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Size isn't everything: Understanding the relationship between police workforce and crime problems

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ABSTRACT

If and how policing affects crime has long been studied. On the relationship between police force size and crime, different authors come to different conclusions. This study examines the relationship between police resourcing, including workforce size, structure and stability over time using data for 42 police forces in the UK over a 13-year period.

We construct two novel panel datasets. The first comprises measures of police workforce *Size, Structure* and *Stability*. The second provides measures of both crime frequency and crime severity. Issues of endogeneity make the modelling of the police-crime association complicated. Consequently, we analyse the data using a panel vector autoregression (PVAR) model which is capable of forecasting a temporal sequence of the interdependencies between police-crime relationships.

Changes in total police personnel play an important role in reducing both crime frequency and severity, but the findings are more nuanced than this. Results highlight that the structure and stability of police organisations are important although these impacts are not always the same for crime volume and crime severity. We find that increases in frontline (non-sworn) support staff are associated with reductions in crime, while turnover rates of police staff are associated with increases in crime. In contrast, changes to the number of sworn police officers do not appear to be a good predictor of crime volume.

The findings suggest that investment in frontline support staff and the development of strategies to retain skills and knowledge by reducing staff turnover may be efficient approaches for Police Forces to maximise the impact on crime of their workforce in resource-pressed policing settings. While previous research has found that police force size has a limited effect on crime, our findings indicate that more nuanced measurements of police resourcing are necessary to understand how police impact upon crime risk. The idea of police forces using basic officer-to-population ratios to make staffing decisions appears outdated and over-simplistic.

1. Introduction

Broadly speaking, police resourcing can have a large impact on crime. For those in doubt, consider what a police-less society would look like in terms of crime risk. However, a detailed understanding of the drivers of police demand, the amount and types of resourcing required, and the optimal organisational structure of these resources has not been the subject of quantitative enquiry. In England and Wales, the Home Office employs a funding formula to assign resources across the 43 Police Force Areas (see 'Guide to the police allocation formula' Home Office, 2013 or 'Police Funding' Johnston & Politowski, 2016). This is, however, used for practical allocation purposes rather than to reflect on the complex relationship between the factors at play. Four main difficulties have hindered such modelling exercises. The first is a lack of comprehensive datasets that allow both police resourcing and police demand to be quantified over time. Second is the paucity of research focusing on policing demand in the academic domain. The third is a lack of variability in police resources over time which increases the risk of Type II statistical error in the statistical modelling enterprise; if little variability exists then any association between police resourcing and crime will likely go undetected. Fourth is the challenge of using an appropriate statistical modelling framework that is flexible enough to

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accommodate spatial and temporal variability and also resilient enough to handle the complex bidirectional relationships between policing and crime, along with the intrinsic issues of endogeneity. The specific challenge concerning the latter is the simple fact that whilst police resourcing can influence crime, crime can also have an impact on resourcing. Further, the expected time scale over which these factors interact remains ambiguous, raising questions about the immediacy or delayed effects of resource allocation on crime levels. For example, over what time period might we expect an injection of resources to have an impact on levels of crime? And is this effect likely to be instantaneous or delayed?

In response to these challenges, and in pursuit of a better understanding of the complex relationship between police resourcing and crime, this paper utilises publicly available data to construct two new datasets that cover 42 police force areas in England and Wales for a period of 13 years from 2006 to 2019. This timeframe allows for a robust analysis by controlling for established factors influencing crime rates, prior to the potential disruptions caused by the major external event of the COVID-19 pandemic. The former provides measures of police force size, structure and stability, while the latter enumerates both crime frequency and severity. Using these datasets, we apply a panel vector autoregression (PVAR) model capable of forecasting the dynamic relationships between variables, with the aim of understanding the causal dynamics between the police workforce and crime across these 42 police forces. In the next section, we review the existing literature on the policing and crime relationship before articulating our hypotheses and approach to analysis.

2. Background and literature review

The subject of how police resourcing influences crime has garnered significant academic attention, as evidenced by numerous studies (e.g., Kelling, 1978; Sherman & Weisburd, 1995; Sherman & Eck, 2002; Frydl & Skogan, 2004; Weisburd & Braga, 2006; Drake & Simper, 2005; Lin, 2009; Lee, Eck, & Corsaro, 2016). Given the localised nature of these interventions, these studies use a random allocation strategy to help rule out potential threats to causal inferences. Consequently, there is growing systematic evidence on whether focused hotspot policing interventions or targeted policing patrols are effective at deterring crime (Braga, Papachristos, & Hureau, 2014; Braga, Turchan, Papachristos, & Hureau, 2019; Sorg, Haberman, Ratcliffe, & Groff, 2013). Less well understood is the more general day-to-day impact of policing activity on rates of crime (see e.g., Gorr & Lee, 2015; Santos & Santos, 2021).

The Kansas City Patrol Preventative Project (Kelling, Pate, Dieckman, & Brown, 1974) was the first to track the movements of officers over a city and estimate the impact of this on crime. Doing this was costly and since that study, there has been something of a hiatus on such formal larger-scale studies. Nevertheless, research that tracks policing presence in detail over larger geographic areas, beyond specific intervention areas, is beginning to re-emerge as a consequence of the wider availability of GPS data that can track the activity of officers during their daily activities (e.g., Ariel, Weinborn, & Sherman, 2016; Davies & Bowers, 2020; Wain & Ariel, 2014). Overcoming the challenges (pragmatic, political, ethical and so on) associated with conducting large-scale randomised controlled trials is immensely challenging, if not entirely infeasible. Consequently, quasi-experimental approaches using 'natural experiments' has emerged to evaluate the effects of policing investments.

MacDonald, Fagan, and Geller (2016) used a geographic discontinuity design to assess private policing's impact, examining crime differences between blocks near patrol boundaries. While such designs do not measure change over time, they exploit the fact that blocks immediately adjacent to (inside or outside of) the boundary should differ only in terms of the additional policing provided within it. Their estimates suggested that the additional patrols provided within the boundary reduced crime by between 43 and 34 %.

In another longitudinal study spanning eight years, MacDonald, Klick, & Grunwald, 2016 used a large-scale policing operation undertaken by the New York Police Department. By increasing investigative stops in high crime blocks notable reductions were achieved. Further opportunities for testing the impact of long-term changes to policing on crime have been provided by The Community Orientated Policing (COPs) program, which contributed to police hires in the US since the 1990s. Evans and Owens (2007), found that the additional hires reduced key crime types and Mello (2019) 3.2 % increase in police led 3.5 % reduction in victimisation. However, not all studies come to the same conclusions. Before discussing this further, we will consider some of the conceptual challenges associated with examining the police-crime relationship.

From a theoretical viewpoint, the degree to which policing can be argued to have an impact on crime depends on the mechanism at play. A widely proposed concept is that the presence of police increases levels of deterrence and the cost of crime (Ehrlich, 1973; Nagin, Solow, & Lum, 2015; Sherman, 1990). This notion, rooted in deterrence theory dating back to the work of Beccaria and Bentham (see Nagin et al., 2015; Sherman, 1990), suggested that individuals are deterred from committing crimes when they perceive that their probability of being detected has increased. Deterrence theory highlights three main elements of the deterrence mechanism- the perceived magnitude, certainty of punishment and severity of punishment. More recently, Nagin (1998) argues that of these elements, certainty of punishment holds greater sway in deterring criminal behaviour than severity. It is obvious that policing activity is not, however, limited to ensuring a law enforcement presence in areas where crime is possible or likely. Instead, much of the activity in policing organisations is aimed at increasing the certainty of detection and punishment through effective crime investigation. There are also many other outcomes that police forces aim to achieve to fulfil broader societal roles- such as maintaining legitimacy, reassuring and engaging with the public, safeguarding those considered most vulnerable populations, and responding to diverse policing demands. Thus, while deterrence remains a crucial aspect of policing, its effectiveness is closely linked with organisational goals and strategies aimed to achieving broader social outcomes.

Laufs, Bowers, Birks, and Johnson (2020) categorise demands into four types: reactive, proactive, internal and failure demands. Reactive or 'public' demand arises in response to reported crimes, while proactive demand is an activity in anticipation of incidents or in response to intelligence. Internal demand involves organisational processes and administration, while failure demand entails correcting, or revisiting missed tasks, and police agencies constantly balance these activity. As such, the exploration of the police and crime relationship, without accounting for organisational differences is likely to be overly simplistic. Indeed, the handful of studies that have additionally examined qualitative differences in management, organisation or type of resources has suggested that they are important in determining impact (e.g., Wilson-Kovacs and Wilcox, 2023). For example, an anti-crime program in New Orleans showed that increased police presence was effective, but improving monitoring and performance incentives had its own positive impact, whereas officer composition (trained existing police officers versus new 'task force' officers) did not drive reductions in crime (Cheng & Long, 2018). Heaton, Hunt, MacDonald, and Saunders (2016) found that private police can be as effective as those publicly funded at controlling crime, at least in certain circumstances. Given the scarcity of such studies, in the empirical analysis that follows, we explore how organisational differences including workforce characteristics, as well as the pure count of available police personnel, affect crime.

A further oversimplification in the literature from a demand viewpoint is the conflation of the volume of crime with the seriousness of the incidents involved. Since not all crimes are equal in terms of their seriousness, the harm inflicted on victims, and/or their complexity with regard to the investigation, there will be certain types of crime that are more likely to generate a greater ask in terms of police time to deal with than others. As a general rule, serious crimes may be assumed to require more police resources, yet most studies overlook different resourcing differences. Whilst multiple studies have looked at the comparative effects of additional police by crime type (e.g., Cheng & Long, 2018; Evans & Owens, 2007), few appear to have factored in likely differences in workload in estimating general effects of policing on crime. An exception is Chalfin and McCrary (2018) who account for these differences to an extent by using the estimated costs of crime to produce a cost-weighted crime variable in dollars per capita. Consequently, it might be that there is a stronger relationship between policing numbers and resources and crime seriousness than the analysis of simple counts of crime would suggest. The academic literature on crime harm proposes several indices and measures that can be used to calculate crime severity or harm. One is the Cambridge Harm Index (CHI). This weights crime using the number of days a person would receive in prison if they were convicted of that offence (Sherman, Neyroud, & Neyroud, 2016). Hence, for more serious crimes such as violence, the index will have a higher value. There are further indices of crime severity and the research described here uses that produced by the UK Office of National Statistics (ONS) (see Ashby, 2018), discussed further in the methodology section.

The spatial and temporal units of analysis, and the methodological design used to explore the policing-to-crime relationship are also important to consider. As discussed above, some studies have exploited opportunities, not unlike a 'natural experiment' afforded by high-impact incidents or longer-term changes in police presence to examine this relationship (e.g., Apel & Nagin, 2011; Cheng & Long, 2018; Di Tella & Schargrodsky, 2004; Draca, Machin, & Witt, 2011; Durlauf & Nagin, 2011; MacDonald, Fagan, & Geller, 2016; MacDonald, Klick, & Grunwald, 2016). Some of these studies (e.g., Cheng & Long, 2018; MacDonald, Klick, & Grunwald, 2016; Mello, 2019) lend themselves well to difference-in-differences frameworks which use a quasi-experimental design to contrast differences in crime counts over time for locations that receive increased police resources and those that do not. Others (e.g., Chalfin & McCrary, 2018) track police numbers and crime across a substantial number of states or cities. It is perhaps interesting to also note that most of these studies are based on trends in the US and only one or two have investigated patterns in (say) England and Wales (Bradford, 2011). Nevertheless, government reactions to crime problems in many countries have, by tradition, often involve expanding police force numbers (Cornwell & Trumbull, 1994). As a contemporary example, consider that in a campaign to tackle rising violent crime in the UK, a few years ago the British Prime Minister pledged to fund an additional 20,000 police officers in England and Wales. Yet, as noted by Bradford (2011), large-scale empirical studies using multiple units of analysis directly aiming to generate evidence either confirming or refuting the crime-reductive effect of police numbers at the force or agency level, only started to emerge in the late 1990s. Thus, while the idea that increasing police numbers will reduce crime remains commonplace – particularly within policy circles - there is clearly potential for a mismatch between empirical evidence and policy development.

Bradford's (2011) rapid evidence review concluded that higher police levels indeed linked to lower crime- however, such reductions appear to apply primarily to property crime and less so to violent crime. Lee et al.'s (2016) systemic review and meta-analysis, which specifically focused on U.S. studies came to a different conclusion, finding the overall effect of police force size on crime was negative but small and insignificant. It appears that these reviews, with different search criteria and frameworks and variations in the types of crime examined, therefore come to different conclusions.

Much like the aforementioned weaknesses associated with reducing measures of crime to simple counts, there is also good reason to suggest that just counting the number of officers is not a satisfactory approach, given the range of ways police forces can be configured and the activities the police can engage in. Taking a more extreme view, Lee et al. (2016) conclude that '*This line of research has exhausted its utility. Changing policing strategy is likely to have a greater impact on crime than adding more police*' (p.431). Whilst we understand the reasoning behind this conclusion, we would argue that this might not be a simple either/or decision to make. Indeed, Lee et al. (2016) cite the lack of variation in police force size as being a major limitation of much of the research that has intended to test its relationship with crime. To address this, we propose that to add to knowledge a method that maximises variation is required. We seek to do this here by using data for multiple police forces for a long time series using data that accounts for strategic and structural changes, as well as the sheer number of police officers.

Despite their differing conclusions, both reviews agree on methodological robustness, with Bradford (2011) concluding that '*the causal claims made by many of them are somewhat doubtful, and care should be taken when interpreting the results*' (p.1). A significant methodological concern is the need for robustly addressing endogeneity in the police-crime relationship, where police numbers might influence crime, but crime levels can also influence policy decisions in terms of police numbers. Where random allocation is not feasible, which is often the case with large-scale changes, there are a number of statistical and analytical methods that can be applied to time-series data to account for bi-directional causality. Some of these methods have been more commonly applied to the police-crime relationship than others. Methods include using time series with a Granger causality test (e.g., Kovandzic & Sloan, 2002; Marvell & Moody, 1996); regression analysis with lagged effects (e.g., Corman & Mocan, 2000) and two-stage least square regression using instrumental variables (e.g., Levitt, 2002; Lin, 2009).

While statistical methods can address some of the complexities, the focus on numbers alone overlooks critical organisational dynamics, such as roles they perform, the balance between different ranks, and organisational stress, particularly regarding turnover intention and rate. While different mechanisms have been used to explain how the organisational structure influences police effectiveness - such as stress (Vuorensyrjä, 2014), rewards (King, 2005), the balance between frontline duties and administrative intensity (King, 2005), and supervisory management (Johnson, 2011) - these studies highlight the balance between ranks and roles within the police workforce as a key factor.

Some research specifically highlights the importance of police staff in supporting roles as essential to effective functioning and critical in maintaining the operational balance between ranks. The literature indicates that civilian employees contribute to the specialised functions, such as administrative tasks, communications, and crime analysis, which are vital for overall productivity and crime reduction (Mendel, Fyfe, & den Heyer, 2017; Brown & Fleming, 2022). For example, the complex hierarchy within police force underscores the contributions of civilian staff, whose has specialised skills, particularly in technology adoption and crime analysis (Randol, 2014). Furthermore, Brown and Fleming (2022) found that frontline officers, whether in operational or support roles, experienced higher stress levels compared to those in more supportive functions, suggesting that balancing between frontline duties and support roles is essential for maintaining workforce effectiveness. This evidence supports the perception that support roles are undervalued compared to officer roles, underscoring the need for a more equitable approach to valuing all contributions. There is also a critical need to explore occupational differentiation and the dynamics of organisational turnover within the force, as these factors are essential to the overall effectiveness of policing.

The analysis in this paper aims to investigate the causal associations between the police workforce and crime by analysing panel data for 42 police forces in the UK from 2006/07 to 2018/19 using vector autoregressive analysis. This method allows for the simultaneous examination of causal associations among multiple variables over time, offering advantages over traditional causality methods such as granger causality tests or regression analysis with lagged effects. The dataset provides a relatively unusually long-time frame of 13 years over which to explore the relationship, which increases the robustness of the analysis and the application of this method to explore the police-crime relationship is novel. Unlike previous studies, which treat the police-crime relationship as unidirectional, our approach captures the bidirectional dynamics, acknowledging that changes in crime can influence police resource allocation just as police resources can influence crime. This allows for a more comprehensive understanding of the mutual interactions between these variables over time.

The research also aims to add to current understanding by (a) investigating the relationship between police numbers and crime severity as well as crime volume (b) incorporating variables that describe the structure of the police workforce rather than just examining its sheer size and (c) estimating the timing of the effects - when they happen and for how long. In particular, we examine the impact of police resourcing structure on crime in terms of the distribution of resources such as the ratio of main to support staff (see below) and the role of police force staff turnover.

The remainder of the paper proceeds as follows - first, we begin by outlining our core datasets describing (i) police *size*, *structure*, and *stability*; (ii) crime *frequency* and *severity*, the measures constructed within them, and (iii) our analytical approach applied to them. A detailed discussion of the model and other methods used is provided below with an account of model optimisation. Subsequently, we present the results of these analyses and discuss their implications for both research and beyond. We conclude by discussing the limitations of the study and proposing several potential avenues for further research.

3. Methods

3.1. Data

Annual data for the period 2006/07 to 2018/19 for 42 police forces in England and Wales were utilised. The data combine both indicators of crime and levels of policing resources, collated from a number of publicly available sources described below. Notably, the longitudinal time frame of the data was unusually extensive, with data encompassing a period of 13 years for all included police forces. While there are 44 police forces in England and Wales, two of these – the City of London police and the British Transport Police – were excluded from analyses due to their specialist nature. The former is the national lead for, and records all offences concerning, financial crime (e.g., fraud) and the latter focuses on crime that occurs on public transport.

To fulfil the aim of this study and, in turn, address the endogeneity issues associated with the police-crime relationship, it was important to build comprehensive panel datasets that offer more insight into police force structure and crime than standard time-series or cross-sectional data typically do. In collating these panel data, multiple public documents and open data sources were reviewed and combined, maximising the time frame over which characteristics of police resourcing could be effectively measured.

Police workforce data spanning from 2010 to 2018 were acquired from statistical publications by the UK Home Office, released biannually.[1] We use data from the main annual release (available 31 March) which covers the full range of police resourcing statistics (e.g., staff composition and allocation). These police workforce data include measures of the numbers of police officers, police staff, Police Community Support Officers (PCSOs),[2] Designated Officers (DOs),[3] special constables,[4] and police support volunteers in each UK police force, with the counts expressed as full-time equivalents (FTEs). Supplementary data on the police workforce preceding 2010 were extracted from the Home Office Statistical Bulletins archive.[5] Some manual coding was necessary to convert the data to a consistent format and where there was overlap in time periods covered, we prioritised the most up-to-date versions of datasets.

For the crime variables, data were obtained from police-recorded crime reports published by the Home Office.[6] Counts of recorded crimes for each 12-month period were aggregated to the police force level. In addition, the Crime Severity Score (CSS) data developed by the Office for National Statistics (ONS)[7] was utilised to measure crime severity and as a means to estimate the broader demand or burden on police resources. The research utilised both crime volumes and severity separately to provide a comprehensive view of the overall demands on police forces. Fraud offences, including computer misuse, were excluded because these offences are primarily handled by specialised units such as Action Fraud or the National Crime Agency (NCA), or specific police forces such as City of London police, rather than by local police forces.[8]

3.2. Police variables and data preparation

To measure the influence of structural variations in police resourcing, it is important to consider the roles and responsibilities associated with different personnel positions. The UK's Police Reform Act 2002[9] set out several designated police staff roles, such as community support officers and local authority designated officers. These roles aimed to enhance workforce flexibility, allowing police officers to concentrate on their core and exclusive policing duties and free them from common frontline duties such as policing anti-social behaviours and road safety (Home Office, 2015). With respect to the functions and powers of each role, we categorised police workers into two main categories: the main workforce, and the support workforce. The main workforce refers to police officers who have powers of arrest and who represent the core frontline workforce for criminal investigation (e.g. those who make arrests, conduct interviews or complete complex criminal investigations) and crime prevention, while the support workforce includes a range of personnel in auxiliary roles – such as PCSOs, DOs, special constables, and civilian staff – aimed at bolstering the effectiveness of the main workforce and ensuring operational efficiency. Whilst special constables possessing the same powers and responsibility in law as regular police officers, they are likely to be relatively less experienced as they are volunteers and not full-time employees (Britton, Callender, Cahalin, & Knight, 2021). For these reasons, special constables are considered to be part of the support workforce alongside other supporting roles that help police officers to perform core policing functions. Table 1 lists each of

[1] *'Police workforce England and Wales statistics'* Source: https://www.gov.uk/government/collections/police-workforce-england-and-wales

[2] PCSOs are publicly facing uniformed officers. They have some powers but not the 'core' list of powers (e.g. the power of arrest, stop and search and power to effect entry to property) as police officers.

[3] DOs include detention officers, investigation officers and escort officers who are intended to support police officers after vetting and training (e.g. entry and search after arrest, taking a person arrested by a police officer to a police station)

[4] Special constables are volunteers, part-timers who have the same powers as police officers.

[5] 'Home Office Statistical bulletins Archive'Source: https://webarchive.nationalarchives.gov.uk/20110218143229/http://rds.homeoffice.gov.uk/rds/hosbarchive.html

[6] *'Official Statistics Historical crime data'* Source: https://www.gov.uk/government/statistics/historical-crime-data

[7] Source: https://www.ons.gov.uk/peoplepopulationandcommunity

[8] See https://publications.parliament.uk/pa/cm5803/cmselect/cmpubacc/40/report.html

[9] Source: https://www.legislation.gov.uk/ukpga/2002/30/contents

the workforce groups employed in the research alongside a variety of police roles associated with each group.

To operationalise the police workforce's organisational characteristics, we identified three variables: *Size, Structure*, and *Stability*, drawn from concepts widely used in the Strategic Human Resource Management literature (see Datta, Guthrie, & Wright, 2005; Rogers & Wright, 1998). *Size* refers to the total number of personnel, including both main and support staff. *Structure* captures the functional composition, reflecting the balance between main and support workforce roles. *Stability* represents turnover rates, providing insight into the inflow and outflow of staff in each function.

3.2.1. Police Size - strength of workforces

Traditionally, police strength, defined as the total number of police officers, has been viewed as a metric strongly associated with police operations and efficacy. Although the findings are not consistent in all set-ups, the studies generally found a negative correlation between police size and crime levels (Kovandzic & Sloan, 2002; Lin, 2009).

As of March 2019, there were nearly 122,000 police officers operating within the 42 territorial UK police forces (153,000 police officers within the United Kingdom in total). As seen in Fig. 1 (a), total workforce numbers in the 42 forces increased slightly, by 1 to 2 % between 2007 and 2010 (from 245,011 to 258,300). Between 2010 and 2017 the numbers fell each year, culminating in a total reduction of 18 % compared to 2009. However, the last two years of the period analysed witnessed 4 % rise in police numbers from 2017 to 2019.

3.2.2. Police Structure - functional/hierarchical balance of organisational composition

Police organisational structures can be operationalised in various ways (e.g., Gaines & Worrall, 2011; Jermier & Berkes, 1979; Kuykendall & Roberg, 1982; Maguire, 2003). Some researchers have explored the structural characteristics of organisations using lists of their component parts such as rates/numbers of employees assigned to different roles (Crank, 1990; Crank & Wells, 1991; Slovak, 1988), a hierarchical ranks system (Crank, 1990; Slovak, 1988), and the use of specialised personnel for new technologies or policing programs (Manning, 1992; Zhao, Ren, & Lovrich, 2010). Early studies of police organisational structure conducted in the 1980s emphasised a vertical control system such as 'the span of control' which refers to the number of officers per supervisor or 'the number of ranks' as a vital measure to understand police organisational structures (see Crank, 1990; Slovak, 1988; Wells & Falcone, 1992). The police hierarchical structure, however, has been continuously transformed over time into a more flattened structure. This is partly because digital technologies and emerging social problems tend to stress functional specialisation rather than emphasise a command-and-control structure. Moreover, structural reforms have led to a proliferation of designated positions and changes to hierarchical levels (Maguire, 1997; Maguire, 2003; Zhao et al., 2010). Technological advances have also created new clerical and technical roles for civilian staff which have increasingly released officers from backroom activities (Maguire, 2003; Home Office, 2015). In the UK, an essential role in community safety has been assigned to PCSOs and other designated roles so that the main workforce can return to frontline duties where their skills are more in demand (Mills, Silvestri, and Grimshaw, 2010).

Recently, the UK National Police Chiefs Council (NPCC) proposed a five-level policing hierarchy that recognises police duties by responsibility, functions and technical expertise rather than rank (College of Policing, 2017). In this hierarchical structure, professional functions are grouped into five organisational levels that are Service deliverer (police personnel with full- or some-powers including police officers, special constables and designated officers) at Level 1, Team leader (Sergeant), Manager (Inspector), Service function leader (Superintendent), and lastly Force leader (Chief police officers) at level 5. As service deliverers, constables, the lowest rank of police officers, take the initial actions for criminal incidents – including responding to 999 emergency calls and conducting criminal investigations – and play a vital role in frontline policing (e.g., local policing and dealing with the public). Although other designated roles at Level 1 have full legal powers (e.g., special constables) or standard/discretionary powers (e.g., PCSOs), these staff concentrate on neighbourhood policing tasks that are unlikely to require the full legal powers commanded by officers, such as arrest or stop and search.

Given the direction of these structural changes in police organisations and current arrangements of police powers in England and Wales, as a way of measuring *compositional differences* in each force we focused on the balance between frontline and other functions (including supporting roles, see Table 1). Consideration is also given to variation in the police command hierarchy by examining variation in the proportion of officers at Level 1 of this hierarchy over time. Taking this approach, we define and operationalise police structure in the following three ways: (1) the proportion of total workforce designated as the main workforce (as defined above); (2) the proportion of support workforce employed for frontline duties (see *frontline supporters* in Table 1); and, (3) the proportion of the main workforce officers at the lowest level of hierarchy (i.e. constables who are at Level 1. Service Deliverer).

Although the main workforce accounts for the largest volume of police service strength across all 42 forces over time (see Fig. 1(a)), the proportion of the total workforce made up of the main workforce varies by force and over time, as the examples in Fig. 2 illustrate. As of March 2019, the proportion ranges from 41.44 to 70.16 %, with a mean of 52.31 % (SD = 5.93). The structural variation between different forces was also measured as the proportion of the supporting workforce in frontline duties. In 2019, this proportion ranges from 5.68 % to 23.93 % (average = 12.49, SD = 3.33 across all forces). The long-term trend in the main workforce proportion shows a decrease from 2007 to 2010 (Fig. 1 (b)), followed by a year-on-year increase up to 2017 (54.61 %). In the last two years, the previous upward trend is has slowed, with lower workforce figures in 2018 and 2019. The frontline supporting workforce increased each year during the first half of the time series but declined thereafter. In the aggregate, the percentage of the main workforce at Level 1 was somewhat stable over time (Fig. 1 (d)), however, further breakdowns of the data by force reveal that the percentage of the lowest ranking officers varies between 73 % to 81.06 % (average = 77.16, SD = 1.90).

Table 1
Descriptions of workforce groups

Workforce Groups	Description	Examples	Superset / Subset of
Total workforce	The total number of police personnel	All personnel	Superset of Main and Support workforces
Main workforce	The total number of sworn police officers	All police officers	Subset of Total workforce
Support workforce	The total number of non-sworn police support staff	Civilian staff, PCSOs, Designated Officers (detention officers, investigation officers and escort officers), Special Constables	Subset of Total workforce
Frontline Supporters	Support workforce members with community-facing roles	PCSOs, Designated Officers, Special Constables	Subset of Support workforce
Low-rank officers	The total number of sworn police officers at the lowest rank	Constables	Subset of Main workforce

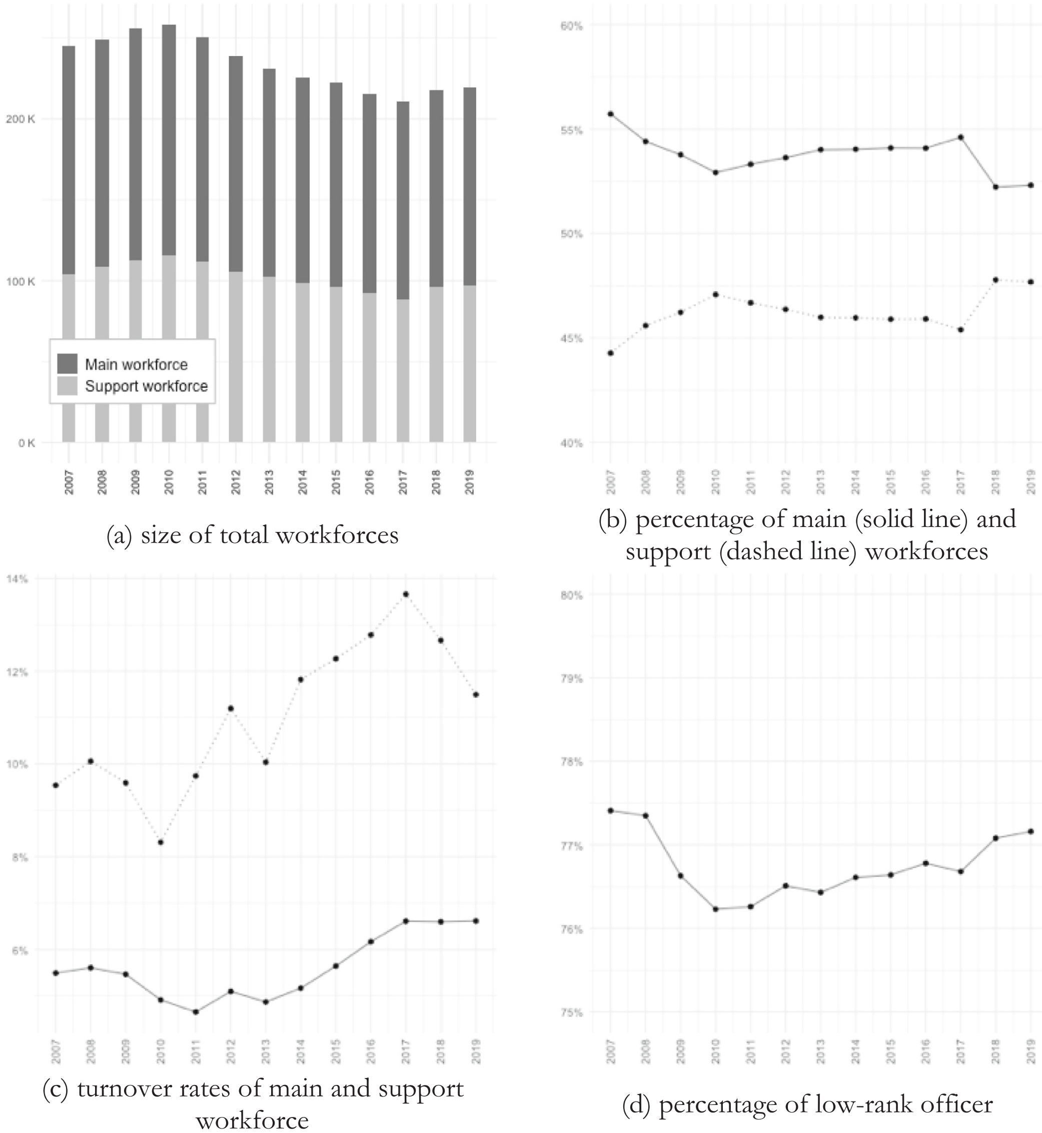

Fig. 1. Changes in workforce resourcing; by (a) size of total workforces, (b) percentage of main (solid line) and support (dashed line) workforces, (c) turnover rates of main and support workforce, and (d) percentage of low-rank officer.

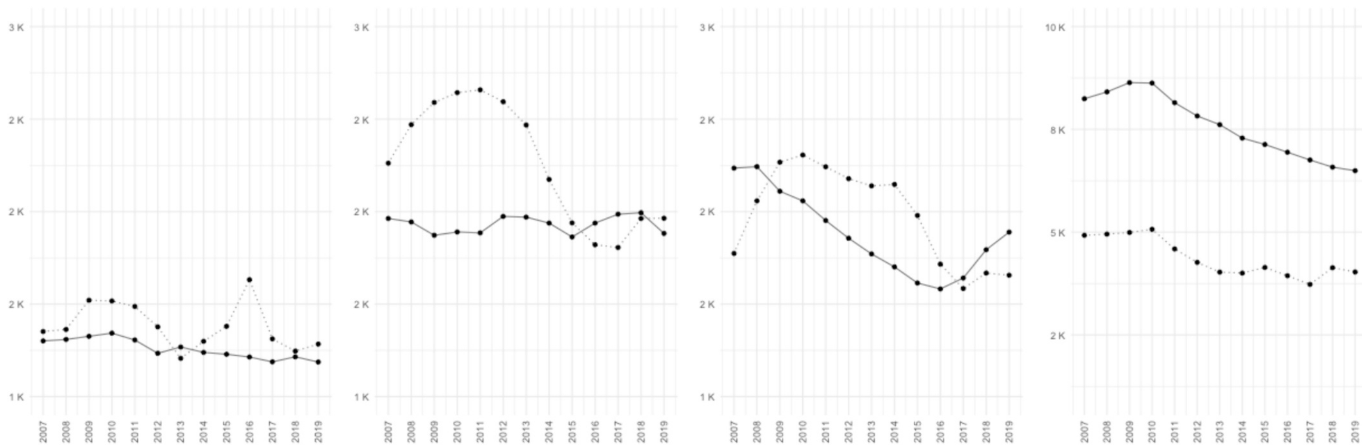

Fig. 2. Illustrative changes in main (solid line) and support (dashed line) workforce sizes.
*Note: (from left to right) Northamptonshire, Surrey, Humberside, and West Midlands

While the compositions of different functions and ranks in police service strength remained relatively stable over time at the national level, force level comparisons reveal noticeable variation (see Fig. 2) – presumably because each force may need to vary its staffing strategies in response to the demands on their services and external conditions (e.g., population changes, funding allocations). We suggest that the different staffing strategies of each force, which show the operational characteristics of each territorial force, will provide more nuanced insight into understanding the complicated relationship between police and crime.

3.2.3. Police Stability - turnover rates of each type of workforce

Stability reflects in- and out- flows in the police workforce over time. High turnover rates pose significant challenges for organisations, being both financially burdensome and detrimental to efficiency (Cohen, Blake, and Goodman, 2016). Among various methods that exist for analysing organisational stability, the most commonly used indicator is the wastage rate, calculated as a function of the number of leavers. However, this termination rate alone may not provide meaningful information to the police organisation due to the requirement for substantial follow-on investments to recruit and train new officers, and most forces expend considerable time and money in the selection process to achieve effective returns from new officers (Orrick, 2015; Wareham et al., 2013). Also, unlike many private sector organisations, police staffing decisions are directly shaped and impacted by external pressures and expectations (e.g., public interest together with political campaigning, cutbacks in budgets, and emerging/changing public demands) and decisions made by each force's internal context. Among different calculation methods, we therefore employed a turnover rate which includes both new hires and departures in a given year (see O'Connell and Kung, 2007; Aksu, 2008) rather than the total number of quits. For instance, for a force that currently employs 1000 officers, hires 50 new officers, and loses 70 officers during the year, the turnover rate would be $70/((1000 + 1050)/2) \times 100 = 6.83$ %. Taking workforce classification by functions into account, the turnover rates for both the main and support workforces were calculated separately.[10]

Variations in turnover rates are primarily influenced by new recruitment and are often attributable to external factors like police funding or government policy directives. As such, the up-and downward trend of turnover rates at the national level show how police staffing decisions have responded to external influences over the past decade. Following a 20 % budget cut in 2010, UK police experienced notably low turnover rates in subsequent years (see Fig. 1(c)). Compared with the previous year, in 2011, there was a fall of nearly 70 % in the number of officers joining the service. Since 2013, this trend has been mitigated by a year-on-year recruitment. This fairly stable upward trajectory is expected to persist, aligned with a government initiative launched in 2019 named '*Be a force for all*' with the objective of bolstering the number of police officers in the UK. A similar long-term trend was also seen in the support workforce turnover rate. Despite the main and support workforces being nearly balanced in terms of proportions, the turnover rates for the support workforce were nearly twice those of the main workforce.

3.3. Crime and Severity- the 'demand' on policing

Previously, we argued that analysis of the police-crime relationship needs to consider factors beyond mere crime volume-related demands. The severity and nature of crime are likely to influence (and be influenced by) police resourcing and demand dynamics. High-harm offences such as violence, sexual offences, and drugs have been growing in volume and this major shift in contemporary crime patterns significantly impacts police resources and investigative capabilities. Hence, our analysis assesses crime using both the total count of crimes within a force's jurisdiction and the aggregate severity attributed to these crimes, defined by the Office for National Statistics' Crime Severity Score (CSS). The CSS was developed to enhance comprehension of policing demand across an array of issues the police need to deal with. It is a measure that seeks to estimate both the severity of crimes, and in turn, the burden placed upon a police force in dealing with them, rather than simple numerical measures such as the number or rate of offences. It helps the police to build a 'crime profile' (ONS, 2021) so that they can prioritise places (and times) with a high representation of more serious incidents (e.g., homicide, sexual offences, assault) over less serious incidents (e.g., shoplifting, theft and criminal damage). To assign greater significance to more severe offences, the CSS uses the average sentence length in days by type of crime, for the last five years of sentencing data. The weight of each individual offence is computed by multiplying the proportion of offenders convicted of that offence who receive a punishment (e.g., custodial sentences, community orders, and fines) by the mean sentence length in days (or equivalent days in prison for community orders and fines). Once a weight for each offence is calculated, the weight is multiplied by the number of incidents reported to the police to generate the CSS. Over the last 15 years, the CSS and police-recorded crime rates have exhibited similar trends, with slight increases observed nationally in the last five years.

3.4. Descriptive statistics

Table 2 provides descriptive statistics for dependent and independent variables and how they varied overall (Overall SD), variance across forces (SD between Police Forces), and temporal fluctuations within forces (SD within Police Forces) across the 13-year time series encompassing 42 Police Forces. The variables that capture the organisational size and crime volumes were highly skewed and were consequently normalised using a log transformation. As of March 2019, the total workforce size across the 42 analysed forces ranged from 1714 to 43,382 full-time personnel with a mean of 5570. Over 90 % of police forces had less than 10,000 personnel, and only three forces had more than 10,000. Notably, there exists substantial variation across and within forces (over time) for all variables, relative to their respective overall means.

3.5. Statistical analysis

As discussed, a number of different methods have been employed in prior studies examining the police-crime relationship. Lee et al. (2016) highlight a progression in statistical models, referencing earlier studies influenced by Levitt (1997), which used instrumental variables to control for endogeneity, and more recently adoption of generalised method of moments (GMM) techniques following Kovandzic, Schaffer, Vieraitis, Orrick, and Piquero (2016). These studies have used methods for causal inference such as natural experiments, propensity score matching, instrumental variables, discontinuity designs, and difference-in-difference estimates, which are commonly recommended strategies for evaluating policy or programme effects. The central idea of those statistical approaches is to mitigate the potential threat of endogeneity. For example, different types of instrumental variables have been employed to address unobserved factors including an election cycle (Levitt, 1997), number of firefighters (Levitt, 2002), the COPs grants (Evans & Owens, 2007) and state tax rates (Lin, 2009). Natural and quasi-experimental approaches using techniques such as difference-in-difference estimates have been a popular choice to overcome simultaneity bias, where both police force action and criminal action influencing crime can be determined simultaneously (e.g., Machin and Marie, 2011; MacDonald, Klick, & Grunwald, 2016; Cheng & Long, 2018; Mello, 2019). These studies often report effect sizes as negative elasticity coefficients (Chalfin &

[10] Note that measures of stability only extend to the main and support workforces, and do not include a measure of lowest rank officer turnover as this turnover rate will be affected by not only of leavers and joiners at this rank, but also internal turnovers such as promotions or leaving a current position for a different role.

Table 2
Descriptive statistics ($N = 546$)

Variable description	Overall Mean	SD (Overall)	Min	Max	SD between Police Forces	SD within Police Forces (overtime)
Crime variables						
Total (annual) Crime Count	101,168	121,240	18,618	897,553	120,918	19,998
ln(total crime)	11.22	0.68	9.83	13.71	0.67	0.17
Cumulative Crime Severity	8.97	2.99	4	20.7	2.21	2.04
Police variables						
Size						
Total workforce	5570	7425	1654	55,693	7469	766
ln(total workforce)	8.33	0.63	7.41	10.93	0.64	0.08
Structure						
% Main workforce	53.78	5.51	41.44	77.45	4.91	2.61
% Support frontline workforce	14.71	3.62	5.68	28.81	2.73	2.41
% Low-rank officers	76.75	2.02	72.30	99.22	1.40	1.47
Stability						
Main workforce turnover rate	5.61	1.23	2.92	10.8	0.52	1.12
Support workforce turnover rate	11.01	3.30	4.22	28.46	1.67	2.86

McCrary, 2018). Thus, prior studies have addressed endogeneity in the police-crime relationship, suggesting an interactional and reciprocal perspective in understanding this relationship (see Lee et al., 2016).

Consistent with this perspective, the current study addresses endogeneity by focusing on autoregressive and bi-causal flows of police and crime, supplementing the literature beyond contemporaneous causation. The assumptions regarding the relationships between police funding allocation, recruitment, and crime are based on previous studies that demonstrate a causal relationship, incorporating both direct and feedback effects (e.g., Evans & Owens, 2007; Levitt, 1997; Mello, 2019). Accordingly, we structure the bidirectional approach to capture how workforce characteristics are conditioned by a combination of levels/ severity of crime and the workforce itself observed in the past, rather than the current or future values. For example, the probability of observing Y_t is determined by the past context such as Y_{t-1}, …. $Y_{t-p}$and X_{t-1}, …. X_{t-p}.

This principle guides the application of the PVAR model to investigate the interdependencies and identify the transmission effect of shocks of the police-crime relationship. This approach offers the advantage of a panel data design whilst accounting for endogeneity. Unlike conventional regression models that assume exogeneity of explanatory variables, it treats all variables endogenously in a flexible framework. The inclusion of panel data allows for the modelling of unobserved individual heterogeneity through fixed effects, a feature critical for capturing nuanced variations across different police forces and temporal shifts in crime patterns. (Abrigo & Love, 2016; Love & Zicchino, 2006). This consideration is important as it accounts for factors like changes to national police recording standards and variation across police forces, which may not be explicitly captured by independent variables. Moreover, the PVAR model facilitates impulse-response analysis enabling dynamic responses of crime to structural changes of policing. Through the forecast error variance decomposition, it quantifies the contribution of police variables to crime variation over time, offering insights into the temporal dynamics the nexus of the police-crime.

Whilst extensively used in economics to estimate the endogenous interaction of variables in systems (Yang, An, Chen, & Yang, 2023), the PVAR model has seldom been used in crime-related research. Exceptions include Drakos and Konstantinou (2014), who used the VAR model to explore the dynamic relationship between spending on public order and safety, and crime and terrorist attacks in 29 European countries; and Nayebyazdi (2017), who employed PVAR to explore the causal relationship between crime and economic growth in EU countries. Relevant to the current topic is the research by Atems (2020), which examined the effects of police expenditure – but not variation in force size, structure or stability – on crime at the state level in the US. To the best of our knowledge, the current study is the first attempt to estimate the dynamic relationship between crime and multiple police workforce characteristics using the PVAR approach.

Prior to the PVAR analysis, we tested the police-crime relationship using the basic panel regression model with fixed effect and dynamic panel models with lagged dependent variable, employing Generalised Method of Moments (GMM). These preliminary models captured statistically significant relationship between police workforce variables and crime but not fully account for the bidirectional dynamics of the relationship. All models yielded statistically significant outcome, providing the foundation for the subsequent PVAR analysis, which capture the dynamic interaction and associated shocks between variables.

Following causality analysis and PVAR model estimation, Impulse-Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVD) were computed using Monte Carlo (MC) simulations to explore the impact of each endogenous variable accumulated over time (see Love & Zicchino, 2006). Details of the validity of these methods and their interpretation as applied to the specific research will be provided subsequently.

3.6. Preliminary tests and optimal lag setting

Prior to estimating the PVAR model, panel unit root tests were conducted to verify whether the data sets were stationary and cointegrated. The challenges of using non-stationary series in the PVAR analysis have been extensively discussed (e.g., Binder, Hsiao, & Pesaran, 2005; Hurlin & Mignon, 2007). The existence of a unit root in the series may lead to spurious regression bias. As such, data transformation using growth rate or differencing is recommended if a unit root is detected (Abrigo & Love, 2016). In this study, three second-generation tests were applied (1) Im, Pesaran and Shin (2003: IPS, Table 3), (2) Augmented Dickey and Fuller (1979: ADF-Fisher, Table 3), and (3) Levin, Lin and Chu (2002: LLC, Table 3).

Following Levin, Lin, and James Chu (2002), panel variables were adjusted by subtracting cross-sectional means to control for contemporaneous correlations. Table 3 reports the results of the panel unit root tests. The finding indicate stationarity for both crime and police resourcing variables, which satisfies a necessary condition for the PVAR model. While CSS and the total workforce size exhibit some evidence of non- stationarity in certain tests, the Levin-Lin-Chu test, considered robust to cross-sectional dependence, strongly rejects the null hypothesis of a unit root. Therefore, we conclude that the panel of 42 police forces are stationary in levels, eliminating the necessity of differencing data. A cointegration test confirmed the absence of long-term cointegration relationships within the model. This supports the suitability of the PVAR model over a Panel Vector Error Correlation Model.

Table 3
Panel unit-root tests

Variables	Panel-specific autoregressive parameter		Common autoregressive parameter
	IPS	ADF-Fisher	LLC
ln(total crime)	−3.61***	203.77***	−1.54*
Cumulative Crime Severity	0.20	92.30	−3.17***
ln(Total workforce)	0.08	99.44	−4.51***
% Main workforce	−1.38*	135.88***	−5.61***
% Support frontline workforce	−1.86**	124.44***	−5.58***
% Low-rank officers	−1.75**	159.49***	−11.81***
Main workforce turnover rate	−5.77***	203.95***	−8.36***
Support workforce turnover rate	−5.08***	202.92***	−7.41***

*Note 1: *p < .10,** p < .05,*** p < .01.
*Note2: The null hypothesis of the tests is that all series contain a unit root.
*Note3: The optimal lag length 1 is based on using conventional information criteria such as Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (BIC).

Next, a set of model selection criteria was employed to determine optimal lag orders for the analysis. Since all inference in the VAR model rely on lag order selections, determining lag order is important (Hatemi-J, 2003). As a rule of thumb, the order length that satisfies Hansen's J statistics and minimises the modified Akaike information criteria (MAIC), the modified Bayesian information criteria (MBIC) and the modified Hannan-Quinn information criteria (MQIC) was chosen (see Akaike, 1969; Andrews & Lu, 2001; Hannan & Quinn, 1979; Hansen, 1982; Schwarz, 1978).

Following these estimations, a second-order PVAR model was selected and estimated using the generalised method of moments (GMM). The first three lags of the endogenous variables were used as instruments. The approach also satisfied the eigenvalue stability conditions, confirming the stability of the models (Abrigo & Love, 2016).

Formalising, given a k-variate PVAR of order p, the model is defined as,

$$X_{it} = \Gamma_1 X_{it-1} + \ldots + \Gamma_p X_{it-p} + u_i + e_{it} = A(\Gamma)X_{it} + u_i + e_{it} \tag{1}$$

where i and t are an index of police forces and years, X_{it} denotes a vector of variables ($k \times 1$) for each force-year combination, u_i and e_{it} are the vector of force fixed effects and the random error terms respectively. $A(\Gamma)$ is the coefficient matrices ($k \times k$) to be estimated. The model assumes no autocorrelation and cross-correlation among error terms. The model is estimated by GMM estimator, and the panel effect due to lags of the dependent variables was removed applying the first differencing transformation (see Arellano and Bond, 1991).

One of challenges in interpretating the PVAR model arises from the presence of contemporaneously correlated innovations (e_{it}). These represent unexpected changes in individual variables that often coincide with shocks in other variables within the system. This contemporaneous correlation complicates causal inference, making it difficult to isolate the unique causal effect of a single shock on a specific variable (Lütkepohl, 2005). To mitigate this and facilitate casual inference, Sims (1980) suggested the Cholesky factorisation to impose a recursive structure on the model. By leveraging the covariance matrix $\Sigma = PP'$ using the lower triangular matrix P and its transpose P', the innovations can be orthogonalised as $P^{-1}e_{it}$. This process transforms the simple IRFs (Φ_i) into $\Phi_i P$ which helps imposing identification restrictions on the system. Additionally, this approach enables the generation of dynamic responses in every other variable within the system, separately influenced by shocks to single variables. Confidence bounds are established through Monte Carlo simulation modelling involving 500 iterations.

The formulation of the h − step ahead forecast-error is as follows:

$$Y_{it+h} - E[Y_{it+h}] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\Phi_i \tag{2}$$

$$\sum_{i=0}^{h-1}\theta_{mn}^2 = \sum_{i=1}^{h-1}\left(i_n' P\Phi_i i_m\right)^2 \tag{3}$$

where Y_{it+h} represents a vector observed h steps ahead at time t, and $E[Y_{it+h}]$ denotes the predicted vector for the same horizon. The summation term accumulates forecast errors e_i over the time horizon h, each weighted by the corresponding impulse response function $\Phi_i P$.

Similarly, shocks are orthogonalised using the matrix P to isolate the contribution of each variable to forecast-error variance. The resulting orthogonalised shocks $P^{-1}e_{it}$ possess a covariance matrix I_k. The contribution of a variable m to the h step ahead forecast-error variance of variable n can be written as Eq. 3, where i_s represents the sth column of I_k.

Having conducted stationarity tests and determined the optimal lag lengths, we established the model setup necessary for subsequent analyses.

4. Results

Following the account of finalisation of the model setup, we now turn to the empirical results. In this section, we present the findings from the three analytical techniques: Granger causality to test directionality, impulse-response functions (IRF) to evaluate the timing of effects, and forecast error variance decomposition (FEVD) to determine the contribution of each variable to variance in crime outcomes. To maximise ease of interpretation, each of these techniques are detailed in the three subsections below followed immediately by the results.

4.1. *Granger causality: directionality of police-crime causal associations*

A causality estimation was performed using the Granger causality test, to explore the police-crime causal association that may exist and identify cross-correlation (see Dumitrescu & Hurlin, 2012; Apergis, Payne, Menyah, & Wolde-Rufael, 2010). For simplicity, consider the simple first order PVAR model which is made up of two equations, where y and x relate to our crime and policing variables, respectively:

$$y_{it} = \Gamma_{11}y_{i,t-1} + \Gamma_{21}x_{i,t-1} + \Gamma_t + \mu_{1i} + \epsilon_{1it} \tag{4}$$

$$x_{it} = \gamma_{21}x_{i,t-1} + \gamma_{11}y_{i,t-1} + \gamma_t + \mu_{2i} + \epsilon_{2it} \tag{5}$$

The null hypothesis for the Granger causality test is $H_0 : \Gamma_{21} = 0 : x_{it} \rightarrow y_{it}$ or $H_0 : \gamma_{11} = 0 : y_{it} \rightarrow x_{it}$. For instance, if $\Gamma_{21} = 0$, the past values of x have no effect on y and we can conclude x does not Granger cause y.

Table 4 reports the results of the panel Granger-causality analysis with Wald test statistics and the corresponding p-values. In the table, the second and third columns show the results of testing whether *Crime 'Granger-causes' changes to the police workforce* (i.e. whether changes in the crime variables are related to subsequent changes in the policing variables) and the fourth and fifth columns test the reciprocal effect; that is, whether *changes to the police workforce 'Granger-causes' Crime* (i.e. whether changes in the policing variables are related to subsequent changes in the crime variables). Model 1 shows the results for crime volumes, and Model 2 shows those for cumulative crime severity. For

Table 4
Results of a causal relationship

	Null hypothesis	Wald Statistic	Null hypothesis	Wald statistic
	Total crime does not cause *Total workforce*	51.12*	*Total workforce* does not cause *Total crime*	21.02*
	Total crime does not cause % *Main workforce*	6.01*	% *Main workforce* does not cause *Total crime*	0.38
	Total crime does not cause *% Support frontline workforce*	1.84	*% Support frontline workforce* does not cause *Total crime*	3.79
Model 1	*Total crime* does not cause % *Low-rank officers*	0.10	% *Low-rank officers* does not cause *Total crime*	0.57
	Total crime does not cause *Main workforce turnover rate*	2.35	*Main workforce turnover rate* does not cause *Total crime*	12.42*
	Total crime does not cause *Support workforce turnover rate*	10.21*	*Support workforce turnover rate* does not cause *Total crime*	0.44
	Cumulative Crime Severity does not cause *Total workforce*	7.11*	*Total workforce* does not cause *Cumulative Crime Severity*	31.07*
	Cumulative Crime Severity does not cause % *Main workforce*	4.90*	% *Main workforce* does not *Cumulative Crime Severity*	7.36*
	Cumulative Crime Severity does not cause *% Support frontline workforce*	22.56*	*% Support frontline workforce* does not cause *Cumulative Crime Severity*	2.61
Model 2	*Cumulative Crime Severity* does not cause % *Low-rank officers*	4.67*	% *Low-rank officers* does not cause *Cumulative Crime Severity*	1.27
	Cumulative Crime Severity does not cause *Main workforce turnover rate*	17.48*	*Main workforce turnover rate* does not cause *Cumulative Crime Severity*	15.67*
	Cumulative Crime Severity does not cause *Support workforce turnover rate*	1.51	*Support workforce turnover rate* does not cause *Cumulative Crime Severity*	7.93*

Note: $^*p < .1$.

robustness and validity, a causality test suggested by Dumitrescu and Hurlin (2012) was also employed and yielded similar results. All tests are bivariate in the sense that they include only the variables shown for each analysis using PVAR models including the panel-fixed effect discussed above.

Beginning with Model 1, the results indicate that there is bidirectional causality between total crime and police total workforce size as there are significant results in both directions. There is also unidirectional causality between total crime volume and (1) the percentage of the main workforce, and (2) the support workforce turnover rate. This suggests that changes in total crime can be used to predict subsequent changes in some police structure and stability variables. Main workforce turnover also shows unidirectional causality for crime volume, suggesting that stability in the main workforce predicts crime volume. Model 2 demonstrates more evidence of bidirectionality between changes in the Crime Severity Score and the policing variables with all but 3 of the 12 tests being statistically significant. Notable exceptions are the fact that changes in CSS appear to influence subsequent changes in two structures that might indicate harder-pressed resources; the ratios of support frontline staff and low-ranking officers, but the reverse is not true (changes in the fraction of these staff do not appear to influence CSS). Model 2 also shows evidence of significant causal dynamics between both staff turnover rates and the CSS. For both types of staff considered, stability appears to predict the CSS. Considering the influence of the CSS on staff stability, this varies by turnover type with CSS predicting turnover in the main workforce but not in the supporting workforce. Collectively, the results of the causality tests of crime frequency and severity indicate that the variables in the system are interchangeably influencing each other overall and confirms that past values of these series are useful predictors of current and future values. Put differently, it appears that police resourcing decisions might be particularly sensitive to or influenced by recent surges or declines in the severity of crimes, and similarly, crime appears to be sensitive to changes in some (but not all) changes to workforce composition.

4.2. The impulse-response functions (IRFs): time scales of police-crime causal dynamics

Impulse-response analyses were conducted using Cholesky Decomposition to test orthogonal shocks, assessing how policing variables respond to crime changes and vice versa over time. Given the sensitivity of the method to the ordering of variables, we assumed police structure and stability would be the most exogenous factors, influencing crime both contemporaneously and with a lag. These assumptions are grounded in the results of the causality tests and prior empirical studies. Shocks to police resourcing are thus expected to affect crime immediately, while crime shocks influence police resourcing with a time lag. To ensure robustness, alternative variable orderings were tested, and the results remained consistent across all configurations. The qualitative robustness of the findings confirms the reliability of this analytical approach, which will not be discussed further here.

The plots shown in row 1 of Fig. 3 illustrate the responses of crime following an impulse of a one standard deviation increase in police workforce changes. The impulse responses are plotted over 10-year time horizons and the two dashed lines illustrate the 95 % confidence intervals. Model 1 shows the impulse of an increase in total workforce numbers and examines the response of crime. For each of the subsequent Models (1 A to 1E), in addition to total workforce numbers, additional police structural or stability variable is included to assess the response of crime to changes in each of these variables. As such, models 1 A-1E show the effects of these variables net of the impact of changes in the volume of the total workforce. Due to the specified ordering, the immediate responses of these additional police variables are constrained to zero in the initial period.

Conversely, the plots shown in row 2 of Fig. 3 show how the policing variables react to one standard deviation increase in crime volume. Model 1 shows the effect on total police personnel numbers, while subsequent models (1 A to 1E) show the effects on the additional variables. In Fig. 4, Models 2 A through 2E replicated these analyses but explore the impacts of changes in crime severity, using the cumulative CSS instead of crime volume. As previously discussed, crime responds contemporaneously to changes in police staffing, while the impact of crime on subsequent police staffing decisions is constrained to zero initially.

The results show that following a shock to total workforce strength, both crime volume and severity decrease, while total workforce strength rises after a crime shock (measured in terms of volume or CSS). The response of crime to total workforce size presents a reductive effect with a peak reached after around 2–3 years. Following this, the peak levels out and the effect on crime is zero after around 6–7 years. On the other hand, following a crime shock, the response of total workforce size is positive (i.e., the workforce increases), with peak effects occurring around 2–3 years later. Although the crime-police relation has not been estimated using a VAR approach in previous studies, the findings of the impulse-response analysis that crime decreases following an increase in workforce strength are consistent with the existing empirical work suggesting an increase in police numbers reduces total crime or certain types of crime (Kovandzic & Sloan, 2002; Levitt, 1997; Vollaard & Koning, 2009). Fig. 3 also shows that there is a substantial variation in crime responses to changes across the structural and stability variables. Results show that crime initially declines following a shock in frontline support strength, while crime initially rises following increases in the

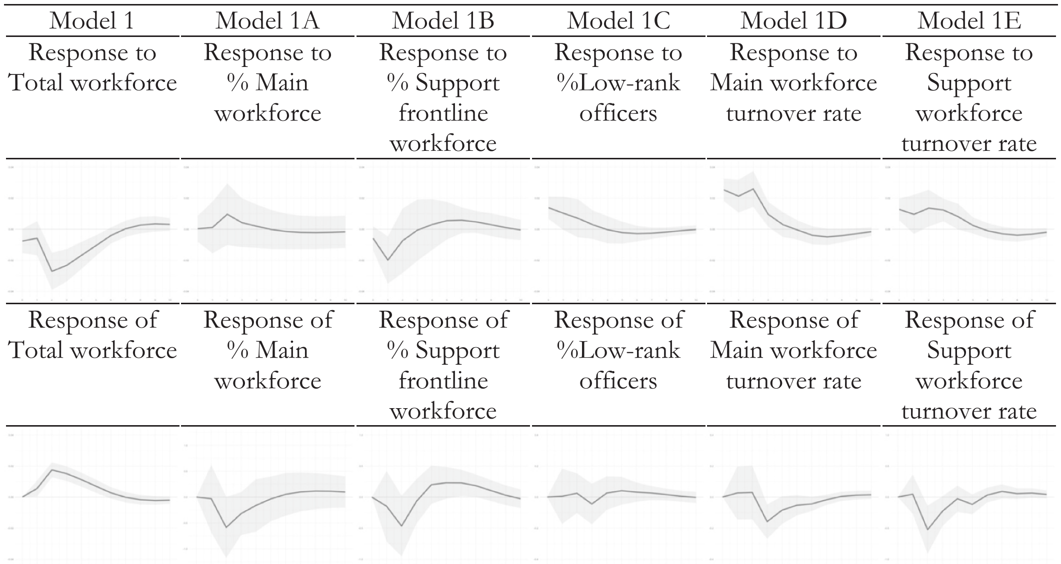

Fig. 3. Impulse Response Functions of Crime and Police.

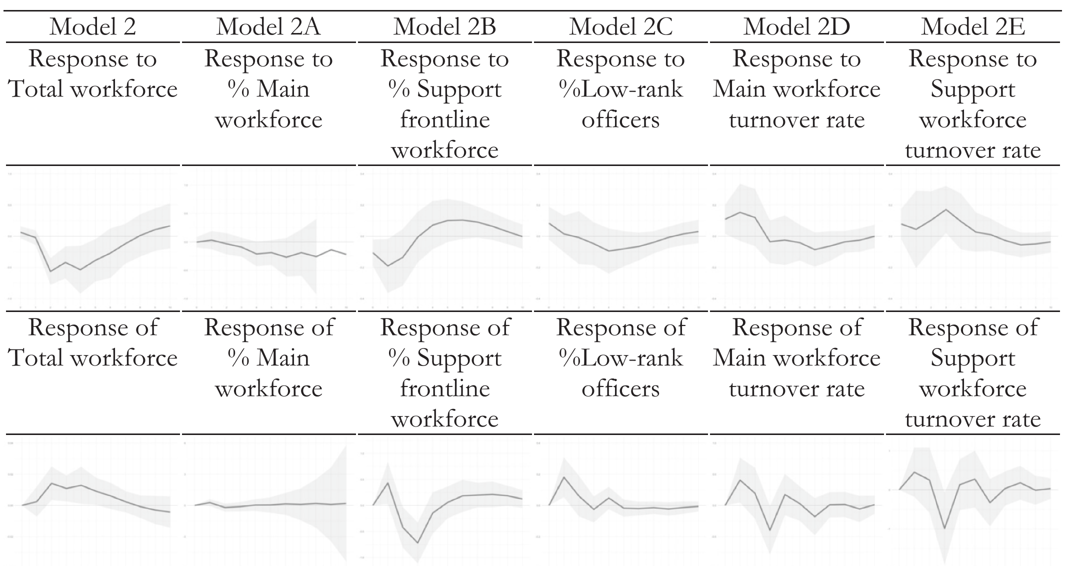

Fig. 4. Impulse Response Functions of CSS and Police.

fraction of low-ranking officers and when turnover rates of both main and support workforces increase. For the stability variables, crime appears to increase in response to turnover shocks although the effect is immediate and short-lived (1–2 years). Notably, and unlike the analyses for total workforce volume, these effects are unidirectional – a selective pattern of results that not only makes sense but provides confidence in the findings.

The responses of CSS are quite similar to those found for crime volume. CSS responds significantly and negatively to total workforce strength and the percentage of personnel who are frontline supporters, however, the persistence of these effects varies across the two crime variables. The results indicate that the effect of total workforce strength shock on CSS levels out after around 5–6 years but CSS responses to the percentage of supporting roles in frontline function are relatively short-lived, with the effect falling rapidly after being significant only for the first few years. Similar to the result for the Granger test, Model 2 also shows that the police structural variables – such as the percentages of support frontline staff, and low-rank officers, – respond positively to CSS (i.e., increase with increased CSS) but do not respond significantly and consistently to total crime. These findings might suggest that police staffing decisions more sensitively respond to and are influenced by police demand as measured (here) by severity rather than the total volume of crime incidents.

4.3. *The forecast error variance decomposition (FEVD): the relative importance of size, structure and stability variables*

Lastly, to estimate how much one variable contributes to explaining changes in another, a variance decomposition was conducted. Tables 5 and 6 present the FEVD results for crime and CSS, based on the PVAR model. The tables show how much variation in each row variable is explained by its own shocks as well as by shocks from other variables. For instance, the final row of Table 5 indicates the percentage contribution of police size, structure (Models 1 A–1C), and stability (Models 1D–1E) to variations in crime volume.

As might be expected, a variable's own shocks have a larger explanatory power of forecast variance than any cross shocks. The results for Model 1 A indicate that total workforce size and the percentage

Table 5
Forecast error variance decomposition of crime and police (in per cent at 10-year horizons)

Model 1 A % Main workforce (M)				Model 1B % Support frontline workforce (S)				Model 1C % Low-rank officers (LR)				Model 1D Main workforce turnover rate (MT)				Model 1E Support workforce turnover rate (ST)			
	M	T	C		S	T	C		LR	T	C		MT	T	C		ST	T	C
M	0.79	0.12	0.08	S	0.66	0.26	0.08	LR	0.88	0.12	0.00	MT	0.86	0.13	0.02	ST	0.92	0.06	0.02
T	0.41	0.33	0.25	T	0.10	0.70	0.20	T	0.01	0.79	0.20	T	0.08	0.69	0.23	T	0.07	0.72	0.21
C	0.01	0.19	0.80	C	0.04	0.29	0.68	C	0.03	0.22	0.75	C	0.15	0.12	0.73	C	0.05	0.24	0.71

*Note: T = Total workforce, C = Total crime.

Table 6
Forecast error variance decomposition of css and police (in per cent at 10-year horizons)

Model 2 A % Main workforce (M)				Model 2B % Support frontline workforce (S)				Model 2C % Low-rank officers (LR)				Model 2D Main workforce turnover rate (MT)				Model 2E Support workforce turnover rate (ST)			
	M	T	CS		S	T	CS		LR	T	CS		MT	T	CS		ST	T	CS
M	0.29	0.71	0.00	S	0.62	0.20	0.17	LR	0.92	0.05	0.03	MT	0.57	0.34	0.10	ST	0.68	0.27	0.05
T	0.25	0.66	0.09	T	0.05	0.81	0.15	T	0.01	0.81	0.17	T	0.03	0.76	0.20	T	0.06	0.78	0.16
CS	0.11	0.33	0.56	CS	0.04	0.30	0.66	CS	0.01	0.38	0.61	CS	0.02	0.36	0.61	CS	0.02	0.41	0.56

*Note: T = total workforce, CS = Cumulative Crime Severity.

of the main workforce explain 19 % and 1 % of the fluctuations of crime respectively. In this model, crime itself accounts for nearly 80 % of its own change at a 10-year time horizon. In Models 1B to 1E, crime is still the most influential variable in explaining its own variation, accounting for around 70 % in all cases. The results in Models 1D and 1E show that the stability variables explain 15 % (for main workforce turnover) and 5 % (for support workforce turnover) of the variation in crime respectively. Conversely, crime accounts for less of the variation in both these turnover rates (approximately 2 % in both cases). This supports the earlier findings and indicates that staff turnover can have a disruptive effect on crime, but not vice-versa. In Table 6, approximately 60 % of the variance in CSS is attributed to its own shock and approximately 35 % is attributed to total workforce size changes in all models. Comparing Tables 5 and 6, total workforce strength has more influence in predicting subsequent crime severity than it does in predicting crime volumes. We also find evidence that frontline personnel (both officers and support staff) play an important role in explaining changes in CSS. This is inferred from the fact that the percentage of all personnel that are officers accounts for 11 % of CSS variance in Model 2 A and the percentage of personnel that are frontline support staff account for 4 % of the variance in Model 2B. Further, considering the reverse directionality, Table 6 also demonstrates that CSS explains 17 % of the fluctuations in the percentage of staff who are frontline supporting staff and 10 % of the changes in officer turnover rate. This is in line with our earlier finding that police resourcing and crime severity are more strongly linked than police resourcing and crime volumes.

Overall, except for Model 1D, it is apparent that of the cross shocks, changes in total workforce size are most influential in explaining changes in both crime volume and severity variables. The variance decomposition shows that total workforce size explains approximately 20 % and 35 % of the fluctuations of crime and CSS respectively. Following this, turnover rates and the percentage of officers in frontline roles are the next most significant variables to be considered in explaining crime and CSS respectively. Lastly, the police structural resourcing variables appear to be a more influential shock in explaining CSS than total crime.

5. Discussion and conclusion

While previous studies of the police-crime relationship have provided some evidence of an association between police strength - that is, the size of the police workforce - and levels of crime, findings have tended to suggest minor and inconsistent effects (Bradford, 2011; Lee et al., 2016). Interpreting these results, one might conclude that, relative to a range of other external factors, such as those created by shifts in demographic, social-cultural, political, and economic circumstances, changes to the police workforce has little to no effect on crime. An alternative interpretation of these findings, however, is that the way in which the independent and dependent variables have been measured in previous studies has failed to capture important pieces of the puzzle. In the case of police resources, the volume of police personnel is important but fails to capture how police resources are organised structurally or impacted by recruitment and retention. For crime, examining simple counts of offences neglects diversity in the nature, severity, and complexity of offending and, in turn, the resources required to address it. Taking these complexities into account, we have argued that changes in police workforce structure, the deployment of existing and new officers and supporting resources could yield critical improvement in crime control efforts.

To better inform discussion of how to manage police resources and how they can most efficiently service policing demand, we need to do more than purely consider the police volume and move towards measures that also incorporate organisational structure. A more nuanced understanding of the police-crime relationship is crucial because it has the potential to assist the police in determining which structural interventions might help them address crime more efficiently. The idea of police forces using basic officer-to-population ratios to make staffing decisions appears outdated and over-simplistic. It is a key time to better understand the relationship between the police and crime. In the UK for example, employee salaries constitute nearly 80 % of the UK's total police budget (see UK Parliament. House of Commons Home Affairs Committee, 2011) and the UK government launched a national campaign to recruit 20,000 new police officers between 2019 and 2023 with the aim of reducing crime. At the same time, in many countries, the functions and roles of existing police staff are changing to reflect new priorities and complexities and hence it would be useful to have an evidence base to inform resource allocation decisions.

As discussed in the introduction, the current literature suggests a great deal of uncertainty about the effects police workforce structure and stability might have on crime. To date, the majority of existing studies have, for a host of reasons, focused mainly on bivariate correlational evidence rather than attempting to unpick the undoubtedly complex causal factors at play. Moreover, most of the existing work focuses on policing in a US context, with a very limited number of studies having been conducted elsewhere. This is a missed opportunity in understanding the universality (or otherwise) of the police-crime dynamic across different countries. Moreover, the UK context studied here provides an ideal opportunity for exploring the impact of organisational change, as the UK police have experienced significant budget cuts in the last 10 years, which in turn has influenced various staffing decisions of police forces. A specific example of this is the strategy of hiring more PCSOs and other frontline support officers, individuals who provide community-facing roles, but who are less expensive to employ than police officers. Similarly, over the same period, social and technical changes have led to significant changes in the nature of crime, with low harm property offences decreasing, while more harmful offences related to vulnerability and the need to collect more complex evidence rising (House of Commons, 2018). This suggests that as well as pure police numbers being an over-simplification in the police-crime relationship, simple counts of crime are likely not adequate in representing the heterogeneity in police demand associated with contemporary offences.

Collectively then, in an attempt to overcome these challenges, the analyses undertaken in this paper have combined a range of publicly available crime and police resourcing data to capture changes in the size, structure and stability of 42 police forces over an extended time period of 13 years, and to measure changes in the estimated severity of crime as well as its frequency. In analysing these data, a panel regression approach was employed to account for the complex bidirectional relationship which is often seen between police numbers and crime and to enable investigation into the longevity of any effects. While other studies have reported that they observed insufficient variation in key variables to adequately test the effect of changes (e.g. Maguire, 2003), our collated data demonstrate adequate variability across all measures studied.

The results of the PVAR analyses provide a number of significant new insights. First, across all models, there was a measurable and significant relationship between police personnel numbers and crime both in terms of volume and severity. This bidirectional relationship is consistent with findings from other studies (e.g., Kovandzic & Sloan, 2002; Levitt, 1997; Vollaard & Koning, 2009) and, we believe, demonstrates the appropriateness of our chosen method in quantifying such relationships.

Our second general finding is that there was a significant relationship between both crime frequency and severity, and the structure and stability of police workforces. First, we find that the percentage of frontline support staff is significantly associated with reductions in crime frequency and cumulative severity. In contrast, changes in the percentage of the workforce that were trained police officers, or that were in higher or lower ranks were not significantly associated with crime. Whilst these are initial results from a single study, an interesting implication is that community facing police support personnel - who work closely with communities and businesses and are likely to be visible on the street - may have value in terms of their reductive effects on crime, despite them not concentrating on core policing tasks that require specific skills and powers. Under the recent UK police reforms, these police support staff are expected to play a vital role in community safety and free up police officers to concentrate on more complex cases and those tasks that only sworn officers can carry out. While their impact on crime was mild, the finding suggests that police support staff indeed may play a key role in community policing and subsequently help reduce crime and crime severity.

A third key finding is increased levels of staff turnover, in both the main and support workforce, were associated with increases in crime frequency and severity. We suggest that high staff turnover could potentially be damaging in terms of police effectiveness. There are a number of reasons why this might be the case. For example, when turnover is high, there may be a deficit in well-trained, sufficiently experienced staff which, among other things, is likely to decrease the organisation's efficiency. High turnover also places a burden on an organisation to recruit and train new staff, which represents an opportunity cost. In the UK, the College of Policing has pointed out the logistical challenges associated with the recruitment process, asserting that some forces do not have enough training instructors and professional support to aid in this process (see Shohel, Uddin, Parker-McLeod, & Silverstone, 2020). As such, our findings suggest the importance of retention policies in maintaining police effectiveness.

A fourth key finding is that police structural resourcing decisions, such as the use of frontline supporting staff and low-rank police officers, reduce crime severity more than volume. This implies that visible policing in the community might be a helpful strategy for dealing with higher-harm crime. Given that both crime and crime severity are related to staff turnover is a useful general finding and strategies to retain staff for longer or to train staff more adequately on initial entry to the police appear relevant.

It is important to acknowledge the limitations of the study. The most salient of these is whilst the PVAR method is well set up to deal with endogeneity, the reality of the causal relationship between crime and policing is inevitably more complex than any statistical model could accommodate. Truly untangling the causal relationships would obviously require experimental methods and systematic evaluation, which is very challenging to organise when the variable of interest is a vital public service. While the PVAR approach allows for the simultaneous estimation of the effects of organisational structure on crime, it offers evidence of association rather than establishing causality. Future research could employ instrumental variable techniques or natural experiments to better identify the causal effects of police workforce changes on crime outcomes. Second, the analysis is based on aggregate data at the police force level, which may obscure important within-force variations in police staffing decisions and crime patterns. Future studies could employ micro-level data to examine how individual-level characteristics of police officers and crime offenders influence the observed relationships. The study also does not consider potential mediating or moderating factors that may influence the relationship between police workforce changes and crime outcomes. Future research could explore how factors such as community demographics, policing strategies, and social policies interact with police workforce dynamics to shape crime patterns of the force.

Moreover, this study is specific to the UK-based policing context. To build solid empirical evidence on policing strategies, future longitudinal studies should explore causal associations in other jurisdictions and over different time spans, and further studies on structural policing variables would assist in establishing the external validity of the results found here.

While not a weakness, it is also important to remind the reader that while this study explored the relationship between measures of police size, structure and stability and crime, much of what the police do, and therefore organise their resources around, is not related to crime. Police demand can manifest in diverse ways (Laufs et al., 2020), with recent research for instance estimating that only 10–20 % of calls for service relate to the occurrence of crime (College of Policing, 2017). As such, it may well be the case that the factors explored here have stronger causal links to the management of non-crime related demand (such as the protection of the vulnerable, dealing with anti-social behaviours, and alcohol-related disorder). This, of course, remains an as yet unexplored empirical question and one for which it may be difficult to identify suitable measures of non-crime related demand at sufficient levels of accuracy to facilitate suitable analyses.

In terms of future research, one natural extension to the work would be to operationalise more detailed crime variables, such as tracking the ratio of low-high harm offences or conducting a longitudinal analysis by disaggregated crime types. The degree to which this would lead to robust analysis would depend on the frequency and the nature of the individual crime types. For example, with disaggregated analysis, we may need to acknowledge that for some offences more officers might in fact be likely to lead to more crime - (i.e., for crimes discovered and recorded by police - such as drug offences). Additionally, we might even consider variables that track stability in crime measures - it could be that if the split of crime by low/high harm keeps changing and is less predictable, it is more problematic for police to deal with. Moreover, applying the PVAR model on the national level or incorporating data from Crime Survey for England and Wales could offer a broader perspective into crime underreporting and its relationship with resourcing

In conclusion, this study shows the potential of considering not only the volume of police personnel in terms of servicing crime-related police demand but also the importance of considering the organisational structure in addressing crime volume and crime severity. While our study focused on a period prior to major external shocks such as Covid-19 pandemic, the Police Uplift Programme, and significant events like the recent 2024 riots, future research should investigate how such factor, alongside administrative changes such as update to crime recording practices, or other societal shifts, might alter the dynamics between police staffing and crime. This could enhance our understanding of effective resourcing strategies across varying contexts. We found that increases in the proportion of frontline support staff are associated with reductions in both crime frequency and severity, while increases in staff turnover are associated with increases in both crime frequency and severity. Our findings suggest that investing in frontline support staff and developing effective retention strategies are key to maximising crime reduction in resource-pressed police environments. Specifically, strategies to improve workforce stability could include enhanced training to improve role-specific skills and task allocations between main and support staff, improved job satisfaction initiatives, and financial or non-financial incentives to reduce turnover. Furthermore, better structuring of police resource management strategies, such as aligning the distribution of police roles across crime and non-crime demands, can lead to more efficient resource use. These changes, when combined with strategic staff allocation and focusing on workforce stability, can enhance police effectiveness, particularly in today's complex and diverse crime landscape. Future research should continue to explore the complex mechanisms underlying the relationship between police workforce dynamics and crime outcomes, with the goal of informing evidence-based policing strategies that enhance public safety.

CRediT authorship contribution statement

Eon Kim: Writing – review & editing, Writing – original draft, Conceptualization, Methodology. **Kate Bowers:** Writing – review & editing, Writing – original draft, Conceptualization, Methodology. **Dan Birks:** Writing – review & editing, Writing – original draft, Conceptualization, Methodology. **Shane D. Johnson:** Writing – review & editing, Writing – original draft, Conceptualization, Methodology.

Declaration of competing interest

The authors have no conflicts of interest to declare.

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