mathcal{J}_{ij}(z) dF(z) \right) \\ (1 - \beta) (w_{ij}(\varphi) - rU_{ij}) = \beta (\varphi - w_{ij}(\varphi)) \\ w_{ij}(\varphi) = \beta\varphi + r(1 - \beta)U_{ij}, \end{aligned}$$

because

$$\beta \int_{\tilde{\varphi}}^1 \mathcal{J}_{ij}(z) dF(z) = (1 - \beta) \left(\int_{\tilde{\varphi}}^1 W_{ij}(z) - U_{ij} \right) dF(z),$$

as this term corresponds to the same sharing rule.

A closed form expression for rU is obtainable as follows:

$$(1 - \beta) (W_{ij}(\varphi) - U_{ij}) = \beta \mathcal{J}_{ij}(\varphi).$$

Combining with the free entry conditions in equations (6.1) and (6.2), we obtain

$$\begin{aligned} (r + \phi_{ij}^U \pi) U_{ij} &= \frac{\beta}{1 - \beta} c_j \theta_j + b_j + \phi_{ij}^U (g_j + \pi J_{ij}) \\ J_{ij} &= \frac{z_j + \rho U_{ij}}{r + \rho} \text{ and } \mathcal{J}_{ij}(\varphi) = \frac{c_j}{q(\theta_j)} \\ rU_{ij} &= \frac{(r + \rho) \frac{\beta}{1 - \beta} c_j \theta_j + b_j + \phi_{ij}^U (g_j + \frac{\pi}{r + \rho} z_j)}{r + \rho + \phi_{ij}^U \pi}, \end{aligned}$$

and plugging back into wage equation gives

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

Finally, the wage equation for $\phi_{ij}^U = 1$ becomes

$$w_{ij}(\varphi) = \beta\varphi + \frac{(r + \rho) \beta c_j \theta_j + (1 - \beta) b_j + (1 - \beta) \left(g_j + \frac{\pi}{r + \rho} z_j \right)}{r + \rho + \pi}. \quad (6.7)$$

Proof of Proposition 3.3

Since productivity is isomorphic to wages, we can analyze an increase in crime-wages. From equation (3.9), an increase is warranted if, ceteris paribus, a financial gain from a crime in region j increases, a probability of getting caught decreases, economic volatility increases, the rate of time preference increases, reservation wage (productivity) decreases, and the consumption of the en-jailed workers increases in j .

Moreover, 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 if criminals are more sensitive to changes in match-specific productivity than wage-earners whose earnings are above a crime wage. Note that more productive job seekers, ceteris paribus, induce an increase in the reservation wage (productivity). This leads to an increase in a crime rate. To see this, we need to calculate crime rate with four segments of population. We split employed into E_{ji}^L which earn less than a crime wage $w_{ij}(\varphi) < C_{ij}$, and those that earn more, E_{ji}^H , $w_{ij}(\varphi) \geq C_{ij}$.

First, unemployed is composed of those employed whose matches are dissolved at rate $\lambda F(\tilde{\varphi})$ and

those released to unemployment from a jail less those who find a job and are enjailed as criminals:

$$\Delta u_i = \lambda F(\tilde{\varphi}) (1 - u_i - n_i) + \rho n_i - (\theta_i q(\theta_i) + \pi) u_i = 0,$$

leading to

$$u_i = \frac{\lambda F(\tilde{\varphi}) + (\rho - \lambda F(\tilde{\varphi})) n_i}{\lambda F(\tilde{\varphi}) + \theta_i q(\theta_i) + \pi}.$$

Then, steady-state workers with a wage lower than C is composed of a share of unemployed who transit into employed and is diminished by those who lose job, transit into higher than crime wage category (with the same probability as finding a new job $\theta_i q(\theta_i)$), and are caught as criminals. Hence,

$$\begin{aligned} \Delta E_{ji}^L &= \theta_i q(\theta_i) F(\varphi_{ij}^C) u_i - (\theta_i q(\theta_i) (1 - F(\varphi_{ij}^C)) + \lambda F(\tilde{\varphi}) + \pi) E_{ji}^L = 0, \\ E_{ji}^L &= \frac{\theta_i q(\theta_i) F(\varphi_{ij}^C)}{\theta_i q(\theta_i) (1 - F(\varphi_{ij}^C)) + \lambda F(\tilde{\varphi}) + \pi} u_i. \end{aligned}$$

The steady-state workers with higher wage than C is composed of those who transit from unemployed and E_{ji}^L and lose jobs:

$$\begin{aligned} \Delta E_{ji}^H &= (1 - F(\varphi_{ij}^C)) \theta_i q(\theta_i) (E_{ji}^L + u_i) - \lambda F(\tilde{\varphi}) E_{ji}^H = 0, \\ E_{ji}^H &= \frac{(1 - F(\varphi_{ij}^C)) \theta_i q(\theta_i)}{\lambda F(\tilde{\varphi})} (E_{ji}^L + u_i) = \frac{(1 - F(\varphi_{ij}^C)) \theta_i q(\theta_i)}{\lambda F(\tilde{\varphi})} \left(\frac{\theta_i q(\theta_i) + \lambda F(\tilde{\varphi}) + \pi}{\theta_i q(\theta_i) (1 - F(\varphi_{ij}^C)) + \lambda F(\tilde{\varphi}) + \pi} \right) u_i. \end{aligned}$$

At last, the enjailed criminals are composed of unemployed and those earning less than a crime wage caught and those released into unemployment:

$$\Delta n_i = \pi (E_{ji}^L + u_i) - \rho n_i = 0,$$

yielding

$$n_i = \frac{\pi}{\rho} (E_{ji}^L + u_i) = \frac{\pi}{\rho} \left(\frac{\theta_i q(\theta_i) + \lambda F(\tilde{\varphi}) + \pi}{\theta_i q(\theta_i) (1 - F(\varphi_{ij}^C)) + \lambda F(\tilde{\varphi}) + \pi} \right) u_i.$$

Then, steady states of the partitioned population are given by

$$\begin{aligned} u_i &= \frac{\rho \lambda F(\tilde{\varphi}_i) (\theta_i q(\theta_i) (1 - F(\varphi_{ij}^C)) + \lambda F(\tilde{\varphi}) + \pi)}{\Omega_i}, \\ E_{ji}^L &= \frac{\rho \lambda F(\tilde{\varphi}_i) \theta_i q(\theta_i) F(\varphi_{ij}^C)}{\Omega_i}, \\ E_{ji}^H &= \frac{\rho (1 - F(\varphi_{ij}^C)) \theta_i q(\theta_i) (\theta_i q(\theta_i) + \lambda F(\tilde{\varphi}) + \pi)}{\Omega_i}, \\ n_i &= \frac{\lambda F(\tilde{\varphi}_i) \pi (\theta_i q(\theta_i) + \lambda F(\tilde{\varphi}) + \pi)}{\Omega_i}, \end{aligned}$$

where $\Omega_i = (\lambda F(\tilde{\varphi}) + \theta_i q(\theta_i) + \pi) (\rho \theta_i q(\theta_i) (1 - F(\varphi_{ij}^C)) + (\rho + \pi) \lambda F(\tilde{\varphi}))$. The crime rate is given by

$$c_i = \frac{E_{ji}^L + u_i}{1 - n_i} = \frac{\rho \lambda F(\tilde{\varphi}_i)}{\theta_i q(\theta_i) (1 - F(\varphi_{ij}^C)) + \lambda F(\tilde{\varphi})}.$$

The sign of the derivative of the above equation with respect to cutoff productivity level is given by

$$\begin{aligned} &\left(\frac{\partial E_{ji}^L}{\partial \tilde{\varphi}_i} + \frac{\partial u_i}{\partial \tilde{\varphi}_i} \right) (1 - n_i) + \frac{\partial n_i}{\partial \tilde{\varphi}_i} (E_{ji}^L + u_i) \\ &= \frac{E_{ji}^H}{\tilde{\varphi}_i} (E_{ji}^L + u_i) (\varepsilon_{E_{ji}^L + u_i, \tilde{\varphi}_i} - \varepsilon_{E_{ji}^H, \tilde{\varphi}_i}), \end{aligned}$$

where ε_f denotes the elasticity of a particular function f . We used the property of the elasticity of a sum of two functions. Hence, the sign is given by $\varepsilon_{E_{j_i}^L+u_i,\varphi} - \varepsilon_{E_{j_i}^H,\varphi}$ which depends on the impact of a threshold productivity on crime productivity, $\partial\varphi_i^C/\partial\tilde{\varphi}_i$. The dependence between reservation and crime wages is obvious from equation (3.9). It is clear that the crime rate increases as long as a change in match-specific productivity affects criminals (unemployed u_i and employed under the lower than a crime wage $E_{j_i}^L$) relatively more than high-income earners $E_{j_i}^H$ (those earning $w_{ij}(\varphi) \geq C_{ij}$). Recall that we are working under the case of $\phi_{ij}^U = 1$, therefore, an increase in reservation productivity for a successful match increases an army of unemployed who will find it optimal to engage in criminal activities (to counteract this effect one needs a very large decrease in criminal wage, so that a distance between two cutoffs becomes small). Yet this is unlikely as in general an increase in reservation productivity induces a rise in a crime wage (see equation (3.9)). To be precise,

$$\text{sign}\left(\frac{\partial c_i}{\partial \tilde{\varphi}_i}\right) = \text{sign}\left(\left(1 - F(\varphi_{ij}^C)\right) f(\tilde{\varphi}_i) + f(\varphi_{ij}^C) \left(\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i}\right) F(\tilde{\varphi}_i)\right).$$

The crime productivity increases given an increase in threshold productivity iff $\left(\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i}\right) > -\frac{(1-F(\varphi_{ij}^C))f(\tilde{\varphi}_i)}{f(\varphi_{ij}^C)F(\tilde{\varphi}_i)}$. Alternatively, the crime rate decreases iff $\left(\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i}\right) < -\frac{(1-F(\varphi_{ij}^C))f(\tilde{\varphi}_i)}{f(\varphi_{ij}^C)F(\tilde{\varphi}_i)}$.⁴⁰ To reassure, explore elasticities $\varepsilon_{E_{j_i}^L+u_i,\tilde{\varphi}_i}$ and $\varepsilon_{E_{j_i}^H,\tilde{\varphi}_i}$:

$$\begin{aligned}\varepsilon_{E_{j_i}^L+u_i,\tilde{\varphi}_i} &= \tilde{\varphi}_i \left[\frac{f(\tilde{\varphi}_i)}{F(\tilde{\varphi}_i)} - \frac{\tilde{\Omega}'_i}{\tilde{\Omega}_i} \right] \\ \varepsilon_{E_{j_i}^H,\tilde{\varphi}_i} &= -\tilde{\varphi}_i \left[\left(\frac{f(\varphi_{ij}^C)}{(1-F(\varphi_{ij}^C))} \right) \left(\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i} \right) \right] + \frac{\tilde{\Omega}'_i}{\tilde{\Omega}_i}\end{aligned}$$

Therefore,

$$\begin{aligned}&\varepsilon_{E_{j_i}^L+u_i,\tilde{\varphi}_i} - \varepsilon_{E_{j_i}^H,\tilde{\varphi}_i} \\ &= \tilde{\varphi}_i \left[\frac{f(\tilde{\varphi}_i)}{F(\tilde{\varphi}_i)} - \frac{\tilde{\Omega}'_i}{\tilde{\Omega}_i} \right] + \tilde{\varphi}_i \left[\left(\frac{f(\varphi_{ij}^C)}{(1-F(\varphi_{ij}^C))} \right) \left(\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i} \right) \right] + \frac{\tilde{\Omega}'_i}{\tilde{\Omega}_i} \\ &= \tilde{\varphi}_i \left[\frac{f(\tilde{\varphi}_i)}{F(\tilde{\varphi}_i)} + \frac{f(\varphi_{ij}^C)}{(1-F(\varphi_{ij}^C))} \left(\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i} \right) \right].\end{aligned}$$

Positive effect materializes iff $\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i} > -\frac{f(\tilde{\varphi}_i)}{F(\tilde{\varphi}_i)} \frac{1-F(\varphi_{ij}^C)}{f(\varphi_{ij}^C)}$. Hence, the result is determined by the hazard ratios (inverse Mill's ratios if Normal distributions are assumed). More precisely, $\lambda(\varphi_{ij}^C) \equiv f(\varphi_{ij}^C) / (1 - F(\varphi_{ij}^C))$ is the hazard function and $r(\tilde{\varphi}_i) \equiv f(\tilde{\varphi}_i) / F(\tilde{\varphi}_i)$ is the reverse hazard function. Intuitively, hazard rate is the probability of observing a match within a neighborhood of φ_{ij}^C , conditional on the productivity being no less than φ_{ij}^C . Finally, the reverse hazard rate is the probability of observing an outcome in a neighborhood of $\tilde{\varphi}_i$, conditional on the match productivity being no more than a threshold $\tilde{\varphi}_i$. Thus, we can express the condition as

$$\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i} > -\frac{r(\tilde{\varphi}_i)}{\lambda(\varphi_{ij}^C)}.$$

⁴⁰One could also explore (3.9) and notice that the integral's f lower limit is variable and endogenous where $f = \int_{\varphi^c}^1 \frac{(1-F(z))dz}{r+\lambda(1-F(z))+\lambda F(\tilde{\varphi})}$. This approach is quite complex for an arbitrary distribution function and is not reported here. Expressions can be shared under request.

We can also use the fact that

$$\begin{aligned} \frac{\partial w(\varphi_i^C)}{\partial \tilde{\varphi}_i} / \frac{\partial w(\varphi_i^C)}{\partial \varphi_i^C} &= \frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i} \\ &= \frac{\left[\lambda f(\tilde{\varphi}) \frac{g_j}{\pi} + \lambda \beta \frac{\partial f_i}{\partial \tilde{\varphi}_i} \right] \frac{\partial \tilde{\varphi}_i}{\partial \varphi_i^C}}{\beta}, \end{aligned}$$

which immediately leads to

$$\frac{\partial \varphi_i^C}{\partial \tilde{\varphi}_i} = \sqrt{\lambda \left(\frac{g_j f(\tilde{\varphi})}{\beta \pi} + \frac{\partial f_i}{\partial \tilde{\varphi}_i} \right)}.$$

Therefore, the derivative is well defined only for the positive domain (ruling out complex solution). This trivially leads to the statement about cutoff productivity and its effect on crime.

Turning to the proposition claims, we note that an increase in a frequency of match-specific shocks increases crime rate follows from the fact that $\rho F(\tilde{\varphi}_i) \left(1 - F(\varphi_i^C)\right) \theta_i q(\theta_i) > 0$. This result can be interpreted as the one stating that an increase in volatility of economic environment tends to increase crime rate.

Second, an increase in the crime wage (or productivity φ_i^C) also increases crime rate since $\lambda F(\tilde{\varphi}_i) \theta_i q(\theta_i) f(\varphi_i^C) > 0$ where $f(\varphi_i^C) \equiv dF(\varphi_i^C)/d\varphi_i^C$ and $\partial \varphi_i^C / \partial \tilde{\varphi}_i = 0$. In other case, refer to discussion above. Intuitively, an increase in a crime-wage increases a number of firms which pay a wage smaller or equal to C and this how it increases a number of criminals.

Thirdly, an increase in job seekers in the other region increases crime rate given the elasticity of the labor market tightness is smaller than minus one (larger than one in absolute value). Recall that $\theta_i \equiv v_i/S_i = v_i/(u_{ii} + u_{ji})$. Hence, the more the job seekers from the other region, the smaller is the labor market tightness, ceteris paribus. Then, differentiating equation (3.12) with respect to θ_i we obtain $-\lambda F(\tilde{\varphi}_i) (q(\theta_i) + \theta_i q'(\theta_i))$. This term is positive if and only if $q(\theta_i) + \theta_i q'(\theta_i) = q(\theta_i) (1 + \theta_i q'(\theta_i)/q(\theta_i)) < 0$ which implies that the elasticity of instantaneous meeting probability for vacancies is $\theta_i q'(\theta_i)/q(\theta_i) < -1$ or $|\theta_i q'(\theta_i)/q(\theta_i)| > 1$.

Fourth, 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 . Note that more productive job seekers, ceteris paribus, induce an increase in the reservation wage (productivity). This leads to an increase in crime rate. To see this, differentiate equation (3.12) with respect to cutoff productivity level. After manipulations, the term that determines the sign is $\left[f(\tilde{\varphi}_i) \left(1 - F(\varphi_i^C)\right) + f(\varphi_i^C) \left(\partial \varphi_i^C / \partial \tilde{\varphi}_i\right) F(\tilde{\varphi}_i) \right] \lambda \theta_i q(\theta_i)$ where $f(\tilde{\varphi}_i) \equiv dF(\tilde{\varphi}_i)/d\tilde{\varphi}_i$, $f(\varphi_i^C) \equiv dF(\varphi_i^C)/d\varphi_i^C$ and the dependence between reservation and crime wages is obvious from equation (3.9). Recall that we are working under the case of $\phi_{ij}^U = 1$, therefore, an increase in reservation productivity for a successful match increases an army of unemployed who will find it optimal to engage in criminal activities (to counteract this effect one needs a very large decrease in criminal wage, so that a distance between two cutoffs becomes small). Yet this is not possible given we rule out complex solutions which then tells that an increase in reservation productivity induces a rise in a crime wage (see equation (3.9)) and the discussion above.

Crime Categories - 2009 Report of the German Federal Criminal Police Office⁴¹

435*00 Theft by Burglary of a Dwelling

including:

436*00 Daytime burglaries of residences (committed between 6:00 a.m. and 9:00 p.m.)

⁴¹http://www.bka.de/nm_242508/DE/Publikationen/PolizeilicheKriminalstatistik/AeltereAusgaben/PksEnglisch/pksEnglisch_node.html?__nnn=true

***50*00 Theft in/ from Motor Vehicles**

674000 Damage to Property

including:

674100 damage to motor vehicles

674300 other damage to property committed in streets, lanes or public places

674500 destruction of important equipment

730000 Drug Offenses - Narcotics Act

including:

731000 general violations

thereof:

731100 involving heroin

731200 involving cocaine

731300 involving LSD

731400 involving amphetamine/ methamphetamine and their derivatives in powder or liquid form

731500 involving amphetamine/ methamphetamine and their derivatives in tablet or capsule form

731800 involving cannabis and preparations thereof

731900 involving other drugs

732000 trafficking in, and smuggling of drugs

thereof:

732100 in/of heroin

732200 in/of cocaine

732300 in/of LSD

732400 in/of amphetamine/ methamphetamine and their derivatives in powder or liquid form

732500 in/of amphetamine/ methamphetamine and their derivatives in tablet or capsule form

732800 in/of cannabis and preparations thereof

732900 in/of other drugs

733000 illegal importation of drugs (significant amounts)

thereof:

733100 of heroin

733200 of cocaine

733300 of LSD

733400 of amphetamine/methamphetamine and their derivatives in powder or liquid form

733500 of amphetamine/ methamphetamine and their derivatives in tablet or capsule form

733800 of cannabis and preparations thereof

733900 of other drugs

734000 other violations of the NCA

899000 Street Crime includes the following offenses:

111100 offenses against sexual selfdetermination by sudden attack (individual offender)

111200 offenses against sexual selfdetermination by sudden attack (group of offenders)

132000 indecent exposure and indecent acts in public

213000 transports of cash and valuables

214000 assault on motorists with intent to rob

215000 robbery following restaurant/bar visit

216000 handbag robbery
217000 other robberies in streets, lanes or public places
222100 dangerous and serious bodily injury in streets, lanes or public places
233300 extortionate kidnapping in connection with robberies of transports of cash and valuables
234300 hostage taking in connection with robberies of transports of cash and valuables
*20*00 theft in/from kiosks
*30*00 in/from store windows, showcases and display cases
*50*00 theft in/from motor vehicles
*55000 theft of motor vehicles
*90*00 pickpocketing
*001001 theft of motor vehicles
*002001 theft of mopeds and motorcycles
*003001 theft of bicycles
*007001 theft of/from coin-operated machines
623000 breach of the public peace
674100 damage to motor vehicles
674300 other damage to property committed in streets, lanes or public places

Table 6.1: First Stages for Table 5.1

Predicted growth in:	UR	UR 15-25	US 15-25	Male UR	Female UR	Foreign UR
(A) Employees under Age 20	0.155 (0.244)	0.144 (0.242)	0.131 (0.241)	0.149 (0.244)	0.153 (0.244)	0.140 (0.244)
Spatial Lag	0.750*** (0.279)	0.755*** (0.277)	0.775*** (0.275)	0.752*** (0.279)	0.753*** (0.279)	0.758*** (0.280)
Employees Age 20 to 25	-1.243*** (0.344)	-1.259*** (0.342)	-1.269*** (0.340)	-1.252*** (0.346)	-1.244*** (0.343)	-1.267*** (0.343)
Part-time Employees	-1.889*** (0.587)	-1.878*** (0.581)	-1.779*** (0.589)	-1.882*** (0.584)	-1.867*** (0.592)	-1.828*** (0.593)
Full-time Employees	0.180 (0.320)	0.201 (0.318)	0.211 (0.317)	0.187 (0.324)	0.206 (0.315)	0.246 (0.374)
(B) Employees under Age 20	-0.026 (0.245)	0.008 (0.243)	0.051 (0.244)	-0.057 (0.246)	0.010 (0.244)	0.002 (0.244)
Spatial Lag	-0.113 (0.301)	-0.119 (0.300)	-0.161 (0.300)	-0.087 (0.301)	-0.141 (0.300)	-0.131 (0.300)
Employees Age 20 to 25	0.369 (0.302)	0.426 (0.299)	0.466 (0.300)	0.333 (0.304)	0.412 (0.301)	0.362 (0.305)
Part-time Employees	-2.891*** (0.567)	-2.861*** (0.579)	-3.051*** (0.584)	-2.814*** (0.564)	-3.003*** (0.571)	-2.302*** (0.579)
Full-time Employees	-3.223*** (0.314)	-3.314*** (0.311)	-3.352*** (0.310)	-3.116*** (0.321)	-3.357*** (0.308)	-2.619*** (0.375)
(C) Employees under Age 20	-0.004 (0.112)	-0.017 (0.111)	-0.007 (0.111)	-0.014 (0.112)	0.004 (0.112)	0.009 (0.112)
Spatial Lag	0.264** (0.128)	0.280** (0.126)	0.282** (0.127)	0.271** (0.127)	0.259** (0.128)	0.257** (0.127)
Employees Age 20 to 25	0.007 (0.160)	0.001 (0.158)	0.013 (0.158)	-0.004 (0.159)	0.018 (0.160)	0.025 (0.160)
Part-time Employees	-0.029 (0.310)	0.049 (0.308)	0.073 (0.311)	-0.008 (0.308)	-0.049 (0.311)	-0.055 (0.323)
Full-time Employees	0.592** (0.245)	0.593** (0.241)	0.581** (0.239)	0.620** (0.244)	0.568** (0.245)	0.562** (0.265)
(D) Employees under Age 20	-0.058 (0.187)	-0.045 (0.187)	-0.056 (0.186)	-0.061 (0.188)	-0.053 (0.187)	-0.041 (0.187)
Spatial Lag	0.127 (0.210)	0.121 (0.209)	0.142 (0.209)	0.130 (0.209)	0.121 (0.210)	0.118 (0.210)
Employees Age 20 to 25	-0.011 (0.283)	0.008 (0.282)	0.001 (0.280)	-0.014 (0.284)	-0.006 (0.282)	0.012 (0.283)
Part-time Employees	-3.148*** (0.473)	-3.158*** (0.472)	-3.056*** (0.474)	-3.138*** (0.471)	-3.176*** (0.475)	-3.171*** (0.465)
Full-time Employees	-2.308*** (0.272)	-2.335*** (0.270)	-2.328*** (0.270)	-2.294*** (0.277)	-2.343*** (0.267)	-2.336*** (0.311)
(E) Employees under Age 20	-0.036 (0.093)	-0.025 (0.092)	-0.009 (0.093)	-0.052 (0.093)	-0.017 (0.093)	-0.019 (0.093)
Spatial Lag	0.435*** (0.106)	0.437*** (0.105)	0.427*** (0.104)	0.448*** (0.106)	0.422*** (0.106)	0.425*** (0.106)
Employees Age 20 to 25	-0.161 (0.145)	-0.137 (0.145)	-0.122 (0.146)	-0.180 (0.145)	-0.139 (0.146)	-0.154 (0.147)
Part-time Employees	-1.863*** (0.258)	-1.826*** (0.261)	-1.867*** (0.258)	-1.822*** (0.255)	-1.914*** (0.262)	-1.665*** (0.260)
Full-time Employees	-1.031*** (0.141)	-1.065*** (0.141)	-1.082*** (0.142)	-0.975*** (0.141)	-1.093*** (0.142)	-0.831*** (0.163)

Note: UR denotes the unemployment rate and US the unemployment share. (A): Theft by burglary of a dwelling. (B): Theft in/ from motor vehicles. (C): Damage to property. (D): Drug-related offenses. (E): Street Crime. Standard errors robust to heteroscedasticity in parentheses. **, *** denote significance at 5% and 1% respectively.

Table 6.2: First Stages for Table 5.2

Theft by Burglary of a Dwelling							
Predicted growth in:	CSL	UR	UR 15-25	US 15-25	Male UR	Female UR	Foreign UR
Employees under	0.142	-2.649***	-3.523***	-1.358***	-3.472***	-1.674*	-3.914
Age 20	(0.244)	(1.000)	(1.135)	(0.476)	(1.037)	(0.983)	(2.379)
Spatial Lag	0.757***	1.401**	3.098***	2.204***	2.154***	0.480	1.634
	(0.280)	(0.560)	(1.004)	(0.556)	(0.633)	(0.521)	(1.692)
Employees Age	-1.261***	-3.525**	-3.303*	-0.981	-4.450***	-2.396	-9.235**
20 to 25	(0.340)	(1.508)	(1.742)	(0.858)	(1.587)	(1.470)	(4.055)
Part-time Employees	-1.870***	3.923*	13.408***	10.821***	6.201**	-0.373	64.660***
	(0.590)	(2.239)	(3.155)	(1.943)	(2.460)	(2.239)	(8.453)
Full-time Employees	0.203	4.676***	3.212*	0.983	7.895***	-0.512	67.333***
	(0.316)	(1.140)	(1.820)	(1.199)	(1.249)	(1.131)	(6.852)
Theft in/ from Motor Vehicles							
Predicted growth in:	CSL	UR	UR 15-25	US 15-25	Male UR	Female UR	Foreign UR
Employees under	0.044	-2.608***	-3.536***	-1.374***	-3.433***	-1.640*	-3.906*
Age 20	(0.243)	(0.994)	(1.138)	(0.480)	(1.030)	(0.976)	(2.345)
Spatial Lag	-0.151	1.406**	3.105***	2.198***	2.165***	0.467	1.752
	(0.299)	(0.567)	(1.005)	(0.555)	(0.639)	(0.527)	(1.703)
Employees Age	0.461	-3.424**	-3.325*	-1.026	-4.345***	-2.330	-9.074**
20 to 25	(0.298)	(1.496)	(1.738)	(0.873)	(1.574)	(1.459)	(4.098)
Part-time Employees	-2.999***	4.052*	13.323***	10.791***	6.294**	-0.181	64.109***
	(0.571)	(2.229)	(3.090)	(1.894)	(2.465)	(2.201)	(9.076)
Full-time Employees	-3.347***	4.673***	3.190*	0.995	7.876***	-0.471	67.030***
	(0.307)	(1.136)	(1.816)	(1.199)	(1.247)	(1.122)	(6.978)

Note: CSL denotes the crime spatial lag, UR the unemployment rate and US the unemployment share. Standard errors robust to heteroscedasticity in parentheses. *, **, *** denote significance at 10%, 5% and 1% respectively.

Table 6.3: First Stages for Table 5.3

	Predicted Growth in Employees:				
	under Age 20	SL under Age 20	Age 20 to 25	Part-time	Full-time
CSL	0.070 (0.239)	0.548** (0.269)	-1.151*** (0.351)	-1.992*** (0.678)	0.164 (0.463)
UR	-2.752** (1.125)	1.711*** (0.630)	-3.601** (1.651)	5.289** (2.294)	4.098*** (1.568)
SLUR	0.260 (0.300)	-0.437 (0.377)	-0.090 (0.678)	5.337*** (1.431)	5.210*** (0.994)
UR 15-25	-3.505*** (1.234)	3.679*** (1.064)	-3.541* (1.825)	15.613*** (3.343)	2.738 (2.300)
SLUR 15-25	0.211 (0.430)	0.390 (0.546)	0.516 (0.857)	18.554*** (1.905)	13.743*** (1.415)
US 15-25	-1.262** (0.492)	2.396*** (0.590)	-0.986 (0.856)	11.856*** (2.137)	1.336 (1.516)
SLUS 15-25	0.231 (0.263)	0.913*** (0.293)	1.162** (0.467)	13.215*** (1.181)	8.878*** (0.863)
Male UR	-3.661*** (1.159)	2.453*** (0.698)	-4.631*** (1.735)	7.815*** (2.568)	7.471*** (1.694)
SL Male UR	0.374 (0.311)	-0.469 (0.391)	-0.316 (0.678)	4.331*** (1.527)	4.717*** (1.064)
Female UR	-1.657 (1.107)	0.760 (0.587)	-2.198 (1.608)	0.751 (2.268)	-1.226 (1.484)
SL Female UR	-0.011 (0.310)	-0.194 (0.385)	-0.042 (0.703)	7.063*** (1.444)	6.641*** (0.954)
Foreign UR	-4.218 (2.642)	2.260 (1.866)	-10.940** (4.436)	60.706*** (7.603)	60.313*** (7.073)
SL Foreign UR	-0.659 (1.254)	0.683 (1.184)	-1.678 (2.600)	11.264*** (4.001)	13.211*** (3.456)

Note: CSL denotes the crime spatial lag, UR the unemployment rate, US the unemployment share and SL the spatial lag. Standard errors robust to heteroscedasticity in parentheses. *, **, *** denote significance at 10%, 5% and 1% respectively.

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