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# Opioid-related emergencies in New York City after the Great Recession

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## 1. Introduction

The U.S. has experienced an epidemic of opioid overdoses and deaths in the 21st century. More than 700,000 people have died from a drug overdose in 1999–2017, half of which involved opioids (Scholl et al., 2018). In 2017, the number of overdose deaths involving opioids was six times greater than in 1999. At the same time, opioid-related emergency department (ED) visits increased by almost 40 percent from 2006 to 2014 (Hollingsworth et al., 2017), with those in the outpatient setting showing the greatest increase (Weiss et al., 2017). The rise in opioid-related mortality and ED visits has stimulated research on whether broader economic declines, such as the Great Recession, may affect opioid-related mortality and morbidity.

The Great Recession in the late 2000s represents one of the most severe economic downturns in the US since the Great Depression. This recession in the US included a sharp drop in employment and a surge of housing foreclosures and delinquencies (Downing, 2016). The US recession also coincided with broader crises of the global financial system. In addition to its financial impacts, the literature reports a variety of population health

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CRediT authorship contribution statement

NTH Trinh: formal analysis, methodology, visualization, writing – review & editing; P Singh: data curation, funding acquisition, methodology, visualization, writing – review & editing; M Cerdá: conceptualization, investigation, methodology, validation, visualization, writing – review & editing; TA Bruckner: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, writing – review & editing.



Conflict of interest

No conflict declared

responses to the Great Recession, including general declines in mental health (Catalano et al., 2011; Goldman-Mellor et al., 2010; Margerison-Zilko et al., 2016). Research on use of mental healthcare services during the Great Recession also reports a decline in utilization of care during this period (Chen & Dagher, 2016).

Hollingsworth and colleagues (Hollingsworth et al., 2017) used data from various sources to examine the relation between annual macroeconomic conditions and opioid-related mortality and ED visits. They found that opioid-related ED visits and deaths increase in years when the economy declines. The analysis by Hollingsworth and colleagues, however, does not address two important issues. First, much research documents acute mental health responses to sudden economic downturns within a span of zero to three months (Bruckner et al., 2010; Goldman-Mellor et al., 2010). If the presumed mechanism for increases in opioid-related ED visits involves an acute increase in psychological distress (Goldman-Mellor et al., 2010) during recessions, examination of monthly (rather than annual) values of opioid-related morbidity would better align with theory and previous empirical research (Zivin et al., 2011). Second, the study examines all opioid-related ED visits in aggregate, without providing information on the specific impact of macroeconomic conditions on the range of opioid-related problems, from opioid dependence and abuse to opioid overdoses.

Other studies reported both increases and declines in substance use following economic decline (Carpenter et al., 2017; Catalano et al., 1993; Catalano et al., 1997; Pacula, 2011). As a result, any relation between opioid-related ED visits and economic downturns at the population-level remains unclear. We contribute to the literature by examining whether opioid-related morbidity (as measured by opioid-related ED visits in the outpatient setting) responded acutely to the large negative "shock" of the Great Recession. We focus on opioid-related ED visits in the outpatient setting because they exhibit substantial month-to-month variation and therefore may capture sensitive behavioral responses to ambient conditions such as economic downturns.

## 2. Methods

### 2.1. Data and study population

We focused our test on the metropolitan statistical area of NYC for two reasons. First, NYC is the most populous metropolitan area in the US. Thus, using NYC data allowed us to avoid the "zero-truncation" problem when examining monthly opioid-related ED visits. Second, NYC, arguably the center of American finance, experienced sharp drops in employment during the Great Recession (Kohli, 2014). In NYC, professional and business services showed the largest drop in employment of all labor market sectors. Declines over time in employment in NYC were not as severe as in the broader US (Jack, 2010; New York State Department of Labor, 2009). However, wholesale and retail trade in NYC was the second hardest hit sector and Bronx and Kings Counties reported the greatest employment declines of all the five boroughs (Jack, 2010). These data, as well as information on increased foreclosures in low-income NYC areas, indicate a widespread impact of the Great Recession across all socioeconomic strata.

We retrieved opioid-related ED visit data that are classified as outpatient stays from the Agency for Healthcare Research and Quality-sponsored Statewide Emergency Department Database (SEDD) (Agency for Healthcare Research and Quality, 2018). SEDD contains encounter-level information on all hospital-affiliated ED visits that received outpatient treatment (SEDD) and were discharged home (i.e., no inpatient admission). We focused on outpatient ED visits to be consistent with prior literature (Hollingsworth et al., 2017) and because they show substantial temporal variation, thereby permitting examination of acute temporal responses to ambient economic downturns. Outpatient ED visits comprise over one-third of all ED visits for opioid-related disorders in NYC (Weiss et al., 2017). Emergency Departments, moreover, are regarded as the 'safety net of safety nets' and are required by law to provide care to every patient, regardless of the ability to pay. We therefore could include ED visits across the entire range of socioeconomic and health insurance status (Hsia et al., 2011).

SEDD is the most comprehensive database of individual level outpatient ED encounters in the U.S. Cross-validation with hospital identifiers from the American Hospital Association survey supports over 99% hospital coverage for SEDD (Wier et al., 2010). Evaluation studies further demonstrate the high internal consistency and validity of SEDD variables (Mukamel et al., 2015). SEDD reports ED visit data in NYC at the month resolution over a time-period spanning the years of the Great Recession (2008-2009). We examined the 72 months from January 2006 to December 2011 (inclusive), which represents the longest time-series of ED visit data in NYC available to us at the time of our tests.

## 2.2. Opioid-related ED visits classification

Previous work finds that the order of diagnoses listed (e.g., primary versus secondary diagnosis) may not necessarily reflect clinical acuity, depends on time lags in receipt of test results, and involves a subset of certain conditions per billing requirements/protocol (Mutter & Stocks, 2014). To overcome this limitation, we classified an ED visit as an opioid-related ED encounter if *any* diagnosis for a visit listed an opioid-related diagnosis code in the Ninth revision of International Classification of Diseases (ICD-9). Scholars endorse this approach for analyzing administrative data (such as the SEDD) as these records are generated for billing purposes and inclusion of all diagnoses per visit better approximates population trends in a diseases/condition relative to only primary diagnosis (Mutter & Stocks, 2014). To examine the association of the Great Recession on a range of manifestations of opioid-related harm, we classified opioid-related ED visits into three types: opioid dependence and abuse, prescription opioid overdose, and heroin overdose (Appendix Table i.). In cases where the ED visit could logically fall under more than one visit type, we counted the visit in each type (i.e., an ED visit classified under heroin overdose and opioid overdose was counted in both groups).

## 2.3. Outcome measures

Our outcome measure was the incidence of opioid-related ED visits in the outpatient setting. We derived the incidence by, first, summing the count of ED visits across 24 counties in NYC Metropolitan Statistical Area (MSA). Next, we retrieved annual estimates of the population in NYC from the US Census Bureau's Population Estimates database (US

Census Bureau, 2018). We then divided the count of ED visits by the population denominators to produce crude monthly incidence. Lastly, to correct for seasonal patterns that may arise purely from differences in length of calendar months (e.g., 28 days in most Februaries vs. 31 days in January), we adjusted the crude monthly incidence by the number of days in each calendar month. This adjustment yields a daily mean incidence for each calendar month (e.g., 9 opioid-related ED visits per 100,000 population in a month with 30 days becomes an incidence of 0.3 per 100,000 population per day in that calendar month—see Figure 1a).

### 2.4. Independent variable

Our research question focuses on whether sudden shocks to the economy precede a change in opioid-related ED visits. This work contrasts other literature focusing on the influence of relatively stable employment levels. We used monthly employment change in NYC to construct our exposure variable. The Bureau of Labor Statistics (BLS) makes publicly available monthly counts (seasonally unadjusted) of total number of people employed per MSA in the US. We retrieved these data from the BLS Local Area Unemployment Statistics series for NYC MSA for 72 months from 2006 to 2011 (United States Bureau of Labor Statistics). The Office of Management and Budget defines MSAs as metropolitan regions that, with adjacent communities, share economic and social integration. The MSA, therefore, serves as a meaningful geographic unit to study population responses to regional economic change (Becker, 2007; Waitzman & Smith, 1998).

We modeled our exposure as the percent change in monthly employment, $((x_m - x_{m-1})/x_{m-1}$, where $x_m$ is the number of people employed in a given month and $x_{m-1}$ is the number employed in the previous month). This specification permits, as described below, the ability to capture employment volatility rather than employment levels. We also capture monthly temporal "shocks" with negative values of percent change in monthly employment indicating sudden macroeconomic decline relative to previous month. Previous work on monthly health responses to economic downturns uses this variable (Bruckner, 2008; Bruckner & Catalano, 2006). This exposure also overcomes limitations of other measures of macroeconomic contractions such as the unemployment rate (which does not account for change in labor force participation) or mass layoffs (which are often limited to specific industries or occupations). In addition, whereas mass layoffs also gauge monthly economic shocks (Bruckner et al., 2010; Dekker & Schaufeli, 1995), these data are not available at the NYC MSA level over our test period.

We operationalized the Great Recession economic variable by identifying negative outliers in employment change in NYC over the test period (Figure 2a). We used the methods of Chang and colleagues (Chang et al., 1988) to identify outlying (i.e., $p < .01$; 2-tailed test) monthly negative "spikes" as well as sequences or "ramps" that began with a negative outlying (i.e., $p < .01$; 2-tailed test) value but also included subsequent values that regressed to expected levels. These values, shown in Figure 1b, capture the influence of both the initial months of the negative outliers as well as their influence on the economic situation in subsequent months. Outlier detection routines identified the "Great Recession" outliers in employment change from November 2008 to December 2009, with large outliers concentrating in November 2008 to February 2009 and August 2009 to December 2009. The Great Recession variable then took the actual negative values spanning through this period and zero otherwise. These negative values capture the "dose" and timing of the sudden downturn in NYC (range of negative employment change outliers: −.05 to −.82; see Figure 1b). This exposure gauges a plausibly exogenous "shock," which permits a rigorous quasi-experimental study design and minimizes the threat of confounding.

## 2.5. Analyses

We hypothesize that the incidence of opioid-related ED visits moves away from its expected value during, and immediately following, the Great Recession. Opioid-related ED visits, however, may show strong patterns over time, including trend, seasonality, regression to the mean, and oscillation. Upward or downward trends, for example, could arise due to well-documented shifts in prescribing practices, changing price and availability of agonist opioids. These patterns, collectively referred to as autocorrelation, could confound our test if economic circumstances in NYC exhibited similar, or opposite, trends.

**2.5.1. Time-series approach—**To control for autocorrelation, we applied well-established time-series routines to the monthly incidence of opioid-related ED visits (Box et al., 1994). This empirical approach, recommended in the literature (Catalano et al., 1997; Catalano & Serxner, 1987; Helfenstein, 1991), detects and models autocorrelation in time series. We used the routines devised by Box and Jenkins (Box et al., 1994) to implement this approach.

We proceeded with the following steps. First, we estimated initial models for the entire series (72 months beginning January 2006) using software from Scientific Computing Associates (version 5.4.6, SCA Corp., Villa Park, IL). Second, we inspected the monthly opioid-related ED series to ensure that it is stationary in its mean and variance. If we found non-stationarity, we performed steps, as recommended in the literature, to render the series stationary. Third, we examined the autocorrelation function and partial autocorrelation function of the residuals to detect potential autocorrelation. If any was found, we specified autoregressive or moving average parameters in the error term of the equation. Fourth, we added the Great Recession economic variable to the equation. We, consistent with the literature, specified a concurrent as well as lagged association of up to three months (i.e., Great Recession at month t may vary with opioid-related ED visits at months t, t+1, t+2, or t+3) to ensure capturing any delayed associations. Fifth, we inspected the residual values of the error term to ensure that they exhibited no temporal patterns.

**2.5.2. Additional analyses—**Visits classified as "opioid dependence and abuse" (ODA) comprise 91.5% of all opioid-related ED visits in NYC over our test period. We therefore focused our test on this group. We repeated our time-series steps separately for three other groups of visits: prescription opioid overdose, heroin overdose, and the sum of prescription opioid and heroin overdose.

Prior work on opioid-related ED using annual macroeconomic conditions as the key exposure reports differential sensitivity to economic downturns by race/ethnicity and gender (Carpenter et al., 2017; Hollingsworth et al., 2017). If our results rejected the null, we then explored whether findings appeared specific to particular racial/ethnic and gender categories. We stratified opioid-related ED visits by six groups: two genders by three race/ethnicity categories available in SEDD (non-Hispanic white, non-Hispanic black, and Other). We applied race/ethnic and gender-specific population counts to derive incidence measures.

In addition, our test focuses on opioid-related ED visits following the acute negative outlier of the Great Recession. However, if we discovered any association between this extreme event and opioid-related ED visits, we then explored whether opioid-related ED visits varied with more common fluctuations in monthly employment, measured continuously over the 72-month period.

Finally, if we discovered any association between the Great Recession and opioid-related ED visits in the outpatient setting, we then explored whether this result may arise from shifts in the classification of ED visits toward the inpatient setting. To examine this possibility of changes in tracking ED visits or in classification shifts in the type of ED visits during the Great Recession, we purchased inpatient ED data on opioid-related ED visits from the federally-sponsored Statewide Inpatient Database (SID) (Agency for Healthcare Research and Quality, 2018). We then repeated the time-series steps described previously but used as the dependent variable inpatient ED visits for opioid use and dependence.

## 3. Results

### 3.1. Description of study population

More than 126,000 ODA ED visits occurred in NYC from January 2006 to December 2011 (monthly mean count= 1,761; standard deviation [SD] = 389). Among the remaining 11,000 visits related to opioid and heroin overdose, 127 visits were classified into both types. Visual inspection of the incidence of ODA ED visits over time shows a “level shift” starting in January 2011 (Figure 2a). This level shift, which begins several years after the Great Recession, appears to reflect an administrative coding shift and persists into the last month of 2011 (i.e., the last value in the series) such that the mean incidence of ODA ED visits in the year 2011 is 45% greater than its mean from 2006 to 2010. We therefore controlled for this administrative shift by including a binary indicator variable, coded as “1” for all months in 2011 and “0” otherwise, in the equation. The adjusted series (Figure 2b) meets the standard time-series assumption of mean stationarity thus required no differencing.

### 3.2. ODA ED visits

The ODA series shows no seasonality. However, time-series routines detected autocorrelation at lag 1 month such that high (or low) values in month t are “remembered” into month t+1, albeit in diminishing amounts, with similarly high (or low) values. We therefore specified an AR(1) parameter in the final time-series equation. The ACF and PACF (Appendix Table ii.) of the residuals from the final equation indicates no remaining autocorrelation.

Results from the final equation indicate that ODA ED visits vary with the strength of the Great Recession. This relation, shown in Table 1, appears in the concurrent month such that unexpectedly large drops in employment coincide with fewer than expected ODA ED visits in that same month. This relation does not persist into subsequent months. The coefficient for the concurrent month (.046, 95% Confidence Interval [CI]: .002, .090) indicates that a one-unit decline in employment during the Great Recession coincides with a decline of .046 visits per 100,000 population in the incidence of ODA ED visits. This result represents a 0.8% drop in overall incidence during the Great Recession.

To give the reader a sense of the magnitude of the findings, we calculated the number of ODA ED visits “statistically averted” by the Great Recession. Fourteen months during 2008-09 showed negative employment change outliers (Figure 1b). Applying the discovered coefficient of employment change to the expected monthly rate of ED visits before the Great Recession yields 950 fewer ODA ED visits in NYC statistically attributable to the Great Recession.

Given the discovered relation between ODA ED visits overall and negative outliers in employment change during the Great Recession, we then explored its potential relation with employment change over all months. We specified as the independent variable the monthly employment change values as shown in Figure 1a and re-estimated the time-series equation. Results, as in the original test, indicate a positive relation in the concurrent month (Table 2). This finding suggests that falls in monthly employment less extreme than the Great Recession correspond with declines in ODA ED visits in that same month.

To examine whether the ODA ED visit result in the outpatient setting arose in part from a corresponding change in the incidence of ODA ED visits in the inpatient setting, we explored the potential relation between the Great Recession and ODA ED visits in the inpatient setting. Results using inpatient data from SID (Appendix Tables iii. and iv.) indicate no relation between economic downturns and inpatient ODA ED visits at any of the four month lags.

### 3.3. Additional analyses by other groups of opioid-related ED visits and by race/ethnicity

Additional analyses with other type of opioid-related visits (Appendix Table v.) indicate no statistical relation between the Great Recession and these ED visits. In analyses by race/ethnicity and gender, as with the main result, we find negatively signed coefficients at lag 0 months for all six subgroups (Appendix Table vi.). However, only the result for Non-Hispanic white women reaches statistical detection (.034, 95%CI= .001, .067).

## 4. Discussion

We use monthly data in NYC to examine whether the sudden economic downturn of the Great Recession preceded an increase in opioid-related ED visits in the outpatient setting. Counter to previous research, opioid-related ED visits fall below their expected value during the same months of the Great Recession. Whereas the magnitude of the reduction in ED visits is small, results remain consistent and robust to alternative specifications. Our findings indicate that, in terms of opioid-related ED visits, short-term responses to the Great Recession may differ fundamentally from longer-term responses to more modest economic downturns.

The NYC findings appear consistent with a subset of empirical research, spanning over the last 25 years, reporting reduced consumption of substances following economic downturns (Catalano et al., 2002; Ettner, 1997; Khan et al., 2002). Researchers have proposed two main explanations for this reduced consumption: an income effect (Khan et al., 2002) and an inhibition effect (Catalano et al., 2002). First, persons with suddenly reduced incomes may purchase fewer substances (i.e., income effect). Second, persons who remain working but fear job loss may be inhibited from deviant behavior (e.g., substance use, antisocial behavior) in order to avoid job loss. We note, however, that Catalano and colleagues' review of substance use following regional economic change concludes that empirical results do not converge (Catalano et al., 2011). Whereas analyses of individuals who lose jobs tend to show elevated alcohol and substance use, the literature on the larger population who remains working during economic downturns remains mixed. Most of the literature cited in their review, however, does not examine opioid use separately.

Strengths of our analyses include use of the universe of opioid-related ED visits in the largest metropolitan area in the US. In addition, our independent variable gauges a plausibly exogenous "shock," which permits a rigorous quasi-experimental study design and minimizes the threat of unmeasured confounding. Next, unlike earlier work, use of monthly data permit estimation of employment volatility and acute behavioral responses. These responses within a few months better aligns with theory and previous empirical work on mental health and substance use than do studies which examine yearly aggregates. We also examine subtypes of opioid-related ED visits, which show distinct responses of some types of ED visits (but not others) to the onset of the Great Recession. Lastly, our time-series methods control for confounding due to well-documented patterns in opioid-related morbidity. Results, therefore, cannot arise from a patterned "third" variable (e.g., prescribing practices, increased availability of opioids) which coincides with, but is not caused by, the Great Recession.

Limitations include that our study focuses on ED visits associated with opioid abuse and dependence and overdose, which only represents the fraction of those affected that sought treatment in an ED. Results may therefore indicate a change in treatment-seeking behavior (Mark et al., 2016; Martin et al., 2019). We could not retrieve information on acuity of ED visit to investigate this possibility. In addition, other prevalence estimates of illicit opioid use in NYC find that ED visits comprise only about seven percent of the "hidden" population of opioid users (McNeely et al., 2012). This circumstance indicates that the large majority of users do not seek care in the ED.

The inpatient setting accounts for ~65% of opioid-related visits to the ED (Weiss et al., 2017). Our exploration using the SID shows no relation between economic downturns and inpatient opioid-related ED visits. This null result indicates that administrative coding shifts or changes in tracking of ED visits (i.e., from the outpatient to the inpatient setting) during the Great Recession cannot explain the pattern of our findings. Inpatient visits, however, likely show greater disease severity and warrant additional research in their own right. Our main findings pertain to the over 150,000 outpatient ED visits and permit comparisons to prior literature which uses outpatient ED visits for opioid use as the outcome variable

(Hollingsworth et al., 2017). We encourage replication of our work in other places and times to determine external validity.

In addition, uncertainties regarding diagnosis may also produce selection bias in our data given that we rely on ICD coding schemes used in SEDD. Furthermore, whereas we control for the 2011 administrative coding shift in ED visits, we are unaware of the factors that led to this coding shift. In addition, our independent variable holds an interpretational caveat in that it reflects a proportionate change and is therefore non-linear with respect to the amount of employed positions lost as a function of the changing base. Lastly, we do not have individual-level information on employment circumstances and substance use. Readers, therefore, should not use our findings to draw inference about individual-level behaviors.

## 5. Conclusion

Our study provides evidence that significant economic downturns, such as the Great Recession, may produce short-term decreases in opioid-related morbidity. Beyond the study of opioid-related morbidity, this study suggests that acute responses to external shocks such as economic downturns may differ from long-term responses following cumulative exposure to adversity. Future research should compare the impact that economic downturns have on short- and long-term patterns of substance examine the factors and the timing driving increases in substance use following such external shocks.

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## APPENDICES

**Table i.**

List of ICD-9 codes used to classify opioid-related ED visits

| Group | ICD 9 |
|---|---|
| Opioid dependence and abuse | 30400 Opioid type dependence, unspecified<br>30401 Opioid type dependence, continuous<br>30402 Opioid type dependence, episodic<br>30403 Opioid type dependence, in remission<br>30470 Combinations of opioid type drug with any other drug dependence, unspecified<br>30471 Combinations of opioid type drug with any other drug dependence, continuous<br>30472 Combinations of opioid type drug with any other drug dependence, episodic<br>30473 Combinations of opioid type drug with any other drug dependence, in remission<br>30550 Opioid abuse, unspecified<br>30551 Opioid abuse, continuous<br>30552 Opioid abuse, episodic<br>30553 Opioid abuse, in remission |
| Prescription opioid overdose | 96500 Poisoning by opium (alkaloids), unspecified<br>96502 Poisoning by methadone<br>96509 Poisoning by other opiates and related narcotics<br>E8501 Accidental poisoning by methadone<br>E8502 Accidental poisoning by other opiates and related narcotics |
| Heroin overdose | 96501 Poisoning by heroin<br>E8500 Accidental poisoning by heroin |
| Prescription opioid and heroin overdose | 96500 Poisoning by opium (alkaloids), unspecified<br>96501 Poisoning by heroin |

| Group | ICD 9 |
|---|---|
| | 96502 Poisoning by methadone<br>96509 Poisoning by other opiates and related narcotics<br>E8500 Accidental poisoning by heroin<br>E8501 Accidental poisoning by methadone<br>E8502 Accidental poisoning by other opiates and related narcotics |

### Table ii.

Coefficients (Standard Errors in Parentheses) for the Lagged Values of the Autocorrelation (ACF) and Partial Autocorrelation (PACF) Functions of the Residualized Value of the ODA ED Visits in the Final Equation.

| Lag at Month: | ACF (SE) | Ljung-Box Q Statistic† | p-value | PACF (SE) |
|---|---|---|---|---|
| 1 | .00 (.12) | .0 | 0.92 | .00 (.12) |
| 2 | −.01 (.12) | .0 | 0.98 | −.01 (.12) |
| 3 | .17 (.12) | 2.1 | 0.55 | .17 (.12) |
| 4 | −.02 (.12) | 2.1 | 0.71 | −.02 (.12) |
| 5 | −.17 (.12) | 4.3 | 0.51 | −.17 (.12) |
| 6 | −.09 (.13) | 4.9 | 0.56 | −.12 (.12) |
| 7 | .05 (.13) | 5.1 | 0.65 | .06 (.12) |
| 8 | −.11 (.13) | 6.1 | 0.63 | −.06 (.12) |
| 9 | −.12 (.13) | 7.3 | 0.61 | −.10 (.12) |
| 10 | .06 (.13) | 7.6 | 0.67 | .01 (.12) |
| 11 | .19 (.13) | 10.7 | 0.47 | .21 (.12) |
| 12 | .14 (.14) | 12.3 | 0.42 | .21 (.12) |

†This Statistic assesses whether a group of overall autocorrelations differs statistically from 0. None of the Q-statistics rejects the null of no difference (based on the chi-square distribution with Lag-1 degrees of freedom).

### Table iii.

Time-Series Results Predicting **Inpatient** ED visits for Opioid Dependence and Abuse in New York City, from January 2006 to December 2011 as a Function of Autocorrelation and **negative outliers in employment change during the Great Recession** (95% Confidence Intervals [CI] in parentheses). Coefficients for the Great Recession Represent Risk Differences.

| Parameter | Lag (months) | ED Visits for Opioid Dependence and Abuse | |
|---|---|---|---|
| | | Coef.* | (95% CI)** |
| Constant | — | .868 | (.801 —.935) |
| Autoregressive Parameter | 1 | .783 | (.622 —.944) |
| | 12 | .447 | (.246 —.648) |
| Moving Average Parameter | — | none | None |
| Negative outliers in employment change | 0 | .045 | (−.030 — .119) |
| | 1 | −.052 | (−.127 — .024) |

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| Parameter | Lag (months) | ED Visits for Opioid Dependence and Abuse | |
|---|---|---|---|
| | | Coef.* | (95% CI)** |
| | 2 | .004 | (−.072 — .080) |
| | 3 | −.034 | (−.039 — .107) |

### Table iv.

Time-Series Results Predicting **Inpatient** ED visits for Opioid Dependence and Abuse in New York City, from January 2006 to December 2011 as a Function of Autocorrelation and **employment change** (95% Confidence Intervals [CI] in parentheses). Coefficients for employment change represent risk differences.

| Parameter | Lag (months) | ED Visits for Opioid Dependence and Abuse | |
|---|---|---|---|
| | | Coef.* | (95% CI)** |
| Constant | — | .870 | (.813 —.927) |
| Autoregressive Parameter | 1 | .759 | (.594 —.924) |
| | 12 | .407 | (.206 —.607) |
| Moving Average Parameter | — | none | none |
| Employment change | 0 | .052 | (−.026— .129) |
| | 1 | −.049 | (−.135 — .037) |
| | 2 | .053 | (−.033 — .139) |
| | 3 | −.020 | (−.094 — .053) |

### Table v.

Time Series Results Predicting the Outpatient ED visits for **prescription opioid overdose, heroin overdose, and the sum of prescription opioid and heroin overdose---** in New York City, from January 2006 to December 2011 a Function of Autocorrelation and negative outliers in employment change during the Great Recession.

| Parameter | Lag (months) | ED Visits for prescription opioid overdose | | ED Visits for heroin overdose | | ED Visits for prescription opioid and heroin overdose | |
|---|---|---|---|---|---|---|---|
| | | Coef.* | (95% CI)** | Coef.* | (95% CI)** | Coef.* | (95% CI)** |
| Constant | — | .017 | (.015 — .018) | .011 | (.009 — .013) | .027 | (.024 — .030) |
| 2011 Level Shift | — | .006 | (.003 — .009) | None | None | .008 | (.003 — .013) |
| Autoregressive Parameter | 1 | .589 | (.406 — .772) | .564 | (.368 — .760) | .641 | (.463 — .818) |

| Parameter | Lag (months) | ED Visits for prescription opioid overdose | | ED Visits for heroin overdose | | ED Visits for prescription opioid and heroin overdose | |
|---|---|---|---|---|---|---|---|
| | | Coef.* | (95% CI)** | Coef.* | (95% CI)** | Coef.* | (95% CI)** |
| Moving Average Parameter | — | None | None | None | None | None | None |
| Negative outliers in employment change | 0 | −.003 | (−.009 — .003) | .001 | (−.006 — .007) | −.002 | (−.012 — .008) |
| | 1 | .004 | (−.003 — .010) | .003 | (−.005 — .010) | .006 | (−.005 — .016) |
| | 2 | .001 | (−.005 — .007) | .00009 | (−.007 — .007) | .001 | (−.010 — .012) |
| | 3 | −.003 | (−.009 — .003) | .001 | (−.006 — .007) | −.002 | (−.012 — .008) |

*Coefficients for the Great Recession Represent Risk Differences

**95% Confidence Intervals [CI] in parentheses

**Table vi.**

By Gender and Race/Ethnicity: Exploratory time Series Results Predicting Outpatient ED visits for Opioid Dependence and Abuse in New York City, from January 2006 to December 2011 as a Function of Autocorrelation and negative outliers in employment change during the Great Recession.

| Race/ethnicity by gender subgroup | AR, MA parameters | ED Visits for Opioid Dependence and Abuse | |
|---|---|---|---|
| | | Coef.* | (95% CI)** |
| Great Recession Lag at 0 months for: | | | |
| White men | AR(1) | .036 | (−.023 — .095) |
| White women | AR(1) | .034 | (.001 — .067) |
| African American men | AR(1), MA(12) | −.030 | (−.165 — .105) |
| African American women | AR(1) | .033 | (−.054 — .120) |
| “Other” men | AR(1) | .044 | (−.058 — .146) |
| ”Other” women | AR(1), MA(1) | .020 | (−.007 — .047) |

*Coefficients for the Great Recession Represent Risk Differences

**95% Confidence Intervals [CI] in parentheses

## Abbreviations

**ARIMA** Autoregressive, Integrated, Moving Average

**BLS** Bureau of Labor Statistics

**CI** Confidence Interval

**ED** emergency department

**MSA** Metropolitan Statistical Area

| | |
|---|---|
| **ODA** | Opioid dependence and abuse |
| **NYC** | New York City |
| **SEDD** | Statewide Emergency Department Database |
| **SD** | standard deviation |

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## HIGHLIGHTS

- Economic downturns may produce short-term decrease in opioid-related morbidity
- Acute and long-term response to external shocks such as economic downturns may differ substantially

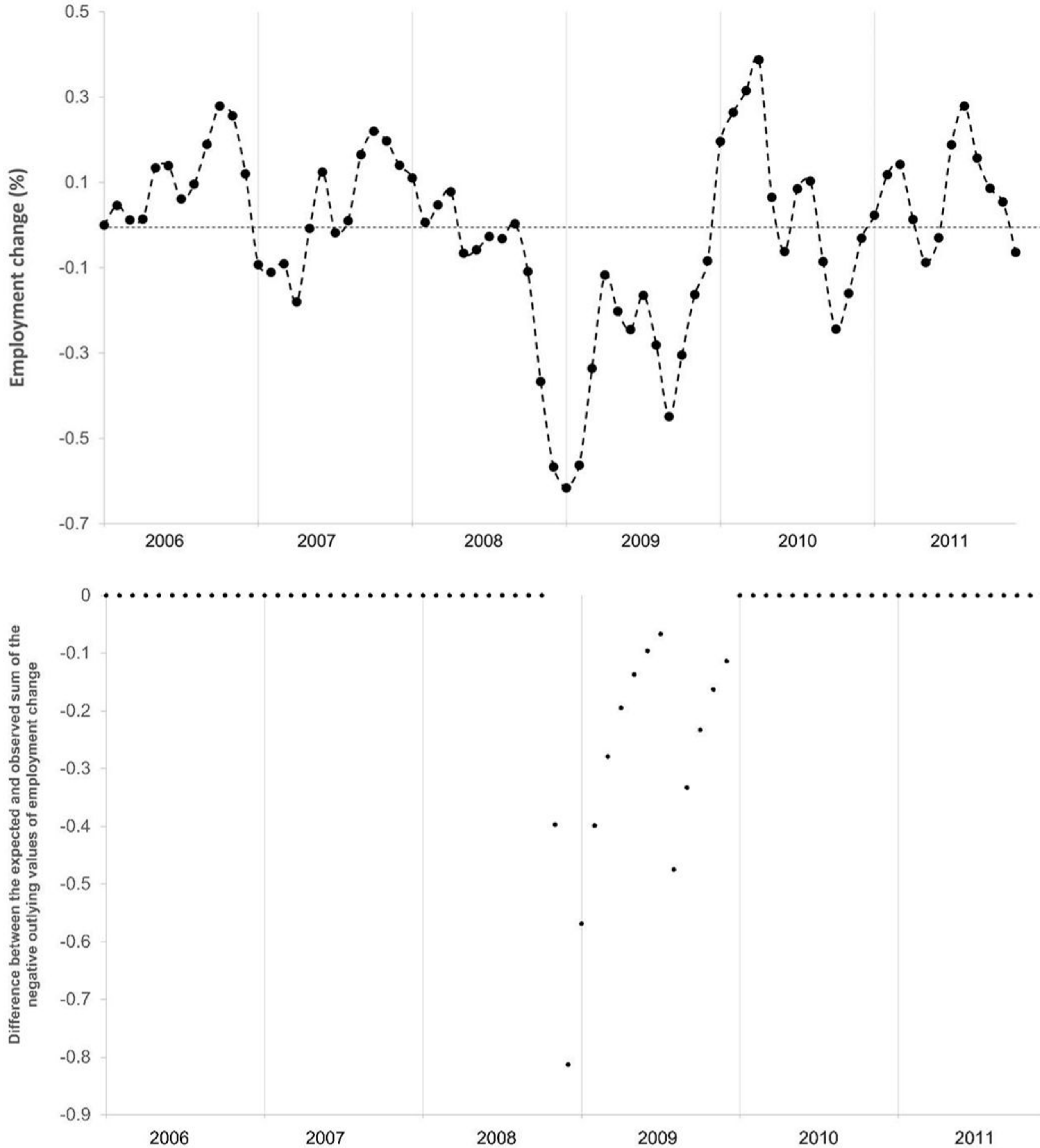


**FIGURE 1.**

**a.** Monthly values of employment change for New York City Metropolitan Statistical Area spanning January 2006 to December 2011. Dashed line represents zero line.

**b.** Difference between the expected and observed sum of the negative outlying values of employment change for 72 months in New York City.

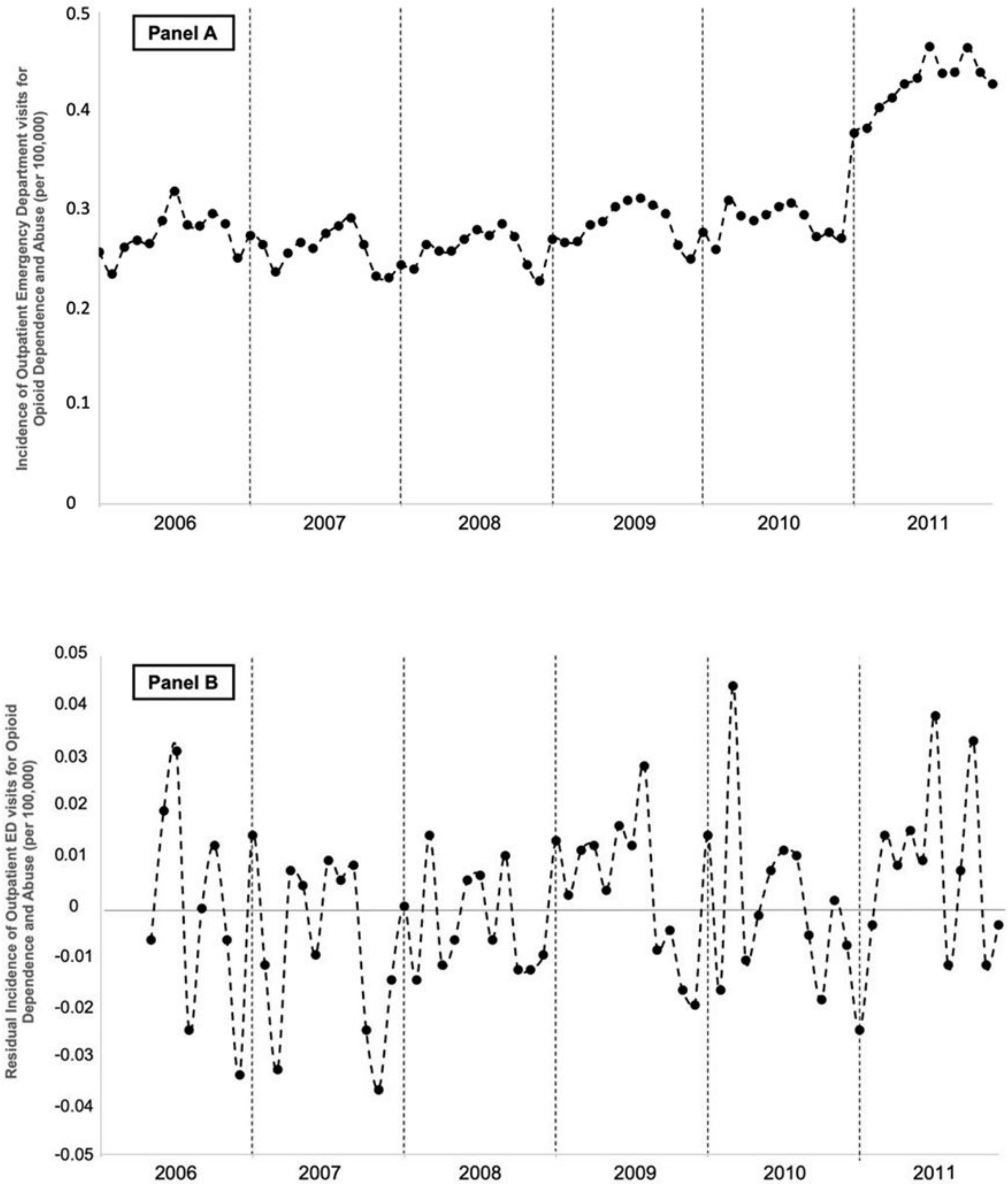


**FIGURE 2.**

Incidence of Outpatient ED visits for Opioid Dependence and Abuse (per 100,000) over 72 Months in New York City. Panel A Plots the Observed Incidence; Panel B Plots the Residual Incidence, with Mean=0, of the final model after inclusion of level shift variable for 2011 months and removal of autocorrelation (first four months lost due to modeling). Dashed vertical lines indicate January of each year.

**Table 1.**

Time-Series Results Predicting Outpatient ED visits for Opioid Dependence and Abuse in New York City, from January 2006 to December 2011 as a Function of Autocorrelation and **negative outliers in employment change during the Great Recession**

| Parameter | Lag (months) | ED Visits for Opioid Dependence and Abuse | |
|---|---|---|---|
| | | Coef.* | (95% CI)** |
| Constant | — | .282 | (.266 —.299) |
| 2011 Level Shift | — | .129 | (.102 —.155) |
| Autoregressive Parameter | 1 | .739 | (.275 —.904) |
| Moving Average Parameter | — | none | none |
| Negative outliers in employment change | 0 | .046 | (.002 — .090) |
| | 1 | −.021 | (−.067 — .025) |
| | 2 | −.004 | (−.050 — .042) |
| | 3 | .029 | (−.015 — .073) |

*Coefficients for the Great Recession Represent Risk Differences

**95% Confidence Intervals [CI] in parentheses

**Table 2.**

Time-Series Results Predicting the Outpatient ED visits for Opioid Dependence and Abuse in New York City, from January 2006 to December 2011 as a Function of Autocorrelation and **employment change.**

| Parameter | Lag (months) | ED Visits for Opioid Dependence and Abuse | |
|---|---|---|---|
| | | **Coef.*** | **(95% CI)**** |
| Constant | — | .279 | (.265 —.294) |
| 2011 Level Shift | — | .131 | (.106 —.157) |
| Autoregressive Parameter | 1 | .712 | (.541 —.882) |
| Moving Average Parameter | — | none | none |
| Employment change | 0 | .042 | (.002 — .081) |
| | 1 | −.044 | (−.090 — .002) |
| | 2 | .039 | (−.007 — .086) |
| | 3 | −.008 | (−.048 — .031) |

*Coefficients for the Great Recession Represent Risk Differences

**95% Confidence Intervals [CI] in parentheses