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Original Article

Forced labour in manufacturing and the local industry structure: the case of Italy

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Abstract

Do spatial socio-economic features influence the demand for forced labour also in places where it is illegal and socially unacceptable? This article provides an answer to this question by estimating the effect of the characteristics of the local industry structure on forced labour in manufacturing (FLM hereafter) using Italy as a case study. Conceptually, we bridge the literature on forced labour with economic geography to empirically test the effect of local industry specialization and firm size. Exploiting a novel database of geo-tagged episodes of FLM across Italian local labour market areas, we find that industry specialization and the share of micro-firms in the industry that specializes a place are key predictors for FLM. Instrumental variable estimates relying on novel data on the geography of Italian firms in 1911 show that results are robust to endogeneity threats. Findings also hold to the inclusion of potential confounding features, like the presence of migrants and institutional quality, and to spatial dependency tests. Moreover, results support the relevance of addressing the spatial dimension for a thorough understanding of FLM. Overall, the article contributes to the currently scant quantitative evidence on the micro-regional determinants of forced labour in the Global North, which is still relatively unexplored.

Keywords: forced labour in manufacturing; local labour markets; local industry specialization; firm size.

JEL classifications: J47, J7, J8, L1, L25, L6, R12, R23

1. Introduction

This article contributes to the still under-investigated issue of forced labour[1] in manufacturing (FLM hereafter) in the Global North,[2] relating to the growing efforts to combat forced labour by national and international institutions.[3] These efforts are bolstered by striking statistics that show that the yearly revenues from forced labour in the private economy have overall reached $236 billion (ILO, 2024). Europe and Central Asia generate the highest annual illegal profits both in absolute terms and relative to the number of victims (ILO, 2014, 2019). Breaking down these illegal profits by sector (which are

[1] 'Forced labour' defines the recruitment of labourers for employment under abusive conditions and by preying on their need. It encompasses commercial sexual exploitation—not considered in this article—and people forced into labour in industry, services, agriculture, and domestic work. The focus of this article is on forced labour in manufacturing.
[2] Global North includes Western European Countries, the USA, Canada, Australia, New Zealand, Israel, Japan, South Korea, Taiwan, and Singapore.
[3] Among others, the UN 2030 Sustainable Development Goal 8.7, the ILO framework to counter forced labour, the EU trade policy schemes, etc., have all specific measures to reduce forced labour exploitation by business firms.

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lower than revenues), the highest amounts are generated by industry ($35 billion), followed by services ($20.8 billion), agriculture ($5 billion), and domestic work ($2.6 billion; ILO 2024).

The frequency of this severe form of exploitation has stimulated a growing body of research. A new conceptual framework has emerged, which models industry characteristics, worker vulnerability, and institutional quality as possible risk factors for FLM (Bauloz, Vathi, and Acosta, 2019; Caruana et al., 2021; Crane et al., 2022). The empirical research validating this framework is still in its infancy and has several shortcomings, starting with the very limited attention to the Global North (Phillips, 2011; Rogoz and Kraler, 2017). Also, existing evidence either considers cross-country comparisons or qualitative case studies (Crane et al., 2019, 2022; Bullock et al., 2024), downplaying the relevance of a spatial approach and colliding with the recognized influence of local features on firms and workers behaviours (Martin et al., 2018; Iammarino, Rodriguez-Pose, and Storper, 2019).

The main reasons for a spatial perspective in the analysis of FLM are two-fold. First, economic geography shows that the speculated risk factors for FLM have strong spatial variability. Research extensively shows the substantial variance in industry characteristics, institutional quality, and workforce availability at the subnational level (e.g. Crescenzi and Rodriguez-Pose, 2011; Iammarino, Rodriguez-Pose, and Storper, 2019). As such, a spatial lens should be used to explore the relationship between these factors and FLM. Second, evidence also indicates that FLM is spatially dispersed (Unseen, 2018; McAuliffe et al., 2019), further emphasizing the need for subnational investigations to better understand FLM and its associated risk factors.

This article contributes to fill this gap, focusing on the effect of the local industry structure and considering the case of Italy. Specifically, we estimate the effect on FLM of the local leading industry,[4] with a focus on the role of micro-firms (below ten employees) in the same industry. This focus appears to be particularly salient in light of the large body of evidence showing that the geography of industry specialization and micro-firms explains socio-economic vulnerabilities (e.g. Affuso, Capello, and Fratesi, 2011; De Marchi & Grandinetti, 2014; Fingleton, Garretsen, and Martin, 2015) and contributes to rising inequality across people, firms, and places (e.g. Ezcurra et al., 2005; Pinheiro et al., 2022).

Studies on forced labour assign a crucial role to industry structure, emphasizing its key influence on the labour cost plans that firms implement as part of their competitive strategies (LeBaron et al., 2018; Crane et al., 2019; Caruana et al., 2021). Also, it is conjectured that micro-firms in the leading industry are particularly responsible for FLM. They are more prone to labour exploitation, due to the heightened competition they face in the globalized market (LeBaron et al., 2018). Further, if they are a sizeable portion of the leading industry, their labour cost plans could create room for a sufficient demand for forced labour (Crane et al., 2019). By merging this work with research in economic geography showing that the effects of industry specialization and micro-firms are better understood through a spatial approach (Frenken, Cefis, and Stam, 2015), we carry out a subnational investigation of the effect of local industry specialization and micro-firm in the leading industry on FLM.

Our empirical investigation faces three main challenges. First, the scarcity of quantitative evidence imposes to account for the broad array of potential confounding features advanced by forced labour literature (ILO, 2014; LeBaron et al., 2018). Therefore, our empirical strategy controls for population that might be vulnerable to exploitation and the quality of institutions. Second, concerns of reverse causality and sorting of people and firms must be alleviated, to provide evidence that goes beyond correlation. We address this point through an identification strategy that relies on a Bartik-like instrumental variable estimation which exploits the historical post-Unification geography of the Italian industry specializations and firm size.[5] Third, adequate data are needed, since FLM goes largely underreported as a crime (Cruyff, van Dijk, and van der Heijden, 2017; Farrel et al., 2019). We alleviate measurement bias concerns with a new database of FLM episodes in Italy, which we have designed by applying machine learning algorithms to different sources (national and local newspapers, NGOs, labour unions and institutions).[6]

Italy is a relevant case for several reasons. First, incidence of forced labour is high, making Italy rank second among Western European countries for the prevalence of modern slavery in 2023

[4] The leading industry is the industry in which a place is mostly specialized (ISTAT, 2015).

[5] By leveraging this historical context, we align with recent developments in economic geography that highlight the lasting impacts of local industry legacies (Huggins et al., 2021; Cainelli, Ciccarelli, and Ganau, 2022) and historical labour market characteristics (Braun et al., 2021).

[6] For further validation, we also conducted several interviews with specialized figures on force labour in Italy, including members of the statistics department of the Italian Ministry of Agriculture and staff members of Caritas Diocesana (the pastoral body of the Italian Bishops' Conference).

according to the Global Slavery Index (Walk Free, 2023). Second, Italian industries have been facing the challenges posed by globalization at different intensities, depending on industry type, geographical location, and firm size (e.g. Bellandi and De Propris, 2012; Dei Ottati, 2018; Giuliani and Rabellotti, 2018). Third, the country has national and EU level ethical and legal barriers opposing forced labour, implying that firms face both legal and social costs when deciding to resort to FLM. Forth, being the key transit point for the '*Central Mediterranean Route*' of migration, Italy has many precarious migrants, who are vulnerable to labour exploitation (Caruana et al., 2021). Finally, we exploit novel FLM geo-tagged data between 2016 and 2020. Therefore, the country appears to have a salient characterization in several speculated risk factors for FLM, which can be tested empirically at fine-grained spatial level.

We find that the relevance of micro-firms in the local leading industry matters for FLM. Through two stage least square estimation with instrumental variable (IV-TSLS), we show that more micro-firms in the local leading industry determine more FLM. Also, we find that the type of local leading industry matters. Places without a dominant specialization have higher incidence of FLM, and the same applies to places specialized in 'Made in Italy' textile and clothing. Notably, we find that the presence of vulnerable groups, such as refugees and unemployed, does not matter for FLM. These findings are robust to the inclusion of control variables which account for potential confounding explanations, falsification tests, robustness checks, and test for spatial dependence.[7] Taken together, these results indicate that FLM in Italy is determined by industry structural features rather than by labour supply ones.

These findings have relevant implications. First, they contribute to build quantitative evidence on the determinants of FLM as advocated by forced labour scholars (Caruana et al., 2021). Second, they add to research on territorial inequality (e.g. Martin et al., 2018; Iammarino, Rodriguez-Pose, and Storper, 2019), by showing the consequences of industrial structure disparities on the exploitative practice of forced labour. Third, they relate to international business studies on supply chain and human rights violation among the workforce (Wettstein et al., 2019; Caruana et al., 2021), by adding evidence on the effect of the local context. Fourth, these results contribute to the literature on left-behind places and people (Dijkstra, Poelman, and Rodríguez-Pose, 2020; Pike et al., 2023), showing that local factors can drive firms towards illegal and unethical behaviours.

The rest of the article is organized as follows. Section 2 details the background literature and the case study. Section 3 outlines the estimation framework, the identification strategy, and the data. Section 4 describes and discusses the findings. The conclusions are presented in Section 5.

2. Forced labour in manufacturing, economic geography, and the Italian case

2.1 Risk factors for forced labour

Established research on the risk factors for FLM largely focuses on the Global South (e.g. Phillips, 2011; Rogoz and Kraler, 2017; Crane et al., 2019). This work has generated country-level evidence and qualitative studies which support globalization-driven competition, poor-quality institutions, and large availability of cheap unskilled labour as triggers for FLM (Rossi, 2015; Baglioni, 2018; Coe and Yeung, 2019). The rationale beyond these findings is that globalization pushes small and geographically dispersed firms relying on unskilled labour to compete among themselves to become lower tier suppliers in global production networks and value chains, which are organized by lead firms exerting high level of control (Pickles et al., 2015; Barbu et al., 2018). These suppliers typically engage in cost competition to keep their contracts. Therefore, cutting unskilled labour costs up to the point of using forced labour arises as an option (Crane et al., 2022), also because it matches with local availability of cheap labour, lack of adequate regulations, and weak rule of law.

Recent contributions have broadened this perspective by advancing a conceptual framework which models the risk factors for FLM in the Global North (LeBaron et al., 2018; Crane et al., 2019; Caruana et al., 2021; LeBaron, 2021; Crane et al., 2022). These efforts are supported by the sizeable incidence of FLM in developed countries (ILO, 2019), even if force labour in all its dimensions is forbidden by law and ethically opposed. According to the Global Slavery Index, there are over 1.8 million individuals in the Global North who are victims of modern slavery, with a significant proportion being forced labour (Walk Free 2020). Data from the European Commission confirm high and growing shares of forced

[7] Among tests, we also performed the required tests on the Bartik-like instruments (Adão, Kolesár, and Morales, 2019; Goldsmith-Pinkham et al., 2020)

labour across the EU-28[8] countries (European Commission, 2020a).[9] These figures affirm the need of a research agenda that specifically addresses the risk factors for FLM in countries that do not occupy the lowest rank in the global value chain (GVC) production hierarchy (Pickles et al., 2015), and that have welfare systems in place to protect vulnerable groups combined with ethical and legal constraints against forced labour (Caruana et al., 2021).

Designed by bridging research from different disciplines (including supply chain management, business studies, human resources management, marketing, law, and political science), the theoretical framework for the risk factors for FLM in the Global North comprises three domains (LeBaron et al., 2018; Caruana et al., 2021). The key domain pertains the industrial structure, because it influences the firm's opportunity-cost decision to exploit FLM even if it is a criminal and socially unacceptable choice (Crane et al., 2019). Firms in industries that rely on low-cost and flexible labour are thought to be more likely to use FLM in the attempt to stay competitive (Kara, 2017). Firm size matters too (Stringer and Michailova, 2018): micro-firms are assumed to be more inclined to use FLM, since they are generally more reliant on flexible labour arrangements and subject to cost constraints (LeBaron et al., 2018). It is also hypothesized that value added per worker can have a role, with low value-added firms more likely to use subpar personnel practices (Caruana et al., 2021). A second domain pertains institutions, both formal and informal. They matter for the presence/absence of ad hoc rules against forced labour, attitudes towards the law (Argentiero, Chiarini, and Marzano, 2020), rule enforcements (OECD, 2016), and discriminatory attitudes (LeBaron et al., 2018). The third factor is represented by labour supply, which can affect FLM through the availability of vulnerable workforce like unemployed and migrants (ILO, 2014). Migrants are a potential source for forced labour due to their limited knowledge of the rights and laws in the hosting country, the lack of a local support network, and the dependence on temporary working status.

Existing evidence validating this framework is limited and largely qualitative (Crane et al., 2019). Recent work supports the importance of the industrial structure. For example, survey data in Italy, Germany and Japan suggest that micro-firms in textile and clothing have higher risk of FLM, due to cost-competition (FairWear, 2020) and limited capacity to enforce laws and perform due diligence (OECD, 2021). According to qualitative data on the food industry in the UK, a highly fragmented labour supply chain could influence FLM, since it gives room to intermediaries (payroll companies, gangmasters, temporary and recruitment agencies) which can hire and manage the workers directly and increase the monitoring cost (Crane et al., 2019). Other data in Western Europe point to the importance of institutions, highlighting an association between high level of corruption and FLM (ILO, 2021). Qualitative evidence in Canada and the UK suggests that FLM relates with the cheap and precarious workforce represented by migrants and the discriminatory attitudes of the natives (Strauss and McGrath, 2017; Crane et al., 2019). Overall, this evidence, although scattered and collected using small samples, gives preliminary support to the relevance of the industrial structure for FLM.

2.2 Economic geography and forced labour

Economic geography research on FLM is extremely limited and largely in the Global South (Baglioni, 2018; Coe and Yeung, 2019). At the same time, economic geographers have extensively researched the spatial relevance of the speculated risk factors for FLM. Hence, we bridge this research to the conceptual framework developed by forced labour scholars to argue that FLM needs to be analysed with a spatial perspective to produce a comprehensive representation of its determinants.

Economic geographers have long addressed the influence of the type of local industrial structure on the strategies adopted by firms to manage labour cost and remain competitive (e.g. Maskell and Malmberg, 1999; Clark et al., 2004; Ter Wal and Boschma, 2011; Neffke et al., 2018). Evidence shows that different industrial sectors in Europe saw distinct consequences stemming from the current phase of globalization and the organization of international production in GVCs (De Marchi, Di Maria, and Gereffi, 2018; Iammarino, McCann, and Ortega-Argilés, 2018; Crescenzi and Harman, 2023). Compared to knowledge-based and high-tech sectors, labour-intensive industries, normally located in non-core regions, were subject to greater competitive pressure from developing locations (Pickles et al., 2015; Smith, 2015). Furthermore, areas without a clear industry specialization showed poorer

[8] EU-28 refers to the European Union Members in 2018, hence including the UK.

[9] Forced labour accounts for 80 per cent of modern slavery in Europe detected in the Counter-Trafficking Data Collaborative database. The Counter-Trafficking Data Collaborative database contains data on human trafficking combining the three global largest case-level datasets. It is a joint data hub by IOM, Polaris, and Liberty Shared.

ability to adapt to the tougher global competition; manufacturing suppliers in labour-intensive activities and in non- or de-specialized areas—often characterizing regions caught in or at risk of development traps—were forced to prioritize cost competition (Iammarino, McCann, and Ortega-Argilés, 2018; Diemer et al., 2022), mainly by cutting labour costs. This dynamic mirrors the cost pressures on suppliers in the Global South highlighted by forced labour scholars (Crane et al., 2022). Consequently, this raises the question of whether a local specialization in an industry substantially disrupted by globalization could incentivize exploiting forced labour also in the Global North.

Economic geography also indicates that globalization poses greater challenges to micro-firms (De Marchi and Alford, 2022), because they have less resources than larger companies, making it more challenging for them to integrate into GVCs led by multinational corporations. Small-sized firms, characterized by limited finance, human capital, and technology access—which vary across industries and regions—cannot achieve the same economies of scale and scope as larger firms (e.g. Freixanet, Rialp, and Churakova, 2020), placing them at a cost disadvantage, particularly against producers from developing countries. Furthermore, complying with international trade regulations creates relatively higher overheads for micro firms (Schmidt and Steingress, 2022). Due to these well-known obstacles, micro-firms in the Global North are more likely to participate in cost competition, with higher likelihood of cutting labour costs.

Micro-firms have a strong spatial footprint and are often the backbone of the productive structure of local labour systems and industrial districts, particularly renowned in the Italian economy (e.g. Cainelli and Leoncini, 1999; Becattini et al., 2003; Bellandi and De Propris, 2012). Evidence shows that the division of labour within each district leads to a large predominance of micro-firms, regardless of the industry of specialization (De Marchi and Grandinetti, 2014). So, the micro-firms' reaction to change, which could include using forced labour to cut labour cost, is place-specific and moulded by the local specialization, suggesting the relevance of their spatial distribution as a risk factor for FLM.

The other important domains for FLM—vulnerable groups like refugees, unemployed and migrants, and institutions—have been widely investigated in economic geography, providing robust evidence of their strong localized dimension. Migrants and refugees display a high level of geographic heterogeneity in the receiving Global North countries (Bauloz, Vathi, and Acosta, 2019), which is associated to a culture of discrimination (Denti and Faggian, 2023) that could support their exploitation even if this conduct goes against legal standards (LeBaron et al., 2018). Regarding institutions, plenty of evidence shows their strong subnational variability across European regions and impact on local economic development (e.g. Becattini, 1991, 2004; Rodríguez-Pose, 1998, 2013; Huggins et al., 2021). If the local institutions, both formal and informal, prioritize short-term interests or existing social hierarchies against the need for openness and change, then the local production system might develop forms of resistance to change against such a need (Bellandi, Santini, and Vecciolini, 2018). When this happens, the ability of the place to react and navigate disruptive challenges is hindered and the economic system might end up in either a lock-in or lagging situation in which local firms end up in lower supply tiers in the GVCs and start competing on cost. This could open to FLM as a strategy to remain in the market.

2.3 The Italian case

According to recent statistics, victims of forced labour in Italy are growing. Ten per cent of victims of human trafficking identified in 2018 were forced into labour. In 2022, they reached 37.8 per cent (Council of Europe, 2023). Since under-reporting is common, it is likely that the true number of victims is far higher than what is shown in these data, which only include victims who have been identified. While agriculture remains the sector with the highest incidence of forced labour, with around 400,000 estimated victims annually (Osservatorio Placido Rizzotto and FLAI, 2018), incidence in manufacturing is also relevant and growing (FairWear, 2020).

These big numbers collide with the institutional setting, since Italy has both laws and policy initiatives to counter forced labour. The Italian legislation targets forced labour through the Criminal Code art. 600 which makes it an offence to reduce or hold a person in a condition of slavery or servitude and provides for severe penalties. Recently, a National Plan to combat labour exploitation and illegal recruitment in agriculture was adopted, combined with an ad hoc legislation which extends the crime of illegal intermediation and work exploitation, including illegal labour brokers ('*Caporali*'), and provides for criminal liability of the employer and the company (Art. 603 bis, Italian Criminal Code). Italy also has a legislative framework for action against trafficking in human beings (Legislative Decree 24/2014), complemented with a National Action Plan against trafficking and serious exploitation of human beings since 2016, and a National Plan to combat labour exploitation and illegal recruitment in agriculture since 2020. Italy ratified the Council of Europe Convention on Action against Trafficking in Human Beings and the ILO Conventions 29 and 105, although it has still to ratify the 2014 ILO Protocol 029 that provides updates.

A structural hallmark of the Italian manufacturing structure relative to other western EU members is the presence of industries producing and exporting relatively low value-added goods, created in highly fragmented production systems primarily by small, on average old, firms with low productivity, a fragile financial structure, ineffective management and persistent difficulties to adopt advanced technology and to internationalize (e.g. Bugamelli et al., 2018).[10] The structural changes brought about by globalization and technological paradigm shifts (ICT, and now green and digital transitions) had a significant negative impact on such small firms (Rabellotti, 2004), which are often geographically clustered according to the industry. Scholarly research has consistently indicated over time that the Italian local production systems and industrial districts specialized in low-tech and traditional goods have largely been negatively impacted by the trends in global competition (Guerrieri, Iammarino, and Pietrobelli, 2001; Rabellotti, Carabelli, and Hirsch, 2009; Giuliani and Rabellotti, 2018) and that micro-firms in those areas have struggled to remain competitive (Bugamelli et al., 2018).

Given these features of the productive structure and the incidence of FLM, Italy appears an interesting case for an empirical investigation into the role of industry characteristics in determining FLM in a Global North country. Additionally, due to European regulations positioning Italy as a primary first-stop for refugees, it is feasible to assess the significance of industry structure for FLM in the presence of other potential confounding factors.

3. Empirical framework, identification strategy, and data

3.1 Least-square model

To explore the association between FLM and the industry structure domain in a multivariate setting, accounting for the potential confounding factors suggested by the forced labour literature, we estimate a least-square model which averages observations between 2016 and 2020, reducing noise due to random jumps in FLM and summarized by Equation (1),

$$lnFLM_{LLMA} = \alpha_0 + \alpha_1 SPEC_{LLMA} + \alpha_2 X_{LLMA} + \mu + \varepsilon_{LLMA} \tag{1}$$

where $lnFLM_{LLMA}$ is the log transformation of the incidence of FLM in each Local Labour Market Area (LLMA), which is a functional area designed by the Italian National Institute of Statistics (ISTAT) based on commuting, hence containing the bulk of the labour force living and working there. The log-transformation is appropriate to account for the high count of zeros.[11] Among robustness checks, we assess the validity of results by considering the inverse hyperbolic sine as alternative transformation (Bellemare and Wichman, 2020). $SPEC_{LLMA}$ is a categorical variable for the LLMA industry specialization, classifying LLMAs into eight categories: '*Non-manufacturing*', '*Heavy manufacturing*', (manufacturing) '*Non-specialized*', (manufacturing) '*Made in Italy—textile & clothing*', (manufacturing) '*Made in Italy—food*', (manufacturing) '*Made in Italy—leather*', (manufacturing) '*Made in Italy—luxury durable goods*',[12] (manufacturing) '*Made in Italy—other*'[13]. X_{LLMA} contains the set of control variables included to account for potential confounding features. As baseline, all model specifications have the size of resident population aged above fifteen as control, which we later replace with working age population in robustness checks. Then, we increase the number of controls. For the institutional domain, we consider measures of formal and informal institutional quality (LeBaron et al., 2018), that is, the presence of criminal organizations (Crane et al., 2022), corruption (OECD, 2016), firm propensity to tax evasion (Argentiero, Chiarini, and Marzano, 2020), and overall crime. For the labour market factors we include the share of foreign population (LeBaron et al., 2018), refugees (Lewis et al., 2015; David, Bryant, and Larsen, 2019), and unemployment (ILO, 2014). $SPEC_{LLMA}$ uses '*Non-manufacturing*' LLMAs as base category in all

10 Italian micro-firms (less than ten employees) account for 95 per cent of total firms, and 29 per cent of total value added (Bugamelli et al., 2018).
11 LLMAs having zero incidence of forced labour between 2016 and 2020: 53.19 per cent.
12 Jewellery, musical instruments, eyeglasses.
13 Wood and machinery.

estimations. All specifications consider regional (NUTS2) fixed effects, μ, to account for unobserved heterogeneity, and robust standard errors clustered at province level.

Then, we introduce a further model which unpacks the industry domain in the key features considered by forced labour research. We consider micro-firms in the local leading industry, since they are assumed to be more likely than other firms to resort to illegal practices to cut costs and remain competitive (LeBaron, 2021; Bullock et al., 2024), and they are highly represented in the production systems of industrial districts (De Marchi and Grandinetti, 2014). We also include the value added per worker, which accounts for the speculated association between FLM and low productivity (Caruana et al., 2021). This additional least-square model is summarized by Equation (2),

$$lnFLM_{LLMA} = \beta_0 + \beta_1 MFIRMS^{SPEC}_{LLMA} + \beta_2 VA_{LLMA} + \beta_3 X_{LLMA} + \varphi + \varepsilon_{LLMA} \tag{2}$$

where $lnFLM_{LLMA}$ and X_{LLMA} are defined as in Equation 1, $MFIRMS^{SPEC}_{LLMA}$ is the percentage of micro-firms (below ten employees) in the industry in which the *i-th* LLMA is currently specialized (leading industry)[14], VA_{LLMA} is the value added per worker in the LLMA, and φ are regional fixed effects. Finally, we assess the sensitivity of the model by adding to the regressors the categorical variable for the LLMA industry specialization type, $SPEC_{LLMA}$.

3.2 Identification and instrumental variable estimation

To provide estimates that do not suffer from endogeneity bias, we must address several issues, starting from sorting of firms across LLMAs. An increase in FLM in a place may push firms which are against labour exploitation to move in areas where FLM is limited to protect their brand reputation. Also, reverse causality could occur since the availability of FLM could encourage firms to remain micro in terms of formal employment, as it is easier for them to resort to labour exploitation. To mitigate these concerns, we introduce a Bartik-like instrumental variable which exploits the country unification as exogenous variation in the spatial distribution of micro-firms per industry type.[15] Our instrument predicts the current percentage of micro-firms in the LLMA leading industry using historical information on the geography of micro-firm per industry in 1911. We start with the initial (1911) geography of micro-firms per industry across Italian LLMA, and we allow the percentage of micro-firms per industry type to grow over time according to the national patterns.[16] The intuition behind the instrument is that national changes in industry type are external to each LLMA, therefore being a 'synthetic' exogenous 'shock' for the LLMA. Formally, the Bartik-like instrument is defined as follows (Goldsmith-Pinkham, Sorkin, and Swift, 2020),

$$z_{LLMA} = q^{SPEC}_{LLMA} \times g^{SPEC}_{IT} \tag{3}$$

where $q^{SPEC}_{LLMA} = MFIRMS^{SPEC,1911}_{LLMA}$ is the 1911 percentage of micro-firms (below ten employees) in the industry in which the *i-th* LLMA is specialized (leading industry), and g^{SPEC}_{IT}measures the 1911–2011 growth of micro-firms in the same industry in Italy.

We choose 1911 for three main reasons. First, it is the first census of firms after the Italian Unification, which was a 'shock' to the Italian territory since it resulted from war with a strong role of foreign powers (Lecce, Ogliari, and Orlando, 2022), and it quickly unfolded into a set of nation-building policies that were primarily aimed at consolidating the new Kingdom by disrupting the mosaic of economic and institutional settings of the pre-existing polities and promoting people's mobility in the national-army building process (Basile, Ciccarelli, and Groote, 2022; Cainelli, Ciccarelli, and Ganau, 2022). The Unification policies encompassed the integration of domestic markets, the construction of transportation infrastructures, the introduction of common institutions, monetary system, and currency (Basile and Ciccarelli, 2018).[17] Second, the 1911 Census shows, for the first time after

[14] For the LLMAs whose leading industry is (manufacturing) '*Non-specialized*', $MFIRMS^{SPEC}_{LLMA}$ is the percentage of all manufacturing micro-firms. For the LLMAs whose leading industry is '*Non-manufacturing*', $MFIRMS^{SPEC}_{LLMA}$ is the percentage of all non-manufacturing micro-firms.

[15] For the unification of a country as source of exogenous variation see also Ahlfeldt et al. (2015), Hyll and Schneider (2018), Kim and Kim (2020).

[16] For the LLMAs in Trentino Alto Adige and parts of Friuli Venezia Giulia (annexed after WWI), we use data from the 1927 Industrial and Commercial Census, the first after their incorporation into Italy (more details in Subsection 3.3).

[17] The post-unification industrialization of Italy, combined with the integration of the previously divided domestic markets and the fall in transportation cost, changed the composition of total gross value added substantially, making industry gain share at the expenses of agriculture. In 1871, agriculture and industry amounted respectively to 44.11 per cent and

Unification, the spatial division of industry into clusters that defines contemporary Italy: this geography structurally differed from the pre-Unification period, as it emerged from constituting reforms (Ciccarelli and Proietti, 2013).[18] Third, extant work supports the relevance and the persistence of the post-unification Italian socio-economic geography described by the 1911 Census on current socio-economic features (Basile, Ciccarelli, and Groote, 2022).

By freezing the geography of micro-firms per leading industry to 1911, we alleviate sorting and reverse causality concerns (Goldsmith-Pinkham Sorkin, and Swift, 2020). To control for features influencing micro-firms and FLM, we follow Mayda, Peri, and Steingress (2021) in using place fixed effect and socio-economic controls. Having identified the instrumental variable, we use Equations (2) and (3) in a IV-TSLS model with space fixed effects and clustered standard errors to estimate the effect of micro-firms on FLM going beyond correlation. We support the IV-TSLS model with its corresponding reduced-form model, which directly regresses the incidence of forced labour on the Bartik-like instrument, and with the robustness checks that are required when using this type of instrument to account for spatial clustering (Adão, Kolesár, and Morales, 2019) and validity of the exclusion restriction (Goldsmith-Pinkham Sorkin, and Swift, 2020).

3.3 Data

Our dataset contains various types of data. Data on FLM in Italy come from different sources. We have used scraping algorithms to collect data about episodes of FLM and services from the web archives of the two main Italian newspapers ('*La Repubblica*' and '*Corriere della Sera*') and from Google News, since the latter allows to detect FLM news that were covered by local newspapers only. The considered time period is 2016–20. Then, we have complemented these data with the information about FLM retrieved from the Observatory maintained by the Italian Government ('*Osservatorio Interventi Tratta*') and from information retrieved from labour unions and advocacy groups. FLM episodes are those that pertain the recruitment of manpower for employment, also through third parties, in conditions of exploitation, taking advantage of the state of need. The conditions of exploitations are met if one or more of the following applies to manpower: (1) the repeated payment of salaries that manifestly differ from collective agreements stipulated by the more representative trade union organizations, or otherwise disproportionate compared to the quantity and quality of the work done; (2) the repeated violation of the legislation on the time of work, rest periods, weekly rest, leave of absence and vacations; (3) violations of safety and hygiene rules in the workplace; (4) the worker's submission to working conditions, to surveillance methods or degrading housing situations. Retrieved data are cross-checked to eliminate double counting (more details on the design of this database are in the Supplementary Appendix).

By referring to several sources, these data allow to alleviate for the limited amount of FLM episodes captured by police records (Cruyff, van Dijk, and van der Heijden, 2017; Farrel et al., 2019; European Commission, 2020a; UNODC, 2020). Data are delocalized and consolidated at the LLMA level, which represents our unit of observation. Italy has 611 LLMAs; however, the thirty-nine LLMAs in the Sardinia region were excluded due to limited availability of FLM data. Our measure for FLM incidence is then given by the LLMA average number of FLM episodes per 100,000 inhabitants between 2016 and 2020. Looking at their geography in Fig. 1, it seems that FLM clusters are in close proximity. This suggests testing for spatial autocorrelation in the empirical part.

The LLMA leading industry is measured by drawing on the ISTAT classification of the Italian economic space according to the prevailing industry specializations of LLMAs.[19] This classification maps leading industries by identifying the different production models and their spatial configurations and assessing their temporal stability (ISTAT, 2015, 2019), and it groups in eight categories the LLMA industry specialization, as detailed in Section 3.1 above. Fig. 2a outlines the resulting map of LLMA leading industries.

15.73 per cent of national gross value added. In 1911, agriculture dropped to 38.31 per cent while industry grew to 24.46 per cent (Basile and Ciccarelli, 2018).

[18] The 1871 indexes of concentration are: textile 4.69, metal-making 6.75, chemical-rubber 3.64, paper-printing 4.9. The 1911 indexes of concentration are: textile 9.25, metal-making 10.22, chemical-rubber 5.57, paper-printing 6.48.

[19] This ISTAT classification identifies the dominant industry in each LLMA through a concentration index regardless of firm size and socio-economic networks and should not be confused with ISTAT's classification of industrial districts (ISTAT, 2011, 2015), which are specifically those LLMAs characterized by a high concentration of manufacturing small and medium enterprises and specific socio-economic networks (ISTAT, 2011). Our analysis considers all 611 LLMAs by their prevailing industry classification rather than focusing only on the 141 industrial districts.

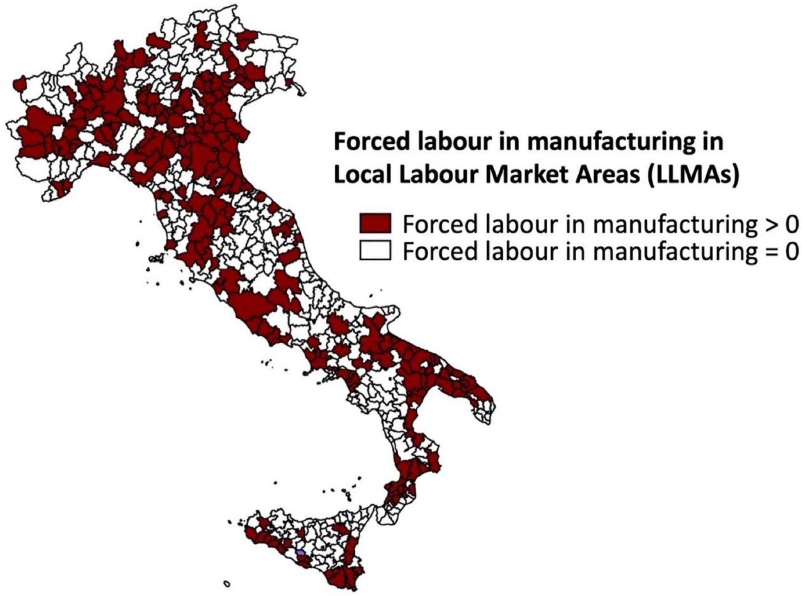

Figure 1. Map of forced labour episodes in manufacturing in Italy between 2016 and 2020.

Current data on firm size per leading industry are from ISTAT and mapped in Fig. 2b, while we retrieved historical data on firms per leading industry by digitizing the 1911 Census of the Italian Ministry of Agriculture, Industry, and Trade ('*Censimento degli Opifici e delle Imprese Industriali*'), obtained from the ISTAT historical archive. To ensure consistency in firm size measurement across time, we specifically use Table II[—]volume II of the 1911 Census, which provides data on firms below ten employees (micro-firms) per industry, corresponding to our current ISTAT definition of micro-firms (up to nine employees). For industry classifications, we follow a careful consolidation process detailed in Table A4 in the Supplementary Appendix, which maps 1911 industry specializations to current ISTAT categories.

We use Tables I and IV of the 1911 Census to digitize the number of firms per industry in all LLMAs. We start by identifying the LLMA representative municipality in the 1911 Census by selecting the one with the highest number of manufacturing firms at that time from among the municipalities within its current boundaries (LLMA main municipality). We then use the 1911 number of firms per industry from this representative municipality. For micro-firms (those with fewer than ten employees), we use Table II of the 1911 Census, which covers all provincial capitals and municipalities with more than 2,000 employed residents. This allows us to directly compute the number of micro-firms per industry for 104 LLMA main municipalities. For the remaining LLMAs, where no municipalities were covered in the 1911 Census municipal-level data, we instead use data from 'circondari' and 'distretti', which were 284 sub-provincial administrative units (ISTAT, 2018). Specifically, we assign to each current LLMA the values of the 1911 '*circondario*' or '*distretto*' which contained most of the current LLMA area. For the thirty LLMAs in Trentino Alto Adige region and portions of Friuli Venezia Giulia region, which were not part of Italy in 1911 but were added after WWI, we use figures from the 1927 Census ('*Censimento Industriale e Commerciale*'), the first census after their annexation.[20]

Our models take into consideration confounding variables that could affect FLM. Annual data for the population size, working-age population, and the share of foreign residents are retrieved from ISTAT and averaged for the period 2016–20. The local annual presence of refugees is measured through figures on local hosting capacity of refugee centres from Openpolis and Centri d'Italia—Openpolis, drawing on previous work providing for this metric as a reliable proxy (Denti and Faggian, 2023); as before, we average between 2016 and 2020. We are prevented from measuring undocumented

[20] Figure A2 illustrates this spatial consolidation: Panel I shows the LLMAs for which we use municipal-level data (in orange), Panel II summarizes the spatial consolidation approach for the LLMAs for which we use data at the '*circondario*'/'*distretto*' level, and Panel III maps the 1911 '*circondari*' and '*distretti*' (in white) and the 1927 additions (in grey).

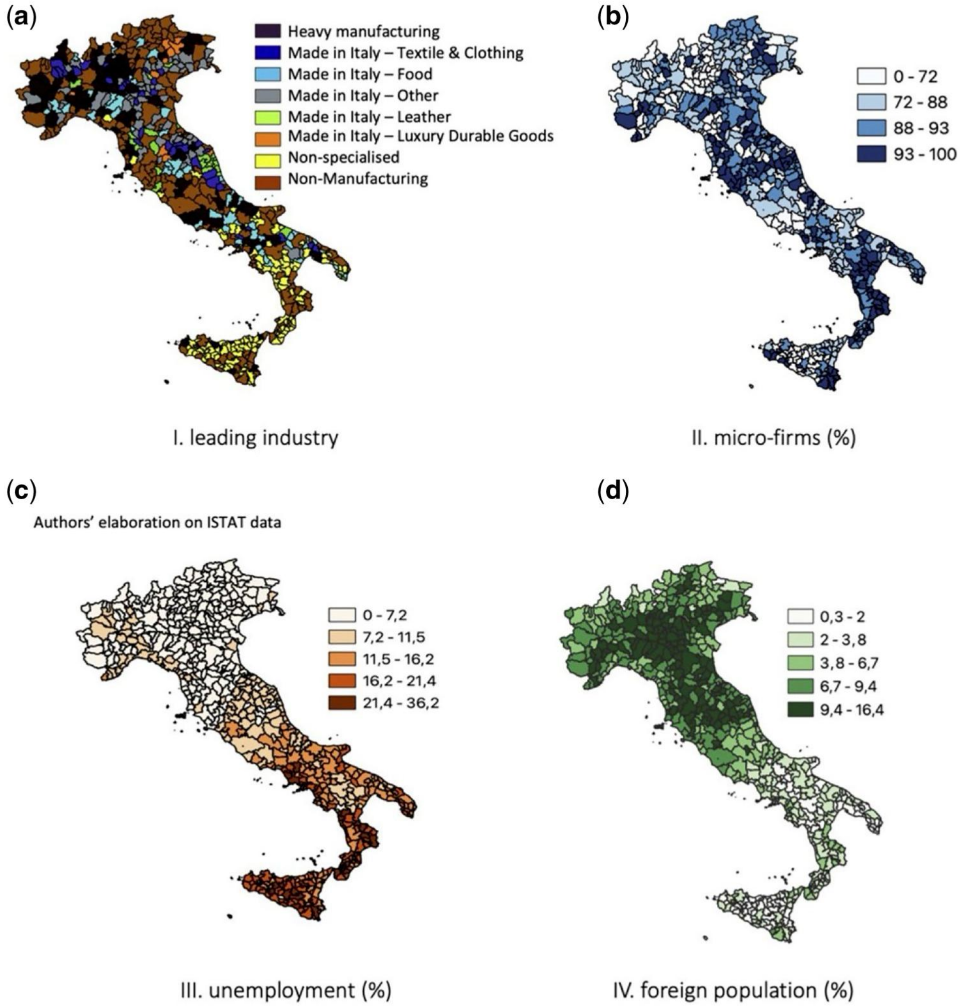

Figure 2. Geographies of speculated risk factors for FLM. Maps of LLMA leading industry (a), micro firms per leading industry (b), unemployment (c), and foreign population (d).

migrants directly due to data unavailability. At the same time, evidence supports a strong association between settlements of regular and undocumented migrants in Italy (Bianchi, Buonanno, and Pinotti, 2012). Hence, we rely on our measure of foreign population as a proxy for the intensity of undocumented migrants. Annual figures on employment, unemployment, people working in agriculture and value added per worker come from ISTAT, like the data on crime, all averaged between 2016 and 2020. Data on the local presence of organized crime is operationalized by averaging between 2016 and 2020 the Bank of Italy figures on suspicious transaction reporting, following Dalla Pellegrina et al. (2020).[21] The firm propensity to tax evasion is measured using figures from Vallanti and Gianfreda (2021)[22], which cover the period 2007–10, while data on local institutional quality come from the measure of corruption developed by Nifo and Vecchione (2014) for the years 2016–20.[23] Tables A1–A3 in the

21 Among robustness checks, we test the sensitivity of estimates to different measures of organized crime by drawing on the work of Bernardo et al. (2021).

22 Using data from the Italian Revenue Agency ('*Agenzia delle Entrate*') on the expected as well as actual financial revenue reported to fiscal authorities, Vallanti and Gianfreda (2021) compute tax evasion, tg_{LLLMA} with the following ratio: tg_{LLLMA}= (*expected tax revenues—reported tax revenues*)/*expected tax revenues* .

23 This measure is a composite index built using figures on the number of local administrations overruled by national authorities, the difference between the amounts of actual public infrastructure and the amounts of money cumulatively spent to create them, and felonies against public institutions (Nifo and Vecchione, 2014). It is one of the most used metrics for the local level of corruption in empirical investigation on Italy (Agostino et al., 2020; Antonietti and Boschma, 2021).

Supplementary Appendix provide more details and summary statistics, while Fig. 2c and d show the geography of unemployment and the share of foreign population.

4. Results

4.1 Descriptive evidence: least-square estimates

Equation (1) is estimated via a least square model with regional fixed effects with 572 LLMAs observations and errors clustered at province level. The results in Table 1, columns 1–3, show that the type of local leading industry matters for FLM, and this holds for the different model specifications (for the detailed results on estimates of the control variables, see Table A5 in the Supplementary Appendix).

Places specialized in 'Made in Italy—textile & clothing' and 'Non-specialized' appear more exposed to FLM. Estimates also show that places specialized in 'Made in Italy—food' and 'Heavy Manufacturing' relate to lower FLM. These estimates suggest that the reputation for high-quality output of the 'Made in Italy' production does not necessarily translate into high quality in employer–employee relationships in all the industries under the 'Made in Italy' branding.

The significant association between 'Made in Italy—textile & clothing', 'Made in Italy—food', 'Heavy Manufacturing', 'Non-specialized' and FLM also holds true to the inclusion of the control variables which account for confounding features, as summarized by the estimates in columns 2 and 3. Column 2 shows estimates when we add unemployment, share of foreign population and presence of refugees among the controls, since they could increase the supply of forced labour. Results confirm our findings and show that neither unemployment nor the presence of refugees correlates with FLM, while the share of foreign resident population has a positive, though mild, association. This finding suggests that FLM is weakly associated with the supply of foreign workforce, even when we consider refugees, who experience precarious living conditions, which could increase their likelihood of being exploited. Column 3 shows that the estimates do not change even when the control variables are broadened to include institutional features like crime rate, presence of organized crime, local level of corruption, and firm propensity to tax evasion.

Column 4 displays the estimates of the model summarized by Equation (2), with the local industry unpacked in the percentage of micro-firms in the leading industry and value added, since they are assumed to be crucial risk factors by the forced labour literature. Findings, which include controls for labour supply and institutions, show that the percentage of micro-firm is a significant risk factor: a ten percentage point increase in micro-firms in the leading industry relates to nearly 5 per cent increase in FLM.

Column 5 summarizes estimates for our most detailed model specification, which serves as a sensitivity test by adding the local leading industry type to the percentage of micro-firms in the leading industry, labour productivity, and including controls for labour supply and institutions. The findings validate that the proportion of micro-firms within the leading industry is a significant risk factor for FLM across all types of leading industries. Estimates in column 5 show that, for a given percentage of micro-firms, 'Made in Italy—textile & clothing' and 'Non-specialized' leading industries are significant risk factors. Conversely, 'Made in Italy—food' and 'Heavy manufacturing' are protective factors (for details on estimates of the control variables, see Table A5 in the Supplementary Appendix).

The least-square results suggest a meaningful correlation between the features of the local industrial structure and FLM, which holds to the inclusion of a wide set of controls accounting for the potential confounding factors.[24] Within the industry domain, results show that the percentage of micro-firms in the local leading industry is relevant, regardless the local leading industry type. At the same time, when comparing places with an equal presence of micro-firms in their respective leading industries, those specialized either in 'Made in Italy—textile & clothing' or 'Non-specialized' tend to experience higher FLM. The opposite applies for places specialized in 'Made in Italy—food' and 'Heavy manufacturing'.

[24] Findings hold also to alternative measures for organized crime (Table A6–A7) and alternative control variables such as working age population instead of resident population (Table A8). Similarly, results are confirmed when we add the share of agricultural employment among controls to account for labour market seasonality (Table A9), as well as when we include net migration rate as proxy for population dynamics and local attractiveness (Table A10).

Table 1. LLMAs leading industry and FLM. Least square estimates with different sets of control variables.

	Dependent variable: FLM (logs)				
	(1)	(2)	(3)	(4)	(5)
Leading industry type:					
Heavy manufacturing	−0.307**	−0.334**	−0.319**	–	−0.250*
	(0.128)	(0.130)	(0.135)	–	(0.141)
Made in Italy-clothing & textile	0.659*	0.624*	0.622*	–	0.738*
	(0.343)	(0.324)	(0.317)	–	(0.432)
Made in Italy-food	−0.298***	−0.340***	−0.323***	–	−0.298***
	(0.0874)	(0.0905)	(0.0984)	–	(0.0997)
Made in Italy-leather	−0.315	−0.391**	−0.403**	–	−0.266
	(0.197)	(0.194)	(0.204)	–	(0.230)
Made in Italy-luxury durable goods	−0.287	−0.246	−0.153	–	−0.055
	(0.232)	(0.227)	(0.226)	–	(0.250)
Made in Italy-other	−0.041	−0.115	−0.077	–	0.0175
	(0.175)	(0.180)	(0.180)	–	(0.187)
Non-specialized	0.349**	0.329**	0.304**	–	0.382**
	(0.149)	(0.155)	(0.152)	–	(0.162)
Leading industry characteristics:					
Micro-firms in leading industry (%)	–	–	–	0.005***	0.007***
	–	–	–	(0.0019)	(0.002)
Value added per worker (logs)	–	–	–	0.191	0.075
	–	–	–	(0.216)	(0.213)
Controls					
Population above 15	✓	✓	✓	✓	✓
Labour market domain		✓	✓	✓	✓
Institutional domain			✓	✓	✓
Regional fixed effects	✓	✓	✓	✓	✓
Observations	572	572	572	572	572

Note: Least square estimation. Robust standard errors in parentheses. Coefficients significant at *** 1 per cent level, ** 5 per cent level, * 10 per cent level. Outcome is FLM per 100,000 inhabitants in logs. Estimation excludes the thirty-nine LLMAs in the Sardinia region due limited availability of data on forced labour. Leading industry type uses '*Non-manufacturing*' LLMAs as base category. '*Made in Italy-other*' includes LLMAs specialized in wood and machinery. Labour market controls are share of foreign population (per cent), refugees per 1,000 inhabitants (logs), unemployment (per cent). Institutional controls are presence of organized crime, corruption index, firm propensity to tax evasion (logs) and crime rate. All models have regional fixed effects.

4.2 Addressing endogeneity: two-stage least-square with instrumental variable estimates

Table 2 details the results of the IV-TSLS model where the percentage of micro-firms in the leading industry is instrumented through the Bartik-like exogenous regressor summarized by Equation (3). Estimation uses 537 LLMA observations, due to the lack of comprehensive local-level data about 'leather' and 'luxury-durable goods' industries in the 1911 Census. Errors are clustered at province level and the model has region fixed effects.

Findings support that the significant link between micro-firms in the leading industry and FLM goes beyond the measures of correlation summarized in Table 1 (for detailed results, see the Supplementary Appendix, columns 1–2 in Table A11). The synthetic percentage of micro-firms in the leading industry, measured by the Bartik-like instrument, is a significant and consistent predictor of the actual percentage of micro-firms in the leading industry, as summarized by the coefficient in column 1. Column 2 shows that a 1 percentage point growth in the actual percentage of micro-firms in the leading industry determines nearly a 6 per cent increase in FLM. The F-statistic value suggests that estimates do not suffer from an issue of weak instrument.

Columns 3–4 display estimates of the IV-TSLS model specification that adds the local leading industry type among regressors. Findings confirm the relevance of the share of micro-firms in the leading industry. In this case, a 1 percentage point increase in micro-firms in the leading industry determines a nearly 10 per cent increase in FLM, as summarized by the coefficient, which equals 0.0973. The

Table 2. Micro-firms in leading industry and FLM. Two-stage least square with instrumental variable estimates.

	(1) 1st stage	(2) 2nd stage	(3) 1st stage	(4) 2nd stage
Leading industry type:				
Heavy manufacturing	–	–	−7.831***	0.613
	–	–	(2.907)	(0.633)
Made in Italy—clothing and textile	–	–	−14.63***	2.197**
	–	–	(2.367)	(0.963)
Made in Italy—food	–	–	−2.503	0.006
	–	–	(2.181)	(0.276)
Made in Italy—other	–	–	−12.60***	1.226*
	–	–	(1.642)	(0.668)
Non-specialized	–	–	−10.81**	1.470**
	–	–	(3.725)	(0.708)
Leading industry characteristics:				
Synthetic micro-firms in leading industry (per cent)	0.235***	–	0.157**	–
	(0.055)	–	(0.0626)	–
2011 micro-firms in leading industry (%)	–	0.058**	–	0.097**
	–	(0.025)	–	(0.049)
Value added per worker (logs)	−4.676	0.418	−7.151	0.717
	(5.752)	(0.385)	(5.138)	(0.616)
Controls				
Population above fifteen	✓	✓	✓	✓
Labour market domain	✓	✓	✓	✓
Institutional domain	✓	✓	✓	✓
Regional fixed effects	✓	✓	✓	✓
Observations	537	537	537	537
First-stage F-statistic	18.332	–	13.787	–

Note: IV regression. Coefficients significant at *** 1 per cent level, ** 5 per cent level, * 10 per cent level. Robust standard errors in parentheses clustered at province level. Outcome is FLM per 100,000 inhabitants in logs. 'Synthetic micro-firms in leading industry' is the Bartik-like instrument summarized by Equation 3. Estimation excludes the thirty-nine LLMAs in the Sardinia region due limited availability of data on forced labour and the thirty-five LLMAs specialized in '*Made in Italy—leather*' and '*Made in Italy—luxury durable goods*' since there are no detailed data on these specializations in the 1911 Census. Labour market controls are share of foreign population (per cent), refugees per 1,000 inhabitants (logs), unemployment (per cent). Institutional controls are presence of organized crime, firm propensity to tax evasion (logs), corruption index, crime rate. All model specifications have regional fixed effects.

findings also reveal that the adoption of the Bartik-like instrument to address endogeneity diminishes the explanatory power of local specialization in 'Heavy manufacturing' and 'Made in Italy—Food'. Simultaneously, the instrumental variable approach corroborates that those places specialized in either 'Made in Italy—textile & clothing' or 'Non-specialized' tend to exhibit higher FLM, for a given number of micro-firms in the leading industry. As before, the F-statistic value supports the strength of the instrumental variable.

4.3 Robustness checks

We assess the validity of the IV-TSLS through several tests. First, we show that results hold to the inclusion of additional control variables,[25] including the presence of irregular employment in local labour markets (Table A13 in the Supplementary Appendix),[26] and the share of people working in agriculture, to account for potential seasonal work patterns where workers might alternate between agricultural and manufacturing work (Table A17). Results also hold when FLM is measured with the inverse hyperbolic sine transformation of its incidence, an alternative transformation for outcomes with zero values which approximates the natural logarithm but retains zero-valued observations (Bellemare and Wichman 2020; see columns 9–10 in Tables A11 and A13). Results are also supported

[25] Additional controls include firm survival rate, North–South divide, total percentage of micro-firms (columns 3–8 in Tables A11–A12 in the Appendix), alternative measures of organized crime (Tables A14–A15), working age population (Table A16), and net migration rate (Table A18).

[26] Following Boeri and Garibaldi (2002, 2007), we measure the rate of irregular jobs as the difference between employment figures from the population census and worker figures reported by employers in their census, normalized by working-age population. This measure exploits the fact that while employers typically report only regular jobs in their census returns, individuals tend to report all forms of employment in population censuses. Results remain robust to the inclusion of this control.

by the reduced-form estimates (see Table A19) and by estimations on a restricted sample excluding LLMAs that were annexed to Italy after 1911 (see Table A27). We further test whether organized crime's persistent influence on firm size and FLM could affect our results. Following Mayda, Peri, and Steingress (2021) in accounting for persistent confounders, we include a historical measure of organized crime, drawing on previous research (Ciconte, 2008; Acemoglu, De Feo, and De Luca, 2020). This measure leverages local exposure to the severe droughts of 1893, which catalysed the geographic expansion of criminal organizations across Italy, which was previously geographically concentrated in a few places.[27] Our main results remain robust to this additional control (see Table A26). Finally, we test whether reverse causation plus the persistence of exploitation drives results. A correlation between past labour exploitation and the current distribution of micro-firms might imply that places with more exploitation historically created conditions deterring the development of larger firms, affecting subsequent industrial structure and generating a correlation that may be due to reverse causation. We address this issue by performing a falsification test following Mayda, Peri, and Steingress (2021), practically regressing the current share of micro-firms in the leading industry on a measure of past labour exploitation, specifically the share of women labour in manufacturing in 1911,[28] to show that there is no significant correlation (see Table A28).

We also check for the relevance of spatial dependence in FLM, since the map in Fig. 1 indicates that LLMAs close in space tend to be more alike than observations geographically apart in terms of FLM. Specifically, we assume that adjacent LLMAs affect each other by estimating a Spatial Autoregressive model with Instrumental Variable that models spatial spillover through the nearest neighbour approach. Results confirm our main findings and support a significant effect of spatial spillover of FLM (see Table A20 in the Supplementary Appendix).[29]

Since we rely on a Bartik-like instrument, we need to assess its robustness against potential bias. First, since our IV-TSLS model uses province-level clustering of errors, we need to account for the bias that could arise when Bartik-like instruments are used with geographic clustering (Adão, Kolesár, and Morales, 2019). We do so by drawing on the approach by Adão, Kolesár, and Morales (2019), which corrects for the bias generated by residuals being correlated across provinces that need not be geographically proximate yet feature similar initial industrial structure. Estimates confirm our main results (see Table A21). An additional threat to identification is that the shift-share instrument may not successfully isolate sources of variation in local economic conditions that are exogenous. We argue that this represents a minor issue, since our setting provides several shocks breaking the serial correlation of micro-firms, like the WWI, the 20-year Fascist regime, the WWII, the post-war reconstruction, the advent of the European Union and the creation of the Schengen area. Nonetheless, we empirically address this point focusing on the share-component of the instrument to estimate a set of models with alternative shifts to check the sensitiveness of estimates to the initial shares. If the models with alternative shocks produce similar estimates to our main findings, it suggests that exploiting different sources of variation leads to the same answer (Goldsmith-Pinkham Sorkin, and Swift, 2020). Estimates considering alternative shifts support our identification strategy, both when alternative shifts are artificially generated and when they are computed considering alternative timing (see Table A22). Overall, the validity of the shift-share instrument is confirmed by consistently high F-statistics (>10), robustness checks using different time periods as shifts, and the Adão, Kolesár, and Morales (2019) test for spatial clustering, indicating that historical firm size distribution effectively predicts contemporary patterns.

[27] Local exposure to the 1893 severe droughts is measured with the Palmer Drought Severity Index (Cook et al., 2015), as proposed and validated by Acemoglu, De Feo, and De Luca (2020).

[28] We measure labour exploitation in 1911 using the share of women working in manufacturing on total manufacturing workers, since women faced systematic wage discrimination, harsher working conditions, and limited legal protections. Firms hired women in the most exploitative segments like textile mills and garment workshops, where workplace safety was poor and piece-rate systems maximized output while minimizing wages (Marangon and Willson, 2020; Pescarolo, 2020). Our data comes from the 1911 Population Census, which provides a more comprehensive and reliable account of manufacturing employment compared to industry surveys, as individuals typically report all forms of work in population censuses, including informal and part-time employment (Boeri and Garibaldi, 2007).

[29] Results also hold when analysis is restricted to pre-COVID years (2016–19) (Table A25). The main specification considers years 2016–20 because substantial portions of manufacturing firms maintained operations throughout 2020 (ISTAT 2020)

4.4 Alternative explanations

To rule out alternative explanations of our findings, we perform several falsification tests. A high prevalence of micro-firms in the local leading industry could lead to a localized tendency to violate laws and regulation in the attempt of cutting costs and maintain a competitive edge. If this is the case, then labour exploitation could be one of several law violations enacted by micro-firms. We test this alternative explanation with two placebo outcome tests. First, we estimate the effect of the percentage of micro-firms in the local leading industry on the firm propensity to tax evasion. Results show a non-significant relationship (detailed estimates in columns 1–2 in Tables A23–A24). Then, we check the association between micro-firms in the leading industry and corruption to see that the nexus is not significant (see columns 3–4 in Tables A23–A24). Overall, these falsification tests provide for micro-firms in the local leading industry to determine FLM specifically, rather than a broader propensity to elude rules to reduce overheads.

Alternatively, it could be that the characteristics of the local industrial specialization have been more conducive to industrial decline and obsolescence (Martin et al., 2018; Iammarino, Rodriguez-Pose, and Storper, 2019; Diemer et al., 2022), which might fuel resentment (Dijkstra, Poelman, and Rodríguez-Pose, 2020) that could manifest through scapegoating of diverse groups (Denti and Faggian, 2021), potentially leading to dehumanized and discriminatory attitudes that could enable labour exploitation. If our findings about industry structure and FLM were merely capturing such discriminatory attitudes in industrially challenged areas, we would expect to see similar patterns when examining racial hate episodes. We test this through a falsification test that considers hate events per 100,000 inhabitants as placebo outcome.[30] Results show that the local characteristics of the leading industry are unrelated to hate (see columns 5–6 in Tables A23–A24 in the Supplementary Appendix), supporting the interpretation that FLM is driven by industry structure rather than being a byproduct of general intolerance towards minorities.

Finally, we need to rule out that our results are explained by the total percentage of micro-firms in manufacturing, rather than by the specific percentage in the leading industry. We test this alternative channel by estimating the IV-TSLS with the percentage of total micro-firms in manufacturing as endogenous regressor. Estimates show a non-significant association with FLM, strengthening our results on the key role of micro-firms in the local leading industry (see columns 7–8 in Tables A23–A24).

5. Conclusions

Using Italy as case study, a novel database of geo-localized episodes of forced labour in manufacturing and digitized historical data on the geography of industries and firms, this article provides evidence that supports the percentage of micro-firms in the industry that specialize a place as a crucial determinant of FLM. This finding is robust to endogeneity threats, and it holds when we account for the potential competing effect of confounding features, like crime and the local presence of refugees and unemployed. Additionally, we show that, for a given percentage of micro-firms in the leading industry, some industry specializations relate to more FLM than others. Specifically, manufacturing places that are either 'Non-specialized' or specialized in 'Made in Italy—textile & clothing' have more FLM compared to other specializations, even when there is no difference in the percentage of micro-firms. This aligns with the forced labour literature on the Global South, stressing how particularly severe pressures are exerted on very small firms in traditional industries to remain flexible in production for adapting to the requests of lead firms in GVCs, at the same time paying obsessive attention to costs for keeping their position in such networks. Based on our Italian case study, the same competitive pressures seem likely to affect micro-firms in the Global North in places non-specialized or specialized in industries long and highly involved in the global slicing-up of production activities: they may adopt risky, even illegal decisions simply for matters of survival. On the other hand, our descriptive story also points to FLM being less associated with industries characterized by higher degrees of unionization, such as heavy manufacturing in Italy, or subject to high quality standards, as is typical in the food industry.

These findings contribute to building large-scale evidence assessing the recent conceptual frameworks on the risk factors associated to FLM in the Global North. In the Italian case, they show the

[30] Hate events are measured exploiting the database designed by Denti and Faggian (2023), which contains geolocalized figures of property damage, threats, assault, murder motivated by prejudice against disempowered groups in Italy.

relevance of the local industry structure—seemingly not always a generator of positive externalities, but rather conducive to negative dynamics—demonstrating the importance of analysing FLM through a spatial perspective and adding the key role of geography to the factors recognized by forced labour scholars.

The evidence supporting micro-firms in the leading industry as determinants of FLM contributes to the debate about the nexus between the profound changes in industry structures of the last two decades and territorial inequality in Europe. While it is already recognized that the competitive struggle of micro-firms has brought along territorial decline and a spatial fine-grained unevenness of winners and losers with a growing divide, less evidence is available regarding how far this competitive struggle can go in terms of human rights violations.

The article results provide important insights in this respect, supporting policy initiatives that complement criminalizing gangmasters with a focus on understanding firm demand for FLM (European Commission, 2020b). Our findings strongly support the recent EU approach to combating forced labour, particularly its focus on the geo-economic proximity of economic operators to forced labour risks (European Parliament[—]Council of the European Union, 2024). By demonstrating that FLM emerges from specific local industry structures rather than isolated firm decisions, we provide empirical support for regulations that target local production systems, especially in areas with high concentrations of micro-firms in vulnerable sectors. Our results also align with national and international anti-FLM initiatives that promote evidence-based data collection (Invert 2024) and emphasize the importance of place-based interventions (ANCI-Cittalia, 2024).

The analysis has some limitations. First, even if our measure for FLM alleviates measurement bias by merging data from different sources, it nonetheless entails some degree of under-reporting. Second, while our findings are robust to controls for irregular employment and some seasonal work patterns, future research could further explore how local industry specialization affects other labour market outcomes that entail some degree of discrimination (such as gender/ethnic employment gap). Third, the external validity of the results will need further case studies to assess across countries and regions spatially specific risk factors, having as a starting point the first small-area estimates of risk factors for firms' demand for forced labour provided by this article.

Supplementary data

Supplementary data is available at *Journal of Economic Geography* online.

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