Crime and Unemployment in Ireland, 2003-2016

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Abstract

This paper investigates the relationship between crime and unemployment in Ireland during the Celtic Tiger boom, Great Recession, and subsequent economic recovery. Using unique administrative police station-level crime data and exploiting large variation in unemployment rates, I first document that a 10% increase in unemployment is associated with a 5% increase in thefts and burglaries. Instrumental variables show that a 1,000-person decline in employment causes 15-25 more thefts or burglaries per quarter. The property crime-unemployment relationship remained robust during the most recent period of substantial economic recovery, with areas where the recovery was fastest also experiencing sharper decreases in property crime.

JEL classification: K42, J64.

Keywords: property crime, unemployment, Ireland, Celtic Tiger, recession.

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1 Introduction

This paper investigates the relationship between crime and unemployment in Ireland during the Celtic Tiger economic boom, financial crisis-induced recession, and subsequent economic recovery. How does the number of burglaries change as the number of people on the unemployment insurance rolls increases? I find that there is a robust and significant increase: instrumental variables estimates suggest a 1,000-person decrease in employment in a county leads to an average of 15–25 extra thefts or burglaries per quarter. In relative terms, I estimate a property crime elasticity of about 0.5: a 10% rise in the number of people on the unemployment register increases the number of property crimes by 5%.

A unique advantage of this setting is the severity of the business cycle in Ireland over the past decade. Ireland's unemployment rate tripled between 2007 and 2010, and then fell by 40% between mid-2013 and the latest results from mid-2016. Such labour market volatility is essentially unprecedented for a developed country. This provides enormous variation in unemployment rates, improving the precision of estimates of the effect of unemployment on crime. Furthermore, job-losses were concentrated in particular sectors, and so the vulnerability to unemployment was differentiated across regions within Ireland. This provides additional variation off which to estimate the effects.

A second advantage of this setting is the fact that the crime statistics used in this paper are from raw administrative data from the Irish police service's integrated computer system. These data are provided at a granular local level, covering a specific set of crimes reported from each of the 563 police stations in Ireland. Similarly the unemployment insurance rolls data are collected from every social welfare office in the country, and the data provide precise counts of the number of individuals on the Live Register.[1] This level of granularity using administrative sources avoids many of the data comparability problems found in the existing literature.

The conclusions on the sign and magnitude of the effect of unemployment on crime are

[1] The Live Register is Ireland's administrative count of the number of people registered for unemployment assistance. It measures how many people, including under-employed people, are receiving benefits while actively seeking employment.

similar for both theft (estimated elasticity of 0.55) and burglary (0.47). As predicted by economic theory, the association with assault is much smaller: I estimate an assault elasticity of 0.01. Sex offences are also strongly correlated with increasing unemployment. The finding that the labour market can determine domestic violence and/or sexual assault has been documented previously, cf. Aizer (2010), Edmark (2005), and Schneider *et al.* (2016).

For causal effects, I approach the question with an instrumental variable that has been exploited previously in the literature (cf. Gould *et al.* (2002), Öster and Agell (2007), Fougére *et al.* (2009)). As sectors were differentially affected by the financial crisis, the extent of unemployment post-2008 was a function of pre-2008 sectoral compositions. In particular, 150,000 of the 350,000 jobs lost during the recession were in construction. Areas that were more vulnerable to a downturn in construction suffered greater job losses as a consequence of the financial crisis than areas with a more diversified employment composition. Using a generalized version of this instrument, under two separate specifications, I find that a 1,000-person decrease in employment causes an extra 15-25 property crimes per quarter.

The time-frame in question, 2003–2016, is a unique chapter in Irish history. The first half captures the Celtic Tiger, a period of remarkable economic growth. During this time the Irish government ran large surpluses, and hundreds of thousands of people from the newly enlarged EU migrated to Ireland. GDP grew at 6% per annum, the construction sector grew by more than 10% per annum, and property prices soared.

The latter half includes the financial crisis, the subsequent severe contraction of the Irish economy, and also the strong recovery in very recent years. The effects of the financial crisis were particularly pronounced in Ireland. Over three years the unemployment rate rose from 4.5% to 14%, and the construction industry contracted by three-quarters. Ultimately, the Irish government required financial assistance from the European Union and the IMF. In contrast, the most recent years have seen a marked improvement in both GDP and employment, with unemployment down 150,000 since its peak. It is highly unusual for a developed country to experience such volatility outside of war-time. The period is thus not only an important chapter for Ireland, but a noteworthy time in economic history more generally. The primary research question of this paper is how property crime responded to these changes in the economy.

The study of criminal behaviour as a consequence of the economic environment is not new. It came to the fore in economics with Becker (1968), whose contribution was seminal for subsequent empirical work. This literature is now vast. Analyses have been conducted in many contexts. For example, see Raphael and Winter-Ebmer (2001), Gould *et al.* (2002), Lin (2008) and Levitt (1996, 1997) on the United States; Machin and Meghir (2004) on England and Wales; de Blasio and Menon (2013) on Italy; Carneiro *et al.* (2016) on Brazil; Dube and Vargas (2013) on Colombia; Fougére *et al.* (2009) on France; Flückiger and Ludwig (2015) for how fishing conditions affect maritime piracy; and Aslund *et al.* (2015) and Anderson (2014) for the effect of schooling laws on youth crime. Though this question has been studied before, the availability of quality administrative data, the extent of the volatility experienced in Ireland over the past ten years, and the precision of the estimates enhance the contribution of this paper.

Section 2 provides an overview of the data used in the analysis, while Section 3 provides a variety of OLS-based estimates of the relationship. Due to endogeneity concerns, the literature has generally not relied on regression-based estimates alone. Consequently in Section 4 I present instrumental variables estimates that are based on the region-sector instrument proposed by Bartik (1991), the results of which confirm the OLS-based estimates. Section 5 concludes.

2 Institutional and Data Overview

Ireland is a country 4.75 million people (Central Statistics Office, 2016a). As of July 2016, the unemployment rate was 7.6% and total GNP in 2015 was approximately €193bn. This paper focuses exclusively on (the Republic of) Ireland; Northern Ireland is a separate political jurisdiction and remains part of the United Kingdom. A single agency, An Garda Síochána ("Garda"), is responsible for policing across the country.

The crime data used in this paper are the reported crime statistics provided by An Garda Síochána to the Central Statistics Office (CSO). CSO is the independent agency charged with publishing official statistics and conducting the census in Ireland. Raw administrative data from the Garda PULSE computing system forms the basis of these reports, and CSO verifies and classifies these records using the Irish Crime Classification System (ICCS). The analyses in Sections 3 and 4 are conducted at the Garda Division level. With the exception of Cork[2] and Dublin[3], Garda divisions largely coincide with county borders.[4] When aggregated, the data show how many crimes were recorded each quarter by Gardaí in every division.

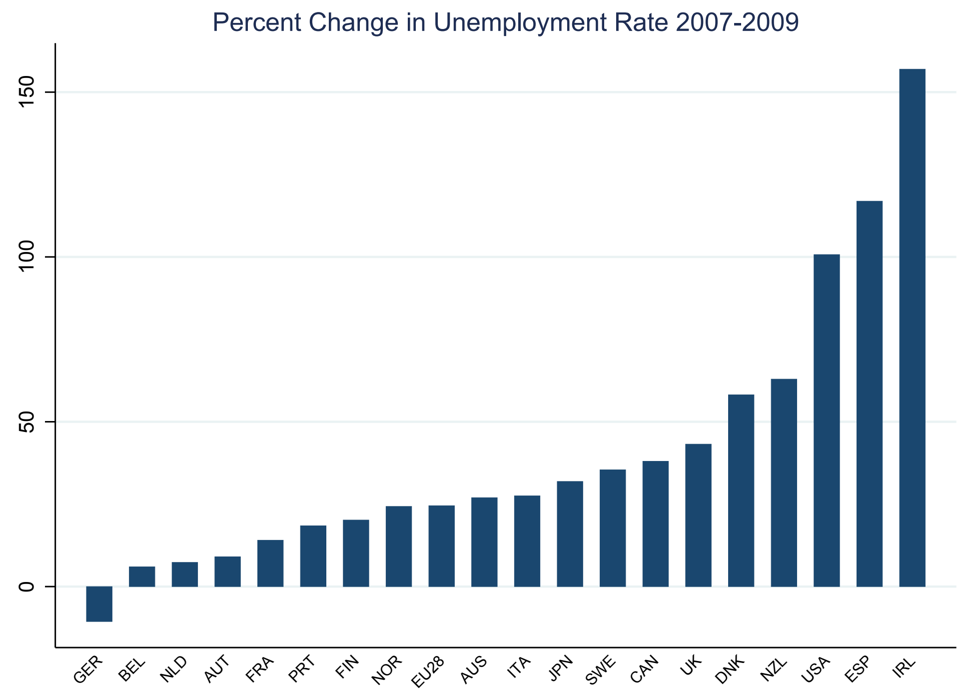

Figure 1: The Irish economy suffered an extreme shock at the time of the Financial Crisis, with the unemployment rate more than doubling in the two years either side of 2008. Source: OECD.

I use the number of people on the unemployment insurance rolls ("Live Register") to measure the labour market. The Live Register (LR) data, also provided by CSO, are recorded at the social welfare office level. LR numbers are released monthly. Crime statistics are released quarterly. To ensure consistency, I combined LR numbers for three months into a quarterly average. I then aggregated the LR numbers from social welfare districts up to the Garda division

[2]Cork is split into Cork City, Cork North, and Cork West.

[3]Dublin is split into six Dublin Metropolitan Regions: North, South, East, West, North Central, and South Central.

[4]The remaining divisions are Cavan/Monaghan, Clare, Donegal, Galway, Kerry, Kildare, Kilkenny/Carlow, Laois/Offaly, Limerick, Louth, Mayo, Meath, Roscommon/Longford, Sligo/Leitrim, Tipperary, Waterford, Westmeath, Wexford, and Wicklow.

level. Ireland's unemployment rate tripled in the immediate aftermath of the financial crisis, generating enormous inter-temporal variation in unemployment rates. There is also considerable cross-sectional variation, as regions more vulnerable to the housing bubble experienced faster growth in unemployment.

Table 1: Summary statistics (21 local areas)

	Mean	Std. Dev	N	Min	Max
Unemployment rolls (thousands)	14.3	16.1	1113	3	111
Unemployment rolls (logged)	9.3	0.7	1113	8	12
Theft	899.6	1860.7	1113	148	10486
Burglary	308.5	536.3	1113	37	3939
Assault	166.5	198.7	1113	39	1232
Sexual offences	22.2	30.8	1113	1	247
All property crime	1269.7	2571.1	1113	194	15142
All violent crime	188.7	227.1	1113	43	1414
Population (thousands)	224.0	268.4	1113	74	1476

Statistics are calculated for Garda Divisions. Due to geographic proximity, divisions in Cork and Dublin are aggregated to the county level.

Summary statistics are presented in Table 1. I focus on four types of crime. Two are standard measures of property crime: thefts and burglaries.[5] The two additional types of crime are assault and sexual offences. The implicit economic theory underlying the analysis is a standard Becker (1968)-type model where crime can be represented as an alternative to traditional employment. A negative shock to the economy transfers people from the labour market to the 'informal alternative'. Consequently we expect a strong relationship between unemployment and property crime, primarily through the mechanism of increased marginal utility of consumption from lower income levels. We have less reason to expect a strong relationship between unemployment and, say, assault. However there may still be an effect of unemployment on assault if e.g. the opportunity cost of incarceration is lower if one does not have a job. Similarly, I investigate the response of sexual offences to unemployment, supplementing the literature finding that the

[5]Robbery is excluded because of its relative infrequency. The median number of thefts per quarter in a division is 408. The median number of robberies is 16. Robberies are included in the 'All property crime' variable.

number of such offences can depend on labour market conditions.[6]

To my knowledge the most comparable analysis from Ireland is Denny *et al.* (2004), over which this paper has at least three advantages. Firstly, the changes in the labour market pre- and post-2008 provide large variation for estimation within a short horizon. Secondly, using local-level crime statistics, this paper can estimate relationships using within-unit variation. This is advantageous as it eliminates many concerns about the crime-labour market relationship varying between differing geographic regions. Finally, rather than being restricted to data on burglary alone, the dataset used in this paper includes several classes of crime such as theft and assault. In the broader context, the provision of high quality administrative data from an entire country, during a time of considerable economic volatility, provides an interesting case for an international audience.

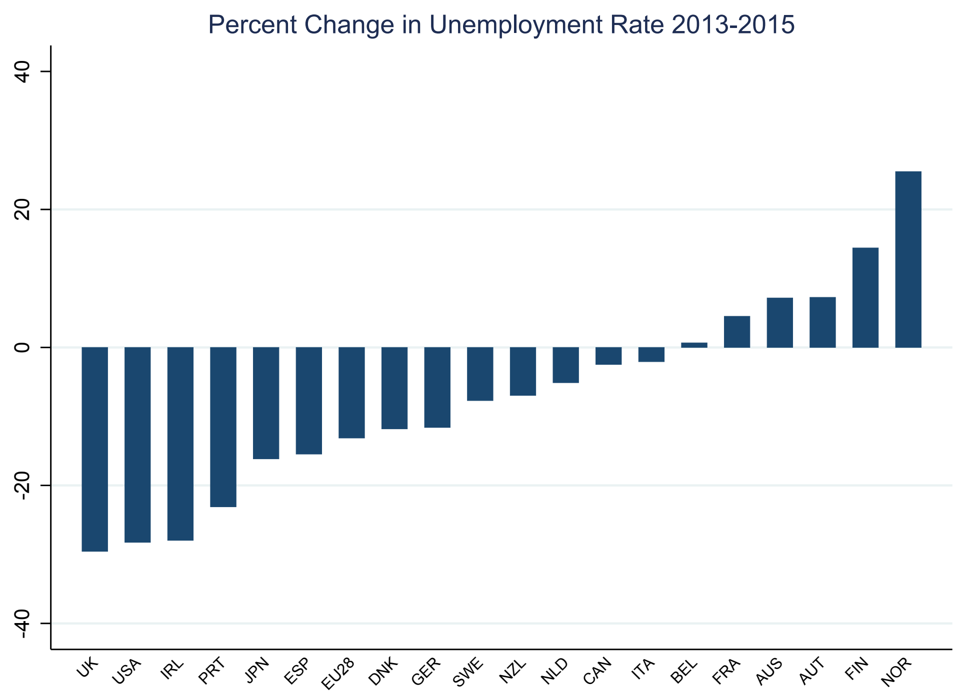

Figure 2: The strong recovery in the labour market in Ireland in recent years has further increased the amount of variation in unemployment rates. Source: OECD.

[6]This analysis assumes that the statistics reported to An Garda Síochána are an accurate measure of crimes committed. Of course if this assumption is violated, specifically if the rate of reporting changes between areas over the period, my results will be invalid. Due to their particularly personal nature, I suspect this is more likely to be the case for sexual offences than property crimes.

3 Regression Results

This section analyzes the relationship between crime and unemployment using the standard empirical tools for regression analysis. Section 4 will address concerns about endogeneity with an instrumental variable approach. The primary method of estimation in this section is Ordinary Least Squares (OLS) with time and district fixed effects.[7] Thus the model is an unobserved heterogeneity model:

$$y_{it} = a_i + \delta_t + \beta x_{it} + \epsilon_{it}$$

where y_{it} is crime in district i at time t, a_i is a district (e.g. county) fixed effect, δ_t represents the time (quarterly $\times$ year) fixed effects, β is our coefficient of interest, x_{it} is the number of people on the Live Register in district i at time t, and ϵ_{it} is the error term.

Unobserved heterogeneity models are estimated on changes within districts rather than between districts. This ensures that any and all time-invariant characteristics are controlled for in the analysis. Consequently concerns that e.g. Dublin might have consistently higher crime than rural areas are quelled by this estimation procedure. The localised nature of the data, which permits the inclusion of district fixed effects, thus gives us a much greater degree of confidence in the estimates. The inclusion of time fixed effects eliminates comparable concerns about time trends in crime: if the national crime rate was unusually high in, say, the third quarter of 2004, this will not distort the estimates.[8] The regression results are reported in Table 2.

It is reasonable to give each unit of observation (i.e. Garda division) an identical weight in the analysis. This would give all divisions equal importance in the estimation. A more nationally representative estimate is obtained by weighting districts by population. Variations in populations can be quite large, e.g. Meath has approximately twice the population of Westmeath. Consequently all tables are weighted by their Census 2002, Census 2006, Census 2011, and Census 2016 populations, with linear interpolations between these years.[9]

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[7] This strategy has been used in other papers in the literature, e.g. Edmark (2005).

[8] Although not included here, the results are also robust to the inclusion of quadratic and cubic time trends.

[9] I have also conducted the analysis using simple Census 2006 or Census 2011 population weights. Magnitudes

Table 2: Effects of the number of people on unemployment rolls on crime

	Theft	Burglary	Assault	Sexual	All Property	All Violent
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rolls (thousands)	11.08***	2.709***	1.511***	0.437***	16.23***	1.948***
	(0.986)	(0.241)	(0.0660)	(0.0191)	(1.366)	(0.0700)
Garda Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1113	1113	1113	1113	1113	1113
Adjusted R^2	0.995	0.974	0.986	0.913	0.994	0.985

Results show the relationship between the total number of people on the Live Register in a division and various forms of crime in that division. The data are quarterly from 2003Q1–2016Q1. Standard errors are clustered at the Garda Division level. All results are weighted by interpolated Census 2002-2016 populations.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 shows that property crime is well correlated with deteriorations in the labour market. The interpretation of the coefficient in column 1 is that a 1,000-person increase in the unemployment rolls is associated with an increase of about 11 thefts per district, per quarter. Similarly an extra thousand unemployed people is expected to increase the number of violent crimes (defined as homicide, sex offences, and assaults) in each district in each quarter by about 1.9. Overall we can see that, holding everything else constant, property crime (defined as all thefts, burglaries, and robberies) is several times more responsive to unemployment than violent crime.

The results in Table 2 are clustered at the Garda Division level. There may be concern in panels like this, where the number of time-periods is greater than the number of cross-sectional units, about also clustering on the time dimension (Cameron and Miller, 2015). To account for this, Table 3 is the analysis from Table 2 but with two-way (i.e. cross-sectional and inter-temporal) clustering. This increases the SE estimates considerably, but does not change the substantive interpretation of the results.

move around by changing population weights, but the qualitative interpretations remain the same.

Table 3: Estimates of the effect of unemployment on crime, with two-way clustered SEs

	Theft	Burglary	Assault	Sexual	All Property	All Violent
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rolls (thousands)	11.08***	2.709*	1.511***	0.437**	16.23***	1.948***
	(2.628)	(1.619)	(0.408)	(0.173)	(3.868)	(0.467)
Garda Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1113	1113	1113	1113	1113	1113
Adjusted R^2	0.995	0.976	0.987	0.919	0.994	0.986

These results replicate those from Table 2, but standard errors are two-way clustered at both the Garda Division and Year × Quarter levels.

These results are all highly statistically significant, but that tells us little about the economic significance. Rather than reporting the effect in terms of absolute numbers, it is informative to consider the results in percentage terms. In particular, taking the log of both the number of crimes and the number of unemployed people permits the interpretation of the coefficients as elasticities: how a percent change in an independent variable leads to a percent change in the dependent variable. Table 4, which reports the results from this specification, further corroborates the evidence in Tables 2 and 3. For example, the coefficient of 0.554 in first column of Table 4 implies that a 10% increase in the number of people on the unemployment insurance rolls in a district is associated with a 5.54% contemporaneous increase in thefts in that district. With an estimated elasticity of 0.465, the magnitude is very similar for burglary. Taking the results in Table 4 collectively, we conclude again that property crime is strongly positively correlated with unemployment; that the effect on assaults is not statistically distinguishable from zero; that sex offences are surprisingly sensitive to the conditions of the labour market; and that overall the results are several times stronger for property crime than for violent crime.

Table 4: Estimates of the unemployment-crime elasticity

	Theft	Burglary	Assault	Sexual	All Property	All Violent
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rolls (logged)	0.554***	0.465***	0.0115	0.552***	0.521***	0.0761
	(0.123)	(0.146)	(0.106)	(0.162)	(0.119)	(0.108)
Garda Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1113	1113	1113	1113	1113	1113
Adjusted R^2	0.994	0.983	0.983	0.924	0.994	0.985

Results show the relationship between the logged number of people on the unemployment rolls in a division and log of various forms of crime in that division.

One further method to investigate the relationship is through first differencing (FD) the variables. The FD approach estimates the same parameter as the fixed effects (FE) approach, but rather than utilizing unit-specific fixed effects to capture unobserved heterogeneity, FD estimation removes unobserved heterogeneity by differencing adjacent periods. The FD approach is thus very similar to the fixed effects/within estimator approach, and identical in the two-period case, but requires a slightly weaker condition for consistency,[10] and thus any great divergences in estimates should raise concerns. Table 5 presents these results.

The results in Table 5 provide further evidence that crime responds to the labour market. This estimation method suggests that a 1,000-person increase in unemployment in a district is associated with about 10 additional property crimes per quarter; whereas the OLS-FE estimate suggested about 16 additional crimes. The 95% confidence intervals for these estimates overlap.

The results in Table 5 are less clear when it comes to violent crime. Though a weaker and less consistent relationship is expected for violent crime than for property crime, it is surprising to see a statistically significant negative relationship between unemployment and violent crime. As the OLS-FE estimates found a positive coefficient, we must conclude that this relationship is less consistent than that for unemployment and property crime.

[10]The strong exogeneity condition for FE is reduced to an adjacent-period exogeneity condition for FD.

Table 5: First differences estimates

	Theft	Burglary	Assault	Sexual	All Property	All Violent
	(1)	(2)	(3)	(4)	(5)	(6)
Change in unemployment (thousands)	1.430***	5.519***	-1.092***	-0.147***	9.757***	-1.238***
	(0.350)	(0.316)	(0.0710)	(0.0359)	(0.780)	(0.0718)
Year × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1029	1029	1029	1029	1029	1029
Adjusted R^2	0.246	0.326	0.305	0.283	0.288	0.291

Results show the relationship between the change in the number of people on the unemployment rolls in a division and the change in various forms of crime in that division.

Taking the estimation results on the whole, I conclude that a deterioration in labour market conditions is associated with an increase in property crime. In particular, my estimates suggest that a 10% increase in the number of people on the unemployment rolls leads to a 5% increase in theft, burglaries, and robberies. As one might expect, there is some evidence for a positive relationship between a poor labour market and violent crime, but that the relationship is considerably weaker and less consistent than the relationship between labour markets and property crime.

Table 6: First differences estimates (2014–2016)

	Theft	Burglary	Assault	Sexual	All Property	All Violent
	(1)	(2)	(3)	(4)	(5)	(6)
Change in unemployment (thousands)	18.92***	-0.631	-15.56***	-2.448***	25.90***	-18.01***
	(0.687)	(0.631)	(0.654)	(0.173)	(1.125)	(0.818)
Year × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	189	189	189	189	189	189
Adjusted R^2	0.374	0.320	0.734	0.416	0.357	0.769

What of the most recent improvement in the labour market? Are these results the same if we focus on the most recent years (since 2014) where there has been a return to economic growth and improved employment opportunities? In short the answer is yes, the substantive conclusions are the same. There is a very strong relationship in recent years in relation to property crime (an extra 26 crimes associated with 1,000 people unemployed), but a surprising negative coefficient in relation to violent crime. On the totality of the evidence, we again conclude that the statistical relationship between unemployment and property crime is clear, and weaker and even ambiguous for violent crime.

As discussed earlier, the inclusion of district fixed effects removes concerns about any time-invariant omitted variables and quarter $\times$ year fixed effects capture time trends. However "there is nothing explicitly causal" (Levitt, 2001) about the interpretation of these parameters. For additional evidence on the effect of unemployment on crime I employ another, explicitly causal, identification strategy: an instrumental variable.

4 Instrumental Variable Estimates

Instrumental variables are a means of identifying causal relationships by generating estimates from a plausibly exogenous mechanism. A large literature exists on the advantages (and disadvantages) of IVs (see e.g. Angrist *et al.* (1996) and Bound *et al.* (1995)), and IV approaches have of course been used extensively for causal analysis in relation to labour shocks, e.g. Bound and Holzer (2000), Diamond (2016).

The instrumental variable strategy I employ in this paper uses regional variation, sectoral intensity, and national growth rates to create an instrument similar to those made popular by Bartik (1991). This Bartik IV approach (or similar) has been used previously in related literatures (e.g. McLaren and Hakobyan (2016), Hanlon (2016), Baum-Snow and Ferreira (2014), Brunner *et al.* (2011) and Lin (2011)), in papers very closely related to this topic (e.g. Fougére *et al.* (2009), Öster and Agell (2007)), and indeed it was the identification strategy of perhaps the best-known paper on crime and unemployment, Gould *et al.* (2002).

The intuition behind the instrument is quite simple: some regions are more affected by sectoral-specific shocks than others. For example, competition from foreign automobile manufacturers will hurt the labour market in Detroit more than in Seattle. Consider the construction sector in Ireland. In 2006, more than 200,000 people were employed in construction. Starting in 2007, the construction sector in Ireland declined rapidly. With a decline in activity of 75%, regions with higher levels of employment in construction during the boom could be expected to see relatively more redundancies later. This is the intuition behind the Bartik instrument, but there is no need to restrict the instrument to the construction sector. By applying this logic across all sectors, we can generate powerful predictors of unemployment for each region. Specifically, let $s_{ir}(t)$ be industry i's share of total employment in region r at time t. Similarly let $g_{ir}(t)$ be the employment growth rate in industry i for region r between times $t-1$ and t. Now let $\hat{g}_{ir}(t)$ be the "almost-national" growth rate in industry i for region r between times $t-1$ and t. It is almost-national because it is the employment growth of that industry in all *other* regions. Formally, in an economy with R regions and I industries, $\hat{g}_{ir}(t) = (R-1)^{-1}\sum_{s\neq r}^{R} g_{is}(t)$. We can then define the Bartik instrument for the percent change in region r's employment between date $t-1$ and t as $z_r(t) = \sum_{i=1}^{I} \hat{g}_{ir}(t)s_{ir}(t-1)$.

The instrument's exclusion restriction is embedded into the creation of the 'almost-national' growth rate. By omitting region r's effect in the calculation of the national growth rate, we create a predicted growth rate that by design excludes the influence of region r.

As construction bore much of the brunt of the recession, young men were particularly at risk of entering spells of unemployment. Previous research has found this group as substantially more likely to commit crimes than, say, young women. The interpretation of these results should therefore be a LATE for this relatively high risk group.

For this portion of the analysis, the data on the labour market come from the CSO's Quarterly National Household Survey (QNHS). The QNHS is the survey conducted to calculate the official unemployment rate in Ireland, and details the number of people employed in each of the fourteen NACE-2 economic sectors[11] by region. Therefore the analysis is conducted at the regional[12] level. Consequently the analysis in this section will focus on changes in employment rather than changes in the unemployment rolls, and by region rather than by Garda Division.

Although most Garda Divisions are easily aggregated up to regional level, complications

[11] Agriculture, forestry and fishing; Construction; Wholesale and retail; Transportation and storage; Accommodation and food service; Information and communication; Professional, scientific and technical; Administrative and support services; Public administration and defence; Education; Human health and social work; Industry; Financial, insurance and real estate; and Other.

[12] The eight NUTS 3 regions of Ireland are Border, West, Midlands, Mid-East, Dublin, South-East, South-West, and Mid-West.

arise for the Tipperary and the Roscommon/Longford Garda Divisions.[13] To ensure consistency in these cases, I use crime data directly from each Garda station[14] and aggregate up to the regional level.[15]

Due to the highly localised nature of the data from the Garda station-level, the number of offences are redacted for particularly sensitive offences such as sexual assault. However they are available for theft and burglary. I therefore restrict attention to these crimes.

Table 7: First stage results for Bartik Instrument

	(1) Actual Employment (level)	(2) Actual Employment (difference)
Predicted Employment	0.718^{***}	0.736^{***}
	(0.0713)	(0.149)
Instrument F-stat	101.3	24.53
Observations	392	392

Results show the relevance of the Bartik instruments for level of and change in employment. The data are quarterly from 2003–2016. Errors are clustered at both the region and quarter level.

The results of the first-stage regressions are shown in Table 7. Consistent with the conclusions from the OLS results that the unemployment-property crime relationship is clear in either levels or differences, I employ the Bartik instrument in both levels- and differences-based specifications. The levels-based specification includes region and time fixed effects, so interpretation is similar to the first differences-based specification.

The results in Table 7 estimate quarterly employment based on Bartik's sectoral share predictions for each region between 2003 and 2016. Perhaps not surprisingly, the Bartik instrument is strongly correlated with employment in both levels and changes. The first-stage coefficients

[13] South Tipperary is in the South-East region, and North Tipperary is in Mid-West. Similarly, Roscommon is in the West region, and Longford is part of Midlands.

[14] The CSO helpfully provides annual recorded crime from every Garda station in Ireland. This facilitates more precise identification of the annual distribution of crime levels, for both theft and burglary, between two counties. For example, 73% of the burglaries in the Roscommon/Longford division in 2015 were recorded by Garda stations in Co. Roscommon. Thus I attribute 73% of the burglaries in 2015 to Roscommon's region, while Longford's region is attributed the remaining 27%.

[15] I classify crimes recorded in Nenagh, Templemore, and Thurles as North Tipperary and therefore as Mid-West. Crimes recorded in the Cahir, Clonmel, and Tipperary districts are attributed to the South-East region. Within the Longford/Roscommmon Division, Roscommon includes any crimes from the Boyle, Castlerea, Roscommon districts; Longford comprises the Longford and Granard districts.

are positive and significant. Importantly, the relationship provides F-statistics on the relevance of the excluded instrument equal to either 101.3 (levels) or 24.5 (differences) depending on the specification. The 'rule of thumb' for IV relevance that the first-stage (excluded) $F \geq 10$ is easily satisfied. Weak instrument tests are rejected with $p < 0.01$.

Table 8: Second stage results of employment (levels) on crime

	(1) Theft	(2) Burglary
Actual Employment (level)	-20.85***	-5.099***
	(4.502)	(1.782)
Observations	392	392
Adjusted R^2	0.064	0.289

Errors are two-way clustered at region and quarter level.

Table 8 presents the first set of second-stage results from the IV regression. These are the levels (with fixed effects) estimates of instrumented numbers employed (*not* unemployed) on property crime.[16] Here we expect negative coefficients as we focus on 1,000 more people *employed*. As has been known for decades, due to contemporaneous changes in the size of the labour force etc., a 1,000-person increase in employment is not precisely the same thing as a 1,000-person decrease in unemployment. Thus although the interpretation of the coefficients in the IV specifications and the regressions presented in Section 3 are not identical, they are both measures of the relationship between the labour market and crime.

Previously we found that 1,000 more unemployed people was associated with approximately 3 extra burglaries and 11 extra thefts per quarter. Here we find that IV estimates suggest 1,000 more people employed causes there to be about 5 fewer burglaries and about 21 fewer thefts. Both results are significant at the 1% level. These results are of course both consistent with each other, and thus I interpret the Bartik IV results as confirmation of the prediction that a deterioration in the labour market results in more crime.

Table 9 presents comparable results to Table 8, but with the first differences specification.

[16]This can be loosely interpreted as the IV version of the estimates from Table 3.

Table 9: Second stage results of employment (differences) on crime

	(1) Theft	(2) Burglary
Actual Employment (difference)	-10.81**	-5.571**
	(5.255)	(2.505)
Observations	392	392
Adjusted R^2	0.212	0.363

The first difference estimates presented earlier in Table 5 found that a 1,000-person increase in unemployment led to about 10 extra property crimes, and these IV estimates find a 1,000-person increase in employment leads to about 16 fewer property crimes. Again, although the coefficients are different, they are both statistically significant and of a comparable absolute magnitude, and I thus interpret this as further evidence supporting the unemployment-crime relationship.

5 Conclusion

Ireland is a developed country that has experienced unprecedented economic volatility in the past decade. Using a unique dataset capturing both crime and labour market statistics at a granular level, I find clear and precisely estimated evidence that unemployment causes crime. As the data are drawn from reliable administrative sources and the large variation in the dependent variable generates precise estimates, this paper makes a considerable contribution to literature on how crime responds to local labour market conditions.

I estimate an elasticity of property crime with respect to unemployment of about 0.5. The results are robust to estimation in levels, logs, and first differences, and to clustering standard errors on both cross-sectional and inter-temporal dimensions. As anticipated, the relationship between unemployment and violent crime is much less consistent and closer to zero.

I confirmed the regression results with a Bartik instrumental variables strategy that has been a mainstay of the existing literature. Instrumenting changes in regional employment with region-specific shocks, I again estimated a significant relationship between property crime and the labour market: I find that an extra thousand people in employment results in 15-25 fewer property crimes per quarter. The coefficients in the IV specifications are significant, of the 'correct' sign, and of the same order of magnitude as the OLS-based estimates.

The data used in this project are current to 2016. Recent trends in employment have been very favourable, and unemployment figures continue to fall. The relationships described above remain robust when restricting the analysis to the most recent years. These continued labour market improvements should provide even more variation for analysis, and future data releases will enable further tests of this relationship.

The overall picture suggests that job creation generates the positive externality of lower crime. Conversely, higher unemployment leads to higher crime. Consistent with the existing literature, I find that this relationship holds cleanly for property crime, with weaker evidence on violent crime and sexual assault. A cohesive crime reduction policy could thus include labour market activation measures.

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