Forecasting Crime:
A City Level Analysis

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Abstract: Using a common panel data set of city level crime rates from 1980-2004, I illustrate the ability of several regression models to forecast crime rates. There is considerable variability in the forecasting performance across models, cities, crimes, and forecast horizons. While there is evidence of heterogeneity across cities, heterogeneous models do not perform notably better than the homogeneous alternatives. A naïve random walk forecasting model performs relatively well for shorter run forecast horizons, but the regression models do better for longer horizons. Out of sample forecasts are sensitive to covariates, with one regression model predicting that city level crime rates will slightly increase over the remainder of the decade, and another predicting a slight drop. In the end, I find forecasting crime rates at the city level to be fragile exercise with few generalizable lessons for how best to proceed.

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It's tough to make predictions, especially about the future.
Yogi Berra

I. Introduction

For nearly three decades, criminologists have tried unsuccessfully to forecast aggregate crime rates. Long-run forecasts have been notoriously poor. Crime rates have risen when forecasted to fall (e.g., the mid-1980s) and have fallen when predicted to rise (e.g., the 1990s).[1] Yet, despite these difficulties, there is little relevant research to guide future forecasting efforts.

In this light, I explore some of the practical issues involved in forecasting city level crime rates using a common panel data set. In particular, I focus on the problem of predicting future crime rates from observed data, not the problem of predicting how different policy levers impact crime. Although clearly important, causal questions are distinct from the forecasting question consider in this paper. Research on cause and effect must address the fundamental identification problem that arises when trying to predict outcomes under some hypothetical regime, say new sentencing or policing practices. My more modest objective is to examine whether historical time-series data can be used to provide accurate forecasts of future crime rates.

To do this, I analyze forecasts from a number of basic and parsimoniously specified mean regression models. While the problem of effectively forecasting crime may ultimately require more complex models, there is ample precedent for applying simple alternatives (Diebold , 1998; Baltagi, 2006).[2] Thus, I focus on basic linear models that do not allow for structural breaks in the time-series process, do not incorporate cross-state or cross crime interactions, and include only a small number of observed covariates. Finally, I focus on point rather than interval forecasts. Sampling variability plays a

[1] Land and McCall (2001) and Levitt (2004) review and critique the crime forecasting literature.
[2] Diebold refers to this idea as the *parsimony principle;* all else equal, simple models are preferable to complex models. Certainly, imposing *correct* restrictions on a model should improve the forecasting performance, but even incorrect restrictions may be useful in finite samples. Simple models can be more precisely estimated, and may lessen likelihood of over-fitting the observed data at the expense of effective forecasting of unrealized outcomes. Finally, empirical evidence from other settings reveals that simpler models can do at least as well and possibly better at forecasting than more complex alternatives.

key role in forecasting, but a natural starting point is to examine the sensitivity of point forecasts to different modeling assumptions. Thus, my focus is on forecasting variability across different models. Adding confidence intervals will only increase the uncertainty associated with these forecasts.

I begin in Section 2 by considering the problem of forecasting the national homicide rate. This homicide series lies at the center of much of the controversy surrounding the earlier forecasting exercises that have proven so futile. Using annual data on homicide rates, I estimate a basic autoregressive model which captures some important features of the time series variation in homicide rates, and does reasonably well at shorter run forecasts. As for the longer run forecasts, the statistical models clearly predict a sharp drop in crime during the 1990s, but fail to forecasts the steep rise in crime during the late 1980s.

After illustrating the basic approach using the national homicide series, I then focus on the problem of forecasting city level crime rates in Section 3. Using panel data on annual city level crime rates from 1980-2000, I again estimate a series of autoregressive lag models for four different crimes -- homicide, robbery, burglary and motor vehicle theft (MVT). Data from 2001-2004 are used for out-of-sample analyses.

The key objective is to compare the performance of various city level forecasting models. First, I examine basic panel data models with and without covariates, and with and without autoregressive lags. Most importantly, I contrast the homogeneous panel data model with heterogeneous models where the process can vary arbitrarily across cities. I also consider two naïve models, one where the forecast simply equals the city level mean or fixed effect – *the best constant forecast* – and the other where the forecast equals the last observed rate – *a random walk forecast*. In addition to considering the basic plausibility of the various model estimates, I examine differences in prediction accuracy and bias over one-, two-,four-, and ten-year forecast horizons.

I find considerable variability in the parameters and forecasting performance across models, cities, crimes, and horizons. While there is evidence of heterogeneity across cities, heterogeneous models do not perform notably better than the homogeneous alternatives. A naïve random walk forecasting model performs quite well for shorter run forecast horizons, but the regression models are superior for longer horizon forecasts.

Finally, I use the basic homogeneous panel data models to provide point forecasts for city level crime rates in 2005, 2006 and 2009. This out of sample forecasting exercise reveals predictions that are sensitive to the covariate specification. All models generally indicate modest changes in city level crime rates over the next several years. However, forecasts found using one model imply that city level crime rates will tend to increase over the remainder of the decade, whereas forecasts from another model imply that crime rates will fall.

In Section 4, I draw conclusions about the limitations of forecasting in general, and the specific problems associated with forecasting crime. Forecasting city level crime rates appears to be a volatile exercise, with few generalizable lessons for how best to proceed.

II. National Homicide Rate Trends

While my primary interest is to forecast city level crime rates, I begin by considering the national time series in homicide rates. Some of the basic issues involved in forecasting crime can be illustrated effectively by considering this single national time series. Attempts to forecasts this series in the 1980s and 1990s have been notoriously inaccurate.

Using data on annual homicide rates per 100,000 persons from the National Center for Health Statistics, I display the annual time series in the log rate from 1935-2002 in Figure 1.[3] The series appears to be quite persistent over time, with some periods of fluctuation and notable turns. From 1935 until around 1960 the homicide rate tended downward, and then began sharply rising until reaching a peak of just over 10 homicides per 100,000 (log-rate of 2.31) in 1974. Over the next 15 years, homicide rates fluctuated between 8 and 10 per 100,000 (log rates between 2.13 and 2.33), and then unexpectedly

[3] Data come from the National Center for Health Statistics, and were downloaded in January 2007 from the Bureau of Justice Statistics Historical Crime Data Series at http://www.ojp.usdoj.gov/bjs/glance/tables/hmrttab.htm. The victims of the 9/11/01 terrorist attacks are not included in this analysis.

began to sharply and steadily fall in the 1990s. By the end of the century, the homicide rate hit a 34 year low of 6.1 per 100,000 (log-rate of 1.81).

A variety of demographic, economic and criminal justice factors are known to be correlated with this series, and have been used to predict aggregate crime rates. Demographic characteristics of the population – namely gender, age and race distributions -- have long played a primary role in crime forecasting models (see Land and McCall, 2001). Criminal justice policies including the number of police and the incarceration rates are also thought to be important factors in explaining aggregate crime rates and trends. Macroeconomic variables appear to play only a modest role in explaining aggregate crime rates, especially for violent crimes such as homicide (Levitt, 2004).

For this study, I use two primary covariates, the percent of the population that are 18 year old males and the fraction of the population (per 100,000) that are incarcerated.   Figure 2 displays the time series for these two random variables along with the homicide rate series. All three series are normalized to be relative to a 1935 base. This figure reveals that the fraction of young men (18 year olds) is closely related to the homicide rate.   In contrasts, the variation in incarceration rates does not mirror the analogous variation in crime rates. Rather, incarceration rates tended to increase over the entire century, with the sharpest increases beginning in the mid-1970s. The notable exceptions are during peak draft years during World War II and the Vietnam War.

I follow the convention in the literature by taking the natural logarithm of the crime and incarceration rates. I estimate the regression models using the annual data from 1935-2000, leaving out pre-1935 data because accurate homicide rate and covariate information is not readily available, and the post 2000 data to assess forecasting performance.

The means and standard deviations of the variables used in the analysis are displayed in Table 1. Figures for 2001-2002 are separated out, as these data are not used to estimate the model. Notice the difference between the historical series from 1935-2000, where mean log-homicide rate equals 7.26 per 100,000 persons, and the 2001-2002 rate, which is over one point less.

A. The Best Linear Predictor

To forecast the homicide series in Figure 1, I fit the following autoregressive regression model:

$$(1.)\qquad y_t = \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + x_t \beta + \varepsilon_t \,,$$

where y_t is the log-homicide rate in year t, x_t is 1xK vector of observed covariates, and ε_t is an iid unobserved random variable assumed to be uncorrelated with x_t.[4] Finally, $\{\gamma,\beta\}$ are unobserved covariates which are consistently estimated using least-squares.

Table 2 displays estimates and standard errors from two variations on this specification: Model A includes the AR(2) lags and Model C presents estimates from the full unrestricted specification. Consistent with Figure 1, there is a strong autoregressive component to the series, with the period t homicide rate being strongly associated with the lagged rates. In the unrestricted Model C, the regression coefficients associated with the incarceration rate is positive, small and statistically insignificant. Likewise, the coefficient on the demographic variable is statistically insignificant and relatively small in magnitude.

B. In-Sample Forecasts

How well does this model do at forecasting crime in the 1980s and 1990s? Figure 3 presents the predicted series under different starting dates for the forecast. In panel A, the forecasted series begins in 1981 (i.e., 1980 is assumed to be the last observed year); in Panel B the forecasts begin in 1986, in Panel C the forecasts begin in 1991, and finally, in Panel D, the series begins in 1996. In each case, the forecasts are dynamic in y_{t-1} and y_{t-2} ; the forecasted lagged homicide rates, not the actual rates, are

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[4] Several statistical tests were used to aid in the selection of the specification in Equation 1. Based on a visual inspection of the correlogram and on an augmented Dickey-Fuller test, I found no evidence of a unit root in the homicide series. Thus, there appears to be no need to difference this series. The AR(2) model was then selected using the AIC and BIC criteria, among the class of ARIMA(3,0,3) models. Finally, McDowall (2001) provides evidence favoring a linear specification over a number of nonlinear alternatives.

used. Importantly, these forecasts are not dynamic in the covariates; for Model C, actual covariate data are used for all forecasts.

The forecasts beginning in 1981 (Panel A) and 1986 (Panel B) suffer the same qualitative errors made by criminologist nearly three decades ago. In particular, the model forecasts a steady drop in homicide rates throughout the 1980s, yet the actual rates rose in the late 1980s.

Ultimately, the ability of this model to effectively forecast crime depends on observed relationships continuing into future periods. The model cannot effectively capture new phenomena such as the rise or fall of new drug markets. What then should forecasters have predicted at the start of the 1990s? Are we to believe that mid-1980s was just a deviation from the norm, or that there had been a regime shift? Normal deviations and turns in a series are notoriously difficult to predict, and the 1980s might be nothing more. If so, then the historical time series might have been used to accurately forecast crime in the 1990s even if it mischaracterized crime trends in the late 1980s. Instead, however, the forecasting errors in the 1980s might have reflected a structural change in the time series process that cannot be identified by the historical data.

With hindsight, we can see that the forecasts made for the 1990s based on the historical series are relatively accurate. Crime is forecasted to fall (see Figure 3c), although the regression models miss the steepness of the realized decline. Thus, the historical time series, as modeled in Equation (1), are sufficient to predict the direction if not the full magnitude of the drop in homicide rates during the 1990s. These general patterns are consistent with the hypothesized notion of a short “bubble” in the homicide rate that was induced by violence associated with the crack epidemic in the 1980s (Land and McCall, 2001).

A more systematic evaluation is found by measuring the errors associated with different fixed forecast horizons. In particular, I compute the two and five year ahead forecasts for each year from 1980-2002. Given these predictions, I then report measures of forecasts bias and accuracy. I compute mean error (ME) as an indictor of the statistical bias of the forecasts, and the root mean squared error (RMSE) and mean absolute error (MAE) as measures of the accuracy of the forecasts (CBO, 2005). The

MAE and RMSE show the size of the error without regard to sign, with RMSE giving more weight to larger errors. If small errors are less important, the RMSE error will give the best indication of accuracy. Also, as a different indictor of systematic one-sided error or forecasting bias, I compute the fraction of positive errors (FPE).

Table 3 displays the realized log-homicide rates and the two- and five-year ahead forecasts for each year from 1980 to 2002. I also include forecasts derived from a naïve random walk model that uses the last observed rate to predict future outcomes. So, in the two-period ahead analysis, the naïve forecast would be the rate observed two periods prior, and likewise the five-period ahead forecast is the rate in period t-5. The bottom rows of Table 3 display the four summary measures of bias and accuracy of the forecasts.

Several general conclusions emerge from the results displayed in this table. First, as expected, the two period ahead forecasts are more accurate than the five-period ahead counterparts. The RMSE for the two period ahead forecasts is about 0.10 and the MAE is around 0.09, whereas for the five period ahead forecasts these measures are around 0.18 and 0.15 respectively. For comparison, the RMSE for the in-sample predictions is about 0.06 (see Table 2). Second, in general, the forecasting models outperform the naïve random walk model, and especially for the longer run forecasts. For the shorter two period ahead forecast, the naïve model performs nearly as well as the AR(2) model in Equation (1). For the shorter horizons, the differences in forecasting performance across these three models appear small and, to a large degree, may reflect sampling variability. Finally, during this 23 year period, the forecasting models consistently under predict during the period from 1989 to 1994 and over predict homicide rates after 1995.

C. Out-of-Sample Forecasts

In Figure 4, I display the actual log-homicide series and the one-step- ahead predictions for each year from 1970-2000. These in-sample predictions nearly match the realized crime rates; the regression model closely fits the observed data.

I also display dynamic forecasts of the homicide rate for 2001 to 2010. For these forecasts, I assume that last observed year is 2000.[5] In this setting, forecasts of the homicide series are sensitive to variations in the choice of explanatory variables included in the regression model. Both models predict relatively modest changes to the homicide rate over the period, yet they have different qualitative implications. The Model A forecasts imply that homicide rates will continue to fall during the period, whereas the Model C forecasts suggests homicide rates will increase.

III. Forecasting City Level Crime Rates

To forecast city level crime rates, the Committee on Law and Justice (CLAJ) provided me with a panel data set of annual crime rates in the 101 largest U. S. cities (approximately all cities with greater than 200,000 persons) over the period 1980 to 2004.[6] The data consists of rates of homicide, robbery, burglary, and motor vehicle theft as measured by the Federal Bureau of Investigations Uniform Crime Reports. The data also include annual measures of drug related arrest, state level incarceration rates, and the number of police per 100,000. I supplement these data with annual county level demographic information on the fraction of the population whom are males between 20-29 and males between 30-39, and the natural logarithm of the total county population. As with the national series, I follow the convention in the literature by taking the natural logarithm of the crime, incarceration and policing rates.

Using these data, I provide out-of-sample city level forecasts for 2005 and 2006. When providing out of sample forecasts, one must either predict contemporaneous covariates or use lagged covariates in the forecasting model. I use lagged covariates. That is, to address the practical problem that arises when forecasting using covariates, I lag all covariates by two periods.

Given this lag structure, I estimate the models using data from 1982-2000, leaving out pre-1982 data to incorporate the lagged covariates and the post 2000 data to assess forecasting performance.

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[5] For the Model C forecasts, observed covariate data from 2001 and 2002 are used in the corresponding forecasts. Unobserved covariate data from 2003-2010 are assumed to be unchanged from the 2002 realizations.

[6] Most of the crime data from Kansas City are missing. Thus, while there are 101 cities in this sample, Kansas City is dropped from most of the analysis.

Thus, for each of the 101 cities, there are 19 years of data used to estimate the parameters and four years of data to evaluate forecasting performance. .

Summary statistics for these variables are provided in Table 4. As in the national homicide series, the pre-2000 average crime rates are notably different than the analogous rates from 2001-2004. The average log-homicide rate, for example, is 2.55 in the 1982-2000 period, and 2.31 from 2001-2004. Likewise, the mean log-incarceration rates from 1982-2000 is 5.50, much less than the average rate of 6.04 from 2001-2004.

By using a common data set and specification, I provide insights into how different regression models perform in forecasting city level crime rates. I examine the suitability of these models in several ways. First, in Section A, I describe the basic model, and examine the estimated parameters. I find considerable variability in the parameter estimates even amongst the models that are restricted to be the same across all cities. In Section B, I assess forecast performance of these models to one-, two-, four- and ten-year ahead forecasts of city level crime rates. I compare the performance of a basic homogeneous panel data regression model with a flexible heterogeneous alternative. These results show much variability in the forecast performance of various models across cities, crimes and forecasts horizons. The heterogeneous models are not always superior. For short run forecasts, a naïve *random walk forecasting* model appears to perform well, whereas the homogeneous models seems to perform relatively well for longer run forecasts.

In Section C, I provide out-of-sample forecast of the city level crime rates using the homogeneous dynamic panel data model. As with the forecasted national homicide rate series, I find the qualitative predictions are sensitive to the underlying model.

A. Best Linear Predictor

To forecast city level crime rates, I begin by considering the following dynamic panel data model:

(2.) $$y_{it} = \gamma_1 y_{i,t-1} + x_{i,t-2}\beta + \nu_i + \varepsilon_{it}$$

where y_{it} is the log-crime rate in state i for year t, x_{it} is the set of observed covariates, ν_i reflects unobserved city level fixed effects, and ε_{it} is an iid unobserved random variable, independent of x and ν. The unknown parameters, {γ, β} are estimated by ordinary least-squares.[7]

Table 5 displays estimates and standard errors from three variations on the specification in Equation (2.): Model A includes the autoregressive lag, β=0; Model B includes the covariates, γ = 0; and Model C is the full unrestricted specification. All three specifications include the city level fixed effects, ν_i.

The estimates from Model A reveal a notable autoregressive component in the four crime rate series, such that the period t crime rate is strongly associated with the lagged rate. There is, however, much variation in this autoregressive coefficient across the four crimes, varying from 0.452 for homicide to 0.923 for burglary. The autoregressive coefficient estimate uniformly falls but still remains substantial and statistically significant when covariates are added to the model.

The association between crime and covariates seems to generally conform to expectations. Log-crime rates increase with the natural logarithm of drug arrests and the fraction of young men, and decrease with the log-incarceration rates and the log-number of police. Again, there is much variability across crimes and specifications. For example, in Model B, the absolute elasticity of the crime rate with respect to the per-capita number of police ranges from a high of 0.362 for homicide to a low of 0.174 for burglary.

In panel data, the forecast precision depends both on the stability of the process over time, and across cross-sectional units. Variation in the slope parameters across the cross-sectional units may compromise the ability of the homogeneous dynamic panel data model in Equation (2) to accurately

[7] The OLS estimator will generally be inconsistent for fixed-T. Alternative instrumental variable estimators are, under certain assumptions, consistent in this situation. I did not evaluate the forecasts found under alternative estimators.

forecast crime rates. There is, in fact, some evidence suggesting heterogeneity in mean crime regression functions across geographic units. DeFina and Arvanties (2002), for example, conclude that a regression coefficient measuring the association between crime and incarceration rates differs widely across states, with the estimated coefficient being negative for some states and positive for others.

To assess whether and how this heterogeneity plays a role in forecasting city level crime rates, I estimate city specific regression models. For this illustration, I focus on the Model A regression with a lag dependent variable but without covariates. That is,

$$(3.)\qquad y_{it} = \gamma_i y_{i,t-1} + \nu_i + \varepsilon_{it}$$

where γ_i is the unobserved city i coefficient on the lagged dependent variable. I estimate this coefficient for all cities in the sample using ordinary least-squares. As before, ε_{it} is assumed to be a mean zero iid unobserved random variable.

Summary information on the city level coefficient estimates are presented in Table 6. In particular, I present the mean, median, maximum, minimum and interquartile range (IQR) of the coefficient estimates. While the means and medians are close to the estimated value from the homogeneous panel data model in Equation (2), there is much variability in the coefficient estimates, particularly for violent crimes. The IQR for the homicide rates estimates, [0.220, 0.751], has a width of over 0.5 and for robbery rates has width of over 0.25. In contrast, the IQR has a width of 0.18 for burglary and 0.11 for MVT.

To gain insight on the variation in the estimates across specific cities, Table 7 displays the coefficient estimates for six selected cities: Denver, Knoxville, Madison, New York, Richmond and San Francisco. These cities were selected to provide diversity in size and the location.[8] In some cases, the

[8] Results for other cities in the sample are available from the author.

city specific coefficients estimates are similar to those found from the homogeneous panel data model in Equation (2), but in others the estimates are notably different. Consider, for example, the coefficient estimates found using the robbery rate series. The autoregressive coefficient estimates found using the homogeneous model is 0.759, similar to the city specific estimates found for Knoxville (0.76), Richmond (0.73) and Madison (0. 65). In contrast, the two sets of estimates are notably different for Denver (0.94), New York (1.13) and San Francisco (0.94).

This heterogeneity in the lagged coefficient would seem to have important implications for our ability to accurately forecast city level crime rates. The heterogeneous estimators have the desirable property of allowing for differences across cities. Yet, one might fit the observed the data quite well at the expense of forecasting the future very poorly. In particular, estimates from the city specific models will be less precise, and may be highly influenced by short run bubbles and other departures from a "stationary" trend. In this application, where the time series includes 19 observations per city, this tradeoff seems especially important. Ultimately, whether and how the heterogeneity in crime rate regression models impacts the forecasting performance of these models is unknown. I take up that issue in the next section.

B. In-Sample Forecasts

How well does the homogeneous panel data model do at forecasting crime rates? Given my focus on two period ahead forecasts, I begin by using this model to predict the 2003 and 2004 crimes rates for each city. Recall, that the models are estimated using data through 2000, so forecasts of the 2003 and 2004 rates constitute an "out of sample" forecasts for which we observe the realized crime rate. For this exercise, I treat 2002 as the last observed year, so that predictions for 2003 are one-period ahead forecasts and predictions for 2004 are two-steps ahead. For each city crime pair, I compute forecasts using the restricted Model A and the unrestricted Model C.

Forecasts for the six selected cities, Denver Knoxville, Madison, New York, Richmond and San Francisco, are presented in Table 8. The results vary across crimes, cities, time and model. The forecast errors are generally smaller in 2003 than 2004, and generally larger for homicide than other crimes. However, models that do relatively well at predicting a particular crime in a particular city need not provide accurate predictions about other crimes, in other time periods or cities. For example, both models do poorly at forecasting the 2003 homicide rate in Madison, yet are relatively accurate at forecasting the 2004 homicide rate, as well as the robbery rate in 2003 and 2004. Likewise, the models do well at predicting the 2003 homicide and MVT rates in Denver, but do poorly at predicting robbery and burglary. There is also variation across forecasting models. In general, Model A appears to provide more accurate forecasts, but there are many notable exceptions (e.g., the 2003 homicide rate in Knoxville).

To provide a more systematic assessment of the capabilities of these models, I compute basic summary measures of the errors in forecasting crime in every city in the sample. Table 9 displays the mean error, the fraction of positive errors, the RMSE and MAE for forecasts from Model A, Model C, and a naïve random walk forecasting model where the 2002 rate is used as the prediction for 2003 and 2004.

In examining these results, it is useful to first compare the summary measures across different crimes. The models do relatively poorly at forecasting homicide. The RMSE and MAE for the 2003 homicide forecasts are around 0.40 and 0.25, substantially larger than analogous measures found for the other three crime rates. These relatively large errors would seem to reflect the wide variation in the city specific coefficient estimates found in Section A above (see Table 6 and 7).

Comparing the results across the different models is also instructive. For these one- and two-year ahead predictions, the naïve random walk forecasts seem to be at least as accurate as the regression model forecasts. In other words, for shorter run forecasts, the basic panel data models do no better, on average, than simply guessing that next year's crime rate will be the same as this year's. In terms of the two regression models, Model A does at least as well if not better than the unconstrained Model C. Moreover, these models seem to lead to qualitatively different prediction errors. The fraction of positive errors for Model A is greater than one-half, implying that the model tends to predict crime rates in excess of the realized outcomes, For Model C, the fraction positive is always less than 0.50, suggesting predictions tend to fall short of the realized crimes rates.

Finally, notice that errors are slightly larger for the one-step ahead 2003 prediction than the 2004 two-step ahead predictions. This paradoxical result can be explained by the forecasting error from a single city, Louisville. The 2003 realizations for Louisville were outliers that were not repeated again in 2004. As a result, 2003 forecast errors were substantially inflated. For example, the log-MVT forecast is 6.70 whereas the realized rate is 4.76, for a forecast error of nearly 2.0. No other absolute forecast error for log-MVT in 2003 exceeded 0.36. If we remove Louisville, the RMSE for the 2003 forecasts made from Model A falls to 0.31 for log-homicide, to 0.15 for log-robbery, to 0.09 log-burglary, and to 0.14 for log-MVT. The analogous figures for the 2004 forecasts errors barely change. Thus, except for Louisville, these summary measures imply that the forecast errors are smaller in 2003 than 2004.

An important objective of this paper is to assess how the dynamic panel data model in Equation (2) performs relative to alternative models, and most notably the heterogeneous model in Equation (3).[9] The two models can produce very different predictions.

Insights into the primary issues are found by comparing forecasts for a particular crime across different cities. Figure 5 displays the log-robbery time series and forecasts for the six cities analyzed above (see Tables 7 and 8). For each city, I display dynamic forecasts that start in 2001 and end in 2004 using both the homogeneous and the heterogeneous models. The one-step- ahead predictions from the heterogeneous model for each year from 1982-2000 are also displayed. These in-sample predictions nearly match the realized crime rates; the heterogeneous model closely fits the observed data.

For the three cities where the coefficient estimates from the two models are similar, namely Knoxville, Madison and Richmond, the two forecasts are nearly identical and seem to provide accurate

[9] There are many other related models, estimators and approaches one might consider. See Baltagi (2006) for examples of forecasting models and estimators within the same structure. Model averaging techniques similar to those described in this volume by Durlauf, Navarro and Rivers (2006) have also been shown to be effective at reducing forecasting errors. Finally, one might consider using entirely different approaches, such as the prediction market forecasting techniques described by Gürkaynak and Wolfers (2006).

four period ahead predictions of general trends and, to some extent, the levels in log-robbery rates. The most striking results are found in the three cities where the autoregressive coefficient estimates are notably different across the two models, Denver (0.94), New York (1.13) and San Francisco (0.94). Forecasts of robbery rates for these cities are sensitive to the underlying model. In particular, for these three cities the homogeneous model suggests an increase in robbery rates over the four-year period, whereas the heterogeneous model leads to the opposite conclusion. Realized robbery rates over this four year period closely track the forecasts from the homogeneous model in Denver, from the heterogeneous model in San Francisco, and lie between the two forecasts for New York.

Clearly, the heterogeneous model does not provide uniformly superior out-of-sample forecasts. Table 10 displays summary measures of how these different models perform on average across all cities and for different forecasts horizons. In addition to analyzing the forecasting performance of the models in Equations (2) and (3), I also consider two naïve models, one where the forecast equals the city level mean or fixed effect – the best constant forecast – and the other where the forecast equals the last observed rate – the random walk forecast. Finally, I display the RMSE from the one-step ahead forecasts that, in practice, is only feasible if the period t-1 realization is known (or perfectly forecasted).

Each model is used to provide forecasts of annual crime rates for three different overlapping horizons, 2003-04, 2001-04, and 1995-04, and three different starting points, 2002, 2000 and 1994. Thus, dynamic forecasts starting in 1994 are used to make 10 year-ahead predictions for the 2004 crime rate. Importantly, these forecasts are not dynamic in the covariates; for Model C, actual covariate data are used for all forecasts, even those that go beyond two year ahead predictions.

Many of the findings reported in this table confirm the earlier results. In particular, for shorter run forecasts, the restricted Model A seems to do at least as well as the unrestricted Model C, and both of these homogeneous models provide slightly less accurate forecasts than the naïve random walk model. As before, these differences are modest and may simply reflect sampling variability rather than true differences in forecasting performance.

In both cases, however, these patterns are not consistent across forecast horizons; models that work relatively well for the shorter run do not necessarily provide accurate forecasts for longer horizons. Long-horizon random walk forecasts, for example, perform poorly. The RMSE for the random walk forecasts of homicide rates in 1995-2004, for instance, is 0.52, much greater than the RMSE of 0.41 found using the sample average (i.e., the best constant predictor), and Model A, where the RMSE is 0.39.

Likewise, for longer run forecasting problems, the unrestricted Model C provides more accurate forecasts than the restricted alternative. For example, the RMSE for the 1995-2004 forecasts of the homicide rate using the unrestricted Model C is 0.33, 0.06 less than the analogous RMSE of the forecasts made from the restricted Model A. This finding, however, may reflect the fact that the long-run (over two year forward) Model C forecasts utilize realized covariate data. In practice, the necessary covariate data will not be observed.

Finally, the added flexibility of the heterogeneous forecasting model in Equation (3.) leads to some improvements in forecasting accuracy. As might be expected, the results are especially striking for homicide, where there is evidence of much heterogeneity in the parameter estimates. Assuming the 2002 log-homicide rate is the last observed data point, the RMSE for the 2003-04 forecasts is 0.37 using the homogeneous Model A and 0.19 using the heterogeneous alternative.

For the other crimes, however, the forecasting gains from the heterogeneous model are less pronounced. For example, the RMSE for forecast of burglary rates in 2003-04 is 0. 16 for both models, and the analogous RMSE for MVT is 023 for the homogeneous model and 0.19 for the heterogeneous alternative. Except for the homicide series, the efficiency gains from the homogeneous model appear to nearly offset any biases due to heterogeneities.

C. Out-of-Sample Forecasts

As noted above, I forecasts city level crime rates using the observations through 2004. For this illustration, I use the panel data models from Equation (2.) to provide forecasts of city level crime rates for 2005 and 2006. I also use Model A to forecasts crime rates in 2009. Without covariate data over this period, long-run Model C forecasts are not feasible.

In Table 11, I present these out of sample forecasts for the six selected cities analyzed throughout this paper. Except for New York City, the forecasted changes across these six cities are generally modest. For example, the log-robbery rates in Denver, Knoxville, and Madison are all predicted to change by less than 0.03 points over the 5-year period from 2004 to 2009. During the preceding five years, from 1999-2004, log-robbery rates increased by 0.23 in Denver and 0.04 in Madison, and decreased by 0.14 in Knoxville.

The specific changes vary by city and by crime. To see this, notice the five year ahead forecasts. In San Francisco, log-robbery rates are forecasted to increase by 0.38 points, whereas forecasts for the other three crime rates are slightly less than the 2004 levels. In Madison, log-homicide rates are forecasted to increase by 0.31 and log-MVT rates by 0.15, whereas the log-crime rates for both robbery and burglary are forecasted to drop over the same period.

Finally, there are notable differences in the predictions made from the two models. In several cases, Model A implies an increase in crime whereas Model C predicts a slight drop, and in nearly every case the Model A forecasts exceed the Model C counterparts.

Overall patterns regarding these forecasts can be found by examining Table 12, which displays summary measures for the forecasts in every city. In particular, for each crime and each forecast period, I report the mean forecast, the mean predicted change, the fraction of positive predicted changes, the IQR of the predicted change, and the mean absolute predicted change.

The results in this table confirm that Models A and C provide different pictures about what to expected for crime in large cities over this period. Forecasts made using Model A generally imply modest increases (e.g., homicide) or little overall change (e.g., burglary) in city level crime rates throughout the reminder of this decade. Forecasts made using Model C paint a different picture, with crime rates continuing to fall, in general, over the period. For example, the IQR in the forecasted change in log-robbery rates from 2004 to 2006 is [0.02, 0.21] when using model A but is [-0.20, 0.02] when using Model C. Likewise, the fraction of cities forecasted to see increases in the robbery rate is 82% under Model A, but only 36% in Model C. Finally, Model C generally predicts slightly larger absolute changes in the crime rates, and both predict much larger absolute changes in the homicide rates than the other three crimes.

Forecasts of the log-crime rate series are sensitive to variation in the choice of explanatory variables in the regression model. That is, whether one concludes that city level crime rates will increase or decrease based on models of this type depends on which control variables are included.

This variability in the forecasts is difficult to reconcile given the current state of the literature. As far as I can tell, there is almost no research on how best to forecast crime, and there is much disagreement about the proper set of covariates to include. The limited results presented in Section B suggest that Model A provides somewhat more accurate forecasts for one and two year horizons. If true, this would imply that city level crime rates will tend to increase over the period. Yet, these results also reveal that for short run forecasts the naïve random walk model provides slightly more accurate forecasts than either panel data model. That is, for these short run forecasts, we might not be able to do better than the predicting that tomorrow will look like today.

IV. Conclusions

In this paper, I compare the forecasting performance of a basic homogeneous model to the heterogeneous counterpart using the city level panel data provided by CLAJ. The results reveal the fragility of the forecasting exercise. Seemingly minor changes to a model can produce qualitatively different forecasts and models that appear to provide sound forecasts in some scenarios do poorly in others. In the end, the naïve random walk forecasts that tomorrow will be like today does quite well relative to the linear time-series models, especially for shorter run forecast horizons.

Two factors contribute to the variability and uncertainty illustrated in this paper. First, forecasting is an inherently difficult undertaking. Social phenomena such as crime can sometimes evolve in subtle but substantial ways that are very difficult to identify using historical data and can take a long time to understand. Forecasts are invariably error ridden around turning points, especially when these movements are largely the result of external events that are themselves unpredictable.

Second, there lacks a well-developed research program on the problem of forecasting crime. For further headway to be made there needs to be a focused and sustained research effort. Periodic efforts to forecast crime or analyze forecasting models cannot hope to provide meaningful guidance. Effective forecasts of social processes that evolve over time would seem to require a scientific process that evolves as well.

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Figure 1: National Annual Homicide Rate, 1935-2002

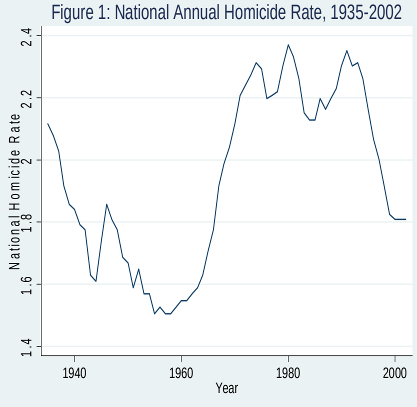
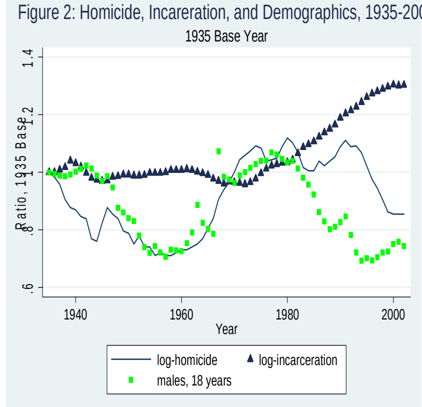


Figure 2: Homicide, Incareration, and Demographics, 1935-2002



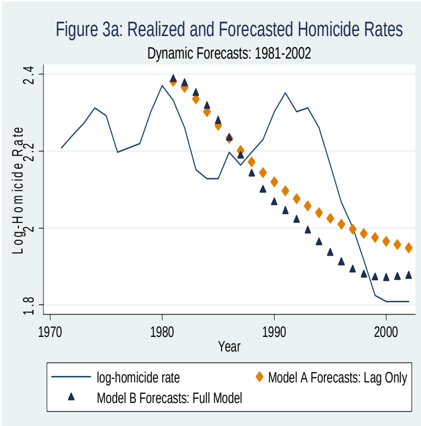


Figure 3a: Realized and Forecasted Homicide Rates

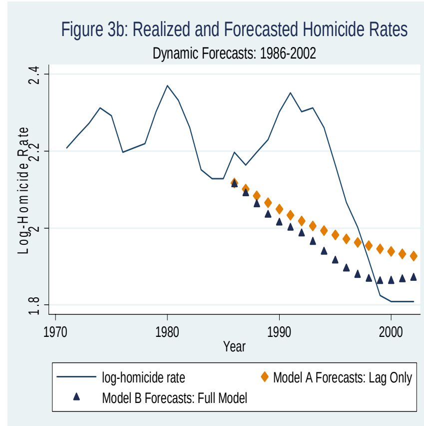


Figure 3b: Realized and Forecasted Homicide Rates

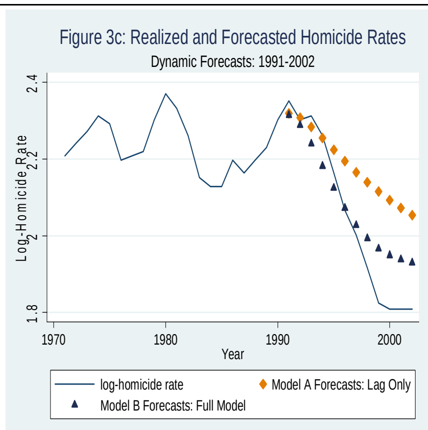


Figure 3c: Realized and Forecasted Homicide Rates

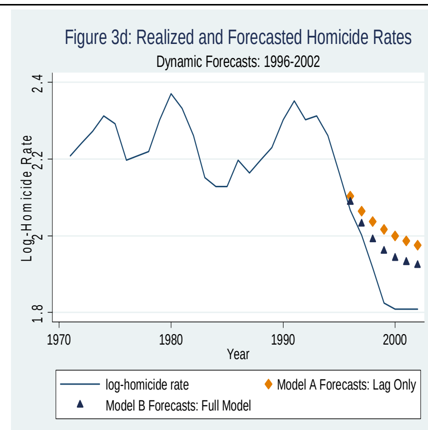


Figure 3d: Realized and Forecasted Homicide Rates

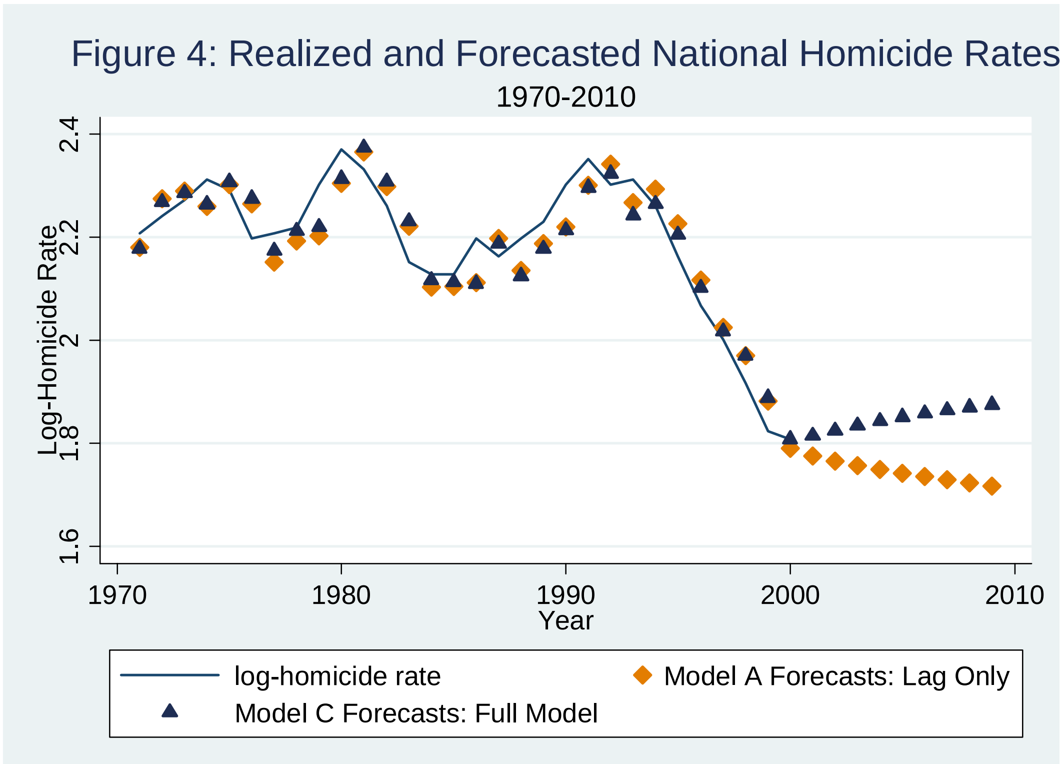


Figure 4: Realized and Forecasted National Homicide Rates
1970-2010
Log-Homicide Rate
2.4
2.2
2
1.8
1.6
1970
1980
1990
2000
2010
Year
log-homicide rate
Model A Forecasts: Lag Only
Model C Forecasts: Full Model

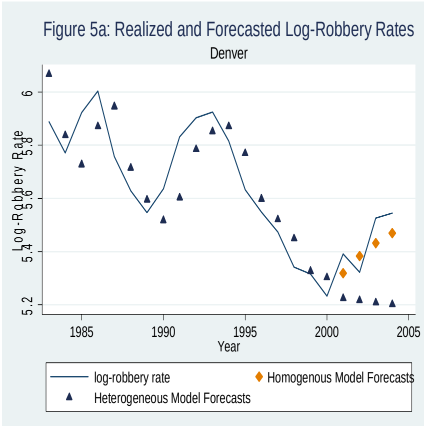


Figure 5a: Realized and Forecasted Log-Robbery Rates
Denver
Log-Robbery Rate
Year
log-robbery rate
Homogenous Model Forecasts
Heterogeneous Model Forecasts

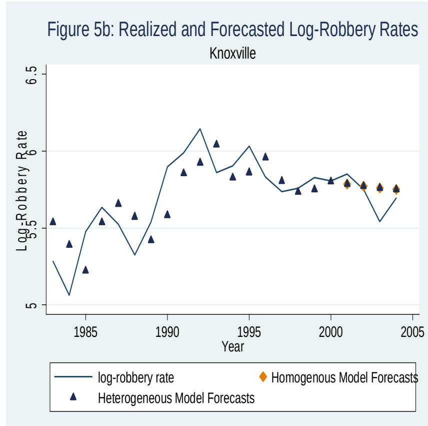


Figure 5b: Realized and Forecasted Log-Robbery Rates
Knoxville
Log-Robbery Rate
Year
log-robbery rate
Homogenous Model Forecasts
Heterogeneous Model Forecasts

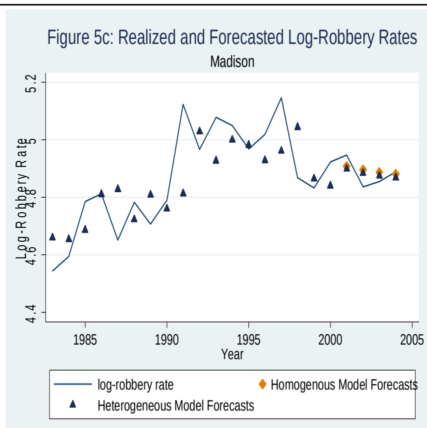


Figure 5c: Realized and Forecasted Log-Robbery Rates
Madison
Log-Robbery Rate
Year
log-robbery rate
Homogenous Model Forecasts
Heterogeneous Model Forecasts

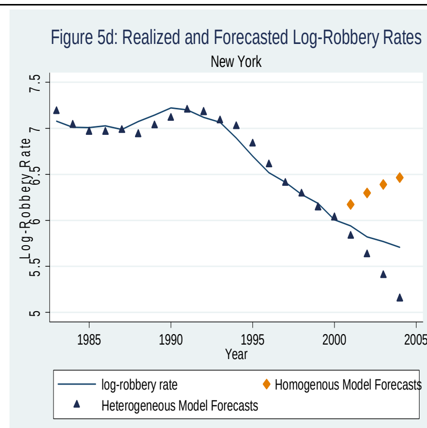


Figure 5d: Realized and Forecasted Log-Robbery Rates
New York
Log-Robbery Rate
Year
log-robbery rate
Homogenous Model Forecasts
Heterogeneous Model Forecasts

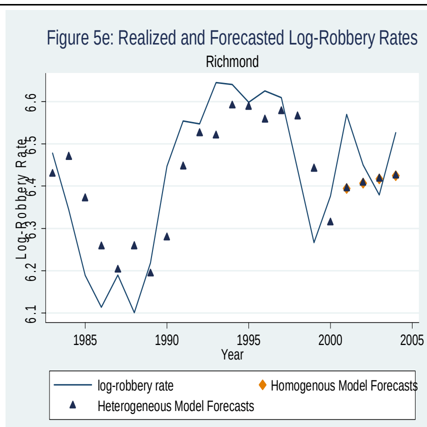


Figure 5e: Realized and Forecasted Log-Robbery Rates
Richmond
Log-Robbery Rate
Year
log-robbery rate
Homogenous Model Forecasts
Heterogeneous Model Forecasts

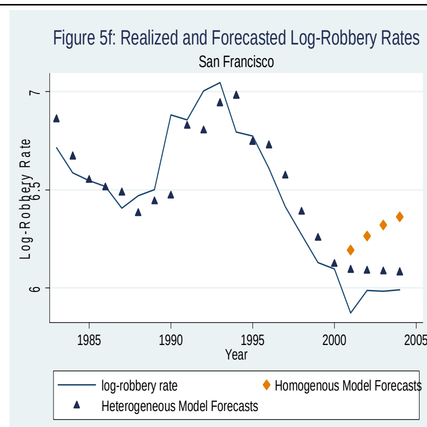


Figure 5f: Realized and Forecasted Log-Robbery Rates
San Francisco
Log-Robbery Rate
Year
log-robbery rate
Homogenous Model Forecasts
Heterogeneous Model Forecasts

Table 1: Means and Standard Deviations by Selected Years for The National Homicide Rate Series Data

	1935-2000		2001-2002
Variable	Mean	Std. Dev	Mean
Homicide Rate	7.26	2.00	6.10
Log-Homicide Rate	1.94	0.28	1.81
Log Incarceration Rate	4.98	0.48	6.16
Fraction Male, 18	0.008	0.001	0.007
N	66		2

Table 2:
National Homicide Rate Regression Model Estimates and Standard Errors,

	A	**C**
y_{t-1}	1.46	1.42
	(0.12)	(0.12)
y_{t-2}	-0.50	-0.48
	(0.12)	(0.13)
Ln(inc)		0.01
		(0.03)
Fraction Male, 18		11.38
		(11.25)
RMSE	0.06	0.06
R^2	0.96	0.96
N	64	64

Notes:
Ln(inc) ≡ log-incarceration rate; y_t ≡ log-homicide rate in year t.

Table 3: Two and Five Year Ahead Forecast of National Log-Homicide Rates, 1980-2002

		Two-Year Ahead Forecasts						Five-year Ahead Forecasts					
year	log-	Model A		Model C		Naïve Model		Model A		Model C		Naïve Model	
	homicide	forecast	error	forecast	error	forecast	error	forecast	error	forecast	error	forecast	error
1980	2.37	2.17	-0.20	2.23	-0.14	2.22	-0.15	2.10	-0.27	2.28	-0.09	2.29	-0.08
1981	2.33	2.28	-0.06	2.31	-0.02	2.30	-0.03	2.02	-0.31	2.21	-0.12	2.20	-0.13
1982	2.26	2.32	0.06	2.36	0.10	2.37	0.11	2.08	-0.19	2.23	-0.03	2.21	-0.05
1983	2.15	2.23	0.08	2.30	0.15	2.33	0.18	2.08	-0.07	2.22	0.07	2.22	0.07
1984	2.13	2.16	0.03	2.23	0.10	2.26	0.13	2.15	0.03	2.28	0.15	2.30	0.17
1985	2.13	2.05	-0.08	2.12	-0.01	2.15	0.02	2.18	0.05	2.30	0.17	2.37	0.24
1986	2.20	2.08	-0.12	2.10	-0.10	2.13	-0.07	2.11	-0.08	2.23	0.03	2.33	0.13
1987	2.16	2.09	-0.07	2.09	-0.08	2.13	-0.04	2.06	-0.10	2.15	-0.01	2.26	0.10
1988	2.20	2.18	-0.01	2.15	-0.05	2.20	0.00	1.99	-0.20	2.05	-0.15	2.15	-0.05
1989	2.23	2.10	-0.13	2.10	-0.13	2.16	-0.07	2.02	-0.21	2.02	-0.21	2.13	-0.10
1990	2.30	2.16	-0.14	2.14	-0.16	2.20	-0.11	2.03	-0.27	2.01	-0.29	2.13	-0.17
1991	2.35	2.19	-0.16	2.18	-0.17	2.23	-0.12	2.10	-0.26	2.07	-0.28	2.20	-0.15
1992	2.30	2.27	-0.03	2.24	-0.06	2.30	0.00	2.03	-0.27	2.03	-0.27	2.16	-0.14
1993	2.31	2.30	-0.02	2.26	-0.05	2.35	0.04	2.08	-0.23	2.05	-0.26	2.20	-0.12
1994	2.26	2.20	-0.06	2.18	-0.08	2.30	0.04	2.10	-0.17	2.05	-0.21	2.23	-0.03
1995	2.16	2.24	0.08	2.20	0.04	2.31	0.15	2.15	-0.01	2.09	-0.08	2.30	0.14
1996	2.07	2.17	0.10	2.15	0.08	2.26	0.19	2.16	0.10	2.09	0.02	2.35	0.28
1997	2.00	2.07	0.06	2.06	0.06	2.16	0.16	2.09	0.09	2.04	0.04	2.30	0.30
1998	1.92	1.99	0.07	1.98	0.06	2.07	0.15	2.13	0.21	2.06	0.14	2.31	0.40
1999	1.82	1.95	0.13	1.94	0.11	2.00	0.18	2.07	0.25	2.02	0.20	2.26	0.44
2000	1.81	1.87	0.07	1.87	0.06	1.92	0.11	2.00	0.20	1.96	0.16	2.16	0.36
2001	1.96	1.80	-0.16	1.79	-0.17	1.82	-0.14	1.96	0.00	1.92	-0.04	2.07	0.11
2002	1.81	1.82	0.02	1.79	-0.01	1.81	0.00	1.94	0.13	1.89	0.08	2.00	0.19
Mean	2.14	2.12		2.12		2.17		2.07		2.10		2.22	
Mean Error			-0.02		-0.02		0.03		-0.07		-0.04		0.08
Fraction Positive			43%		39%		52%		35%		43%		57%
RMSE			0.10		0.10		0.11		0.18		0.16		0.20
Mean Absolute Error			0.08		0.09		0.09		0.16		0.13		0.17

NOTES: Model A includes the AR(2) parameters, and Model C is includes both the AR(2) terms and the covariates.
The naïve model simply forecasts crime as the last observed crime rate, a random walk forecast.

Table 4 : Means and Standard Deviations by Selected Years for City Level Crime Panel

	1982-2000		2001-2004	
Variable	Mean	Std. Dev	Mean	Std. Dev
Log-Homicide	2.55	0.77	2.31	0.77
Log-Robbery	5.96	0.72	5.71	0.62
Log-Burglary	7.45	0.45	7.00	0.46
Log- MVT	6.78	0.63	6.69	0.56
Log-Drug_t-2	4.83	1.65	5.46	1.08
Log-Prison_t-2	5.50	5.30	6.04	0.38
Log-Police_t-2	5.35	0.35	5.45	0.36
pp2029_t-2	17.71	2.83	14.95	2.12
pp3039_t-2	16.56	1.67	15.80	1.27
Log-pop_t-2	13.46	0.78	13.56	0.81

Note: There are 1919 potential observations, but data for certain city-year pairs is missing.

Table 5: City Level Crime Rate Regressions, 1982-2000

	Homicide			Robbery			Burglary			Motor Vehicle Theft		
	A	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**
y_{t-1}	0.452		0.343	0.759		0.672	0.923		0.623	0.851		0.765
	(0.022)		(0.024)	(0.016)		(0.020)	(0.012)		(0.021)	(0.012)		(0.017)
$Ldrug_{t-2}$		0.051	0.036		0.052	0.018		0.032	0.012		0.069	0.016
		(0.010)	(0.009)		(0.007)	(0.005)		(0.006)	(0.004)		(0.009)	(0.006)
$Linc_{t-2}$		-0.246	-0.148		-0.323	-0.054		-0.362	-0.068		-0.271	-0.055
		(0.050)	(0.047)		(0.037)	(0.029)		(0.030)	(0.026)		(0.045)	(0.030)
$Lpolice_{t-2}$		-0.362	-0.272		-0.195	-0.099		-0.174	-0.122		-0.181	-0.060
		(0.077)	(0.073)		(0.058)	(0.043)		(0.046)	(0.037)		(0.070)	(0.045)
$pp2029_{t-2}$		0.016	0.020		0.008	0.023		0.063	0.039		0.002	0.022
		(0.009)	(0.009)		(0.007)	(0.005)		(0.005)	(0.004)		(0.008)	(0.005)
$pp3039_{t-2}$		0.094	0.070		0.097	0.044		0.051	0.020		0.159	0.052
		(0.010)	(0.009)		(0.007)	(0.006)		(0.006)	(0.005)		(0.009)	(0.006)
$Lpop_{t-2}$		0.080	1.130		8.789	4.829		6.494	3.449		9.111	5.052
		2.130	(2.003)		(1.596)	(1.194)		(1.261)	(1.007)		(1.922)	(1.248)
$Lpop^2_{t-2}$		-0.015	-0.051		-0.309	-0.175		-0.258	-0.137		-0.302	-0.178
		(0.078)	(0.073)		(0.058)	(0.044)		(0.046)	(0.037)		(0.070)	(0.046)
RMSE	0.306	0.315	0.296	0.181	0.238	0.177	0.158	0.188	0.149	0.188	0.287	0.186
R^2	0.846	0.833	0.852	0.940	0.892	0.940	0.884	0.844	0.902	0.916	0.797	0.915
N	1963	1586	1572	1980	1594	1585	1980	1594	1585	1980	1594	1585

Note: All regressions include city level fixed effects

Table 6: Summary of 100 City Specific AR(1) Coefficients

	Homicide	Robbery	Burglary	MVT
Heterogeneous Model				
IQR	[0.220,0.751]	[0.634, 0.894]	[0.832, 1.012]	[0.805, 0.919]
Median	0.567	0.798	0.963	0.861
Mean	0.486	0.752	0.902	0.822
Minimum	-0.585	0.023	0.029	-0.021
Maximum	1.059	1.129	1.371	1.117
Homogeneous Model	0.452	0.759	0.923	0.851

Table 7: Heterogeneous Model Coefficient Estimates for Selected Cities

	Homicide	Robbery	Burglary	MVT
Denver	0.63	0.94	1.02	0.68
Knoxville	-0.03	0.76	1.01	0.73
Madison	0.25	0.65	0.95	0.93
New York	1.06	1.13	1.07	1.12
Richmond	0.76	0.73	0.90	0.67
San Francisco	0.73	0.94	0.94	0.95

Table 8: Homogeneous Model Forecasts for Selected Cities, , 2003-04

		2003					2004				
		Model A			Model C		Model A			Model C	
		y	Forecast	Error	Forecast	Error	y	Forecast	Error	Forecast	Error
Homicide	Denver	2.41	2.40	-0.01	2.35	-0.06	2.73	2.50	-0.23	2.42	-0.32
	Knoxville	2.33	2.54	0.21	2.27	-0.06	2.43	2.56	0.12	2.21	-0.23
	Madison	1.31	0.51	-0.80	0.27	-1.04	0.34	0.59	0.25	0.23	-0.10
	New York	2.00	2.49	0.48	2.46	0.46	1.95	2.71	0.77	2.60	0.66
	Richmond	3.83	3.76	-0.07	3.62	-0.21	3.86	3.78	-0.08	3.60	-0.26
	San Francisco	2.19	2.30	0.12	2.31	0.12	2.45	2.38	-0.07	2.37	-0.08
Robbery	Denver	5.53	5.39	-0.14	5.43	-0.10	5.54	5.44	-0.11	5.50	-0.05
	Knoxville	5.54	5.74	0.20	5.63	0.09	5.69	5.74	0.04	5.56	-0.13
	Madison	4.86	4.84	-0.01	4.69	-0.16	4.89	4.85	-0.04	4.59	-0.30
	New York	5.77	6.03	0.26	6.04	0.27	5.71	6.19	0.48	6.18	0.48
	Richmond	6.38	6.45	0.07	6.30	-0.08	6.53	6.45	-0.08	6.20	-0.32
	San Francisco	5.98	6.11	0.13	6.19	0.20	5.99	6.20	0.21	6.33	0.33
Burglary	Denver	7.13	6.94	-0.19	7.10	-0.04	7.17	6.92	-0.25	7.19	0.02
	Knoxville	7.20	7.08	-0.12	6.99	-0.21	7.27	7.07	-0.20	6.93	-0.34
	Madison	6.61	6.58	-0.03	6.49	-0.12	6.49	6.55	0.06	6.42	-0.07
	New York	5.86	5.93	0.08	6.17	0.31	5.78	5.95	0.17	6.32	0.54
	Richmond	7.25	7.30	0.04	7.25	0.00	7.24	7.30	0.06	7.23	-0.01
	San Francisco	6.62	6.60	-0.02	6.71	0.09	6.69	6.59	-0.10	6.78	0.10
MVT	Denver	7.14	7.13	-0.01	7.14	0.00	7.20	7.11	-0.09	7.14	-0.06
	Knoxville	6.69	6.57	-0.12	6.51	-0.19	6.67	6.61	-0.06	6.49	-0.18
	Madison	5.67	5.71	0.04	5.57	-0.10	5.54	5.73	0.19	5.47	-0.07
	New York	5.68	5.95	0.28	6.02	0.34	5.56	6.07	0.51	6.16	0.60
	Richmond	7.21	7.11	-0.11	6.91	-0.30	7.10	7.10	0.00	6.75	-0.35
	San Francisco	6.81	6.67	-0.13	6.76	-0.05	6.97	6.70	-0.27	6.85	-0.11

Table 9: Homogeneous Model Forecast Error Summary, All Cities, 2003-2004

	2003			2004		
	Model A	Model C	Naïve_02	Model A	Model C	Naïve_02
Homicide						
Mean	2.32	2.32	2.32	2.29	2.29	2.29
Mean Forecast	2.44	2.16	2.31	2.49	2.16	2.31
Mean Error	0.12	-0.09	-0.01	0.20	-0.08	0.02
Fraction Positive	0.67	0.36	0.46	0.71	0.36	0.52
RMSE	0.37	0.41	0.40	0.37	0.35	0.34
Mean Absolute Error	0.25	0.28	0.25	0.30	0.28	0.25
Robbery						
Mean	5.68	5.68	5.68	5.67	5.67	5.67
Mean Forecast	5.78	5.59	5.73	5.82	5.58	5.73
Mean Error	0.10	-0.004	0.05	0.14	-0.04	0.05
Fraction Positive	0.75	0.38	0.59	0.77	0.42	0.59
RMSE	0.24	0.25	0.22	0.23	0.22	0.17
Mean Absolute Error	0.14	0.14	0.11	0.19	0.18	0.13
Burglary						
Mean	6.99	6.99	6.99	6.99	6.99	6.99
Mean Forecast	7.01	6.90	7.01	7.01	6.87	7.01
Mean Error	0.01	-0.04	0.01	0.01	-0.08	0.02
Fraction Positive	0.52	0.35	0.50	0.59	0.29	0.59
RMSE	0.18	0.23	0.18	0.13	0.23	0.13
Mean Absolute Error	0.09	0.13	0.08	0.10	0.16	0.10
MVT						
Mean	6.69	6.69	6.69	6.66	6.66	6.69
Mean Forecast	6.72	6.59	6.71	6.73	6.55	6.71
Mean Error	0.03	-0.06	0.02	0.07	-0.10	0.05
Fraction Positive	0.58	0.43	0.54	0.59	0.29	0.59
RMSE	0.24	0.28	0.23	0.22	0.29	0.20
Mean Absolute Error	0.13	0.18	0.12	0.17	0.24	0.16

Note: Naive(02) is a random walk forecasts where 2002 is treated as the last observed year.

Table 10: Root Mean Squared Forecast Error for Different Prediction Horizons and Models, All Cities

Model	Homicide			Robbery			Burglary			MVT		
	2003-04	2001-04	1995-04	2003-04	2001-04	1995-04	2003-04	2001-04	1995-04	2003-04	2001-04	1995-04
Homogeneous Models												
Lag, No Cov, 2002	0.37			0.24			0.16			0.23		
Lag, No Cov, 2000	0.43	0.39		0.32	0.26		0.22	0.19		0.32	0.26	
Lag, No Cov, 1995	0.44	0.43	0.39	0.41	0.38	0.31	0.31	0.29	0.25	0.42	0.38	0.32
Lag, No Cov, t-1	*0.35*	*0.34*	*0.32*	*0.21*	*0.18*	*0.16*	*0.17*	*0.15*	*0.14*	*0.21*	*0.19*	*0.17*
No Lag, Cov	0.42	0.39	0.35	0.36	0.34	0.27	0.33	0.32	0.24	0.48	0.46	0.37
Lag, Cov, 2002	0.38			0.24			0.23			0.28		
Lag, Cov, 2000	0.42	0.38		0.33	0.28		0.33	0.28		0.43	0.36	
Lag, Cov, 1995	0.40	0.36	0.33	0.37	0.33	0.25	0.30	0.27	0.21	0.49	0.43	0.32
Lag, Cov, t-1	*0.37*	*0.35*	*0.31*	*0.21*	*0.20*	*0.16*	*0.21*	*0.19*	*0.16*	*0.25*	*0.23*	*0.19*
Naïve, 2002	0.37			0.20			0.16			0.22		
Naïve, 2000	0.42	0.40		0.26	0.21		0.22	0.19		0.30	0.24	
Naïve, 1995	0.61	0.60	0.52	0.57	0.54	0.45	0.50	0.48	0.39	0.55	0.51	0.42
Average	0.46	0.45	0.41	0.45	0.42	0.34	0.58	0.57	0.48	0.45	0.42	0.37
Heterogenoeus Models												
Lag, No Cov, 2002	0.19			0.19			0.16			0.19		
Lag, No Cov, 2000	0.23	0.20		0.21	0.17		0.20	0.16		0.23	0.20	
Lag, No Cov, 1995	0.36	0.33	0.30	0.36	0.33	0.29	0.24	0.24	0.22	0.36	0.33	0.30
Lag, No Cov, t-1	*0.18*	*0.16*	*0.16*	*0.17*	*0.15*	*0.14*	*0.15*	*0.13*	*0.13*	*0.18*	*0.16*	*0.16*

Notes:

Lag:	Autoregressive lag inluded in the regression.
No Cov/Cov	Indicates if covariates are included.
1995, 2001, 2003	Last observed year for dynamic forecasts; t-1 indicates one-step-ahead forecasts
t-1	Year t-1 is assumed to be observed. This is the one step-ahead forecasts.
Naïve	Forecast equals the crime rate in the "last observed" year, namely 2002, 2000 and 1995.
Average	Forecast is the city specific average crime rate from 1980-2000.

Table 11: Homogeneous Model Forecasts for Selected Cities, , 2005-2009

		2004	2005 Model A	2005 Model C	2006 Model A	2006 Model C	2009 Model A	2009-2004
Homicide	Denver	2.73	2.65	2.55	2.61	2.47	2.59	-0.15
	Knoxville	2.43	2.51	2.25	2.54	2.20	2.56	0.13
	Madison	0.34	0.51	0.25	0.59	0.22	0.64	0.31
	New York	1.95	2.47	.	2.70	.	2.88	0.93
	Richmond	3.86	3.82	3.66	3.81	3.58	3.79	-0.06
	San Francisco	2.45	2.45	2.41	2.45	2.40	2.45	-0.01
Robbery	Denver	5.54	5.55	5.58	5.56	5.59	5.58	0.03
	Knoxville	5.69	5.70	5.60	5.71	5.54	5.72	0.02
	Madison	4.89	4.88	4.72	4.88	4.60	4.87	-0.02
	New York	5.71	5.94	.	6.12	.	6.44	0.73
	Richmond	6.53	6.51	6.35	6.49	6.22	6.47	-0.06
	San Francisco	5.99	6.11	6.19	6.20	6.32	6.37	0.38
Burglary	Denver	7.17	7.14	7.23	7.11	7.27	7.03	-0.14
	Knoxville	7.27	7.24	7.10	7.21	6.99	7.14	-0.12
	Madison	6.49	6.47	6.41	6.45	6.36	6.41	-0.08
	New York	5.78	5.80	.	5.82	.	5.88	0.11
	Richmond	7.24	7.24	7.21	7.25	7.19	7.26	0.02
	San Francisco	6.69	6.67	6.76	6.66	6.81	6.62	-0.07
MVT	Denver	7.20	7.17	7.18	7.14	7.15	7.09	-0.11
	Knoxville	6.67	6.69	6.61	6.71	6.57	6.75	0.08
	Madison	5.54	5.58	5.44	5.61	5.37	5.69	0.15
	New York	5.56	5.74	.	5.89	.	6.22	0.66
	Richmond	7.10	7.09	6.89	7.08	6.73	7.06	-0.03
	San Francisco	6.97	6.95	7.01	6.93	7.03	6.90	-0.07

Table 12: Homogeneous Model Forecasts Summary, All Cities, 2005-2009

	2004	2005 Model A	2005 Model C	2006 Model A	2006 Model C	2009 Model A
Homicide						
Mean Forecast	2.29	2.42	2.17	2.49	2.14	2.53
Mean Change from 2004		0.14	-0.07	0.20	-0.10	0.24
Fraction Positive Change		0.75	0.35	0.75	0.34	0.75
IQR		[0.01,0.26]	[-0.23,0.07]	[0.01, 0.37]	[-0.30, 0.10]	[0.01, 0.46]
Mean Abosolute Change		0.19	0.20	0.27	0.27	0.33
Robbery						
Mean Forecast	5.67	5.73	5.57	5.78	5.54	5.87
Mean Change from 2004		0.06	-0.04	0.11	-0.07	0.20
Fraction Positive Change		0.82	0.350	0.82	0.36	0.82
IQR		[0.01, 0.12]	[-0.12,0.01]	[0.02, 0.21]	[-0.20, 0.02]	[0.04,0.37]
Mean Abosolute Change		0.08	0.09	0.13	0.15	0.23
Burglary						
Mean Forecast	6.99	6.99	6.91	6.99	6.88	6.99
Mean Change from 2004		0.00	-0.06	0.00	-0.09	0.00
Fraction Positive Change		0.54	0.28	0.54	0.28	0.54
IQR		[-0.01, 0.01]	[-0.10, 0.01]	[-.0.02, 0.02]	[-0.18,0.01]	[-.0.04, 0.05]
Mean Abosolute Change		0.01	0.09	0.03	0.15	0.06
MVT						
Mean Forecast	6.66	6.68	6.59	6.70	6.52	6.74
Mean Change from 2004		0.02	-0.08	0.03	-0.14	0.07
Fraction Positive Change		0.68	0.19	0.68	0.17	0.68
IQR		[-0.02, 0.05]	[-0.14, -0.03]	[-0.04, 0.10]	[-0.25,-0.05]	[-0.08,0.20]
Mean Abosolute Change		0.05	0.11	0.09	0.20	0.18