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Finding the European crime drop using a panel data model with stochastic trends

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Finding the European Crime Drop using A Panel Data Model with Stochastic Trends

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Abstract

We develop a panel data model with stochastic dynamic processes to empirically verify the possible existence of the European crime drop. This time-varying effect can be captured by the stochastic trend and can be interpreted as the "potential" European crime drop. Due to the flexibility of our modeling framework, it is not needed to make the existence of the crime drop explicit beforehand. We consider three variants of the model, from pooling all parameters over the countries to the possibility of estimating country-specific loadings for the cross-national crime drop. To have an equivocal measure of crime over the countries for the considerable period of interest, we create homicide rates based on the World Health Organization Mortality Database. Our proposed model is able to extract the European crime drop as the underlying time-varying factor of the data. The partially pooled variant of the model is most similar to a two-way fixed effects model. The empirical results from both of these models are aligned. The none pooled variant of the model shows the usefulness of allowing for country-specific crime drop loadings. It is also beneficial to allow for a second stochastic trend for East-European countries. The findings are robust against the inclusion of macroeconomic variables in the model. In an additional explorative analysis, univariate results for the US show that the timing of the European and US crime drops coincide.

Keywords: Crime Drop, Europe, Macroeconomy, Time Series Econometrics

1 Introduction

There is a growing literature on the phenomenon known as the "crime drop" in the United States (e.g., Blumstein & Wallman, 2006; Zimring, 2007; Farrell, Tilley, & Tseloni, 2014; Berg, Baumer, Rosenfeld, & Loeber, 2016). The literature about the crime drop in Europe is also expanding and is outlined in the book of Van Dijk, Tseloni, and Farrell (2012). While the US crime drop is quite clear in terms of timing (see the review by Killias & Aebi, 2000), the European crime drop is not so strongly established as of yet. There are even contributions where the European crime drop is disputed and its evidence is taken as rather weak (Aebi & Linde, 2010). It is, however, important to understand whether there are differences between the crime drops in the US and Europe, especially for policy makers. When the crime drops are identified and when their possible differences can be established, the next step is to explain the mechanisms behind the crime drop. But also, when no European crime drop is found, what is the reason and what makes Europe different from the US? Hence, there is societal relevance to establish a possible crime drop in Europe and, if yes, to distinguish it from the one in the US.

Most empirical studies about the European crime drop thus far have been mostly descriptive. Historical homicide rates in Europe were collected for the study of Eisner (2003), for which a database is created for eight countries divided over five regions, even going back to the Middle Ages. Zooming in on the second half of the 1900s, the difference in homicide rates across countries becomes smaller and the rates are increasing until the early 1990s. Killias and Aebi (2000) analyse the rates of property offences, drug offences and violent crimes in 36 European countries between 1990 and 1996, and the resulting trends are compared with those of the US. They suggest that explanations of the US crime drop might not be generalizable to the rest of the world. In a series of papers, Aebi and Linde (2010, 2012, 2014) also describe crime trends across several Western European countries and make a good effort in explaining them. One overall finding is that property offences and homicides are decreasing from the mid 1990s onward, but some opposite patterns exist for other types of crime.

In several studies in the last decade or so, various attempts have been made to model the crime drop. We highlight the contributions that have incorporated macroeconomic variables in their analyses. Rosenfeld and Messner (2012) employ a two-way fixed effects model for burglary growth rates in nine mainly West-European countries and the US for 1993 - 2006. They find that decreasing crime rates are associated with improved economic circumstances, especially reflected by a higher consumer confidence. In a study covering 1960 - 2012 and only concerning US data, Rosenfeld and Levin (2016) use error correction models to show that growth in inflation Granger causes growth in acquisitive crime rates. Van Dijk, Nieuwbeerta, and Joudo Larsen (2021) use commercially produced crime data from more than 160 countries worldwide, however, their analysis starts in 2006, and runs until 2019. Using linear regression models in the main text, and multi-level models in the appendix, they find that organised crime is inversely related with economic activity as measured by gross domestic product (GDP). Recently, Spelman (2022) deployed a linear regression model for the age-period-cohort identification problem. On the basis of US state-level data for 1980 - 2016, this study shows that current period effects (from economic, social and criminal justice system covariates) are as important in determining crime as birth cohorts.

Most of these earlier studies have in common that their focus is on the analysis or modeling of the cross-sectional dimension. The time series dimension is either ignored or not treated with much attention. The study of Rosenfeld and Levin (2016) is the exception but here the emphasis is only on the time series dimension. In our present study, we treat the cross-sectional and time series dimensions equally by introducing the crime drop as a dynamic process in a standard panel data model. We implicity argue with this new development that both dimensions can be treated equally in a modeling framework that is well established in the statistical and econometric literature.

In this paper, we provide the details of the proposed panel data model with stochastic dynamic processes and we use it to test for the absence or presence of the crime drop in Europe. The time-varying effect that is captured by the stochastic trend can be interpreted as the potential European crime drop and it is possible to estimate to which extent each country relies on it. Moreover, we investigate whether there is a surplus crime drop factor for East-European countries. By casting the multivariate model into state space form, we base the analysis on the Kalman filter methods of Durbin and Koopman (2012), which also allows for unbalanced panels.

Since each European country has its own judicial system, we need to ensure that we have a measure of crime that is comparable over countries. Therefore, we collect victim data from the Mortality Database by the World Health Organization (WHO). By using violence as cause of death, we assume that we have a reliable measure to compare homicide rates. Another advantage of this source is the lengthiness of the available time series. We collect data for 19 countries throughout Europe for the period between 1968 and 2015.

Apart from trying to extract the crime drop as a common time-varying factor across countries, we also investigate whether this potential phenomenon remains if we additionally estimate the association with macroeconomic variables. To that order, we collect data from the Penn World Table version 10.0 by Feenstra, Inklaar, and Timmer (2015). We extract measures for the variables gross domestic product (GDP) and welfare. We notice that welfare could represent an additional factor of well-being on top of GDP.

We find that our developed panel data model is able to capture the European crime drop. The partially pooled model is most similar to a two-way fixed model and also gives similar estimation results. In the more extensive none pooled model, we find that each country relies to another extent on the crime drop, which is modeled as the cross-national time-varying factor. There is also an additional factor present for East-European countries (Bulgaria, Hungary and Poland). Even if we include GDP growth rates and welfare growth in the models, we still establish that the crime drop remains a strong phenomenon. We also perform an univariate analysis for the US in order to compare the model performance with earlier research. Here we find that the timing of the US crime drop is similar to the one that is found for Europe.

2 Methodology

We define the dependent variable y_{it} as the homicide rate of country i in year t, with indices $i = 1, \cdots, N$ and $t = 1, \ldots, T$, so that we have N countries and T time periods (years) in a given data set. Furthermore, we denote the k-th explanatory variable of country i in year t as $x_{k,it}$ with scalar regression parameter β_k, for $k = 1, \ldots, K$, so that we have K explanatory variables and parameters. In our empirical analysis, we will use two macroeconomic indicators as explanatory variables.

In a typical two-way fixed effects model, one proceeds with allowing for fixed effects for both the cross-section dimension (countries, with fixed effects denoted by $\mu_i, \forall i$) as well as the time series dimension (years, with fixed effects denoted by $\xi_t, \forall t$). Together with the constant term α, the model is given by

$$y_{it} = \alpha + \mu_i + \xi_t + \sum_{k=1}^{K} \beta_k x_{k,it} + \epsilon_{it}, \tag{1}$$

where ϵ_{it} is an error term with mean 0 and variance σ_ϵ^2. The parameters in such a model are typically estimated by "within-estimation" (via, for example, the `xtreg, fe` command of the statistical software-package `Stata SE 17.0`), which is a standard panel regression method. To account for further serial correlation in the data, the robust standard errors can be clustered at a country-level.

In the context of model (1) and the investigation of the existence of a crime drop, we should focus on the characteristics of ξ_t. When the estimates of the time effects change through time, its pattern will indicate whether there are changes that support a crime drop after, say, the early 1990s. The associated standard errors of these estimates will indicate whether the pattern implies significant changes over time, and hence whether we can conclude that the crime drop is significant. In the setting of model (1), the time fixed effect is equal for each country, assuming that all countries are affected in the same way by the crime drop. In large country panels (large N), it can be rather cumbersome to select or de-select time effects from the equations. The fixed time effects only provide an all-or-nothing strategy for the crime drop in this panel data model. This is a particular shortcoming of model (1) in the context of measuring the crime drop.

In order to account for this shortcoming of the model, we propose to treat the time effects as part of a stochastic trending process instead. This modification of the model allows us to describe the crime drop as a common stochastically time-varying factor across countries, and for which each country can rely on this factor to its own extent. Effectively, we treat the fixed year effects jointly through a stochastic dynamic process which can have different impacts for different countries. We specify the overall crime drop as τ_t and the country-specific crime drop as $\lambda_i \cdot \tau_t$, where λ_i is an unknown fixed parameter and τ_t is subject to a stochastically time-varying trend process. The modified panel data model is then specified as

$$y_{it} = \alpha + \mu_i + \lambda_i \tau_t + \sum_{k=1}^{K} \beta_k x_{k,it} + \epsilon_{it}, \tag{2}$$

where the error term ϵ_{it} is assumed normally distributed with zero mean, that is $\epsilon_{it} \sim \mathcal{N}(0, \sigma_\epsilon^2)$.

The country and time effects are now combined into $\mu_i + \lambda_i \tau_t$, where λ_i is the country-specific "loading" on the time-varying crime drop factor τ_t. The fixed parameters μ_i and λ_i allow for variation over countries while τ_t is specified as a stochastic dynamic process rather than as a set of time fixed effects. As a default, we adopt the stationary autoregressive process of order one for τ_t, that is

$$\tau_{t+1} = \phi \tau_t + \eta_t, \qquad |\phi| < 1, \qquad t = 1, \ldots, T, \tag{3}$$

where ϕ is the autoregressive parameter and disturbance η_t has mean zero, variance $\sigma_\eta^2 > 0$, is mutually and serially uncorrelated, and is uncorrelated with disturbance ϵ_{is}, at all time combinations $t, s = 1, \ldots, T$.

The developed model given by equations (2) and (3) has a very flexible specification. Lagged terms for τ_t can be included in equation (3) to obtain a higher-order autoregressive process. The stationary condition $|\phi| < 1$ can be relaxed as the methodology can also handle non-stationary processes for τ_t such as the random walk process, that is (3) with $\phi = 1$. Finally, the panel data model (2) can be extended with multiple stochastic dynamic processes such as τ_t. This extension will be illustrated in the empirical study of Section 3.

The parameters in the proposed model with the stochastic trend can be pooled and restricted to limit its number. We therefore identify three different variations of equation (2):

(a) Fully pooled	$\mu_i = 0 \ , \ \lambda_i = 1$	$y_{it} = \alpha + \tau_t + \sum_{k=1}^{K} \beta_k x_{k,it} + \epsilon_{it}$
(b) Partially pooled	$\mu_i \in \mathbb{R} \ , \ \lambda_i = 1$	$y_{it} = \alpha + \mu_i + \tau_t + \sum_{k=1}^{K} \beta_k x_{k,it} + \epsilon_{it}$
(c) None pooled	$(\mu_i \ , \ \lambda_i) \in \mathbb{R}^2$	$y_{it} = \alpha + \mu_i + \lambda_i \tau_t + \sum_{k=1}^{K} \beta_k x_{k,it} + \epsilon_{it}$

For the fully pooled model (a), we have no parameters that vary over the countries. The partially pooled model (b) is closely aligned with the two-way fixed effects model of equation (1), with the time fixed effects ξ_t replaced by the stochastic trend τ_t. The none pooled model (c) can be regarded as the most general framework that we consider in this study. All variations of the model have the flexibility to specify a dynamic process for τ_t as an alternative to equation (3).

The estimation of the parameters, including the country effects μ_i, and the estimation of τ_t cannot be done by panel regression methods as they do not account for the dynamic specification of τ_t in equation (3). Instead, we consider linear state space methods as discussed in Durbin and Koopman (2012). For this purpose, we cast the model in state space form where equation (2) is the observation equation and equation (3) is the state update equation for τ_t. This formulation requires some parameters to be known, a-priori, including λ_i and σ_ϵ^2 for equation (2), and ϕ and σ_η^2 for (3). These parameters are collected in the parameter vector ψ. The other unknown (linear) parameters, including α, μ_i, $\{\beta_k\}_{k=1}^K$ and τ_t are placed in the so-called state vector.

The state vector, for each time point t, is estimated by the Kalman filter. The Kalman filter produces the minimum mean squared estimator of the state vector given the observations upto time t. As a by-product, the Kalman filter delivers the one-step prediction errors, including their variances, from which we can compute the (logged) likelihood function, for a given value of ψ. This result follows from the prediction error decomposition of the joint observation density function. By varying the values in ψ and applying the Kalman filter for the new ψ, we obtain the likelihood value associated with the new ϕ. This opens the way to estimate the unknown parameter vector ψ by the method of maximum likelihood, using numerixal optimization methods. Hence the estimation of all parameters is done in two different ways: the parameters in the state vector are treated directly by the Kalman filter (for a given value of ψ) and the parameters in ψ are treated by maximum likelihood where the Kalman filter is used for likelihood evaluation. The Kalman filter methods can handle missing observations so that an unbalanced panel data set can be analysed without further modifications. We use `OxMetrics 9.0` of Doornik (2022) as the programming environment for implementing the estimation methods, with the support of `SsfPack 3.0`, the state space library of Koopman, Shephard, and Doornik (1999).

3 Empirical evidence of an European Crime Drop

In this section, we present our empirical findings and focus on the key questions of whether and how strong the crime drop phenomenon is applicable to Europe by examining a European panel data set of yearly homicide rates for 19 countries and over a period from 1968 to 2015. After a detailed introduction of the data set, we present the results from analyses that are based on on the three variants of our proposed model. Moreover, we allow for a second stochastic process to incorporate for a “surplus crime drop factor” for East-European countries. Finally, we also carry out an univariate analysis for a US time series of yearly homicide rates, in order to compare our European findings.

3.1 Data

The design and construction of our data set have focused on three types of variables: a crime measure, a few macroeconomic indicators and a binary classification for West-/East-European countries. As the early 1990s are typically thought of as the start of the crime drop, the sample period should start well before 1990. Furthermore, we need to ensure that the data that is comparable over all countries, regardless of their specific institutional settings which can, for example, lead to different definitions of crime types.

For our analysis of the crime drop, we have collected data on homicide rates as these are an unequivocal measure of crime across countries[1]. As homicide rates are not directly available for the time period we are interested in[2], we have instead gathered victim data from the World

[1] We also considered police registration data from Eurostat, however, such numbers are potentially too much affected by differences in legal definitions over the countries.

[2] Eurostat, The World Bank and United Nations have homicide data only available from 1990 onward or later.

Health Organization (WHO). From their mortality database, we have used violence as cause of death[3] to extract homicide rates per 100,000 inhabitants. For some countries there is even data available from 1950 onwards, but we start our analysis somewhat later to have a group of 19 European countries for which most data is available for the 48 years between 1968 and 2015[4], we refer to Appendix A for the full list of countries[5]. We plan to model a crime drop for Europe as a whole and also allow for a surplus factor for East-European countries. The classification is based on the Regional Groups of Member States of the United Nations, where Bulgaria, Hungary and Poland are grouped as East-Europe[6].

For all countries together, we present time series plots of the homicide rates in Figure 1. For most countries, we have data for the complete sample period, but there are also some countries with missing observations. As discussed in Section 2, our estimation methodology can handle such unbalanced panel data sets. In the top panel, there are three countries that are on much higher levels than the other European countries, namely Bulgaria, Finland and Hungary. In the early 1990s, also Italy and Poland come close these levels. Therefore, the left panel of Figure 1 only plots these "top 5" countries (the East-European countries Bulgaria, Hungary and Poland as classified before plus Finland and Italy) and the right panel the other 14 countries. For the top 5 countries, the homicide rates fluctuate quite a bit from 1968 until the 1990s between one and three homicides per 100,000 inhabitants. Thereafter, it increases a lot to four to five homicides per 100,000 inhabitants (for Bulgaria the rate even doubles between 1989 and 1995), but also starts to rapidly decrease between 1995 and 2000, which continues until the end of the sample period in 2015 where all five countries are around one homicide per 100,000 inhabitants. Italy and Poland are back on the rates of 1968 in 2015, while Bulgaria, Finland and Hungary are on their lowest point of the sample period in 2015. For the 14 other countries, the development over time is more subtle: it increases slightly until 1990, after which it also slightly decreases. For these countries, the homicide rates in 2015 are on a similar level as in 1968. For most countries, it varies between one-half and just above one homicide per 100,000 inhabitants throughout the sample period.

The Penn World Table version 10.0 of Feenstra et al. (2015) contains the data for the

[3]WHO: Data: Mortality Database: Injuries: Intentional Injuries: Violence.

[4]For Germany, we added data for 1980 - 1989 through the German Federal Statistics Office GENESIS, and we compared the post-1990 period with WHO data to verify its reliability for the pre-1990 decade.

[5]We dropped Iceland, Luxembourg and Malta because of their small population sizes, moreover, we also dropped Russia because its homicide rates were considered to be outliers throughout the sample period.

[6]Other East-European countries cannot be included, because the macroeconomic data is lacking until the mid-1990s or later.

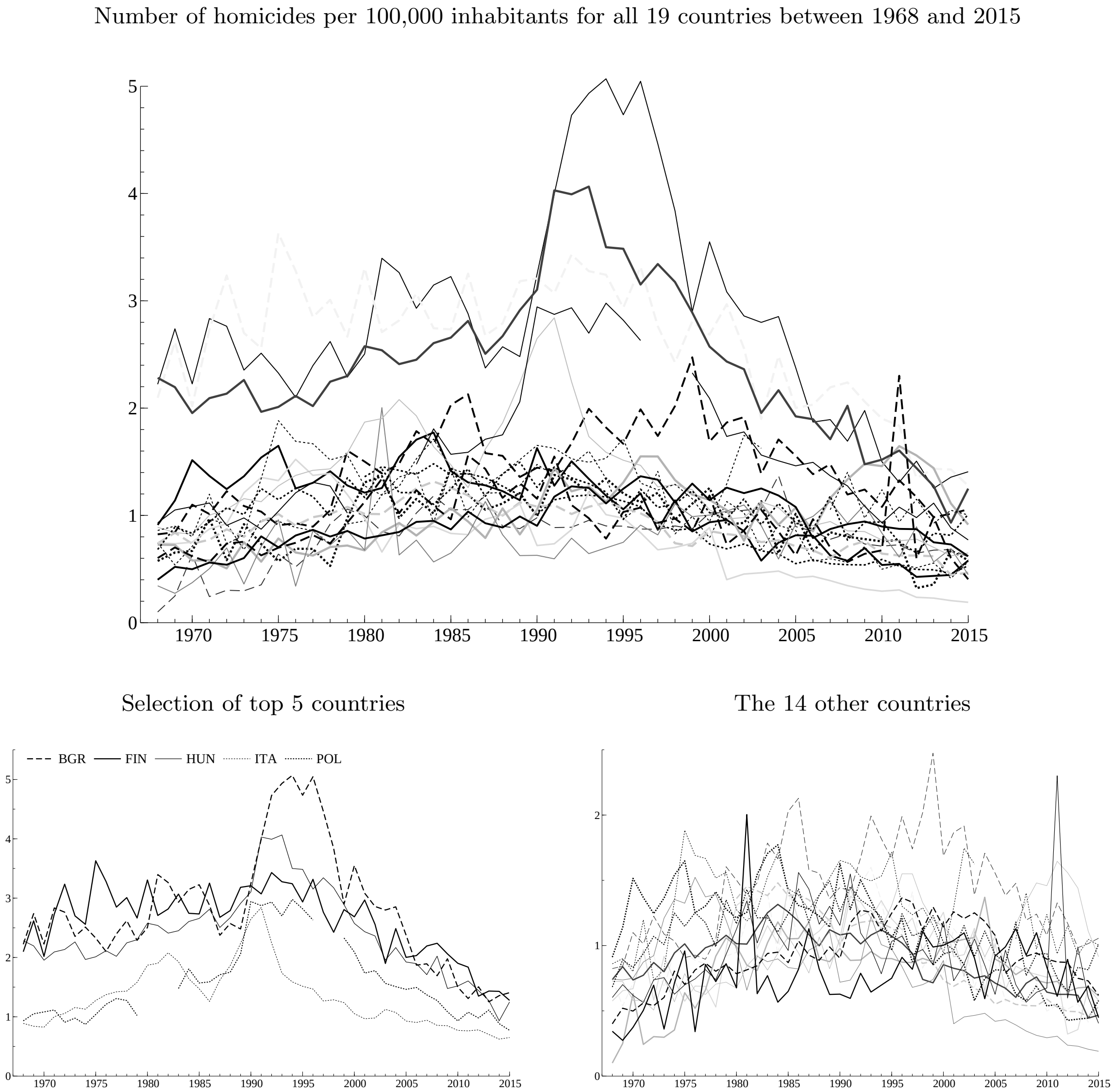

Figure 1: Time series plots of the homicide rates per 100,000 inhabitants between 1968 and 2015. Top panel for all 19 European countries, lower-left panel for the top 5 countries (East-European countries Bulgaria, Hungary and Poland plus Finland and Italy), and lower-right panel for the remaining 14 countries. The full list of countries is given in Appendix A.

macroeconomic variables of each country in the panel, and for the time period under investigation. We have collected expenditure-side real gross domestic product (GDP) at chained purchasing-power-parity, such that comparisons between countries and over the years can be made. Augmented Dickey-Fuller tests based on Dickey and Fuller (1979) are used to test for the presence of an unit root in the time series and as GDP tends to be non-stationary, we create an approximation for percentage growth in GDP per 100,000 inhabitants by taking first differences of the logarithms. As GDP is mostly an indicator of the country's economic performance, we also have collected welfare data as a more broad concept of well-being. For our analysis between European countries, we prefer the use of welfare-relevant total factor productivity levels at current purchasing-power-parity[7] and taking first differences to create growths. We use the term "growth rates" for relative growth or differences in logs (as for GDP), while we use "growth" for absolute growth or first differences (as for welfare).

The time series plots of GDP growth rates and welfare growth for all 19 countries between 1968 and 2015 are plotted in Figure 2. We clearly see that for both macroeconomic series, expansions are followed by contractions and vice versa. However, on the outset it might seem that the two are almost perfectly co-moving with each other and that the one does not add much to the other. Therefore, Appendix B presents counts per year for how many countries GDP increased or decreased and simultaneously welfare increased or decreased. It shows that it is not always the case that as GDP increases/decreases that welfare also increases/decreases, hence the signs of GDP growth rates and welfare growth do not necessarily align, which is the variation in the data that we need.

3.2 Models With and Without Macroeconomic Regressors

In this empirical study, we consider our proposed model as given by equations equations (2) and (3) and use it for the modeling of our data set of 19 European countries, and for the years from 1968 to 2015. In the specification of the time-varying crime drop factor τ_t, as defined in (3), we take $\phi = 1$ so that we have effectively a random walk process for τ_t. Furthermore, we consider the fully pooled, partially pooled and none pooled variants. Apart from the model specification with all explanatory variables included ($K = 2$, with GDP growth rate and welfare growth as exogenous variables), we also consider the model specification without explanatory variables ($K = 0$). The parameters of the models are estimated partly by the Kalman filter directly and

[7]The alternative would be to use welfare-relevant total factor productivity levels at constant national prices, however, these are comparisons within countries over time and not between countries.

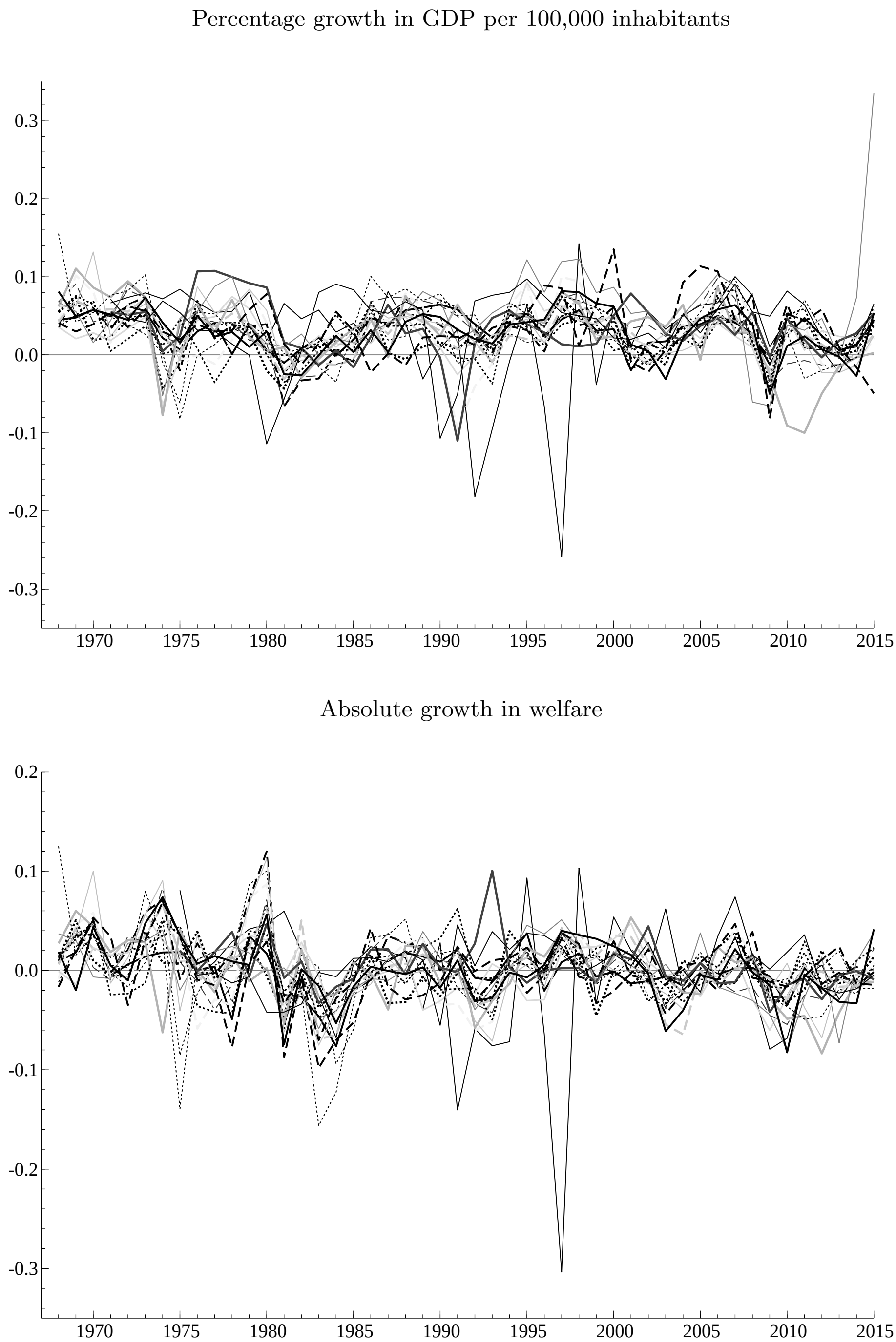

Figure 2: Time series plots of growth domestic product (GDP) growth rates (top panel) and welfare growth (bottom panel) for all 19 countries between 1968 and 2015. The 19 countries with their three-letter country codes are listed in Appendix A.

partly by the method of maximum likelihood as discussed in Section 2. The resulting maximized log likelihood values (LL) are reported in Table 1, as well as the estimated parameters with standard errors for all models[8].

In all model variants, the inclusion of the two explanatory variables in the model specification leads to higher likelihood values. For example, for the fully pooled model, the difference in logged likelihood values between the model with $K = 2$ and $K = 0$ is 39.86. This distance-measure for partially pooled and none pooled models is also large, that is 25.7 and 21.32, respectively. We can further conclude from the results in Table 1 that the none pooled variant is the preferred model. The maximized logged likelihood value is the largest for the none pooled with $K = 2$.

Model	Effects	$\text{LL}_{K=0}$	$\text{LL}_{K=2}$	GDP		Welfare	
Fully pooled	τ_t	-976.35	-936.49	-1.13^{*}	(0.78)	-0.24	(0.90)
Partially pooled	$\mu_i + \tau_t$	-388.79	-363.05	-2.07^{**}	(0.41)	-0.19	(0.46)
None pooled	$\mu_i + \lambda_i \tau_t$	-172.94	-151.62	-0.77^{**}	(0.31)	-0.66^{*}	(0.36)

Table 1: Estimation results of all three variants of the developed model. The first two columns give the exact specification of the model, where μ_i is the country fixed effect, τ_t the stochastic time trend and λ_i its country-specific fixed loading. The third and fourth columns give the maximized logged likelihood value for the models without ($K = 0$) and with macroeconomic regressors ($K = 2$), respectively. The estimated parameters of GDP growth rate and welfare growth are given in the final columns, with standard errors in parentheses, and where * denotes a 10% significance level, ** 5% and *** 1%.

From the parameter results in Table 1, we find that the estimates vary widely between the different levels of pooling. For example, the estimates for GDP growth rate vary between -0.77 and -2.07, while in all three cases the estimates are significantly different from zero, at least at the 10% significance level. Despite the fact that the estimates are somewhat different amongst the several model specifications, the signs of the estimates are the same amongst the models. Overall, we can conclude from the model estimates that a positive GDP growth rate leads to a decline in the number of homicides. This conclusion also applies to welfare growth (positive welfare growth leads to a decline in homicides) but this effect is only significant at the 10% significance level for the none pooled model.

A key defining element of our proposed model is the stochastic trend τ_t which we can refer

[8] We also have estimated the parameters in the two-way fixed effects model equation (1); these results are close to those reported for our partially pooled model which has a comparable specification (the country effects are both fixed, and both have a time effect of which for the latter model is fixed and for the former is stochastic).

to as the "potential" European crime drop factor. A particular feature of the specification of τ_t and the method of its estimation is that they do not require an a-priori decision on where and how the crime drop takes place for a given data set. At the same time, the adopted methods are still able to infer whether the crime drop actually took place and after which particular year. The smoothed estimates[9] of τ_t for all model variants are presented in Figure 3. The solid line is the estimate of the time-varying τ_t based on the maximum likelihood estimate of σ_η^2 and it is surrounded by dotted lines which indicate the 95% confidence interval. In all model specifications, the time-varying trends are clearly significantly varying over time. We can conclude that all model variants are able to capture the crime drop. In the model specifications without explanatory variables, the time-varying factor is increasing until the early 1990s. It decreases directly after, to the level of the 1970s. When the explanatory variables are included in the model, this pattern remains. Hence, the crime drop phenomenon persists in the data, even when we control for macroeconomic circumstances. We further find that no impact of the crime levels around the start of the European debt crisis in 2009 can be detected.

For the none pooled model, the loading parameters λ_i, for $i = 1, \ldots, N$, allow some countries to rely strongly on τ_t, with its crime drop feature, while other countries may rely on it less strongly. The estimated loadings of the individual countries λ_i on the crime drop factor are visualized in Figure 4, where we have Germany chosen as the reference country and its loading has been fixed at unity. The differences in the loading estimates for the models without or with the macroeconomic variables are negligible. In both models, Bulgaria, Finland, Hungary, Italy and Poland (the "top 5" countries of Figure 1) rely on the time-varying factor strongly, while the loading estimates of Greece and Ireland are very small. Furthermore, there is only some moderate variation within the loading estimates of the other countries. The main conclusion here is that most European countries have been subject to the crime drop.

3.3 Including an Eastern European Factor in the Crime Drop

To address our main question of whether there is significant evidence of a European Crime Drop, we have considered the model equations (2) and (3) with the inclusion of a single stochastic trend τ_t of which the dynamic specification is given by equation (3) with $\phi = 1$. However, the model can be extended with more stochastic dynamic processes in order to provide a better

[9] The smoothed estimate of a time-varying effect, such as τ_t, is constructed by using all data, those at time points in past, present and future, with respect to t. The smoothing method is associated with the Kalman filter, see Durbin and Koopman (2012, Chapter 4).

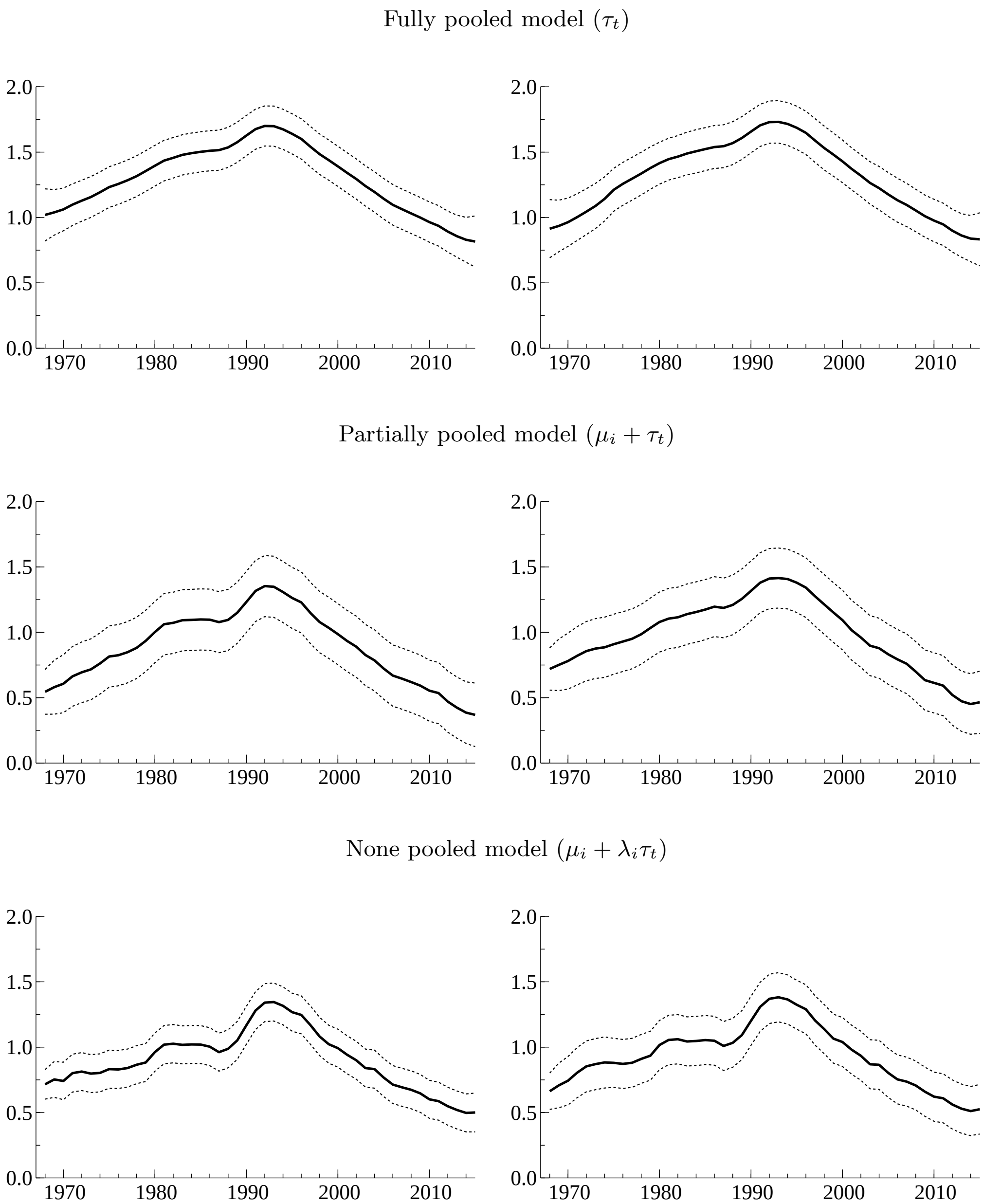

Figure 3: Time effects from all three variants of the developed model. Left panels for models without regressors ($K = 0$) and right panels for models with GDP growth rates and welfare growth included ($K = 2$). μ_i is the country fixed effect, τ_t the stochastic time trend (plotted with confidence intervals) and λ_i its country-specific fixed loading.

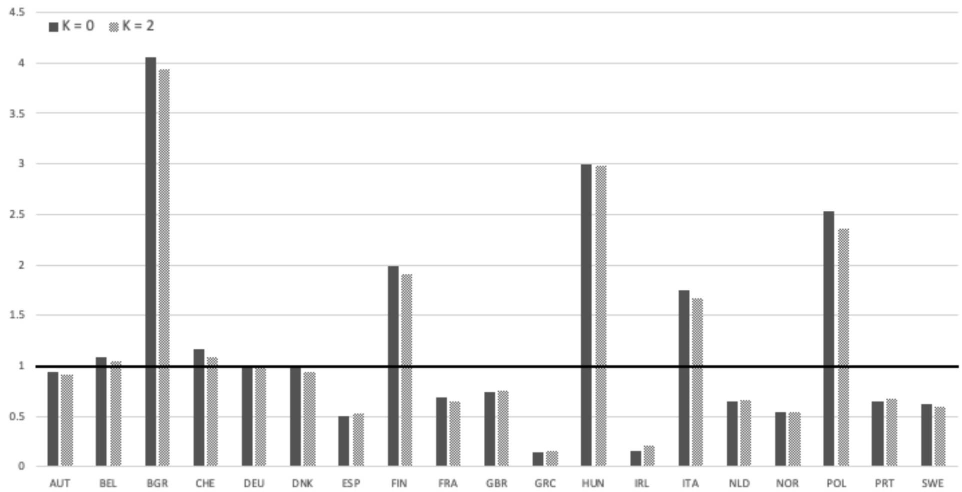

Figure 4: Country-specific crime drop loadings estimated from the none pooled model. Solid left bars for model without macroeconomic regressors ($K = 0$) and dotted right bars with GDP growth rates and welfare growth ($K = 2$) included. Germany has value one for both because it is the reference category. Three-letter country codes are listed in Appendix A.

description of the dynamic properties of the time series in our European country panel. In particular, we can include a second time-varying effect, denoted by δ_t, that we exclusively associate with the East-European countries Bulgaria, Hungary and Poland. In this way, we can analyse whether there is a "surplus factor" for these countries on top of the "general crime drop" for all European countries. Below, we present and discuss the estimation results for the none pooled model where both explanatory variables are included.

The maximized logged likelihood value and the estimated parameters are given in Table 2. When compared to the earlier results, based on the model with only one stochastic trend τ_t for all countries, the maximized logged likelihood increased much (from -151.62 to -93.97). Moreover, the effect of the GDP growth rate remains similar (from -0.77 to -0.60, both significant at the 5%-level), as well as the effect of welfare growth (from -0.66 significant at 10% to -0.85 significant at 5%). This implies that positive GDP growth rates and welfare growth are still associated with a decrease in the homicide rates.

Analysis with "Eastern surplus factor"	$\text{LL}_{K=2}$	GDP		Welfare	
None pooled model ($\mu_i + \lambda_i \tau_t + \delta_t$)	-93.97	-0.60^{**}	(0.30)	-0.85^{**}	(0.33)

Table 2: Results estimating the none pooled model with both macroeconomic regressors and a second time trend added for East-European countries. μ_i the country fixed effect, τ_t the stochastic time trend with λ_i its country-specific fixed loading and δ_t the "surplus factor" for East-European countries. The second column gives the maximized logged likelihood value. The estimated parameters of GDP growth rate and welfare growth are given in the final columns, with standard errors in parentheses, and where * denotes a 10% significance level, ** 5% and *** 1%.

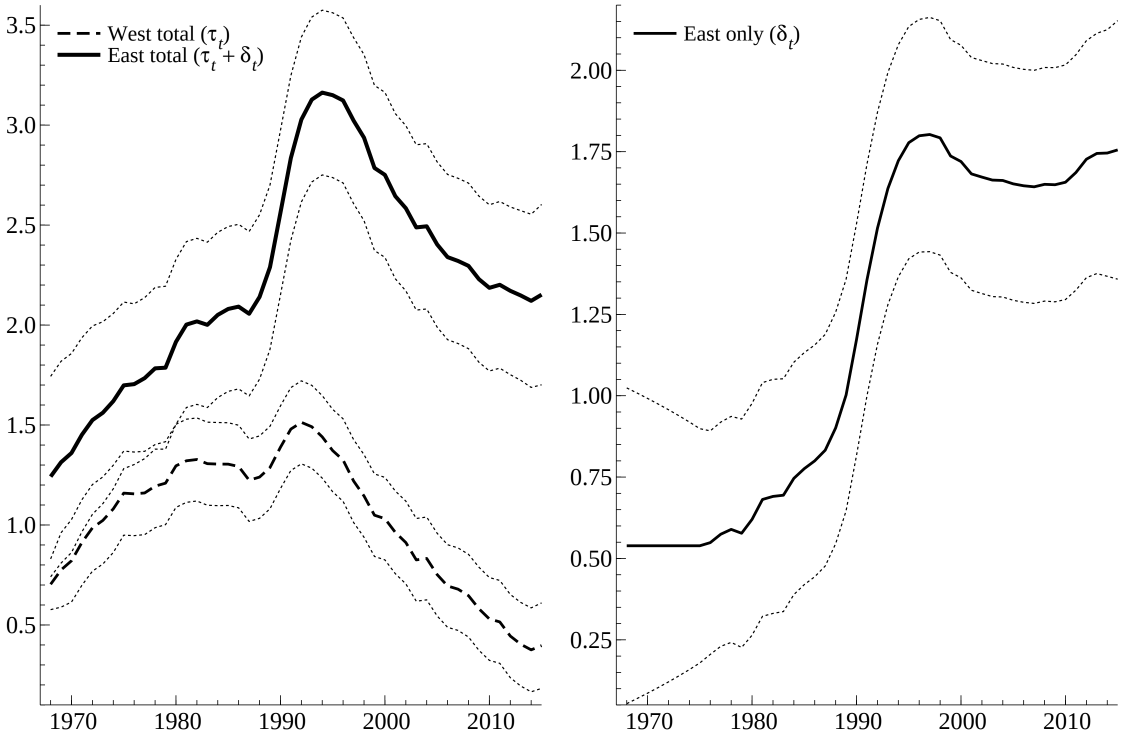

Figure 5: Time effects from the none pooled model with both macroeconomic regressors and a second time trend added for East-European countries. τ_t is the regular stochastic time trend (left panel, dashed) and δ_t the "surplus factor" for East-European countries (right panel). The solid line in the left panel is $\tau_t + \delta_t$, the crime drop for the East-European countries Bulgaria, Hungary and Finland. All time trends are plotted with their confidence intervals.

The estimates of the two stochastic trends in the none pooled model are presented in Figure 5. The estimate of the stochastic trend δ_t for East-European countries is pictured in the right panel. The left panel can be interpreted as follows: the lower trend estimate is for τ_t and is the crime drop factor for West-European countries (all European countries, except Bulgaria, Hungary and Poland), while the upper trend estimate is for $\tau_t + \delta_t$ and is the crime drop for the three East-European countries specifically. There is a clear difference between these two estimates because of the inclusion of δ_t. It makes the presence of the crime drop in West-European countries even more convincing: after the peak of the estimate of τ_t in the early 1990s, it decreases to a level much lower than in the 1970s. The crime drop is also present in East-European countries, as the estimate of $\tau_t + \delta_t$ peaks in the early 1990s and it decreases in the years after, but it remains below the level of the 1970s, because the estimate of δ_t does not truly decrease after 1990.

Also for this none pooled model, we extracted the country-specific loading estimates for the crime drop τ_t. These estimates are visualized in Figure 6, with the loading of Germany fixed at unity. The left solid bar for each country is the same as in Figure 4 for the none pooled model with the two macroeconomic regressors (which were almost identical to the none pooled model without those regressors) but without the East-European "surplus factor". The right dotted bar is for the model with δ_t included. We still find that countries have different loading estimates for the crime drop, but they broadly have decreased in value.

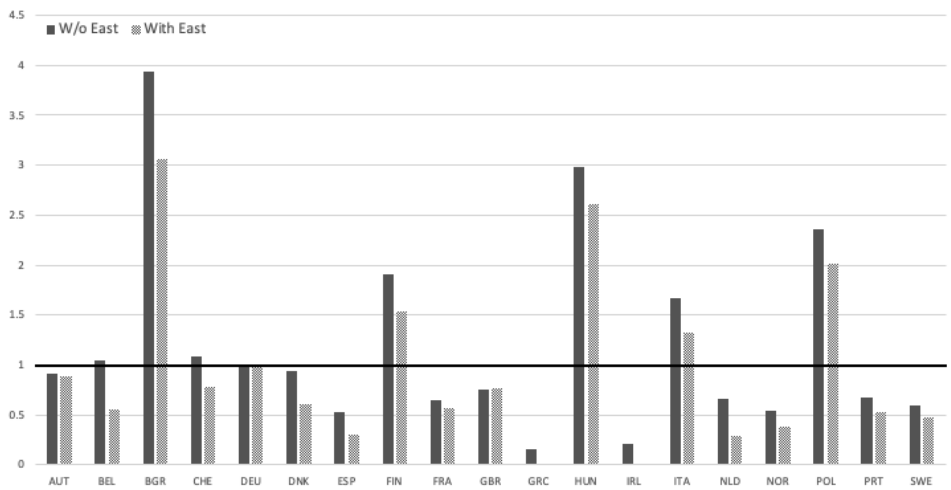

Figure 6: Country-specific crime drop loadings estimated from the none pooled model with both macroeconomic regressors. Solid left bars for model without East-European trend and dotted right bars with it. Germany has value one for both because it is the reference category. Three-letter country codes are listed in Appendix A.

3.4 Comparison with the US Crime Drop

In order to put our European results into some perspective, we want to compare our results with those of the United States (US). For this purpose, we perform the same analysis for the US. We use a database created from the same sources as for the European analysis (discussed in Section 3.1), but with a slightly different measure of welfare (recall footnote 7). The number of homicides per 100,000 inhabitants in the US is plotted in the left panel of Figure 7. Comparing it to the European data of Figure 1, we see that US homicides are on a much higher levels, with 7 to 11 homicides per 100,000 inhabitants until the early 1990s. There is a rapid decrease after 1994, but it never falls below 5 homicides per 100,000 inhabitants.

Since we no longer gave a cross-national analysis, we base the US analysis on a single equation model. This implies that country fixed effects are no longer needed (the constant term takes over this role) and country-specific loadings can also be omitted (there is only one country). Hence, we only consider the fully pooled model, with both macroeconomic variables included. We present the maximized logged likelihood values and the estimated parameters in Table 3. Although the signs of the parameters for GDP growth rates and welfare growth are still the same, thus negative, they are no longer significant at the 10%-level. That is, we do not find any explanatory power from the macroeconomic regressors for homicide rates in the US.

Analysis for US only	$LL_{K=2}$	GDP		Welfare	
Fully pooled model (τ_t)	-32.18	-4.90	(4.36)	-5.69	(8.05)

Table 3: Results estimating the fully pooled model with both macroeconomic regressors for US data. τ_t is the stochastic time trend. The second column gives the maximized logged likelihood value. The estimated parameters of GDP growth rate and welfare growth are given in the final columns, with standard errors in parentheses, and where * denotes a 10% significance level, ** 5% and *** 1%.

The estimate of the stochastic trend of the model, which can be interpreted as the US crime drop, is depicted in Figure 7 as the solid line in right panel. The dashed line in this panel is the estimated European crime drop factor that we have established in Figure 3 earlier, for the none pooled model with both macroeconomic regressors included. To compare the timing of the European crime drop with the US one, we matched the location and scaling. We actually can conclude that the crime drop estimates for Europe and US are fairly similar: there is an increase between 1968 and 1992/1993, after which it rapidly decreases until the end of the sample period. So, it seems that for both continents, the timing of the crime drop aligns.

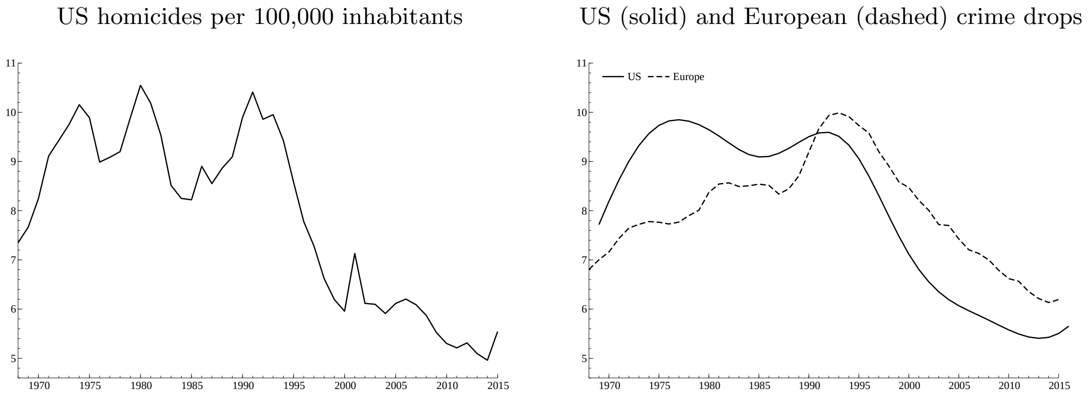

Figure 7: Data and results for univariate analysis of US. Left panel: time series plot of US homicide rates per 100,000 inhabitants between 1968 and 2015. Right panel: crime drops for US (solid, fully pooled model with both macroeconomic regressors) and Europe (dashed, none pooled model with both macroeconomic regressors), for which location and scaling are matched.

4 Discussion and Conclusion

In this paper, we have developed a panel data model with stochastic dynamic processes to verify the existence of the European crime drop. We created a data set with homicide rates based on the WHO Mortality Database to have an unequivocal measure for crime in 19 European countries during 1968 – 2015. With our model, we could estimate and plot the underlying stochastic time trend. The time-varying effect that was captured by the stochastic trend could be interpreted as the "potential" European crime drop. Due to the flexible modeling approach, it was not needed to make the existence of the crime drop explicit beforehand. Our analysis showed that the European crime drop exists and started in the early 1990s.

We have considered three variants of the model, from pooling all parameters over the countries to the possibility of estimating country-specific loadings on the crime drop. The partially pooled model "in between" was most similar to a two-way fixed effects model, where the time fixed effects are replaced by a stochastic time trend, but both have the rather restrictive assumption that all countries experience the exact same crime drop. Our none pooled model showed that the country-specific crime drop loadings actually differ. More specifically, Bulgaria, Finland, Hungary, Italy and Poland relied much more heavily on the crime drop than the reference category Germany, while Greece and Ireland just had minor loadings. Countries like Austria, Belgium, Czech and Denmark are similar to Germany, while Spain, France, the UK, Netherlands, Norway, Portugal and Sweden have a somewhat lower loading. This important distinction adds to the more overall findings in the chapters of Van Dijk et al. (2012) and also to the debate opened by Aebi and Linde (2010).

It was also beneficial to allow for a second stochastic trend for East-European countries. We saw the crime drop is also present in East-European countries but to a lesser extent than for West-European countries, showing that the results of, for example, Aebi and Linde (2010, 2012, 2014) for West-European countries are not generalizable to the whole continent. Moreover, we found that the European and US crime drops took place around the same time, which is somewhat different from those found by Killias and Aebi (2000), which is a descriptive analysis, and Rosenfeld and Messner (2012), employing a two-way fixed effects model.

The most important limitation of the current research, is that we did not attempt to make any causal claims regarding the macroeconomic variables and its mechanisms for explaining homicide rates. We just found that our crime drop findings were robust against including macroeconomic variables and that positive GDP growth rates and welfare growth were associated with lower homicide rates. Therefore, future research could benefit from moving into this direction and we present some possibilities. Differences in policies or unexpected events in European countries could be exploited to achieve causality. Harvey and Thiele (2021) recently showed that this can also be done with time series models. Moreover, it is challenging to find sufficient data for the pre-1990 period. This not only holds for analysing different types of crime, but also for the macroeconomic variables. Since Rosenfeld and Levin (2016) showed that inflation growth Granger caused acquisitive crime growth in the US, it would be worthwhile to add inflation as another explanatory variable to our model if such data becomes available. Also other macro-level variables, for example related to social and criminal justice systems as was done for the US by Spelman (2022), could be interesting to add.

Generally speaking, our research adds to the (European) crime drop literature by showing that it is beneficial to treat the cross-sectional and time series dimensions equally. To our knowledge, this research is the first to extract the crime drop as a stochastic factor. In more traditional models, such as the two-way fixed effects model, it would be too cumbersome, if not impossible, to vary the time fixed effects over the countries. By modeling the crime drop as a stochastic trend instead, we were able to allow for country-specific loadings on this crime drop and therefore could show that not all European countries experience the crime drop in the same way.

A Country Codes

AUT	Austria
BEL	Belgium
BGR	Bulgaria
CHE	Switzerland
DEU	Germany
DNK	Denmark
ESP	Spain
FIN	Finland
FRA	France
GBR	United Kingdom of Great Britain and Northern Ireland
GRC	Greece
HUN	Hungary
IRL	Ireland
ITA	Italy
NLD	Netherlands
NOR	Norway
POL	Poland
PRT	Portugal
SWE	Sweden

B Sign Counts of Macroeconomic Regressors

	Increasing GDP		Decreasing GDP		
Year	Incr. welfare	Decr. welfare	Incr. welfare	Decr. welfare	Total
1968	12	4	0	0	16
1969	14	2	0	0	16
1970	15	1	0	0	16
1971	7	9	0	0	16
1972	10	6	0	0	16
1973	15	1	0	0	16
1974	11	0	4	1	16
1975	11	1	3	4	19
1976	9	8	0	2	19
1977	7	10	0	2	19
1978	12	7	0	0	19
1979	16	2	0	1	19
1980	16	1	0	2	19
1981	2	4	0	13	19
1982	7	4	3	5	19
1983	1	10	0	8	19
1984	0	15	0	4	19
1985	4	11	0	4	19
1986	10	8	1	0	19
1987	12	6	0	1	19
⋮					

Continues on next page

Table B.1: Counts per year for how many countries GDP increased or strictly decreased and simultaneously welfare increased or strictly decreased. The total number of countries in the sample is 19, but the macroeconomic data is not available for the East-European countries until 1975.

	Increasing GDP		Decreasing GDP		
Year	Incr. welfare	Decr. welfare	Incr. welfare	Decr. welfare	Total
⋮	*Continuing from previous page*				
1988	12	5	0	2	19
1989	13	5	0	1	19
1990	8	8	1	2	19
1991	9	4	1	5	19
1992	2	12	0	5	19
1993	4	8	0	7	19
1994	14	4	0	1	19
1995	15	4	0	0	19
1996	8	10	0	1	19
1997	18	0	0	1	19
1998	16	3	0	0	19
1999	8	10	0	1	19
2000	15	4	0	0	19
2001	12	2	1	4	19
2002	7	6	1	5	19
2003	2	13	0	4	19
2004	5	14	0	0	19
2005	8	10	0	1	19
2006	6	13	0	0	19
2007	15	4	0	0	19
2008	11	7	0	1	19
2009	1	1	0	17	19
2010	2	15	0	2	19
2011	8	8	0	3	19
2012	5	8	0	6	19
2013	1	6	1	11	19
2014	3	9	0	7	19
2015	8	10	0	1	19

Table B.2: Counts per year for how many countries GDP increased or strictly decreased and simultaneously welfare increased or strictly decreased. The total number of countries in the sample is 19, but the macroeconomic data is not available for the East-European countries until 1975.

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