Kyklos

WILEY

KYKLOS

ORIGINAL ARTICLE OPEN ACCESS

Inside the 'Black Box' of the Nexus Between Economic Conditions and Crime: Can the Relationship Be Mitigated?

Alban Asllani[1] | Eleftherios Goulas[2] | Socrates Karidis[3]

[1]Department of Business, Entrepreneurship & Finance, Royal Docks School of Business and Law, University of East London, London, UK | [2]Department of Economics, University of Patras, University-Campus Rio, Patras, Greece | [3]Vice-Chancellor's Office, Coventry University, Coventry, UK

Correspondence: Alban Asllani (a.asllani@uel.ac.uk)

Received: 27 February 2025 | **Revised:** 27 February 2025 | **Accepted:** 31 March 2025

Keywords: business cycle | labour market policies | mitigation effects | property crime | shadow economy

ABSTRACT

This study examines how the impact of economic conditions on criminal activity is mitigated by the presence of labour market policies and that of a sizeable shadow economy. The analysis reveals a positive relationship between economic downturns and property crime, supporting the well-documented idea that economic hardships intensify criminal activity. Most importantly, however, we find that the relationship is mitigated when active labour market policies, as well as labour training, are employed by enhancing skills and productivity, thus lowering incentives for criminal behaviour. Passive policies, on the other hand, also weaken the link, primarily through the income effect, with their effectiveness being increased in the presence of high levels of the shadow economy. High levels of both kinds of labour market policies and of the shadow economy significantly reduce crime, though additional investment in those shows different returns. These findings suggest that a comprehensive approach is required when effective crime reduction is considered during economic downturns, accounting for both formal and informal sector dynamics.

JEL Classification: E24, I38, J08, K42, O17

1 | Introduction

Examining criminal behaviour and its motivation, as well as creating effective policies to address it, has been a major focus in both Economics and Criminology. Becker's (1968) seminal work framed these policies within the context of optimal resource allocation. Becker's model[1] provides important insights into the economic aspects of criminal behaviour where the supply of crime depends on a cost–benefit analysis. An individual will participate in a crime if the expected benefit outweighs the expected cost, which includes the income that can be acquired by a noncriminal activity as well as the risk of foregone future income and career prospects associated with being caught, making it dependent on the business cycle and/or labour market conditions. Over the decades, numerous studies have confirmed this relationship using various methods across different regions (Freeman 1999; Bushway et al. 2012; Bell et al. 2018). Building on Becker's framework, a substantial body of economic literature has emerged, surveying the development of economic approaches to crime determinants (Buonanno 2003; Machin and Meghir 2004; Chalfin and McCrary 2017). This literature has predominantly evolved into two main streams: one focusing on the debate between incapacitation and deterrence and the other on the economic determinants of crime.

Changes in unemployment have been a prominent factor in economic considerations related to crime (Papps and Winkelmann 2000; Raphael and Winter-Ebmer 2001; Buonanno and Montolio 2008; Cook 2014). Several channels link unemployment to criminal activity, including loss of income necessitating compensation through illicit means, changes in the opportunity cost of committing crimes, and psychological and social factors such as peer pressure and perceived inequality. Economic downturns with high unemployment can often lead to increased property crimes like theft due to financial strain (Cook and Zarkin 1985; Deadman and Pyle 1994). Conversely, during economic prosperity with low unemployment, crime rates generally decrease as better job access reduces criminal incentives (Ishak and Bani 2017; Brosnan 2018). However, the relationship between the business cycle and crime varies by crime type and socio-economic factors (Detotto and Otranto 2012).

Our motivation stems from two key observations. Firstly, there has been a noticeable downward trend in crime data following the 2008–2009 economic crisis in Europe. With rising unemployment rates during this time, one would expect that, given the above logic, crime (Bell et al. 2018) and, in particular, criminal activity against property would have risen (Bushway et al. 2012). This did not happen, and property crime has either remained unchanged or decreased on average in the period from 2008 to 2017. However, it would be premature to dismiss the effects of unemployment, earnings and other economic variables on criminal activity based solely on recent crime data trends. The link between crime and economic fluctuations remains debated, as the mechanisms connecting crime to downturns are often not explicitly assessed. Lower GDP growth reflects only part of the socio-economic cost, which includes reduced income and life dissatisfaction from job insecurity (Ishak and Bani 2017; Brosnan 2018). Economic conditions are often accounted for through unemployment indicators, as unemployed individuals are generally more prone to crime than those employed. Long-term unemployed individuals, especially those who are jobless for 15 weeks or more, have lower expectations for lifetime income due to diminished human capital (Chamlin and Cochran 2000). Conversely, those newly unemployed and actively seeking work are less likely to resort to property crime (Chamlin and Cochran 2000). Secondly, a thorough review of the existing literature reveals a significant gap in research connecting the theories of property crime, economic downturns and informality in the economy.[2] This gap highlights the need for further investigation into the mitigating factors that influence the relationship between economic conditions and crime. Following most of the empirical literature, we aim to investigate whether there exists a countercyclical relationship between changes in economic activity and crime, but more importantly, we seek to identify any mitigating effects that might influence this relationship.

Furthermore, we explore the thesis that the relationship between economic conditions and unemployment, on the one hand, and crime, on the other, is characterised by asymmetries generated by mitigating factors that may be policy-driven or relevant to the structural characteristics of a particular economy. As such, we aim to show that labour market policies (LMTs) and the presence of active or passive labour market programmes affect the crime–business cycle relationship[3] in a way that mitigates the effect of the latter on the former.[4] Improved job skills and work ethic, the psychological effect of becoming more productive and the positive influence of social interaction through these programmes are also factors found in the literature (Otto et al. 2009; Eriksson et al. 2016; Rose 2018). Passive labour -market support (PLMP) support, including unemployment benefits and other cash transfers, lessens the likelihood of criminal activity by reducing income uncertainty among those in vulnerable employment (Martin and Grubb 2005; Malo 2018). Active labour market policy (ALMP) measures, on the other hand, including training programmes, direct job creation, employment incentives and start-up incentives, may also be effective (Kluve 2010), by providing optimism about the future through improved employability or acquisition of skills (Grogger 1998; Fajnzylber et al. 2002a; Aaltonen et al. 2011). Labour market training (LMT) programmes are considered separately from other active measures since they represent the bulk of government spending on total ALMPs (Kluve 2010). These programmes enable unemployed individuals to improve their skills and expand their competencies, making them less prone to incur the potential cost associated with criminal behaviour.

In addition to PLMPs, certain structural characteristics of an economy can mitigate the effects of worsening economic conditions, particularly when these conditions persist over several years. In particular, the presence of a shadow economy may provide additional income, productive activity and social engagement opportunities, which can have similar mitigating effects. This is especially relevant in countries where unregistered economic activity constitutes a significant portion of the GDP (Rocque et al. 2019). Despite its potential significance, the empirical literature has largely overlooked the shadow economy as a mitigating factor of criminal activity. Income compensation, either directly through income generation or indirectly through tax and contributions avoidance, is a primary reason for this argument (Goulas and Karidis 2020). Additionally, the continuation of productive activity and its impact on time usage and social interaction are also important.

To our knowledge, this is the first empirical study on crime to compare the potential mitigating effects of passive and active interventions alongside the structural characteristics of an economy (such as the shadow economy). This paper, therefore, contributes to the existing literature in several ways. Firstly, it expands the work on the influence of unemployment on crime across European countries over a period of 17 years. Secondly, it assesses the role of PLMPs in moderating the role of economic downturns on crime. Thirdly, it investigates the impact of the shadow economy on the relationship between crime and economic conditions. Lastly, by accounting for different kinds of PLMPs, it examines whether these mitigating forces exhibit cyclical or countercyclical effects on crime reduction and, importantly, whether there is an element of substitutability or complementarity among these mitigation effects. Current literature predominantly focuses on the economy's impact on crime, often overlooking how specific conditions may vary this effect. Various factors identified as potential mitigators suggest that the economy's influence on crime is not uniform across different contexts (Rocque et al. 2019). The complex interplay of these factors can further diversify the relationship between economic conditions and criminal behaviour.

The rest of this paper is structured as follows: Section 2 provides the background and reviews the literature on the economic determinants of crime, including the relationship between economic activity, unemployment and crime, and the mitigating effects of PLMPs and the shadow economy. Section 3 presents our methodology and model. Section 4 discusses the results, and Section 5 provides concluding remarks.

2 | Background and Literature

The relationship between the business cycle and crime remains unclear despite the sizeable body of relevant literature. Criminal activity has significant negative effects on society and the individuals participating in such activities. The importance of mitigating these effects has generated a body of literature that investigates the determinants of criminal behaviour. The complexity of the issue has produced different streams within the literature, and the determinants of crime range from socio-economic (Fajnzylber et al. 2002a; Aaltonen et al. 2011) to historical and geographical (Campbell et al. 2015). For the purpose of this work, we concentrate on measures associated with unemployment, as it is widely accepted that property crime is mainly determined by jobless (or disadvantaged) individuals (Detotto and Otranto 2012). We use alternative business cycle definitions, including the unemployment gap, the change in the annual unemployment rate and the Beveridge curve, which is measured by the job vacancy rate over the total unemployment rate. We believe that these measures better capture the developments and efficiency in the labour markets and economic conditions (Hosios 1990; Pissarides 2000; Michaillat and Saez 2021). Our baseline model assumes that deteriorating economic conditions may lead jobless individuals to engage in criminal activities associated with thefts or burglaries (i.e. illegal activities associated with an economic reward), since the opportunity cost of committing crime becomes lower.

2.1 | Economic Conditions and Criminal Behaviour

The notion that fluctuations in crime[5] rates correlate with shifts in business cycles has been examined extensively in the field of crime economics. However, existing literature shows mixed findings on the relationship between crime rates and the business cycle, often measured by unemployment rates. Results vary significantly based on the methodology used. Some research utilising macro-level, cross-sectional or longitudinal approaches suggests a positive correlation, indicating that a weak economy is associated with increased crime rates (Rocque et al. 2019; Rosenfeld and Fornango 2007; Arvanites and Defina 2006; Kizilgol and Selim 2017). Crime generates significant socio-economic burdens (Cohen 1988; Detotto and Vannini 2010), making it imperative to alleviate its impact on the sustainable development of communities and businesses. Conversely, other studies propose a negative correlation, suggesting that a downturn in the economy leads to a decrease in criminal activity (Cohen and Felson 1979; Melick 2003; Ishak and Bani 2017; Brosnan 2018). Additionally, some studies suggest that economic conditions have a negligible impact on criminal behaviour (Blomquist and Westerlund 2014). This suggests that the literature is inconclusive on the relationship between the business cycle and crime levels.

Earlier studies (Cook and Zarkin 1985; Howsen and Jarrell 1987; Allen 1996; Witt et al. 1999) explored the relationship between fluctuations in the business cycle, unemployment rates and crime rates. Most find that economic downturns, with high unemployment rates and stagnant growth, tend to be associated with increases in certain types of crime, including property crime, attributed to financial strain and desperation among individuals facing unemployment or economic hardship (Cook and Zarkin 1985; Deadman and Pyle 1994). During periods of economic prosperity and low unemployment, crime rates may decrease as individuals have better access to employment opportunities and financial resources, reducing thus incentives for criminal behaviour. However, some studies conclude that while economic factors influence criminal behaviour, they cannot completely explain it (Howsen and Jarrell 1987). Witt et al. (1999) provide similar conclusions, suggesting that factors other than economic ones play an important role. For example, Allen (1996) highlights the significance of criminal justice system interventions and macroeconomic stability in lowering property crime rates. Reductions in inflation appear to reduce property crime, while age demographics and family/community structure have negligible effects on the analysed property crime trends. Jennings et al. (2012) further analyse variables such as unemployment, inequality, welfare spending and incarceration rates, finding that while three of these factors significantly affect property crime rate changes, income inequality does not. Furthermore, Lochner (2020) finds that incarceration during late adolescence negatively impacts educational attainment. Empirically, higher educational attainment is associated with a significant reduction in subsequent violent and property crime, leading to substantial social benefits. This underscores the need to understand the role of economic conditions and their impact on crime rates in the presence of mitigating effects. By recognising that economic factors are only one aspect of the complex constellation of influences on property crime, policymakers can develop more holistic approaches to crime reduction that address underlying social, economic and psychological determinants.

Later studies empirically test the relationship between the business cycle and crime to understand whether changes in economic indicators (such as GDP growth and unemployment rates) precede, coincide with or follow changes in crime rates. Detotto and Otranto's (2012) results show that most crime types exhibit countercyclical behaviour concerning the overall economic conditions. They do, however, find that certain offenses, such as bankruptcy, fraud and fraudulent insolvency, seem to anticipate the business cycle. Literature also suggests that the duration of unemployment, business cycles, geographical location and demographic characteristics can influence crime rates. Öster and Agell (2007) and later Sameem and Sylwester (2018) find that the unemployment rate has a significantly positive effect on crime rates. Sameem and Sylwester's (2018) results also suggest that more populous urban areas drive the positive relationship between property crime and unemployment. Conversely, the business cycle has a significantly negative effect, suggesting that a rising business cycle is associated with lower crime rates. On the other hand, Chamlin and Cochran's (2000) analysis indicates that while the unemployment rate does not affect crime, the number of individuals unemployed for 15 weeks or more and the capacity utilisation rate can significantly affect the level of property crime.

Individuals are not more inclined to commit burglary or robbery solely because they are either completely unemployed or underemployed by official standards (Kleck and Jackson 2016). Rather, a significant and positive correlation with serious property offenses emerges when individuals are out of the labour force for reasons not widely perceived as legitimate. Kleck and Jackson's (2016) findings suggest that involvement in criminal activities among the unemployed may stem from pre-existing differences in criminal tendencies among those who choose to stay out of the labour force rather than being directly caused by joblessness itself. Engaging in part-time work shows a notable decrease in property crime. The relationship between unemployment and employment status and crime is also evident in that being employed increases the positive influence on an individual who could otherwise be prone to commit a crime. On the contrary, a lack of engagement in any productive activity enhances the sentiment of injustice and inequality and makes individuals more vulnerable to peer pressure and other ways of encouragement to engage in criminal activity (Cohen and Felson 1979; Otto et al. 2009; Aaltonen et al. 2011). Initially, empirical evidence on this relationship was conflicting. Freeman (1983) found that when aggregate data is used, the evidence of a relationship between crime and unemployment is weak and dubious. However, more conclusive results were produced in recent studies (particularly concerning property crime) where the use of larger datasets allows for both cross-sectional and time variation (Edmark 2005; Bushway et al. 2012). Other studies extend the idea to include the level of wages. Evidence for the negative effect of wages on crime can be found in Gould et al. (2002) and Machin and Meghir (2004) for the United States and the United Kingdom, respectively, while Grogger (1998) found that decreasing wages was strongly related to increasing crime rates among young people. Changes to the wage rate affect the opportunity cost of criminal activities; a decrease in wages decreases the opportunity cost of crime and, as a result, is positively associated with crime rates (Braun 2019).

It is, therefore, reasonable to consider the existence and value of alternatives to criminal behaviour to understand the opportunity cost and design policies to deter crime. Much of the literature has focused on the impact of labour market conditions, such as the unemployment rate and wages, to understand the economic determinants of crime. In general, during economic downturns and periods of high unemployment, crime rates are expected to increase either as an income substitute or as a result of psychological pressure (Chalfin and Raphael 2011; Chalfin and McCrary 2017). The effect of unemployment on crime is, therefore, twofold. Firstly, unemployed people, especially when there is inadequate support from the state and/or society, may see crime as a substitute for legal work or as the only means of acquiring income. Secondly, ample spare time may increase the probability of getting involved in crime (Raphael and Winter-Ebmer 2001).

2.2 | The Role of Mitigating Factors

It is the proposition of this work that the otherwise direct relationship between fluctuations in unemployment (and the available opportunities to find work) and criminal activity can be mitigated either by the impact of government policy aimed at reducing the effects of unemployment or by the presence of certain structural characteristics in an economy. Building on this proposition, we examine the presence of non-linearities in the relationship between property crime and changing economic conditions. The baseline model is extended to account for possible policy-driven or institutional factors, focusing on the role of government spending on PLMPs, as well as for the presence of a sizeable shadow economy. Both influences are thought to affect the behaviour of jobless individuals—unemployed and of those who are marginally attached to the labour market (Rocque et al. 2019), especially during recessionary periods when their access to the formal sector becomes limited (Goulas and Karidis 2020). In other words, involvement in the informal sector of the economy or participation in an active or passive programme could offer alternative opportunities in the form of income, employment or training, inducing participants to abstain from criminal activities (Bajada and Schneider 2009).

2.3 | PLMPs: Active Vs. Passive

Several works have attempted to identify possible deterrents to criminal behaviour by examining the direct effects of PLMPs on crime or their impact on jobless individuals (Martin and Grubb 2005; Fallesen et al. 2018). LMTs can be active (ALMPs) or passive (PLMPs).[6] ALMPs have become more popular in recent decades due to their direct effect in decreasing unemployment and their indirect effects, such as increasing human capital, social interactions and tackling inequality (Fajnzylber et al. 2002a; Rufrancos et al. 2013; Wang et al. 2021). During economic downturns, when formal sector employment opportunities are limited and income prospects are lower, individuals are more likely to engage with ALMPs, such as training programmes or subsidised job vacancies (Malo 2018). These policies provide participants with income, boost productivity by developing new skills and improve their connection to the labour market, fostering optimism about future employment opportunities in the formal sector. This increased optimism and skill development further contribute to the reduction of the tendency to commit crime by offering better economic prospects and reinforcing socially acceptable behaviours.

Through redistribution, ALMPs achieve positive externalities when acting as a deterrent to criminal behaviour by increasing the opportunity cost of crime. When designed appropriately, they can mitigate the effects of other socio-economic factors that contribute to crime rates, such as sex and age (Grogger 1998; Fajnzylber et al. 2002a; Aaltonen et al. 2011). There is also evidence of a positive impact on well-being through re-employment and the alleviation of the negative psychological impact of unemployment (Layard et al. 2005). The effect of ALMPs on social behaviour is evident in several studies, showing that positive influence through social networking leads to higher ambition and, similar to normal employment, limits opportunities for crime even in societies with different development levels (Ivaschenko et al. 2017; Fallesen et al. 2018). ALMPs significantly increase the probability of future employment and expected income through upskilling participants and improving their work ethic. Besides improving workforce skills, they better align available human resources with existing labour demand gaps (Card et al. 2018; Malo 2018). Fallesen et al.'s (2018) study reveals a significant decrease in crime rates among unemployed men who participated in a workfare programme compared to those who did not, indicating a direct effect of workfare participation. Other indirect benefits include increased productivity through improved participant psychology and economies of scale achieved through the positive influence of peers and adherence to socially acceptable norms (Coutts et al. 2014; Wang et al. 2021). These findings suggest that workfare policy has a substantial and potentially long-lasting effect on reducing crime.

Despite these benefits, Kluve (2010) highlights a persistent lack of conclusive evidence on ALMP effectiveness across Europe. Although many econometric evaluations exist, understanding 'what programme works for which target group under what circumstances' remains unclear. Kluve's (2010) meta-analysis of 137 programme evaluations from 19 countries found that contextual factors like labour market institutions or economic conditions are less influential than the type of programme. Public sector employment programmes often yield negative outcomes, while wage subsidies and 'Services and Sanctions' improve employment prospects. Training programmes, the most common ALMP type, show moderately positive effects. This indicates that the programme type is crucial for ALMP efficacy. Additionally, the literature suggests that higher benefit replacement rates reduce criminal activities and increased educational levels in the working-age population as well as education attainment correlate with lower crime rates (Ehrlich 1975), though this relationship is often not statistically significant or inconclusive (Ochsen 2010; Lochner 2020; Bell et al. 2022). A lack of conclusive evidence is also presented by Ivaschenko et al. (2017), who investigate the crime rates and scarce employment opportunities for youth in Papua New Guinea. Through the analysis of the Urban Youth Employment Project, they find that while the programme positively influences participants' social behaviour, its impact on addressing the socio-economic roots of crime is limited. Similarly, Butkus et al. (2019) do not find statistically significant relationships between socio-economic factors and most European crime rates despite several robustness checks.

PLMPs, on the other hand, focus more on income benefits, typically referring to measures like unemployment benefits and income support that do not require active participation in employment or training programmes by the recipients. PLMPs may substitute for illegal income and mitigate the decline in economic status for individuals and may contribute to crime reduction by alleviating the economic desperation that can drive individuals to engage in criminal activities (Ochsen 2010). PLMPs compensate part of the lost income for the unemployed (Malo 2018). As such, by providing financial support, these policies reduce the relative attractiveness of crime as a means of financial gain. However, these policies do not require the participant to engage in time-consuming activities. Thus, the incapacitation effects do not apply here. PLMPs offer moderate benefits, limited to income compensation for the unemployed (Martin and Grubb 2005). Passive benefits might lead to longer periods of unemployment and a higher risk of antisocial behaviour due to a lack of engagement in productive activities (Fallesen et al. 2018). Öster and Agell (2007) found only weak evidence that such labour market programmes, whether general or specifically targeted at young individuals, contribute significantly to crime reduction. Similarly, Caliendo and Schmidl (2016) find limited evidence on the impact of PLMPs on reducing unemployment and job quality in European countries, particularly among youth, thereby questioning their potential impact on crime reduction.

Empirically, as the literature above has highlighted, the PLMPs on their own have limited effect on reducing crime rates. However, their effectiveness can be significantly enhanced when combined with ALMPs. Combining PLMPs and ALMPs creates a comprehensive support system. While PLMPs ensure immediate financial stability, ALMPs actively work towards reintegrating individuals into the labour market, thus potentially having an impact on crime rate reduction (Ochsen 2010; Fallesen et al. 2018).

2.4 | The Shadow Economy

Apart from the policy-driven mitigating factors, we consider the possibility that certain structural characteristics and, in particular, the level of the shadow economy can mitigate the effect of worsening economic conditions (Adriaenssens and Hendrickx 2015). Vulnerable individuals resort to (legal) underground activities, especially when their incomes fall and/or their probability of obtaining a job vacancy in the formal sector becomes lower (OECD/ILO 2019). Levels of the shadow economy in Europe range from around 10% of GDP in the United Kingdom to more than 20% in most of the Southern European countries (with some super periphery European countries experiencing over 30% of informality) (Schneider and Enste 2013; Medina and Schneider 2019, 2021). Several works have examined its determinants and have found that tax burden, state of the official economy, bureaucracy and other institutional characteristics of the country have a significant impact on the size of the shadow economy (Schneider 2012; Asllani and Schneider 2025). Although the shadow economy is seen by many economists as being associated with adverse effects, there are some advantages, often ignored by the empirical literature, around its role as a safety net for people at risk of poverty or social exclusion (Cling, Razafindrakoto, and Roubaud 2010; Cling, Lagrée, et al. 2014). For instance, various unregistered activities provide individuals with opportunities for informal employment, allowing them to acquire new skills through informal training and gain income or other non-monetary benefits.

The presence of prominent levels of unregistered economic activity[7] may be responsible for the weakening relationship between crime and unemployment in these economies. Income compensation (directly through income generation or indirectly through tax and contributions avoidance) tops the list of reasons behind this argument, while the continuation of productive activity and its effect on time usage as well as social interaction are also of importance. A recent study by Rocque et al. (2019) examines the relationship between traditional measures of the official economy (proxied by the level of unemployment) and crime as well as whether the shadow economy modifies this relationship. Their findings indicate that the level of the shadow economy affects the extent to which the legitimate economy and crime are related and that the existence of the shadow economy weakens this relationship. Similarly, Goulas and Karidis (2020) explore the impact of fiscal policies on criminal activity across 25 EU countries. They discover that stringent fiscal measures are associated with increased crime rates, particularly in non-violent offenses. Notably, the presence of a substantial shadow economy mitigates this effect, suggesting that informal economic opportunities can alter the dynamics between fiscal policies and criminal behaviour. However, both studies do not examine the complex interplay of different mitigating factors, which could further diversify the relationship between economic conditions and criminal behaviour.

It is recognised that any economic downturn due to a slowdown in the economic activity of a country exacerbates poverty levels and income distribution. Labour market theories suggest that there will be an increase in informal activities due to these economic downturns (Asllani and Schneider 2025). Consequently, it is expected that the unemployment rate in a country will increase as jobs will be. Informal employment, on the other hand, is expected to increase as there will be new entrants for various economic, and social reasons (Finnegan and Singh 2004). It is assumed that the informal economy can act as a refuge in coping with an economic decline, which affects the formal economy directly (Cunningham and Maloney 2000; Cling, Razafindrakoto, and Roubaud 2010). However, at times and at controllable levels, it can act as a cushion for survival for many people around the world (Finnegan and Singh 2004; Chen 2012). When the informal economy was first 'discovered' in the early 1970s, many observers argued the notion that it was marginal, peripheral and not related or linked to the official economy of modern capitalist development, a view that has changed today.

Certain official economic recessions have been disputed as illusory due to the oversight of the informal sector (Fleming et al. 2000). Bajada and Schneider (2009) elaborate on the impact of unemployment on the shadow economy, highlighting both income and substitution effects that fluctuate over the business cycle. During economic expansions, the shadow economy may benefit from spillovers, such as increased outsourcing, leading to an income effect. Conversely, during downturns, unemployed individuals may turn to underground work with low entry costs to supplement their income, contributing to a substitution effect. Both dynamics can potentially serve as a mitigating force for property crime levels, influencing the overall crime landscape. Moreover, they interact with other factors, such as labour market interventions, which can provide additional insights into the enigmatic trend of stagnant crime rates during economic downturns. We, therefore, examine the role of the shadow economy as an alternative means of acquiring income. For this paper, the characteristics of unregistered economic activity are like those of registered activities. We expect that the mitigating effects would be similar to those of employment.

2.5 | Substitutability or Complementarity of the Mitigating Factors

A PLMP usually coexists with institutional factors such as the shadow economy, making it more complex to distinguish between the mitigating effects. When government spending on active policies is taking place simultaneously with the existence of a large-scale shadow economy, one would expect that individuals may not be able to engage in both since they (i) require participants to allocate their time on activities that take place during day time (incapacitation effect) (Fallesen et al. 2018); (ii) provide various forms of training, especially for unskilled individuals, leading to increased productivity; and (iii) offer income support (Engelhardt et al. 2008). Any income benefits arising are conditional on the hours worked or on the training programme attended, thus requiring individuals to allocate their time between these two options. The strength of the incapacitation effect, which depends on the type of activities that each person is engaged with, determines the degree of substitutability between active policies and the shadow economy.

On the other hand, when PLMPs are implemented in conjunction with underground activities, one could expect a complementary behaviour since no incapacitation effects are now in place (Rocque et al. 2019). Individuals can join the informal sector without incurring any opportunity cost associated with their daytime activities. In other words, formal income support could be received together with participation in informal activities that offer unregistered remuneration. Therefore, income opportunities (formal and informal though) stemming from both sources make formal unemployed individuals less prone to commit property crimes (i.e. theft or burglary) since their opportunity cost increases. The strength of the income effect determines the degree of complementarity between passive policies and the shadow economy.

3 | Data and Modelling Strategy

3.1 | Econometric Specification and Variables Construction

Using a panel dataset of 28 European countries[8] during the period 2002–2018, we employ a typical crime model with the view to examine any potential effects of worsening economic conditions on criminal activity. This panel is unbalanced because reliable data are not available for all 28 countries across the entire time period. Various socio-economic and demographic covariates associated with criminal activity have been accounted for, following much of the related literature. The baseline model we use can be seen below:

$$ln(crime)_{it} = \alpha ln(crime)_{it-1} + \beta_\kappa x'_{it,\kappa} + \gamma (cycle)_{it} + \zeta_i + \theta_t + \eta_{it} + \varepsilon_{it} \tag{1}$$

with

$$x'_{it,\kappa} = \big[ln(prison)_{it}, (education)_{it}, (male\ population)_{it}$$
$$(poverty\ gap)_{it}, (consumption)_{it}\big]$$

where i and t are country- and time subscripts, α, $\beta'_\kappa s$ and γ are unknown parameters to be estimated, and ε_{it} is a disturbance term. The dependent variable is the log of (per capita) property crime rate $ln(crime)_{it}$, while $ln(crime)_{it-1}$ is its lagged value, capturing crime dynamics. In the set of controls x', the variable $ln(prison)_{it}$ measures the log of (per capita) prison population rate,[9] $(education)_{it}$ denotes human capital measured by the duration of upper secondary education, $(male\ population)_{it}$ is the annual growth rate of the male population, $(poverty)_{it}$ represents the poverty gap[10] at \$1.90 a day (2011 PPP), and $(consumption)_{it}$ measures final consumption spending (% of GDP).

The variable of main interest for the baseline model is the business cycle, $(cycle)_{it}$, where higher values signify deep recession, thus facilitating the comparison among alternative business cycle indicators. Our analysis pays more attention to jobless individuals since criminal activity is mainly driven by this segment of the labour force (Martin and Grubb 2005; Fallesen et al. 2018). Fluctuations in unemployment rates determine the level of expected earnings of individuals and, therefore, affect the probability of committing a crime. The literature that focuses on the effects of deteriorating economic conditions or higher unemployment on criminal behaviour reveals a positive relationship, especially when property crime is considered, and in contrast with violent crime, property crime is essentially committed during daytime when economic activity is higher (Öster and Agell 2007; and later Sameem and Sylwester 2018; Fallesen et al. 2018).

As a measure of business cycle fluctuations, we apply a Hodrick–Prescott (HP) filter to the total unemployment rate to obtain its cyclical component. Alternative business cycle indicators with unemployment orientation have also been used, such as the annual changes in the total unemployment rate and the Beveridge curve—the ratio of job vacancy rate to the total unemployment rate—with the view to test the validity of these measures. Lastly, time-invariant country-specific characteristics ζ_i refer to factors or attributes of a country that do not change over time or are unique to each country and help explain differences in crime rates across countries. Examples include the legal system, geographic factors and cultural factors. Common time trends (θ_t) across countries signify a single trend that applies to all countries. This captures time-related factors that affect all countries similarly, such as global economic cycles, technological progress or worldwide policy shifts. On the other hand, each country has its own time trend, allowing for differences in how they evolve over time. Thus, country-specific time trend (η_{it}) captures country-specific dynamics such as local policies, institutional changes or unique economic developments. Relying only on common time trends, one assumes that time-related changes are uniform across all countries, simplifying analysis but possibly ignoring country-specific differences.

In addition to Equation (1), our aim is to investigate the interplay of LMPs and the level of shadow economy[11] on property crime rates. LMPs usually concentrate on unemployed and disadvantaged individuals by activating them to participate in the labour market and/or by providing income support, especially during periods of economic slowdown. It is expected that a higher level of LMPs spending serves as a mitigating factor on the adverse impact of falling periods on criminal behaviour. Similarly, under conditions of low government spending on LMPs, property crime tends to be driven by recessionary periods. To pin down the heterogeneous effects of PLMPs, we use alternative government-spending categories, including ALMPs, LMT and PLMPs, expressed as real expenditures[12] per member of the labour force. Thus, we define the dummy, $(\textit{high lmp})_{it}$, which takes the value of 1 when a country's LMP spending in year t is above the median[13] obtained from the overall distribution, and a dummy low LMP for spending below the median, $(\textit{low lmp})_{it}$. It is also expected that a higher level of shadow economy will eliminate or at least restrain any unfavourable effects of recessions on crime. The size of the shadow economy is based on multiple indicators multiple causes (MIMIC)[14] estimates of informal output (% of official GDP). Alternative indicators from various sources have been employed as a means of robustness check. Similarly, we define the dummy, $(\textit{high shadow})_{it}$, that takes the value of 1 when a country's level of shadow economy in year t is above the median obtained from the distribution of all countries, and a dummy identifying a low level of shadow economy otherwise, $(\textit{low shadow})_{it}$. The median values for each of the above LMP measures expressed as real euros per LF member are €172.921 for ALMPs, €51.271 for LMT and €394.436 for PLMPs, while that for the shadow economy indicator measured as a percentage of GDP is 22.8.

There is a theoretical justification for categorising data based on the median of a sample (see Tukey 1977; Hampel et al. 1986). Using the median rather than the mean ensures that classifications are less affected by extreme values, making results more robust and reliable. For instance, when the data distribution is skewed or contains outliers, the mean may be disproportionately influenced, leading to misleading classifications. Moreover, the median value ensures that approximately half of the observations fall into each category making the statistical analysis more balanced. This is also supported by many empirical studies. Mendoza et al. (1997) adopted median tax burden thresholds to analyse the relationship between tax structures and economic performance. Acemoglu et al. (2001) used median GDP per capita to distinguish between high- and low-income countries when analysing the role of institutions in economic growth. In the same spirit, Piketty and Saez (2003) utilised median income levels showing that median-based classifications are more stable than mean-based ones. Autor et al. (2008) analysed US wage polarisation by splitting workers into above-median and below-median wage growth categories. Finally, Goulas and Zervoyianni (2023) assessing the moderating role of PLMPs on the effect of long-term unemployment on working-age suicides, they distinguished between high- and low-commitment to PLMPs based on the sample's median.

Table 1A provides descriptive statistics for all variables, while Table 1B gives the mean values of the main variables of the model as distributed across the sample of EU countries. Appendix S1 presents detailed variable definitions and data sources.

The analysis is carried out by employing an econometric model that encompasses the joint effects of structural factors (i.e. the shadow economy) and PLMPs in the formation of crime and economic fluctuations relationship. To do so, we proceed by defining three dummy variables that split the sample into four mutually exclusive segments:

$$D_{lmp} = \begin{cases} 1 \; if \, (high \; lmp)_{it} \cap (low \; shadow)_{it} \\ 0 \; otherwise \end{cases},$$

indicating time periods where only the level of LMP spending is considered as high.

$$D_{shadow} = \begin{cases} 1 \; if \, (low \; lmp)_{it} \cap (high \; shadow)_{it} \\ 0 \; otherwise \end{cases},$$

indicating time periods where only the level of shadow economy is considered as high.

$$D_{lmp,\; shadow} = \begin{cases} 1 \; if \, (high \; lmp)_{it} \cap (high \; shadow)_{it} \\ 0 \; otherwise \end{cases},$$

indicating time periods where the levels of LMP spending and shadow economy are considered as high.

TABLE 1A | Statistical properties of variables in the sample.

Variable ($N = 369$)	Mean	Std. Dev.	Min	Max
Property crime rate (per 100,000 pop.)	416.119	270.398	48.924	1261.557
Property crime rate (per 100,000 pop.), log	5.793	0.730	3.890	7.140
Prison population rate (per 100,000 pop.)	132.386	64.945	53.617	336.742
Prison population rate (per 100,000 pop.), log	4.779	0.454	3.982	5.819
Duration of upper secondary education, years	3.355	0.708	2.000	5.000
Male population growth rate (%)	0.273	0.905	−2.963	3.857
Poverty gap, % of the poverty line	0.305	0.409	0.000	2.700
Final consumption expenditure (% of GDP)	75.126	7.631	45.589	92.452
Cyclical total unemployment rate (%)	0.013	1.042	−3.755	5.140
Informal output (% of official GDP)—from Elgin et al. *(2021)*	21.950	6.744	9.400	34.700
Active LMP spending (per LF member)	272.978	296.335	3.144	1325.858
Active LMP spending (% of GDP)	0.420	0.316	0.019	1.556
Labour market training spending (per LF member)	92.583	108.551	0.087	469.031
Labour market training spending (% of GDP)	0.144	0.142	0.000	0.609
Passive LMP spending (per LF member)	557.584	523.938	7.572	2073.880
Passive LMP spending (% of GDP)	0.899	0.678	0.036	3.152

Note: Variables correspond to the sample covering 28 EU countries from 2001 to 2018. Detailed variable definitions and data sources appear in Appendix S1.

We allow the business cycle measure to influence crime rates with varying magnitudes between (i) both low spending on LMPs and low level of shadow economy, (ii) high level of shadow economy only, (iii) high spending on LMPs only, and (iv) both high spending on LMPs and high level of shadow economy. To account for these effects, we augment the model in Equation (1) by the following interaction terms:

$$\left[D_{lmp} \times (cycle)_{it}, D_{shadow} \times (cycle)_{it}, D_{lmp,shadow} \times (cycle)_{it}\right]$$

Apart from the above effects that operate only through the stage of the business cycle, we also assume that combinations of structural and LMP influences exert a direct impact on crime rates. Thus, the transformed model takes the following form:

$$\begin{aligned} ln(crime)_{it} = {} & \alpha ln(crime)_{it-1} + \beta_\kappa x'_{it,\kappa} + \gamma_1 (cycle)_{it} + \gamma_2 D_{lmp} \times (cycle)_{it} + \gamma_3 D_{shadow} \times (cycle)_{it} + \\ & + \gamma_4 D_{lmp,shadow} \times (cycle)_{it} + \delta_1 D_{lmp} + \delta_2\, D_{shadow} + \delta_3\, D_{lmp,shadow} + \zeta_i + \theta_t + \eta_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

Regardless of the business cycle measure used, the variable $(cycle)_{it}$ has been constructed to capture the effects of economic downturns. Our priors are that contractionary periods will mostly affect criminal activity under conditions of concurrent low LMP spending and low levels of the shadow economy. In this case, minimal mitigation is present, which can be shown by the coefficient γ_1. Any intermediate case where only one mitigation is present is captured by γ_2 and γ_3, indicating, respectively, countries with higher LMP spending or countries with higher levels of the shadow economy. A negative and statistically significant coefficient, i.e. $\gamma_2, \gamma_3 < 0$, would confirm the hypothesis that any moderating effects of economic slowdown on crime rates could be attributed to each factor. For instance, the magnitude of γ_2 signifies the differential effect of the business cycle on property crime between countries with higher LMP government spending and the reference category, i.e. countries with both low levels of LMP spending and of shadow economy. Similarly, the coefficient γ_3 represents the differential between countries having high shadow economy and the reference category. Finally, the extreme case where both mitigations are jointly considered is captured by γ_4. A negative and statistically significant coefficient, i.e. $\gamma_4 < 0$ gives the differential between the group of countries having high levels of both characteristics and the reference group—the other extreme where the size of LMP spending and shadow economy are limited. In addition, we examine whether a large shadow economy or more spending on LMPs or their combination exerts any potential direct effect on crime. We expect their occurrence to reduce property crime rates with $\delta_1, \delta_2, \delta_3 < 0$. It is crucial to account for these effects in order to attribute and quantify the 'net' effects of PLMPs and shadow economies on crime that arises through business cycle variations.

3.2 | Investigating Substitutability and Complementarity of Mitigation Effects

The voluminous literature on the heterogeneous effects of active and passive LMPs and the various mechanisms through which the underground economy influences disadvantaged groups, especially during downturns, enables us to explore further whether (i) one needs to distinguish between passive and active LMPs and (ii) passive or active LMPs produce similar outcomes when they coexist with higher levels of shadow economy. In other words, the size of the coefficient γ_4 in Equation (2) indicates the degree of substitutability or

TABLE 1B | Mean values of the main variables by country.

Country	Obs	Property crime rate	ALMP spending	LMT spending	PLMP spending	Informal output
Austria	16	288.437	388.931	294.875	958.787	9.794
Belgium	13	782.459	390.861	122.879	1507.915	22.254
Bulgaria	10	173.400	24.128	2.475	38.868	33.530
Croatia	7	139.177	70.863	32.440	80.975	30.986
Cyprus	7	400.724	50.182	18.227	334.110	28.457
Czech Republic	16	401.007	53.278	4.186	69.551	17.813
Denmark	16	1013.561	1142.192	325.080	1399.358	17.925
Estonia	16	291.313	32.225	17.071	100.292	30.250
Finland	16	336.340	563.099	309.444	1185.088	18.006
France	14	654.648	475.447	211.193	1339.694	15.286
Germany	15	259.184	360.246	206.093	865.369	15.720
Greece	15	449.026	70.645	19.822	217.524	28.787
Hungary	12	281.022	113.497	11.795	102.165	24.375
Ireland	6	869.815	394.364	170.890	652.903	15.850
Italy	13	686.094	260.480	113.989	664.413	28.146
Latvia	13	175.282	33.484	18.261	85.960	27.692
Lithuania	15	219.120	43.763	12.980	53.946	30.320
Luxembourg	14	535.471	750.793	131.724	1176.932	10.143
Malta	13	279.711	30.501	6.397	95.753	26.177
Netherlands	15	660.605	459.871	68.511	1133.573	13.400
Poland	12	125.201	86.618	9.216	80.849	26.225
Portugal	16	389.378	154.585	91.992	438.867	22.688
Romania	13	85.306	5.647	0.686	27.794	31.446
Slovak Republic	14	111.258	42.020	2.265	100.184	17.314
Slovenia	13	165.363	74.585	19.722	203.978	25.877
Spain	16	383.649	265.196	63.557	962.728	22.963
Sweden	16	765.741	685.166	101.070	582.115	18.938
United Kingdom	7	818.144	28.895	11.569	126.422	12.771

Note: Property crime is expressed as offenses per 100,000 population. LMP measures denote amounts per LF member (labour force member), while informal output is calculated as a percentage of official GDP.

complementarity that may exist in each pair of LMP categories and the shadow economy.

When higher spending on active LMPs is combined with a large shadow economy, we expect a sufficiently small (in absolute terms) size coefficient γ_4, with $\gamma_4 < \gamma_2, \gamma_3$, indicating an asymmetric response of crime to economic conditions depending on the extent of LMPs and the level of the shadow economy. This hypothesis states that any individual factor itself would be more effective in reducing property crime rates instead of allowing a large shadow economy to exist in conjunction with more government spending on active policies. The coexistence of both mitigations exhibits diminishing returns, indicating their overlapping nature, thus providing evidence in favour of the substitution hypothesis between active LMPs and the shadow economy as crime-reducing mechanisms. From a policy perspective, this means that, conditional on the size of the underground economy, any additional spending on active LMPs is insufficient to reduce crime rates under worsening economic conditions. In other words, one could argue that there are enough similarities concerning the effects of both mitigating factors on crime.

Unemployed individuals will choose to share their time between participating in an activation programme or engaging in the activities of the shadow economy. We anticipate these effects on crime to be mainly attributed to incapacitation once individuals are able to allocate more time attending a workfare program, which mandates various activities related to education, training and work or engaging in various (legal) activities in the shadow economy, thus abstaining from antisocial behaviour (see Fallesen et al. 2018). Participants in active LMPs are required to follow a time schedule, which exhibits similar features to a regular (formal or informal) work schedule in order to be able to obtain welfare benefits. Further, activation policies or participation in the shadow economy could lead to lower criminal activity due to the income effect stemming from the availability of employment opportunities they offer to engage individuals (Engelhardt et al. 2008). Socialisation effects arise as well due to mandatory attendance of training programmes or (subsidised) job vacancies occupied by the participants in an activation program. Similarly, informal employment, in conjunction with other activities in the informal sector, implants individuals in new social groups, influencing their lifestyle and their objectives. In the same context, both states have an impact on human capital, especially through the acquisition of new skills and increased productivity (formally and informally, however). Thus, both could be considered as a prestage, facilitating unemployed or disadvantaged individuals to pass from the unemployment or inactivity stage to the formal employment stage, enabling them to substitute illegal earnings from crime with legal earnings from occupation and alleviating the hardship of long unemployment spells.

When PLMPs are implemented in conjunction with underground activities, we anticipate a sufficiently larger (in absolute terms) size coefficient γ_4, with $\gamma_4 > \gamma_2, \gamma_3$. This pair of mitigations could be more effective in reducing the adverse effects of the business cycle on crime, indicating that their combination intensifies the crime-reducing effects stemming from each factor separately, revealing a complementary behaviour. Unemployed individuals would be able to alleviate any income uncertainties through passive support programmes and simultaneously engage in underground activities such as informal employment or training. Thus, the opportunity cost of committing a crime becomes higher in terms of income loss and employment opportunities in the informal sector. Furthermore, beneficiaries of passive support (i.e. the receipt of welfare benefits) are not required to devote any of their time when participating in such programmes. Alternatively, they would be able to engage in the informal economy without incurring the costs arising from overlapping activities that might take place simultaneously.

To this end, we expect that both active and passive LMPs are crime-reducing; however, their effects on criminal behaviour seem to be distributed unevenly. Active policies, due to the requirements they impose on welfare recipients, could be more effective in reducing crime by themselves, as they exhibit sufficient similarities with the shadow economy (therefore, no additional crime-reducing effects arise). On the contrary, passive policies are assumed to display weaker crime-reducing effects when they are implemented with low levels of shadow economy as they operate primarily through the income effect. However, their ability to influence crime rates is amplified by the level of the shadow economy demonstrating complementary behaviour.

4 | Results and Discussion

4.1 | Business Cycle Effects on Crime

Estimation of Equations (1) and (2) are carried out by applying the system-GMM technique (Arellano and Bover 1995; Blundell and Bond 1998) to address potential bias in fixed-effects estimates due to the presence of the lagged dependent variable among the regressors as well as possible nonstrict exogeneity of other explanatory variables. For instance, the related literature on crime determinants has highlighted the issue of endogeneity between crime and deterrence covariates, such as the prison population variable (Reilly and Witt 1996; Saridakis and Spengler 2012). Estimating Equations (1) and (2) with fixed-effects may produce dynamic-panel bias due to the correlation of the error term with the fixed-country effects, which can inflate the coefficient of lagged crime. Bias in fixed-effects estimation may also result from potential two-way causality between the dependent variable and one or more regressors. Instead of searching for appropriate external instruments to address potential two-way causality, something difficult in panel data, in system-GMM estimation, lagged levels and lagged first-differences[15] of RHS variables are used as instruments, ensuring that the estimated coefficients reflect causation running from the RHS variables to the dependent variable and not vice versa. The adequacy of the model is established when the generated residuals do not exhibit second-order autocorrelation and when the overidentifying restrictions are not rejected, a property checked by the Sargan test. Since many instruments can overfit endogenous variables and bias the coefficient estimates, we limit the lag length to keep the number of instruments manageable. At the same time, most of the explanatory variables in our model are treated as potentially endogenous and have been accordingly instrumented.

System-GMM results[16] are presented in Table 2. The Sargan statistic confirms the joint validity of the instruments used (i.e. the instruments are not correlated with the error term), implying that all models are well specified. The hypothesis of no second-order serial correlation is also not rejected in all specifications. The main variable of interest is the business cycle, which is proxied by cyclical (total) unemployment (obtained using the HP filter). In Column 1, the estimates provide supporting evidence to the thesis that recessionary periods have a systematic crime-increasing effect, even when controlling for standard socio-economic and demographic variables. For instance, a one percentage increase in our cyclical unemployment measure will result in a 1.3% increase in the annual property crime rate. Other studies in this field provide similar estimates. Cook and Zarkin (1985) report that an increase in the unemployment rate by one percentage point will result in a 1.6% increase in the burglary rate. Raphael and Winter-Ebmer (2001) using US state data from 1971 to 1997 postulate that a one percentage point drop in the unemployment rate causes a decline in the property crime rate of between 1.6% and 2.4%. Similarly, Rocque et al. 2019 using a panel of 50 US states from 1997 to 2008, reveal that unemployment increases property crime by 1.4%. According to Levitt (2004), a typical estimate implies that a one percentage point increase in the unemployment rate is linked with a 1% increase in property

TABLE 2 | Crime and cyclical unemployment under regimes of the shadow economy and LMP categories.

Variable	Baseline model (1)	ALMP (2)	LMT (3)	PLMP (4)	ALMP (5)	LMT (6)	PLMP (7)
$ln(crime)_{it-1}$	0.702***	0.684***	0.679***	0.666***	0.684***	0.669***	0.698***
	(0.088)	(0.086)	(0.086)	(0.085)	(0.085)	(0.091)	(0.094)
D_{shadow}		−0.123***	−0.076	0.057	0.002	0.010	−0.149**
		(0.025)	(0.075)	(0.067)	(0.076)	(0.052)	(0.059)
D_{lmp}		−0.156*	−0.085	−0.069	0.023	0.014	−0.025
		(0.080)	(0.069)	(0.054)	(0.040)	(0.019)	(0.037)
$D_{lmp,shadow}$		−0.147***	−0.153*	−0.080***	−0.031	−0.030	−0.049
		(0.029)	(0.080)	(0.029)	(0.061)	(0.047)	(0.057)
$(cycle)_{it}$	0.013*	0.068***	0.061***	0.068***	0.070***	0.065***	0.064**
	(0.008)	(0.019)	(0.021)	(0.020)	(0.018)	(0.021)	(0.027)
$D_{shadow} \times (cycle)_{it}$		−0.056***	−0.049**	−0.051**	−0.054***	−0.044**	−0.037
		(0.018)	(0.021)	(0.020)	(0.017)	(0.022)	(0.025)
$D_{lmp} \times (cycle)_{it}$		−0.056**	−0.043*	−0.050**	−0.055**	−0.046**	−0.031
		(0.022)	(0.022)	(0.023)	(0.022)	(0.022)	(0.029)
$D_{lmp,shadow} \times (cycle)_{it}$		−0.070**	−0.045	−0.093***	−0.076***	−0.063***	−0.083***
		(0.028)	(0.029)	(0.026)	(0.025)	(0.021)	(0.029)
$ln(prison)_{it}$	−0.699**	−0.774***	−0.777***	−0.788**	−0.758***	−0.812***	−0.747**
	(0.281)	(0.296)	(0.290)	(0.309)	(0.276)	(0.284)	(0.294)
$(education)_{it}$	−0.081***	−0.083***	−0.102***	−0.090***	−0.088***	−0.088***	−0.090***
	(0.025)	(0.029)	(0.020)	(0.030)	(0.024)	(0.026)	(0.022)
$(male\ population)_{it}$	0.117**	0.108**	0.106**	0.125**	0.103**	0.107**	0.115**
	(0.048)	(0.052)	(0.050)	(0.050)	(0.048)	(0.054)	(0.050)
$(poverty\ gap)_{it}$	0.084**	0.097**	0.097**	0.096**	0.096**	0.101**	0.084*
	(0.041)	(0.041)	(0.041)	(0.042)	(0.040)	(0.042)	(0.044)
$(consumption)_{it}$	−0.025**	−0.026**	−0.025**	−0.025**	−0.027***	−0.026**	−0.032**
	(0.011)	(0.011)	(0.011)	(0.012)	(0.010)	(0.011)	(0.013)
Constant	7.064***	7.663***	7.726***	7.692***	7.499***	7.815***	7.831***
	(1.684)	(1.749)	(1.735)	(1.790)	(1.654)	(1.733)	(1.921)
Observations	369	369	369	369	369	369	369
Number of countries	28	28	28	28	28	28	28
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.278	0.203	0.196	0.273	0.275	0.405	0.188
Sargan (p-value)	0.616	0.699	0.642	0.730	0.712	0.602	0.474
Number of instruments	84	90	90	90	90	90	90

Note: The variable $(cycle)_{it}$ denotes cyclical unemployment, which is measured by applying the Hodrick–Prescott filter to the total unemployment rate series (15–74 years). In Columns (2)–(4) categories of LMPs are measured as real expenditures per LF member, and in Columns (5)–(7) as % of GDP. Robust standard errors in parentheses. The set of RHS variables includes time effects, country effects and country-specific time effects, but their coefficient estimates are not reported due to space limitations.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

crime. On the other hand, violent crime seems not to be systematically influenced by the unemployment rate. The relevant literature has concluded that a one percentage point increase in the unemployment rate leads to a higher property crime by 1%–2% (see Machin and Meghir 2004; Lin 2008; Mustard 2010, among others).

The estimated coefficients on the RHS variables in all specifications are in accordance with our priors. The effects of past property crime rate and incarcerated population are as expected; the past crime rate is a strong predictor of current crime, confirming crime inertia (coefficient is positive and significant), while the prison population acts as a crime deterrent, appearing with a negative and highly significant coefficient. The poverty gap and male population variables enter the regressions with positive and significant coefficients. On the other hand, the education and final consumption expenditure variables (i.e. income level proxy) appear with negative and statistically significant coefficients in all models.

4.2 | Pairs of LMP Categories and Shadow Economy

We now turn our focus on the role of LMPs and the shadow economy as mitigating factors in the relationship between criminal activity and worsening economic conditions. In Columns (2)–(7) of Table 2, which presents estimates of model in Equation (2), we account for various combinations of LMPs and shadow economy and examine the heterogeneous effects of different types of LMPs, such as ALMPs, LMT and PLMPs. Columns (2)–(4) portray the regression results when the corresponding LMP measures are expressed as real expenditures per member of the labour force, whereas Columns (5)–(7) assume LMP expenditures as a percentage of GDP. We expect that such government initiatives will moderate (or eliminate) the effect of recessions on crime. The impact of LMPs is captured by the inclusion of its interactions with the cyclical unemployment variable. A similar mitigating effect should be observed when an economy is structurally embedding high levels of unregistered activity, as this is expressed via the level of the shadow economy (as a % of GDP).

A positive and highly significant coefficient is reported for $(cycle)_{it}$ in Column (2), which reflects the impact of recessions on crime when both ALMP spending and the shadow economy are low (i.e. the reference category). In other words, we show that recessions are crime-enhancing by 6.8% when such policies are limited and take place in conjunction with low levels of informality. Regarding the coefficients on the interactions $D_{lmp} \times (cycle)_{it}$, $D_{shadow} \times (cycle)_{it}$ and $D_{lmp,shadow} \times (cycle)_{it}$, they all appear with the expected negative signs, and they are statistically significant, indicating a decreasing crime effect in relation to the reference group that operates through business cycle fluctuations. In other words, each individual factor (ALMPs only or shadow economy only) is adequate to restrict the harmful effects of recessions on crime by 5.6% producing thus a total crime effect equal to the sum $0.068–0.056 = 0.012$ or 1.2%, which is still positive albeit smaller in size. As we previously explained, we expect the role of government spending on ALMPs to be threefold: Firstly, ALMPs compensate for the loss of income due to recessions; secondly, they act as a substitute for employment in terms of time spent, and lastly, they can have a significant impact on the psychology of individuals both by increasing their productivity and the prospects of future income and by increasing positive social interactions. On the other hand, the level of informality acts as a property crime deterrent if it is viewed as a substitute for formal employment. The informal sector, mainly through unregistered employment and unreported income, could provide an alternative option to, in other ways, illegal activity.

It should be noted here that it is not this paper's intention to advocate higher levels of unregistered economic activity under any circumstances. The effect of unregistered employment is similar to that of PLMPs in several ways, including income earned, time spent in productive activities (the incapacitation effect) and improved productivity, social interaction and the higher opportunity cost of committing a crime. However, assessing the social and economic effects of both mitigations, one could argue that registered activity in PLMPs is always more preferable, as the economy is able to avoid any adverse effects associated with the existence of the shadow economy.[17]

In Column (2), when a higher level of the shadow economy jointly exists with more spending on ALMPs, then a negative and significant coefficient is reported equal to −0.070. This is slightly greater than the coefficients observed when each factor is in abundance (−0.056 for each one). This points out that any additional gains, in terms of crime reduction, are very limited, giving rise to the substitution hypothesis. In other words, similar effects are achieved irrespective of (i) the form of mitigating factor and (ii) whether these mitigations operate as a pair or individually. From a policy point of view, however, we need to note the possibly unwanted, positive externality of the structural presence of shadow economy and to highlight the effectiveness similarity between the two mitigating factors, one of which results in higher expenditure (albeit with some productivity benefits) and the other in forgone tax revenue.

In Column (3), we employ the LMT variable, which represents the bulk of active policies (35% of spending on average in the EU sample) and is considered the most representative. The literature supports that government-sponsored training programmes, by focusing on skills development and human capital increase, not only act as a substitute for work but also have an additional and significantly positive impact on the mental health and well-being of participants through confidence boost and improved matching in the labour market (Coutts et al. 2014; Wang et al. 2021). In this context, it is also worth highlighting the effectiveness of LMT programmes when associating them with total ALMPs, as they produce a comparable level of mitigation with only 1/3 of their spending on average (see Table 1A). Inspecting the estimation results obtained in Column (3), we confirm the mitigating effects of training PLMPs, as they operate in a similar manner to total active policies. In particular, the impact of each individual factor is statistically significant with similar magnitude (−0.049 and −0.043). Under the extreme case of a higher level of shadow economy and higher spending on LMT mixture, diminishing returns are observed since the coefficient on the interaction $D_{lmp,shadow} \times (cycle)_{it}$ is not statistically significant with a value of −0.045, which is in-between the estimates on the individual interaction terms $D_{shadow} \times (cycle)_{it}$ and $D_{lmp} \times (cycle)_{it}$. This means that there are no gains in crime reduction from investing in LMT in countries where the underground activities are large enough due to the incapacitation effect, among others. The substitutability assumption is again confirmed, indicating that under periods of contraction, work-seeking individuals will be able to reduce the probability of committing property crime by gaining more access to either training programmes or shadow economy activities. In other words, and notwithstanding the overall negative implications of high shadow economy levels, policymakers could achieve a lower impact of recessions on property crime either by investing more in total ALMPs or LMT or by allowing a higher level of informality to exist.

With the view to further explore whether the type of LMP matters when it is combined with structural factors, we also account for the efficiency of passive measures in Column (4). Although the coefficients on the interactions capturing the individual effects of passive policies and shadow economy are negative (with almost equal size in absolute terms) and statistically significant at the 5% level, the coefficient on the interaction term indicating the pair of high level the shadow economy and high spending on passive LMPs is highly significant at the 1% with a magnitude equal to −0.093, which is close to the sum of the two individual effects. It becomes apparent that the total effect on crime is fully reversed from a positive to a negative one and is equal to 0.068–0.093 = −0.025 or −2.5%. This finding provides evidence that both mitigating effects could behave as complements since the role of passive policies as a crime-reducing factor is amplified under the existence of a higher level of shadow economy. This pair of mitigations seems to operate more effectively as passive policies primarily focus on compensating for the loss of income. In contrast, the incapacitation effect is relevant only to active policies since its occurrence increases the degree of substitutability.

Assessing whether there is a direct impact of mitigations on crime, we also add to the model in Equation (2) the three dummy variables that have been constructed to partition the sample. Their inclusion facilitates our analysis in that we are now able to distinguish any potential effects that arise directly from both mitigations on criminal activity and those stemming from their interaction with the business cycle variable. Omitting these influences from the model would lead to biases regarding the effects attributed to the interaction terms. In most cases in Table 2, we report negative coefficients on the three dummies D_{lmp}, D_{shadow} and $D_{lmp,shadow}$ indicating that alternative types of LMPs and the level of shadow economy exhibit crime-reducing effects.

4.3 | Robustness Checks

To evaluate the robustness of our results regarding the way we measure LMPs, we repeat the previous estimates by using data on public spending on LMPs as a percentage of GDP instead. The results presented in Columns (5)–(7) of Table 2 remain qualitatively similar to those discussed previously. The estimates on the interaction terms in the three models verify the previous findings supporting that the pairs ALMPs-shadow economy and LMT-shadow economy could be treated as substitutes. In contrast, the pair PLMPs-shadow economy could be considered complements.

We also proceed by estimating variants of Equations (1) and (2) where the dependent variable is calculated as the difference in the log of property crime rate, $dln(crime)_{it}$, while the lagged dependent variable, $ln(crime)_{it-1}$, is now omitted from the set of the regressors. The results are shown in Table 3. Again, we are able to confirm that diminishing returns are observed when a higher level of shadow economy is combined with a higher spending on ALMPs or LMT as the coefficient on the corresponding interaction term is always insignificant. On the other hand, the coefficient referring to the case of the joint influence of shadow economy and the passive measures is statistically significant in Columns (4) and (7). Further, its size is more than double (−0.077 and −0.071) compared to the cases when only one mitigating factor is in operation.

We also test whether our baseline results could be driven by specific countries. To do so, we exclude from our sample the countries that correspond to the highest 10% of the distribution of property crime rates after inspecting the mean values shown in Table 1B. Specifically, we drop Denmark, Ireland and the United Kingdom from the sample and replicate the previous analysis for the remaining group of countries. The results are displayed in Columns (1)–(4) of Table 5. Further, we also proceed by excluding countries with gaps in the data. In Columns (5)–(8), the analysis is conducted by considering only countries with balanced data; thus, we are left with 10 countries and a total of 150 observations. Despite these amendments, our main conclusion that the role of passive policies as a crime-reducing factor is amplified under the existence of a higher level of shadow economy is again confirmed.

In addition, Table 5 shows the regression results of Equations (1) and (2) assuming alternative indicators of the business cycle.

It is a straightforward assumption that unemployed decision-making is highly dependent on their capacity to (i) enter the shadow economy and/or (ii) participate in LMPs. Further, the crime literature has also highlighted the crucial role of joblessness in criminal behaviour. Consistent with the previous analysis, we adopt additional measures of the stage of the business cycle concentrating on unemployed individuals. In this context, Columns (1) and (5) of Table 5 show the estimates of Equation (1) when the annual change in total unemployment rate and the ratio between the job vacancy rate[18] and the unemployment rate, which represents the Beveridge curve, are used, respectively, as a source of recession.[19] Both regressions consistently reveal a positive effect of depression indicators on crime. The results that appear in the remaining columns refer to the model that nests the various factors affecting the crime and business cycle relationship. Again, we provide evidence in favour of substitution effects between active LMPs and the shadow economy. On the other hand, this relationship is amended into complementary as passive policies are introduced instead, thus leading to the same conclusions as in Table 2.

TABLE 3 | Changes in crime and cyclical unemployment under regimes of the shadow economy and LMP categories.

Variable	***Baseline model*** (1)	***ALMP*** (2)	***LMT*** (3)	***PLMP*** (4)	***ALMP*** (5)	***LMT*** (6)	***PLMP*** (7)
D_{shadow}		−0.153***	−0.059	0.100	−0.017	0.018	−0.176*
		(0.030)	(0.075)	(0.096)	(0.102)	(0.096)	(0.095)
D_{lmp}		−0.296***	−0.102**	−0.111	0.017	0.017	−0.050
		(0.081)	(0.051)	(0.082)	(0.056)	(0.020)	(0.036)
$D_{lmp,shadow}$		−0.201***	−0.152*	−0.087*	−0.015	−0.008	−0.051
		(0.025)	(0.091)	(0.051)	(0.091)	(0.087)	(0.085)
$(cycle)_{it}$	0.010	0.048*	0.038	0.046	0.051**	0.039	0.046
	(0.008)	(0.025)	(0.031)	(0.029)	(0.025)	(0.032)	(0.035)
$D_{shadow} \times (cycle)_{it}$		−0.039	−0.028	−0.031	−0.039	−0.021	−0.020
		(0.026)	(0.032)	(0.029)	(0.026)	(0.035)	(0.034)
$D_{lmp} \times (cycle)_{it}$		−0.060**	−0.038	−0.050	−0.055*	−0.034	−0.028
		(0.029)	(0.033)	(0.032)	(0.030)	(0.036)	(0.037)
$D_{lmp,shadow} \times (cycle)_{it}$		−0.056	−0.024	−0.077**	−0.054*	−0.037	−0.071*
		(0.041)	(0.041)	(0.036)	(0.030)	(0.033)	(0.037)
$ln(prison)_{it}$	−0.803**	−0.815**	−0.843**	−0.860**	−0.833**	−0.886**	−0.839**
	(0.343)	(0.355)	(0.352)	(0.381)	(0.335)	(0.358)	(0.362)
$(education)_{it}$	−0.091***	−0.081**	−0.111***	−0.096***	−0.094***	−0.095***	−0.098***
	(0.026)	(0.032)	(0.028)	(0.032)	(0.027)	(0.028)	(0.028)
$(male\ population)_{it}$	0.139**	0.140**	0.135**	0.149**	0.126**	0.138**	0.141**
	(0.060)	(0.067)	(0.065)	(0.058)	(0.061)	(0.067)	(0.062)
$(poverty\ gap)_{it}$	0.085*	0.086*	0.087*	0.090*	0.089**	0.090*	0.078
	(0.047)	(0.047)	(0.047)	(0.048)	(0.045)	(0.049)	(0.050)
$(consumption)_{it}$	−0.033**	−0.034***	−0.034***	−0.032**	−0.034***	−0.034***	−0.041***
	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.015)
Constant	6.484***	6.713***	6.868***	6.705***	6.586***	6.920***	7.238***
	(1.961)	(1.936)	(1.927)	(2.033)	(1.828)	(1.973)	(2.114)
Observations	369	369	369	369	369	369	369
Number of countries	28	28	28	28	28	28	28
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.258	0.198	0.199	0.247	0.232	0.337	0.188
Sargan (p-value)	0.562	0.616	0.594	0.568	0.607	0.547	0.477
Number of instruments	82	88	88	88	88	88	88

Note: The dependent variable is the change in the log of property crime rate. The variable $(cycle)_{it}$ denotes cyclical unemployment, which is measured by applying the Hodrick–Prescott filter to the total unemployment rate series (15–74 years). In Columns (2)–(4) categories of LMPs are measured as real expenditures per LF member, and in Columns (5)–(7) as % of GDP. Robust standard errors in parentheses. The set of RHS variables includes time effects, country effects and country-specific time effects, but their coefficient estimates are not reported due to space limitations.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

TABLE 4 | Changes in crime and cyclical unemployment under regimes of the shadow economy and LMP categories using alternative subsamples.

	Subsample excluding countries with the highest 10% of crime rates				*Sub-sample using countries with balanced data*			
	Baseline model	*ALMP*	*LMT*	*PLMP*	*Baseline model*	*ALMP*	*LMT*	*PLMP*
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**s**
D_{shadow}		−0.162***	−0.065	0.087		−0.107***	0.059	0.012
		(0.030)	(0.076)	(0.101)		(0.018)	(0.072)	(0.042)
D_{lmp}		−0.298***	−0.104**	−0.116		−0.218*	0.002	−0.090**
		(0.077)	(0.052)	(0.082)		(0.115)	(0.034)	(0.036)
$D_{lmp,shadow}$		−0.209***	−0.160*	−0.099*		−0.128***	−0.051	−0.079**
		(0.025)	(0.092)	(0.052)		(0.030)	(0.048)	(0.034)
$(cycle)_{it}$	0.010	0.057**	0.045	0.055**	0.013**	0.076**	0.021	0.063*
	(0.008)	(0.022)	(0.028)	(0.026)	(0.005)	(0.037)	(0.056)	(0.037)
$D_{shadow} \times (cycle)_{it}$		−0.048**	−0.036	−0.041		−0.065*	−0.010	−0.052
		(0.022)	(0.029)	(0.025)		(0.035)	(0.057)	(0.035)
$D_{lmp} \times (cycle)_{it}$		−0.070**	−0.045	−0.060*		−0.051	0.020	−0.036
		(0.028)	(0.032)	(0.031)		(0.032)	(0.047)	(0.032)
$D_{lmp,shadow} \times (cycle)_{it}$		−0.063	−0.030	−0.085**		−0.073	−0.011	−0.070*
		(0.039)	(0.039)	(0.034)		(0.053)	(0.065)	(0.043)
$ln(prison)_{it}$	−0.804**	−0.844**	−0.871**	−0.898**	−0.148	−0.116	−0.153	−0.077
	(0.348)	(0.372)	(0.367)	(0.400)	(0.173)	(0.156)	(0.168)	(0.135)
$(education)_{it}$	−0.094***	−0.085***	−0.116***	−0.101***	−0.041	0.006	−0.147**	−0.032
	(0.026)	(0.032)	(0.029)	(0.032)	(0.061)	(0.082)	(0.067)	(0.060)
$(male\ population)_{it}$	0.131**	0.134**	0.130**	0.144**	0.118	0.152*	0.107	0.115
	(0.058)	(0.065)	(0.064)	(0.058)	(0.072)	(0.091)	(0.081)	(0.071)
$(poverty\ gap)_{it}$	0.085*	0.089*	0.090*	0.094**	−0.076	−0.075	−0.080	−0.055
	(0.046)	(0.047)	(0.047)	(0.047)	(0.064)	(0.062)	(0.067)	(0.059)
$(consumption)_{it}$	−0.033**	−0.034***	−0.034***	−0.032**	−0.014	−0.016	−0.012	−0.010
	(0.013)	(0.012)	(0.013)	(0.013)	(0.009)	(0.011)	(0.010)	(0.010)
Constant	6.174***	6.985***	7.021***	6.987***	46.343***	47.093***	2.060	43.899***
	(1.927)	(1.990)	(1.926)	(2.068)	(4.156)	(4.941)	(1.401)	(4.411)
Observations	340	340	340	340	150	150	150	150
Number of countries	25	25	25	25	10	10	10	10
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.022	0.020	0.028	0.023
AR(2) (p-value)	0.247	0.163	0.169	0.201	0.099	0.062	0.074	0.090
Sargan (p-value)	0.544	0.621	0.606	0.587	0.242	0.290	0.169	0.174
Number of instruments	76	82	82	82	44	50	50	50

Note: The dependent variable is the change in the log of property crime rate. In Columns (1)–(4) we exclude Denmark, Ireland, and the United Kingdom, which correspond to the highest 10% of the distribution of property crime rates, while in Columns (5)–(8) we use only countries with balanced data. The variable $(cycle)_{it}$ denotes cyclical unemployment, which is measured by applying the Hodrick–Prescott filter to the total unemployment rate series (15–74 years. All categories of LMPs are measured as real expenditures per LF member. Robust standard errors in parentheses. The set of RHS variables includes time effects, country effects and country-specific time effects, but their coefficient estimates are not reported due to space limitations.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

TABLE 5 | Crime and unemployment-related business cycle measures under regimes of the shadow economy and LMP categories.

Variable	Baseline model	ALMP	LMT	PLMP	Baseline model	ALMP	LMT	PLMP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ln(crime)_{it-1}$	0.731***	0.698***	0.687***	0.695***	0.632***	0.623***	0.604***	0.592***
	(0.084)	(0.071)	(0.068)	(0.073)	(0.068)	(0.070)	(0.074)	(0.069)
D_{shadow}		−0.171***	−0.115*	−0.017		0.023	0.134	0.210*
		(0.038)	(0.060)	(0.052)		(0.120)	(0.158)	(0.125)
D_{lmp}		−0.146*	−0.065*	−0.085		−0.050	0.070	−0.085
		(0.075)	(0.034)	(0.058)		(0.181)	(0.076)	(0.244)
$D_{lmp,shadow}$		−0.195***	−0.182***	−0.148***		−0.108	0.029	0.149
		(0.040)	(0.060)	(0.040)		(0.110)	(0.141)	(0.143)
$(cycle)_{it}$	0.013**	0.100***	0.101***	0.099***	0.003	0.012**	0.018**	0.020**
	(0.006)	(0.038)	(0.037)	(0.038)	(0.003)	(0.006)	(0.008)	(0.008)
$D_{shadow} \times (cycle)_{it}$		−0.088**	−0.088**	−0.086**		−0.010	−0.014**	−0.013**
		(0.038)	(0.037)	(0.038)		(0.006)	(0.006)	(0.007)
$D_{lmp} \times (cycle)_{it}$		−0.057	−0.058	−0.059		−0.004	−0.012	−0.005
		(0.041)	(0.041)	(0.040)		(0.010)	(0.008)	(0.013)
$D_{lmp,shadow} \times (cycle)_{it}$		−0.091**	−0.082**	−0.092**		−0.004	−0.014*	−0.017**
		(0.039)	(0.038)	(0.038)		(0.006)	(0.007)	(0.008)
$ln(prison)_{it}$	−0.743***	−0.804***	−0.780***	−0.833***	−0.635**	−0.672**	−0.713**	−0.775***
	(0.267)	(0.276)	(0.268)	(0.284)	(0.303)	(0.289)	(0.291)	(0.297)
$(education)_{it}$	−0.067**	−0.074***	−0.082***	−0.079***	−0.144	−0.252*	−0.270**	−0.121
	(0.031)	(0.026)	(0.025)	(0.025)	(0.106)	(0.135)	(0.130)	(0.101)
$(male\ population)_{it}$	0.087*	0.046	0.037	0.061	0.117**	0.110**	0.107**	0.121**
	(0.051)	(0.051)	(0.049)	(0.054)	(0.053)	(0.056)	(0.053)	(0.048)
$(poverty\ gap)_{it}$	0.091**	0.111***	0.110***	0.112***	0.064	0.078*	0.078*	0.077*
	(0.042)	(0.040)	(0.039)	(0.040)	(0.043)	(0.042)	(0.041)	(0.043)
$(consumption)_{it}$	−0.033***	−0.037***	−0.036***	−0.036***	−0.034**	−0.036**	−0.036**	−0.037**
	(0.011)	(0.012)	(0.012)	(0.012)	(0.016)	(0.017)	(0.017)	(0.018)
Constant	7.648***	8.563***	8.405***	8.555***	7.757***	8.821***	8.836***	89.756***
	(1.560)	(1.712)	(1.714)	(1.673)	(2.643)	(2.800)	(2.740)	(21.863)
Observations	369	369	369	369	267	267	267	267
Number of countries	28	28	28	28	24	24	24	24
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.210	0.181	0.173	0.196	0.798	0.787	0.801	0.806
Sargan (p-value)	0.930	0.951	0.917	0.975	0.977	0.974	0.975	0.950
Number of instruments	84	90	90	90	75	81	81	81

Note: The variable $(cycle)_{it}$, in Columns (1)–(4) is measured by the annual change in the total unemployment rate, while in Columns (5)–(8) it is measured by the ratio unemployment rate over the job vacancy rate, and thus higher values of these variables correspond to recessionary periods. All LMP categories are expressed as real expenditures per LF member. Robust standard errors in parentheses. The set of RHS variables includes time effects, country effects and country-specific time effects, but their coefficient estimates are not reported due to space limitations.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

In Appendix S2, we repeat our analysis focusing on the male unemployment series (15–74 years) to obtain its cyclical component by applying the HP filter as a measure of business cycle fluctuations. The reason for this is that males are more likely to participate in criminal activities, which is supported by the literature (Corman et al. 1987; Heidensohn 1989; Broidy and Agnew 1997; Entorf and Spengler 2000; Levitt 2001; Fallesen et al. 2018) and by data.[20] The results are almost identical to those obtained in Table 2, both in terms of significance and magnitude. It is also evident from many studies that youth populations are more prone to commit crimes since they lack the relevant qualifications and skills to find employment or to be able to stay aligned with the labour market and, therefore, suffer from high unemployment rates (see, e.g. Grogger 1998). Similar conclusions can be drawn from the results presented in Appendix S3, where youth unemployment (15–24 years) is used instead of total or male unemployment rates.

To further confirm our results, we employ an alternative shadow economy proxy obtained from Medina and Schneider (2019). Estimation results presented in Appendix S4 are almost unchanged, and conclusions drawn are similar to those arising from the baseline estimates of Table 2, although data on shadow economy estimates are available up to 2017, leading to a smaller number of observations. Finally, in Appendix S5, we provide estimates for Equations (1) and (2) incorporating robbery offenses in the definition of property crime. This is also supported by various studies that categorise robberies as property crimes with a violent component (see Ehrlich 1973; Fajnzylber et al. 2002a, 2002b; Machin and Meghir 2004; Buonanno and Montolio 2008). Our results remain unchanged.

5 | Conclusion

This study has examined the impact of economic conditions on criminal activity across 28 European countries from 2002 to 2018. Regardless of the specification used, the findings support the hypothesis that economic recessions exacerbate criminal activities, particularly property crime. However, although this aligns with previous research, indicating that high levels of unemployment and economic hardship increase property crime, it is not the whole story.

The primary thesis of this work is that this well-established relationship is, often significantly, mitigated by acts of economic policy as well as by the presence of certain structural characteristics, i.e. labour market-related policies and high levels of shadow economy. Moreover, we sought to, not only uncover possible inconsistencies in the economic conditions–crime relationship because of the presence of mitigating factors but also to establish whether these operate as complements, amplifying therefore their mitigating effect or substitutes, thus reducing it.

We differentiate between actively participatory policies, such as Active Labour Market Programmes and LMT, which focus on skills development and human capital alongside possible financial reward, and more passive ones, which mainly provide income support without requiring participation in training. They both exhibit crime-reducing effects, complicating, therefore, the crime–economic conditions relationship, but their effectiveness differs in the presence of high levels of the shadow economy.

The shadow economy, representing informal and unregistered economic activities, serves as a substitute for formal employment and reduces the likelihood of criminal behaviour in its own right through income and time allocation effects. When high levels of LMPs and a significant shadow economy are present, the crime-reducing effects are notable. However, the benefits from additional investment in them differ. The study has explored whether ALMPs or PLMPs produce different outcomes when combined with a high level of shadow economy, indicating their potential substitutability or complementarity in reducing crime. The findings suggest that ALMPs when combined with a large shadow economy show diminishing returns in reducing crime, supporting the substitution hypothesis. This means that additional spending on ALMPs alone, without a corresponding effort to reduce the levels of informality, is insufficient under worsening economic conditions.

Conversely, PLMPs combined with a high shadow economy demonstrate enhanced crime-reducing effects, indicating a complementary relationship. Unemployed individuals benefit from income support through passive policies while participating in informal economic activities, raising the opportunity cost of crime. Thus, both active and passive LMPs reduce crime, but their effects vary, with active policies being more effective on their own and passive policies benefiting significantly from the presence of a substantial shadow economy. The robustness of these findings is confirmed using various measures and alternative indicators of business cycles, such as annual changes in total unemployment rates and the Beveridge curve. The consistency of results across different specifications further validates the conclusions.

From a policy perspective, enhancing LMPs, particularly ALMPs and LMTs, can effectively reduce property crime rates during economic downturns. The presence of a substantial shadow economy also plays a crucial role in mitigating the adverse effects of recessions on crime. Policymakers should consider the interplay between formal labour market interventions and the informal economy when designing strategies to combat crime during economic slowdowns. This study has highlighted the complex relationship between economic conditions, PLMPs, structural characteristics and criminal activity. It underscores the importance of comprehensive policy approaches that address both formal and informal sectors to reduce crime rates effectively. This nuanced understanding adds a new dimension to existing literature, which has typically examined these factors in isolation.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] Although simplistic for assuming discrete choice between work and crime as well as homogeneity in crimes. The analysis of Becker's (1968)

model is outside the scope of this paper. For further discussion, see Draca and Machin (2015).

[2] Throughout this paper, we use the term shadow economy, informal sector and informality, informal economy or underground activity interchangeably.

[3] Previous research has sought to improve the economic indicators used in crime analysis (see, e.g. Mustard 2010). In most of the literature, we see that the rate of unemployment is the only measure used regarding the strength of the economy. However, this is potentially misleading, since it does not include those who are underemployed or discouraged. Some use the official GDP and find a strong negative relationship between lagged changes in GDP and property crime (Arvanites and Defina 2006), while others use perceptions on the economy by utilising the consumer sentiment as an indicator of economic health and reach similar conclusions (see, e.g. Rosenfeld and Fornango 2007).

[4] This may happen through the compensation of income loss, the lack of opportunity given the time dedicated to participating in a programme and the increased probability of future employment and potential future income (Kluve 2010).

[5] We use the Eurostat definition of Property Crime and we remain consistent in its use throughout our analysis. Our term crime mainly refers to property crime throughout this paper unless otherwise stated. Property crime involves theft, destruction or damage of someone's property without force or threat. Examples include burglary, theft, motor vehicle theft, arson and vandalism. Unlike violent crimes, which involve physical harm, property crimes focus on unlawfully acquiring or damaging physical assets.

[6] ALMPs include government policies providing training to the unemployed, employment incentives, supported employment and rehabilitation, direct job creation or start-up incentives. In contrast, Passive Labour Programmes compensate for part of the lost income for the unemployed (Malo 2018).

[7] For the purposes of this work, we use Schneider's (2012) definition of Shadow Economy as '...all market-based legal production of goods and services that are deliberately concealed from public authorities...' (pg. 6, 2012).

[8] Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden and the United Kingdom.

[9] Becker (1968) postulated that a higher probability of conviction or punishment would generally lead to a lower number of crime offenses a person commits. A similar view has been also adopted by Ehrlich (1973) who argued that the probability and severity of punishment, which is implied by imprisonment, could reduce the total number of offenses. In the same spirit, Fajnzylber et al. (2002b) among others, developed a crime model that accounts for the probability of being caught and for the corresponding severity of the punishments as well.

[10] This measure reflects the depth of poverty as well as its incidence.

[11] To capture the impact of the shadow economy, we employ data from Elgin et al. (2021), who estimate the shadow economy as a percentage of official GDP based on the MIMIC. As a further robustness check of our results, we employ an alternative shadow economy proxy obtained from Medina and Schneider (2019), who also employ MIMIC to estimate the shadow economy in 157 countries worldwide. These datasets are widely used in the literature to analyse the effects of the shadow economy, ensuring consistency and comparability across studies.

[12] We also collect data on various LMP spending categories expressed as a percentage of GDP.

[13] Partitioning the sample in this manner provides more flexibility by allowing countries to move states from year to year.

[14] The MIMIC model, based on Structural Equation Models (SEM), links the shadow economy (an unobserved variable) to observable indicators and causal factors of unreported economic activity (Dell'Anno 2022). It estimates this relationship by minimising the gap between the sample and predicted covariance matrices (Dell'Anno 2023). The model consists of a structural equation and a measurement model (Schneider et al. 2010), with its mathematical formulation detailed in various studies (Schneider et al. 2011). MIMIC can be applied to time series and panel data to estimate the shadow economy's size and trends.

[15] As we deal with an unbalanced panel with gaps, we resort to using a forward orthogonal transformation instead of first differencing (see, e.g. Arellano and Bover 1995). This transformation can be computed even in the presence of gaps in a panel, thus minimising data loss.

[16] Clustered robust standard errors at the country level are assumed in all models.

[17] The shadow economy could lead to significant adverse effects such as loss of tax revenue, exploitation of workers, unfair competition and erosion of public trust in institutions (Schneider and Enste 2013). The shadow economy can distort economic indicators, undermines social security systems and may also fuel corruption (Asllani and Schneider 2025). Furthermore, Williams and Schneider (2016) show that the official and shadow economies interact, but there is ongoing debate over whether the positive or negative effects prevail.

[18] The number of observations has been reduced due to data unavailability on job vacancy rate series.

[19] The inverse of the job vacancy rate to the unemployment rate ratio has been calculated, so as higher values indicate more severe recession. Thus, the results can be comparable with that in Table 2.

[20] In most EU countries the adult prison population consists of more than 90% males (*Source*: Eurostat 2024).

References

Aaltonen, M., J. Kivivuori, and P. Martikainen. 2011. "Social Determinants of Crime in a Welfare State: Do They Still Matter?" *Acta Sociologica* 54, no. 2: 161–181. https://doi.org/10.1177/0001699311402228.

Acemoglu, D., S. Johnson, and J. A. Robinson. 2001. "The Colonial Origins of Comparative Development: An Empirical Investigation." *American Economic Review* 91, no. 5: 1369–1401.

Adriaenssens, S., and J. Hendrickx. 2015. "Can Informal Economic Activities Be Explained by Social and Institutional Factors? A Comparative Analysis." *Socio-Economic Review* 13, no. 4: 627–649. https://doi.org/10.1093/ser/mwv017.

Allen, R. C. 1996. "Socioeconomic Conditions and Property Crime: A Comprehensive Review and Test of the Professional Literature." *American Journal of Economics and Sociology* 55, no. 3: 293–308. https://doi.org/10.1111/j.1536-7150.1996.tb02311.x.

Arellano, M., and O. Bover. 1995. "Another Look at the Instrumental Variable Estimation of Error-Components Models." *Journal of Econometrics* 68, no. 1: 29–51. https://doi.org/10.1016/0304-4076(94)01642-D.

Arvanites, T. M., and R. H. Defina. 2006. "Business Cycles and Street Crime." *Criminology* 44, no. 1: 139–164. https://doi.org/10.1111/j.1745-9125.2006.00045.x.

Asllani, A., and F. Schneider. 2025. "A Review of the Driving Forces of the Informal Economy and Policy Measures for Mitigation: An Analysis of six EU Countries." *International Tax and Public Finance* 32: 310–344. https://doi.org/10.1007/s10797-024-09842-z.

Autor, D. H., L. F. Katz, and M. S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics* 90, no. 2: 300–323. https://doi.org/10.1162/rest.90.2.300.

Bajada, C., and F. Schneider. 2009. "Unemployment and the Shadow Economy in the OECD." *Revue Économique* 60, no. 5: 1033–1067. https://doi.org/10.3917/reco.605.1033.

Becker, G. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76, no. 2: 169–217. https://doi.org/10.1086/259394.

Bell, B., A. Bindler, and S. Machin. 2018. "Crime Scars: Recessions and the Making of Career Criminals." *Review of Economics and Statistics* 100, no. 3: 392–404. https://doi.org/10.1162/rest_a_00698.

Bell, B., R. Costa, and S. Machin. 2022. "Why Does Education Reduce Crime?" *Journal of Political Economy* 130, no. 3: 732–765. https://doi.org/10.1086/717895.

Blomquist, J., and J. Westerlund. 2014. "A Non-Stationary Panel Data Investigation of the Unemployment–Crime Relationship." *Social Science Research* 44: 114–125. https://doi.org/10.1016/j.ssresearch.2013.11.007.

Blundell, R., and S. Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87, no. 1: 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8.

Braun, C. 2019. "Crime and the Minimum Wage." *Review of Economic Dynamics* 32: 122–152. https://doi.org/10.1016/j.red.2019.02.002.

Broidy, L., and R. Agnew. 1997. "Gender and Crime: A General Strain Theory Perspective." *Journal of Research in Crime and Delinquency* 34, no. 3: 275–306. https://doi.org/10.1177/0022427897034003001.

Brosnan, S. 2018. "The Socioeconomic Determinants of Crime in Ireland From 2003–2012." *Economic and Social Review* 49, no. 2: 127–143.

Buonanno, P. 2003. The Socioeconomic Determinants of Crime. A Review of the Literature. 1–33. https://hdl.handle.net/10281/22981.

Buonanno, P., and D. Montolio. 2008. "Identifying the Socio-Economic and Demographic Determinants of Crime Across Spanish Provinces." *International Review of Law and Economics* 28, no. 2: 89–97. https://doi.org/10.1016/j.irle.2008.02.005.

Bushway, S. D., P. J. Cook, and M. Phillips. 2012. "Economics and Youth Violence: Crime, Disadvantage, and Community." In *The Net Effect of the Business Cycle on Crime and Violence*, edited by R. Rosenfeld, M. Edberg, X. Fang, and C. S. Florence, 23–52. New York University Press.

Butkus, M., K. Matuzevičiūtė, and A. Mačiulytė-Šniukienė. 2019. "Do economic Conditions Still Cause Crime? Some Comforting Empirical Evidence From EU Panel." *Zbornik radova Ekonomskog fakulteta u Rijeci: časopis za ekonomsku teoriju i praksu* 37, no. 2: 603–628. https://doi.org/10.18045/zbefri.2019.2.603.

Caliendo, M., and R. Schmidl. 2016. "Youth Unemployment and Active Labour Market Policies in Europe." *IZA Journal of Labor Policy* 5: 1–30. https://doi.org/10.1186/s40173-016-0057-x.

Campbell, M. C., M. Vogel, and J. Williams. 2015. "Historical Contingencies and the Evolving Importance of Race, Violent Crime, and Region in Explaining Mass Incarceration in the United States." *Criminology* 53, no. 2: 180–203. https://doi.org/10.1111/1745-9125.12065.

Card, D., J. Kluve, and A. Weber. 2018. "What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations." *Journal of the European Economic Association* 16, no. 3: 894–931. https://doi.org/10.1093/jeea/jvx028.

Chalfin, A., and J. McCrary. 2017. "Criminal Deterrence: A Review of the Literature." *Journal of Economic Literature* 55, no. 1: 5–48. https://doi.org/10.1257/jel.20141147.

Chalfin, A., and S. Raphael. 2011. *Work and Crime*. Oxford University Press.

Chamlin, M. B., and J. K. Cochran. 2000. "Unemployment, Economic Theory, and Property Crime: A Note on Measurement." *Journal of Quantitative Criminology* 16: 443–455. https://doi.org/10.1023/A:1007599232183.

Chen, M. A. 2012. The Informal Economy: Definitions, Theories and Policies. Available at: ttps://www.wiego.org/sites/default/files/migrated/publications/files/Chen_WIEGO_WP1.pdf (last accessed 01.07.2024).

Cling, J. P., S. Lagrée, M. Razafindrakoto, and F. Roubaud, eds. 2014. *The Informal Economy in Developing Countries*. Routledge.

Cling, J. P., M. Razafindrakoto, and F. Roubaud. 2010. "Assessing the Potential Impact of the Global Crisis on the Labour Market and the Informal Sector in Vietnam." *Journal of Economics & Development* 38: 16–25.

Cohen, L. E., and M. Felson. 1979. "Social Change and Crime Rate Trends: A Routine Activity Approach." *American Sociological Review* 44, no. 4: 588.

Cohen, M. A. 1988. "Some New Evidence on the Seriousness of Crime." *Criminology* 26, no. 2: 343–353. https://doi.org/10.1111/j.1745-9125.1988.tb00845.x.

Cook, P. J. 2014. *Lessons From the Economics of Crime*, 1–14. MIT Press.

Cook, P. J., and G. A. Zarkin. 1985. "Crime and the Business Cycle." *Journal of Legal Studies* 14, no. 1: 115–128. https://doi.org/10.1086/467767.

Corman, H., T. Joyce, and N. Lovitch. 1987. "Crime, Deterrence and the Business Cycle in New York City: A VAR Approach." *Review of Economics and Statistics* 695-700: 695. https://doi.org/10.2307/1935965.

Coutts, A. P., D. Stuckler, and D. J. Cann. 2014. "The Health and Wellbeing Effects of Active Labor Market Programs." In *Wellbeing*, 1–18. John Wiley and Sons, Ltd. https://doi.org/10.1002/9781118539415.wbwell048.

Cunningham, W., and W. F. Maloney. 2000. Measuring Vulnerability: Who Suffered in the 1995 Mexican Crisis? World Bank mimeo.

Deadman, D. F., and D. J. Pyle. 1994. "Crime and the Business Cycle in Post-War Britain." *British Journal of Criminology* 34, no. 3: 339–357. https://doi.org/10.1093/oxfordjournals.bjc.a048427.

Dell'Anno, R. 2022. "Theories and Definitions of the Informal Economy: A Survey." *Journal of Economic Surveys* 36, no. 5: 1610–1643. https://doi.org/10.1111/joes.12487.

Dell'Anno, R. 2023. "Measuring the Unobservable: Estimating Informal Economy by a Structural Equation Modelling Approach." *International Tax and Public Finance* 30, no. 1: 247–277.

Detotto, C., and E. Otranto. 2012. "Cycles in Crime and Economy: Leading, Lagging and Coincident Behaviours." *Journal of Quantitative Criminology* 28: 295–317. https://doi.org/10.1007/s10940-011-9139-5.

Detotto, C., and M. Vannini. 2010. "Counting the Cost of Crime in Italy." *Global Crime* 11, no. 4: 421–435. https://doi.org/10.1080/17440572.2010.519523.

Draca, M., and S. Machin. 2015. "Crime and Economic Incentives." *Annual Review of Economics* 7, no. 1: 389–408. https://doi.org/10.1146/annurev-economics-080614-115808.

Edmark, K. 2005. "Unemployment and Crime: Is There a Connection?" *Scandinavian Journal of Economics* 107, no. 2: 353–373. https://doi.org/10.1111/j.1467-9442.2005.00412.x.

Ehrlich, I. 1973. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." *Journal of Political Economy* 81, no. 3: 521–565. https://doi.org/10.1086/260058.

Ehrlich, I. 1975. "On the Relation Between Education and Crime." In *Education, Income, and Human Behaviour*, 313–338. NBER. https://www.nber.org/system/files/chapters/c3702.

Elgin, C., M. A. Kose, F. Ohnsorge, and S. Yu. 2021. Understanding Informality, C.E.P.R. Discussion Paper 16497, Centre for Economic Policy Research, London. https://cepr.org/publications/dp16497.

Engelhardt, B., G. Rocheteau, and P. Rupert. 2008. "Crime and the Labour Market: A Search Model With Optimal Contracts." *Journal of Public Economics* 92, no. 10–11: 1876–1891. https://doi.org/10.1016/j.jpubeco.2008.04.016.

Entorf, H., and H. Spengler. 2000. "Socioeconomic and Demographic Factors of Crime in Germany: Evidence From Panel Data of the German States." *International Review of Law and Economics* 20, no. 1: 75–106. https://doi.org/10.1016/S0144-8188(00)00022-3.

Eriksson, K. H., R. Hjalmarsson, M. J. Lindquist, and A. Sandberg. 2016. "The Importance of Family Background and Neighborhood Effects as Determinants of Crime." *Journal of Population Economics* 29, no. 1: 219–262. https://doi.org/10.1007/s00148-015-0566-8.

Eurostat. 2024. "Prisoners by Age and Sex - Annual Data." European Commission. https://ec.europa.eu/eurostat/databrowser/view/crim_pris_age/default/table?lang=en.

Fajnzylber, P., D. Lederman, and N. Loayza. 2002a. "Inequality and Violent Crime." *Journal of Law and Economics* 45, no. 1: 1–39. https://doi.org/10.1086/338347.

Fajnzylber, P., D. Lederman, and N. Loayza. 2002b. "What Causes Violent Crime?" *European Economic Review* 46, no. 7: 1323–1357. https://doi.org/10.1016/S0014-2921(01)00096-4.

Fallesen, P., L. P. Geerdsen, S. Imai, and T. Tranæs. 2018. "The Effect of Active Labour Market Policies on Crime: Incapacitation and Program Effects." *Labour Economics* 52: 263–286. https://doi.org/10.1016/j.labeco.2018.03.002.

Finnegan, G., and A. Singh. 2004. *Role of the Informal Sector in Coping With Economic Crisis in Thailand and Zambia*. Vol. No. 993657013402676. International Labour Organization.

Fleming, M. H., J. Roman, and G. Farrell. 2000. "The Shadow Economy." *Journal of International Affairs* 53, no. 2: 387–409. https://www.jstor.org/stable/24357758.

Freeman, R. 1983. "Crime and Unemployment." In *Crime and Public Policy*, 89–106. ICS Press.

Freeman, R. B. 1999. The Economics of Crime. *Handbook of Labor Economics* 3, no. 3: 3529–3571. https://doi.org/10.1016/S1573-4463(99)30043-2, Elsevier.

Goulas, E., and S. Karidis. 2020. "Crime and Fiscal Policy in Europe: The Effect of Shadow Economy." *Global Economy Journal* 20, no. 03: 2050017. https://doi.org/10.1142/S2194565920500177.

Goulas, E., and A. Zervoyianni. 2023. "Suicide Mortality, Long-Term Unemployment, and Labor-Market Policies: Evidence From European Countries." *Bulletin of Economic Research* 75, no. 4: 1112–1139. https://doi.org/10.1111/boer.12397.

Gould, E. D., B. A. Weinberg, and D. B. Mustard. 2002. "Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997." In *Review of Economics and Statistics*, vol. 84, 45–61. MIT Press. https://doi.org/10.1162/003465302317331919.

Grogger, J. 1998. "Market Wages and Youth Crime." *Journal of Labor Economics* 16, no. 4: 756–791. https://doi.org/10.1086/209905.

Hampel, F. R., E. M. Ronchetti, P. J. Rousseeuw, and W. A. Stahel. 1986. *Robust Statistics: The Approach Based on Influence Functions*. Wiley.

Heidensohn, F. 1989. "Gender and Crime." In *Crime and Society*, 85–111. London: Springer. https://doi.org/10.1007/978-1-349-19763-7_5.

Hosios, A. J. 1990. "On the Efficiency of Matching and Related Models of Search and Unemployment." *Review of Economic Studies* 57, no. 2: 279–298. https://doi.org/10.2307/2297382.

Howsen, R. M., and S. B. Jarrell. 1987. "Some Determinants of Property Crime: Economic Factors Influence Criminal Behavior but Cannot Completely Explain the Syndrome." *American Journal of Economics and Sociology* 46, no. 4: 445–457. https://doi.org/10.1111/j.1536-7150.1987.tb01992.x.

Ishak, S., and Y. Bani. 2017. "Determinants of Crime in Malaysia: Evidence From Developed States." *International Journal of Economics and Management* 11, no. 3: 607–622.

Ivaschenko, O., D. Naidoo, D. Newhouse, and S. Sultan. 2017. "Can Public Works Programs Reduce Youth Crime? Evidence From Papua New Guinea's Urban Youth Employment Project." *IZA Journal of Development and Migration* 7: 1–32. https://doi.org/10.1186/s40176-017-0101-7.

Jennings, W., S. Farrall, and S. Bevan. 2012. "The Economy, Crime and Time: An Analysis of Recorded Property Crime in England and Wales 1961–2006." *International Journal of Law, Crime and Justice* 40, no. 3: 192–210. https://doi.org/10.1016/j.ijlcj.2012.03.004.

Kizilgol, O., and S. Selim. 2017. "Socio-Economic and Demographic Determinants of Crime by Panel Count Data Analysis: The Case of EU 28 and Turkey." *Journal of Business Economics and Finance* 6, no. 1: 31–41. https://doi.org/10.17261/Pressacademia.2017.383.

Kleck, G., and D. Jackson. 2016. "What Kind of Joblessness Affects Crime? A National Case–Control Study of Serious Property Crime." *Journal of Quantitative Criminology* 32: 489–513. https://doi.org/10.1007/s10940-016-9282-0.

Kluve, J. 2010. "The Effectiveness of European Active Labour Market Programs." *Labour Economics* 17, no. 6: 904–918. https://doi.org/10.1016/j.labeco.2010.02.004.

Layard, P. R. G., R. Layard, S. J. Nickell, S. Nickell, and R. Jackman. 2005. *Unemployment: Macroeconomic Performance and the Labour Market*. Oxford University Press on Demand.

Levitt, S. D. 2001. "Alternative Strategies for Identifying the Link Between Unemployment and Crime." *Journal of Quantitative Criminology* 17: 377–390. https://doi.org/10.1023/A:1012541821386.

Levitt, S. D. 2004. "Understanding Why Crime Fell in the 1990s: Four Factors That Explain the Decline and Six That Do Not." *Journal of Economic Perspectives* 18, no. 1: 163–190. https://doi.org/10.1257/089533004773563485.

Lin, M.-J. 2008. "Does Unemployment Increase Crime? Evidence From U.S. Data 1974–2000." *Journal of Human Resources* 43, no. 2: 413–436. https://doi.org/10.3368/jhr.43.2.413.

Lochner, L. 2020. "Education and Crime." In *The Economics of Education*, 109–117. Academic Press. https://doi.org/10.1016/B978-0-12-815391-8.00009-4.

Machin, S., and C. Meghir. 2004. "Crime and Economic Incentives." *Journal of Human Resources* 39, no. 4: 958–979. https://doi.org/10.3368/jhr.XXXIX.4.958.

Malo, M. Á. 2018. Finding Proactive Features in Labour Market Policies: A Reflection Based on the Evidence. ILO Research Papers Series, 8.

Martin, J. P., and D. Grubb. 2005. "What Works and for Whom: A Review of OECD Countries' Experiences With Active Labour Market Policies." *Swedish Economic Policy Review* 8, no. 2: 9–56. https://doi.org/10.2139/ssrn.348621.

Medina, L., and F. Schneider. 2019. Shedding Light on the Shadow Economy: A Global Database and the Interaction With the Official one. CESifo Working Paper Series 7981. https://doi.org/10.2139/ssrn.3502028.

Medina, L., and F. Schneider. 2021. "The Evolution of Shadow Economies Through the 21st Century." In *The Global Informal Workforce: Priorities for Inclusive Growth*, 10–16. International Monetary Fund.

Melick, M. D. 2003. "The Relationship Between Crime and Unemployment." *Park Place Economist* 11, no. 1: 30–36.

Mendoza, E. G., G. M. Milesi-Ferretti, and P. K. Asea. 1997. "On the Effectiveness of Tax Policy in Altering Long-Run Growth: Harberger's

Superneutrality Conjecture." *Journal of Public Economics* 66, no. 1: 99–126. https://doi.org/10.1016/S0047-2727(97)00011-X.

Michaillat, P., and E. Saez. 2021. "Beveridgean Unemployment Gap." *Journal of Public Economics Plus* 2: 100009. https://doi.org/10.1016/j.pubecp.2021.100009.

Mustard, D. B. 2010. *How Do Labor Markets Affect Crime? New Evidence on an old Puzzle*. IZA Discussion Papers, no. 4856. Edward Elgar Publishing. https://doi.org/10.4337/9781849806206.00023.

Ochsen, C. 2010. "Crime and Labor Market Policy in Europe." *International Review of Law and Economics* 30, no. 1: 52–61. https://doi.org/10.1016/j.irle.2009.08.004.

OECD/ILO. 2019. "Protecting Informal Economy Workers and Their Dependents." In *Tackling Vulnerability in the Informal Economy*. New Brunswick, New Jersey: OECD Publishing, Paris. https://doi.org/10.1787/120e596f-en.

Öster, A., and J. Agell. 2007. "Crime and Unemployment in Turbulent Times." *Journal of the European Economic Association* 5, no. 4: 752–775. https://doi.org/10.1162/JEEA.2007.5.4.752.

Otto, K., D. Glaser, and C. Dalbert. 2009. "Mental Health, Occupational Trust, and Quality of Working Life: Does Belief in a Just World Matter?" *Journal of Applied Social Psychology* 39, no. 6: 1288–1315. https://doi.org/10.1111/j.1559-1816.2009.00482.x.

Papps, K., and R. Winkelmann. 2000. "Unemployment and Crime: New Evidence for an Old Question." *New Zealand Economic Papers* 34, no. 1: 53–71. https://doi.org/10.1080/00779950009544315.

Piketty, T., and E. Saez. 2003. "Income Inequality in the United States, 1913–1998." *Quarterly Journal of Economics* 118, no. 1: 1–39. https://doi.org/10.1162/00335530360535135.

Pissarides, C. A. 2000. *Equilibrium Unemployment Theory*. MIT Press.

Raphael, S., and R. Winter-Ebmer. 2001. "Identifying the Effect of Unemployment on Crime." *Journal of Law and Economics* 44, no. 1: 259–283. https://doi.org/10.1086/320275.

Reilly, B., and R. Witt. 1996. "Crime, Deterrence and Unemployment in England and Wales: An Empirical Analysis." *Bulletin of Economic Research* 48, no. 2: 137–159. https://doi.org/10.1111/j.1467-8586.1996.tb00629.x.

Rocque, M., J. W. Saunoris, and E. C. Marshall. 2019. "Revisiting the Relationship Between the Economy and Crime: The Role of the Shadow Economy." *Justice Quarterly* 36, no. 4: 620–655. https://doi.org/10.1080/07418825.2018.1424230.

Rose, E. 2018. The Effects of job Loss on Crime: Evidence From Administrative Data. Available at SSRN 2991317. Available at SSRN: https://ssrn.com/abstract=2991317.

Rosenfeld, R., and R. Fornango. 2007. "The Impact of Economic Conditions on Robbery and Property Crime: The Role of Consumer Sentiment." *Criminology* 45, no. 4: 735–769. https://doi.org/10.1111/j.1745-9125.2007.00096.x.

Rufrancos, H. G., M. Power, K. E. Pickett, and R. Wilkinson. 2013. "Income Inequality and Crime: A Review and Explanation of the Time–Series Evidence." *Social Criminology* 1, no. 1: 103.

Sameem, S., and K. Sylwester. 2018. "Crime During the Business Cycle: Urban–Rural Differences." *Applied Economics* 50, no. 22: 2500–2508. https://doi.org/10.1080/00036846.2017.1400653.

Saridakis, G., and H. Spengler. 2012. "Crime, Deterrence and Unemployment in Greece: A Panel Data Approach." *Social Science Journal* 49, no. 2: 167–174. https://doi.org/10.1016/j.soscij.2011.08.005.

Schneider, F. 2012. *The Shadow Economy and Work in the Shadow: What Do We (Not) Know?* Bonn: Institute for the Study of Labour. Available at SSRN: https://ssrn.com/abstract=2031951 or https://doi.org/10.2139/ssrn.2031951.

Schneider, F., A. Buehn, and C. E. Montenegro. 2010. "New Estimates for the Shadow Economies all Over the World." *International Economic Journal* 24, no. 4: 443–461. https://doi.org/10.1080/10168737.2010.525974.

Schneider, F., A. Buehn, and C. E. Montenegro. 2011. "Shadow Economies all Over the World: New Estimates for 162 Countries From 1999 to 2007." In *Handbook on the Shadow Economy*. Edward Elgar Publishing Shadow Economies All Over the World: New Estimates for 162 Countries from 1999 to 2007.

Schneider, F., and D. H. Enste. 2013. *The Shadow Economy: An International Survey*. Cambridge University Press.

Tukey, J. W. 1977. *Exploratory Data Analysis*. Addison-Wesley.

Wang, S., A. Coutts, B. Burchell, D. Kamerāde, and U. Balderson. 2021. "Can Active Labour Market Programmes Emulate the Mental Health Benefits of Regular Paid Employment? Longitudinal Evidence From the United Kingdom." *Work, Employment and Society* 35, no. 3: 545–565. https://doi.org/10.1177/0950017020946664.

Williams, C. C., and F. Schneider. 2016. *Measuring the Global Shadow Economy: The Prevalence of Informal Work and Labour*. Edward Elgar Publishing.

Witt, R., A. Clarke, and N. Fielding. 1999. "Crime and Economic Activity. A Panel Data Approach." *British Journal of Criminology* 39, no. 3: 391–400. https://doi.org/10.1093/bjc/39.3.391.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.