Crime, Social Capital and Entrepreneurship: Evidence from Australian Communities

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Sefa Awaworyi Churchill
School of Economics, Finance & Marketing
RMIT University, VIC, Australia
Email: sefa.churchill@rmit.edu.au

Mathew Hayward
Department of Management, Monash Business School
Monash University, VIC 3800, Australia
Email: mathew.hayward@monash.edu

Russell Smyth
Department of Economics, Monash Business School
Monash University, VIC 3800, Australia
Email: russell.smyth@monash.edu

Trong-Anh Trinh
Melbourne Institute of Applied Economic and Social Research
University of Melbourne, VIC, Australia
Email: tronganh.trinh@unimelb.edu.au

Abstract

Social capital is integral to business formation. Because crime can damage social capital within communities, we examine the links between crime rates and the propensity for entrepreneurship within those communities. Drawing on Australian longitudinal data, we match entrepreneurship rates with types of crime at the community level where crime occurs. We find that higher crime rates cause lower rates of entrepreneurship and that the presence of social capital mediates this relationship as a core explanatory mechanism. We also show that the relationship between crime rates and propensity for entrepreneurship is not deterministic. Being more internal on locus of control dampens the adverse effect of local area crime on the likelihood of being an entrepreneur.

Keywords: crime, social capital, entrepreneurship, Australia

1. Introduction

Social capital – individual and organizational capacity to gain and lose access to resources within their community – exists to varying degrees within communities and helps explain and predict entrepreneurship (Bourdieu, 2018; Nahapiet & Ghoshal, 1998). More social capital gained and extended within communities allows individuals to better locate and access the full range of opportunities and resources vital to venture inception and success (Davidsson & Honig, 2003; Stam et al., 2014). Such resources include financial capital (Hsu, 2007), expertise (Mosey & Wright, 2007), knowledge (Inkpen & Tsang, 2005), commercial partners (Coviello, 2006) and supportive others (Ucbasaran et al., 2013). Since social capital improves entrepreneurial outcomes, research attention naturally focuses on how individuals can access and build it.

Nevertheless, in many communities, social capital is destroyed and undermined by harmful individuals and organizations. Criminals significantly erode the resources available within one's community and one's ability to access what remains (Sampson et al., 2002). Thieves, for instance, rob resources, disregard their operating environment and discourage enterprise (Shepherd et al., 2022). When corrupt officials appropriate wealth, they deplete community resources and deter entrepreneurs from starting and (re)investing in ventures (Avnimelech et al., 2014). Studies of the mafia show that individuals shun entrepreneurship if they believe that organized criminals will take the fruits of their labor (Gambetta, 2011). While crime is not the only way social capital is destroyed in communities, it is our focus here because it is a ubiquitous, everyday occurrence. Policymakers may look to strengthening law enforcement as an indirect means of promoting business formation.

Mindful that social capital can be destroyed and built, we seek to study the implications of crime on entrepreneurship within communities. Specifically, we ask three questions: Does crime reduce entrepreneurship, and does the type of crime matter? How does social capital, and facets thereof, affect the relationship between crime and entrepreneurship? Furthermore, what is the role of entrepreneurial agency or locus of control (LoC) in offsetting the pernicious effects of crime on entrepreneurship? With these questions, we use the entrepreneur as the unit of analysis and, in the spirit of meso-theorizing, examine how community outcomes affect entrepreneurial outcomes (Rousseau & House, 1994).

We shall work toward three contributions. First, we position crime as destructive to social capital and entrepreneurship as a material outcome of social capital. Specifically, we examine aspects of crime that destroy social capital and entrepreneurship. Second, we examine whether social capital is the causal mechanism of crime affecting entrepreneurship. Third, we consider the role of the entrepreneur in affecting this relationship and whether their LoC attenuates or exacerbates the effects of crime on entrepreneurship. We propose that being more internal on LoC attenuates the adverse effect of community crime rates on the propensity for entrepreneurship (Awaworyi Churchill et al., 2020; Cobb-Clark et al., 2014; Cobb-Clark & Schurer, 2013; Lekfuangfu et al., 2018).

Overall, we redress the paucity of studies that link crime to the proclivity for entrepreneurship by presenting results for a representative longitudinal dataset from Australia that matches crime rates with entrepreneurship intentions at the community level (Matti & Ross, 2016). This approach reflects evidence that "crime is predominantly a local issue. Most violent and nonviolent offences take place less than one mile from victims' homes, and most government expenditures on police protection are local" (Linden & Rockoff, 2008, p. 1103).

Australia offers an ideal setting in which to position our study. Australia is reasonably representative of high-income countries regarding the key variables being studied. Australia ranks 17th out of 38 Organization for Economic Development (OECD) countries in total early-stage entrepreneurial activity (Bosma et al., 2020). According to the OECD Better Life Index, 67 per cent of Australians report that they feel safe walking alone at night, compared with an average of 74 per cent for the OECD (OECD, 2021). As a practical consideration, the Australian dataset, Household Income Labour Dynamics Australia (HILDA), is one of the few continuous longitudinal datasets globally. It is possible to obtain information on the location of the neighbourhood where the respondent lives, allowing us to match individual data on entrepreneurship with local crime rates, controlling for endogenous sorting and factors that eliminate the influence of unobserved individual time-variant fixed effects.

2. Crime and Entrepreneurship

Few studies address the effect of crime on the proclivity for entrepreneurship (Matti & Ross, 2016). One is Rosenthal and Ross (2010), who examine the effect of violent crime on restaurant location decisions in five United States (US) cities (Atlanta, Chicago, Houston, Indianapolis and Seattle). They show that restaurants tend to be found in cities with higher violent crime rates, perhaps because crimes tend to be inflicted on restaurateurs. Another is Sloan et al. (2016), who examine the effect of violent crime on restaurant openings in a single city (Memphis). They find more restaurant openings in areas with higher violent crime. This research underscores that crime rates are higher in some communities, creating social and economic disadvantageous 'hot spots' (Sampson et al., 2002). We work to complement research that links crime to entrepreneurship across the board by matching crime rates with entrepreneurship intentions within communities.

By using a comprehensive sample of crime and venture formation across varied communities, we can examine whether higher crime rates reduce the propensity for entrepreneurship. The conceptual framework we deploy features in Figure 1.

In effect, higher local crime reduces the propensity for entrepreneurship directly and via the mediating mechanism of social capital. We also examine the heterogeneous effects of property crime and crimes against the person on the propensity for entrepreneurship and whether property crime and crimes against the person have differential effects on entrepreneurship in manufacturing and services. Because individuals retain agency even when crime is high, we further analyze whether a stronger internal LoC attenuates the adverse effects of local crime.

Exposure to local crime increases the costs of starting and doing business. Theft prevents businesses from selling products and services. Victims of violent crime are less able to attend to their ventures. More indirectly, customers avoid doing business in communities when they feel unsafe. Reduced demand is compounded as wealthier people leave higher communities (Cullen & Levitt, 1999; Sampson et al., 2002). Crime also leads prospective employees to seek employment in other communities, increasing the challenges of retaining and attracting staff (Brown & Velásquez, 2017; Cullen & Levitt, 1999). For retail businesses, higher crime reduces opening hours and increases the cost of securing premises due to the need to employ security guards and instal surveillance equipment (Acolin et al., 2021). Insurance premiums tend to be higher in neighbourhoods with higher crime rates (Squires, 2003). Because crime increases the costs of starting and doing business, we would also expect that it will lead to lower levels of venture formation in communities with higher crime rates. Hence, a baseline hypothesis is that:

H1A. Higher crime rates reduce the propensity for entrepreneurship within communities.

Crime attracts community and government attention because it imposes high social and financial costs on communities. Some types of crime impose more costs than others. Legal/judicial systems distinguish between crimes that cause physical or mental harm to persons (e.g., murder, aggravated assault, rape, and robbery) and crime on property that involves damage to and theft of property without bodily harm (e.g., burglary, larceny, auto theft, and arson). Evidence suggests that crimes against persons are more destructive to communities than property crimes because the former undermines one's sense of safety and welfare. Thus, we expect that they inhibit business formation. Relative to property crimes, crimes against persons question whether community networks can keep people safe, reducing the trust and goodwill that community members have in each other. Therefore, we suggest that:

H1B: Crimes against the person will have a stronger effect than property crime in reducing community entrepreneurship propensity.

Crimes against property and crimes against persons may affect prospective entrepreneurs' founding activities differently depending on whether they operate in the manufacturing or service sector. Crimes against property include property-related crimes that could damage firms' physical assets (e.g., theft, robbery, vandalism, and arson). In contrast, crimes against persons represent contact-related crimes that could injure firms' human assets (i.e., employees), customers, and outside associates during firm operations (e.g., homicide, assaults, and threats of violence). Hence, we expect that prospective entrepreneurs' founding activities for manufacturing firms will be influenced more by property-related local crimes than by contact-related local crimes, and vice versa for service firms.

H1C: Property crimes will adversely affect entrepreneurship in manufacturing, while crimes against the person will adversely affect entrepreneurship in services.

2.1. Crime, types of social capital and entrepreneurship.

Earlier, we suggested that crime impedes entrepreneurship by depriving communities of social capital. Social capital provides a vehicle or avenue through which community members can communicate to suggest business opportunities and evaluate their respective merits (Awaworyi Churchill et al., 2021; Coleman, 1988; Greve & Salaff, 2003). In turn, those interactions inform the risks of such opportunities, reduce transaction costs via resources that enable potential entrepreneurs to gain insights, and serve as reference points for acquiring customers (Davidsson & Honig, 2003; Gedajlovic et al., 2013).

Crime, in which pain and costs are inflicted on others, is anti-social, as documented in the criminology literature (Abadinsky, 2013; Schelling, 1971). Criminals engage in a zero-sum game by preying on fellow citizens (Gambetta, 2011). As local crime intensifies, people are less willing to circulate within and cooperate with others in their communities. Community crime can pit groups of individuals against each other, heightening social tension and preventing good faith negotiations and interactions that can generate business opportunities (Lorenc et al., 2012; Saegert & Winkel, 2004).

We suggest the following hypothesis regarding social capital as a mediator:

H2: Social capital mediates the relationship between local area crime and entrepreneurship, such that those who live in areas with higher crime will have lower social capital, which will lead to a lower probability of being an entrepreneur.

A more nuanced view of social capital is that crime affects the presence and quality of relational social capital or the value accessible from relationships between individuals and firms. Three central features of relational social capital within communities are a) trust (the willingness to make oneself vulnerable to another based on confidence in the other), b) support (the willingness to help others) and c) collaboration (the willingness to team with community members to work towards shared goals) (Nahapiet & Ghoshal, 1998).

Trust arises when individuals are perceived as trustworthy, which, in turn, is a function of their perceived ability, benevolence and integrity (Mayer et al., 1995). It arises from repeat interactions within communities as individuals learn about such qualities in others. Crime destroys trustworthiness because it involves violations of social norms of acceptable standards.

Criminals demonstrate that they lack the willingness to make a legal living and, instead, seek to profit by denying others of their rights and liberties, which promotes norms and rituals of fear and mistrust within communities (Gambetta, 2011). Without trust, individuals are more reluctant to extend goodwill. Instead, they avoid interaction and use contracts rather than handshakes to secure interests.

Because crime destroys trust, it suppresses entrepreneurship (Fukuyama, 1996). Studies using global rankings of generalized trust show that trust positively correlates with entrepreneurship. When people trust each other in communities, they are more likely to share opportunities and support those who pursue them. Trust is found to lower transaction costs (by lowering the need to monitor others); promote sharing and cooperation; and foster social and financial commitments in and by, entrepreneurs (Aldrich & Fiol, 1994). Fukuyama (1996) distinguishes between high and low trust environments in which demonstrations of trust build virtuous cycles whereby community groups who are trusted are more likely to extend trust to others. As crime intensifies, however, such cycles become vicious rather than virtuous (Welter, 2012). Overall, trust mediates the relationship between local area crime and entrepreneurship. In effect, higher crime lowers community-based trust, which quells entrepreneurship; thus:

H2A: *Social capital in the form of trust mediates the relationship between local area crime and entrepreneurship. Those who live in areas with higher crime will have lower trust, which will lead to a lower probability of being an entrepreneur.*

Relatedly, crime impedes supportive actions and attitudes, reflected in the willingness of others to extend goodwill and resources to entrepreneurs. Support can be altruistic, but it is often predicated on norms of reciprocity (Halbesleben & Wheeler, 2015). Support also sustains communities because it promotes norms of 'paying favors forward', such that when one receives a favor, one is more likely to return that favor to a third party. This is particularly evident for venture formation, where entrepreneurs often give back to communities by supporting fellow entrepreneurs (Bosma et al., 2012).

Crime, however, jeopardizes one's willingness to grant and repay support because it invokes harmful or negative norms of reciprocity (Eisenberger et al., 2004). In effect, it leads community members, especially victims, to self-protection, restitution, and revenge. Negative reciprocity arises when unfavourable treatment to others is a response to another's misdeed. Studies have shown that individuals with a propensity towards anger might more strongly endorse the negative reciprocity norm to justify consummating their hostility by punishing the instigator of mistreatment (Eisenberger et al., 2004). For these reasons, crime discourages granting and repaying support and thus suppresses entrepreneurship. Consequently, we hypothesize that:

H2B: *Social capital in the form of support mediates the relationship between local area crime and entrepreneurship. Those who live in areas with higher crime will have lower support, which will lead to a lower probability of being an entrepreneur.*

Relatedly, crime can suppress collaboration or the shared tasks that are integral to willingness of community members to work together on to entrepreneurship and, particularly, social initiatives. Crime prevents people from being at peace within their communities (Schelling, 1971). As crime intensifies, it becomes more accepted as a social norm for behaving and doing business (Gambetta, 2011). In this way, it encourages the inception of criminal businesses predicated on intimidation and fear while driving out legitimate ones, as seen in a study of oil thieves in the Niger delta (Shepherd et al., 2022).

Studies show that goodwill and collaboration, rather than fear, promote entrepreneurship. Individuals are more likely to work with each other, including in the context of venture formation, when they perceive the work to be socially responsible and meaningful.

Collaboration requires a sense that individuals see themselves as one with fellow community members (Merton, 1968; Tajfel & Turner, 1982). When individuals identify more with their community, they are more motivated to find opportunities to exchange with each other, including supporting new ventures. This creates localized 'ecosystems', in which highly cooperative individuals, often championed by more socially and financially successful networkers, work together on opportunities of lasting benefit within and outside their communities.

Because crime inhibits collaboration, we suggest that it is also a facet of social capital that mediates the relationship between local crime and entrepreneurship:

H2C: *Social capital in the form of collaboration mediates the relationship between local area crime and entrepreneurship, such that those who live in areas with higher crime will have lower collaboration, which will lead to a lower probability of being an entrepreneur.*

While community-level crime may reduce community entrepreneurship, this relationship is not necessarily deterministic. In other words, individuals may still pursue entrepreneurship subject to their beliefs that entrepreneurial outcomes are a function of their efforts rather than the social characteristics of their communities.

2.2.*Locus of control's role in attenuating crime's effects on entrepreneurship.*

An essential dimension of entrepreneurial agency concerns one's LoC or the extent to which prospective business founders believe that venture outcomes are a function of their choices, actions and efforts versus the crime-affected environment in which they do business (Rotter, 1954). People with a more robust internal LoC will likely have more effective strategies to manage the uncertainty associated with new ventures (Pahlevan Sharif, 2017). Additionally, they tend to be better informed and seek more information to help attenuate fallout from the uncertainty of crime (Lin & Tsay, 2005; Pahlevan Sharif, 2017; Watson et al., 1990).

In this vein, individual differences in LoC have been linked with the ability to cope with adverse shocks, including those from crime (Awaworyi Churchill & Smyth, 2022; Buddelmeyer & Powdthavee, 2016; Stillman & Velamuri, 2016). Individuals who are more internal on LoC take proactive steps to find solutions to problems they face, and are more likely to cope with the effects of local crime without relying on support from others (Gianakos, 2002; Ng et al., 2006). Evidence suggests that those with a stronger internal LoC are better able to accumulate social capital (Massari & Rosenblum, 1972; Rodriguez-Ricardo et al., 2019), which can moderate the negative effects of local area crime (Awaworyi Churchill & Smyth, 2022).

H3: LoC moderates the relationship between local area crime and entrepreneurship, such that higher internal LoC will attenuate the adverse effects of crime on the likelihood of being an entrepreneur.

3. Research Methods

3.1. Data and sample

We rely on data from multiple sources. We use individual-level data from restricted Release 19 of the HILDA survey, a nationally representative longitudinal survey of Australians. HILDA commenced in 2001 and surveys respondents annually, meaning that Release 19 contains 19 waves. While we use restricted Release 19, our main analysis relies on data from 2008 to 2019, given that we only have data on school quality (a key control), which we merge with the HILDA dataset for our analysis, from 2008.[1] The advantage of employing the

[1] The initial wave of HILDA covered 19,914 individuals in 7,682 households. In wave 11, an additional 5,462 individuals and 2,153 households were added to account for the changes in the composition of the original households. See Summerfield et al. (2011) and Watson and Wooden (2012) for further details on the HILDA dataset.

restricted Release is that it provides information on the postcode in which each respondent lives. This information allows us to merge data from the HILDA survey with our longitudinal dataset on crime rates, which we collected for each postcode.

Australia has approximately 3,000 postcodes that vary widely in size, reflecting Australia's vast landmass and a population that is concentrated unevenly across postcodes. The average area of each postcode is approximately 2,900 square kilometres, and the average population in each postcode is 9,075 people. In terms of geographical coverage, each postcode broadly maps to a suburb in the major cities. At the same time, a postcode can represent an entire township and surrounding areas in regional Australia where the population is sparser. HILDA has, on average, 237 respondents per postcode, representing 2.6 per cent of the population per postcode.

Crimes rates at the postcode level are not publicly available. We collected data on crime rates by requesting this information from each state and territory police force or relevant government agencies. We obtained annual official police statistics on total crime, property crime and crime against the person at the postcode level for each state and territory except Tasmania. For each state, crime data are available from 2001 except for Western Australia and South Australia, whose data start from 2005 and 2010, respectively.[2]

3.2. Variables and measures

Entrepreneurship: Our measure of entrepreneurship is consistent with the literature that has used indicators of self-employment (see, e.g., Hessels et al., 2020; Nikolaev et al., 2020; Van Praag et al., 2013). Respondents were asked about their employment status in each wave of the HILDA survey. Based on the employment status question, respondents are classified as

[2] Given that our study covers the period 2008 to 2019, we have annual crime data at the postcode level for every mainland state and territory over the entire period, except for Western Australia, for which we have annual data from 2010.

"employee", "employee of own business with other employees", or "employee of own business without other employees". Using this information, our primary measure of entrepreneurship is a binary variable set equal to one for respondents who own a business either with or without employees and zero if they are in paid employment. In robustness checks, we distinguish between those with or without employees in alternating models.

We also focus on entrepreneurial exit and entry as alternative ways of measuring entrepreneurship. We measure entrepreneurial entry using a binary variable set equal to 1 if a respondent transitioned from wage-employment to self-employment in the past 12 months and 0 if otherwise. Entrepreneurial exit is measured using a binary variable set equal to 1 if a respondent transitioned from self-employment to paid employment in the past 12 months. These indicators act as functional robustness checks for at least two reasons. First, we expect local area crime to have opposite effects on both indicators, which should reinforce the effect of local area crime on the probability of being an entrepreneur. Second, although the most common measure of entrepreneurship using survey data is the indicator of self-employment, the indicators of entrepreneurial exit and entry allow us to examine transitions in and out of entrepreneurship, which we cannot do with the measure of self-employment.

Community or local area crime: We measure local area crime rates as the total number of crimes or offences in each postcode divided by the population in the postcode. In addition to total crime rates at the postcode level, we examine the impact of crimes against the person and property crime computed as the number of offences in each category adjusted for population.

Social capital (mediator): We use four indicators of social capital, consisting of three single-item indicators capturing trust, support and collaboration, and a composite indicator. We use a measure of neighborhood trust, which is a form of social or generalized trust based on the question asked in waves 6, 10, 14, and 18 of the HILDA survey: “To what extent do you agree or disagree with the following statements about your neighbourhood? People in this neighbourhood can be trusted.” The responses are coded on a seven-point scale, where one means "strongly disagree" and seven means "strongly agree".

In waves 1 to 4, 6, 8, 10, 12, 14, 16 and 18, respondents are asked the question, "How common are the following things in your local neighbourhood? (1) Neighbours helping each other out, and (2) Neighbours doing things together”. The measure of support is based on the response to the statement relating to “neighbours helping each other out". In contrast, the measure of collaboration is based on the response to the statement "Neighbours doing things together”. Responses to each indicator are on a five-point scale, where one means “never happens” and five means that it is “very common”.

The composite indicator is based on a 6-item questionnaire available in waves 6, 10, 14, and 18 of the HILDA survey. The six items reflect the extent to which respondents agree with statements regarding the level of social cohesion and networks with their neighbours (Clark & Lisowski, 2018), some of which overlap with the single indicators discussed above. The first two items relate to the question: “How common are the following things in your local neighbourhood? (1) Neighbours helping each other out, and (2) Neighbours doing things together”. Responses are on a five-point scale, where one means “never happens” and five means that it is “very common”. The next four items depend on responses to statements in response to the question: “To what extent do you agree or disagree with the following statements about your neighbourhood? (1) This is a close-knit neighbourhood, (2) People in this neighbourhood can be trusted, (3) People in this neighbourhood generally do not get along with each other, and (4) People in this neighbourhood generally do not share the same values”. The responses are coded on a seven-point response scale, where one means “strongly disagree” and seven means “strongly agree”, with responses to questions (3) and (4) being reverse coded.

The composite indicator of social capital, which is widely used in the literature, is derived as the average of the six questions, such that increasing values of the scale represent higher levels of social capital (see, e.g., Awaworyi Churchill & Farrell, 2020; Clark & Lisowski, 2018).

Locus of control (moderator): LoC is measured in HILDA using the Psychological Coping Resources of the Mastery Scale (Pearlin & Schooler, 1978), which is a psychometric validated instrument based on seven questions: "(1) I have little control over the things that happen to me, (2) There is really no way I can solve some of the problems I have, (3) There is little I can do to change many of the important things in my life, (4) I often feel helpless in dealing with the problems of life, (5) Sometimes I feel that I'm being pushed around in life, (6) What happens to me in the future mostly depends on me, and (7) I can do just about anything I really set my mind to do". We derive a composite indicator of LoC that combines all the items of the Mastery Scale, such that lower values represent more external LoC, while higher values represent more internal LoC (see. e.g., Awaworyi Churchill et al., 2020; Buddelmeyer & Powdthavee, 2016; Cobb-Clark & Schurer, 2013). We reverse code scores for items one to five on the Mastery Scale (i.e., the external LoC items on the scale) and add them to items six and seven (i.e., the internal items). As a way to address measurement error in LoC, following Buddelmeyer and Powdthavee (2016), instead of using the raw LoC values, we use predicted individual fixed effects that represent the time-invariant LoC from a first stage regression for LoC that retains the explanatory variables we use in our entrepreneurship regressions.

Covariates: Consistent with the literature, we control for individual and neighborhood factors likely to be correlated with the probability of being self-employed. The individual-level covariates are age (in years), income (real household income), education status (binary variables for postgraduate degree, graduate diploma, bachelor's degree, diploma and certificate, while we leave Grade 12 or below as the reference category), marital status (binary variables for respondents who are divorced/separated, single, widowed or in a de facto relationship with married as the base category), number of dependents and health status.

We also control for local area indicators of institutional quality. Specifically, we control for school quality at the postcode level measured using an annual index of community socio-educational advantage (ICSEA) covering 2008 to 2019 taken from the My School website.[3] The ICSEA is derived based on information on the performance of every Australian school. The ICSEA has a median value of 1,000 and a standard deviation of 100. Values range from 500, denoting extremely disadvantaged schools in relatively disadvantaged communities, to 1,300, which would be an affluent school. We also control for the unemployment rate at the postcode level, which is an indicator of labor market institutional quality and controls for local economic conditions, which could influence both entrepreneurship and crime rates.

Abortion rates: We use annual abortion rates at the state and territory level 15 years prior to the relevant HILDA wave to instrument for postcode crime rates as one identification strategy. Wm. Robert Johnston compiles state and territory abortion rates.[4]

Table A1 provides a description and summary statistics of variables used in our analysis, while Table A2 provides further details focused on each year. Figures A1 and A2 provide an overview of trends in self-employment and crime rates across states and territories, demonstrating the variation in our main variables.

3.3. Empirical strategy

We estimate the following equation:

$$E_{i,p,t} = \gamma_0 + \gamma_1 C_{p,t-1} + \boldsymbol{\gamma_2 X_{i,t}} + \boldsymbol{\gamma_3 Z_{p,t}} + \varphi_i + \mu_p + \delta_t + \varepsilon_{i,p,t} \qquad (1)$$

[3] https://www.myschool.edu.au
[4] https://www.johnstonsarchive.net/policy/abortion/index.html

where E is the indicator of entrepreneurship capturing if an individual i living in postcode p in year t is self-employed or not; $C_{p,t-1}$ is the total crime rate, rate of crime against the person or property crime rate in postcode p at time $t-1$ (i.e., in the previous 12 months prior to the HILDA interview date); $\boldsymbol{X_{i,t}}$ is a vector of individual time-varying characteristics; $\boldsymbol{Z_{p,t}}$ is the unemployment rate at the postcode level; φ_i, μ_p and δ_t denote individual, postcode and time fixed effects, respectively; and $\varepsilon_{i,p,t}$ is an idiosyncratic error term.

Our main identification strategy follows the approach in Dustmann and Fasani (2016), who estimate the effect of local area crime on mental health in the UK. Essentially, this approach removes the effects of residential sorting and correlates crime with time-varying unobserved entrepreneurship determinants if there is no endogenous migration from local crime. It assumes that local crime rates are exogenous to individual shocks to self-employment, which seems plausible, given a shock to individual self-employment in any period is unlikely to affect local crime rates in that or any other period. The key parameter is γ_1, which measures the impact of local area crime on the probability of being an entrepreneur.

A threat to this identification strategy in estimating γ_1 is sorting individuals into neighbourhoods, which may affect the causal interpretation of the relationship between crime and entrepreneurship. We address this threat in several ways. Initially, assume that individuals do not move across postcodes over our sample period. If individuals do not move, controlling for individual fixed effects φ_i would be sufficient to allow us to take advantage of within-individual and within-area variations in crime; therefore, eliminating any bias that may arise through sorting. Additionally, by controlling for local area fixed effects μ_p, we can eliminate unobserved postcode effects likely to be correlated with local area crime and entrepreneurship (Dustmann & Fasani, 2016). We condition on a wide range of time-varying individual characteristics from HILDA, as well as postcode labour market conditions and school quality, which partially captures time-varying postcode characteristics.

In robustness checks, we show that results are robust to omitted variable bias and controlling for several alternative combinations of fixed effects that include linear time trends and their interaction with location fixed effects, as well as month of interview fixed effects.

Consider the effect of having respondents move across postcodes during our observation window. Approximately 12 per cent of respondents in our HILDA sample moved across postcodes throughout the study timeframe. Following the approach in Dustmann & Fasani (2016), we address this issue by only considering respondents who have lived in the same postcode for at least two consecutive years and treat them as a different individual in each subsequent area (postcode) of residence. We assign them a unique individual fixed effect for each postcode to which they move. Adopting this approach raises two issues. One is that this may create across-individuals correlation in error terms, but this can easily be addressed by differencing out all fixed effects. The other is that it might introduce selection bias if variation in the crime rate in a given period influences the moving decision in the following period. To address this concern, we assess the extent to which those individuals who moved were motivated by high crime rates. We show that movements across postcodes are not related to crime and that crime-related moving decisions are virtually irrelevant for our data.

A limitation of the Dustmann and Fasani (2016) identification strategy is that we lose a proportion of our sample, given that only respondents who lived in the same postcode for at least two consecutive years are assigned new fixed effects to address the problem of endogenous sorting. Hence, we supplement our main identification strategy using an instrumental variable (IV) strategy. The IV approach's advantage is that it allows us to use the full sample of respondents while instrumenting for local area crime.

We adopt two instruments in alternating models, both of which are time-varying. First, following the IV strategy used in Dustmann and Fasani (2016), we instrument for local area crime to which movers are exposed using the contemporaneous crime rate in the postcode in which they lived in the first wave of our observation window. Dustmann and Fasani (2016, Appendix B.1.1) show that using contemporaneous crime rates in the initial postcode of residence as an IV for actual crime rates leads to unbiased estimates under the plausible assumption that crime in one postcode is not correlated with the area fixed effect from an entrepreneurship equation in another postcode.

Second, we instrument for crime at the postcode level in each wave using the abortion rates in the state or territory where the postcode is located 15 years prior to the relevant HILDA wave. This IV is based on the economics literature that has proposed a link between historical abortion rates and crime. The theory is that ‘unwanted’ children are at an elevated risk of less favourable outcomes, including a higher propensity of being involved in committing a crime. Donohue and Levitt (2001) found that crime rates decreased by up to 50 per cent 15–25 years after the legalization of abortion in the US in *Roe v Wade*, when these ‘unwanted’ cohorts would have reached their peak crime ages. Donohue and Levitt (2020), using more recent data for the period 1998 to 2014, reaffirm their original results, finding that over this period abortions were responsible for a reduction in about 20 per cent of crime in the US. Leigh and Wolfers (2000) review the evidence in the Australian context and conclude that abortion rates are inversely related to the crime rate. In addition to being time-varying, this IV has the advantage of using abortion rates at a broad geographical level (state/territory) to instrument crime at a much smaller geographical area (postcode). Dustmann and Preston (2001) show that location decisions tend to be endogenous for small geographic areas, but the extent of endogeneity is inversely related to the geographic size of the area.

As a robustness check on our external instruments, we complement the external IVs with the Lewbel (2012) 2SLS approach that does not rely on a valid exclusion restriction but on heteroskedasticity in the data to achieve identification. Lewbel (2012) proposes an identification strategy based on internally generated instruments that rely on heteroskedastic covariance restriction. Lewbel (2012, p. 67) notes that the internally generated instruments "could be used along with traditional instruments to increase efficiency". This approach has been widely used in the literature either in the absence of external instruments or as a robustness check on findings with external instruments (see, e.g., Koomson & Awaworyi Churchill, 2022; Koomson & Churchill, 2021; Mishra & Smyth, 2015; Prakash et al., 2020, 2022).

4. Results

4.1. Main results

Table 1 presents results for the relationship between local area crime and self-employment. We present baseline results from pooled OLS in Columns (1) and (2), while in Columns (3) and (4), we present fixed effect results. In Columns (5) and (6), we present IV results based on the contemporaneous crime rate in the postcode where the respondent lived in the first wave they were in the survey as an instrument. In contrast, in Columns (7) and (8), we present IV results based on abortion rates as instruments. Unconditional estimates of local area crime on the probability of self-employment are presented in Columns (1), (3), (5) and (7), and estimates conditioned on individual and postcode characteristics in Columns (2), (4), (6), and (8). In all regressions, we control for time fixed effects and cluster standard errors at the postcode level.[5]

[5] The full set of results, including all covariates are reported in Table A3. The first stage results for the IV estimates are reported in Table A4. The contemporaneous crime rate in the postcode in which movers lived in the first wave in which they were in the survey is positively correlated with the crime rate and historical abortion rates are negatively associated with the crime rate. The first stage F-statistics, which are greater than 10, suggest that our instruments are not weakly correlated with the crime rate (Stock & Yogo, 2005).

Consistent with hypothesis H1A, we find that local area crime is associated with a decline in the probability of being self-employed, with effect sizes ranging between 0.006 and 0.065 depending on the specification. Focusing on our preferred panel FE specification in Column (4), which controls for individual fixed effects together with individual and postcode characteristics, we find that a standard deviation increase in local area crime is associated with a 0.015 standard deviation decline in the probability of being self-employed. The average self-employment rate is 0.153, with a standard deviation of 0.360 (see Table A1). A coefficient of 0.015, therefore, implies that a one standard deviation increase in the local area crime rate causes a 9.8 per cent increase in the rate of self-employment.

To test hypothesis H1B, in Table 2 we separate the effect of crimes against the person and property crime on entrepreneurship. The results suggest that both crime types negatively affect the probability of being self-employed. However, comparing the coefficients on crime, we find that the magnitude of the effect of crime against the person is more significant than the effect of property crime. This finding is consistent with hypothesis H1B.

In Figure 2, we examine if the effects of different types of crime differ according to whether the business is in the services or manufacturing sectors. Consistent with hypothesis H1C, we find that the effects of property crimes are more pronounced in the manufacturing sector. In contrast, the effects of crimes against the person are more pronounced in the services sector.

4.2. Social capital as a mediator

To examine whether social capital mediates the relationship between local area crime and self-employment, we first use PROCESS (Preacher & Hayes, 2008). Following Wiklund et al. (2017), we use 1,000 replications of bootstrapping and the bias-corrected percentile approach to deal with potential non-normality in our data. The advantages of specifying and testing a single multiple mediation model, such as PROCESS, instead of separate simple mediation models include: (1) the ability to determine if the overall effect of mediation exists; (2) the ability to identify the extent to which each of the mediating variables intervenes between the independent and dependent variables in the presence of other potential mediators; (3) limiting missing parameter bias; and (4) the ability to determine relative magnitudes of specific indirect effects (Preacher & Hayes, 2008). A limitation of using PROCESS is that the identified relationship cannot be interpreted as causal. To examine if the relationship is causal, we adopt two further methods. We perform a causal mediation analysis following the approach in Liu et al. (2014) and employ structural equation modelling (SEM).

We report the results for the composite measure of social capital in Table 3. Based on the PROCESS results in Panel A, we find evidence of complete mediation for social capital. Specifically, we find evidence that the inclusion of social capital in the model renders the direct effect of crime on entrepreneurship statistically insignificant. However, based on the causal mediation in Panel B, we find evidence of partial mediation where the direct negative effect of local area crime is reinforced. Turning to the indirect effects, we find that local area crime reduces the probability of self-employment through social capital, with estimates ranging between -0.00044 and -0.00173. Thus, consistent with our second hypothesis, local area crime reduces entrepreneurship by negatively influencing social capital, which is relevant for entrepreneurship. These findings are consistent with the results from SEM, which we report in Table 4, where we find evidence of partial mediation.

In Table 5, local area crime reduces the probability of self-employment through each trust, support and collaboration with indirect effects ranging from -0.0012 and -0.0029 with $p<0.001$. Thus, consistent with hypotheses H2A to H2C, social capital in the form of trust, support and collaboration mediates the relationship between local area crime and entrepreneurship, such that those who live in local communities with higher crime will have lower trust, support and collaboration, which will lead to lower probability of being an entrepreneur. The SEM results reported in Table 6 are consistent with this conclusion.

In Table 7, we examine whether each of trust, support and collaboration is a mediator for crime against the person and property crime considered separately. The results are qualitatively similar to the findings in Table 5 and consistent with hypothesis H2A–H2C.

4.3.LoC as a moderator

Next, we investigate whether LoC affects an individual's ability to cope with adverse shocks from local area crime. Table 8 reports results for LoC as a moderator. Given that our measure of LoC is time-invariant (Buddelmeyer & Powdthavee, 2016), in a standard fixed-effect model, this indicator naturally drops out. However, the interaction term with crime rate remains. This does not pose a problem, as our focus on LoC as a moderator is on the interaction term. To aid in interpreting the interaction effect, we standardize LoC to have a mean of zero and a standard deviation of one. Thus, we can interpret the coefficient on local area crime as the entrepreneurship effect of crime on respondents with an average LoC of zero. Also, the coefficient on the interaction term is the entrepreneurship effect of local area crime for respondents with standardized LoC is one standard deviation above the mean. Although the coefficient on crime is now statistically insignificant, the coefficient on the interaction term is positive and statistically significant. This result suggests that being more internal on LoC dampens the adverse effect of local area crime on the probability of being an entrepreneur. This finding is consistent with our third hypothesis.

4.4. Robustness checks

Threats to identification and further checks on endogeneity. Our main identification strategy removes the effects of residential sorting and correlates crime with time-varying unobserved entrepreneurship determinants if there is no endogenous migration from local crime. In our sample 12 percent of respondents changed postcodes over the period studied, which would be problematic if these respondents were moving in response to crime. To address this issue, we estimate the probability that respondents move across postcodes as a function of the local crime rate. The results, reported in Table A5, show that migration decisions are unrelated to crime rates. We examine if our results are robust when focusing on movers and non-movers separately. In Table A6, we find that our results are robust when focusing on a sub-sample of movers and non-movers. Similarly, in Table A6, we show that our results continue to hold when we further focus on a sub-sample of movers who migrate within and across states.

In our primary identification strategy, we have controlled for several time-varying, individual-level characteristics, as well as time-varying measures of labour markets and school quality at the postcode level, as well as individual and postcode fixed effects. However, it is not possible to control for all variables that are potentially correlated with entrepreneurship. In our case this is particularly true of time-varying institutional characteristics at the postcode level. Including law enforcement variables. We use the Oster (2019) bounds analysis to examine the stability and sensitivity of our estimates to the inclusion of observed covariates, which has been employed as a check on endogeneity due to unobserved heterogeneity or omitted variable bias in the economics literature (see, e.g., Awaworyi Churchill & Smyth, 2021; Clark et al., 2021; Davillas et al., 2021; Hailemariam et al., 2021).

The results, reported in Table A7, show that the impact of unobservable covariates relative to the observed covariates in our model that would be needed to drive the point estimate for local crime to zero is 3.402. This suggests that for omitted variable bias to be a problem, the effects of unobservable variables would have to be about three times greater than the effect of the observed control variables in our model. Given that we do control for a large number of individual characteristics known to be correlated with the propensity for entrepreneurship, including education, health and income, this seems unlikely. This provides reassurance that our results are robust to omitted variable bias.

Next, we examine the robustness of our results to the control of alternative fixed effects in our model. We consider different combinations of fixed effects that include linear time trends and their interaction with location fixed effects as well as the month of interview fixed effects. We also consider clustering our standard errors at the individual level instead of the postcode level. The results, reported in Table A8, show that our findings robust.

Our results using external IVs rely on satisfying the exclusion restriction that the IV only affects entrepreneurship through local crime rates. This seems reasonable for both IVs. Dustmann and Fasani (2016, Appendix B.1.1) show that using contemporaneous crime rates in the initial postcode of residence as an IV for actual crime rates is likely to satisfy the exclusion restriction. It seems unlikely that historical abortion rates at the state level would directly affect the decision to be self-employed at the individual level. To the extent that one is concerned about either or both IVs not satisfying the exclusion restriction, in another check, we examine the robustness of our results using the Lewbel (2012) 2SLS estimation strategy, which does not rely on satisfying the exclusion restriction.

Table A9 reports findings from Lewbel regressions that alternatively use internally generated instruments and estimates that combine internally generated instruments with historical abortion rates. The heteroskedasticity assumption for the Lewbel (2012) method is fulfilled given that the Brush and Pagan test for heteroskedasticity is significant. We find that the Lewbel 2SLS results are qualitatively consistent with the main results in Table 1.

Are the results affected by where entrepreneurs work? We assume that crime rates in locales where respondents live shape their social capital and, subsequently, their decision to start a business. This assumption might be violated if entrepreneurs commute across locales to their place of work. To check this, we focus on the postcodes where prospective entrepreneurs establish their new firms. HILDA provides information on the location of work, although only for selected waves of the survey, which significantly reduces our number of observations. In Tables A10 and A11, we reproduce our results from Tables 1 and 2 for the sub-sample from which we have information on work location. We find that our results remain robust using crime rates for the postcode where the respondent works (i.e., respondents living and working in the same postcode, as well as those working in a different postcode to which they live). Importantly, for those respondents for whom we know where they work, about three-quarters of those who are self-employed have their businesses in the same postcode in which they live.

Our main results focus on crime rates at the postcode level, given that this is the most localized level available, increasing the estimates' precision. However, employing a higher geographic level, such as the local government area (LGA), means that a higher proportion of respondents in our total sample are likely to live in the same LGA as their businesses.[6] Thus, in Tables A12 and A13, we reproduce our results from Tables 1 and 2 using crime rates at the LGA level and find that our results remain robust, although, as expected, the standard errors are generally higher. In Tables A14 and A15, we also reproduce our results from Tables 1 and 2 for regional and country areas only, where postcodes are geographically more extensive. Hence, there is a higher likelihood that small business owners live in the same town or surrounding area covered by the postcode. We find that our results remain robust.

In another check, we conduct a placebo test to ensure our results are not spurious. Suppose that, instead of estimating the impact of the crime rate in which respondents live or work on the probability of self-employment, we replace the true value of crime rates in the respondent's postcode with a random crime rate from another postcode. In that case, we can

[6] LGAs are the next administrative tier below states/territories, often corresponding to councils or shires. There are 566 LGAs in Australia, compared with over 3,000 postcodes.

expect the estimates to be insignificant. Thus, we estimate the impact of crime rates on self-employment using randomly assigned crime rates from different postcodes to respondents. We repeat this randomization 1,000 times and run regressions each time. The results, presented in Figure A3, suggest that none of the placebo runs generated estimates close to the actual derived effect, as denoted by the dashed line. Results seem to reflect the actual effect of the crime rate in the postcode where respondents live or work.

Other robustness checks and additional analysis: The results in Table 1 focus on self-employment status. It is, however, plausible that some respondents in the HILDA survey have been self-employed for a relatively long time and in, some cases, even before the start of the HILDA survey. Thus, in Appendix Table A16, instead of focusing on self-employment, we use entrepreneurial entry or exit indicators that reflect transitions in and out of self-employment. The results in Column (1) of Table A16 examine the impact of local area crime on the probability of transitioning from wage-employment to self-employment (i.e., entrepreneurial entry). In Column (2) we examine the impact of crime on exit from self-employment into wage-employment (i.e., entrepreneurial exit). We find that an increase in local area crime is associated with a lower probability of transitioning from wage-employment to self-employment and a higher likelihood of transitioning from self-employment to wage employment. Specifically, a standard deviation increase in local area crime is associated with a 0.012 standard deviation decline in the probability of entrepreneurial entry, but a 0.034 standard deviation increase in the probability of entrepreneurial exit.

Our main results do not distinguish between entrepreneurs who employ others and those without employees. In Table A17, we distinguish between these categories of entrepreneurs. As an additional check, we exclude hobby entrepreneurs and farmers and farm managers in alternating models. In each case, we find that the results reinforce the conclusion of an adverse effect of local area crime on the likelihood of being an entrepreneur.

The main results examine the effect of local area crime in the past year on the probability of being an entrepreneur. In Table A18, we report results that examine whether local area crime in the previous two years (t-2) and three years (t-3) affect the likelihood of being an entrepreneur and, if so, if the effects dissipate over time. We find that the negative effect of crime still holds, with effect sizes that have not significantly changed over time.

We examine the robustness of our results to alternative estimation approaches. First, we adopt an alternative approach suitable for addressing potential bias from attrition. A common issue with longitudinal survey data is that not all individuals remain in the sample for the duration of the study. As respondents drop out of longitudinal surveys over time, a concern is whether this attrition is random. If attrition is not random and correlated with our outcome variable, this could lead to potential selection bias. We conduct two checks to deal with attrition bias. One, we estimate a binary model of attrition conditioned on the set of covariates used in our primary analysis to examine if attrition is a problem in our case. The results, which are reported in Column (1) of Table A19, show no significant correlation between the crime rate and the likelihood of a respondent being missing, suggesting that attrition is not biasing our results. Two, we apply inverse probability weighting, as proposed by Fitzgerald et al. (1998). The results, presented in Column (2), confirm that crime and entrepreneurship are inversely related. This result is consistent with the conclusions from Column (1), suggesting that attrition bias is not a problem in our case.

In additional checks, we examine if the effects of crime rates are robust to controlling the Big Five personality traits, given evidence that personality influences the propensity for entrepreneurship (Kerr et al., 2018). We take advantage of the Big Five Personality Inventory questions administered in waves 5, 9, 13 and 17 of the HILDA survey to examine if the inclusion of these personality traits as additional covariates in our baseline model will influence the effect of crime rates. The results, which are reported in Table A20, suggest that the effect of crime is robust to controlling the Big Five personality traits.

In Table A21, we examine if the effect of crime is non-linear by including a quadratic term for the crime rate. We find that the effect of crime is not non-linear.

Next, we distinguish between the voluntary pursuit of entrepreneurship (i.e., opportunity entrepreneurs) and the necessity to engage in entrepreneurship because of lack of employment opportunities (i.e., necessity entrepreneurs) (Reynolds et al., 2002). Consistent with the literature, we treat respondents, who in the previous period were unemployed but in the current period are now entrepreneurs, as necessity entrepreneurs. Respondents who reported being in paid employment in the previous period but in the current period are entrepreneurs are treated as opportunity entrepreneurs (see, e.g., Block and Wagner, 2010). The results, which are reported in Table A22, show that crime harms both types of entrepreneurship and that the magnitude of the coefficient on crime is very similar across specifications.

A postcode with crime rates could have neighbouring postcodes with similar crime rates because of the potential spatial interdependence across neighbouring postcodes. In Table A23, we conduct two tests to examine the robustness of our results to spatial interdependence. First, we report results from the Conley (1999) spatial regressions. Second, we run spatial autoregressive models of first and second order. We find that our results remain robust.

One might be concerned that the negative relationship between crime and entrepreneurship is being driven by one of the more populous states, such as Victoria and New South Wales, where crime rates and entrepreneurship are higher. To address this concern, we re-estimate our models by excluding each state one at a time to examine if the exclusion of any specific state alters the observed relationship. In Figure A4, we find that the results remain robust.

5. Discussion

5.1. Contributions

In this study, we have matched postcode-level crime data from official police statistics with a household longitudinal dataset that is representative of the Australian population, in order to examine the effect of crime at the community level on the propensity for entrepreneurship. Our main identification strategy removes the effects of residential sorting and correlates crime with time-varying unobserved entrepreneurship determinants, provided that there is no endogenous migration from local crime, which we show there is not.

Our preferred estimates suggest that a standard deviation increase in local area crime is associated with a 0.015 standard deviation decline in the probability of being self-employed, equating to a 9.8 per cent decrease in the self-employment rate. These results are robust to alternative identification strategies, including using abortion rates at the state level 15 years prior to the relevant HILDA wave as an external IV. We find that social capital and its three constituent facets, collaboration, support and trust, mediate, while LoC moderates, the relationship between crime rates and propensity for entrepreneurship. We find that crimes against the person have more potent effects than property crimes on entrepreneurship. We also find that crimes against the person affect the propensity for entrepreneurship in services, while property crimes affect the propensity for entrepreneurship in manufacturing.

We sought to make three contributions to understanding the relationship between crime and entrepreneurship. First, we proposed and tested a framework for considering the effect of crime on entrepreneurship by focusing on the destructive influence of crime on social capital.

The second is to understand better the mediating role of social capital and its elements as a key causal mechanism for linking the crime to a diminished propensity for entrepreneurship. The third contribution has been to show that this relationship is not deterministic, but rather the entrepreneur's LoC attenuates the effects of crime on entrepreneurship.

In examining the role of these variables, our contribution relates to the literature that has emphasized the importance of context for entrepreneurship (see, e.g., Welter, 2011). Crime is a contextual factor influencing entrepreneurship. Recently, Welter and Baker (2021, p. 1155) lament that most studies that have examined the importance of context for entrepreneurship have "portrayed contexts as ‘out there’, treating contexts as given and as exhibiting a direct and unmediated influence on entrepreneurs, their behaviour and their outcomes". We seek to study the importance of context for *where* entrepreneurship takes place (i.e., the role of crime rates in influencing the locales where propensity for entrepreneurship is higher) and *how* crime rates, as a contextual factor, influence entrepreneurship. Considering LoC as a moderator is particularly important because, as Baker and Welter (2020) and Welter and Baker (2021) emphasize, it is essential to understand how entrepreneurs interact with context, which extends to how they cope with and shape that context. Non-cognitive traits are likely to be particularly important in influencing the ability to shape context (Huber et al., 2014).

Our contribution is related to and extends literature that has examined the externalities of crime. Existing studies have shown that local crime rates are a cause of urban flight (Cullen & Levitt, 1999), lower property values (Linden & Rockoff, 2008) and impact on local economic activities (Greenbaum & Tita, 2004; Hipp et al., 2019; Niño et al., 2015; Rozo, 2018). Other studies have shown that crime rates adversely affect consumer confidence, contributing to economic uncertainty (Fe & Sanfelice, 2020). Each of these studies speaks to the effect of crime on neighbourhood climate, likely influencing the risk-return profile of an investment opportunity for a potential entrepreneur. According to Weterings (2014, p. 1614): "Neighbourhood conditions may matter as entrepreneurs are likely to be concerned about the socioeconomic status and general social climate of the neighbourhood as they prefer safe, well-maintained locations for their customers and employees".

However, few studies have explicitly studied the relationship between crime and entrepreneurship. Existing studies are limited in that they have focused on the effect of violent crime on where restaurants are located in a few specific US cities. Rosenthal and Ross (2010) and Sloan et al. (2016) find that there are more restaurant openings in areas where violent crime is higher. Both studies measure entrepreneurship using aggregate statistics on the number of restaurants in a zip code (postcode), rather than the individual entrepreneurship decision. Because they do not employ household data, they are not able to control for individual characteristics known to be correlated with entrepreneurship. Both studies also employ a lagged cross-sectional design, which prevents them from using time-fixed effects that eliminate the possible correlation between crime and entrepreneurship resulting from sorting.

Compared to these studies, we focus on proclivity to be an entrepreneur in general rather than on decisions in one sector. We also employ a nationally representative individual panel dataset rather than aggregate data for a few cities. We match our dataset on individual entrepreneurial intentions with data on all crimes and separately consider crimes against the person and property crime. Lévesque and Stephan (2020, p. 164) note that “time and time-sensitive processes play a key role in entrepreneurship” and urge researchers to move away from cross-sectional designs and allow for time in the study’s methodical design. Our study responds to calls for more longitudinal studies of the antecedents of entrepreneurship more generally by using a particularly long panel. We pay particular attention to addressing endogeneity of crime rates using a range of identification strategies.

5.2. Practical implications

Our results have important practical implications for local areas wanting to attract entrepreneurs. The most obvious and direct way would be to reduce local crime rates. While a detailed discussion of the merits of alternative ways to reduce crime rates is beyond the scope of this study, how best to achieve this is a hotly contested space in the literature. Economists have a long tradition, beginning with Becker (1968), of arguing that the best way to reduce crime is to increase the expected costs of punishment and the opportunity costs of crime by creating more labour market opportunities. The policy suggestion from this approach is to invest more resources in law enforcement and give longer sentences. However, the empirical evidence on whether such measures are effective is, at best, mixed (see, e.g., Lewis (1987) and Cameron (1988) for reviews of this literature). Criminologists tend to downplay the potential effectiveness of punitive measures to reduce crime and, instead, emphasize the importance of addressing the motivational reasons for offending. As such, criminologists view 'social measures' to reduce crime rates as more effective, including the rejuvenation of local communities, creating jobs and providing sport and leisure facilities (see, e.g., Clarke, 1980).

Our findings for social capital as a link between crime and entrepreneurship suggest the potential for reinforcing effects from such social measures, where lower crime promotes opportunities for social interaction that, in turn, facilitate entrepreneurship. Our finding that those more internal on LoC are better able to cope with uncertainty due to higher crime also has important practical implications. This result suggests that programs to build resilience in prospective entrepreneurs have the potential to nudge such individuals toward being more internal on LoC. Other research has pointed to the benefits of teaching resilience to nascent entrepreneurs. For example, drawing on the broaden and build theory by Fredrickson (2001), Chadwick and Raver (2020) highlight the cognitive and behavioural ways in which psychological resilience can help first-time entrepreneurs deal with uncertainty in the start-up phase. Those authors suggest that interventions to increase resilience, such as the Penn Resiliency Program,[7] are more effective among entrepreneurs and better equip them to deal with uncertainty. LoC is most malleable in childhood and early adolescence (Awaworyi Churchill et al., 2020; Cobb-Clark et al., 2014; Cobb-Clark & Schurer, 2013; Lekfuangfu et al., 2018). Several programs already exist in schools designed to build resilience and teach positive control beliefs (see Schurer (2017) for a review). Such programs have not been linked to strategies to promote entrepreneurship as an employment path later in life. Our results suggest that further promotion of programs designed to develop self-control and build resilience among school-age children would assist in helping potential entrepreneurs deal with uncertainty later in life, such as local crime rates.

5.3. Limitations and future research

Our study has some limitations. First, although we have data on crimes against the person and property crime at the community level, we do not have crime disaggregated into other categories, such as organized crime, which has been shown to affect business activity. The lack of data on organized crime is significant given that we have posited that crime adversely affects social capital. Organized crime may prefer densely connected social cliques to enable network/family-like control on individuals, but we cannot test this. Equally, we do not have crime at a more disaggregated level, so we cannot, for example, distinguish between, say, the effect of assault and homicide (as specific types of crimes against the person) or theft and burglary (as types of property crimes) on entrepreneurship.

Second, we do not have longitudinal data on police numbers or other law enforcement variables at the postcode level, or even at a more aggregated level, corresponding to the

[7] https://ppc.sas.upenn.edu/services/penn-resilience-training

timeframe for the study. If we had, we could control for these variables. If we had data on police numbers, this would also represent an excellent candidate for another external instrument for crime rates. Third, relatedly, we control for school quality and the unemployment rate as proxies for institutional quality at the community level. However, ideally, we would like to have better measures of institutional quality. The problem is that while ultimately it is much easier to measure variation in institutional quality at a more aggregated geographical level, such as between states within a country or between countries, at this level of aggregation, estimates of the relationship between crime and entrepreneurship become too imprecise to be meaningful.

A fourth limitation is that we do not have the data to examine how crime affects business performance, such as investment, profit, and sales. Fifth, while we have considered the moderating role of LoC, a limitation on the use of that variable is that LoC is not randomized across the sample. Finally, our unit of analysis is the postcode level, the most granular geographical unit in Australia. While most postcodes correspond to smaller geographical areas, such as suburbs in urban areas, some postcodes in country areas cover large areas. Because crime is local, we expect results to be less pronounced in postcodes with more expansive geographic areas.

One suggestion for future research that would help overcome the limitations of observational data in this context is to use experimental methods to examine how crime rates affect various aspects of entrepreneurship. This suggestion is consistent with recent calls for greater use of experiments in entrepreneurship research (Williams et al., 2019). Evidence-based policing, including randomized controlled trials (RCTs), has become increasingly common in assessing the efficacy of various aspects of crime prevention (Feder & Boruch, 2000). RCTs would provide a valuable vehicle to examine how crime affects entrepreneurship. They would also have the added advantage that various treatments could be employed to examine the effect of alternative policies on the propensity for entrepreneurship, guiding policy makers on the best way to reduce crime to stimulate entrepreneurship. This would address the limitation of this study and similar studies that do not address the best way to reduce crime rates and stimulate entrepreneurship. Running RCTs requires high-level cooperation from local government and/or law enforcement, which is not easy to obtain; however, this is not an insurmountable barrier and has been achieved in other contexts. Specific guidance on attracting entrepreneurs by using urban renewal to reduce crime rates remains a critical issue for local governments.

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Table 1: Effect of local area crime on self-employment

	Dependent variable: Self-employment							
	OLS	OLS	Panel FE	Panel FE	IV – Crime rate in 1st wave as instrument	IV – Crime rate in 1st wave as instrument	IV – Abortion as instrument	IV – Abortion as instrument
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total crime rate	-0.013*	-0.017**	-0.015***	-0.015***	-0.006***	-0.008***	-0.065**	-0.065**
	(0.007)	(0.007)	(0.004)	(0.004)	(0.002)	(0.002)	(0.027)	(0.027)
Other controls	No	Yes	No	Yes	No	Yes	No	Yes
Individual FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Postcode/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	88,294	88,294	88,294	88,294	115,687	85,881	88,294	88,294

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality. Full results are presented in Table A3 (appendix).

Table 2: Effect of local area crime on self-employment – Types of crime

Dependent variable: Self-employment	OLS		Panel FE		IV – Crime rate in 1st wave as instrument		IV – Abortion as instrument	
	Person	Property	Person	Property	Person	Property	Person	Property
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crime rate	-0.016*	-0.014**	-0.015**	-0.012***	-0.017***	-0.010***	-0.083***	-0.066***
	(0.009)	(0.006)	(0.006)	(0.004)	(0.004)	(0.002)	(0.031)	(0.024)
Equality test (*p-value*)	0.267		0.016		0.073		0.030	
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Postcode/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,327	68,327	68,356	68,349	85,906	85,906	68,321	68,321

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table 3: Mediation analysis – Social capital as the mediator

Dependent variable: Self-employment	Indirect effect		Direct effect	
	Estimate	95% confidence interval	Estimate	95% confidence interval
Panel A: PROCESS approach (Preacher & Hayes, 2008)				
Total crime rate => Composite measure => Self-employment	-0.00144***	[-0.00170, -0.00122]	-0.0023	[-0.0048, 0.0003]
	(0.00013)		(0.0014)	
Panel B: Causal mediation approach				
Total crime rate => Composite measure => Self-employment	-0.00173***	[-0.00207, -0.00137]	-0.0025*	[-0.0053, 0.0003]
	(0.00018)		(0.0014)	

Notes: Bootstrap standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4: SEM results (crime and social capital composite measure)

Dependent variable:	Self-employment	Social capital
	(1)	(2)
Total crime rate	-0.007***	-0.062***
	(0.002)	(0.006)
Social capital	0.017***	
	(0.002)	
Other controls	Yes	Yes
Observations	41,008	41,008

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table 5: Mediation analysis – Alternative measures of social capital

Dependent variable: Self-employment	Indirect effect		Direct effect	
	Estimate	95% confidence interval	Estimate	95% confidence interval
Panel A: PROCESS approach (Preacher & Hayes, 2008)				
Total crime rate => Neighborhood trust => Self-employment	-0.0025***	[-0.0029, -0.0019]	-0.0038**	[-0.0074, -0.0003]
	(0.0003)		(0.0019)	
Total crime rate => Neighborhood support => Self-employment	-0.0014***	[-0.0017, -0.0011]	-0.0024*	[-0.0049, 0.0001]
	(0.0001)		(0.0013)	
Total crime rate => Collaboration => Self-employment	-0.0012***	[-0.0014, -0.0009]	-0.0026**	[-0.0050, 0.0003]
	(0.0001)		(0.0019)	
Panel B: Causal mediation approach				
Total crime rate => Neighborhood trust => Self-employment	-0.0029***	[-0.0035, -0.0022]	-0.0050**	[-0.0091, -0.0009]
	(0.0003)		(0.0021)	
Total crime rate => Neighborhood support => Self-employment	-0.0016***	[-0.0019, -0.0013]	-0.0082**	[-0.0150, -0.0014]
	(0.0002)		(0.0035)	
Total crime rate => Collaboration => Self-employment	-0.0013***	[-0.0016, -0.0010]	-0.0056*	[-0.0112, 0.0001]
	(0.0001)		(0.0029)	

Notes: Bootstrap standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: SEM results (crime and single measure indicators)

Dependent variable:	Self-employment	Trust	Support	Collaboration
	(1)	(2)	(3)	(4)
Total crime rate	-0.005*	-0.115***	-0.045***	-0.045***
	(0.003)	(0.010)	(0.006)	(0.006)
Neighborhood trust	0.012***			
	(0.002)			
Neighborhood support	0.009**			
	(0.004)			
Collaboration	0.010***			
	(0.003)			
Other controls	Yes	Yes	Yes	Yes
Observations	41,008	41,008	41,008	41,008

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table 7: Mediation analysis – Types of crime

Panel A: Crime against person

Dependent variable: Self-employment	Indirect effect		Direct effect	
	Estimate	95% confidence interval	Estimate	95% confidence interval
Panel A: PROCESS approach (Preacher & Hayes, 2008)				
Crimes against the person => Neighborhood trust => Self-employment	-0.0055***	[-0.0065, -0.0046]	-0.0068**	[-0.0147, -0.0020]
	(0.00003)		(0.0011)	
Crimes against the person => Neighborhood support => Self-employment	-0.0007***	[-0.0011, -0.0004]	-0.0041***	[-0.0068, -0.0014]
	(0.0002)		(0.0014)	
Crimes against the person => Collaboration => Self-employment	-0.0006***	[-0.0009, -0.0003]	-0.0043***	[-0.0074, -0.0019]
	(0.0001)		(0.0015)	
Panel B: Causal mediation approach				
Crimes against the person => Neighborhood trust => Self-employment	-0.0059***	[-0.0075, -0.0044]	-0.0133***	[-0.0205, -0.0062]
	(0.0008)		(0.0037)	
Crimes against the person => Neighborhood support => Self-employment	-0.0031***	[-0.0038, -0.0025]	-0.0235***	[-0.0357, -0.0112]
	(0.0003)		(0.0062)	
Crimes against the person => Collaboration => Self-employment	-0.0023***	[-0.0029, -0.0018]	-0.0215***	[-0.0316, -0.0114]
	(0.0003)		(0.0051)	

Notes: Bootstrap standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Panel B: Property crime

Dependent variable: Self-employment	Indirect effect		Direct effect	
	Estimate	95% confidence interval	Estimate	95% confidence interval
Panel A: PROCESS approach (Preacher & Hayes, 2008)				
Property crime => Neighborhood trust => Self-employment	-0.0034***	[-0.0042, -0.0029]	-0.0060***	[-0.0104, -0.0030]
	(0.0003)		(0.0017)	
Property crime => Neighborhood support => Self-employment	-0.0024***	[-0.0028, -0.0021]	-0.0045***	[-0.0070, -0.0017]
	(0.0002)		(0.0014)	
Property crime => Collaboration => Self-employment	-0.0019***	[-0.0022, -0.0016]	-0.0052***	[-0.0080, -0.0020]
	(0.0002)		(0.0016)	
Panel B: Causal mediation approach				
Property crime => Neighborhood trust => Self-employment	-0.0041***	[-0.0049, -0.0033]	-0.0087***	[-0.0129, -0.0044]
	(0.0004)		(0.0022)	
Property crime => Neighborhood support => Self-employment	-0.0026***	[-0.0030, -0.0022]	-0.0063*	[-0.0131, 0.0004]
	(0.0002)		(0.0034)	
Property crime => Collaboration => Self-employment	-0.0020***	[-0.0025, -0.0017]	-0.0060**	[-0.0118, -0.0003]
	(0.0002)		(0.0029)	

Notes: Bootstrap standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: LoC as moderator

Dependent variable:	Self-employment
Total crime rate	-0.008
	(0.008)
Total crime rate*Locus of control	0.022***
	(0.008)
Other controls	Yes
Individual FE	Yes
Postcode FE/Time FE	Yes
Observations	20,415

Notes: Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Figure 1: Conceptual framework (model of crime, social capital and entrepreneurship)

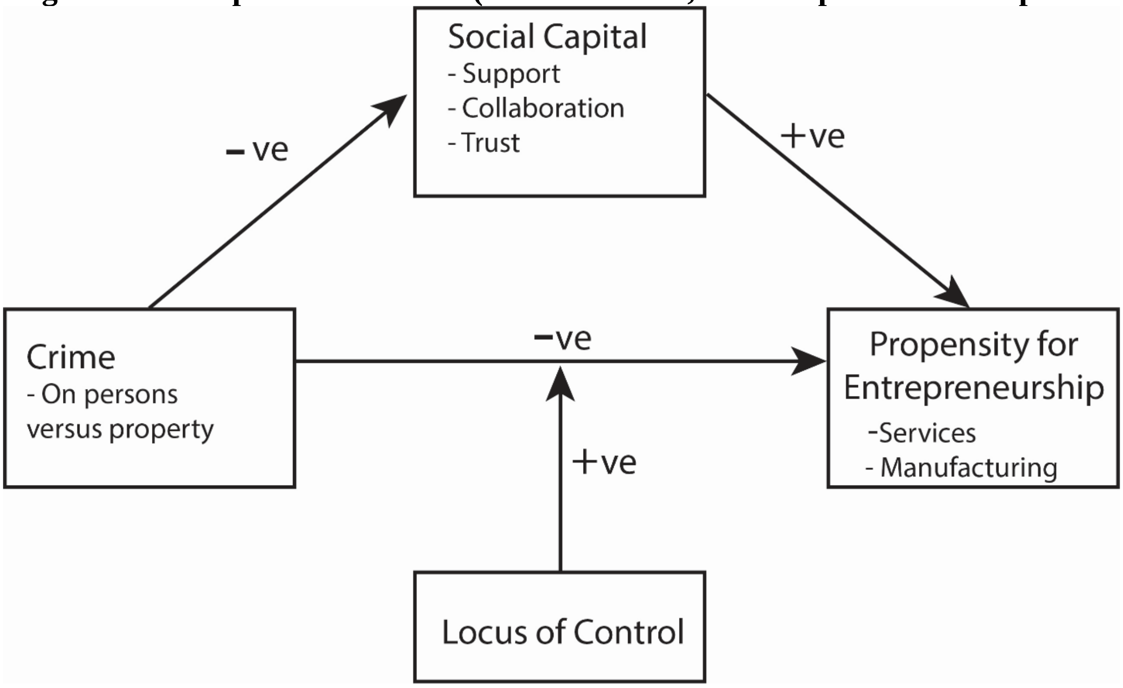
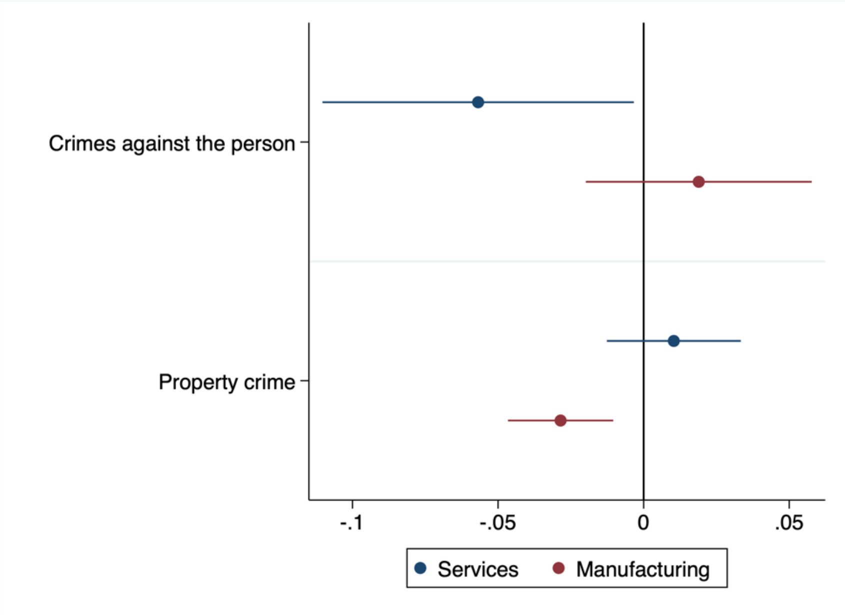


Figure 2: Effects by industry



Notes: Reported are treatment effect estimates and their 95% confidence intervals. Each estimate comes from a panel fixed-effects regression of self-employment on crime rates and other control variables. The state indicated is the excluded state. Standard errors are clustered at postcode level.

Appendix

Table A1: Variable descriptions and summary statistics

Variables	Description	Mean	St. Dev
Self-employment variables			
Self-employment	=1 if employment status is employer or employee of own business	0.153	0.360
Employer	=1 if employment status is employer	0.104	0.305
Employee of own business	=1 if employment status is employee of own business	0.061	0.239
Transition to entrepreneur	=1 if employment status changes from non-entrepreneur to entrepreneur	0.037	0.189
Exit from entrepreneur	=1 if employment status changes from entrepreneur to non-entrepreneur	0.159	0.366
Crime rate			
Total crime rate	Total crime rate at postcode level adjusted for population	0.091	0.066
Crimes against the person	Crimes rate in the stated category at postcode level adjusted for population	0.014	0.017
Property and deception offences	Crimes rate in the stated category at postcode level adjusted for population	0.055	0.040
Other variables			
Age	Age in years	36.354	22.713
Income	Disposable income (in log)	10.461	0.650
Postgraduate	Having post-graduate degree=1	0.043	0.203
Graduate diploma	Having graduate diploma degree=1	0.051	0.221
Bachelor	Having bachelor’s degree=1	0.133	0.340
Diploma	Having diploma degree=1	0.089	0.284
Certificate	Having certificate degree=1	0.209	0.406
Year 12	Year 12 completion=1	0.153	0.360
Worse health	Having worse health degree=1	2.445	1.132
De facto	Marital status, de facto=1	0.144	0.351
Separated	Marital status, separated=1	0.027	0.163
Divorced	Marital status, divorced=1	0.060	0.238
Widowed	Marital status, windowed=1	0.050	0.217
Single	Marital status, single=1	0.241	0.428
Unemployment rate	Unemployment rate at SA level	5.619	1.667
School quality	Index of Community Socio-Educational Advantage score	1,019.602	69.602
Abortion	Abortion rate at state level	8.866	2.720
Mediators			
Social capital	Composite index of social capital -- average of responses from six items with higher and lower scores representing higher and lower social capital, respectively.	3.662	1.109
Neighborhood trust	Single item indicated of neighborhood trust	4.706	1.403
Neighborhood support	Single item indicated of neighborhood support	3.558	1.009
Collaboration	Single item indicated of collaboration	2.960	1.130

Notes: Monetary units are adjusted for inflation.

Table A2: Summary statistics per year

Wave	Observations	Self-employment	Crime rate
8	4,631	0.148	0.092
9	5,415	0.153	0.094
10	5,706	0.149	0.088
11	7,746	0.152	0.082
12	7,991	0.145	0.083
13	7,976	0.145	0.083
14	8,136	0.141	0.087
15	8,107	0.143	0.086
16	8,473	0.146	0.092
17	8,458	0.145	0.092
18	8,356	0.142	0.085
19	7,299	0.148	0.084

Table A3: Effect of local area crime on fertility self-employment – Full results

	Dependent variable: Self-employment							
	OLS	OLS	Panel FE	Panel FE	IV – Crime rate in 1st wave as instrument	IV – Crime rate in 1st wave as instrument	IV – Abortion as instrument	IV – Abortion as instrument
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total crime rate	-0.013*	-0.017**	-0.015***	-0.015***	-0.006***	-0.008***	-0.065**	-0.065**
	(0.007)	(0.007)	(0.004)	(0.004)	(0.002)	(0.002)	(0.027)	(0.027)
Income		-0.051***		-0.029***		-0.043***		-0.029***
		(0.006)		(0.004)		(0.003)		(0.002)
Age		0.005***				0.005***		0.000
		(0.000)				(0.000)		(0.000)
Postgraduate		-0.006		0.007		-0.016***		0.008
		(0.014)		(0.015)		(0.006)		(0.012)
Graduate diploma		-0.042***		-0.000		-0.034***		-0.001
		(0.014)		(0.015)		(0.006)		(0.012)
Bachelor		-0.006		-0.013		-0.009**		-0.013
		(0.010)		(0.010)		(0.004)		(0.009)
Diploma		0.007		-0.003		-0.012**		-0.001
		(0.012)		(0.012)		(0.005)		(0.010)
Certificate		0.034***		0.013		0.019***		0.013**
		(0.009)		(0.010)		(0.004)		(0.007)
Year 12		-0.004		-0.005		0.004		-0.005
		(0.009)		(0.006)		(0.004)		(0.006)
Worse health		-0.000		0.002**		-0.003**		0.002**
		(0.002)		(0.001)		(0.001)		(0.001)
De facto		-0.022***		-0.017***		-0.027***		-0.018***
		(0.008)		(0.006)		(0.004)		(0.004)
Separated		-0.055***		-0.021		-0.060***		-0.020***
		(0.016)		(0.013)		(0.008)		(0.007)
Divorced		-0.087***		-0.007		-0.085***		-0.007
		(0.012)		(0.015)		(0.006)		(0.008)
Widowed		-0.063**		-0.008		-0.069***		-0.010

		(0.031)		(0.026)		(0.013)		(0.016)
Single		-0.054***		-0.027***		-0.054***		-0.028***
		(0.008)		(0.009)		(0.004)		(0.006)
Unemployment rate		0.001		-0.000		-0.006***		0.000
		(0.001)		(0.001)		(0.001)		(0.001)
School quality		-0.000		0.000		0.000***		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Individual FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Postcode/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	88,294	88,294	88,294	88,294	115,687	85,881	88,294	88,294

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1.

Table A4: First stage results from both IV strategies

	Dependent variable: Total crime rate	
	(1)	(2)
Crime rate in 1st wave	0.598***	
	(0.003)	
Abortion rate		-0.011***
		(0.001)
Kleibergen-Paap F statistic	1,619.40	90.963
Other controls	Yes	Yes
Individual FE	Yes	Yes
Postcode/time FE	Yes	Yes
Observations	85,881	88,294

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A5: Effect of crime on moving

Dependent variable:	Probability of moving
Total crime rate	0.010
	(0.006)
Other controls	Yes
Individual FE	Yes
Postcode/time FE	Yes
Observations	118,745

Table A6: Effects of crime (movers vs. non-movers)

	Dependent variable: Self-employment			
	Non-mover	Mover	Mover within state	Mover across states
	(1)	(2)	(3)	(2)
Total crime rate	-0.013***	-0.020*	-0.007*	-0.006*
	(0.004)	(0.011)	(0.004)	(0.003)
Other controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Postcode FE/Time FE	Yes	Yes	Yes	Yes
Observations	79,492	7,850	5,173	2,677

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A7: Parameter stability and robustness to omitted variable bias

Treatment variable	(1) Baseline effect, $\dot{\beta}$ (Std. error)[$\dot{R}$]	(2) Controlled effect, $\tilde{\beta}$ (Std. error)[$\tilde{R}$)	(3) Identified set $[\widetilde{\beta}, \beta^*(\min\{1.3\tilde{R}, 1\}, 1)]$	(4) Exclude zero?	(5) $\bar{\delta}$ for $\beta = 0$ given R_{max}
Total crime rate	-0.008*	-0.015***	[-0.008, -0.015]	Yes	3.402
	(0.004) [0.792]	(0.004) [0.812]			
Observations	88,294	88,294			

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Alternative fixed effects models

Dependent variable:	Self-employment			
	(1)	(2)	(3)	(4)
Total crime rate	-0.011**	-0.010**	-0.015***	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)
Other controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Postcode FE/Time FE	Yes	Yes	Yes	Yes
Postcode FE*Linear time	Yes	No	No	No
LGA FE* Linear time	No	Yes	No	No
Month interview FE	No	No	Yes	No
Observations	88,294	88,290	88,260	88,294

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level except for Columns (4) where standard errors are clustered at the individual level, respectively; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A9: Lewbel 2SLS results

Dependent variable:	Self-employment	
	Internal instrument	Internal and external instrument
	(1)	(2)
Total crime rate	-0.052**	-0.051**
	(0.024)	(0.021)
Other controls	Yes	Yes
Individual FE	Yes	Yes
Postcode FE/Time FE	Yes	Yes
Observations	88,294	88,294

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality; external instrument is abortion rates.

Table A10: Effect of local area crime on self-employment (location of work)

	Dependent variable: Self-employment							
	OLS	OLS	Panel FE	Panel FE	IV – Crime rate in 1st wave as instrument	IV – Crime rate in 1st wave as instrument	IV – Abortion as instrument	IV – Abortion as instrument
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total crime rate	-0.016***	-0.013***	-0.009**	-0.009**	-0.029***	-0.029***	-0.297**	-0.291**
	(0.005)	(0.004)	(0.005)	(0.004)	(0.006)	(0.006)	(0.126)	(0.126)
Other controls	No	Yes	No	Yes	No	Yes	No	Yes
Individual FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Postcode/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,140	54,140	52,383	52,401	65,388	65,388	52,383	52,383

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A11: Effect of local area crime on self-employment – Types of crime (location of work)

Dependent variable: Self-employment	OLS		Panel FE		IV – Crime rate in 1st wave as instrument		IV – Abortion as instrument	
	Person	Property	Person	Property	Person	Property	Person	Property
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crime rate	-0.010**	-0.016***	-0.007	-0.011*	-0.024***	-0.040***	-0.183**	-0.259***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.006)	(0.008)	(0.072)	(0.100)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Postcode/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,140	54,140	52,401	52,401	65,388	65,388	52,383	52,383

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A12: Effect of local area crime on self-employment (LGA analysis)

	Dependent variable: Self-employment							
	OLS	OLS	Panel FE	Panel FE	IV – Crime rate in 1st wave as instrument	IV – Crime rate in 1st wave as instrument	IV – Abortion as instrument	IV – Abortion as instrument
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total crime rate	-0.004	-0.005**	-0.003*	-0.003*	-0.006***	-0.005***	-0.033**	-0.033**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.016)	(0.016)
Other controls	No	Yes	No	Yes	No	Yes	No	Yes
Individual FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
LGA/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90,019	90,019	90,019	90,019	113,857	113,857	73,055	73,055

Notes: Robust standard errors in parentheses; standard errors are clustered at LGA level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A13: Effect of local area crime on self-employment – Types of crime (LGA analysis)

Dependent variable: Self-employment	OLS		Panel FE		IV – Crime rate in 1st wave as instrument		IV – Abortion as instrument	
	Person	Property	Person	Property	Person	Property	Person	Property
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crime rate	-0.004	-0.006***	-0.004*	-0.004***	-0.302**	-0.108***	-0.025**	-0.019**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.128)	(0.037)	(0.012)	(0.009)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
LGA/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90,019	90,019	90,019	90,019	103,599	103,599	73,055	73,055

Notes: Robust standard errors in parentheses; standard errors are clustered at LGA level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A14: Effect of local area crime on self-employment (regional analysis)

	Dependent variable: Self-employment							
	OLS	OLS	Panel FE	Panel FE	IV – Crime rate in 1st wave as instrument	IV – Crime rate in 1st wave as instrument	IV – Abortion as instrument	IV – Abortion as instrument
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total crime rate	-0.008	-0.011	-0.018***	-0.018***	-0.015***	-0.016***	-0.094***	-0.094***
	(0.010)	(0.010)	(0.006)	(0.006)	(0.002)	(0.003)	(0.028)	(0.030)
Other controls	No	Yes	No	Yes	No	Yes	No	Yes
Individual FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Postcode /time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,695	34,695	34,695	34,695	57,432	44,176	34,695	34,695

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A15: Effect of local area crime on self-employment – Types of crime (regional analysis)

Dependent variable: Self-employment	OLS		Panel FE		IV – Crime rate in 1st wave as instrument		IV – Abortion as instrument	
	Person	Property	Person	Property	Person	Property	Person	Property
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crime rate	-0.005	-0.001	-0.013**	-0.009***	-0.017***	-0.015***	-0.092***	-0.070***
	(0.005)	(0.003)	(0.006)	(0.003)	(0.003)	(0.004)	(0.030)	(0.023)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Postcode /time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,695	34,695	34,695	34,695	44,178	44,178	34,695	34,695

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A16: Transition to/exit from entrepreneur

Dependent variable:	Transition to entrepreneur	Exit from entrepreneur
	(1)	(2)
Total crime rate	-0.012***	0.034***
	(0.004)	(0.011)
Other controls	Yes	Yes
Individual FE	Yes	Yes
Postcode FE/Time FE	Yes	Yes
Observations	59,027	9,838

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A17: Alternative measures of self-employment

Dependent variable:	Employer	Employee of own business	Excluding 'hobby' entrepreneurs	Excluding farmers and farm managers
	(1)	(2)	(3)	(4)
Total crime rate	-0.010**	-0.008***	-0.014***	-0.016***
	(0.004)	(0.003)	(0.004)	(0.004)
Other controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Postcode FE/Time FE	Yes	Yes	Yes	Yes
Observations	83,373	79,567	85,935	85,263

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A18: Lagged effects of crime

	Dependent variable: Self-employment	
	(1)	(2)
Total crime rate at (t-2)	-0.013***	
	(0.004)	
Total crime rate at (t-3)		-0.009**
		(0.004)
Other controls	Yes	Yes
Individual FE	Yes	Yes
Postcode FE/Time FE	Yes	Yes
Observations	87,507	86,692

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A19: Attrition test

Dependent variable:	Non missing	Self-employment
	(1)	(2)
Total crime rate	-0.026	-0.017***
	(0.019)	(0.004)
Other controls	Yes	Yes
Individual FE	Yes	Yes
Postcode FE/Time FE	Yes	Yes
Observations	88,230	88,206

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A20: Controlling for Big Five traits

Dependent variable:	Self-employment
Total crime rate	-0.025***
	(0.007)
Openness	0.006
	(0.005)
Extroversion	0.001
	(0.004)
Emotional stability	0.003
	(0.004)
Conscientiousness	-0.002
	(0.005)
Agreeable	-0.013***
	(0.004)
Other controls	Yes
Individual FE	Yes
Postcode FE/Time FE	Yes
Observations	12,760

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A21: Non-linear effects of crime

Dependent variable:	Self-employment
Total crime rate	-0.018***
	(0.005)
Total crime rate squared	0.001
	(0.001)
Other controls	Yes
Individual FE	Yes
Postcode FE/Time FE	Yes
Observations	88,294

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A22: Necessity vs. opportunity entrepreneurship

Dependent variable:	Necessity entrepreneur	Opportunity entrepreneur
	(1)	(2)
Total crime rate	-0.004***	-0.005**
	(0.002)	(0.002)
Other controls	Yes	Yes
Individual FE	Yes	Yes
Postcode FE/Time FE	Yes	Yes
Observations	75,320	76,608

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Table A23: Spatial regression

Dependent variable:	Self-employment		
	Conley spatial regression	Spatial autoregressive model - first-order contiguity	Spatial autoregressive model - second-order contiguity
	(1)	(2)	(3)
Total crime rate	-0.006***	-0.017**	-0.018**
	(0.002)	(0.008)	(0.008)
Other controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Postcode FE/Time FE	Yes	Yes	Yes
Observations	88,294	88,294	88,294

Notes: Robust standard errors in parentheses; standard errors are clustered at postcode level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include age, educational levels, health, marital status, income, unemployment rate, and school quality.

Figure A1: Self-employment rate across states and over time

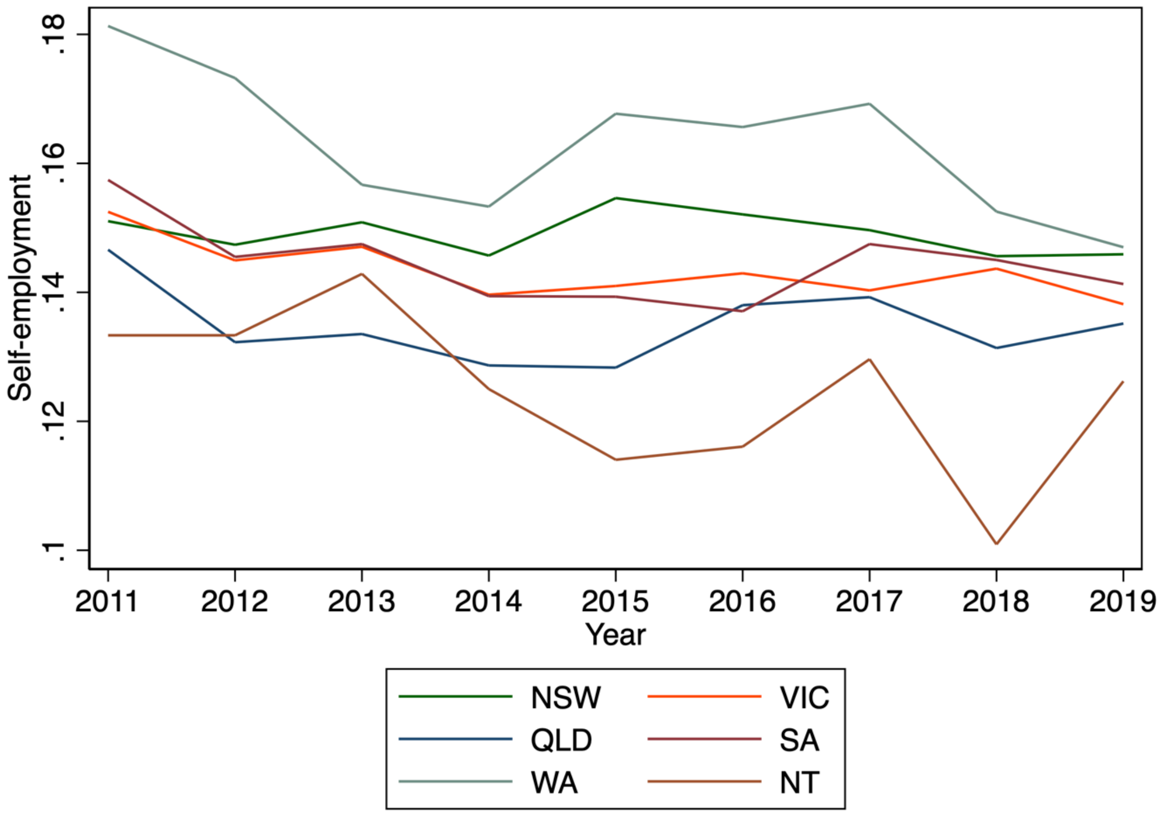


Figure A2: Crime rate across states and over time

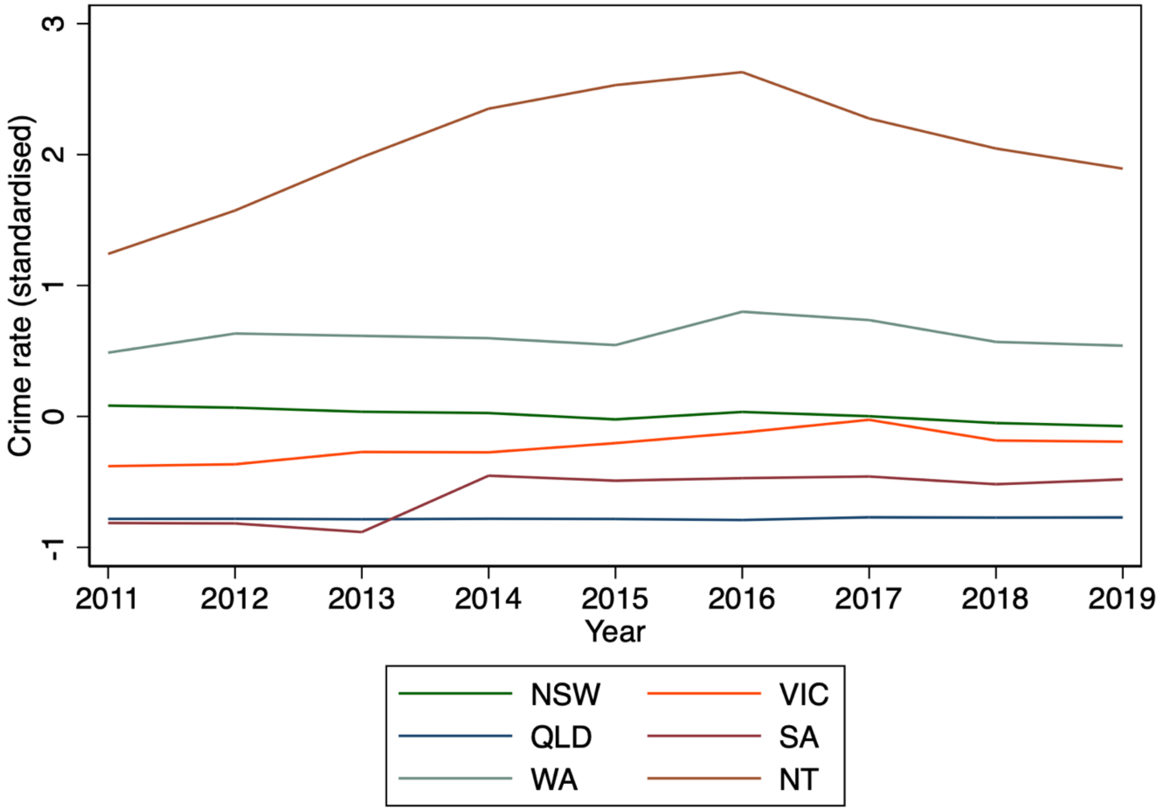


Figure A3: Placebo test results

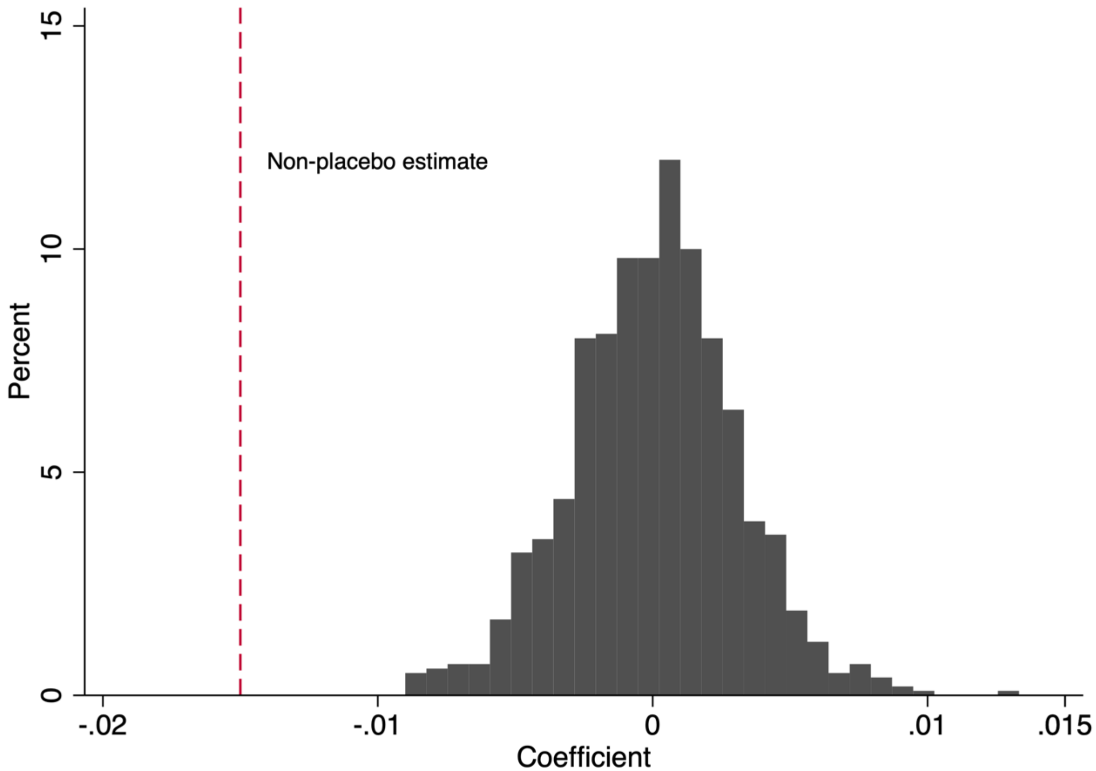
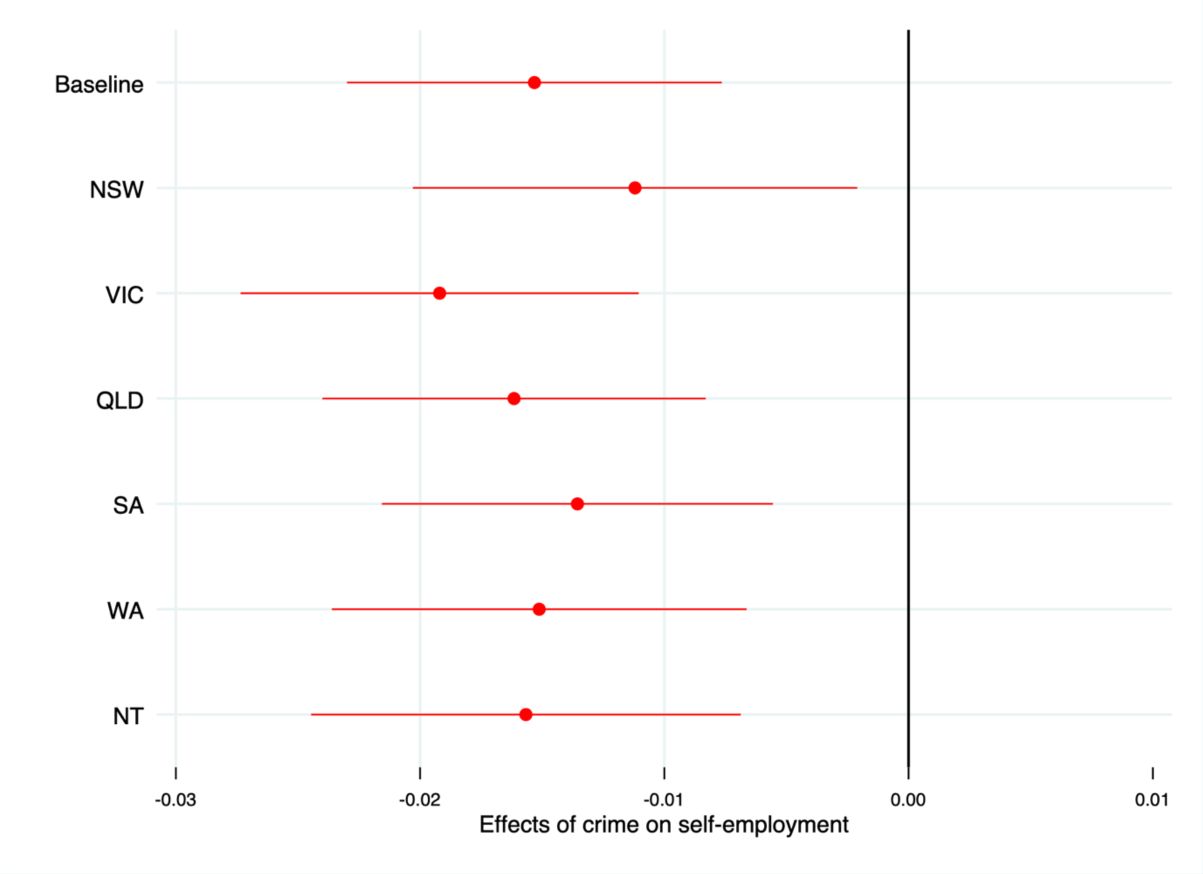


Figure A4: Robustness to dropping states one by one



Notes: Reported are treatment effect estimates and their 95% confidence intervals. Each estimate comes from a panel fixed-effects regression of self-employment on crime rates and other control variables. The state indicated is the excluded state. Standard errors are clustered at postcode level.