De jure vs de facto lockdown measures and domestic violence. Evidence from Italy.

Lucia dalla Pellegrina
Department of Economics, Management and Statistics (DEMS) and CISEPS, University of Milano-Bicocca

Matteo Migheli
Department of Economics and Statistics, University of Torino

Irene Paximadas
Department of Law, University of Pavia

Margherita Saraceno
Department of Law and MERGED, University of Pavia

Davide Valeri Peruta
School of Economics and Statistics, University of Milano-Bicocca

Abstract

This paper investigates the impact of COVID-19-related restrictions on domestic violence (DV) in Italy, distinguishing between formal policy measures (*de jure* restrictions) and actual behavioral responses (*de facto* mobility reduction). We assess how regulatory and behavioral lockdowns affected DV incidence using a novel identification strategy that leverages the Oxford COVID-19 Government Response Tracker's Stringency Index and reductions in traffic-related air pollutants. DV is measured using three complementary indicators: police reports for mistreatment and stalking, helpline calls, and Google Trends searches for DV-related terms. Fixed-effects panel regressions, including dynamic lag structures and time-varying covariates, reveal that DV increased significantly following restrictions. Crucially, the strongest effects occurred not immediately after the formal lockdown announcements but with a time delay, coinciding with actual mobility reductions. These time-sensitive effects are consistent with the exposure theory and support the relevance of mechanisms related to the relative power in the intimate relationships. Findings highlight the importance of anticipatory policy design: support services and interventions must be deployed promptly to mitigate the rising risk of DV during periods of forced cohabitation and social constraint.

Keywords: COVID-19 lockdown; Domestic violence; Exposure theory; Male backlash; Bargaining Theory.
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1. Introduction

Domestic violence (DV, hereafter, intended as gender violence in the intimate sphere) is a critical and multifaceted social issue shaped by cultural, economic, and behavioral dynamics. This paper explores how the COVID-19 pandemic and the related lockdown measures affected DV in Italy, with particular attention to the theoretical frameworks of exposure theory, bargaining power theory, and male backlash.

According to the exposure theory, prolonged cohabitation resulting from mobility restrictions may have increased the likelihood of DV, as victims were confined with potential aggressors for extended periods, often in environments of heightened stress and limited escape options (Arenas-Arroyo et al., 2021). While this mechanism represents the core theoretical lens of our analysis, bargaining power theory offers a complementary perspective, suggesting that DV risk may also negatively depend on the relative economic and social autonomy of household members, particularly women. In parallel, male backlash theory posits that DV can arise as a reaction to perceived threats to male power—such as job loss, changing gender roles, or reduced control within the household—especially under crisis conditions.

Measuring DV remains notoriously challenging due to chronic underreporting and heterogeneity in available data. To address this, we construct a multi-source measure of DV using: (i) calls to the national anti-violence helpline (1522); (ii) police reports for mistreatment and stalking; and (iii) Google Trends search data on DV-related terms. These indicators provide complementary insights into latent concerns, help-seeking behavior, and formal reporting, allowing us to triangulate the incidence and dynamics of DV during lockdown.

We propose two sets of complementary proxies to capture the degree of restricted mobility and lockdown stringency. First, we use the Stringency Index provided by the Oxford COVID-19 Government Response Tracker to capture the *de jure* severity of policy restrictions, including stay-at-home orders, business and school closures, and curfews. Second, we exploit localized reductions in air pollution as an indirect measure of actual mobility behavior, thus serving as a *de facto* proxy for compliance with restrictions. These two indicators jointly allow us to measure both formal regulation and realized behavior.

The first wave of the pandemic provides a compelling quasi-experimental setting for our study. The abrupt and exogenous imposition of restrictions across all Italian provinces and the limited opportunities for self-selection or avoidance enable credible identification of causal effects. Our empirical strategy uses panel data with region and time fixed effects, lagged regressors to reflect cumulative exposure, and multiple robustness specifications to capture both immediate and delayed effects of restrictions on DV outcomes.

Focusing on Italy offers a particularly relevant context for studying the effects of lockdowns on DV. Italy was the first Western country to be severely hit by the COVID-19 pandemic, and the government responded with some of the strictest mobility restrictions worldwide, particularly during the first wave. Northern regions such as Lombardy, Emilia-Romagna, and Veneto were among the earliest and most intensely affected, both in terms of infection rates and lockdown severity. This unique combination of early exposure, high stringency, and regional variation in timing and intensity of restrictions provides a compelling natural laboratory for investigating the behavioral consequences of confinement, including the incidence and dynamics of DV.

Our results show that DV increased following the imposition of lockdowns and associated reductions in mobility, providing robust empirical support for the exposure theory: it is the actual lack of mobility—rather than the regulatory imposition—that triggers heightened violence risk. This is confirmed by the consistent lagged relationship we uncover between *de jure* lockdowns and *de facto* compliance, as mobility reductions—proxied by declines in traffic-sensitive pollutants—typically follow formal announcements with a one- to two-week delay, and DV outcomes respond more strongly to this behavioral component. Moreover, the inclusion of covariates in the regression model also reveals complementary dynamics. On the one hand, the relative power within the intimate relationship matters—see i.e., the protective role of income and autonomy—; on the other hand, alcohol consumption and further social stressors seem to trigger violence.

Together, our findings suggest that while exposure remains the dominant channel, multiple mechanisms contribute to shaping DV risk under mobility restrictions. Behavioral lag in compliance with formal lockdown restrictions provides both theoretical and policy-relevant insights. Theoretically, our findings support the idea that DV risk emerges from the cumulative interaction between stress, constraint, and isolation—rather than instantaneously from formal announcements. From a policy perspective, this lag opens a window of intervention: a period during which social services and protective measures can be activated *before* mobility restrictions take full effect.

The findings of this study thus call for the integration of DV risk assessments into emergency preparedness plans. During periods of anticipated enforced cohabitation, authorities should immediately reinforce access to emergency services, shelters, and reporting mechanisms, while anticipating rising tensions in the most vulnerable households. The time-lag structure uncovered by our empirical analysis suggests that relying on policy declarations alone may delay the deployment of protective resources until it is too late. Real-time monitoring of behavioral proxies—such as mobility-derived pollution or digital activity—can serve as early warning signals for targeted DV prevention.

The paper contributes to the broader literature on DV during crises, particularly in the context of pandemics and natural disasters (Anastario et al., 2009; Bermudez et al., 2019; Campbell, 2020; Cesur and Sabia, 2016; La Mattina, 2017). It also complements recent work documenting rising intimate partner violence under lockdown (Arenas-Arroyo et al., 2021; Agüero, 2021) by advancing a novel methodological approach that distinguishes between the *intentions* and the *effects* of policy restrictions. By capturing both the *de jure* and *de facto* dimensions of mobility, the study offers a complete and dynamic picture of the pathways through which lockdowns affect domestic safety.

The remainder of the paper is structured as follows: Section 2 reviews the related literature; Section 3 outlines our empirical strategy and hypotheses; Section 4 presents the results; and Section 5 concludes with a discussion of policy implications and future research directions.

2. Related literature

DV is a pervasive social problem, typically implying gender violence. Approximately one woman out of three in the world has experienced violence once in her life (WHO 2013 and 2019, EIGE 2020, FRA 2021). The literature indicates that DV entails issues related to severe limitations for sustainable development (García-Moreno et al., 2005; Jutta, 1999; FRA, 2014).

DV is also a complex and multifaceted phenomenon (Collins and Bilge, 2020), often affected by specific socio-economic events. In particular, the empirical literature witnesses its systematic worsening during and immediately after crises originating from natural disasters (Anastario, 2009; Bermudez et al., 2019; Campbell, 2020; Schwefer, 2018), conflicts (Cesur and Sabia, 2016; La Mattina, 2017), and pandemics (UNDP, 2015; Oxfam International, 2017; Kourti et al., 2023). Recent evidence from Sub-Saharan Africa shows that even environmental stressors like rainfall shocks can trigger higher levels of intimate partner violence, reinforcing the role of economic strain and household vulnerability in DV dynamics (Cools et al., 2020).

In this framework, the COVID-19 pandemic represented a major negative shock to the socio-economic situation in many countries; there is evidence that it increased the risk of within-household violence around the globe (Boserup et al., 2020). Most literature indicates that DV dramatically augmented, correlating with victims' isolation due to mobility restrictions, despite the decreased occurrence of both reports to the police and requests for help (see Brink, 2021, on Western and Southern European countries; Henke and Hsu, 2022, on the U.S.; Barchielli et al., 2021, on Italy). However, Miller et al. (2024) found that reporting activity increased during the first phases of the COVID-19 lockdown, while arrests and hospitalizations, especially for physical injuries, decreased.[1]

Reasons and drivers that can exacerbate DV during a pandemic are various (Peterman et al., 2020): greater vulnerability is often associated with several demographic and socioeconomic factors (UN Women, 2020), including financial instability and excessive female workload (de Souza Santos et al., 2022, on data from Latin America), inability to meet financial obligations and maintaining social ties (Beland et al., 2021, on Canadian data), adverse shocks on the labor market (Bhalotra et al., 2022, on data from Cile, Fereidooni et al., 2023, on data from Iran), presence of children (Barchielli et al., 2021, on Italian data), lack of access to care services (Sacco et al., 2020, on Italian data), living in rural areas (de Lima eta al., 2020, on Brazilian data), worsening/spread of post-traumatic stress symptoms and substance abuse (Moreira and Da Costa, 2020; Pretto, 2021, on Italian data), and lower age (Gama, 2021, on Portuguese data). Recent evidence from Peru also shows that income shocks linked to rainfall variability significantly increase spousal abuse, reinforcing the connection between economic distress and DV, particularly in low-income and gender-unequal settings (Díaz and Saldarriaga, 2023). Several theories concerning the drivers for DV exist and, possibly, coexist. Those considered in the literature are mainly three.

[1] The reduction in the number of hospital admissions may have been influenced by the health system situation caused by the pandemic itself.

The first is the so-called *exposure theory*. The literature provides evidence that the likelihood that an individual becomes a victim of DV heavily depends on exposure to would-be offenders (Kuo and Putra, 2021; Sween & Reyns, 2017; Madero-Hernandez, 2019), while the possibility for the victims to step away from the perpetrator easily, meet other people, or perform activities far from the perpetrator reduces the phenomenon, also allowing victims to report violence to the police (Amaral et al., 2023). A major reason for the increase in DV during the first phases of the COVID-19 pandemic rests on the restrictions aimed at limiting the spread of the virus, particularly during lockdown periods. The exposure theory has been assumed to *directly* explain the increase in DV during the COVID-19 pandemic because the stay-at-home and lockdown measures resulted in a significant growth of time spent by partners at home and in social isolation.

The *backlash theory* explains violence against women as a reaction to their relative empowerment: the man punishes the woman because she (somehow) emancipates. In the context of the lockdown, when several workers either lost their jobs or were obliged to be unoccupied at home (especially in some sectors, this happened relatively more to men than to women), most men may have felt a loss of authority and control over their partners, therefore leading to episodes of violence.

The third most inquired explanation of DV grounds on the *bargaining power theory*, according to which DV occurs as a non-cooperative situation where the bargaining power of each player (partner) depends on several socio-economic factors (Aizer, 2013; Hidrobo and Fernal, 2013; Hsu, 2017; and Buller et al., 2018). The resulting bargaining power determines the individual's behavior such that the greater the relative power, the lower the probability of being a victim of violence. Within a household, women with higher bargaining power are more independent from their partner and (from an economic standpoint) may react more to episodes of violence, such as divorcing. In this context, the greater the women's bargaining power, the lower the DV. However, in a lockdown situation, the impossibility of moving and leaving a violent partner may temporarily decrease individuals' bargaining power.

Several empirical studies have tested these hypotheses, finding robust confirmation in different cultural, ethnic, and socio-economic contexts. This paper proposes to interpret DV through the results of a natural experiment using data collected during the COVID-19 pandemic. The extant literature suggests that the various theories on DV can coexist in the same context with encroaching effects, reinforcing the drivers of DV and confirming its complexity. The main aim of this paper is to show that events such as a pandemic and the consequent containment measures are likely to increase the power of these various drivers, finally boosting episodes of DV. The coexistence of effects of different signs is observed when multiple drivers tend to offset each other. For example, Tauchen et al. (1991) show that men living in a family that receives public subsidies are more prone to commit DV, consistent with the bargaining power hypothesis. However, if the family income is high and largely depends on men's earning capacity, an increase in the income of both partners leads to less DV. Instead, when family income mostly depends on women's earning capacity, DV increases due to backlash. Although backlash is often associated with paternalistic contexts characterized by low education and social capital (Srinavisan and Bedi, 2007; Chin, 2017), it can become harsher as women's education increases (Dhanaraj and Mahambare, 2022; Kayaoglu, 2022) and rooted even in countries with high gender equality and

considerable female financial independence and economic empowerment, such as Sweden (Ericsson, 2020; Bergvall, 2022; and Wemrell, 2023).

The lockdown period had a particularly relevant economic (and organizational) impact on workers who had to temporarily suspend their job activities (e.g., shopkeepers, self-employed, artisans, etc.) or were left home at a reduced or no wage or kept working at home. As a result, Beland et al. (2021, on Canadian data) found that the inability to meet financial obligations and maintain social ties significantly increased DV, consistently with both increasing exposure and decreased bargaining power for women. Similarly, Bonacini et al. (2021) document that women in Italy faced disproportionate economic disadvantages during the lockdown, being overrepresented in sectors with low teleworkability, which likely compounded financial dependency and increased DV vulnerability. Roesch et al. (2020) confirm that spending a long time at home in close contact with the partner was detrimental to couple relationships and reduced access to basic needs, leading to stress and, consequently, an increase in DV. Consistent with the exposure hypothesis, data on the evolution of intimate partner violence in Italy (Romito et al., 2021) show that it increased for women cohabiting with a partner while decreased for non-cohabiting women; instead, the impossibility of reaching a non-coresident partner necessarily reduced the chances of violent acts. Similar evidence exists for the United States (U.S.), where Hsu and Henke (2021 and 2022) find that staying at home increased DV during the pandemic period (March-May/June 2020), again consistent with the exposure theory. Analogously, Bullinger et al. (2021) and McCrary and Sanga (2021), using U.S. data, and Agüero (2021), using Peruvian data, provide evidence that the pandemic increased DV because of the longer exposure of women to their abusive partners. In contrast with the exposure theory, Leslie and Wilson (2020) found that the increase in DV in the U.S. began before any mandated stay-at-home orders and was driven by subjects without any previous history of DV.

However, the effects of the pandemic-related restrictions on DV continued after the lockdown, and their economic consequences lasted longer. For instance, Arenas-Arroyo et al. (2021) show that in Spain the impact of the economic consequences of the pandemic was twice as the impact of the lockdown: they observe a relevant increase in violence also in the aftermath of the worst months of the disease when the relative position of the man worsened, consistently with the backlash theory.

Supporting the bargaining theory, Bhalotra et al. (2021), using data from various countries, show that an improvement in female employment is associated with lower DV, except for countries where women have limited access to divorce due to backlash. Henke and Hsu (2020, on U.S. data) and Fajardo-Gonzalez (2021, on Colombian data) tested the bargaining power hypothesis, confirming that female employment can be a protective factor from DV in some countries. However, further evidence in developing countries shows that this effect tends to disappear where women can more easily separate and divorce (Bobonis et al., 2020)

In addition to the drivers involved in the three aforementioned theories, public health literature has shed light on the contribution of some addictions (alcohol and drug abuse) to DV. In developed countries, alcohol use is implicated in approximately 50 percent of violent crimes and sexual assaults (Heinz et al., 2011) and has been linked to DV (Caetano et al., 2001; Srinavisan and Bedi, 2007; Foran and O'Leary, 2008; Livingston, 2010;

Carpinielli, 2018). During the most severe phases of the COVID-19 pandemic, empirical evidence witnessed that domestic alcohol consumption increased, even very significantly (Usher et al., 2021), likely leading to a growth in DV (de Lima, 2020; Chalfin et al., 2021).

A major problem faced when studying DV is represented by the widespread underreporting of episodes by the side of the victims (Durose et al., 2005; Myhill, 2017; Fernández-Fontelo, 2019) and the lack of standardized data (Dwyer, 1999; Miller et al., 2020). Moreover, existing laws do not identify DV as a unitary crime (Braschi 2022a and 2022b). Consequently, police reports, the number of convictions for DV-related crimes, and hospital reports significantly underestimate the phenomenon and strongly depend on the general propensity to report. Helplines and shelters might provide complementary data about requests for help, but the absence of any standardization procedure renders their use complex.

For the pandemic period, and with a specific focus on Italy, Barbara et al. (2020) provide evidence of a reduction in the number of women seeking help from anti-violence and/or hospital emergency services, despite the dramatic increase in the cases of DV, certified by international and national data. Evidence from hospital emergency departments in Milano (Italy) shows no significant increase in the number of cases between 2020 and previous years (Nittari et al., 2021), although the same data report a notable increase in the severity of injuries. However, this phenomenon may be a direct consequence of the pandemic: the extremely high number of patients hospitalized for COVID decreased the quantity of health services available for all other needs. Moreover, the presence of COVID-19 patients in hospitals exposed the other patients to the contagion. These reasons disincentivized people from seeking hospital assistance, but for the most severe situations. Del Casale et al. (2022) confirm the evidence of an increase in DV during the COVID-19 pandemic in Italy and find a positive correlation between the number of daily calls to the national anti-violence number and the number of quarantined people in the 30 days before. These pieces of evidence suggest that, while underreporting remains a problem, evidence in favor of episodes of DV increased during the pandemic.

A possibly useful tool to shed clearer evidence on actual DV episodes is the use of searches of keywords such as DV on Google: victims may refrain less from (and may have had more time to devote to) searching how to protect themselves than formally reporting episodes to the authorities. Indeed, Köksal et al. (2022) show that online searches for Italy, as reported by Google Trends, are a powerful tool to track potential threats of intimate partner violence during the COVID-19 pandemic and actual cases in post-outbreak scenarios.

A distinguishing contribution of this paper lies in its original treatment of the regulatory dimension of pandemic responses. Unlike most previous studies that treat lockdowns as a singular or homogeneous event, we consider temporal and geographical differences and even explicitly differentiate between *de jure* and *de facto* restrictions. The former refers to the formal enactment of restrictive rules, while the latter reflects actual behavioral changes to comply with restrictions. This conceptual and empirical separation enables us to analyze not only the presence of regulatory restrictions but also their effective uptake and behavioral consequences at the population level. Importantly, we aim to uncover possible systematic lags between these two dynamics. This *de jure* vs. *de facto* framing is novel in the literature and offers a more nuanced view of how institutional

action translates into social outcomes. It also provides a valuable policy lever, suggesting that anticipatory interventions can be most effective if deployed in the interval between rule enactment and behavioral compliance. This paper bridges regulatory studies, behavioral economics, and public health by showing how timing, rather than just the content of rules, mediates the relationship between crisis governance and domestic safety.

Finally, this study contributes to the existing literature by employing a novel approach that leverages reductions in air pollution as a proxy for mobility restrictions, complemented by an analysis of the formal stringency of lockdown measures. By integrating diverse data sources—ranging from police reports and helpline calls to Google Trends searches—our methodology captures both reported and unreported dimensions of DV, addressing significant gaps in traditional datasets. Grounded in exposure, backlash, and bargaining power theories, this paper not only disentangles the complex drivers of DV during lockdowns but also underscores the behavioral and socio-economic mechanisms at play. In doing so, it offers a comprehensive perspective on the dual role of forced cohabitation and economic stress in amplifying DV, providing insights that are both theoretically enriching and policy relevant. These findings are particularly pertinent for designing interventions that mitigate DV during future crises, ensuring that support systems are adaptive, proactive, and informed by robust empirical evidence.

3. Empirical hypotheses and methodology

This section sets out the empirical framework used to identify the effect of lockdown-related mobility restrictions on domestic violence (DV) in Italy, interpreted through the lenses of exposure theory, male backlash, and household bargaining models. Restrictions are conceptualized as shocks to both mobility and interpersonal dynamics within the household, potentially intensifying DV through mechanisms of increased exposure and changes in partners' relative power.

The core empirical strategy leverages variation in both formal restrictions and behavioral responses. To this end, we define two complementary proxies for lockdown intensity:

- Behavioral proxies based on the variation in air pollutants, which capture actual (*de facto*) reductions in population mobility.
- A formal policy proxy based on the Stringency Index from the Oxford COVID-19 Government Response Tracker, which encodes *de jure* government-imposed mobility restrictions.[2]

We assume that reductions in mobility, de jure or de facto, are associated with increased DV; more precisely:

- H1 (Behavioural restriction): Declines in air pollution are associated with increases in DV indicators, mainly due to higher exposure and loss of social interactions.

[2] The correlation between individual pollutants and the Stringency index is reported in Table A1 in Appendix 1.

The incidence of DV increases when mobility restrictions are effectively implemented, as these restrictions prolong exposure to potential perpetrators within the household. Importantly, this effect is not immediate: it follows a behavioral adjustment lag after the formal imposition of lockdown measures, during which actual compliance (proxied by reductions in traffic-related pollution) materializes.

- H2 (Formal restriction): Increases in the Stringency Index are associated with DV increases, independent of actual behavioral compliance.

Formal restrictions can serve as regulatory triggers for changes in domestic behavior. However, their impact on domestic violence is mediated by subsequent behavioral compliance. Therefore, the strongest association with DV outcomes is expected not at the time of the restriction enactment, but after a short delay, once mobility patterns adjust and exposure intensifies.

To test these hypotheses, we rely on three sources of outcome data. First, weekly Google Trends data captures normalized search intensity for DV-related terms. In particular, we used a text-mining algorithm designed to consider all the relevant couples and triplets of words related to DV. Google Trends data is available daily at the regional level. Google Trends returns two types of values: a unique national historical series for the selected period and a set of regional indices showing Google search in each topic, in each region, and for the selected period. To obtain a panel-type response variable for each week and for each Italian region, we calculated the products of the two. Following Köksal et al. (2022), we constructed our response variable by combining five strings obtained from different combinations of keywords related to DV (i.e., "1522", "abuse", "rape", "domestic violence", and " sexual violence"). We performed variable smoothing techniques to reduce the seasonal effect (e.g., in correspondence with key dates, such as November 25th, the International Day for the Elimination of Violence against Women), using a moving average of 4 weekly observations. The data were also normalized to set them in a range of values from 0 to 100, where 0 indicates a very low number of searches, while 100 represents the moment of the highest records in each region and given period. Moreover, the values are compared to all searches carried out in the same region and period, as follows:
The normalization procedure is reported in Equation (1).

$$GT_{d,i} = \frac{S_{d,i}}{\max(S_{d,i})} \times 100 \quad (1)$$

Second, we use quarterly data from the National Statistics Institute (ISTAT, 2020) on the number of calls to the national anti-violence helpline 1522, disaggregated at the provincial level.

Third, we analyze annual provincial-level police reports for mistreatment and stalking, under articles 572 and 612 bis of the Italian Penal Code. The Google Trends series is smoothed using a 4-week moving average to reduce weekly volatility, particularly in low-search-volume provinces.

Lockdowns induced immediate and significant declines in air pollutants, as widely documented (Beria and Lunkar, 2021; Collivignarelli et al., 2020). However, regional variation in enforcement and compliance implies that actual behavioral changes were not uniform across space or time. We use data on mobility-related air

pollution to capture the *realized* effect of lockdowns on mobility, as opposed to their *intended* regulatory effect (Stringency Index). This is particularly important in the Italian context, where behavioral responses varied substantially across municipalities and regions (Barbieri and Bonini, 2021; Panarello and Tassinari, 2022; Briscese et al., 2023).

We focus on four key pollutants to measure *de facto* compliance with restriction measures: carbon monoxide (CO), benzene (C_6H_6), nitrogen dioxide (NO_2), and nitrogen oxides (NOx). These indicators are sourced from the Italian national air quality monitoring network (ISPRA elaborations on SNPA data, 2022). The literature showed the negative relation between pollutants and mobility extensively, including Dimitriou & Kassomenos (2019), Carslaw & Beevers (2005), Horner (2000), Guerra et al. (1995)[3]

To remove structural variation in both pollution and DV due to persistent differences across regions and seasonal cycles, we compute annual differences using a 52-week lag. This transformation aligns comparisons across the same week of adjacent years, eliminating time-invariant local confounders and structural seasonality.

Our main model specification is reported in Equation (2). The baseline analysis employs OLS panel estimations with regional fixed effects and robust standard errors. Each specification includes one-week lagged same-week yearly variations of different pollutants individually, as follows:

$$y_{j,k,t} = \beta_0 + \beta_{1i}\Delta P_{i,k,t-1} + \varphi_k + \varepsilon_{i,k,t} \quad (2)$$

where $y_{i,k,t}$ is the dependent variable representing the variation of DV in week *t* and region *k*, influenced by the variation in the level of pollutant i, in region k, in week *t-1* ($P_{i,k,t-1}$). φ_k are regional fixed effects and $\varepsilon_{j,k,t}$ is the error term. The use of lagged pollutants helps to capture the effect of the variation in vehicular traffic in the week before the variation of DV, under the hypothesis that the effects of de facto reduced mobility on DV could be delayed. We test robustness using a two-week lag and possible autocorrelation in the dependent variable.

We repeat the same exercise, replacing the pollutants with the Stringency Index, lagged by one week, to estimate the association between formal (*de jure*) restrictions and DV, as shown in Equation (3). The Stringency Index varies weekly but is relatively stable, and since it was not defined before 2020, we use absolute levels rather than differenced values. We also estimate versions using alternative specifications of the index, accounting for the restrictions holding for vaccinated and unvaccinated populations.[4]

[3] Data from ISPRA (elaborations on SNPA, 2022) are not publicly available.

[4] Two versions of the index exist, one for vaccinated people and the other for unvaccinated people; we considered the weighted average of the two. The index was calculated daily, but as the government measures did not change frequently, the values remained constant for several days, leading to 54 unique values. Hence, we use the value at the beginning of each week without carrying out transformations of the original index. This choice rests on the fact that the index is available for the pandemic period only; therefore, no possibility of calculating its variations for the pre-pandemic period exists. One may argue that before the inception of COVID, the value of such an index should equal the situation of no restriction. Although true, this implies that the use of variations with respect to a fixed invariant level would not be different than the use of absolute levels.

$$y_{k,t} = \beta_0 + \beta_{2i} S_{t-1} + \varphi_k + \varepsilon_{k,t} \quad (3)$$

We also estimate dynamic models with lagged dependent variables to account for persistence in DV behavior and potential effects triggered by recent regulatory events. While this may introduce bias in short panels due to the correlation between the lagged dependent variable and the fixed effects (Nickell, 1981), the risk is reduced here given the relatively long time series available for this study (208 weeks).

For robustness, we include the following time-varying controls in all specifications: weekly rainfall (which affects pollutant dispersion), average labor income, the proportion of mixed-nationality marriages, the share of single-parent households, and per capita alcohol consumption. These variables are known to correlate with DV and, therefore, mitigate omitted variable bias. Throughout, standard errors are clustered at the regional level, and regressions are weighted by regional population size.

4. Results

This section presents the empirical results on the actual effects of mobility restrictions and formal lockdown intensity on DV, estimated using fixed-effects panel regressions, as outlined in Section 3. For each DV outcome, we estimate three sets of specifications: (1) regressions using air pollution as a proxy for the *de facto* reduced mobility; (2) regressions using the Stringency Index to capture *de jure* restrictions; and (3) dynamic models including further lagged mobility restriction proxies and covariates. All specifications include region fixed effects, and standard errors are clustered at the regional level.

4.1 Baseline Estimates: The Impact of Mobility Restrictions on Domestic Violence

Table 2 presents the baseline results assessing the relationship between mobility constraints—both behavioral and institutional—and three distinct indicators of DV: helpline calls, police-reported events, and Google Trends searches related to violence against women. The estimates reveal a consistent pattern that supports our hypotheses: as mobility is restricted, whether de facto (proxied by air pollutants) or de jure (measured by the Stringency Index), DV tends to increase.[5]

The results are particularly compelling when considering air pollution as a behavioral proxy for de facto mobility. Among the pollutants considered, nitrogen dioxide (NO_2) stands out with the most consistent and significant association across all DV indicators. In particular, the coefficients for NO_2 are negative and statistically significant at the 1% level across helpline calls, police reports, and Google Trends data. This suggests that reduced levels of this pollutant are systematically linked to increases in DV. Nitric oxides (NO_x) yield similar, though slightly weaker, results. Their negative coefficients are statistically significant at conventional levels (10%, 5%, and 1%), reinforcing the interpretation that lower mobility increases exposure to abusive domestic environments. Other pollutants produce weaker findings: carbon monoxide (CO) exhibits

[5] Table A2 in Appendix shows the results obtained assuming path dependence of the dependent variable.

the expected negative sign but fails to achieve statistical significance; benzene (C_6H_6) is significant only for helpline calls (at the 10% level). This evidence may stem from differences in the dispersion patterns of these pollutants.

Across all specifications, the Stringency Index—a proxy for formal lockdown policies—emerges as a strong and robust predictor of increased DV. Its coefficient is positive and statistically significant at the 1% level for both helpline calls and police reports, confirming that stricter government-imposed lockdown measures were associated with heightened instances of domestic violence or increased help-seeking behavior. This is also consistent with existing literature that identifies home confinement as a key stressor exacerbating household tensions and limiting victims' ability to seek refuge or external support. Notably, the Stringency Index does not yield significant effects on Google Trends searches, which may reflect limitations in internet access or changing coping behaviors under heightened restrictions.

Overall, the baseline estimates offer a first strong empirical support for the hypothesis that DV increased during periods of constrained mobility, whether due to formal policy interventions or changes in individual behavior. The fact that de jure and de facto measures operate in parallel, and often reinforce each other, highlights the multidimensional nature of mobility during crises. Importantly, the results underline the value of combining administrative and behavioral proxies to capture the full impact of lockdowns on vulnerable populations.

These findings are particularly consistent with the exposure theory, which posits that increased time spent in close proximity to a potential aggressor—due to either behavioral immobility or formal lockdowns—heightens the risk of domestic abuse. However, while the baseline models capture immediate associations, they may overlook lagged or cumulative effects, such as psychological deterioration or escalating tensions over time. For this reason, the next section explores the impact of second-period lags of both behavioral and institutional variables, aiming to provide a more comprehensive understanding of how sustained or delayed exposure influences the dynamics of domestic violence.

4.2 Second-Period Lag Effects: Delayed Exposure and Escalation Dynamics

Building on the baseline evidence, Table 3 explores whether the effects of mobility restrictions—both *de facto* and *de jure*—are also detectable with a temporal delay. The inclusion of second-period lags allows us to assess whether the relationship between immobility and domestic violence is not only immediate, but also cumulative or delayed, as posited by theories of exposure and stress escalation. This is particularly important in the context of DV, where tensions may accumulate over time before leading to observable acts of aggression or help-seeking behavior.[6]

The results for air pollutants remain broadly consistent with the baseline estimates, but with notable nuances. NO_2 continues to display a negative and statistically significant effect at the 1% level on both helpline calls

[6] Table A3 in Appendix shows the results obtained assuming path dependence of the dependent variable.

and police reports, both in first and second lags. The parameter associated with NO_2 is also negative and significant at the 5% level for Google Trends records. The temporal persistence of the NO_2 effect (significance at the second lag) underscores the potential for cumulative household stress and aligns with the idea that prolonged confinement exacerbates interpersonal tensions.

NO_x also maintains its predictive power, with negative coefficients that are statistically significant at the 10% to 5%, depending on the specific pollutant. While slightly less robust than NO_2, the results related to NO_x also support the interpretation of this pollutant as a relevant behavioral proxy for exposure, albeit with somewhat weaker explanatory power.

CO remains statistically not significant across all specifications, and weakly significant at the first lag for emergency calls. This indicates its limited utility in capturing behaviorally relevant mobility patterns over time. A similar pattern is shown by C_6H_6. The lack of robust lagged effects for CO and benzene supports the conclusion that some specific pollutants—most notably nitrogen dioxide, NO_2—are more effective in capturing prolonged reductions in human mobility with high predictive power for DV outcomes. Indeed, NO_2 is a key byproduct of internal combustion engines and is widely used as an indicator of road traffic intensity in environmental health and urban mobility studies (Račić et al. 2025, Jenkin 2004, Carslaw & Beevers, 2005; WHO, 2021). Other pollutants like CO and C_6H_6 originate from a broader range of sources –such as industrial processes– and can be characterized by different dispersion patterns; these factors may dilute their sensitivity to short-term behavioral shifts in daily mobility patterns.

Furthermore, the results in Table 3 reveal a temporal asymmetry in the relationship between institutional lockdown measures and DV. The first lag of the Stringency Index becomes negative and statistically significant for emergency calls and Google Trends searches, suggesting that stricter lockdowns were initially associated with a decrease in DV outcomes—a finding that runs counter to prevailing expectations. Nonetheless, in the second lag, the Stringency Index parameters become positive and statistically significant for emergency calls, crimes, and Google Trends searches, indicating that formal lockdown provisions ultimately led to a delayed rise in DV, in line with theoretical expectations, but with a significant time lag.

This inversion of signs over time is at the core of our investigation issue and can be meaningfully interpreted by contrasting the institutional nature of the Stringency Index with the behavioral information embedded in pollution data. Whereas specific air pollutants provide real-time, de facto indicators of human mobility (and thus exposure to potential DV), the Stringency Index reflects top-down mandates that require time to translate into actual behavioral change. In other words, at a certain point governments imposed lockdowns, however compliance—or full behavioral adjustment—emerged gradually. This delay is captured in the second-period effect, which shows that only after some time did the restrictions meaningfully confine individuals to their homes and, consequently, elevate their exposure to domestic risk. These findings underscore the importance of distinguishing between the announcement of lockdown measures and their effective implementation within households, particularly when analyzing outcomes like DV that depend critically on lived, rather than merely legislated, confinement. In other words, while governments acted swiftly, it took time for people to adjust their

behavior in ways that reduced mobility and, inadvertently, increased exposure to domestic risks. This staggered effect reflects not just policy enforcement, but also the population's behavioral response to confinement mandates.

Overall, the results from Table 3 suggest that the effects of immobility on DV are not limited to the short term. Both behavioral proxies and formal policy measures display significant effects. These findings provide empirical support for exposure theory, indicating that risk intensifies not only from immediate confinement but also from its actual, prolonged, and cumulative nature. The robustness of the lagged relationship emphasizes the need for time-sensitive policy responses that account for both immediate and deferred risks of household violence.

Overall, results from Table 3 allow us to draw a meaningful distinction between the effects of *de jure* restrictions and *de facto* behavioral responses. The coefficient on the Stringency Index—our measure of formal restriction severity— suggests that stricter government-imposed lockdown rules were associated with rising levels of DV after some lag. Instead, the effects produced by pollution-based proxies, which capture actual reduced mobility are more immediate. This empirical evidence is notable: it suggests that not only the enactment of restrictions, but also the degree to which people behaviorally comply, had an impact on DV.

Finally, from a modeling standpoint, the dynamic specification in Table 3 shows that the observed associations are not simply artifacts of omitted time dynamics but rather reflect genuine and temporally concentrated impacts of lockdown measures. These insights have practical implications: effective interventions to mitigate DV during future mobility-restricting events must be deployed rapidly, as the window of heightened vulnerability appears to be relatively narrow.

4.3 Models with Covariates

To assess the robustness of the core findings, Tables 4 and 5 introduce additional covariates into the regressions to account for time-varying socio-economic and demographic characteristics across provinces.[7] We include average labor income, percent of mixed-nationality marriages, alcohol consumption, and mono-parental households. Based on the literature, these variables likely influence DV dynamics independently of mobility restrictions. In particular, DV incidence may vary depending on how the economic situation affects the bargaining power within couples. Moreover, in mixed-nationality marriages, gender stereotypes may emerge with strength, depending on the cultural background of the spouses. Noteworthy, lone mothers are generally more exposed to violence from the fathers of their offspring; hence, restrictions on movement could decrease violence as the fathers have fewer opportunities to meet the mothers. The available variable refers to lone parents in general, without any possibility of disentangling fathers and mothers; nevertheless, the share of lone mothers is likely highly and positively correlated to that of single-parent households. Finally, given that

[7] Table A4 in Appendix show the results obtained assuming path dependence of the dependent variable.

consumption of alcohol could be associated with DV, we considered the number of people aged 11 or more per 1,000 inhabitants who consume alcohol outside of meals.

Regarding air pollutants, the results in Table 4 indicate that both the first and second lag of NO_2, the leading measure of actual restricted mobility according to the previous analysis, maintain a robust and statistically significant negative relationship with DV outcomes. As in previous models, we interpret this outcome as an effective brake on mobility, expressed by reductions in pollutant concentrations, which translates in a short time into an increase in DV episodes. The results regarding NO_x in Table 4 confirm the pattern followed by NO_2, although significant at 1% level only in regressions having Google Searches as a response variable. The findings for carbon monoxide (CO) and benzene (C_6H_6) are in line with the previous outcomes. They provide the same implications as those associated with NO_2 and NO_x, although with a weaker relationship with DV outcomes. Overall, the results of the model with covariates reinforce the conclusion that some pollutants are more informative than others as proxies for human mobility over extended timeframes. In particular, NO_2—and to a lesser extent NO_x—continue to offer strong behavioral signals. These findings underline the importance of establishing correlations between specific pollutants and behavioral changes and interpreting delayed effects with caution, as they ~~may~~ reflect complex interactions between mobility, adaptation, and structural constraints.

In Table 4, the results for the Stringency Index remain unchanged. The coefficients associated with the covariates (Table 5) provide valuable insights into the social and cultural conditions that mediate the relationship between mobility restrictions and DV. By controlling for socio-economic status, family composition, alcohol use, and household diversity, the model allows for a more nuanced understanding of vulnerability under lockdown.

Average labor income is negatively associated with DV outcomes, particularly for Google Trends searches. This result is consistent with bargaining power theory, which posits that women with relatively greater economic resources are better positioned to negotiate within relationships or exit abusive environments. Financial stability enhances women's fallback options, reduces dependence on potentially violent partners, and may help to lower household tensions overall—especially during periods of forced cohabitation.

The percentage of mixed-nationality marriages emerges as negatively associated with DV, potentially due to more balanced intra-household power dynamics or greater female autonomy. From the perspective of bargaining theory, this result may reflect contexts in which women in mixed-nationality couples enjoy stronger fallback options—such as independent income, legal status, or broader social support—compared to more homogeneous households where traditional gender norms may dominate. In these settings, greater female bargaining power may act as a deterrent against violence, as women are better positioned to resist or leave abusive situations. While mixed-nationality marriages can pose cultural and communicative challenges, they may also promote more equitable negotiations within the household, reducing the likelihood of coercive or violent behavior. This interpretation is consistent with empirical findings that link female empowerment and economic agency to lower DV risk across diverse contexts.

Alcohol consumption per capita is another important covariate, showing a positive and significant relationship with DV. This finding reinforces existing evidence that alcohol is often associated with violent behavior, can be an indirect amplifier of household tension, particularly under crisis conditions, and represents a red flag of abusive environments. From the perspective of exposure theory, substance use lowers self-control for both potential aggressors and potential victims, finally increasing the risk of violence when individuals are confined in proximity over extended periods. Simultaneously, in line with male backlash theory, alcohol consumption may heighten violent responses among men who perceive a loss of control or authority due to job loss or other lockdown-related stressors. Notably, the association between alcohol consumption and DV emerges as significant only in models using behavioral proxies of mobility (de facto exposure)—such as declines in pollution—rather than formal policy measures (de jure stringency). This pattern suggests that the positive association between alcohol and DV becomes most salient when actual confinement occurs, intensifying daily interactions within the household. Formal lockdown mandates may not uniformly alter exposure or interpersonal dynamics, especially if enforcement is uneven or behavioral compliance is delayed. In contrast, when individuals are *actually* restricted—whether voluntarily or due to socioeconomic constraints—alcohol-fueled tensions are more likely to escalate into violence. These findings support the view that the risks linked to substance use are mediated by real patterns of cohabitation and interaction, not merely by institutional declarations.

Finally, the share of mono-parental households—predominantly single-mother households—is negatively associated with DV indicators, though the effect is weak and not consistently significant across specifications. This result may reflect reduced exposure to intimate partners, in line with exposure theory, as the absence of a cohabiting partner eliminates the immediate risk of DV. However, given the marginal significance, the association should be interpreted with caution and may also reflect unobserved protective dynamics or reporting differences in these household types.

Taken together, the results from Table 5 underscore that DV during crises is shaped not only by institutional factors like lockdown stringency or behavioral responses to restrictions, but also by deeper structural and behavioral dynamics. The findings demonstrate how socio-economic and cultural conditions resulting in constrained bargaining power for victims or even male backlash interact with the augmented exposure to an aggressor, finally generating layered and differentiated risks. As such, policies aimed at reducing DV during emergencies must move beyond one-size-fits-all approaches, addressing economic insecurity, alcohol misuse, gender dynamics, and the specific needs of culturally diverse and non-traditional households.

5. Conclusions

This study set out to explore how domestic violence (DV) responded to COVID-19 lockdown measures in Italy, to disentangle the effects of formal restrictions (de jure) from the actual behavioral responses to the restrictions (de facto). By leveraging a novel dual approach that includes both institutional policy data (the Stringency Index) and environmental proxies for mobility (air pollutants such as NO_2, NO_x, CO, and C_6H_6), this paper contributes to a more dynamic and granular understanding of the mechanisms behind DV during crises.

The paper offers several original contributions to the literature. First, it introduces a clear distinction between the timing and effect of regulatory mandates and actual behavioral adjustments, thereby offering new insight into how policy signals differ from real-world compliance in their impact on intra-household violence. Second, by integrating multiple indicators of DV—Google Trends data, helpline calls, and police reports—it captures both latent concern and formal help-seeking behavior, mitigating issues of underreporting. Third, the analysis tests the exposure theory, by accounting for backlash and bargaining power mechanisms—in a unified empirical setting, revealing the complexity and heterogeneity of DV risk during crises.

Methodologically, the study applies panel data regressions with regional and time fixed effects, incorporates lag structures to account for behavioral delays, and adds several robustness checks. It also includes a suite of socio-demographic covariates to explore structural sources of heterogeneity and to assess other predictions highlighted in the literature beyond pure exposure.

The results offer strong empirical support for exposure theory. Regression outcomes consistently indicate that actual reductions in mobility are associated with increases in DV outcomes. These results persist even after controlling for rainfall and time-invariant provincial differences. Importantly, the effects suggest that prolonged forced confinement, rather than immediate mobility reduction, drives the surge in violence.

The role of formal restrictions, as captured by the Stringency Index, is more nuanced. In early lags, the associated parameter is sometimes negative or statistically weak, but when lagged and controlled for covariates, it becomes positive and statistically significant across key DV outcomes. This suggests that policy imposition alone does not instantly translate into higher risk of violence—rather, it is the delayed behavioral response to these policies that creates conditions conducive to increased DV. The evidence thus supports a temporal mediation between *de jure* mandates and actual exposure, reinforcing the need to interpret lockdown impacts dynamically.

Further nuance emerges from the model with covariates, which allows us to test the broader relevance of specific socioeconomic factors. The negative and significant effect of average labor income on DV indicators supports the relevance of relative power within intimate relationships, implying that higher economic stability can reduce the likelihood of abuse. The positive effect of alcohol consumption per capita support the well-established evidence that, especially in contexts of stress, substance abuse and DV exacerbate.

These findings carry important implications for crisis management and violence prevention. Most critically, they highlight a window of opportunity for policy intervention: the period between the announcement of lockdowns and the behavioral adaptation that follows. It is during this gap that protective services, helplines,

shelters, and silent reporting tools must be urgently reinforced. Relying solely on formal policy triggers may delay lifesaving measures. Behavioral indicators, such as real-time pollution monitoring or digital search behavior, can serve as early warning systems to anticipate rising risk and enable geographically targeted action.

Moreover, structural factors like income, alcohol availability, and family structure must be integrated into DV response strategies. This suggests that multifaceted approaches—combining economic support, mental health services, and culturally sensitive outreach—are essential for mitigating violence in periods of collective stress.

While this study offers a robust analytical framework and a novel empirical contribution, it is not without limitations. First, although air pollutants serve as effective proxies for mobility, they may also be influenced by exogenous factors such as weather or industrial production. Second, DV remains difficult to measure comprehensively, and while multiple data sources were triangulated, underreporting and measurement heterogeneity remain concerns. Finally, the lack of individual-level data limits the ability to observe intra-household dynamics directly.

Future research could address these limitations by incorporating individual-level administrative records or qualitative interviews to better understand mechanisms of backlash and bargaining power. Moreover, extending the model to cross-national comparisons or to different types of crises (e.g., climate shocks, economic downturns) would further test the generalizability of the findings.

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TABLES

Table 1. Descriptive statistics

	Mean	Standard deviation	Minimum
Calls to 1522	280.49	275.73	0
Crimes	137.46	139.95	0
Google Trends searches	17.99	11.57	0
Nox (μg/Nm3)	24.97	23.13	0.13
NO_2 (μg/Nm3)	18.36	8.29	2.61
CO (mg/Nm^3)	0.624	0.313	0.00
C_6H_6 (μg/Nm^3)	0.960	0.635	0.140
Stringency index (0 minimum - 100 maximum)	32.53	35.26	0.00
Rainfalls (mm/m^2)	78.59	66.81	0.00
Average labour income (thousands of euro)	14.06	1.45	11.54
Percentage of mix-nationality marriages	25.09	8.07	9.26
People aged 11 or more drinking alcohol per 1,000 inhabitants	0.0006	0.0002	0.0003
Share of mono-parental households	18.75	2.84	11.60

Table 2. Episodes of violence and keyword searches on Google: effects of pollutants with one time lag.

		CALLS		CRIMES	
		(1)	(2)	(1)	(2)
	Rainfalls	NO	YES	NO	YES
(a)	NO_x (1 lag)	-2.012	-2.142	-1.002	-1.052
		(1.018)*	(1.095)*	(0.507)*	(0.536)*
(b)	NO_2 (1 lag)	-7.835	-8.092	-4.233	-4.353
		(2.367)***	(2.488)***	(1.188)***	(1.236)***
(c)	CO (1 lag)	-30.33	-32.86	-16.01	-16.99
		(18.78)	(19.84)	(13.03)	(13.05)
(f)	C_6H_6 (1 lag)	-25.08	-26.50	-11.15	-11.86
		(12.82)*	(13.98)*	(8.039)	(8.240)
(g)	Stringency index (1 lag)	0.662	0.661	0.820	0.821
		(0.135)***	(0.135)***	(0.165)***	(0.165)***

OLS panel estimates: coefficients and standard errors in brackets. *** p-values ≤ 0.01; ** 0.01 < p-value ≤ 0.05; * 0.05 < p-value ≤ 0.10. Notes. 1) Each dependent va
taken one by one. Coefficients shown in each column are a synthesis of these regressions, i.e., each cell reports the result of one regression where calls, victims, and sea

Table 3. Episodes of violence and keyword searches on Google: effects of pollutants with two time lags.

		CALLS		CRIMES	
		(1)	(2)	(1)	(2)
	Rainfalls	NO	YES	NO	YES
(a)	NO_x (1 lag)	-1.523	-1.657	-0.755	-0.808
		(0.754)*	(0.826)*	(0.368)*	(0.395)*
	NO_x (2 lags)	-1.474	-1.539	-0.750	-0.776
		(0.687)**	(0.725)*	(0.359)*	(0.374)*
(b)	NO_2 (1 lag)	-5.095	-5.341	-2.697	-2.812
		(1.709)***	(1.827)***	(0.843)***	(0.891)***
	NO_2 (2 lags)	-5.492	-5.548	-3.058	-3.085
		(1.669)***	(1.700)***	(0.865)***	(0.878)***
(c)	CO (1 lag)	-24.92	-26.90	-11.99	-12.78
		(14.62)	(15.50)*	(9.392)	(9.496)
	CO (2 lags)	-10.96	-12.20	-8.106	-8.597
		(9.628)	(10.18)	(8.895)	(8.955)
(f)	C_6H_6 (1 lag)	-22.94	-24.10	-9.415	-10.00
		(10.66)**	(11.59)*	(6.235)	(6.407)
	C_6H_6 (2 lags)	-5.211	-5.788	-3.750	-4.040
		(6.910)	(7.508)	(4.361)	(4.548)
(g)	Stringency index (1 lag)	-0.821	-0.821	-0.0662	-0.0648
		(0.200)***	(0.201)***	(0.0682)	(0.0677)
	Stringency index (2 lags)	1.496	1.496	0.894	0.894
		(0.314)***	(0.314)***	(0.207)***	(0.207)***

OLS panel estimates: coefficients and standard errors in brackets. *** p-values ≤ 0.01; ** 0.01 < p-value ≤ 0.05; * 0.05 < p-value ≤ 0.10. Notes. 1) Each dependent va variable taken one by one. Coefficients shown in each column are a synthesis of these regressions, i.e., each cell reports the result of one regression where calls, victim at a time.

Table 4. Episodes of violence and keyword searches on Google: effects of pollutants with two time lags and covariates.

		CALLS			CRIMES		
		(1)	(2)	(3)	(1)	(2)	(3)
	Rainfalls	YES	YES	YES	YES	YES	YES
	Average labour income	YES	YES	YES	YES	YES	YES
	Percentage of mix-nationality marriages	NO	YES	YES	NO	YES	YES
	People aged 11 or more drinking alcohol	NO	NO	YES	NO	NO	YES
	Share of mono-parental households	NO	NO	YES	NO	NO	YES
(a)	NO_x (1 lag)	-0.990	-0.553	-0.638	-0.0756	-0.0159	-0.0897
		(0.735)	(0.650)	(0.657)	(0.301)	(0.311)	(0.311)
	NO_x (2 lags)	-0.944	-0.444	-0.480	-0.280	-0.212	-0.232
		(0.625)	(0.528)	(0.526)	(0.286)	(0.297)	(0.290)
(b)	NO_2 (1 lag)	-4.799	-3.325	-3.249	-1.715	-1.577	-1.527
		(1.656)***	(1.393)**	(1.321)**	(0.707)**	(0.694)**	(0.614)**
	NO_2 (2 lags)	-5.247	-3.821	-3.691	-2.307	-2.173	-2.077
		(1.583)***	(1.328)***	(1.239)***	(0.695)***	(0.684)***	(0.591)***
(c)	CO (1 lag)	-34.73	-18.45	-19.76	-5.172	-2.814	-4.418
		(22.51)	(20.53)	(19.33)	(10.49)	(10.17)	(8.750)
	CO (2 lags)	-20.29	-2.749	0.679	-10.25	-7.710	-5.510
		(13.25)	(14.52)	(14.03)	(7.402)	(7.028)	(4.898)
(d)	C_6H_6 (1 lag)	-25.90	-10.37	-9.515	-8.662	-6.216	-5.165
		(9.395)**	(7.609)	(7.797)	(5.356)	(5.542)	(4.908)
	C_6H_6 (2 lags)	-7.645	5.087	5.093	-4.739	-2.733	-2.448
		(6.049)	(6.211)	(6.720)	(3.071)	(3.353)	(3.265)
(e)	Stringency index (1 lag)	-2.267	-2.218	-2.340	-1.434	-1.428	-1.515
		(0.615)***	(0.630)***	(0.621)***	(0.450)***	(0.451)***	(0.445)***
	Stringency index (2 lags)	3.459	3.381	3.413	2.459	2.448	2.471
		(0.791)***	(0.799)***	(0.798)***	(0.579)***	(0.578)***	(0.577)***

OLS panel estimates: coefficients and standard errors in brackets. *** p-values ≤ 0.01; ** 0.01 < p-value ≤ 0.05; * 0.05 < p-value ≤ 0.10. Notes. 1) Each dependent va
taken one by one. Coefficients shown in each column are a synthesis of these regressions, i.e., each cell reports the result of one regression where calls, victims, and sea

Table 5. Effects of covariates on episodes of violence and keyword searches on Google.

	CALLS		CRIMES		GOOGLE TRENDS SEARCHES	
	Stringency index	(1 and 2 lags)	Stringency index	(1 and 2 lags)	Stringency index	(1 and 2 lags)
Average labour income	-0.379		2.398		2.423	
	(3.122)		(2.181)		(0.383)***	
Share of mixed-nationality marriages	-1.239		-0.308		-0.0989	
	(0.329)***		(0.0841)***		(0.0164)***	
Alcohol consumption	8.808		20.298		5.729	
	(24.063)		(15.668)		(8.691)	
Share of monoparental households	-0.717		-0.396		0.0722	
	(0.325)**		(0.219)*		(0.0897)	

OLS panel estimates: coefficients and standard errors in brackets. The specifications are the same as those presented in columns (3) of table 4. Column titles indicate the main regressor used in the specification. *** p-values ≤ 0.01; ** 0.01 < p-value ≤ 0.05; * 0.05 < p-value ≤ 0.10