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The trade-off between security and privacy: An empirical investigation using Pakistani survey data

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ABSTRACT

This study investigates the complex trade-off between security and privacy in the context of Pakistan's evolving urban landscape with a particular focus on the controversial Safe Cities initiative in Lahore. Despite the growing global interest in smart and safe city frameworks, there remains a significant research gap in understanding how such projects affect individual preferences in developing countries, especially where legal protections for privacy are weak or absent. Addressing this gap, the study aims to empirically examine how citizens perceive and prioritize security versus privacy, and how these preferences vary across socio-demographic groups. Using survey data collected from two major Pakistani cities, Multan and Rawalpindi, the research employs a conceptual utility model and econometric analysis to quantify individual preferences. The model incorporates comparative statics and budget constraints to derive optimal levels of security and privacy, while the econometric strategy explores heterogeneity across gender, age, education, employment status, and income. Findings reveal a strong unconditional preference for security among respondents. However, when socio-demographic factors are introduced, significant variation emerges, indicating that preferences are not uniform across individuals, or regions. These insights underscore the need for localized, evidence-based public policy that balances safety with privacy, rather than adopting a one-size-fits-all approach. The paper concludes with policy recommendations aimed at fostering inclusive and context-sensitive urban governance.

1. Introduction

Urban centres and metropolises across the world are expanding at a pace that reshapes how people live, work, and interact. As urban centres grow denser, governments face a pressing dilemma: how to keep citizens safe without eroding their privacy and well-being. Scholars have long noted that liberty depends on security, yet excessive surveillance risks undermining trust and personal freedoms (Regan, 2004; Sætra, 2022). This is not merely a theoretical debate, as it directly affects how ordinary people experience daily life in crowded, fast-changing cities (Khalid et al., 2015). Decision-makers should address this policy gap through innovative and evidence-based policymaking that not only increases in breadth, i.e., ensuring safety for all, but at the same time ensures depth as well, accounting for individual differences that may affect well-being (see Arinder & Arinder, 2016; Kitchin, 2015). From a public policy perspective, the challenge lies in striking the right balance between the notions of privacy and security. Implementing an unbalanced policymaking approach could put pressure on the socioeconomic conditions and dimensions of human well-being in urban areas (Enns & Bersaglio, 2019).

In Pakistan, the tension between privacy and security is particularly pronounced. The country is the fifth most populous in the world and is experiencing rapid urbanization. Cities like Lahore and Karachi are thriving economically, but are also hot-spots for crime, terrorism, and socioeconomic inequality (Javed et al., 2020). In this context, the government launched the ambitious "Safe Cities" project in the provincial capital Lahore in 2016, aimed at enhancing public reassurance and projecting a modern international image (Pakistan Vision, 2014). Equipped with thousands of CCTV cameras and advanced monitoring systems, the initiative has been hailed as a milestone in urban security. Yet critics argue it has overlooked fundamental questions regarding privacy, data governance, and individual rights (Alizadeh & Prasad, 2024; Hong, 2022). The initiative's perceived success, along

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with strong governmental support, has generated momentum for its expansion to other urban areas. However, security policies that ignore privacy concerns risk alienating the very people they are meant to protect.

The paper provides evidence to support informed policymaking in addressing this security-privacy dilemma. In Pakistan, where institutional trust is fragile and socioeconomic divides are stark, striking the right balance between safety and privacy is not merely a technical challenge but a social necessity (Caragliu & Del Bo, 2019). If surveillance becomes too intrusive, it may deepen regional inequalities and undermine sustainable development pathways. If privacy is prioritized without adequate boundaries, public safety could be compromised. Navigating this trade-off is therefore essential for Pakistan's future.

Existing research highlights the need for more evidence-based, people-centred policymaking that accounts for heterogeneity within populations (Galvin & Arndt, 2014; Kitchin, 2015). Addressing this gap, the paper adopts a comparative, people-centred perspective to examine whether current policies adequately reflect diverse privacy preferences across social and geographic groups. In doing so, it engages with the broader challenge of reconciling top-down (homogeneous) approaches to public policy with bottom-up (heterogeneous) perspectives that account for individual variations.

From a theoretical perspective, we propose a model of individual well-being that accounts for the tension between security and privacy (see, e.g., Gorham-Oscilowski & Jaeger, 2008). Empirically, the study draws on original survey data collected in two Pakistani cities, Rawalpindi and Multan, to quantify individual preferences regarding policy initiatives in the domains of privacy and security. These cases are particularly informative, as neither city has yet implemented CCTV-based surveillance systems, although plans for the establishment of a new PPIC3 centre are already underway in Rawalpindi. As a result, the local populations have had limited direct exposure to such initiatives. The empirical findings of this paper suggest that efforts to promote urban safety must be complemented by a commitment to inclusivity and fairness. In this respect, our results indicate that citizens view Pakistan's pathway to safer cities as one that should also safeguard individual dignity and personal freedoms.

The paper is structured as follows: Section 2 provides a short literature review on smart and safe cities and how these two concepts impact privacy and security. Section 3 presents the basic economic model, while Section 4 describes the dataset and the data collection method. Section 5 deals with the econometric strategy used in the paper, and Section 6 presents and discusses the paper's empirical findings. Finally, Section 7 discusses policy implications, and Section 8 concludes the paper.

2. Review of literature

The *smart city* concept originated in the 1990s through the "smart development" term (Hong, 2022) that was used to prioritize efforts by urban planners and policymakers to combat the adverse effects of increased urbanization, declining inner city living conditions (poverty and criminal activity), and urban land use problems (mainly housing and urban planning). Essentially, the term "smart city" describes the different ways in which technology interacts with the various fabrics, layers, and community groups to be found within a city environment as a means to improve living conditions and enhance public safety (Grossi & Welinder, 2024). As urban settlements gradually grew larger in size and population, the issue of public safety became more prominent in the discussion (Goldsmith & Dinnen, 2007; Khalid et al., 2015).

Notwithstanding the support the concept of smart cities has received in the literature, most of the existing work focuses on technological implementation, or macro-level policy outcomes, overlooking the micro-level variation in public preferences (Ehwi et al., 2022). While the international literature has examined the implications of smart surveillance in developed contexts, there is a notable absence of empirical research on how citizens in developing countries perceive and negotiate the trade-off between security and privacy. Moreover, existing studies rarely account for differences in preferences between safety and privacy due to socio-demographic heterogeneity, nor do they explore how local governance structures and legal frameworks shape public attitudes (Ardabili et al., 2024). This leaves a critical gap in understanding how individuals in such contexts weigh the benefits of security against the costs to privacy, especially when surveillance is externally funded and politically sensitive (Kitchin & Moore-Cherry, 2021).

2.1. Safe city projects in Pakistan–promise and controversy

The safe city concept emerged in Pakistan in 2009, driven mainly by security and safety concerns (Hong, 2022) and fuelled by a tense relationship with India. In 2009, the Pakistani government unveiled, for the first time, its plans to develop a Safe City project. These plans finally came to fruition in 2018, when the Pakistani government introduced Pakistan's first *Safe City* project in Lahore, Punjab's regional capital city. The main arguments in favour of the development of Lahore's Safe City project, otherwise known as the "Punjab Police Integrated Command, Control and Communication Centre" (PPIC3) project, featured, *inter alia*, safety and security issues (Alizadeh & Prasad, 2024), as well as a high and increasing urbanization rate (Rana & Bhatti, 2018). The PPIC3 project includes a streamlined emergency response system and approximately 10,000 surveillance cameras installed across Lahore (Hong, 2022). Following the development of Lahore's Safe City project, the Pakistani government approved the implementation of a series of new *safe cities* in Pakistan, namely in Multan, Rawalpindi, and other major urban settings across Punjab.

Multan and Rawalpindi are two major cities in Pakistan's Punjab region. Both cities are almost equally distant from the region's capital, Lahore. They are both almost equal in size (with Rawalpindi being slightly larger in size and population; 5.5 million versus 4.7 million inhabitants, respectively). Both cities share similar demographics, with almost 51% of residents being male and 49% being female. In terms of the differences between the two cities, Rawalpindi differs from Multan in that it has a strong armed forces presence and is regarded as a garrison city. Additionally, Rawalpindi is closer to the capital city of Pakistan, Islamabad. Therefore, Rawalpindi is closer to the national bureaucracy and the administrative centre of the state.

The Safe City initiative in Pakistan has attracted both praise for its crime-reduction capabilities and criticism for its top-down implementation and potential privacy violations (Caragliu & Del Bo, 2019; Hong, 2022). On the one hand, the PPIC3 project is favoured in other parts of the region, due to the reduced crime statistics, as well as the lower number of traffic violations and accidents. On the other hand, critics maintain that the PPIC3 project has been *ineffective*, in the sense that it neither fulfils its social mandate nor takes into consideration a more bottom-up public policy perspective. In this respect, Alizadeh and Prasad (2024) and Enns and Bersaglio (2019) maintain that the PPIC3 project will contribute to Pakistan's image as a *security state*, implicitly arguing that safe city projects give priority to safety, ignoring other liveability and sustainability goals.

Ultimately, however, this will lead to serious privacy breaches, as the surveillance capabilities of the system are constantly improving. Reflecting on these privacy concerns, Meijer and Bolívar (2016) also points to the inherent disadvantage of safe cities in *jeopardizing* individual privacy and freedoms. As a consequence, critics of the Lahore Safe City project tend to argue that PPIC3's role is tied to street-level surveillance, causing it to ignore its duty to generate knowledge that contributes to effective and informed policymaking (e.g., Hong, 2022).

Perhaps the most alarming criticism rests on the fact that Lahore's Safe City project neither aligns nor contributes towards a bottom-up policymaking (Cugurullo, 2018). In particular, critics argue that safe

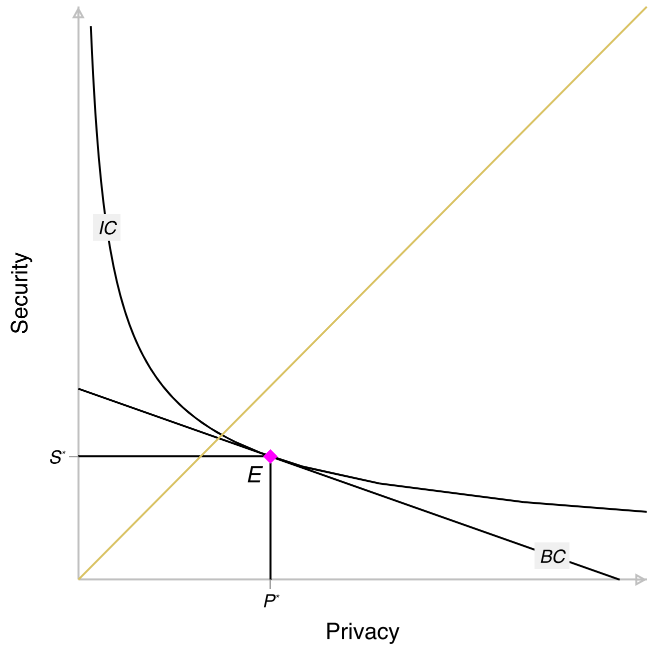

Fig. 1. Optimal levels of security and privacy under a budget constraint.
Notes: The dark yellow line is a 45-degree line. The figure illustrates the optimal bundle of security and privacy (S^*, P^*) at point E, where the indifference curve IC is tangent to the budget constraint line BC.

city projects (including the Lahore Safe City project) tend to be elitist and authoritarian in nature, adopting a top-down approach in their policy priorities and implementation. By focusing almost exclusively on this top-down decision-making, policymakers fail to acknowledge individual as well as social differences across the population and local communities (D'Arcy & Hovav, 2009).

3. The conceptual model

Assume that the utility function of a representative individual consists of security S and privacy P according to the following log–log relationship[1]:

$$U(S,P) = \ln S + \beta \ln P, \tag{1}$$

which mathematically describes an indifference curve between security and privacy in a two-dimensional $P - S$ space. The first implicit assumption is that both security and privacy are normal goods. Second, with other things being equal, more security/privacy is preferred to less security/privacy. The parameter β indicates the preferences of an individual for security and privacy accounting for tension between security and privacy (see, e.g., Gorham-Oscilowski & Jaeger, 2008). If $\beta = 1$, the individual desires security and privacy equally. If $\beta < 1$, security is more valuable than privacy, and if $\beta > 1$, privacy is more valuable than security. Fig. 1 illustrates an indifference curve IC for which $\beta < 1$.

The individuals are bound by how much they are willing to spend on security. Their budget constraint is given by

$$S + \omega P = B, \tag{2}$$

[1] Another way to model the relationship is to assume, for example, that $U(S,P) = \sqrt{S} + \beta\sqrt{P}$. The formulas for optimal values are bulkier but the derivations using this assumption are straightforward and are available upon request.

where ω is the relative price of privacy and B is the willingness to pay for security. For simplicity, we assume that the price of security is a numeraire; then, the willingness B is implicitly scaled by the actual price of security in (2). Another way to think about (2) is that $\omega = \omega_P/\omega_S$, where ω_P and ω_S are the absolute prices of privacy and security, and $B = \text{Willingness}/\omega_S$. Such a formulation is easy to work with and implement empirically, as we shall see below. An individual wishes to maximize his or her utility in (1) subject to the budget constraint in (2). The budget constraint is shown in Fig. 1 by the downward-sloping BC line. A simple optimization performed by setting a Lagrangian yields the following optimal levels of security and privacy:

$$S^* = \frac{B}{1+\beta}, \tag{3}$$

$$P^* = \frac{\beta}{\omega}\frac{B}{1+\beta}. \tag{4}$$

Whether an individual prefers more security than privacy depends not only on the parameter β but also on the relative price of privacy. Thus, even if $\beta < 1$, an optimal level of privacy may be larger than an optimal level of security if $\beta > \omega$. Fig. 1 presents a case in which $S^* < P^*$ since the E point is to the right of the 45-degree line even though $\beta < 1$. This is because the BC line is flat. If ω were larger, the BC line would be steeper, and E could be to the left of the 45-degree line. The equilibrium thus depends not only on the preference for privacy but also on the relative price. Below, we analyse how changes in the parameters alter the equilibrium.

The quantities in (3) and (4) are the result of assuming that there is a representative individual. If this assumption is relaxed, the utility function of an individual i becomes

$$U(S_i,P_i) = \ln S_i + \beta_i \ln P_i. \tag{5}$$

The budget constraint of the individual i is given by

$$S_i + \omega_i P_i = B_i. \tag{6}$$

The optimal levels of an individual i who wishes to maximize his or her utility in (5) subject to the budget constraint in (6) are

$$S_i^* = \frac{B_i}{1+\beta_i}, \tag{7}$$

$$P_i^* = \frac{\beta_i}{\omega_i}\frac{B_i}{1+\beta_i}. \tag{8}$$

3.1. Comparative statics

The quantities in (7) and (8) depend on three parameters: B_i, β_i and ω_i. We consider the changes in the optimal levels of security and privacy one by one.

First, the optimal levels of both security and privacy are increasing in B_i. It is intuitive that an individual desires more security and privacy as their willingness to pay for security increases. Fig. 2 shows that an increase in the willingness to pay for security B causes the parallel shift of the budget constraint from the black solid line BC_1 to the red dotted line BC_2. The equilibrium moves from point E_1 to E_2. The increase amounts to a pure "income" effect: the individual transitions to a higher level of utility (indicated by IC_2), the demand for security increases from S_1 to S_2 and the demand for privacy increases from P_1 to P_2. The individual is better off.

Second, as an individual desires more privacy in comparison to security, i.e., as the preference for the privacy parameter β_i increases, the indifference curve changes its shape. Fig. 3 shows a scenario in which the β parameter increases. The budget, shown by the budget constraint line BC, is still exhausted, so this increase implies movement along the budget constraint. The equilibrium moves from point E_1 to E_2. Thereby, the demand for security decreases from S_1 to S_2 and the demand for privacy increases from P_1 to P_2.

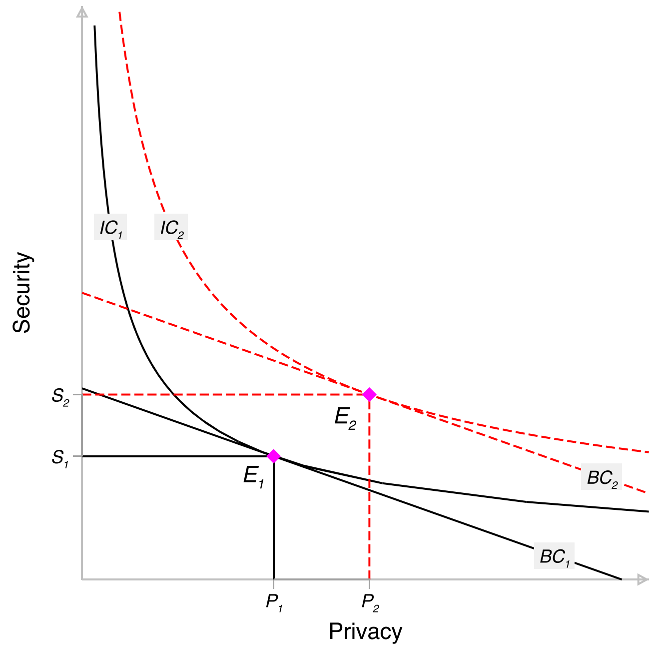

Fig. 2. The effect of an increase in the willingness to pay for security.
Notes: An increase in B has a pure "income" effect: the demand for both security and privacy increases.

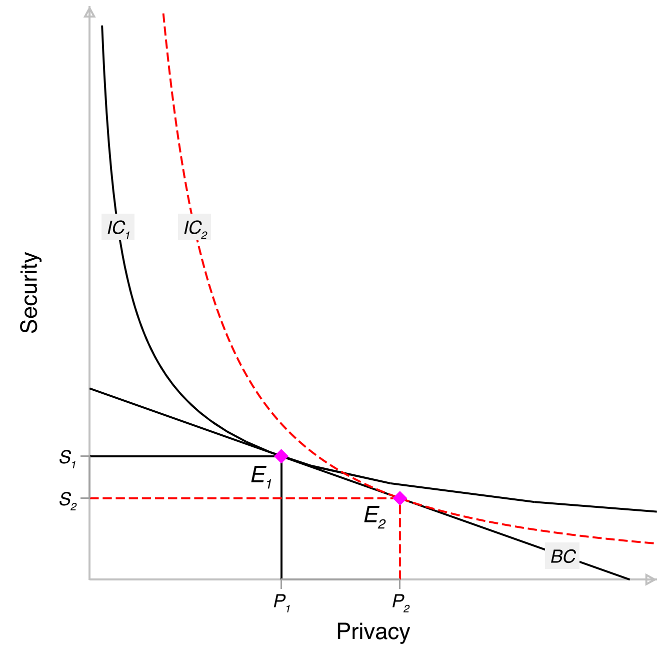

Fig. 3. The effect of an increase in the preference for privacy.
Notes: The effect of an increase in the preference for privacy β changes the shape of the indifference curve, thereby decreasing the demand for security, increasing the demand for privacy and increasing the level of utility.

Numerically, it can be established that the optimal level of security is decreasing. More precisely,

$$\frac{\partial S_i^*}{\partial \beta_i} = -\frac{1}{(1+\beta_i)^2} B_i. \tag{9}$$

With the same budget constraint, the demand for privacy should be increasing:

$$\frac{\partial P_i^*}{\partial \beta_i} = \frac{1}{(1+\beta_i)^2} \frac{B_i}{\omega_i}. \tag{10}$$

Whether the demand for privacy is increasing by more than the demand for security is decreasing depends on whether ω_i is larger or smaller than 1. Another way to think about ω_i is that it is the marginal rate of substitution of security for privacy. In Fig. 3, the increase in privacy $(P_2 - P_1)$ is lower than the decrease in security $(S_1 - S_2)$; however, this will not always be the case.

The second effect of the preference for more security is the change in utility. Differentiate (5) with respect to β_i to obtain $\ln P_i$. Thus, the increase in β_i leads to an increase in overall utility since the effect of the increase in β_i on the demand for privacy is positive, as shown in (10). In Fig. 3, the utility represented by the red dotted indifference curve IC_2 is larger than that of the black solid indifference curve IC_1. The individual is better off.

Finally, the demand for privacy is decreasing in ω_i. The demand for security does not depend on ω_i. This is because ω_i is the relative price of privacy. An increase in ω_i may mean increases in the prices of both privacy and security, with the increase in the price of privacy being larger than the increase in the price of security. As Fig. 4 shows, the increase in ω_i implies the inward pivot of the budget constraint line around the point S_0 on the vertical axis: the new budget line is the red dotted line BC_2. The equilibrium moves from point E_1 to E_2. The new equilibrium of the security-privacy bundle E_2 is where the new red dotted indifference curve is tangent to the new budget constraint BC_2. The demand for privacy will decrease from P_1 to P_2. Numerically, the decrease in the demand for privacy is

$$\frac{\partial P_i^*}{\partial \omega_i} = -\frac{1}{\omega_i^2} \beta_i \frac{B_i}{1+\beta_i}. \tag{11}$$

The change in the preference parameter for privacy implies opposite changes in security and privacy. The individual transitions from indifference curve IC_1 to IC_2 and enjoys a higher level of utility if their preference leans more towards privacy. The change in β_i implies movement along the budget constraint. When privacy becomes more expensive, i.e., when ω_i is increasing, the optimal level of privacy decreases, while the optimal level of security remains the same. This yields a lower level of utility. Fig. 4 demonstrates the transition to a lower level of utility. Hence, the change in ω_i implies a shift of the indifference curve inward. More specifically, the decrease in utility is

$$\frac{\partial U(S_i^*, P_i^*)}{\partial \omega_i} = \frac{\partial\left(-\beta_i \ln \omega_i\right)}{\partial \omega_i} = -\frac{\beta_i}{\omega_i}. \tag{12}$$

To summarize, the analysis has shown that, in social terms, an increase in the willingness to pay for security leads to an improvement. Second, a greater preference for privacy yields an improved social optimum. However, the demand for security is lower. Third, the increase in the relative price of privacy leads to a lower social outcome, reducing the demand for privacy and leaving the demand for security at the same level.

4. Data and sample construction

4.1. The survey

The data for this empirical research were collected through a questionnaire administered as part of the survey "Surveillance Programme in the City", with an aim to evaluate individual preferences for policy initiatives in the fields of privacy and security in Pakistan. The data were collected by a research team comprised of 5 individuals who were briefed and trained on the specifics of the survey instrument by the lead investigator. Special effort was taken to cover both residential and commercial districts in the two cities. Overall, 1000 observations were collected from the two cities, with an equal sample from each city (500 respondents). Out of these 1000 responses, 915 were finally used and 85 were discarded from the final dataset due to

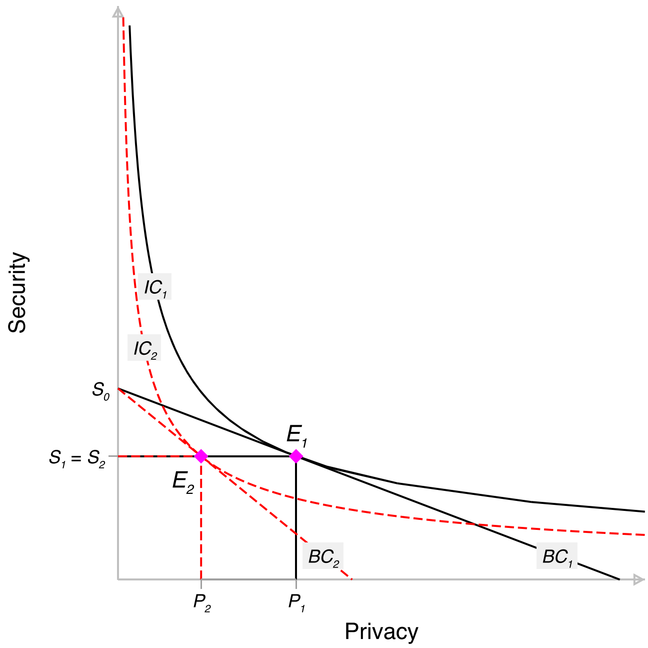

Fig. 4. The effect of an increase in the relative price of privacy.
Notes: The effect of an increase in the relative price of privacy ω has both "income" and substitution effects that leave the demand for security at the same level, decrease the demand for privacy and decrease the level of utility.

errors in the data collection stage, or incomplete survey questionnaires. Respondents were selected through convenience sampling. Given that representativeness of the survey to the general public in the two cities was difficult to achieve due to limited resources, the research team opted for a "quasi-stratified" data collection strategy, that aligns with the population census in the two cities.

To extend the PPIC3 programme to two additional cities, it is imperative to assess public preferences. Given the direct impact of such policies on individual well-being, evidence-based decision-making is crucial. Accordingly, a survey questionnaire was designed to capture individual perceptions for privacy and security in the two cities. Respondents were asked to express their *unconditional* preferences regarding privacy and security policies in each respective city. After consulting with the literature review, the research team engaged with senior ranking members of the Pakistan police force and academics, in order to scrutinize the survey questions. Next, the survey questionnaire was piloted to the public for clarity and understanding. Finally, the questionnaire was submitted to the ethics committee of one of the three universities involved in the study. Once these three steps were completed, the survey questionnaire was distributed to the public.

4.2. Security and privacy measures

The survey includes seven questions designed to elicit preferences related to trade-offs involving security and privacy. Directly asking about security and privacy could create discomfort and introduce response biases. For this reason, an indirect approach was adopted. More specifically, the survey was designed in collaboration with 'local experts' so that each question reflects a piece of information about both security and privacy. In this sense, the paper adopts Fazey's approach in identifying experts as those with departmental experience in relation to a topic of interest (Gosselin et al., 2018). In particular, a team of senior and medium-ranking police officers with prior knowledge of the PPIC3 project was selected and recruited for a focus group discussion regarding the concepts of privacy and security, prior to the construction of the survey instrument. We argue that police officers hold knowledge and experience grounded in everyday law enforcement practices that is not readily available among the public. During the course of the discussion, they reached a consensus regarding the "information weights".[2]

Table 1 shows the information weights that were attached to each question by local experts when the survey was designed. For example, the first question is about the "Proposed number of cameras in the city"; respondents are asked to choose the number of cameras that should be required to cover the major public roads, entry/exit points, road crossings, and areas that people visit as part of their daily routine. The team of expert estimated that half of the answer to this question reveals preferences about security, and the other half reveals preferences about privacy. Question 5, "Public will be exposed to all surveillance as people may be observed through CCTV cameras daily", is 20% about preferences regarding security and 80% about preferences regarding privacy. Questions 3, 4 and 6 are only about preferences regarding security.

The information weights from Table 1 are used to construct indices that are attributed to the demand for security and privacy of an individual j:

$$S_j = \frac{1}{\sum_{j=1}^{7} w_{s_j}} \sum_{j=1}^{7} w_{s_j} Q_j, \tag{13}$$

$$P_j = \frac{1}{\sum_{j=1}^{7} w_{p_j}} \sum_{j=1}^{7} w_{p_j} \left(5 - Q_j\right), \tag{14}$$

where Q_j is the value of the answer to question j and w_{s_j} and w_{p_j} are the information weights presented in Table 1. Q_j can take a value of 1, 2, 3 or 4; hence, a larger value of S_j implies a larger demand for security. A larger value of Q_j in (13) implies less privacy, so the answers to the questions enter (14) inverted; hence, a larger value of P_j in (14) implies a larger demand for privacy.

Our empirical analysis relies on indices constructed from responses to seven individual questions. To test the robustness of our findings, we conduct an analysis by creating alternative privacy and security indices based on the choices made by survey respondents when presented with two cards containing fixed values on the seven attributes. The results are available upon request. Despite using these alternative indices, our primary conclusions remain unchanged.

Additionally, the survey asks which characteristics from the second part of the survey were the most and second most important. To reflect this importance in calculating indices using (13) and (14), w_{s_k} and w_{p_k} are multiplied by a factor of 2 if a characteristic k is indicated to be either the most *or* second most important. w_{s_k} and w_{p_k} are multiplied by a factor of 3 if a characteristic k is identified as the most *and* second-most important. The histograms of the resulting indices are shown in Fig. 5 for Multan and Fig. 6 for Rawalpindi.

5. Econometric strategy

This section explains the approach used to estimate the parameters of the model presented in Section 3. Building on the theoretical framework outlined there, we employ specific statistical and empirical techniques selected to align with the research objectives. More specifically, these methods were chosen because they enable estimation of the model parameters not only for a representative individual but also in a way that accounts for heterogeneity across the population. We begin by estimating the model for a representative individual. To identify the preference parameter β, as defined in (1), we use the following equation:

$$\ln S_i = \beta_0 + \beta_1 \ln P_i + u_i, \tag{15}$$

[2] For robustness checks, we tested multiple sets of information weights. The results proved stable, showing no sensitivity to changes in weighting schemes.

Table 1
Information weights.

	Security, w_s	Privacy, w_p
Number of cameras *to be installed* in the city	0.5	0.5
Types of cameras in the city	0.3	0.7
Preventive actions taken through cameras *before* incident	1	0
After the crime-event assistance provided by cameras every month	1	0
Public exposure of people through the cameras every day	0.2	0.8
Expected annual reduction in crime	1	0

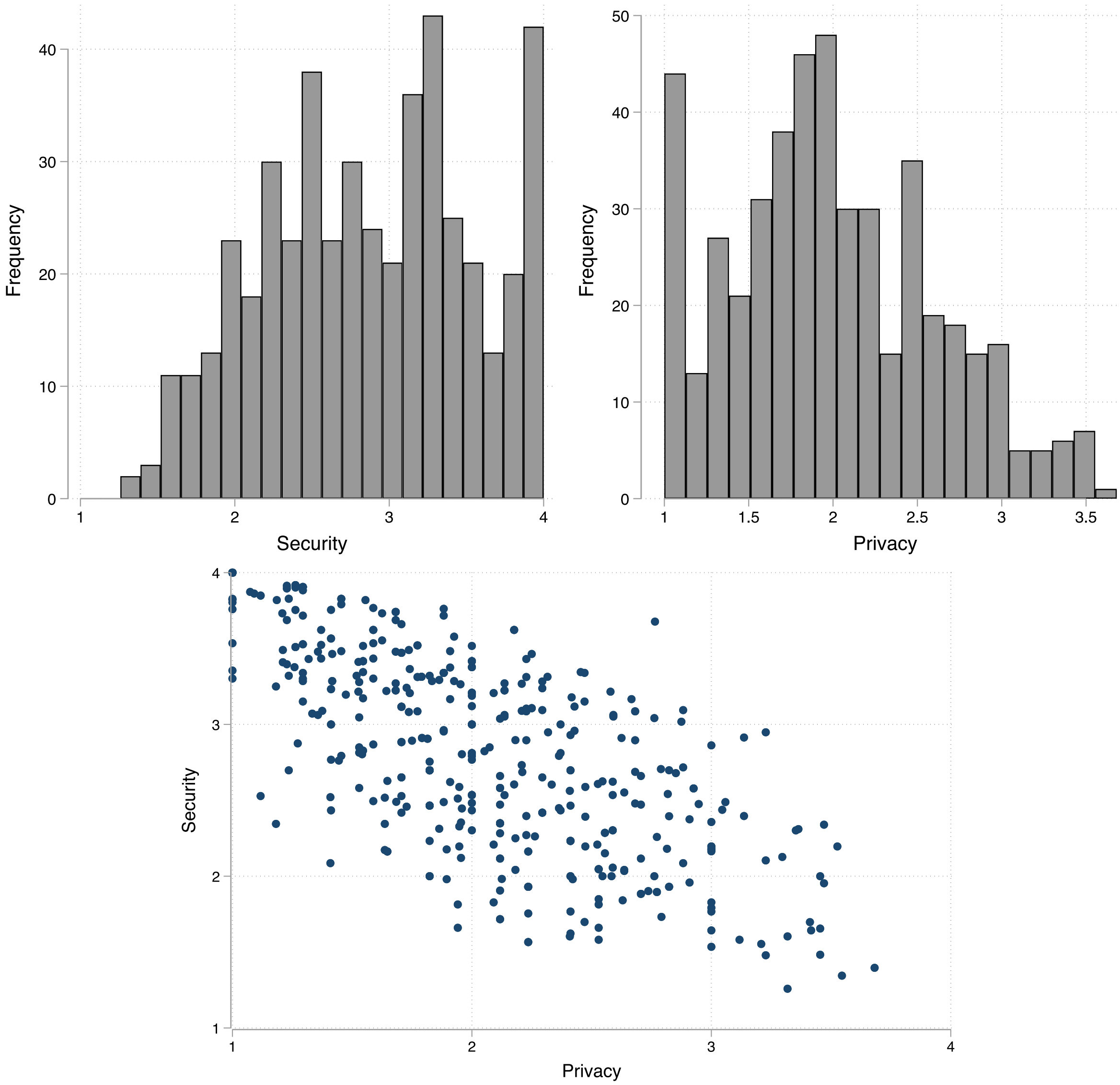

Fig. 5. Distributions and scatter plot of the security and privacy indices in Multan.

where S and P are the security and privacy measures discussed in the previous section and u is the symmetric error term. Once the estimate from Eq. (15) is obtained, the negative of the coefficient $\hat{\beta}_1$ serves as the preference parameter β for a representative individual. According to the model, if $-\hat{\beta}_1 > 1$, security is considered more important than privacy; if $-\hat{\beta}_1 < 1$, privacy is considered more important than security. Finally, if $\hat{\beta}_1$ is statistically insignificant, meaning it is not different from zero, privacy does not have a meaningful impact on the well-being of a representative individual.

To estimate the relative price parameter ω, as defined in (2), the following regression is used:

$$S_i = \omega_0 + \omega_1 P_i + \omega_2 B_i + v_i. \quad (16)$$

We cannot identify the individual absolute prices of security and privacy because we do not have data on the overall budget constraint. However, this does not pose a problem for our analysis, as the trade-off between security and privacy depends on their relative valuation rather than their absolute levels. In other words, the exact prices are not required separately, and it is sufficient to determine which one is relatively higher. Accordingly, following the discussion around (2), we adopt a "relative" approach.

To ensure comparability of results across different cities and experimental settings, we adopt a strategy in which the average response to Question 7 ("Annual security fee from residents of the city may be charged for program") serves as a measure of the valuation of security. Accordingly, B_i in (16) is calculated by dividing individual i's response

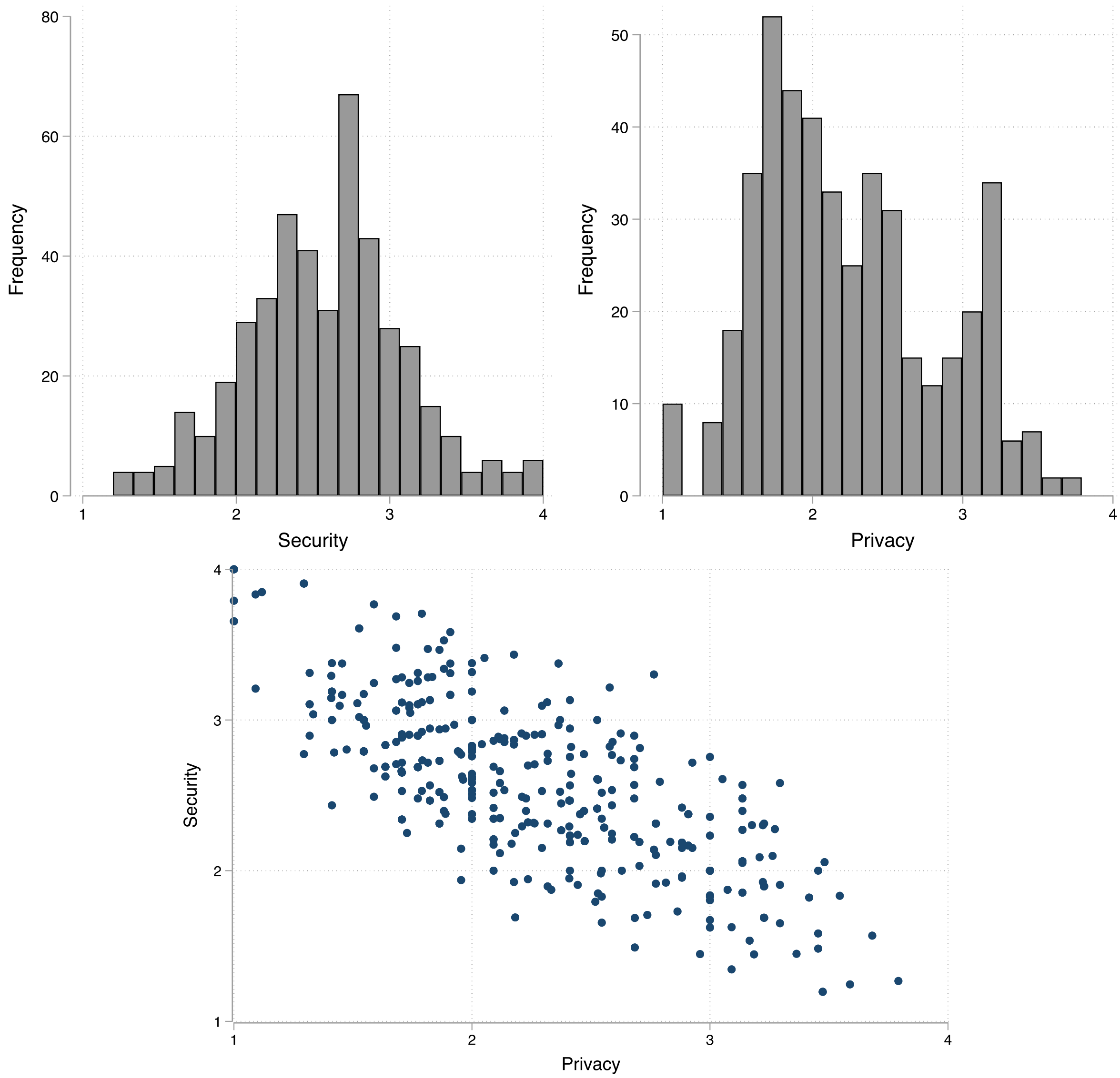

Fig. 6. Distributions of the security and privacy indices in Rawalpindi.

to Question 7 by the overall average across all respondents. Under this specification, a negative estimate of ω_1 represents the relative price parameter ω for a representative individual. To satisfy the budget constraint in (2), we impose the restriction $\omega_2 = 1$ when estimating (16). This approach is consistent with the theoretical framework outlined in Section 3, where the trade-off between security and privacy is governed by their relative prices rather than absolute levels. By normalizing responses in this way, we operationalize the model's assumption that utility depends on comparative valuation, enabling us to capture the substitution effect between security and privacy without requiring data on absolute prices or total budgets. In addition, we implement an alternative approach that involves transforming the variables and estimating the model through a regression.

$$SB_i = \omega_0 + \omega_1 P_i + v_i, \tag{17}$$

where $SB_i = S_i - B_i$. The interpretation of the estimate of ω_1 is as follows. It corresponds to the parameter ω in (2). If $-\hat{\omega}_1 < 1$, the representative individual is willing to pay a higher price for security than for privacy; conversely, if $-\hat{\omega}_1 > 1$, privacy is valued more highly than security. Finally, if $\hat{\omega}_1$ is statistically insignificant, the representative individual is not willing to pay anything for privacy.

To operationalize the second component of the theoretical framework presented in Section 3, where individuals are heterogeneous and their preferences depend on observable characteristics such as gender or age, we hypothesize, by introducing (5), that the preference parameter β_i is not constant across individuals. To gain insight into the potential drivers of this heterogeneity, we estimate the following regression:

$$\ln S_i = \beta_0 + \left(\beta_1 + \beta_{11} \boldsymbol{D}_i\right) \times \ln P_i + u_i, \tag{18}$$

where $\boldsymbol{D}_i$ represents the individual-specific characteristics (such as age), which enter (18) as either a continuous variable or a vector containing dummy variables that represent each category of individual-specific characteristics. The preference for privacy is now expressed as $\beta_1 + \beta_{11} \boldsymbol{D}_i$. This specification allows us not only to estimate preferences for different groups defined by the characteristics $\boldsymbol{D}_i$ but also to capture differences in preferences across these groups. Our primary interest lies in the coefficient(s) $\boldsymbol{\beta}_{11}$, which indicate how individual-specific characteristics such as gender, or age affect preferences for privacy. Since β_1 is expected to be negative, a negative and statistically significant $\boldsymbol{\beta}_{11}$ implies that the preference for privacy increases with the characteristic $\boldsymbol{D}_i$. Conversely, $\boldsymbol{\beta}_{11}$ being not statistically significant, suggests that there are no meaningful differences in preferences between groups defined by $\boldsymbol{D}_i$. Therefore, in the interpretation of results, the statistical significance and sign of $\boldsymbol{\beta}_{11}$ will be central to our analysis.

Table 2
Empirical estimation of privacy preference and relative price of privacy for Multan.

	Dependent variable	
	ln S (for β)	SB' (for ω)
Constant	1.379***	2.639***
	(105.139)	(25.854)
Privacy (ln)	−0.556***	
	(−24.459)	
Privacy		−0.387***
		(−8.270)
R-squared	0.508	0.113
N	470	470

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the willingness to pay for security scaled by its mean value.

Table 3
Empirical estimation of privacy preference and relative price of privacy for Rawalpindi.

	Dependent variable	
	ln S (for β)	SB' (for ω)
Constant	1.370***	2.703***
	(77.111)	(30.254)
Privacy (ln)	−0.583***	
	(−22.925)	
Privacy		−0.506***
		(−13.614)
R-squared	0.554	0.252
N	445	445

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the willingness to pay for security scaled by its mean value.

To examine the heterogeneity of the relative price parameter ω, we run the following regression:

$$SB_i = \omega_0 + \left(\omega_1 + \boldsymbol{\omega}_{11} \boldsymbol{D}_i\right) \times P_i + v_i. \tag{19}$$

As above, ω_1 is expected to be negative. As with $\boldsymbol{\beta}_{11}$, if the coefficient(s) $\boldsymbol{\omega}_{11}$ are negative and statistically significant, this indicates that the valuation of privacy relative to security increases with the characteristic $\boldsymbol{D}_i$. This specification enables us to estimate not only valuations for different groups defined by $\boldsymbol{D}_i$ but also the differences in those valuations. Conversely, if $\boldsymbol{\omega}_{11}$ is statistically insignificant, we conclude that there are no meaningful differences in the valuation of privacy relative to security between groups defined by $\boldsymbol{D}_i$. These interpretations are directly grounded in the second part of the theoretical framework outlined in Section 3, where heterogeneity in preferences and relative prices is modelled as a function of individual characteristics. Therefore, when analysing the results, the statistical significance and sign of $\boldsymbol{\omega}_{11}$ will be central to assessing whether the theoretical prediction of heterogeneous valuations holds in practice.

Table 4
Empirical estimation of privacy preference and relative price of privacy for Multan and Rawalpindi.

	Dependent variable	
	ln S (for β)	SB' (for ω)
Constant	1.370***	2.703***
	(77.116)	(30.256)
Privacy (ln)	−0.583***	
	(−22.926)	
Multan	0.008	−0.065
	(0.381)	(−0.476)
Multan × Privacy (ln)	0.027	
	(0.778)	
Privacy		−0.506***
		(−13.615)
Multan × Privacy		0.119**
		(1.985)
R-squared	0.546	0.207
N	915	915

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the willingness to pay for security scaled by its mean value.

6. Empirical results

6.1. Representative individual

Table 2 summarizes the empirical results regarding individual preferences for privacy and security in the city of Multan. The results indicate that if $\beta < 1$, individual consumers will be more positively disposed towards security as opposed to privacy. At the same time, the SB' column indicates that Multan residents would also be willing to forego greater values of privacy for more security to stay on the same indifference curve. The findings are qualitatively the same for Rawalpindi, although the quantitative effect in the SB' column (the slope of the budget line) appears to be greater in this case. In other words, the trade-off between privacy and security in Rawalpindi appears to be larger. This finding can be justified based on Rawalpindi's city context and economy. The local economic structure, bureaucratic considerations, and the degree of the local population's familiarity with security forces tend to exert an influence on preferences concerning the privacy versus security nexus (Mason et al., 2014). In the same fashion, a spatial unit's historical and social context exerts a significant effect on residents' preferences towards security and privacy (e.g., Chellappa & Sin, 2019; Kitchin, 2015).

Table 4 also indicates that there are no statistically significant differences between the two cities as far as their preferences for security are concerned. When comparing the relative price of privacy in the two cities, the relative price of privacy in Multan is lower than that in Rawalpindi. Residents in Multan value their privacy less than their counterparts in Rawalpindi. As a consequence, this statistically significant finding confirms the evidence from Tables 2 and 3, in the sense that Rawalpindi residents would have to forego greater amounts of money in order to enjoy the same levels of privacy as their counterparts in Multan. This statistical difference between the relative price for privacy in the two cities could be an early indication of the effect of the regional economic structure on national security policymaking.

Fig. 7 shows the estimated indifference curves and budget constraints for the four willingness-to-pay levels for security. The budget constraint (in red) that is closest to the origin corresponds to zero willingness to pay, which is associated with the "No fee from residents" response to Question 7. The budget constraint furthest from the origin corresponds to the largest willingness to pay for security, which is associated with the "More than 2001 rupees/year" response to Question 7. Indifference curves further away from the origin indicate a larger utility and hence represent individuals who are better off. Points where indifference curves are tangent to the budget constraint lines reveal the optimal bundle of security and privacy at a specific willingness-to-pay level.

The results in Table 4 demonstrate that there is no difference in the preference for privacy between Multan and Rawalpindi; hence, the shapes of the indifference curves in the left and right panels of Fig. 7 are the same. Since the interaction term "Multan × Privacy" in Table 4 is positive and statistically significant, the budget constraint lines are flatter for Multan. Thus, the panels illustrate the three points discussed above. First, the individuals in Rawalpindi are worse off than those in Multan because privacy is relatively more expensive in Rawalpindi. Second, in equilibrium, individuals in Multan demand

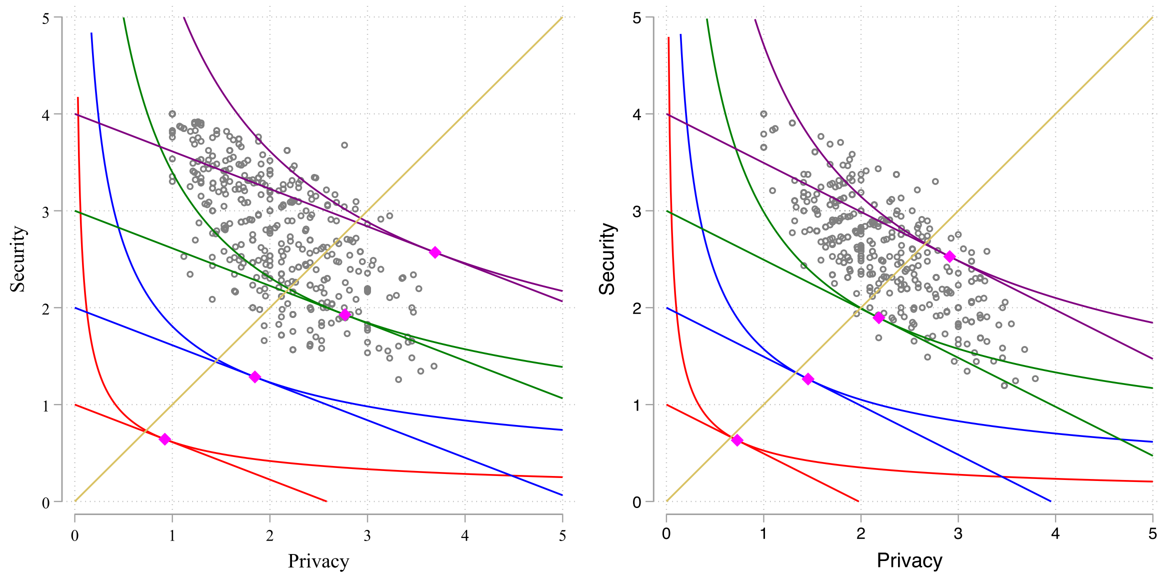

Fig. 7. Indifference curves in the security-privacy space and optimal levels of security and privacy for Multan (left) and Rawalpindi (right).

more privacy and less security than individuals in Rawalpindi. Finally, the low willingness to pay for security can result in much lower levels of security and privacy than individuals would desire.

6.2. Heterogeneity according to sociodemographic factors

Table 5 below summarizes the sociodemographic profile of the sample in the two cities. The sociodemographic information summarized in Table 5 will also be used as the basis for identifying sources of heterogeneity in our sample. According to the findings, there is an over-representation of male respondents in Multan compared to Rawalpindi. On the other hand, respondents in Rawalpindi tend to be older than those in Multan. In Multan, respondents seem to be less academically qualified, perhaps due to their young age, whereas in Rawalpindi, the majority of respondents (67%) are graduates. The percentages of those still in the process of gaining an education in both cities are significant (31% and 40% for Rawalpindi and Multan, respectively). The proportion of those who are employed is higher in Rawalpindi than in Multan, whereas the proportion of business people in Multan is more than twice as large as that in Rawalpindi. Finally, respondents in Rawalpindi tend to be more affluent than their counterparts in Multan.

6.2.1. The effect of gender

The paper begins by examining how respondents' sociodemographic characteristics affect their preferences for privacy and security. The analysis first considers the impact of gender on individual preferences. Table 6 summarizes the discussion for Multan. According to the empirical findings, females do not seem to differ in terms of their preferences for privacy and security from their male counterparts, although the preferences as a whole are still skewed towards security (as shown in Table 2). Furthermore, the column referring to the relative price of privacy (SB') indicates that females are less well off than males in Multan. This is because the relative price of privacy for females is increasing (a negative and statistically significant (Female × Privacy) interaction coefficient).

The empirical findings in Table 7 are somewhat comparable to the findings in Table 6. More specifically, gender does not seem to exert any statistically significant influence on preferences for privacy in Rawalpindi, which is similar to the pattern emerging in Multan. Thus, whereas individuals as a whole expressed stronger preferences for security over privacy in Rawalpindi, females' preferences for privacy and security did not differ statistically from males' preferences. At the same time, females did not feel any worse off than males in Rawalpindi. The relative price of privacy (as shown by the SB' regression) does not seem to exert any statistically significant influence on female respondents in Rawalpindi. The relative price for the (Female × Multan × Privacy) interaction coefficient is statistically significant.

6.2.2. The effect of age

Next we consider the effect of age on individual preferences for privacy and security in the two cities. According to the information presented in Tables 8 and 9, there are some marked differences between the two cities. First, when considering age as a continuous variable, individuals in Multan and Rawalpindi adopt different stances when it comes to privacy and security. On the one hand, as people get older in Multan, their preferences seem to shift closer to security and further away from privacy. This is not the case for Rawalpindi, where age does not seem to have any statistically significant effect on preferences for privacy . A similar conclusion is reached when age is considered a dummy variable. In this case those in the 41 to 55 years old age category in Multan are more positively disposed towards security than their younger (25 years of age) counterparts. Again, this is not confirmed in Rawalpindi's case. Thus, the empirical findings tend to suggest that age seems to be a significant influential factor for Multan residents' preferences for privacy and security, but not for Rawalpindi's.

On the other hand, the relative price of privacy in Multan (SB' coefficient) is positive and statistically significant. This implies that the relative price of privacy for Multan decreases as people grow older. Older individuals in Multan value their privacy less than younger individuals. Exactly the same conclusion applies to the 41–55-year-old age group. They seem to value their privacy less than younger respondents. These empirical findings align with the standard literature and suggest that as people mature, their preferences naturally shift towards security (Sørensen, 2013). Apparently, older people who have completed their social security obligations feel that this is the time to reap the benefits of their (financial) contributions. Interestingly, no such conclusion can be reached for residents of Rawalpindi.

A third point relates to the fact that there are statistical differences across individuals in the two cities due to the age effect. More specifically, there are differences in the relative price of privacy across the two cities, as indicated by the (Multan × Privacy × Age) interaction coefficient and the dummy interaction coefficient (41–55 × Multan × Privacy). Both of these cases indicate that Multan respondents are better off than Rawalpindi residents since the relative price of privacy is going down (and hence, they can afford more privacy as they get older).

Table 5
Sociodemographic factors.

	Rawalpindi (north of Punjab)		Multan (south of Punjab)	
	Freq.	Percentage	Freq.	Percentage
Gender				
Male	221	49.7	347	74.2
Female	219	49.2	114	24.4
Prefer not to say	5	1.1	7	1.5
Age in years				
18–25	123	27.6	241	51.5
26–40	202	45.4	156	33.3
41–55	94	21.1	50	10.7
56 or above	26	5.8	21	4.5
Academic qualifications				
Up to matriculation	47	10.6	119	25.4
Up to O-level/GCSE	8	1.8	28	6.0
FA-FSc/A-Level	93	20.9	118	25.2
Graduate or above	297	66.7	203	43.4
Employment status				
Employed	194	46.5	118	25.3
Unemployed	60	14.4	78	16.7
Studying	131	31.4	182	39.0
Business person	32	7.7	89	19.1
Approximate monthly income in rupees				
15,000–40,000	106	29.1	192	45.1
40,001–65,000	99	27.2	107	25.1
65,001–90,000	92	25.3	75	17.6
90,001 or above	67	18.4	52	12.2

Table 6
Empirical estimation of privacy preference and relative price of privacy depending on gender for Multan.

	Dependent variable			
	$\ln S$ (for β)		SB' (for ω)	
Constant	1.379***	1.379***	2.632***	2.646***
	(105.003)	(104.782)	(25.771)	(26.327)
Privacy (ln)	−0.557***	−0.564***		
	(−24.426)	(−23.544)		
Female × Privacy (ln)		0.033		
		(1.070)		
Prefer not to say × Privacy (ln)		−0.029		
		(−0.256)		
Privacy			−0.383***	−0.373***
			(−8.188)	(−8.059)
Female × Privacy				−0.073**
				(−2.207)
Prefer not to say × Privacy				−0.086
				(−0.747)
R-squared	0.508	0.507	0.111	0.116
N	468	468	468	468

Notes: *t*-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

6.2.3. *The effect of academic qualifications*

Tables 10 and 11 summarize the effect of respondents' academic qualifications on individual preferences for privacy and security in the two cities. More specifically, Tables 10 and 11 consider academic qualifications using both continuous and dummy variable specifications. In Multan, the results indicate that the more educated individuals are, the stronger their preferences for privacy will be (the (Privacy (ln) × Qualifications) coefficient is negative and statistically significant). Interestingly, this finding is not confirmed in Table 11 (Rawalpindi). Actually, the opposite is true: the more academically qualified respondents are in Rawalpindi, the more security they prefer compared to respondents educated up to matriculation level in the same city.

When considering the effect of academic qualifications using a dummy variable specification, there are also a number of interesting observations to note. The results from the dummy variable specification in Multan seem to confirm earlier findings. More academically qualified individuals have positive and statistically significant preferences for privacy over security compared to respondents educated up to matriculation level in Multan. On the contrary, Rawalpindi residents expressed diametrically opposing preferences. Individuals with low academic qualifications (up to O-levels) in Rawalpindi expressed stronger preferences for security over privacy than respondents with basic educational qualifications.

The examination of the willingness to pay estimate also reveals a number of notable differences across the two cities. First, it is interesting to note that academic qualifications do not seem to exhibit any statistically significant effect on Multan residents' willingness to pay for privacy. The relative price of privacy is the same as the relative price of security in Multan. Hence, whereas more academically qualified

Table 7
Empirical estimation of privacy preference and relative price of privacy depending on gender for Rawalpindi.

	Dependent variable			
	$\ln S$ (for β)		SB' (for ω)	
Constant	1.370***	1.370***	2.703***	2.696***
	(77.111)	(76.652)	(30.254)	(30.137)
Privacy (ln)	−0.583***	−0.587***		
	(−22.925)	(−21.874)		
Female × Privacy (ln)		0.014		
		(0.748)		
Prefer not to say × Privacy (ln)		−0.128		
		(−1.288)		
Privacy			−0.506***	−0.515***
			(−13.614)	(−13.549)
Female × Privacy				0.026
				(1.251)
Prefer not to say × Privacy				0.032
				(0.384)
R-squared	0.554	0.555	0.252	0.251
N	445	445	445	445

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

Table 8
Empirical estimation of privacy preference and relative price of privacy depending on age for Multan.

	Dependent variable					
	$\ln S$ (for β)			SB' (for ω)		
Constant	1.379***	1.373***	1.373***	2.632***	2.598***	2.601***
	(105.003)	(106.469)	(107.140)	(25.771)	(25.266)	(25.513)
Privacy (ln)	−0.557***	−0.601***	−0.564***			
	(−24.426)	(−17.865)	(−22.319)			
Privacy (ln) × Age		0.033**				
		(2.146)				
26–40 × Privacy (ln)			0.002			
			(0.055)			
41–55 × Privacy (ln)			0.150***			
			(4.588)			
56 or above × Privacy (ln)			−0.018			
			(−0.319)			
Privacy				−0.383***	−0.419***	−0.395***
				(−8.188)	(−8.231)	(−8.473)
Privacy × Age					0.032*	
					(1.692)	
26–40 × Privacy						0.050
						(1.578)
41–55 × Privacy						0.098*
						(1.763)
56 or above × Privacy						−0.001
						(−0.009)
R-squared	0.508	0.512	0.520	0.111	0.115	0.115
N	468	468	468	468	468	468

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

individuals in Multan tend to prefer privacy over security, they are not willing to pay for higher amounts of it . Nevertheless, when one considers academic qualifications as a dummy variable, it emerges that the relative price of privacy for those educated up to A-levels is increasing. This category of respondents values privacy more than security, and they would also be willing to pay more for it compared to those with basic educational qualifications.

Second, the examination of Rawalpindi residents' willingness to pay reveals that they are also indifferent when it comes to choosing between privacy and security. Thus, as in Multan's case, residents in Rawalpindi are not particularly willing to pay a higher amount of money for privacy, even though the preferences for privacy and security are qualitatively different. When considering the dummy variable specification, the findings in Table 11 indicate that the relative price for privacy is going up for those educated up to O-levels compared to those in the base educational category. For this group, the price of security is higher now, and they are left less well off than those at the base educational level. Those educated up to O-levels in Rawalpindi value privacy less compared to their less academically qualified counterparts.

6.2.4. The effect of employment status

The impact of employment status on individual preferences for privacy and security in the two cities (shown in Tables 12 and 13) follows a familiar path. In this case, employment status is captured through dummy variables. Initially, whereas individuals from both cities expressed preferences that were skewed towards privacy (−0.518 versus −0.567 for Multan and Rawalpindi, respectively), only in Multan does the employment status seems to exert some degree of influence over individual preferences for privacy.

More specifically, those who identified themselves as still completing their education in Multan expressed strong and statistically significant preferences towards privacy compared to those who were

Table 9
Empirical estimation of privacy preference and relative price of privacy depending on age for Rawalpindi.

	Dependent variable					
	$\ln S$ (for β)			SB' (for ω)		
Constant	1.370***	1.370***	1.371***	2.703***	2.703***	2.709***
	(77.111)	(77.206)	(76.653)	(30.254)	(30.227)	(30.202)
Privacy (ln)	−0.583***	−0.595***	−0.589***			
	(−22.925)	(−16.154)	(−17.833)			
Privacy (ln) × Age		0.006				
		(0.561)				
26–40 × Privacy (ln)			0.007			
			(0.296)			
41–55 × Privacy (ln)			0.000			
			(0.000)			
56 or above × Privacy (ln)			0.039			
			(1.028)			
Privacy				−0.506***	−0.504***	−0.501***
				(−13.614)	(−10.993)	(−12.066)
Privacy × Age					−0.001	
					(−0.070)	
26–40 × Privacy						−0.006
						(−0.251)
41–55 × Privacy						−0.037
						(−1.237)
56 or above × Privacy						0.054
						(1.068)
R-squared	0.554	0.553	0.552	0.252	0.251	0.254
N	445	445	445	445	445	445

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

Table 10
Empirical estimation of privacy preference and relative price of privacy depending on academic qualifications for Multan.

	Dependent variable					
	$\ln S$ (for β)			SB' (for ω)		
Constant	1.379***	1.376***	1.372***	2.632***	2.636***	2.598***
	(105.003)	(104.789)	(104.262)	(25.771)	(25.363)	(24.930)
Privacy (ln)	−0.557***	−0.481***	−0.465***			
	(−24.426)	(−11.876)	(−14.577)			
Privacy (ln) × Qualification		−0.024**				
		(−2.168)				
Upto O-level/GCSE × Privacy (ln)			−0.069			
			(−1.009)			
FA- FSc/A-Level × Privacy (ln)			−0.135***			
			(−3.868)			
Graduate or above × Privacy (ln)			−0.082**			
			(−2.530)			
Privacy				−0.383***	−0.394***	−0.337***
				(−8.188)	(−5.998)	(−5.756)
Privacy × Qualification					0.003	
					(0.227)	
Upto O-level/GCSE × Privacy						−0.090
						(−1.347)
FA- FSc/A-Level × Privacy						−0.080**
						(−2.021)
Graduate or above × Privacy						−0.007
						(−0.174)
R-squared	0.508	0.512	0.521	0.111	0.110	0.118
N	468	468	468	468	468	468

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

employed. One could attribute the difference in the effect of an individual's employment status on preferences for privacy to the nature and economic basis of the two cities, as salaried occupations are more strongly represented in Rawalpindi.

With regard to individual willingness-to-pay estimates, the findings in Tables 12 and 13 indicate that the relative price of privacy, and thus the willingness to pay for it, depends on individuals' employment status. More specifically, those still studying tend to value privacy

Table 11
Empirical estimation of privacy preference and relative price of privacy depending on academic qualifications for Rawalpindi.

	Dependent variable					
	$\ln S$ (for β)			SB' (for ω)		
Constant	1.370***	1.370***	1.369***	2.703***	2.703***	2.709***
	(77.111)	(77.212)	(79.181)	(30.254)	(30.217)	(30.163)
Privacy (ln)	−0.583***	−0.637***	−0.605***			
	(−22.925)	(−15.044)	(−17.633)			
Privacy (ln) × Qualification		0.016*				
		(1.671)				
Upto O-level/GCSE × Privacy (ln)			0.127**			
			(2.155)			
FA- FSc/A-Level × Privacy (ln)			−0.027			
			(−0.762)			
Graduate or above × Privacy (ln)			0.041			
			(1.388)			
Privacy				−0.506***	−0.497***	−0.522***
				(−13.614)	(−10.216)	(−11.568)
Privacy × Qualification					−0.003	
					(−0.255)	
Upto O-level/GCSE × Privacy						0.188**
						(2.235)
FA- FSc/A-Level × Privacy						0.013
						(0.386)
Graduate or above × Privacy						0.011
						(0.378)
R-squared	0.554	0.556	0.566	0.252	0.251	0.257
N	445	445	445	445	445	445

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

Table 12
Empirical estimation of privacy preference and relative price of privacy depending on employment status for Multan.

	Dependent variable			
	$\ln S$ (for β)		SB' (for ω)	
Constant	1.380***	1.377***	2.643***	2.627***
	(105.706)	(104.909)	(25.909)	(26.011)
Privacy (ln)	−0.560***	−0.518***		
	(−24.794)	(−18.121)		
Unemployed × Privacy (ln)		−0.038		
		(−1.015)		
Studying × Privacy (ln)		−0.087***		
		(−2.783)		
Business Person × Privacy (ln)		0.014		
		(0.351)		
Privacy			−0.390***	−0.355***
			(−8.355)	(−7.163)
Unemployed × Privacy				−0.001
				(−0.018)
Studying × Privacy				−0.091***
				(−2.663)
Business Person × Privacy				0.043
				(0.895)
R-squared	0.512	0.523	0.115	0.133
N	467	467	467	467

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

over security compared to salaried individuals in the city. In this case, the relative price of privacy for students is going down relative to security, and thus they would be able to afford less security than their counterparts. This finding also partially aligns with earlier findings regarding the effect of education on the willingness to pay (Table 10). Likewise, business people in Rawalpindi tend to find the relative price of security higher than that of salaried workers, and thus they are able to afford less security and more privacy. Security is more expensive for them than it is for those in salaried occupations.

There are statistically significant differences between individuals in the two cities with respect to their employment status. Students in Multan tend to exhibit stronger and more positive preferences for privacy than their counterparts in Rawalpindi. At the same time, the opposite was the case for business people in Rawalpindi and Multan.

6.2.5. The effect of income

Finally, the analysis concludes by considering the effect of income on individual preferences for privacy and security in the two cities in our sample. Interestingly, income does not seem to exert

Table 13
Empirical estimation of privacy preference and relative price of privacy depending on employment status for Rawalpindi.

	Dependent variable			
	$\ln S$ (for β)		SB' (for ω)	
Constant	1.364***	1.363***	2.670***	2.664***
	(75.009)	(75.516)	(29.227)	(29.139)
Privacy (ln)	−0.578***	−0.567***		
	(−21.933)	(−20.238)		
Unemployed × Privacy (ln)		−0.005		
		(−0.174)		
Studying × Privacy (ln)		−0.014		
		(−0.594)		
Business Person × Privacy (ln)		−0.048		
		(−1.405)		
Privacy			−0.499***	−0.496***
			(−13.003)	(−12.397)
Unemployed × Privacy				0.011
				(0.362)
Studying × Privacy				0.009
				(0.384)
Business Person × Privacy				−0.060*
				(−1.661)
R-squared	0.551	0.550	0.253	0.252
N	417	417	417	417

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

Table 14
Empirical estimation of privacy preference and relative price of privacy depending on monthly income for Multan.

	Dependent variable					
	$\ln S$ (for β)			SB' (for ω)		
Constant	1.383***	1.380***	1.380***	2.653***	2.633***	2.647***
	(105.318)	(105.213)	(104.539)	(25.377)	(24.910)	(25.220)
Privacy (ln)	−0.591***	−0.654***	−0.626***			
	(−24.943)	(−18.593)	(−22.699)			
Privacy (ln) × Income		0.037**				
		(2.408)				
40,001–65,000 × Privacy (ln)			0.066**			
			(2.131)			
65,001–90,000 × Privacy (ln)			0.097**			
			(2.583)			
90,001 or above × Privacy (ln)			0.080			
			(1.299)			
Privacy				−0.426***	−0.454***	−0.456***
				(−8.722)	(−8.521)	(−9.220)
Privacy × Income					0.020	
					(1.281)	
40,001–65,000 × Privacy						0.068**
						(1.968)
65,001–90,000 × Privacy						0.088*
						(1.964)
90,001 or above × Privacy						0.005
						(0.088)
R-squared	0.547	0.556	0.556	0.135	0.136	0.141
N	426	426	426	426	426	426

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

any statistically significant effect on individual preferences for privacy in Rawalpindi, either as a continuous or as a dummy variable. For individuals in Multan, income does seem to exert some influence in both specifications. In other words, financial security seems to affect preferences for public safety and security (Hummelsheim et al., 2011).

Initially, when income is treated as a continuous variable, preferences are skewed towards security. Thus, the more affluent an individual in Multan is, the stronger the preference for security over privacy will be. This pattern is also confirmed by the dummy specification of the income variable, where middle of the range (40,001 to 65,000 rupees) and higher (65,001 to 90,000 rupees) income groups tend to

Table 15
Empirical estimation of privacy preference and relative price of privacy depending on monthly income for Rawalpindi.

	Dependent variable					
	$\ln S$ (for β)			SB' (for ω)		
Constant	1.367***	1.367***	1.364***	2.703***	2.710***	2.712***
	(68.264)	(68.348)	(69.667)	(28.109)	(28.220)	(27.708)
Privacy (ln)	−0.582***	−0.580***	−0.587***			
	(−20.204)	(−15.615)	(−17.492)			
Privacy (ln) × Income		−0.001				
		(−0.079)				
40,001–65,000 × Privacy (ln)			0.032			
			(1.137)			
65,001–90,000 × Privacy (ln)			0.001			
			(0.032)			
90,001 or above × Privacy (ln)			0.005			
			(0.162)			
Privacy				−0.517***	−0.488***	−0.505***
				(−12.960)	(−10.563)	(−11.686)
Privacy × Income					−0.014	
					(−1.324)	
40,001–65,000 × Privacy						−0.009
						(−0.275)
65,001–90,000 × Privacy						−0.021
						(−0.722)
90,001 or above × Privacy						−0.045
						(−1.289)
R-squared	0.555	0.553	0.553	0.256	0.257	0.253
N	364	364	364	364	364	364

Notes: t-statistics based on the robust standard errors are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; $SB' = S - B'$, where B' is the scaled willingness to pay for security.

be more positively disposed towards security than the lower income groups (below 40,000 rupees).

At the same time, Table 14 indicates that middle-range and higher income groups value privacy less than security compared to the lower income groups. For them, the price of security is higher, and they could buy more privacy than less affluent groups of the local population. Overall, both of these groups (middle-income and higher income groups) are better off than their lower income counterparts in Multan since privacy is now much cheaper for them (see Table 15).

7. Policy implications

First of all, the current research unequivocally confirmed that public policymaking and implementation (in this case referring to national security) should not only be considered at the macro level or the national level, but should also take into consideration regional, spatial-level variations and societal heterogeneity (Pakistan Vision, 2014). Although the sociodemographic information in Table 5 indicates that the two cities differ not only in their spatial characteristics but also in the composition of their populations, the empirical findings show that respondents in both Multan and Rawalpindi are generally positively disposed towards security. However, when the analysis delves further into individual preferences, a less clear-cut and uniform picture emerges. Hence, the current paper quantifies the need to adapt national policymaking to spatial and individual differences for the first time and provides hard evidence to support the theoretical discussion of this topic in the literature (Masur et al., 2025). This is an important point in policymaking, both in general terms and more specifically for Pakistan. Thus, the paper extends the discussion in the field of welfare policy analysis in Pakistan by incorporating spatial and socio-demographic heterogeneity into decision-making.

The paper provides, for the first time, justifiable evidence regarding the compartmentalization of public policy into two distinct stages: formulation and implementation (Khalid et al., 2015). Whereas formulation can be considered uniform for all, implementation should accommodate the social, cultural, and economic conditions prevailing in different parts of the country. This does not imply that different regions should formulate national policies in different ways. Instead, it implies that national policymakers should rely on regional and local strengths to ensure the best possible implementation of the policy (Harknett & Stever, 2011; Sanderson, 2002).

Taking this point further, the current empirical findings suggest a step towards greater autonomy in terms of the operational and administrative implementation of public policies. This is clearly in line with the recently proposed policy reforms (National Internal Security Policy (NISP) 2018–2023). Practically, officials and decision-makers should consider local sensitivities and culture in public policy implementation. This two-step method, which distinguishes between legislative creation and its execution, is evident at an international level in major supranational entities like the European Union. In particular, the EU is accommodating, through regulations and directives, a spatially differentiated policymaking in terms of timing, scope, and enforcement. This spatial differentiation allows for regional variations across member-states depending on prevailing socioeconomic circumstances.

The paper also illustrates the significant effect that individuals' socio-demographic characteristics exert on their preferences for privacy and security. The empirical findings highlight clear demographic differences on how citizens weigh privacy against security, offering valuable guidance for policy design. The issue of preference heterogeneity in national policymaking is central to the discussion regarding social well-being and policy depth (Howell & Howell, 2008; Hummelsheim et al., 2011). Policymakers and bureaucrats need to consider the welfare effects of policymaking for different parts of society and how the implementation of particular pieces of regulation will affect different groups within a society.

For policymakers in Pakistan, especially in Lahore, these insights point to the need for differentiated strategies rather than one-size-fits-all approaches. Strengthening privacy protections in areas such as intellectual property rights, academic freedom, and cultural expression would directly address the concerns of younger and more liberal groups. At the same time, initiatives that link economic stability with enhanced security could resonate with older populations. By acknowledging these diverse preferences, decision-makers can design Safe City policies that balance surveillance with privacy safeguards, ensuring that security frameworks are both effective and socially desirable.

In terms of the theoretical implications arising from the study, the empirical findings emphasize significant consequences for community welfare. Specifically, the empirical evidence suggests that the cost of maintaining privacy increases as one approaches the nation's capital. Thus, privacy is comparatively less costly in regions farther from the capital, while closer proximity, such as in Rawalpindi, intensifies the trade-off between privacy and security compared to cities like Multan. The resulting spatial disparities in terms of privacy provision and cost reflects how geography affects public welfare and shapes government security priorities. This point echoes arguments in the literature advocating for a regionalized privacy landscape, where the balance between security and privacy is not uniform (Milberg et al., 2000).

Another theoretical contribution arising from the empirical findings of the study relates to the people-centred transformation of public policy. As the discussion regarding smart cities intensifies both in the literature and in real life, the direction of policymaking in this field is bound to experience a dramatic overhaul. More specifically, as the role of safe cities starts to dominate the discussion in the near future, concerns about the qualitative footprint of any future policymaking related to public safety and privacy will arise. In the past, policymaking relied mainly on uniformity and enforcement for the general population. In the future, this trend is going to reverse, putting more emphasis on people. Thus, public policy is going to experience a transformation away from state-driven approaches (emphasis on enforcement from top to bottom) and towards more service-driven approaches (emphasis on people, or from bottom to top).

This development is consistent with World Bank statements (World Bank, 2003) on the need for public policy to transform in order to overcome its market-failure characteristics. In other words, public policy must undergo a cultural shift from a state-driven to a people-driven approach in order to adopt, or possibly redefine, its role as a merit good. Thus, for public policy related to either safe cities or smart cities to be effective, it must embody service characteristics that will allow it to be closer to the people it is designed to serve.

The abovementioned theoretical and practical policy implications provide some interesting directions for future work in the field of security and privacy. More specifically, on a purely theoretical level, the current work could drive a more informed debate around the impact of technology on society and decision-making. By examining how surveillance technologies affect society and influence peoples' preferences, future work in the field could inform a more localized, and evidence-based policymaking. This could lead to a more extensive overhaul of governance, as a result of technological innovations and breakthroughs. On a more practical level, the current research could be extended, or replicated to more diverse spatial settings, at an ever greater scale. Indicatively, in the Global North, strong privacy laws (e.g., GDPR in Europe) shape how citizens perceive surveillance. People may be more sensitive to privacy intrusions because they expect legal protections. In the Global South, limited or absent privacy frameworks mean citizens often prioritize security over privacy, especially in contexts of crime, terrorism, or political instability. Analysing the security–privacy trade-off across these settings would help reveal how institutional safeguards shape the balance between safety and privacy.

8. Conclusion

The current paper focuses on the recent developments underway in Lahore, Pakistan, regarding the implementation of the "Punjab Police Integrated Command, Control and Communication Center" (PPIC3) project and the related "Safe Cities" project, which are both part of the China-Pakistan Economic Corridor (CPEC) agreement and are to be expanded to major urban areas in Pakistan. The main arguments regarding the implementation of the "Safe Cities" project revolved around public safety, as well as the improvement of social well-being, especially in densely populated areas such as Lahore. However, the implementation of the "Safe Cities" project was met with substantial criticism and scepticism, largely driven by the inherent trade-off between increased security and diminished privacy.

The empirical findings based on the proposed model reveal that individuals appear to have strong preferences for security in two major urban centres in the province of Punjab, namely Multan and Rawalpindi. The paper further examines the influence of various individual socio-demographic characteristics on preferences regarding two key facets of safe-city policy. These are effectiveness, referring to the quantitative impact, and efficiency, referring to the qualitative dimension of policymaking, as well as the trade-offs that may arise between them. By incorporating socio-demographic variables into the analysis, the study reveals that preferences for security and privacy are not uniform, but vary significantly across gender, age, education, and income groups. These findings challenge the assumption of homogeneous public support for surveillance-based safety measures and emphasize the need for localized and inclusive policy designs.

CRediT authorship contribution statement

Alexandros Apostolakis: Writing – original draft, Writing – review & editing, Validation, Supervision, Investigation, Formal analysis, Conceptualization. **Oleg Badunenko:** Writing – original draft, Writing – review & editing, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Shabbar Jaffry:** Conceptualization, Project administration, Resources, Validation, Supervision, Data curation, Writing – original draft, Writing – review & editing. **Akbar Nasir Khan:** Validation, Supervision, Data curation, Conceptualization, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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