The Effect of Unemployment on Crime for High Risk Families in The Netherlands between 1920 and 2005

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February 18, 2013

Abstract

In this paper we analyze the relationship between unemployment and crime. Using individual-level data for the members of approximately 180 high risk families between 1920 and 2005, we estimate the effect of the national unemployment rate on the probability of being convicted for a serious, property or violent crime. We control extensively for family-specific and macroeconomic variables and include both static and time-varying random effects. Our results show small, but significantly positive, effects of unemployment on property crime after 1950 that are stable across various model specifications. Testing whether the observed findings are causal, time-varying effect of the unemployment rate were estimated and showed that indeed the families became more responsive to changes in the unemployment rate with respect to property crimes after 1960. Our estimates suggest that a substantial portion of the fluctuation in property crime after 1950 is attributable to the fluctuation in the national unemployment rate.

Some keywords: Unemployment; Convictions; Property; Panel Data; Binomial.

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1 Introduction

The relationship between the labor market and criminal behavior has been of long-standing interest in the social sciences. The economic analysis of this relationship started with the seminal contributions of Becker (1968) and Ehrlich (1973). The intuitive appeal of the argument that improving labor market conditions cause individuals to commit less crime is apparently so self-evident that the empirical evidence should be overwhelming. However, only in roughly the last decade have researchers been able to document reliable significant effects of various labor market conditions on crime rates. By employing novel panel data strategies Doyle, Ehsan Ahmed & Horn (1999), Raphael & Winter-Ebmer (2001), Gould, Weinberg & Mustard (2002), Papps & Winkelmann (2002), Machin & Meghir (2004), Ihlanfeldt (2007) and Lin (2008) have been able to identify causal effects of labor market outcomes on crime rates. A typical analysis by one of the aforementioned authors exploits geographical variation in crime rates and labor market opportunities to estimate the effect of the labor market outcomes, while controlling for a host of confounding variables. Further, to establish the direction of causality[1] various combinations of instrumental variables have been suggested to instrument for the labor market outcomes. Mustard (2010) surveys the economic-crime literature, with an emphasis on modeling difficulties and international comparison.

To this date, little evidence has been produced for a relationship between crime and labor market opportunities in the Netherlands. Jongman (1982), Jongman (1988) and Ploeg (1991) discuss this relationship from various angles, but their work is mainly descriptive. Further, using individual-level data, Miedema (1997), Geest, Bijleveld & Blokland (2011) and Geest (2011) investigate the criminal and employment careers of high risk males. From their work it can be concluded that employment is likely to be negatively correlated with criminal behavior for low-skilled males. However, the direction of causality that is implied remains unclear.

[1] This is necessary as the direction of causality in the relationship between labor market outcomes and crime rates is not known a priori. Crime rates can causally influence labor market outcomes and vice versa, see Grogger (1998) and Raphael & Winter-Ebmer (2001) for a more elaborate discussion.

This paper examines the degree to which changes in the conviction rates of 181 high risk families from the Netherlands can be explained by changes in the national unemployment rate. The families consist of four generations, that are observed between 1920 and 2005. The first generation consists of males who were institutionalized in a reform school in their teenage years. They come from low social classes and they and their descendants are at high risk of offending compared to the average Dutch population. Bijleveld, Wijkman & Stuifbergen (2007) discuss the sample and its origins in detail. Their characteristics makes these families a very interesting subgroup of the population to examine, as Grogger (1998), Gould et al. (2002) and Machin & Meghir (2004) find that unskilled workers are more likely to commit crimes when their labor market prospects decrease. In this paper we establish whether the national unemployment rate has a causal effect on the criminal behavior of the families and whether this effect varies over time.

Very few studies so far have examined crime and unemployment trends over such a long time span - 85 years. This approach gives a chance to challenge the perception that the association between crime and unemployment may be unchanging. It is rather likely that the relationship is influenced by for example societal and political changes. Furthermore, the family-level of analysis provides several modeling benefits compared to the standard individual-level or macro-level analyses. First, it allows us to control for demographic and socio-economic status variables at the family level. Second, the constructed family-specific time series are more informative compared to individual-specific time series. Third, the family-level avoids the explicit modeling of correlations between family members, which is shown to be quite complicated even in a static framework, see Durlauf & Ioannides (2009). Fourth, simultaneity problems, thus reverse causality from crime on unemployment rate, are virtually non-existent as the effect of the criminal behavior of the families on the national unemployment rate is negligible. Fifth, we limit a bias caused by omitting of variables by controlling extensively for national trends in criminal opportunities, justice policies and criminogenic factors, as a large sample of these measures is available at the national level.

The analyses in this paper are divided in two parts. First, we estimate a large variety of model specifications to establish the overall robustness of the effect of the unemployment rate on the conviction outcomes. This is done for two time periods: 1920-2005 and 1950-2005. We consider three samples of convictions. A full sample containing all convictions for serious crimes and two samples containing only property or violent convictions. The models that we consider are included in the class of generalized dynamic panel data models proposed by Mesters & Koopman (2012). The estimated models differ with respect to the inclusion of control variables. Three types of control variables can be distinguished in our models. First, a set of family-specific control variables is included to control for the demographic and economic composition of the family. Second, a set of macro-level trends is included to control for pro-cyclically varying factors. These factors have been categorized by Cook & Zarkin (1985) and their exclusion can understate or overstate the effect of the unemployment rate, see the discussion in Raphael & Winter-Ebmer (2001). Third, we exploit the features of our panel data by including time-invariant family-specific effects, time-varying common effects and lagged offending outcomes. The latter capture the causal effect of crimes committed in the family in the previous time period, see also Machin & Meghir (2004).

In our second analysis we seek to establish whether similarities in the fluctuations in the conviction rates and the national unemployment rate can be considered due to a changing causal effect. The two rates show more similarities after 1950, see Figure **??**. To formally investigate whether a changing effect is present, we estimate a time-varying regression effect for the unemployment rate, see Durbin & Koopman (2001, Chapter 3). Between 1920 and 2005 Dutch society changed in many respects. For example, society has evolved and consumerism rather than frugality has become the norm, implying that the possession and flaunting of material goods has become more important than modesty and restraint. Also, social control through institutions, such as the church and the extended family or the neighborhood has strongly declined. The impact of these secular changes on the effect of unemployment is unknown. We discuss what factors might be causing the changes.

The remainder of this paper is organized as follows. The next section describes the data. Special interest is in describing the trends that exist in the conviction outcomes and the unemployment rate. Section 3 discusses our main empirical strategy. Here we describe our basic panel data models and discuss our control variables. In Section 4 we allow for time-varying effects of the unemployment rate. In Section 5 we present our conclusions and possibilities for further research.

2 Data

The crime data originates from the TRANS-5 study, see Bijleveld et al. (2007). The TRANS-5 dataset consists of observations for five generations of families, G1-G5, as shown in Figure 1. Permission for the study was obtained from the legal successor of the Harreveld institution, the Frentrop foundation, as well The Netherlands Minister of Justice. The five generations are ancestors and descendants of the original sample (G2), which consists of 198 males who were institutionalized in a Catholic reform school between 1911 and 1914. They were sent there for various reasons, such as criminal behavior or disrupted family situations. In the reform school, they received, if necessary, elementary education and stayed until they had finished accredited vocational training to become, for example, a carpenter, baker, painter, or shoemaker. The offspring of the G2 males and their spouses were traced in Dutch genealogical and municipal records, resulting in a 100% retrieval rate. Sample members of G2 who had emigrated, or died before the age of 21, were considered lost to follow-up and their descendants were not traced. After removing these, 181 men remained who had offspring that is labeled G3; subsequent generations are labeled as G4 and G5.

In this paper, we rely on four generations, G2-G5, as criminal data for the G1 generation was available but was probably incomplete. In total, we included 4,120 individuals, to which an additional 1,919 spouses could be linked, resulting in 6,039 men and women. Each individual is included from age 12 to 60. The lower limit is chosen as 12 years is the age of legal accountability in the Netherlands. The upper bound is chosen for two reasons. First, little criminal acts can be expected from older individuals (the records also show this) and second, until recently, most individuals quit working around age 60, either voluntary

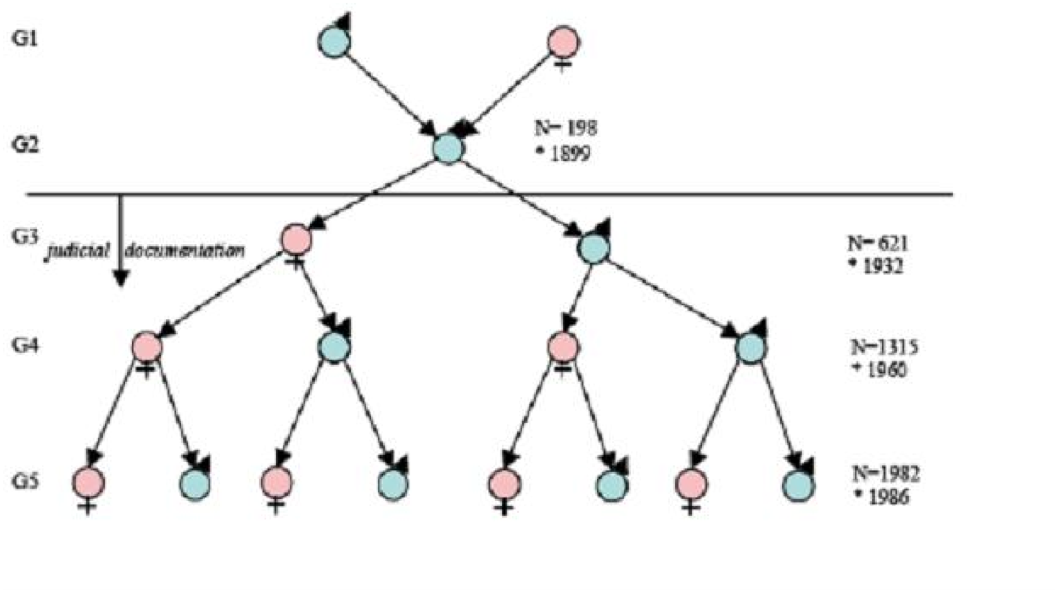

Figure 1: Design of the five-generation sample

or forced. Observations between 1920 and 2005 are included for generations G2 to G5. The individual-level information on these individuals is aggregated to extended family level, where the 181 males are considered as the original family members. The 181 male members were on average 21 years of age in 1920. The family data and its retrieval procedure are described below.

2.1 Conviction data

For all sample members born after 1916, judicial information was collected from the archives of the Dutch Criminal Records Documentation Service. As a result, detailed information concerning the complete criminal career for the generations G3, G4 and G5 is available. For those born before 1916 (G2), information about delinquency was gathered from several sources: district court archives, police archives, prison archives and beggars' colonies' records. We will consider three different samples of convictions: serious convictions, property and violent convictions. We operationalized serious criminal behavior according to the definition of Loeber, Farrington & Washbush (1998). Sample members who had been convicted for one or more of the following crimes were defined as serious offenders: violent offenses, property offenses, drugs offenses, arson and violations of weapons and firearms regulations. In constructing our dependent variable, only those registrations were used that were not acquitted or dismissed for 'technical' reasons (predominantly because the prosecutor deemed that insufficient proof was available). Consequently, the collected data represent the lower limit of actual offending. We time delinquency to the date the offense was committed. If no date was known, we estimated it as date of conviction minus the average duration of disposition, set at one year. If no disposition date was known we estimated it at 1 July of the year of registration. Following these rules, we therefore always classify crimes in the manner in which the last criminal justice institution that dealt with the case classified it. More information may be found in Bijleveld et al. (2007). Prevailing definitions of the period under investigation were used to define acts as delinquent, see Bijleveld et al. (2007). As data on matched controls are also available, we are able to assess that these respondents are indeed high-risk: around 50 per cent of the G3, G4 and G5 men were convicted for at least one offense against around 20 per cent of control men, the women are also at elevated risk, see Bijleveld et al. (2007).

In Figure 2 we show the sample conviction rate (left column). This is the number of individuals who got convicted for a serious, property or violent crime in each year, divided by the total number of individuals present in each year. For example in 2005, approximately 2% of the individuals present in the sample was convicted for a serious crime. In the period between 1920 and 1930 higher levels of convictions are found. This is caused by the fact that fewer individuals are present in these periods (approximately 400-500) and that the majority of these are young males. The serious convictions rate is similar to the property convictions rate as a large proportion of the serious convictions are property convictions. In later years this close connection disappears, although the trends remain similar. The violent sample conviction rate fluctuated more highly, but the rate is generally low.

In the right column of 2 we show the mean residual conviction rates and the smoothed levels, for serious, property and violent convictions. The residuals are obtained after running family-level OLS regressions, correcting for the demographic (age, gender and family) and

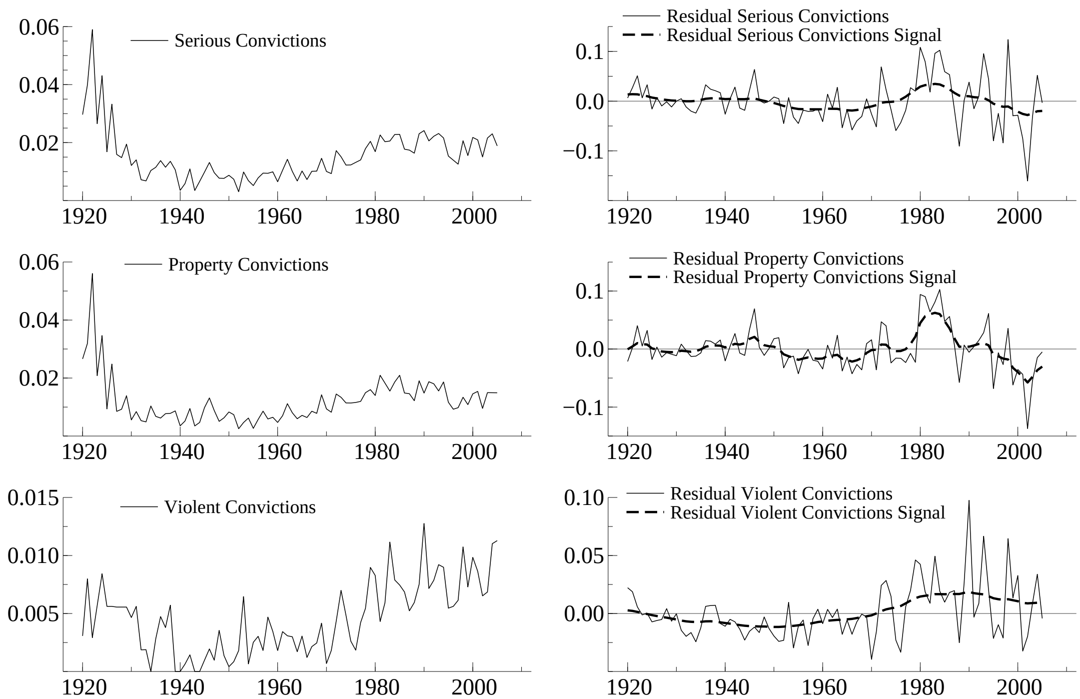

Figure 2: The left column shows the sample conviction rate for serious, property and violent convictions. The rate is computed as the number of individuals convicted for serious, property, or violent crimes, divided by the total number of individuals between 12-60 years of age in the corresponding year. The right column shows the residual sample conviction rate. The residuals were computed by running OLS regressions on the family level. The dependent variables were the sample conviction rates per family. The regressions included a constant, four age variables (the ratio of 12-17, 18-24, 25-34 and 35-44 year olds), the ratio of males, the ratio of family relationships (father-mother, father-son, father daughter) and the socio-economic status indicators.

economic (socioeconomic status) composition of the families. The exact construction of these variables is discussed below. The smoothed level is computed by applying the Kalman filter and smoothing recursions to the residuals using a simple local level model, see Durbin & Koopman (2001). The smoothed level can be seen as the mean level of the convictions. The heavy fluctuations in the 'raw' conviction data are now almost completely removed.

2.2 Additional family information

Next to the conviction data, we have some demographic and socioeconomic status information at our disposal. The demographic information was traced in the Dutch municipal and administrative records. First the members of the original sample (G2) were identified and their ‘gezinskaarten’ (family cards) traced a family-based registration system operational from the first decades of the 20th century until just before the Second World War. In this system all family members residing at one address were registered on one card. This gave us the family composition, and information on for example the professions of the head of household.

The information on the professions was supplemented by screening the non-medical part of the Netherlands Ministry of Defense DARIC archives. In principle all men from birth year 1930 onwards until 1996 in the Netherlands were screened for military service; the screening contained a ‘family interview’ in which the father’s profession was listed. The screening records of any descendants of the 181 men thus contain information on the profession of their father. Permission was obtained from the Netherlands Ministry of Defense for this part of the data collection.

From the municipal achieves and the non-medical part of the military records we constructed family level control variables. To control for the changing age composition within the families control variables were constructed as the ratio of family members who were between the ages (in years) 12-17, 18-24, 25-34 and 35-44. The final age group ratio, 45-60, was left out to avoid multicollinearity. A control for the gender composition of the family was computed as the ratio of males in each family in each year. Further we aim to control for the family relations within each family. We constructed variables for the number of father-mother, father-son, father-daughter, mother-son and mother-daughter relationships that were found in each family for each year. The numbers were scaled with respect to the total number of family members. Finally, a socioeconomic status variable was constructed by recoding the professions of the male members. In particular, all occupations were coded into occupational class categories according to the Historical International Standard Classification of Occupations (HISCO) classification, see **?**. This was done as our observation period is 85 years containing thus contemporary and historical occupations. HISCO offers the chance to standardize the changes in occupations over time and make occupational statuses comparable. HISCO occupational codes were then grouped into seven social class categories (HISCLASS): 1 lower-skilled and unskilled farm workers, 2 unskilled workers, 3 lower-skilled workers, 4 farmers and fishermen, 5 foremen and skilled workers, 6 lower managers and professionals, clerical and sales personnel, 7 higher managers and professionals. Men in our data were assigned the highest social class occupation we had on them (either from DARIC or *gezinskaart* information). For the females in our data no information on occupations is available. We assigned them the socioeconomic status of their father and when they married the socioeconomic status of their husband. This seems an appropriate method for earlier years when females did not work very often, but much less so for recent years.

2.3 Relation to the national unemployment rate

In Figure 3 we show the mean corrected unemployment rate together with the filtered conviction signals, which are the same as in Figure 2. The unemployment rate is obtained from Statistics Netherlands and contains information on registered unemployment. The unemployment rate shows large fluctuations between 1920 and 2005. Two periods of elevated unemployment can be distinguished. First, in the 1930's during the Great Depression the unemployment rate increased to nearly 20%. In this period the conviction rates remained largely unchanged. This holds for serious, property and violent convictions. The rather remarkable none-response of the conviction rates during the great depression in also found at the national level. Leistra & Nieuwbeerta (2003) confirm this for homicide rates, which are probably the best recorded historical time series, but are likely to be the least responsive to changes in the unemployment rate. **?** find little responses for a broader sample of crime types during the great depression. They concluded that the increased levels of poverty did not correspond to the unchanged crime rates. The consistency of these findings leads us to believe that we are not looking at an artifact of our own data sample.

Internationally, similar results for the great depression period have been documented. **?** find no increases in property crime rates for a sample of 114 US cities. They argue that this is caused by large increases in government spending in this period. In The Netherlands no such increases in government spending are documented, see **?**. The national rate of offenses known to the police in England and Whales is also unaltered during the 1930's, see **?**. Similar findings are documented for Belgium in **?**.

The conviction rate remained apparently stable even as the unemployment rate fall again from its peak. The unemployment rate declined to around 3% for most of the 1950's, 1960's and 1970's.

The second period of increasing unemployment in The Netherlands takes place in the 1980's. In this period the unemployment rate increases to approximately 10%. Interestingly, all conviction rates of the 181 families seem to show a response to this increase, although this holds more for property crimes (theft, burglary, embezzlement fraud) and much less so for violent crimes (mainly: assault, sex offenses, extortion, threat and homicide). In international studies similar findings have been documented for this recent increase, see Doyle et al. (1999), Raphael & Winter-Ebmer (2001) and Papps & Winkelmann (2002). To sum, prior to 1950 little relation can be observed between the conviction rates and the unemployment rate. Conviction rates remain largely stable while the unemployment rate first increases rapidly after which it decreases. The overall pattern that emerges leads us to suspect that the relationship between (property) crime and the unemployment rate is non-existent, or weak, prior to 1950 but emerges afterwards. However, the similarities between the signal for property crime and the unemployment rate after 1950 are not necessarily the result of any causal connection. The next sections seek to determine whether a causal effect of the unemployment rate on the conviction outcomes exists.

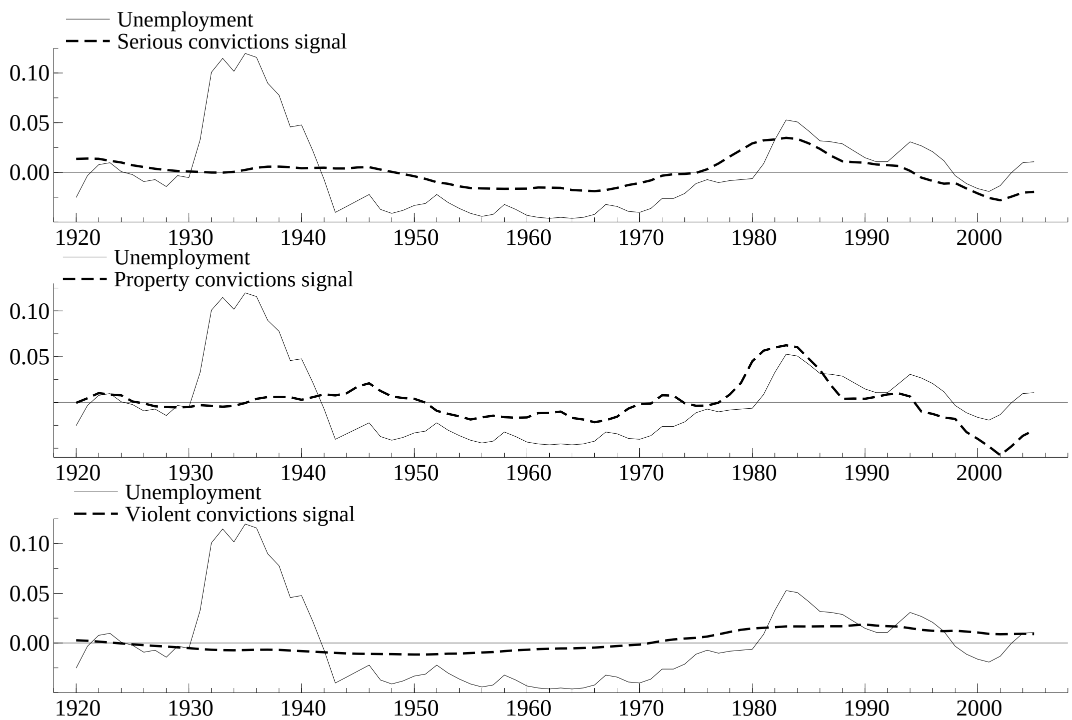

Figure 3: From top to bottom we show the serious, property and violent conviction signals, as computed in Figure 2, together with the mean corrected national unemployment rate, which is obtained from Statistics Netherlands (www.cbs.nl).

3 Empirical panel data strategy

In this section we discuss our basic panel data models that we used to identify the effect of the unemployment rate on the conviction outcomes of the families. The models included fall in the class of generalized dynamic panel data models proposed by Mesters & Koopman (2012). We propose a large variety of models, which differ with respect to the inclusion of control variables. Further, we estimate the models for three different groups of convictions; serious, property and violent, and two different time periods; 1920-2005 and 1950-2005. In this manner we aim to establish the robustness of the overall effect of the unemployment rate on the convictions.

3.1 The observation model

There are $N = 181$ families, with each family indexed by i for $i = 1, \ldots, N$. In each year τ_t there are n_{i,τ_t} members in family i, for $t = 1, \ldots, T$, with $T = 85$, where $\tau_1 = 1921$ and $\tau_{85} = 2005$. The number of individuals who are convicted from family i in year τ_t is denoted by y_{i,τ_t}. This can be seen as the number of 'successes' stemming from n_{i,τ_t} trials. Therefore, the observations y_{i,τ_t}, for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, are modeled by the binomial density given by,

$$y_{i,\tau_t} \sim \text{Binomial}(n_{i,\tau_t}, \pi_{i,\tau_t}), \qquad i = 1, \ldots, N, \qquad t = 1, \ldots, T, \tag{1}$$

where n_{i,τ_t} is the number of family members and π_{i,τ_t} is the conviction probability for an individual from family i in year τ_t. Of main interest in this paper is the effect that the unemployment rate has on the conviction probability. The conviction probability is restricted between zero and one. To avoid difficulties during estimation procedures we model the transformed conviction probability, $\theta_{i,\tau_t} = \log[\pi_{i,\tau_t}/(1 - \pi_{i,\tau_t})]$, which is equivalent to the log odds ratio. We refer to θ_{i,τ_t} as the signal.

The conditional density for y_{i,τ_t}, given θ_{i,τ_t}, is given by

$$p(y_{i,\tau_t}|\theta_{i,\tau_t},\psi) \equiv \exp\left[y_{i,\tau_t}\theta_{i,\tau_t} - n_{i,\tau_t}\log(1+\exp\theta_{i,\tau_t}) + \log\begin{pmatrix} n_{i,\tau_t} \\ y_{i,\tau_t} \end{pmatrix} \right], \tag{2}$$

where ψ is the parameter vector. Density (2) is discussed more elaborately in Durbin & Koopman (2001, Section 10.3.3). As n_{i,τ_t} is known and fixed, density (2) is entirely determined by signal θ_{i,τ_t}, which may depend on parameters ψ. Further, density (2) is considered independent given signal θ_{i,τ_t}, for all $i = 1, \ldots, N$ and $t = 1, \ldots, T$. All dynamics and variables are modeled through signal θ_{i,τ_t}. It follows that

$$p(y|\theta,\psi) = \prod_{i=1}^{N}\prod_{t=1}^{T} p(y_{i,\tau_t}|\theta_{i,\tau_t},\psi), \tag{3}$$

where $y = \{y_{i,\tau_t}\}_{i=1,\ldots,N,\ t=1\ldots,T}$ and $\theta = \{\theta_{i,\tau_t}\}_{i=1,\ldots,N,\ t=1\ldots,T}$.

3.2 The signal

The signal θ_{i,τ_t} is of central interest in our model. In our base model for θ_{i,τ_t} we assume that the unemployment rate affects θ_{i,τ_t} similarly for each family i and year τ_t. We vary the construction of the signal with respect to the inclusion of control variables. The most general signal that we include is given by

$$\theta_{i,\tau_t} = \delta \mathrm{UN}_{\tau_t} + x_{i,\tau_t}\beta + w_{\tau_t}\lambda + \gamma y_{i,\tau_{t-1}} + \mu_i + \xi_{\tau_t}, \qquad i = 1, \ldots, N, \qquad t = 1, \ldots, T, \tag{4}$$

where UN_{τ_t} is the unemployment rate in year τ_t, x_{i,τ_t} is a vector of family-specific control variables, w_{τ_t} is a vector of time-varying common control variables, $y_{i,\tau_{t-1}}$ is the outcome from the previous time period, μ_i is the family-specific effect and ξ_{τ_t} is the time-varying effect.

The vector of family-specific control variables x_{i,τ_t} includes the four age variables, the ratio of males, the family relationship ratios, and the socioeconomic status indicator, see the discussion in Section 2. The age variables are constructed to control for changes in the age composition of the families. We include the ratios of the age groups (in years); 12-17, 18-24, 25-34 and 35-44, in each family in each year. The family relationship ratios are included to control for the fact that the within family conviction probabilities might not be independent. More specific, if the members of the families had independent and identical probabilities of getting convicted, density (1) would be entirely correct. This is however not the case. For example, if in a certain period two persons from one family are convicted of a crime it could be that the two outcomes had a causal affect on each other. To capture the impact of these within-family effects we include controls that account for the number of father-mother, father-son, father-daughter, mother-son and mother-daughter relationships. The socioeconomic status variable is averaged from the individual level socioeconomic status variables as discussed in Section 2. It is possible that the socioeconomic status variables are simultaneously determined with the conviction outcomes; therefore the corresponding coefficients may be biased. To investigate this we estimated models without these controls and also while including the first lag of the socioeconomic status variables. In all cases the estimates for the unemployment rate remained similar.

The vector of common control variables includes variables that are known to vary procyclically with the unemployment rate and can possibly also affect the conviction outcomes. Excluding these may lead us to not actually measure the impact of unemployment, but rather some composition of similar varying national trends, see the discussion in Raphael & Winter-Ebmer (2001). Cook & Zarkin (1985) discuss four broad categories of such procyclical aspects that are known to vary with the business cycle. They are: (1) variation in legal employment opportunities, (2) variation in criminal opportunities, (3) consumption of criminogenic commodities and (4) variation in the response of the criminal justice system. While the variation in legal employment opportunities is of central interest in this paper we aim to reduce the influence of the other categories. We include the national hourly wage and the logarithm of the gross domestic product to control for the general economic conditions in the Netherlands. Criminogenic commodities are items such as drugs, guns and alcohol.

To control for influences of these we include beer consumption in liters. Unfortunately reliable drugs consumption rates are not available to us for our sample period. Given the unique position of drugs in the Netherlands its exclusion can be important. Guns have less relevance to the setting in The Netherlands. The variation in the response of the criminal justice system is measured by including the national conviction rate and the incarceration rate. By including the national conviction rate we make sure that the observed variation in the number of convicted family members is not due to nationwide changes in the criminal justice system, but rather due to changes in criminal behavior.

The family-specific effect μ_i is included to capture all time-invariant unobserved differences that exist between the families. The family-specific effect is given by

$$\mu_i \sim NID(\mu^0, \sigma^2_\mu), \qquad i = 1, \ldots, N, \tag{5}$$

where μ^0 is the overall mean and σ^2_μ is the variance. The normality assumption is standard in random effects models, see the discussion in Baltagi (2005). To make sure that the family-specific means μ_i can be correctly identified we standardize all family-specific and common variables, $x_{i,t}$ and w_t, to have mean zero and unit variance. The family-specific means are then interpretable as the mean family conviction log odds ratio with average covariates. Similar strategies to avoid biases from correlation between x_{i,τ_t}, w_{τ_t} and μ_i are considered by Juarez & Steel (2010) and Mesters & Koopman (2012).

In addition to the family-specific effect we also include time-varying effect ξ_{τ_t}. The time-varying effect captures unobserved factors that affect the offending outcomes that are common to all families, but may vary over time. We model the time-varying effect by a random walk process, given by

$$\xi_{\tau_t} = \xi_{\tau_{t-1}} + \eta_{\tau_t}, \qquad \eta_{\tau_t} \sim NID(0, \sigma^2_\eta), \qquad t = 2, \ldots, T, \tag{6}$$

where the initial time-varying effect, ξ_{τ_1}, is fixed to zero for identification purposes. Autoregressive processes were also investigated but did not lead to substantial improvements.

The family-specific and time-varying random effects are considered independent for all $i = 1, \ldots, N$ and $t = 1, \ldots, T$. The binomial dynamic panel data model is summarized by equations (2), (4), (5) and (6). The parameters are summarized in the parameter vector $\psi = \{\delta, \gamma, \beta, \lambda, \mu^0, \sigma_\mu, \sigma_\eta\}$.

3.3 Results

The parameters of the binomial panel data model are estimated for three types of convictions: serious, property and violent convictions, and for two time periods; the full time period 1921-2005 and the subsample 1951-2005. The data and trends were described in Section 2. Variables y_{i,τ_0} are fixed at their 1920 and 1950 values for $i = 1, \ldots, N$, respectively. The parameters are estimated using the Monte Carlo maximum likelihood methods developed in Mesters & Koopman (2012). The implementation of this method for the binomial dynamic panel data model is discussed in Appendix A.

Table 1.a presents the results for the models where the dependent variable, y_{i,τ_t}, is the number of members from each family convicted for serious offenses. The first three columns give the results for the period 1920-2005, while the next three give the results for the period 1950-2005. For each period we estimated three different models that vary with respect to the inclusion of control variables. They are summarized as; (a) including only statistical controls, (b) including statistical and family controls and (c) including statistical, family and macro-level controls. The results indicate that the effect of the unemployment rate is weak and becomes insignificant when controlling for macro-level trends. The effects found for the period 1950-2005 are stronger than for the 1920-2005 period.

Table 1.b presents the results for property convictions. The effect of unemployment is positive and significant at the 5% level of confidence for all model specifications for the 1950-2005 sample period. The magnitude of the relationship indicates that a 1 percentage point decrease in the unemployment rate causes a decline in the property crime probability of between 2.9 and 4.6 percentage points. A decline of 3.8 percentage points is recorded for our model including all control variables. The magnitude of the found effect is comparable

to the results found for property crime in Lin (2008) and somewhat higher compared to the results of Raphael & Winter-Ebmer (2001). For the period 1920-2005 the effect sizes are smaller and become insignificant when the macro-level control variables are added to the model.

The results for violent convictions are presented in Table 1.c. In the first specification, only including statistical controls, the coefficient for unemployment is positive and significant. However, when adding control variables to correct for family composition, the effect of the unemployment rate is not significant. This is found for both sample periods and remains so when including macro-level control variables. The effect of the unemployment rate even becomes slightly negative (insignificant) for the 1920-2005 sample period when the latter control variables are added. These results imply that the unemployment rate has no influence on violent offending. This is also found for US state level panel data by Raphael & Winter-Ebmer (2001) and Lin (2008).

Concerning the performance of the other variables listed in Tables 1.a,b,c, the family control variables seem important. Consistent with previous research on the age-crime profile, the conviction probabilities increase when more individuals below the age of 25 are present in the family. Also, higher ratios of males in the family increases conviction probabilities. This corresponds to the fact that the majority of crimes is committed by males. For violent crimes the documented age-crime profile is somewhat different. Increasing ratios of the youngest age group, consisting of 12-17 year olds, is found to decrease the conviction probabilities. This corresponds to the general finding that violent crimes are more likely to be committed by older males. For violent crimes the magnitude of the effect of the male ratio is found much higher compared to the effects found for serious and property crimes. The socio-economic status variable lowers the conviction probabilities for all crime categories. The family relationship variables indicate that increasing numbers of father-son and mother-son pairs in the family increases the conviction probability. Also increasing numbers of father-mother relationships decreases the conviction probability. This is consistent with criminological life course theories that suggest that marriage lowers criminal propensity.

The controls for the common national trends are interesting in their own right. Much to our own surprise we are unable to identify significant effects of any other trend consistently. The estimated standard errors are much higher compared to those estimated for the unemployment rate. The estimates for the national conviction rate and the prison population are positive indicating their relationship to our dependent variables, which were measures of convictions. The effect for beer consumption is also positive. It is significant for serious and property crimes for the sample period 1920-2005. The control variables for general economic conditions, i.e. log GDP and log wages, are found to be insignificant in all models. Contrary to the findings of Grogger (1998), Gould et al. (2002) and Machin & Meghir (2004), the national wage rate does not seem an important determinant in the crime rates. This is possibly caused by the specific situation in the Netherlands, where minimum wages are typically high. This would imply that the mere fact of having a job would be more important compared to the actual wage that is received.

The statistical controls reveal some interesting information. The differences between the families are large for all three types of convictions. These differences remain visible for all models, despite the inclusion of the control variables. This is mainly caused by the fact that we standardized all variables to have mean zero and unit variance. The time-varying effects show low variance, which rapidly decreases when control variables are added. The state dependence variables are positive and significant in all model specifications. This indicates that some causal effects of previous crimes committed within the family exist. A more specific explanation for the meaning of this variable can possibly be found by analyzing conviction rates at the individual level. In this manner it would be possible to analyze which family members influence each other, or whether the same individuals are responsible for sequences of convictions.

Overall the results lead us to conclude that the effect of the unemployment rate is significant for property crimes for the period 1950-2005. This is the only sequence of models that has given us these consistent results. The magnitude of a 2.9% and 3.8% increase is found similar to Lin (2008). For all other crime types the effect of the unemployment rate is found lower in magnitude and often not significant.

	Serious Convictions					
		1920-2005			1950-2005	
Unemployment	0.0180^{*} $_{0.0078}$	0.0142^{*} $_{0.0074}$	0.0007 $_{0.0092}$	0.0350^{*} $_{0.0090}$	0.0363^{*} $_{0.0093}$	0.0249 $_{0.0138}$
Controls for trend (λ)						
log GDP	-	-	0.2330 $_{0.4981}$	-	-	1.0088 $_{0.6885}$
log Wages	-	-	-0.8975 $_{1.2236}$	-	-	-0.4506 $_{0.4038}$
Alcohol consumption	-	-	0.6189 $_{0.1662}$	-	-	0.0945 $_{0.5564}$
Conviction rate	-	-	0.2841 $_{0.1085}$	-	-	0.1898 $_{0.4275}$
log Prison population	-	-	-0.1355 $_{0.2765}$	-	-	0.0142 $_{0.2993}$
Controls for Family (β)						
Age 12-17	-	0.0742 $_{0.0409}$	0.1110 $_{0.0549}$	-	0.0361 $_{0.0348}$	0.0526 $_{0.0495}$
Age 18-24	-	0.2488 $_{0.0441}$	0.2634 $_{0.0525}$	-	0.0917 $_{0.0347}$	0.1070 $_{0.0440}$
Age 25-34	-	0.2057 $_{0.0530}$	0.2078 $_{0.0411}$	-	0.0092 $_{0.0365}$	0.0015 $_{0.0382}$
Ratio males	-	0.0525 $_{0.0334}$	0.0647 $_{0.0337}$	-	0.0385 $_{0.0299}$	0.0391 $_{0.0302}$
SES	-	-0.0209 $_{0.0314}$	-0.0117 $_{0.0318}$	-	-0.0218 $_{0.0287}$	-0.0168 $_{0.0290}$
Father-Son	-	0.0493 $_{0.0295}$	0.0734 $_{0.0311}$	-	0.0214 $_{0.0314}$	0.0295 $_{0.0334}$
Father-Daughter	-	-0.0118 $_{0.0387}$	-0.0267 $_{0.0396}$	-	-0.0345 $_{0.0322}$	-0.0445 $_{0.0331}$
Mother-Daughter	-	-0.0561 $_{0.0406}$	-0.0411 $_{0.0422}$	-	-0.0298 $_{0.0329}$	-0.0286 $_{0.0333}$
Mother-Son	-	0.1169 $_{0.0246}$	0.0847 $_{0.0281}$	-	0.0809 $_{0.0279}$	0.0612 $_{0.0300}$
Father-Mother	-	-0.1478 $_{0.0365}$	-0.1298 $_{0.0381}$	-	-0.0184 $_{0.0276}$	-0.0194 $_{0.0294}$
Statistical controls						
Mean (μ^0)	-4.7940 $_{0.0921}$	-4.8249 $_{0.0923}$	-4.8377 $_{0.0927}$	-4.9098 $_{0.0948}$	-4.9251 $_{0.0948}$	-4.9353 $_{0.0949}$
State dependence (γ)	0.1501 $_{0.0160}$	0.1434 $_{0.0166}$	0.1394 $_{0.0168}$	0.1315 $_{0.0169}$	0.1295 $_{0.0174}$	0.1291 $_{0.0175}$
Family-specific (σ_μ)	0.9956 $_{0.0788}$	0.9966 $_{0.0793}$	0.9968 $_{0.0795}$	0.9328 $_{0.0764}$	0.9380 $_{0.0768}$	0.9377 $_{0.0769}$
Time-varying (σ_η)	0.1134 $_{0.0359}$	0.0591 $_{0.0476}$	0.0438 $_{0.0599}$	0.0797 $_{0.0351}$	0.0308 $_{0.0727}$	0.0201 $_{0.0736}$
Loglikelihood	-28917	-28871	-28860	-18643	-18624	-18622
$N \times T$	15385	15385	15385	10136	10136	10136

Table 1.a: Baseline parameter estimates for serious convictions. The are obtained by estimating the binomial panel data model given by equations (2) and (4). The observations used are the number of family members that are convicted for serious crimes for $N = 198$ families as described in Sections 2 and 3. The three columns on the left correspond to the sample period 1920-2005, $T = 85$, and the three columns on the right correspond to the sample period 1950-2005, $T = 55$. The parameter estimates are obtained by maximizing the log likelihood using the BFGS algorithm, see Nocedal & Wright (1999). The log likelihood is evaluated as discussed in Appendix A. The * indicates that the variable is found statistically significant with 95% confidence.

	Property Convictions					
	1920-2005			1950-2005		
Unemployment	0.0109* $_{0.0095}$	0.0151* $_{0.0079}$	0.0041671 0.010479	0.0292* $_{0.0108}$	0.0399 $_{0.0155}$	0.0353* $_{0.0146}$
Controls for trend (λ)						
log GDP	-	-	0.1016 $_{1.3751}$	-	-	1.6684 $_{1.9095}$
Wage rate	-	-	-0.2278 $_{0.5581}$	-	-	-0.7586 $_{0.8193}$
Alcohol consumption	-	-	0.5936 $_{0.1874}$	-	-	-0.0115 $_{0.5722}$
Conviction rate	-	-	0.1936 $_{0.1186}$	-	-	0.2181 $_{0.4489}$
Prison population	-	-	-0.1510 $_{0.2994}$	-	-	-0.1671 $_{0.3112}$
Controls for Family (β)						
Age 12-17	-	0.1633 $_{0.0460}$	0.1324 $_{0.0627}$	-	0.1212 $_{0.0448}$	0.0677 $_{0.0575}$
Age 18-24	-	0.3138 $_{0.0501}$	0.2759 $_{0.0599}$	-	0.1459 $_{0.0404}$	0.1043 $_{0.0512}$
Age 25-34	-	0.2153 $_{0.0608}$	0.1782 $_{0.0678}$	-	0.0522 $_{0.0463}$	0.0257 $_{0.0522}$
Age 35-44	-	0.0638 $_{0.0453}$	0.0426 $_{0.0470}$	-	0.0153 $_{0.0428}$	0.0093 $_{0.0452}$
Ratio males	-	0.0443 $_{0.0379}$	0.0533 $_{0.0383}$	-	0.0025 $_{0.0350}$	0.0012 $_{0.0351}$
SES	-	-0.0079 $_{0.0370}$	-0.0011 $_{0.0376}$	-	-0.0227 $_{0.0338}$	-0.0208 $_{0.0341}$
Father-Son	-	0.0052 $_{0.0341}$	0.0409 $_{0.0361}$	-	-0.0117 $_{0.0404}$	0.0040 $_{0.0392}$
Father-Daughter	-	-0.0018 $_{0.0446}$	-0.0107 $_{0.0458}$	-	-0.0310 $_{0.0416}$	-0.0325 $_{0.0384}$
Mother-Daughter	-	-0.0310 $_{0.0467}$	-0.0061 $_{0.0488}$	-	-0.0255 $_{0.0387}$	-0.0185 $_{0.0386}$
Mother-Son	-	0.0957 $_{0.0284}$	0.0778 $_{0.0331}$	-	0.0712 $_{0.0401}$	0.0664 $_{0.0353}$
Father-Mother	-	-0.1681 $_{0.0418}$	-0.1655 $_{0.0436}$	-	-0.0191 $_{0.0320}$	-0.0353 $_{0.0340}$
Statistical controls						
Mean (μ^0)	-5.1474 $_{0.0982}$	-5.1775 $_{0.0979}$	-5.1818 0.097968	-5.2898 $_{0.1044}$	-5.3081 $_{0.1043}$	-5.3103 $_{0.1042}$
State dependence (γ)	0.1902 $_{0.0205}$	0.1851 $_{0.0206}$	0.1847 0.020868	0.1642 $_{0.0216}$	0.1619 $_{0.0216}$	0.1621 $_{0.0218}$
Family-specific (σ_μ)	1.0067 $_{0.0824}$	1.0126 $_{0.0834}$	1.0041 0.082933	0.9795 $_{0.0846}$	0.9885 $_{0.0853}$	0.9848 $_{0.0851}$
Time-varying (σ_η)	0.1645 $_{0.0423}$	0.0001 $_{0.0626}$	0.0001 0.055352	0.1090 $_{0.0383}$	0.0002 $_{0.0441}$	0.0049 $_{0.0394}$
Loglikelihood	-28082	-28035	-28026	-17946	-17924	-17922
$N \times T$	15385	15385	15385	10136	10136	10136

Table 1.b: Baseline parameter estimates for property convictions. See Table 1.a.

	Violent Convictions					
		1920-2005			1950-2005	
Unemployment	0.0280* $_{0.0136}$	0.0052 $_{0.0145}$	-0.0097 $_{0.0193}$	0.0411* $_{0.0165}$	0.0253 $_{0.0134}$	0.0008 $_{0.0243}$
Controls for trend (λ)						
GDP	-	-	1.9285 $_{1.0458}$	-	-	0.8826 $_{1.4452}$
Wage rate	-	-	-4.4516 $_{2.5531}$	-	-	-1.4608 $_{3.3369}$
Alcohol consumption	-	-	0.5272 $_{0.3548}$	-	-	-0.0740 $_{0.9563}$
Conviction rate	-	-	0.3256 $_{0.2291}$	-	-	0.0295 $_{0.5182}$
Prison population	-	-	-0.3270 $_{0.5770}$	-	-	-0.2059 $_{0.8061}$
Controls for Family (β)						
Age 12-17	-	-0.1759 $_{0.0842}$	0.0246 $_{0.1163}$	-	-0.1467 $_{0.0221}$	-0.0371 $_{0.0941}$
Age 18-24	-	0.0318 $_{0.0909}$	0.1857 $_{0.1118}$	-	-0.0637 $_{0.0541}$	0.0311 $_{0.0866}$
Age 25-34	-	0.1276 $_{0.1048}$	0.2454 $_{0.1207}$	-	-0.0902 $_{0.0401}$	-0.0139 $_{0.0872}$
Age 35-44	-	0.0612 $_{0.0788}$	0.0790 $_{0.0834}$	-	0.0001 $_{0.0489}$	-0.0015 $_{0.0745}$
Ratio males	-	0.1016 $_{0.0696}$	0.1116 $_{0.0714}$	-	0.0915 $_{0.0221}$	0.0943 $_{0.0591}$
SES	-	-0.1512 $_{0.0588}$	-0.1325 $_{0.0599}$	-	-0.0509 $_{0.0292}$	-0.0439 $_{0.0548}$
Father-Son	-	0.1210 $_{0.0593}$	0.1219 $_{0.0629}$	-	0.0980 $_{0.0484}$	0.0935 $_{0.0649}$
Father-Daughter	-	-0.0151 $_{0.0791}$	-0.0465 $_{0.0805}$	-	-0.0162 $_{0.0444}$	-0.0366 $_{0.0664}$
Mother-Daughter	-	-0.1361 $_{0.0838}$	-0.1629 $_{0.0863}$	-	-0.1085 $_{0.0225}$	-0.1208 $_{0.0677}$
Mother-Son	-	0.1985 $_{0.0473}$	0.1221 $_{0.0540}$	-	0.1160 $_{0.0409}$	0.0772 $_{0.0577}$
Father-Mother	-	-0.0914 $_{0.0747}$	-0.0479 $_{0.0809}$	-	-0.0343 $_{0.0289}$	-0.0107 $_{0.0588}$
Statistical controls						
Mean (μ^0)	-6.2285 $_{0.1159}$	-6.3327 $_{.1173}$	-6.4043 $_{0.1252}$	-6.1771 $_{0.1139}$	-6.2168 $_{0.0237}$	-6.2486 $_{0.1168}$
State dependence (γ)	0.3095 $_{0.0629}$	0.2250 $_{0.0644}$	0.2116 $_{0.0647}$	0.2692 $_{0.0643}$	0.1942 $_{0.0428}$	0.1916 $_{0.0658}$
Family-specific (σ_μ)	0.9411 $_{0.0970}$	0.9468 $_{0.0985}$	0.9689 $_{0.1018}$	0.8738 $_{0.0903}$	0.8895 $_{0.0498}$	0.89742 $_{0.0921}$
Time-varying (σ_η)	0.1375 $_{0.0735}$	0.0001 $_{0.2923}$	0.0156 $_{0.1986}$	0.1096 $_{0.0841}$	0.0001 $_{0.1991}$	0.0142 $_{0.1419}$
Loglikelihood	-25961	-25934	-25927	-16410	-16394	-16392
$N \times T$	15385	15385	15385	10136	10136	10136

Table 1.c: Baseline parameter estimates for violent convictions. See Table 1.a.

4 Time-varying unemployment effects

Next we examine whether the effect of the unemployment rate on the conviction outcomes changes significantly between 1920 and 2005. In Section 3 we found that the effect of the unemployment rate is higher for the period 1950-2005 compared to the period 1920-2005. More specific, all estimates for the models including all control variables for the 1920-2005 period were found insignificant. This was found for all three conviction samples. The largest increase between the two sample periods was found for property convictions. Despite these results, the choice for the sample split at year 1950 remains quite arbitrary. It was mainly determined by the visual analysis of Figure 2.

To formally investigate whether the effect of the unemployment rate is increasing, we estimate a time-varying effect for the unemployment rate. Time-varying regression models are discussed in detail by **?**. To implement the time-varying effect we decompose δ in equation (4) into a deterministic, family-specific and time-varying component. In particular

$$\delta = \delta^0 + \delta_i + \delta_{\tau_t}, \qquad \delta_i \sim N(0, \sigma^2_\delta), \qquad \delta_{\tau_t} = \delta_{\tau_{t-1}} + \epsilon_{\tau_t}, \qquad \epsilon_{\tau_t} \sim NID(0, \sigma^2_\epsilon), \tag{7}$$

where δ^0 is the deterministic effect, δ_i is the family-specific and δ_{τ_t} is the time-varying effect. The deterministic and family-specific effect are modeled as in equation The time-varying effect δ_{τ_t} is modeled by a random walk process, with a normally distributed disturbance term ϵ_{τ_t}. The disturbance term has mean zero and variance σ_ϵ To achieve identification we fix $\delta_{\tau_1} = 0$. Appendix C discusses the estimation procedure for the binomial panel data model with family-specific and time-varying random effects for the unemployment rate.

4.1 Results

The parameters of the binomial dynamic panel data model with a time-varying effect for the unemployment rate are estimated for the three conviction samples. We only estimated the model for the entire sample period 1920-2005. The estimates for the time-varying effect for the unemployment rate, $\tilde{\delta}_{\tau_t}$ are visually displayed in Figure 4. For serious and violent convictions no significant changes in the effect of the unemployment rate are found. The estimated changes in the time-varying effect never exceed above 0.2 percentage points. This confirms the findings in Section 3, where we found no significant overall effect for the unemployment rate for serious and violent convictions. Figure 4 shows that these findings are not resulting from an unlucky, or lucky, sample split.

The estimated time-varying effect for property convictions increases significantly between 1920 and 2005. Moreover the overall magnitude of the increase between 1920 and 2005 is between 2 and 6 percentage points. This indicates that during the sample period the families have become more responsive to changes in the unemployment rate with respect to property crimes.

Essentially this result formally confirms Figure 3, in establishing that the effect of the unemployment rate was insignificant prior to approximately 1960 and becomes significant after this period. The main question that remains is why this increase occurred. Or when formulated differently, why was there little response to the unemployment rate during the period of mass unemployment in the 1930's.

Several possible explanations spring to mind, but are hard to test. Firstly, it can be argued that during the Great Depression, poverty was so widespread in the Netherlands, that very few objects to steal were around. Objects stolen before that era were much more often than now food items, such as eggs or windfall apples, that incurred hefty penalties. Such thefts by nature occurred and could take place more easily in more agrarian areas, and not in the inner city slums where the unemployed were more concentrated. Indeed, a number of US authors have shown that little evidence exists for a link between the widespread unemployment during the Great Depression and crime. The same was stated for England too, for an overview see **?**. For completeness reasons, it must be stated that several authors have found a positive association between unemployment and crime levels during this period too. All in all, the evidence is contradictory.

One explanation for the emergence of significance just before 1960 may be the increasingly widespread availability of luxury goods that were tradable, relatively light (and thus easy to carry) and not easily traceable to the legal owner: the transistor radio appeared in the Netherlands in 1957. Before that period, burglars had to transport items such as Persian carpets, or family silver. Several other explanations spring to mind, and even though they cannot be regarded as more than musings, and even though some are perhaps too abstract to be at all testable, they may provide a starting point to think about explanations.

Since the early sixties, citizens' respect for the 'state' has decreased. In the sixties, with hippies, drugs, protests against the Vietnam war, against nuclear arms, the state became increasingly portrayed as the State and as the Enemy. This pervaded general thinking about prosecution and the criminal justice system as well. Criminal law theorizing was abolitionistic, the state and the criminal justice system should refrain from messing around in people's private lives. Prosecution was extremely restrained ('dismiss, unless') and sentences were low. Thus, one could argue, people knew they would likely not be prosecuted and if so not be punished severely, and the 'blemish' of arrest might even flip to become an heroic act ('proletarisch winkelen' [proletarian shopping = thieving]) in some circles ('die pet pakt ons allemaal' ['the copper's hat nicks us all' as a rewording of 'that copper's hat fits us all').

Another explanation might be the advent of drugs and hard drugs around that time, and the quick appearance on the scene of junkies, who had to steal extensively if they had no source of income to finance their drug habit. In the 1970's the Netherlands has the lowest incarceration rate in Europe (and the lowest ever recorded for the Netherlands), and possibly it is simply the case that very few criminals are incapacitated, and thus are able to steal.

A methodological problem for our series is that there is some volatility in definitions of unemployment in the 1980s as successive governments tried to show the success of their policies by definitional fiddling.

Crime and the perception and role of the criminal justice system changed over the years too. As crime levels increased, the public and authorities became increasingly fed up with insecurity and public disorder, and the discourse shifted to a victim-oriented one: the state should protect victims, not norms or the social order. By the early 90s, the Dutch state starts building prisons to make up for lacking prison space (in the 80s a number of scandals showed that prison space was so scarce that sex offenders could not be housed and were sent home through the back door). Simultaneously, possibly to cope with rising numbers of arrestees and defendants, prison sentences became increasingly reserved for violent offenders and drugs offenders. The 'officiersmodel' whereby also a prosecutor could impose non-custodial sentences, meant that you could essentially plea bargain your theft case so that you would not have a criminal record and came away with a 'taakstraf' (community sanction or a fine. Soon after the so-called 'Wet Mulder' came into force where drunk driving and speeding (up to a certain severity) became something you 'bought' - you simply got an 'acceptgiro' (bank transfer card) at home and you paid up. Thus, a prosecution for a non-serious crime (such as theft or speeding) became not a transgression against the social order that carried the risk of incarceration (in the 1970s many prison sentences were for drunk driving) but a nuisance that was simply costly - and that you could of course steal for again. This fed into the changing perception of the state and politicians who were less and less seen as respectable old men who knew what is good for the citizen, but as a set of crooks (as opposed to 'politically wrong' in the sixties): the public discourse and discontent reflected thoughts along the line of: 'well the government robs me and cheats me so I can rob them/ cheat them'.

By the early 1990s, the welfare state started to break down. Unemployment became increasingly costly for the state and it became less easy for citizens to get welfare support. The allowances were tightened, enforcement of rules was increased, fraud was actively targeted. Especially for juveniles it became less easy to get social benefits. The allowance of those who did not apply for jobs frequently enough could be reduced, or withheld altogether. The government now requested some effort from the unemployed - contrary to the previous period - and welfare support was neither sure nor generous. Also, governmental policies to aid the unemployed were now restricted to the long-term unemployed only: the recently unemployed had to fend for themselves. All in all, one could argue that the unemployed were having a tougher time making ends meet from this period onwards.

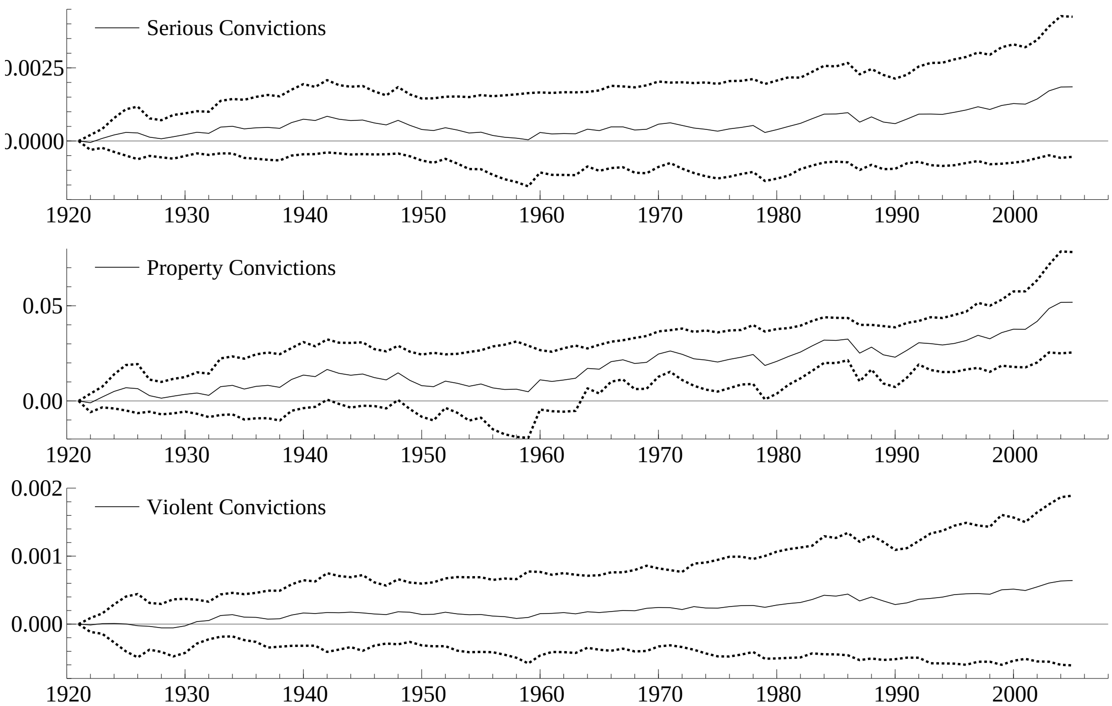

Figure 4: The estimated time-varying effects for the unemployment rate.

5 Conclusion

In this paper we estimated the effect of the national unemployment rate on the serious, property and violent convictions time series of 181 families from The Netherlands. Two analysis were performed and discussed. First, we showed for all families that only property conviction time series starting after 1950 responds to changes in the unemployment rate. This result was consistent for models that differed with respect to the inclusion of control variables. Second, a time-varying effect for the unemployment rate was estimated. The results clearly showed that the effect of the unemployment rate on property crimes is increasing between 1920 and 2005. The changes become significant after approximately 1960.

Appendix A

In this appendix we discuss the evaluation of the likelihood for the binomial panel data model, given by equations (1), (4), (5) and (6). An exact exposition is presented in Mesters & Koopman (2012). The likelihood is defined as $\ell(\psi) = \log p(y)$, where $y = \{y_{i,\tau_t}\}_{i=1,\ldots,N,\ t=1\ldots,T}$. From the nonlinearity of the observational density and the presents of the random family-specific and time-varying components it follow that the likelihood does not exists in closed from. Nonetheless, the joint density of the observations can be expressed as

$$p(y) = \int_\theta p(y, \theta; \psi)\mathrm{d}\theta = \int_\mu \int_\xi p(y, \mu, \xi; \psi, x, w)\mathrm{d}\mu\mathrm{d}\xi, \tag{8}$$

where $\mu = (\mu_1, \ldots, \mu_N)'$ is the vector of family specific effects, $\xi = (\xi_1, \ldots, \xi_{\tau_t})'$ is the vector of time-varying effects, $x = \{x_{i,\tau_t}\}_{i=1,\ldots,N,\ t=1\ldots,T}$, is the collection of family control variables and $w = (w_1, \ldots, w_{\tau_t})'$ is the vector of common control variables. The joint density can be rewritten as

$$p(y) = \int_\mu \int_\xi p(y|\mu, \xi; \psi, x, w)p(\mu)p(\xi)\mathrm{d}\mu\mathrm{d}\xi, \tag{9}$$

where $p(y|\mu, \xi; \psi, x, w) \equiv p(y|\theta; \psi)$, which is given in equation (3) which follows from the independence between the family-specific and the time-varying random effects. To evaluate the high-dimensional integral in (9) efficiently we use the importance sampling technique. An importance sampling representation for (9) is given by

$$p(y) = g(y; \hat{\xi})g(y; \hat{\mu}) \int_\xi \int_\mu \frac{p(y|\mu, \xi; \psi, x, w)}{g(y|\mu; \hat{\xi})g(y|\xi; \hat{\mu})} g(\mu|y; \hat{\xi})g(\xi|y; \hat{\mu})\ \mathrm{d}\mu\ \mathrm{d}\xi, \tag{10}$$

where $g(\mu|y; \hat{\xi})$ and $g(\xi|y; \hat{\mu})$ are the importance densities. We define $\hat{\mu}$ and $\hat{\xi}$ as the posterior modal values of $p(\mu, \xi|y; x)$, that is $\{\hat{\mu}, \hat{\xi}\} \equiv \mathrm{argmax}_{\mu,\xi}\, p(\mu, \xi|y; x)$. The choice for the posterior modal values is not necessary as any sufficient statistic can be used for the conditioning. It is used for computational convenience. Given the posterior modal values and the importance densities the joint density can be estimated by

$$\hat{p}(y) = g(y;\hat{\xi})g(y;\hat{\mu}) \sum_{i=1}^{M} \frac{p(y|\mu^{(i)},\xi^{(i)};\psi,x,w)}{g(y|\mu^{(i)};\hat{\xi})g(y|\xi^{(i)};\hat{\mu})}, \tag{11}$$

where samples $\mu^{(i)}$ and $\xi^{(i)}$ are drawn from the importance densities $g(\mu|y;\hat{\xi})$ and $g(\xi|y;\hat{\mu})$, respectively.

Next we discuss the construction of the importance densities. We choose both densities to follow Gaussian distributions and modify their means and variances such that their modes are equal to the modes of the original posterior density $p(\mu,\xi|y;\psi,x,w)$. So (2003) and Jungbacker & Koopman (2007) argue that this strategy can be implemented by numerically maximizing $\log p(\mu,\xi|y;\psi,x,w) = \log p(y|\mu,\xi;\psi,x,w) + \log p(\mu,\xi) - \log p(y;\psi,x,w)$ with respect to μ and ξ. The instrumental basis to facilitate this numerical maximization is given, for variable $y_{i,t}$, by the linear Gaussian panel data model

$$y_{i,t} = c_{i,t} + \theta_{i,t} + u_{i,t}, \qquad u_{i,t} \sim NID(0, d_{i,t}^2), \tag{12}$$

where $c_{i,t}$ is a fixed constant, stochastic component $\theta_{i,t}$ is given by equation (4) and $u_{i,t}$ is a random variable with mean zero and fixed variance $d_{i,t}^2$. The constants $c_{i,t}$ and $d_{i,t}$ are chosen such that (12) can be used to compute the posterior modal values $\hat{\mu}$ and $\hat{\xi}$, respectively. The elements $u_{i,t}$ and $\theta_{j,s}$ are uncorrelated with each other, for all $i,j = 1,\ldots,N$ and $s,t = 1,\ldots,T$. Furthermore, $u_{i,t}$ is serially uncorrelated. It follows that

$$g(y|\mu,\xi) = \prod_{i=1}^{N}\prod_{t=1}^{T} g(y_{i,t}|\mu_i,\xi_t), \qquad \text{with} \qquad g(y_{i,t}|\mu_i,\xi_t) \equiv NID(c_{i,t}+\theta_{i,t}, d_{i,t}^2). \tag{13}$$

The maximization of $\log p(\mu,\xi|y;x)$ with respect to μ and ξ can be carried out via the Newton-Raphson method. This procedure is summarized in the following algorithm.

Algorithm A

(i) Initialize the algorithm by choosing μ^* and ξ^* as starting values, which gives $\theta_{i,t}^*$, for all $i = 1, \ldots, N$ and $t = 1, \ldots, T$;

(ii) Given the set of two equations

$$\frac{\partial \log p(y_{i,t}|\theta_{i,t};\psi)}{\partial \theta_{i,t}} = \frac{\partial \log g(y_{i,t}|\theta_{i,t})}{\partial \epsilon_{i,t}}, \qquad \frac{\partial^2 \log p(y_{i,t}|\theta_{i,t};\psi)}{\partial \theta_{i,t}\partial \theta_{i,t}} = \frac{\partial^2 \log g(y_{i,t}|\theta_{i,t})}{\partial \theta_{i,t}\partial \theta_{i,t}},$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, where $p(y_{i,t}|\theta_{i,t})$ is the observation model (1) and $g(y_{i,t}|\theta_{i,t})$ is given by (13), we can deduct expressions for $c_{i,t}$ and $d_{i,t}$ as functions of $\theta_{i,t}$, and compute $c_{i,t} = c^*_{i,t}$ and $d_{i,t} = d^*_{i,t}$ for $\theta_{i,t} = \theta^*_{i,t}$;

(iii) Compute $\tilde{\mu} = \mathrm{E}_g(\mu|y;\xi^*)$ from the resulting model (12) with $\xi = \xi^*$, $c_{i,t} = c^*_{i,t}$ and $d_{i,t} = d^*_{i,t}$;

(iv) Replace μ^* by $\mu^* = \tilde{\mu}$;

(v) Compute $\tilde{\xi} = \mathrm{E}_g(\xi|y;\mu^*)$ from the resulting model (12) with $\mu = \mu^*$, $c_{i,t} = c^*_{i,t}$ and $d_{i,t} = d^*_{i,t}$;

(vi) Replace ξ^* by $\xi^* = \tilde{\xi}$

(vii) Iterate from (ii) to (vi) until convergence.

Since the mode and the mean of the approximating linear Gaussian model are set equal to the mode of the original model, it holds that $\tilde{\mu} = \hat{\mu} = \mathrm{argmax}_\mu\, p(\mu|y;\hat{\xi};x)$ and $\tilde{\xi} = \hat{\xi} = \mathrm{argmax}_\mu\, p(\xi|y;\hat{\mu};x)$. Further, as μ and ξ are independent, it holds that $\{\hat{\mu}, \hat{\xi}\} = \mathrm{argmax}_{\mu,\xi}\, p(\mu,\xi|y;x)$.

The computation of $\mathrm{E}_g(\mu|y;\xi^*)$ and $\mathrm{E}_g(\xi|y;\mu^*)$, in steps (iii) and (v), respectively, is handled by applying the Kalman filter and smoothing recursions to the approximating model. This procedure can be accelerated by first collapsing the approximating model twice. Once over the cross-section and once over the time series dimension, see Mesters & Koopman (2012) for further details. After the posterior model values are obtained and the approximating model is fitted, sampling $\mu^{(i)}$ and $\xi^{(i)}$ can be drawn from the importance densities using the simulation smoother methods of Durbin & Koopman (2002). The likelihoods of the approximating model $g(y;\hat{\xi})$ and $g(y;\hat{\mu})$ can be evaluated by the prediction error decomposition provided by the Kalman filter.

Appendix B

This appendix discusses the estimation of the binomial dynamic panel data model with heterogeneous slope effects, given by equations (1), (4), (5) and (6). For this model signal (4) can be rewritten as

$$\theta_{i,\tau_t} = \delta^0 \mathrm{UN}_{\tau_t} + x_{i,\tau_t}\beta + w_{\tau_t}\lambda + \gamma y_{i,\tau_{t-1}} + a'_{\tau_t} m_i + \xi_{\tau_t}, \tag{14}$$

where $a_{\tau_t} = (1, \mathrm{UN}_{\tau_t})'$ and $m_i = (\mu_i, \delta_i)'$. The family-specific effect m_i is here a vector consisting of the mean family-specific effect μ_i and the family-specific effect of the unemployment rate δ_i. These effects are loaded to the signal by the partially time-varying loading vector a_{τ_t}. When replacing μ_i by m_i in Appendix A the estimation procedure is carried out in exactly the same manner .

Appendix C

This appendix discusses the estimation of the binomial dynamic panel data model with heterogeneous and time-varying slope effects, given by equations (1), (4), (5), (6) and (7). For this model signal (4) can be rewritten as

$$\theta_{i,\tau_t} = \delta^0 \mathrm{UN}_{\tau_t} + x_{i,\tau_t}\beta + w_{\tau_t}\lambda + \gamma y_{i,\tau_{t-1}} + a'_{\tau_t} m_i + b'_{\tau_t} f_{\tau_t}, \tag{15}$$

where $b_{\tau_t} = (1, \mathrm{UN}_{\tau_t})'$ and $f_{\tau_t} = (\xi_{\tau_t}, \delta_{\tau_t})'$. The time-varying effect f_{τ_t} is here a vector consisting of the mean time-varying effect ξ_{τ_t} and the time-varying effect of the unemployment rate δ_{τ_t}. These effects are loaded to the signal by the partially time-varying loading vector b_{τ_t}. Note that b_{τ_t} is fixed and known for each year τ_t. When replacing ξ_{τ_t} by f_{τ_t} in Appendix

A the estimation procedure is carried out in exactly the same manner.

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