Papers in Regional Science 104 (2025) 100083

Contents lists available at ScienceDirect

Papers in Regional Science

journal homepage: www.sciencedirect.com/journal/papers-in-regional-science

Labour demand in the wake of a shock: A dose–response approach

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ARTICLE INFO

JEL classification:
R10
J23
R23

Keywords:
Covid-19
Labour demand
Dose-response

ABSTRACT

This paper examines the impact of varying COVID-19 exposure levels on local labour demand in Italy during the first years of the pandemic. Using a dose–response framework and province-level monthly data on online job postings (NUTS3), we find a predominantly non-linear, negative relationship between COVID-19 exposure — measured by the contagion rate — and labour demand growth. However, at high exposure levels, a positive effect emerges, driven by increased demand for essential roles in Northern Italy. Our findings reveal significant regional disparities. Southern provinces experienced sharper declines in labour demand, despite lower exposure levels, reflecting their weaker economic structures and reliance on non-essential jobs. Conversely, Northern provinces with high exposure levels sustained a higher ratio of essential-to-non-essential vacancies, demonstrating greater economic resilience during the crisis. This study contributes to the literature by examining the underexplored effects of COVID-19 on labour demand in a European context, positioning Italy as a critical case study. It emphasises the pivotal role of essential jobs in mitigating economic disruption and highlights the Italian labour market's non-linear responses to shocks and regional inequalities, offering insights into how sudden crises shape labour dynamics.

1. Introduction

The COVID-19 pandemic had an unprecedented impact on labour markets. In Europe, many governments prioritised essential sectors and occupations, potentially reshaping the labour market landscape. Policymakers also sought to mitigate unemployment through job retention programs, contrasting sharply with the United States, where the pandemic caused a rapid and severe loss of employment. As highlighted by Aaronson et al. (2021), labour demand in the US showed erratic signals, with job vacancies (as a proxy of labour demand) rebounding even as unemployment rates increased. Meanwhile, evidence on European labour market dynamics, particularly concerning labour demand, remains limited, leaving key aspects of the pandemic's impact underexplored.

Italy exemplifies the heterogeneity of European responses, combining stringent lockdown measures with significant government intervention in the economy. These measures restricted mobility, disrupted supply chains, and dampened consumption while aiming to shield workers and businesses from the worst effects of the crisis. This duality — severe economic disruption counterbalanced by robust policy measures — makes Italy a crucial case for understanding the broader implications of the pandemic on labour demand in Europe.

Despite extensive research on the impact of COVID-19 on the labour market, evidence of its effects on the labour demand remains limited. In particular, the responsiveness of local labour demand to sudden increases in exposure to the virus and the underlying adjustment mechanisms remain underexplored. This study aims to address this gap by examining how marginal increases in COVID-19 exposure affected labour demand and its composition between essential and non-essential activities during the first two years of the pandemic.

To analyse the impact of COVID-19 on labour demand, we adopt a dose–response framework. This approach leverages variations in COVID-19 exposure levels — measured through monthly contagion rates — to estimate their effects on local labour demand in the absence of pre-pandemic control groups. By distinguishing between low and high exposure areas, the dose–response model accommodates continuous treatments within the potential outcomes framework. This allows us to examine how differing contagion rates (t) influence job vacancies (y), offering a nuanced understanding of the pandemic's effects on labour market dynamics.

Due to the absence of official vacancy data, this study employs the Lightcast dataset (formerly Burning Glass Technologies), which provides high-frequency, web-scraped online vacancy data. This dataset offers immediate and granular insights into labour demand, specifically at the province level, for Italy during 2020 and 2021. Italy serves as a compelling case study given its geographical heterogeneity and its position as the first European country severely impacted by the pandemic,

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https://doi.org/10.1016/j.pirs.2025.100083
Received 5 June 2024; Received in revised form 20 January 2025; Accepted 26 January 2025
Available online 5 February 2025

making it a key reference point for policy responses worldwide.

We integrate a geographical perspective into our analysis by assessing COVID-19 exposure at the province level (NUTS3) to explore the spatially heterogeneous impacts of the pandemic across Italy.

First, it aims to contribute to the literature by examining the effects of COVID-19 on labour demand within the European context. Our findings shed light on the state of the labour market following significant government interventions during the crisis, including the partial or total suspension of activity in certain sectors. These insights offer valuable policy lessons for managing future economic disruptions, such as pandemics, global energy crises driven by climate change, or geopolitical conflicts like Russia's war against Ukraine[1]. From a policy perspective, these findings highlight the need for adaptive labour market strategies that enhance regional resilience and mitigate the impact of sudden shocks.

Second, this research provides a methodological contribution by applying the dose–response approach, a relatively underutilised method in labour market analysis. This framework enables us to estimate the effects of varying levels of COVID-19 exposure on labour demand, addressing the challenge of identifying effects in the absence of a clear counterfactual.

Finally, the study makes an empirical contribution by utilising non-traditional data sources obtained through web scraping, following approaches similar to those of Hershbein and Kahn (2018) and Campos-Vazquez et al. (2020). This innovative use of data expands the toolkit for labour market analysis, particularly in rapidly evolving contexts such as the pandemic.

Our findings reveal a predominantly non-linear and negative Average Treatment Effect (ATE), indicating that heightened exposure to COVID-19 generally led to a decline in local labour demand growth rates. However, a positive ATE emerges at a high exposure to COVID-19 (around the 90th level), driven primarily by increased demand for essential job vacancies in Northern Italy. Provinces with positive labour demand growth and high contagion levels maintained a balanced but higher essential-to-non-essential vacancy ratio during the emergency period, particularly in 2021 as government job schemes expired.

When examining the demand for essential workers, it remained negative up to moderate levels of COVID-19 exposure but became positive and statistically significant at higher exposure levels. This stresses the role of essential jobs in regions facing the most severe pandemic conditions. A similar pattern is observed for non-essential workers; however, the increase in demand at higher exposure levels does not reach statistical significance.

These results align with pre-pandemic evidence of the Italian labour market's non-linear responses to shocks, where adverse effects tend to be amplified (see Ciani et al. (2017); Garibaldi and Taddei (2013)).

Moreover, prior research about Italy highlights regional variations in response to economic shocks (Duran and Fratesi, 2023; Faggian et al., 2018). Our heterogeneous analysis by macro-regions confirms this: the South experienced a worsening negative ATE with increased COVID-19 exposure. Despite lower exposure levels than the North, the South's weak economic structure, heavily reliant on non-essential workers, exacerbated the adverse effects on labour demand.

The study is structured as follows: Section 2 examines the relationship between economic structure and pandemics and the effects of COVID-19 on the labour market, focusing on labour demand, alongside a brief overview of the Italian case. Section 3 describes the pandemic's evolution in Italy as well as the policies undertaken. Sections 4 and 5, detail the data and empirical strategy. Section 6 presents results and Section 7 concludes.

[1] https://www.oecd.org/ukraine-hub/policy-responses/confronting-the-energy-crisis-changing-behaviours-to-reduce-energy-consumption-5664e8a9/

2. Literature review

2.1. The spatial heterogeneous incidence of COVID-19

This paper contributes to the growing body of literature analysing the effects of the COVID-19 pandemic on local economic structures, with a particular focus on labour demand. It also aligns with empirical studies exploring the spatial dimensions of the pandemic, which have gained prominence in recent years.

Research has long established that factors such as socioeconomic status and social support are critical determinants of health outcomes (Link and Phelan, 1995). Contextualising the social and economic environment is therefore essential for understanding how individuals are exposed to "individually-based risk factors". For instance, Chang et al. (2022) identified 21 pre-outbreak determinants of COVID-19 mortality across 99 countries, highlighting the importance of broader social and economic contexts in shaping pandemic outcomes.

However, such contextualisation requires a granular geographic lens, as the spread of COVID-19 has been highly localised, with significant variations within countries (Bailey et al., 2020). Regional and provincial analyses have thus been crucial for identifying the specific characteristics of areas most affected by the pandemic.

In the Italian context, Ascani et al. (2021) found that regions with higher infection rates were often those that concentrated economic activities. Similarly, Bloise and Tancioni (2021) observed that wealthier and more productive areas also experienced higher infection rates. These findings underscore the geographically uneven impact of COVID-19 and the need for spatially nuanced approaches to pandemic analysis.

2.2. Labour markets and labour demand

The labour market is crucial in shaping a region's reach for opportunities and outcomes (Clark and Bailey, 2018). In addition, the labour market can reflect local socioeconomic variables, such as income, skills, well-being and crime amongst others (Kitsos et al., 2019). Hence, after an economic downturn, the labour market is a priority for governments, especially due to the uncertainty and the asymmetry caused by shocks such as the Great Recession or the COVID-19 pandemic.

During the pandemic, the labour market underwent a complete reconfiguration. There was a sharp increase in the demand for certain jobs, such as health workers. In contrast, other occupations, such as those in hotels and food services, experienced prolonged stagnation (Barbieri et al., 2021).

In the United States, nearly 28 million people filed new claims for unemployment benefits over six weeks ending April 25th. According to estimates by the Survey of Business Uncertainty (SBU), Barrero et al. (2020), found that during the pandemic, for every three new hires, there were ten layoffs. The same study documented that approximately 42% of layoffs during the first months of the pandemic would result in permanent job loss.

Similarly, Italy faced severe effects due to its pre-pandemic conditions. Despite a mild recovery from the Great Recession, driven mainly by employment growth incentivised by structural reforms, Italy had one of the highest unemployment rates compared to other OECD countries (OECD, 2019).

Ciani et al. (2017), found that Italy's labour market has a limited reaction to demand shocks due to nominal wage rigidity. At the same time, housing exhibits procyclical variations that absorb the benefits of rising employment rates. Consequently, shocks to the Italian labour market are amplified by non-linear employment adjustments, which magnify adverse shocks more than positive ones. This suggests a potentially negative effect on labour demand due to COVID-19. This non-linearity component of the labour demand is included in our estimates by assuming a cubic functional form (See Methodology section).

Moreover, Garibaldi and Taddei (2013) characterised the Italian labour market before the pandemic as defined by three key fault lines: gender, generational and regional. These fault lines were evident during the pandemic, which disproportionately affected female workers (Casarico and Lattanzio, 2022; Fiaschi and Tealdi, 2022), young people (Casarico and Lattanzio, 2022) and the Southern regions. Similar to trends observed in other economies, low-educated workers were also more severely affected (Barbieri et al., 2021).

On the labour demand side, existing academic evidence is scarce and primarily focused on the US. Shuai et al. (2021), Forsythe et al. (2020), and Tsvetkova et al. (2020) found a decline in labour demand across most industries and occupations. These studies observed a contraction in demand for jobs requiring face-to-face interactions and increased demand for essential workers. Regarding the characteristics of labour demand, Grabner and Tsvetkova (2022) found that teleworkable vacancies enhance labour market resilience in the US, and Soh et al. (2022) highlighted that regions most affected by the COVID-19-induced recession increased their share of digital occupations. These findings suggest that regions able to mitigate the pandemic's adverse effects were those with greater job flexibility or the capacity to enhance technological job conditions. This body of research relies on high-frequency data collected via web-scraping algorithms, enabling the real-time analysis of the event.

Regarding the Italian context, two papers use administrative data to discuss job flows during the pandemic. Basso et al. (2023), use job contracts data to compare the outcomes of workers with different employment statuses covering 20 months starting in early 2020. They found that labour mobility across firms and sectors was restricted during the pandemic and that the recovery phase, with job-to-job transitions, only increased in late 2021. The second paper by Citino et al. (2023), analyse data from the Italian Social Security Institute (INPS) concerning the entire universe of firms and employees in the non-farm private sector. Their findings indicate that the share of expanding firms decreased from 60% to 40% during the pandemic, leading to a significant decline in job creation. At the same time, job destruction also fell in 2020 as a result of government interventions, including a layoff freeze and a short-time work scheme. Although both papers focus on labour reallocation — a topic beyond the scope of our analysis — they highlight the pandemic's significant impact on employment dynamics, particularly through restrictions on labour mobility and job creation. Building on this evidence, we anticipate a decline in labour demand performance.

3. The Italian case

Italy was the second country globally, after China and the first in Europe to adopt severe lockdown measures in response to COVID-19. The initial local lockdown was imposed on February 21, 2020, targeting ten municipalities in the northern province of Lodi. On March 8, lockdowns were extended to 26 additional provinces, culminating in a nationwide and stringent lockdown implemented on March 10 2020.

Given the gravity and uncertainty of the situation, the Italian government issued a decree in March 2020 to shut down all non-strategic sectors, dividing the workforce into essential and non-essential categories. Essential sectors included healthcare, food production, and public safety services, while non-essential sectors encompassed industries such as tourism, entertainment, and non-urgent retail. This measure sought to minimise the virus's spread while maintaining the functionality of critical services. Initial estimates by Barbieri et al. (2021) suggest these lockdown measures affected nearly 8 million workers, out of a total workforce of approximately 25 million. Furthermore, Cetrulo et al. (2020) reported that only 30% of Italian workers were potentially able to telework, highlighting the challenges posed by the lockdown on labour market dynamics.

To mitigate the economic fallout, the government introduced a layoff ban policy, effective from February 2020 to October 2021. This policy prohibited collective and individual dismissals on financial grounds, with some exceptions. Large firms, excluding those in the textile sector, were permitted to dismiss workers starting 1 July 2021, while individual dismissals for breach of contract and the expiration of temporary contracts were allowed throughout the ban period (Basso et al., 2023).

In parallel, the government significantly expanded the scope of short-term employment schemes. Previously limited to firms with at least five employees or those in the industrial sector, these programs were expanded to provide greater protection during the crisis. Additionally, a lump sum bonus averaging approximately 600 euros was introduced for nearly all self-employed workers who had not been covered by social insurance before the pandemic, offering financial support to this vulnerable group. This comprehensive response helped mitigate the decline in labour income in the short term (Carta and De Philippis, 2021).

In early June 2020, as pandemic conditions partially improved, the government allowed the reopening of restaurants and retail activities and lifted restrictions on interregional movement. However, by late summer 2020, cases began to rise again, prompting the government to introduce a regional "colour" policy on 6 November 2020. This system assigned regions different levels of restrictions based on the severity of the pandemic in each area.

Three colours were established: yellow zone (light restrictions), orange (moderate restrictions), and red zone (severe restrictions). According to Conteduca and Borin (2022), significant variation was observed between regions. For example, the Autonomous Province of Bolzano was the region that spent most of the time in the red zone, and regions like Abruzzo, Aosta Valley and Sicily spent most of the emergency periods between the intermediate and severe restrictions.

In March 2021, an intense vaccination campaign, jointly with the strengthening of the measures in the red zone, led to the re-opening of most of the activities in late April and to the implementation of the "Green Pass", which attested as proof of vaccination or recovery.

The COVID-19 policy adopted an "individual" turn since from this point onward, regulation was less stringent for vaccinated individuals. By the 1st of September 2021, the green pass was mandatory in schools, selected public transport and eventually in workplaces (October 2021). By November, the government introduced the Super Green Pass to incentivise vaccination, limiting the accessibility of places for non-vaccinated people.

Due to the increase of cases and the surge of the Omicron variant, the decree-law of the 24th December 2021 and, ultimately, the decree-law of the 30th December 2021 increased the list of places whose access was uniquely granted with the Super Green Pass, such as museums, swimming pools or gyms. By the end of March 2022, due to the minor severity on the population of the Omicron variant, the government announced the end of the state of emergency.

4. Data and descriptives

We compile data from multiple sources, as outlined in Table 1. To analyse local labour demand, we use vacancy data from Lightcast as the dependent variable. Our treatment variable is the monthly COVID-19 contagion rate at the provincial level (NUTS 3). Key control variables are included to address factors relevant to the COVID-19 crisis. The provincial mortality rate, derived from Italian administrative records, acts as a proxy for COVID-19-related deaths and the pandemic's severity while also reflecting each province's demographic structure. It is calculated as the total number of deaths in a province divided by its population and multiplied by 1,000.

We also include the Italian Stringency Index (ItSIs), a localised version of the Oxford Stringency Index, to measure the intensity of local restrictions (Conteduca and Borin, 2022). This index ranges from 0 (least

Table 1
Main variables.

Type of variable	Variables	Frequency	Year	Geographic unit	Source
Treatment	Contagion rate	Monthly	2020–2021	NUTS 3	EpiCentro
Dependent variable	Log. of the Nº of vacancies total, essential and non-essentials	Monthly	2020–2021	NUTS 3	Lightcast
Controls	Mortality rate	Monthly	2020–2021	NUTS 3	ISTAT
	Italian stringency Index (ItSIs)	Monthly	2020–2021	NUTS 3	Conteduca and Borin (2022)

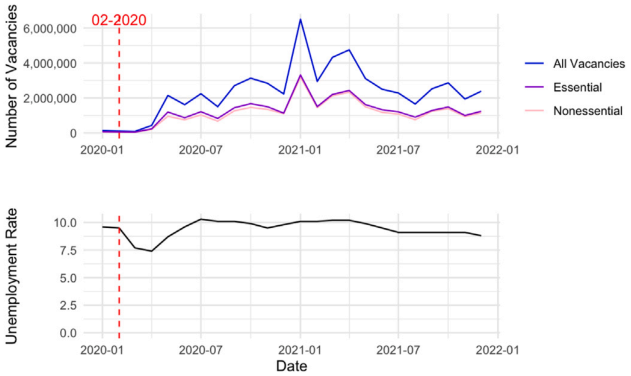

Fig. 1. Monthly number of vacancies and monthly unemployment rate.
Notes: All, essential and non-essential vacancies are from the Lighcast dataset. The monthly unemployment rate is from ISTAT.

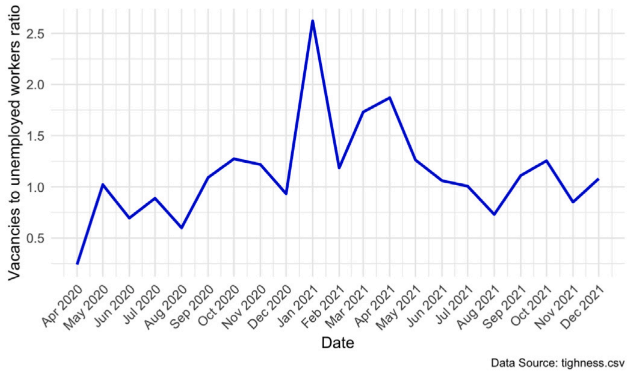

Fig. 2. Labour market tightness: Number of vacancies to unemployed workers ratio.
Notes: Vacancies are from the Lightcast dataset. The monthly number of unemployed workers (15 years old and more) is from ISTAT. Data is from April 2020 to December 2021.

stringent) to 100 (most stringent) and is calculated as a population-weighted average of restrictions at the provincial, regional, and national levels. Monthly provincial-level ItSIs data capture temporal variations in the severity of restrictions.

The complete dataset covers the period from April 2020 to December 2021, corresponding to the introduction of major government policies, including stringent lockdown measures. Due to the high frequency of the Lightcast dataset, we are unable to obtain additional information at the NUTS3 level with matching monthly time variations. However, we include a set of additional controls in the Appendix (Table 9) to test the robustness of our results.

The descriptive statistics (see Table 2) reveal that the mean Stringency Index indicates a moderate level, though a large standard deviation highlights significant variability.

The Lightcast dataset provides detailed information, including NACE codes that can be matched to Italian sectoral codes (ATECO), enabling the classification of sectors as essential or non-essential according to the Italian government's decree of 22 March 2020.

The distribution of essential and non-essential vacancies, observed in Fig. 1, is relatively balanced in our sample, with essential vacancies making up 52% of the total—almost a one-to-one average essential to non-essential vacancy ratio. This suggests that our data are not heavily biased towards any specific category. During the emergency period, vacancies exhibited significant fluctuations, with notable peaks and sharp declines. We compared vacancy dynamics with unemployment rate (from ISTAT) movements to contextualise these trends within the broader macroeconomic environment. Unemployment, however, increased only a few months after the onset of the emergency and remained stable until mid-2021, showing the efficacy of the job retention schemes. Meanwhile, vacancies show changes likely reflecting labour demand's response to various government policies, such as lockdown measures and waves of COVID-19 contagion. Both essential and non-essential vacancies followed a similar trajectory, although essential vacancies slightly outnumbered non-essential ones for most of the period (see Fig. 1).

In line with Aaronson et al. (2021), we visualise labour market tightness from April 2020 to December 2021, defined as the ratio of job openings to unemployed workers. A "tight" labour market arises when job openings significantly exceed the number of available or willing workers, reflecting an imbalance. Fig. 2 shows that the ratio was at a low 0.24 in April 2020, indicating severe slack due to widespread economic disruptions. It recovered by late 2020 with notable volatility, which may reflect the Italian government's policy responses. However, this aggregate measure cannot fully capture the nuanced effects of COVID-19 on local labour markets. A dose–response framework addresses these limitations by analysing labour demand as a function of varying exposure to COVID-19, accounting for the non-linear dynamics between contagion rates and labour demand.

Furthermore, our dependent variable is the monthly number of vacancies by province. Due to the right skewness of this variable, we applied a log transformation (see Fig. 3). This transformation changes the interpretation of our dependent variable, allowing it to be understood as a rate of growth.

4.1. Treatment variable: COVID-19 cases and contagion rate

Since we are using a dose–response approach, an epidemiology model embedded in a continuous potential outcome setting, we start by defining a treatment that represents exposure to COVID-19 at a province level. We use the number of COVID-19 cases for each province. Italy's data regarding contagions is highly reliable, due to the strict surveillance imposed by the government during the first year of the pandemic. The number of cases was obtained from EpiCentro, the website of the Health Institute (Instituto Superiore di Sanita, ISS).

This dataset is derived from Italy's surveillance system, incorporating epidemiological data from regional authorities, autonomous provinces, and the National Reference Laboratory for SARS-CoV-2. Following international standards, the ISS defines a confirmed case as any individual with laboratory confirmation of the virus, irrespective of clinical symptoms. Consequently, this dataset is the most comprehensive source of COVID-19 case data in Italy. However, it is important to note that systematic data collection from this data source only began in April 2020, leaving the first two months of the pandemic undocumented. To standardise the data for analysis, the daily case

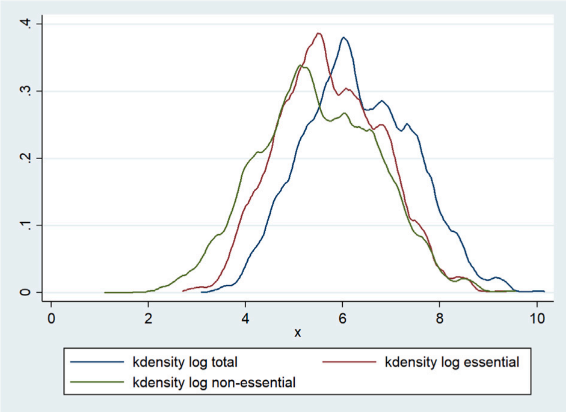

Fig. 3. Distribution of the total, essential and non-essential vacancies.
Notes: All, essential and non-essential vacancies from the Lighcast dataset. Essential and non-essential vacancies were created using the ATECO codes from the Italian government decree.

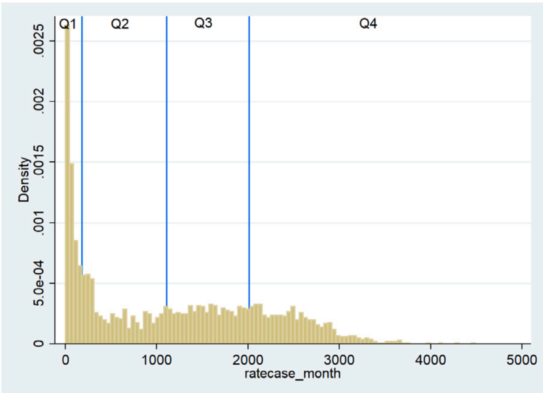

Fig. 4. Distribution of province-level monthly COVID-19 cases.
Notes: Number of monthly contagions by province from Epicentro's website of the Health Institute (Instituto Superiore di Sanita, ISS).

counts were aggregated at the provincial level on a monthly basis and converted into a rate by dividing by the province's population for that year and multiplying by 1,000 (See Eq. (1)).

$$\text{Exposure to COVID-19} = \frac{\text{Monthly province}_i \text{ cases}}{\text{province}_i \text{ population}} \times 1,000, \tag{1}$$

Fig. 4 shows the distribution of the contagion rate. The data is skewed to the right, which is due to high values of contagion rates that mostly occurred during 2021. These higher values could be due to changes in testing protocols. Initially, only PCR tests were accepted as evidence of COVID-19 positivity, but starting in October 2020, the Italian government allowed pharmacy-based antigen tests as well (see Fig. 5).

To facilitate the interpretation of the continuous treatment framework, we transform the contagion rate in a range from 0 to 100, where the "zero" or non-treated units represent low exposure to COVID-19. To choose the treatment several factors were taken into account.

We define as untreated or "zero" the first quartile of the distribution of COVID-19 rates. This threshold was decided upon two considerations: first, that all 107 provinces have been in the first quartile at least once over the sample period and second, when aggregating the provinces in four macro geographical areas, almost the third part of the contagion rates in the Centre, South and islands is on the first

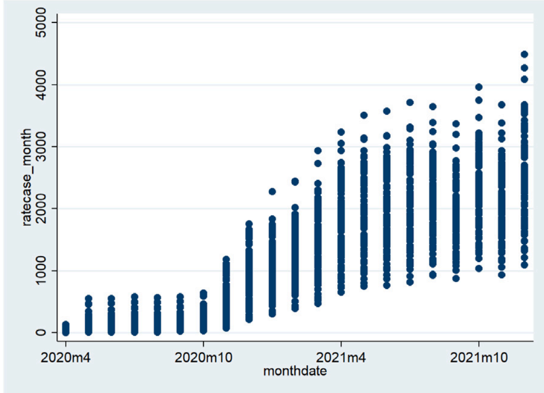

Fig. 5. Monthly contagion rate per province and time.
Notes: Number of monthly contagions by province from Epicentro's website of the Health Institute (Instituto Superiore di Sanita, ISS).

quartile. Therefore, we guarantee that most of the provinces were in the treatment group at least once so that we minimise the possible imbalances in treated and non-treated groups.

After transforming the contagion rate into our treatment variable, we find that the average treatment level is 26, though it exhibits considerable variation, as indicated by a high standard deviation (see Table 2).

This choice of treatment definition has important implications for our estimates. For instance, the "zero" or "low-treated" units that are a hypothetical counterfactual that makes the Average Treatment Effect on the Non-Treated (ATENT) constant per estimate. Consequently, the Average Treatment Effect (ATE) is dominated by the effect on the treated units (ATET), which is also reported in the results. Nevertheless, the method still allows us to capture the functional relationship and assess how labour demand responded to varying levels of exposure to the virus.

4.2. Evidence and caveats from job ads data

Online vacancies have become an important source of information about the health of the labour market, particularly for the labour demand. Whilst national statistical offices could take months to release data, sources like Lightcast can provide a glimpse of the economic landscape quicker at a granular scale level. In the context of the current pandemic, Campos-Vazquez et al. (2020) used web-scraped job ads in Mexico and found that the number of vacancies declined by 38%. Forsythe et al. (2020), using Lightcast data, estimated that by late April, job vacancies had fallen by over 40% in the US.

Similar to the aforementioned studies, we intend to use the Lightcast dataset to proxy labour demand responsiveness to varying levels of COVID-19 exposure. Consistent with existing literature, we anticipate a negative impact on labour demand due to the severity of lockdowns, with distinctions between essential and non-essential workers.

However, it is important to acknowledge the limitations of our analysis. One significant drawback of using online vacancy data is that it only represents a subset of the total vacancies in the economy. We attempted to benchmark the Lightcast dataset for Italy (specifically, the number of vacancies by province) against official vacancy data; however, this data is unavailable (Vermeulen and Gutierrez Amaros, 2024). In the absence of official data, we chose to correlate the vacancies with other economic indicators, such as the unemployment rate by province and employment in manufacturing. Our findings indicate a negative and statistically significant correlation with the provincial unemployment rate (−0.501) and a positive and statistically significant correlation with employment in manufacturing (0.502), suggesting that

Table 2
Summary of variables.

	Total vac.	Essential	Non-essential	ItSIs	Mortality rate	Treatment	Contagion rate
Mean	967.647	508.495	459.152	55.211	1.060	26.008	1183.201
SD	1502.03	724.567	782.347	15.807	.2450	22.43	989.397
Min	22	15	3	30.912	.5155	0	1.713
Max	25 727	11 658	14 069	91.152	2.492	99.99	4488.75

Treatment corresponds to the transformed contagion rate

the vacancy data trends similarly.

Another shortcoming of the data is that it overrepresents certain sectors and occupations, such as "Professionals", or contains more vacancies from medium to big cities (Grabner and Tsvetkova, 2022; Vermeulen and Gutierrez Amaros, 2024). Further interpretations of our results should consider this data bias.

Finally, one significant drawback of the data we have been able to access is that we do not know if vacancies are teleworkable positions or not.

5. Methodology

5.1. Impact evaluation using dose response

Causal and statistical models such as the Neyman-Holland-Rubin (Holland, 1986; Rubin, 2005) and its simplest version of "potential outcomes" have been the main bone of policy evaluation. Their methodology consists of dividing the sample into two groups, treatment and control, and assessing their difference in a certain outcome y, after an intervention. The difference between both groups' outcomes is the unit's causal effect. Since it is not possible to observe both potential outcomes simultaneously, only three parameters can be estimated based on a sample: The average response of the treated (ATET), the average response of the control (ATENT) and the difference between both groups commonly known as the average treatment effects (ATE).

During the pandemic, a key challenge lies in the absence of a true counterfactual, as all units experienced some level of exposure to the treatment. To address this, we adopt Cerulli's (2015) dose–response framework, which estimates the effects of varying levels of exposure to COVID-19. Unlike binary treatment models, the dose–response approach allows for a continuous treatment variable, defined here as the monthly COVID-19 case rate at the NUTS3 level, which we refer to as "exposure to COVID-19".

Examples of the implementation of the dose–response can be found in the analysis of policies that gave public funding or credits to regions such as Adorno et al. (2007), Cerulli et al. (2022) and Cerulli and Ventura (2021). The dose–response framework has also been formulated as a propensity score method extended to a continuous treatment setting (Hirano and Imbens, 2004).

Cerulli's (2015) framework allows us to capture how treated units may respond differently to cofounders and levels of treatment and we can also obtain the ATET and the ATENT. Additionally, this approach does not need the assumption of normality and units can have a treatment level of zero. Thus, this framework allows for a non-nil probability mass at zero.

Another advantage is that it allows estimating a dose–response function (DRF) which in this context is equivalent to the average treatment effect (ATE) given the level (t) of the continuous treatment variable.

Visualising the dose–response function is crucial because it shows us the progression of labour demand when the emergency is more severe. The shape of this function provides valuable insights into labour demand patterns. For instance, a flat function might suggest that labour outcomes remain unchanged regardless of the level of exposure to the virus. Furthermore, the dose–response framework allows us to derive additional causal estimates, such as the Average Treatment Effect on the Treated (ATET) and the Average Treatment Effect on the Non-Treated (ATENT), as well as conditional effects based on confounders (x) and the continuous treatment variable (t).

As previously stated, our study uses COVID-19 contagion rates as the treatment variable, designating "low-treated" units as the control group. We transformed the treatment variable on a scale from 0 to 100 to facilitate the interpretation (we refer to them as "levels").

5.2. Potential outcomes on a continuous framework

Following Cerulli's (2015) framework, the starting point of our methodology is Rubin's potential outcome equation

$$y_i = y_{0,i} + w_i \left(y_{1,i} - y_{0,i} \right), \tag{2}$$

where $y_{0,i}$ denotes the potential outcome not affected by the treatment; $y_{1,i}$ is the potential outcome of unit i when treated; w is a dummy variable that denotes the treatment status.

Expanding this equation into a continuous framework, we define t_i as the continuous treatment indicator that is within a range from 0 to 100. $x_i = [x_{1,i}, x_{2,i}, \dots, x_{M,i}]$ as an M vector of different cofounders for units $i = 1, \dots, N$,where N is the total number of units. We define $g_1(x_i)$, $g_0(x_i)$ as functions of the response to the cofounders which we consider as $g_1(x_i) = \delta_1 x_i$ and $g_0(x_i) = \delta_0 x_i$. Finally, w indicates treatment status. Thanks to these definitions, we can prescribe an alternative model to (2) which generates the population in a continuous way with respect to the cofounders, namely

$$\begin{cases} w = 1: & y_1 = \mu_1 + g_1(x) + h(t) + e_1, \\ w = 0: & y_0 = \mu_0 + g_0(x) + e_0, \end{cases} \tag{3}$$

where $h(t)$ is a general derivable function of t_i and is different from zero only if treated.

Given this model, we can define the casual parameters of interest as functions over the cofounders x_i and the treatment level t so that:

$$\text{ATE}(x, t) = E(y_1 - y_0 | x, t)$$

which can be split in ATET for $t > 0$ and ATENT for $t = 0$

$$\text{ATET}(x, t > 0) = E(y_1 - y_0 | x, t > 0)$$
$$\text{ATENT}(x, t = 0) = E(y_1 - y_0 | x, t = 0)$$

In the model, averaged with reference to x and t we have

$$\begin{cases} \text{ATE} = p(w = 1) \left(\mu + \bar{x}_{t>0}\delta + \bar{h}_{t>0} \right) + p(w = 0) \left(\mu + \bar{x}_{t=0}\delta \right) \\ \text{ATET} = \mu + \bar{x}_{t>0}\delta + \bar{h}_{t>0} \\ \text{ATENT} = \mu + \bar{x}_{t=0}\delta \end{cases}$$

where $\delta = \delta_1 - \delta_0$, $\bar{h}$ is the average treatment intensity and $\mu = \mu_1 - \mu_0$ which yields the following dose–response function (DRF)

$$\text{ATE}(t) = \begin{cases} \text{ATET} + \left\{ h(t) - \bar{h}_{t>0} \right\} & \text{if } t > 0 \\ \text{ATENT} & \text{if } t = 0, \end{cases}$$

computed by averaging with respect to x.

5.3. Regression model

Let us consider the definitions given in the previous section and define the regression model as

$$y_i = \mu_0 + w_i \,\text{ATE} + x_i\delta_0 + w_i \left(x_i - x\right)\delta + w_i \cdot \left(h\left(t_i\right) - \bar{h}\right)\eta_i, \tag{4}$$

where η_i is $\eta_i = e_{0,i} + w_{0,i}.(e_{1,i} - e_{1,0})$; where ATE is the unconditional average treatment effect, x_i is a set of control variables; $h(t_i)$ is the response function of y_i to the level of treatment t_i; μ_0, δ and δ_0 are parameters. Thus, we can write the regression line as

$$E(y_i|w_i, t_i, x_i) = \mu_0 + w_i \,\text{ATE} + x_i\delta_0 + w_i\left(x_i - \overline{x}\right)\delta + w_i \cdot \left(h\left(t_i\right) - \bar{h}\right), \tag{5}$$

and we use OLS to estimate ATE, δ_0, δ_1, μ_0, μ_1 and the parameters of the cubic $h(t)$.

We adopt a cubic specification of the dose–response function (DRF) to capture the non-linear effects of the pandemic's adverse shock on labour demand (Ciani et al., 2017). This cubic form allows us to compute the function's first derivative, which indicates changes in the concavity of the DRF, thereby enabling us to identify at which levels of COVID-19 exposure significant changes occur. We also report this plot in our results. Hence, it is assumed a cubic parametric form of the dose–response function $h(t)$, which reads

$$h(t_i) = a.t_i + b.t_i^2 + c.t_i^3, \tag{6}$$

where a, b and c are parameters to be estimated in the regression. Namely, the model reads

$$\widehat{\text{ATE}}\left(t_i\right) = (1 - w)\widehat{\text{ATENT}}(t_i) + w\left[\widehat{\text{ATET}}\left(t_i\right)_{t>0} + \hat{a}\left(t_i - \sum_{i=1}^{N} t_i\right) + \hat{b}\left(t_i^2 - \sum_{i=1}^{N} t_i^2\right) + \hat{c}\left(t_i^3 - \sum_{i=1}^{N} t_i^3\right)\right], \tag{7}$$

where $\hat{a}$, $\hat{b}$ and $\hat{c}$ are the parameters of $h(t)$ where $\widehat{\text{ATE}(t_i)} = \widehat{\text{ATET}(t_i)}$ for $t_i > 0$ If $\widehat{\text{ATET}(t_i)}$ is plotted with respect to t for every $t_i > 0$, we can observe the DRF. It is also possible to observe for each t level, the α-confidence interval around the dose–response curve.[2] By defining $T_1 = t - E\left(t\right)$, $T_2 = t^2 - E\left(t^2\right)$, and $T_3 = t^3 - E\left(t^3\right)$, the standard error of the DRF is

$$\hat{\sigma}_{\widehat{\text{ATE}(t)}} = \left(T_1^2\hat{\sigma}_a^2 + T_2^2\hat{\sigma}_b^2 + T_3^2\hat{\sigma}_c^2 + 2T_1T_2\hat{\sigma}a, b + 2T_1T_3\hat{\sigma}a, c + 2T_2T_3\hat{\sigma}b, c\right)^{1/2}, \tag{8}$$

To ensure the consistency of the causal parameters, we rely on the assumption of unconfoundedness (Wooldridge, 2010). This assumption posits that, conditional on the observed covariates, the key variables are appropriately exogenous.[3] As a final note, we emphasise that the econometric model not only depends on Conditional Mean Independence (CMI) to handle selection on observables, but it also requires "additive separability" of unobservable time-varying factors. This latter assumption accounts for selection-on-unobservables by incorporating unit (province) and time fixed-effects (Cerulli, 2015; Cerulli and Ventura, 2021).

6. Results

For each model, we used as dependent variables the total number, essential and non-essential vacancies. Additionally, as time-variant control variables, we used mortality rate and ItSIs index. Our estimates remain robust across various checks, including rerunning the analysis without these controls as well as incorporating additional socioeconomic controls.

We conducted several estimations with fixed-effects for time and/or province to control for idiosyncratic sources of heterogeneity. The time fixed-effects account for month-year variations, capturing fluctuations in the economic cycle, the evolving nature of the pandemic, and seasonal trends in job postings. The province fixed-effects are essential for accounting for time-invariant geographic characteristics.

Since the dependent variables — total, essential, and non-essential vacancies — were log-transformed, the ATE coefficients (Treatment) indicate the growth rate of the labour demand. Given that our Average Treatment Effect on the Non-Treated (ATENT) remains constant due to the transformation of the treatment variable, the ATE obtained in our estimation is primarily driven by the Average Treatment Effect on the Treated (ATET), as reported in our regression tables. We also display the DRF plot alongside its first derivative to highlight the function's inflection points.

6.1. All, essential and non-essential vacancies

The results for the three dependent variables are summarised in Table 3, which includes province-level controls (ItSIs and mortality rate) and polynomial adjustments (Tw). These adjustments describe the shape of the DRF, which is assumed to follow a cubic form to capture the non-linear effects on the Italian labour market.

The treatment coefficient for total vacancies (column 1, Table 3) indicates that labour demand experienced an average 14% decrease in growth rate for treated units, with an ATET of −18%. Fig. 6 corroborates this finding, showing a negative DRF up to the 80th level of COVID-19 exposure. However, beyond the 90th level, the labour demand growth rate becomes positive and statistically significant, suggesting that provinces with very high contagion rates experienced an increase in local labour demand. The plot of the first derivative Fig. 7 also displays that the function changes after the 50th level.

The Italian Stringency Index (ItSIs) is positive and statistically significant, reflecting the worsening of the COVID-19 situation and the severity of its local diffusion. This finding aligns with Grabner and Tsvetkova (2022), who observed that stricter restrictions were positively associated with greater resilience in metropolitan labour markets.

When focusing on essential vacancies, the negative growth rate for treated provinces is 13%, with an ATET of −16.5%. The Dose-Response Function (DRF) for essential vacancies differs subtly from the baseline model, showing a steeper slope. The DRF becomes positive around the 70th level of COVID-19 exposure and statistically significant at approximately the 90th level (Fig. 8). The plot of the first derivative Fig. 9 shows also a change in the slope around the 40th and 50th level.

For non-essential vacancies, the results and DRF follow a similar pattern to the baseline and essential vacancy models. According to the consulted literature, this group exhibits high heterogeneity due to the inclusion of diverse sectors, such as hospitality (hotels, restaurants, and bars) employing approximately 5 million workers (Barbieri et al., 2021), alongside professional services requiring higher education. Although the ATE for non-essential vacancies remains consistent in direction and statistical significance, its magnitude differs, as reported in column 4. The decrease in the labour demand rate for this type of vacancy is 18%. The discrepancy between the effect on treated provinces (ATET) and the ATE is also higher than in the previous models (see Fig. 7).

For the non-essential vacancies, the DRF shape changes its concavity around the 50th level (this can also be observed in the first derivative plot Fig. 9) and then there is an increase in the rate of labour demand. However, this increase is not statistically significant. This is clear from the plot since the confidence intervals contain zero (Fig. 10).

[2] Therefore, the α-confidence interval of $\widehat{\text{ATE}}(t)$ for each t is given by $\left\{\widehat{\text{ATE}}(t) \pm Z_{\alpha/2} \times \hat{\sigma}_{\text{ATE}(t)}\right\}$.

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[3] According to Cerulli (2015) this implies that given the set of random variables y_{0i}, y_{1i}, w_i, x_i, t_i unconfoundedness in this specific case refers to

$$E\left(y_{ji} \mid w_i, t_i, \mathbf{x}i\right) = E\left(yji \mid \mathbf{x}_i\right) \text{ with } j = \{0, 1\}$$

which allows us to identify ATEs and the DRF in this context.

Table 3
Regression results for all, essential and non-essential vacancies.

	(1) Log of number of vacancies	(2) Log of number of essential vac.	(3) Log of number of non-essential vac.
Treatment	−0.141***	−0.132***	−0.180***
	(0.040)	(0.041)	(0.0476)
ItSIs	0.00542**	0.00458**	0.00750***
	(0.002)	(0.002)	(0.00258)
Mortality rate	0.0453	0.0753*	0.00569
	(0.038)	(0.039)	(0.0460)
Tw_1	−0.00833*	−0.00704	−0.0108**
	(0.004)	(0.00448)	(0.00519)
Tw_2	0.0000234	0.00000449	0.0000350
	(0.0001)	(0.0001)	(0.000119)
Tw_3	0.00000114	0.00000125	0.00000117
	(0.0000007)	(0.0000007)	(0.000000887)
Constant	7.052***	6.474***	6.120***
	(0.205)	(0.210)	(0.243)
Fixed-effects	Province and time	Province and time	Province and time
N	2247	2247	2247
Adjusted_R2	0.957	0.950	0.950
ATET	−.180	−.1654	−.236

Robust SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

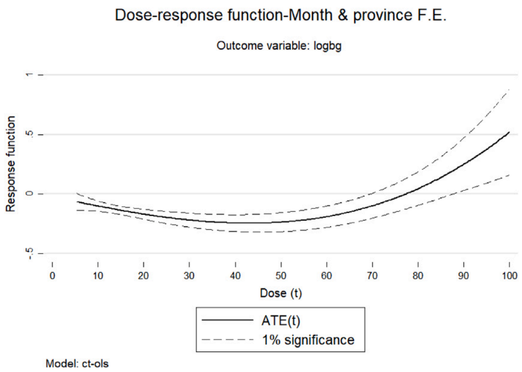

Fig. 6. Dose response function all vacancies. Province and month FE.

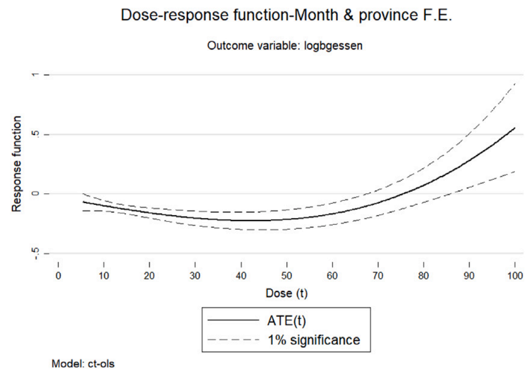

Fig. 8. Dose response function for essential vacancies. Month and province FE.

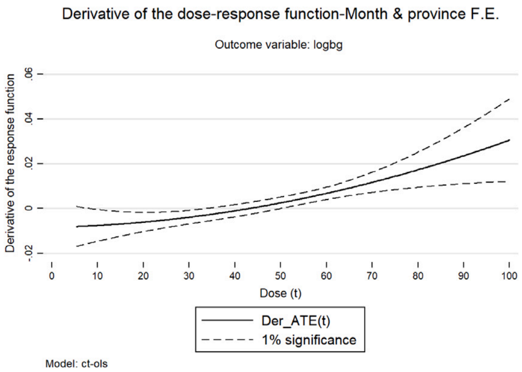

Fig. 7. Derivative DRF all vacancies. Province and month FE.

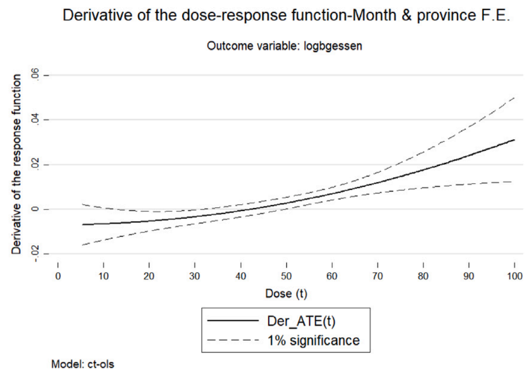

Fig. 9. Derivative DRF for essential vacancies. Month and province FE.

Although the segmentation of the workforce into essential and non-essential categories was expected to yield distinct effects on labour demand dynamics, the results do not indicate substantial differences. Additional analysis, detailed in the Appendix (Table 17), examines the difference between essential and non-essential vacancies as the dependent variable. The results, which include time and province fixed-effects, are not statistically significant, suggesting no structural differences between the two groups. These findings align with Barbieri et al. (2021), who highlight heterogeneity even within essential and non-essential classifications. For instance, while manufacturing, which accounts for 18% of total employment in Italy, continued operations during the pandemic, it encompasses varying degrees of physical proximity, questioning the adequacy of government-defined workforce classifications (see Fig. 9).

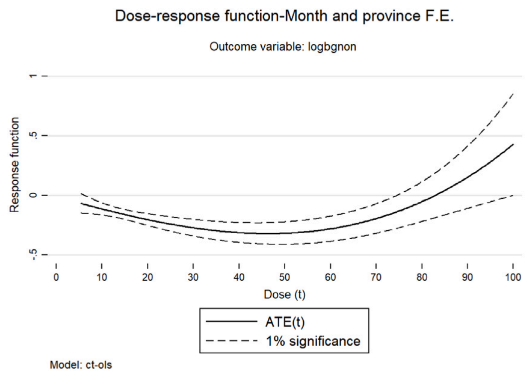

Fig. 10. Dose response function for non-essential vacancies. Month and province FE.

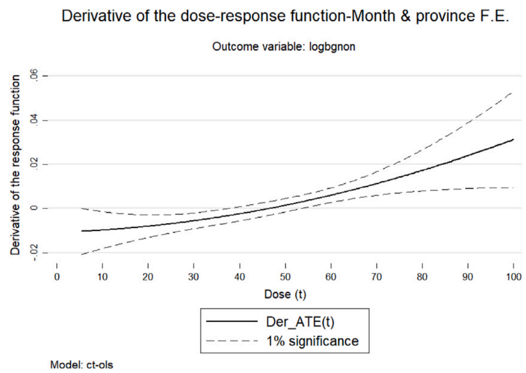

Fig. 11. Derivative DRF for non-essential vacancies. Month and province FE.

We also tested alternative thresholds for defining treatment based on the monthly contagion rate distribution (see Table 14 in the Appendix). Our findings remain robust up to the 30th percentile of the contagion rate distribution as the control group.

As mentioned, we identified a threshold around the 90th level of COVID-19 exposure, above which labour demand increases. The provinces that surpassed this threshold — Bolzano, Rimini, and Trieste — demonstrated lower unemployment rates than the national average during 2020 and 2021, along with below-average female unemployment. Additionally, these provinces had higher GDP per capita than the Italian average in 2020 and are classified as small to medium in terms of population.

A closer examination of Rimini (Fig. 13), Bolzano (Fig. 14), and Trieste (Fig. 15) illustrates how local economic conditions influenced labour market trends. These provinces maintained higher ratios of essential to non-essential vacancies (1.48, 1.47, and 1.36, respectively) compared to the national average of 1.1 (Fig. 12). However, the ratios are not excessively skewed, indicating that there is also considerable dynamism in the non-essential sector.

This resilience of these provinces allowed them to keep unemployment rates below the national average throughout the pandemic. Their capacity to sustain demand for essential and non-essential workers, even amidst rising COVID-19 exposure, indicates a strategic alignment between the local labour force's skills and the economic needs during the crisis.

The essential-to-non-essential vacancy ratios in these provinces (see Figs. 13, 14, and 15) fluctuated significantly throughout the emergency, consistently remaining above the one-to-one ratio. This trend reflects a greater demand for essential workers, particularly in 2020

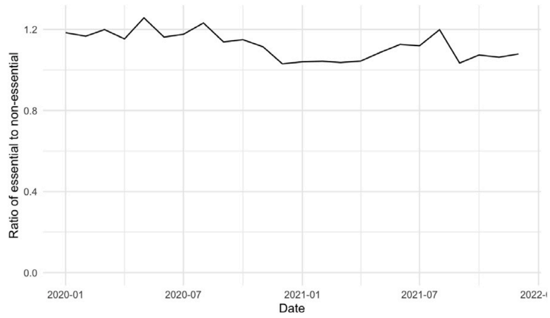

Fig. 12. National essential to non-essential vacancy ratio.

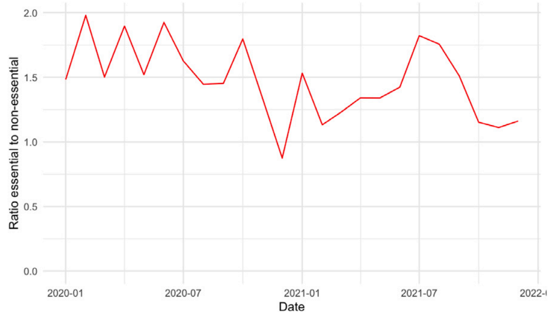

Fig. 13. Rimini's essential to non-essential vacancy ratio.

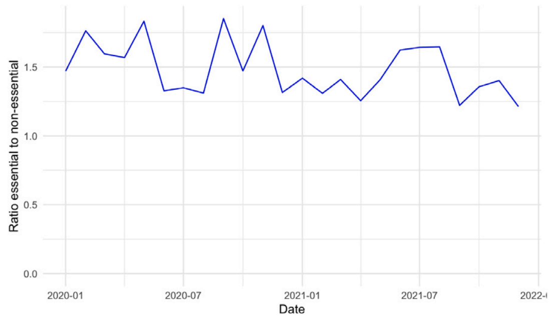

Fig. 14. Bolzano's essential to non-essential vacancy ratio.

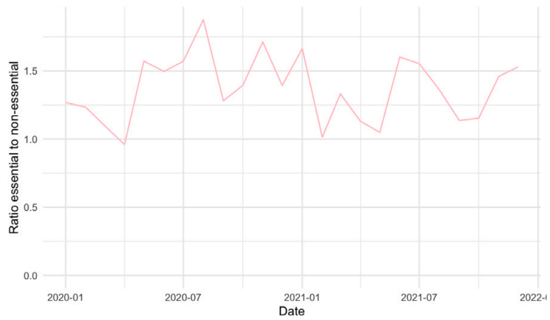

Fig. 15. Trieste's essential to non-essential vacancy ratio.

and mid-2021, when the government job schemes expire (see Fig. 11).

By lowering the threshold to a level where the dose–response function (DRF) becomes positive, even if the average treatment effect (ATE) is not statistically significant, we observe that most identified provinces

Table 4
Average essential to non-essential ratio by provinces over the 70th level of treatment (contagion) for 2020 and 2021.

Province	2020	2021
Valle d'Aosta	2.219	1.821
Varese	1.124	1.014
Como	1.410	1.161
Monza e della Brianza	1.146	0.993
Verona	1.030	0.954
Vicenza	1.122	0.945
Belluno	1.280	1.144
Treviso	1.023	1.067
Venezia	1.260	1.159
Padova	1.021	0.886
Udine	1.231	1.214
Gorizia	1.631	1.321
Reggio nell'Emilia	1.090	0.949
Modena	1.111	1.005
Bologna	1.129	1.079
Forlì-Cesena	1.137	1.139

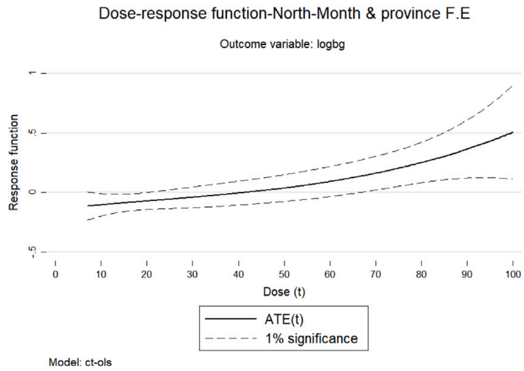

Fig. 16. North DRF. Month and province FE.

are located in Northern Italy. Table 4 lists the 16 provinces that exceed the 70th percentile of treatment. Many of these provinces sustained a slightly higher number of essential vacancies during the emergency period, which may have supported their resilience during the crisis. Additionally, it is noteworthy that many of these provinces are located in regions with special status granted by constitutional law (statuto speciale), providing them with a degree of self-governance and autonomy. This status could have influenced both financial support, policies and the management of the pandemic response (Accetturo et al., 2023).

Concerning our counterfactual group, which includes the "low-treated" provinces (those falling below the 25th percentile of the monthly contagion distribution by province), we note that all observations are from the year 2020. According to the ISTAT classification of regions into North, Centre, and South, 46.17% of the provinces in the counterfactual group are located in the South, while the Centre and North account for 25.13% and 28.70%, respectively (see Fig. 12).

These results suggest the existence of a geographical pattern in the growth rate of labour demand, whereby better performance has occurred in Northern NUTS-3 provinces as compared to other areas of the country. The next section presents a straightforward geographical approach by aggregating the provinces into three regions: North, Centre, and South and islands.

6.2. Geographical heterogeneity

Italy's stark geographical economic divide between the North and South significantly influences local dynamics. Recent studies highlight spatial variations in the relationship between COVID-19 incidence and socioeconomic factors (Ascani et al., 2021; Bloise and Tancioni, 2021). Porto et al. (2022) identify a higher concentration of essential workers in the northern regions. Our findings align with and further support this observed pattern.

In the context of this paper, more than 70% of online vacancies are observed in the North and, on average, the North also exhibits the highest contagion rates during the study period. Furthermore, in our previous analysis, half of the treated units are concentrated in the North (see Fig. 17).

To address this geographical divide and capture the differences in response curves from a more spatial perspective, we consider the typical three macro areas of the country: North, Centre and South & Islands. Hence, we re-run the model for each area, thus estimating different area-specific treatments. To assign the treatment, we follow the same reasoning where the 25th level of the distribution of infections (which is different per area) corresponds to the non-treated units. This exercise also served to compare units with similar social, economic, and other non-observed features given their geographic location.

Table 5 displays the regression results using the total number of vacancies and their subdivision into essential and non-essential workers per area. We only report the results that account for time and province fixed-effects (see Fig. 19).

The results of the Northern area are very similar to those obtained in the baseline model, and although the ATE from the Northern area preserves the same sign (negative) it is not statistically significant. This can be observed in the DRF (Fig. 16) because the confidence intervals contain zero. However, it is relevant to highlight the increasing trend of the DRF, which is positive but not significant from the 40th level onwards. Compared to Fig. 6, which includes all vacancies and accounts for time and province fixed-effects, the trend is steeper. This signals that in the North, overall, labour demand increased with medium to high levels of exposure to COVID-19 (this pattern can be seen in the first derivative plot Fig. 16).

In Italy's central region, the Average Treatment Effect (ATE) was not statistically significant, and the Dose-Response Function (DRF) exhibited a stable trend compared to other regions (Fig. 18). Similarly, the plot with the first derivative is almost flat (Fig. 19). In contrast, the southern region displayed a negative and statistically significant ATE in the baseline estimates (column 1, Table 5), which accounted for time and province fixed-effects. This indicates a 27% decline in the growth rate of labour demand in the treated provinces (see Fig. 21).

The DRF plot for total vacancies in the southern region (Fig. 20) remains below zero, with the trend worsening as provincial exposure to COVID-19 increases, reaching a plateau around the 80th level. A notable decline in the labour demand growth rate begins around the 50th level, where the curve's concavity shifts (Fig. 21).

The results from the southern area display the severe effects of COVID-19 regardless of the degree of exposure. Additionally, when we disentangle this negative ATE into types of vacancies, we observe a decrease of 25.5% in the labour demand growth rate for essential vacancies, whereas for non-essential vacancies, the decrease is 34.3%.

This might indicate that the southern provinces had a sensitive economic structure that relied more on non-essential sectors and/or occupations than the other areas. Hence, given the uncertainty faced during the pandemic, the negative effect on labour demand was considerable.

Compared to other geographic areas, the South's average unemployment rate in 2020 and 2021 was 15.53%, while the national average for these two years was 9.7%. The GDP per capita is also significantly lower than the national average. Under these circumstances, despite having lower mortality and contagion rates in comparison to other areas, labour demand in the South was substantially weaker.

Table 5
Regression results by area.

		(1) Log of number of vacancies	(2) Log of number of essential vac.	(3) Log of number of non-essential vac.
North	Treatment	−0.0190	−0.0134	−0.0286
		(0.0455)	(0.0646)	(0.0671)
	ItSIs	−0.00342	−0.00343	−0.00362
		(0.00353)	(0.00421)	(0.00437)
	Mortality rate	0.0797*	0.0759	0.0900
		(0.0456)	(0.0539)	(0.0560)
	Constant	7.807***	7.206***	7.013***
		(0.320)	(0.379)	(0.394)
	Fixed-effects	Province and time	Province and time	Province and time
	Adjusted_R2	0.953	0.9440	0.9527
	N	1029	1029	1029
	ATET	.021	.0299	.0058
Center	Treatment	0.0632	0.0604	0.0506
		(0.105)	(0.121)	(0.130)
	ItSIs	−0.00511	−0.00878*	−0.000223
		(0.00449)	(0.00514)	(0.00554)
	Mortality rate	0.0556	0.140	−0.0806
		(0.0939)	(0.105)	(0.113)
	Constant	5.100***	4.785***	3.935***
		(0.387)	(0.457)	(0.492)
	Fixed-effects	Province and time	Province and time	Province and time
	Adjusted_R2	0.969	0.9559	0.9617
	N	462	462	462
	ATET	.079	.0735	.0646
South & Southern islands	Treatment	−0.272**	−0.255**	−0.343**
		(0.117)	(0.104)	(0.137)
	ItSIs	0.0135***	0.0127***	0.0160***
		(0.00401)	(0.00364)	(0.00479)
	Mortality rate	−0.183	−0.116	−0.289**
		(0.125)	(0.1000)	(0.131)
	Constant	4.059***	3.602***	2.881***
		(0.384)	(0.338)	(0.444)
	Fixed-effects	Province and time	Province and time	Province and time
	Adjusted_R2	0.910	0.9115	0.8843
	N	756	756	756
	ATET	−.317	−.291	−.41

Robust SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.
The polynomial term (Tw) was omitted in this table due to space.

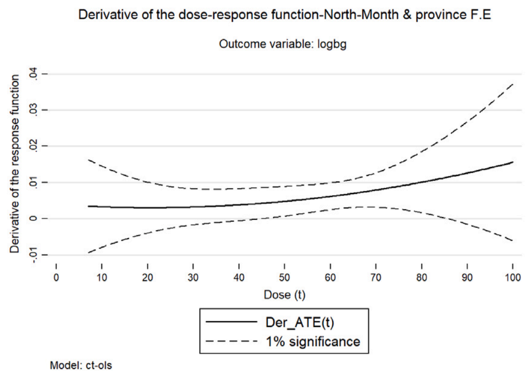

Fig. 17. North derivative DRF. Month and province FE.

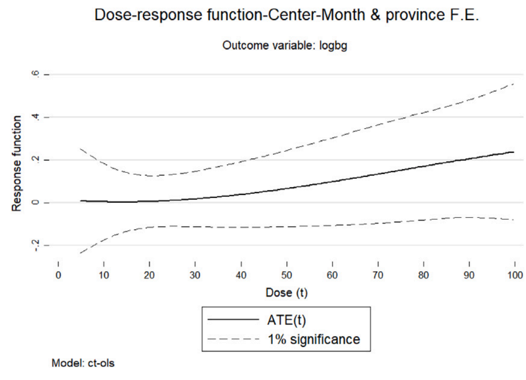

Fig. 18. Center DRF. Month and province FE.

7. Conclusion

This study investigated how exposure to COVID-19 affected the local labour demand. This is a scarcely addressed – yet very relevant – area of inquiry within the vast and fast-growing literature that links the pandemic to the labour market performance. Understanding how and to what extent the pandemic-induced disruption of the labour market affects the demand for workers is paramount in the recovery phase to sustain and promote a fair and equitable set of interventions. Labour demand policies remain crucial to retain jobs, re-orient workers

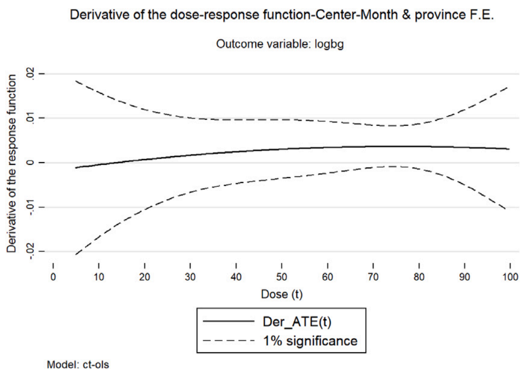

Fig. 19. Center derivative DRF. Month and province FE.

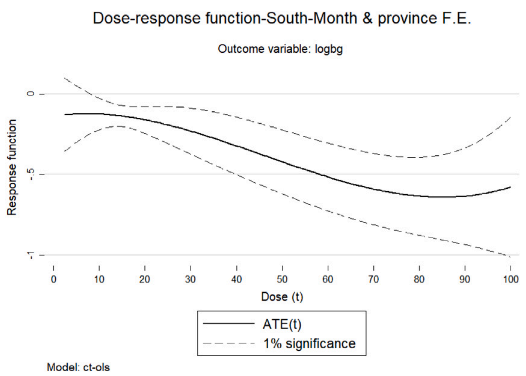

Fig. 20. South DRF. Month and province FE.

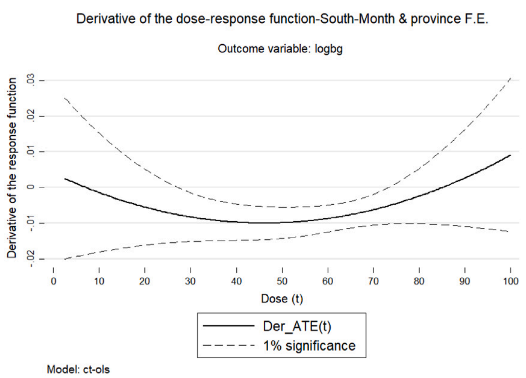

Fig. 21. South derivative DRF. Month and province FE.

through training schemes, and support displaced labour.

As an additional layer of complexity, the pandemic crisis also entails a spatially heterogeneous impact on the labour market, thus calling for careful consideration from academics and policy-makers of the geography of the relationship between COVID-19 exposure and labour demand.

In this context, our investigation provides evidence that, in the case of Italy, the effect of COVID-19 on the local labour demand is non-linear and mostly negative, as predicted by economic theory. However, we also detected a threshold at the 90th level of exposure to COVID-19 where the labour demand turns positive and exhibits a clear growth path. This tends to be mostly driven by vacancies in essential activities located in the North of the country. This is a relevant feature of the data since it signals that the economic dynamism of the North may prevent the labour demand from decreasing monotonically.

Additionally, the lack of substantial differences in the shape of the dose-response function (DRF) between essential and non-essential sectors at most levels of COVID-19 exposure suggests that the classification may not have been accurate. This similarity could be due to the interconnectedness of the sectors or potential misclassification. Therefore, a reassessment of how the workforce is divided into essential and non-essential roles is needed, along with an in-depth discussion of its heterogeneous geographic impact in the event of another pandemic or economic disruption. This presents an open area for further research to investigate these dynamics more comprehensively.

Nevertheless, our study does not contemplate other policy interventions of the Italian government. For instance, we are not evaluating the effects of the lay-off ban. Moreover, we do not assess the supply side of the labour market, where the effect on young or female workers is crucial in terms of the policy we reserve for future work.

This study may also shed some light on how to methodologically approach complex phenomena with no “control groups”, in which the dose–response framework could be a good alternative for policy evaluation. Our research also contributes to the study of other phenomena that involve a complete cessation of economic activities, such as the energy crisis.

CRediT authorship contribution statement

Fernanda Gutiérrez Amaros: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andrea Ascani:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Alessandra Faggian:** Writing – review & editing, Methodology, Conceptualization. **Wessel N. Vermeulen:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

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

Appendix

A.1. Complete estimates

In this section, we document the estimates for each dependent variable (total vacancies, essential and non-essential vacancies), including the baseline model, time and/or province fixed-effects. The plots of the DRF of specifications 1 to 3 can be obtained upon request (see Table 6).

A.2. Model 1: All types of vacancies

See Table 6 where we report all vacancies model with and without province and time fixed effects.

Table 6
Regression results for all vacancies.

	(1) Log of number of vacancies	(2) Log of number of vacancies	(3) Log of number of vacancies	(4) Log of number of vacancies
Treatment	0.797***	2.077***	0.175***	−0.141***
	(0.059)	(0.094)	(0.026)	(0.040)
ItSIs	0.0228***	−0.0106	0.00685***	0.00542**
	(0.001)	(0.007)	(0.0007)	(0.002)
Mortality rate	−0.810***	−1.093***	−0.202***	0.0453
	(0.101)	(0.122)	(0.051)	(0.038)
Tw_1	−0.0795***	0.0987***	0.0320***	−0.00833*
	(0.011)	(0.014)	(0.005)	(0.004)
Tw_2	0.00219***	−0.000665**	−0.000951***	0.0000234
	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Tw_3	−0.0000135***	0.00000182	0.00000733***	0.00000114
	(0.000002)	(0.000002)	(0.000001)	(0.0000007)
Constant	5.303***	7.964***	7.868***	7.052***
	(0.126)	(0.676)	(0.111)	(0.205)
Fixed-effects	No	Time	Province	Province and time
N	2247	2247	2247	2247
Adjusted_R2	0.151	0.371	0.865	0.957
ATET	.694	2.706	.017	−.180

Robust SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table 7
Regression results for essential vacancies.

	(1) Log of number of vacancies	(2) Log of number of vacancies	(3) Log of number of vacancies	(4) Log of number of vacancies
Treatment	0.713***	1.909***	0.127***	−0.132***
	(0.056)	(0.090)	(0.026)	(0.041)
ItSIs	0.0216***	−0.00944	0.00669***	0.00458**
	(0.001)	(0.006)	(0.0007)	(0.002)
Mortality rate	−0.769***	−1.002***	−0.205***	0.0753*
	(0.095)	(0.11)	(0.051)	(0.039)
Tw_1	−0.0768***	0.0902***	0.0277***	−0.00704
	(0.0109)	(0.0136)	(0.00522)	(0.00448)
Tw_2	0.00205***	−0.000629**	−0.000861***	0.00000449
	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Tw_3	−0.0000123***	0.00000212	0.00000678***	0.00000125
	(0.000002)	(0.000002)	(0.000001)	(0.0000007)
Constant	4.816***	7.206***	7.284***	6.474***
	(0.119)	(0.640)	(0.110)	(0.210)
Fixed-effects	No	Time	Province	Province and time
N	2247	2247	2247	2247
Adjusted_R2	0.145	0.366	0.853	0.950
ATET	.605	2.485	.165	−.1654

Robust SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

A.3. Model 2: Essential vacancies

In this section, we document the results for essential vacancies (see Table 7). Specifically, without fixed effects (1), with only time fixed effects (2), and with only province fixed effects (3). Last column corresponds to the baseline model.

A.4. Model 3: Non-essential vacancies

In Table 8, we present the estimates of the dose–response function for non-essential vacancies under three different specifications: (1) without fixed effects, (2) with only time fixed effects, and (3) with only province fixed effects. Column 4 corresponds to the baseline model.

A.5. Robustness checks

To see if our results hold, we ran the same estimates without controls (Table 13) and with more socioeconomic controls (Tables 9 to 12).

For the specifications with additional controls, in addition to the mortality rate and the Italian Stringency Index (ItSIs), we included the unemployment rate, population, population density, percentage of college graduates, GDP per capita and percentage of employment in manufacturing. The tables also contain the results with and without fixed-effects (see Table 9).

The province's population and population density were included as control variables to capture demographic characteristics and serve as proxies for urbanisation. Given that COVID-19 is an airborne disease, population density is particularly relevant and may also account for agglomeration effects (Cho et al., 2021). Additionally, previous research

Table 8
Regression results for non-essential vacancies.

	(1) Log of number of vacancies	(2) Log of number of vacancies	(3) Log of number of vacancies	(4) Log of number of vacancies
Treatment	0.919***	2.325***	0.242***	−0.180***
	(0.0654)	(0.103)	(0.0291)	(0.0476)
ItSIs	0.0242***	−0.0116	0.00678***	0.00750***
	(0.00185)	(0.00798)	(0.000795)	(0.00258)
Mortality rate	−0.858***	−1.209***	−0.194***	0.00569
	(0.111)	(0.136)	(0.0567)	(0.0460)
Tw_1	−0.0835***	0.112***	0.0392***	−0.0108**
	(0.0126)	(0.0156)	(0.00580)	(0.00519)
Tw_2	0.00238***	−0.000737**	−0.00111***	0.0000350
	(0.000358)	(0.000345)	(0.000165)	(0.000119)
Tw_3	−0.0000151***	0.00000155	0.00000835***	0.00000117
	(0.00000290)	(0.00000236)	(0.00000132)	(0.000000887)
Constant	4.322***	7.289***	7.049***	6.120***
	(0.138)	(0.743)	(0.122)	(0.243)
Fixed-effects	No	Time	Province	Province and time
N	2247	2247	2247	2247
Adjusted_R2	0.153	0.369	0.865	0.950
ATET	.824	3.033	.314	−.236

Robust SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table 9
Variables.

Type of variable	Variables	Frequency	Year	Geographic unit	Source
Treatment	Contagion rate	Monthly	2020–2021	NUTS 3	EpiCentro
Dependent variable	Log. of the Nº of vacancies (total, essential, non-essential)	Monthly	2020–2021	NUTS 3	Lightcast
	Mortality rate	Monthly	2020–2021	NUTS 3	ISTAT
	Population	Yearly	2020–2021	NUTS 3	ISTAT
	Population density	Yearly	2020–2021	NUTS 3	OECD
Controls	Percentage of college graduates	Yearly	2020–2021	NUTS 3	ISTAT
	Unemployment rate	Yearly	2020–2021	NUTS 3	ISTAT
	Italian stringency Index (ItSIs)	Monthly	2020–2021	NUTS 3	Conteduca and Borin (2022)
	Percentage of employment in manufacturing	Yearly	2019	NUTS 2	OECD
	GDP per capita	Yearly	2020	NUTS 2	ISTAT

has shown a strong correlation between urbanisation and the severity of past pandemics (Clay et al., 2019).

The estimation also included the percentage of college graduates in the province in a given year to gauge human capital.

Furthermore, according to Phelan et al. (2010), in general, all-cause, age-adjusted death rates for adults are strongly correlated with education level. The provincial unemployment rate was included as an indicator of economic health. However, if the estimated coefficient shows a positive relationship with the number of vacancies–indicating that higher unemployment coincides with more job openings–this could suggest a labour market mismatch in at least part of the provincial economy. Similarly, the percentage of employment in manufacturing was included as a control variable due to its historical significance (Basile and Ciccarelli, 2018) and its spatial concentration, as highlighted in recent studies on Italy (Ascani et al., 2021) and the United States (Dingel and Neiman, 2020). Given the nature of manufacturing work, these studies also indicate that workers face higher exposure risks due to close interactions in the workplace.

As a measure of economic growth, it is included as one of the controls, the regional GDP per capita at current prices.

Overall, our estimations remain largely consistent with the main results, which incorporate time and province fixed effects (Table 3). This suggests that the fixed effects capture key demographic and economic characteristics. Notable differences arise primarily in the first specification (first column), which does not include any fixed effects (Table 10).

Likewise for essential vacancies and non-essential, we observed that our estimations do not vary significantly in comparison to our main results. The difference is mostly observed in the first estimate (see Table 11 and Table 12).

As mentioned, we ran estimates using the same specification for the main outcomes without any controls but with province and/or time-fixed effects. Our results hold in terms of the sign of the coefficients and the fact that they are statistically significant. Nevertheless, the magnitude is higher (see Table 13).

A.6. Robustness check of the threshold

We conducted the following robustness check to assess whether our results hold across different thresholds for defining low exposure to COVID-19. Specifically, we defined low exposure (control group) using the 5th, 10th, 15th, 20th, and 30th percentiles of the monthly contagion distribution by province (see the "Treatment Variable" section).

Our main findings, which incorporate time and province fixed-effects, remain negative and statistically significant for all thresholds except the 30th percentile, where the coefficient retains its negative sign but loses statistical significance.

Table 10
Regression results accounting for all vacancies.

	(1) Log of number of vacancies	(2) Log of number of vacancies	(3) Log of number of vacancies	(4) Log of number of vacancies
Treatment	0.234***	0.0521	0.177***	−0.123***
	(0.0321)	(0.0579)	(0.0265)	(0.0405)
Unemployment rate	−0.0282***	−0.0317***	0.00271	−0.0147**
	(0.004)	(0.003)	(0.0104)	(0.006)
Percentage of college graduates	0.00243	0.00199	0.150**	0.0239
	(0.015)	(0.011)	(0.06)	(0.034)
ItSis	0.0077***	0.00324	0.00667***	0.00497*
	(0.0008)	(0.004)	(0.0008)	(0.002)
Mortality rate	−0.132**	0.0584	−0.187***	0.0879**
	(0.055)	(0.050)	(0.049)	(0.036)
Percentage of employment in manufacture	0.0378***	0.0344***	0.0511	0.0526*
	(0.0027)	(0.002)	(0.044)	(0.028)
log GDP per capita	1.116***	1.044***	1.167**	1.446***
	(0.0917)	(0.0661)	(0.558)	(0.295)
Log Pop. density	0.00176	0.00553	−0.242	0.0357
	(0.019)	(0.0138)	(0.208)	(0.117)
Log Pop.	1.002***	1.008***	1.102*	1.098***
	(0.0212)	(0.015)	(0.637)	(0.42)
Tw_1	0.0181***	−0.00871	0.0322***	−0.00757
	(0.006)	(0.007)	(0.005)	(0.004)
Tw_2	−0.000602***	0.000138	−0.000965***	0.0000232
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Tw_3	0.00000538***	0.0000004	0.000007***	0.00000107
	(0.000001)	(0.000001)	(0.000001)	(0.0000008)
Constant	−18.87***	−18.64***	−20.68	−25.14***
	(1.004)	(0.856)	(14.64)	(9.347)
Fixed-effects	No	Time	Province	Province and time
N	2247	2247	2247	2247
Adjusted_R2	0.774	0.865	0.865	0.957
ATET	.264	.040	.227	−.157

SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.
GDP per capita, population density and population were log-transformed.

Table 11
Regression results for essential vacancies.

	(1) Log of number of vacancies	(2) Log of number of vacancies	(3) Log of number of vacancies	(4) Log of number of vacancies
Treatment	0.191***	0.0390	0.130***	−0.116***
	(0.031)	(0.056)	(0.026)	(0.041)
Unemployment rate	−0.0275***	−0.031***	−0.001	−0.0187***
	(0.004)	(0.003)	(0.01)	(0.006)
Percentage of college graduates	−0.00753	−0.00714	0.166***	0.0503
	(0.014)	(0.011)	(0.06)	(0.036)
ItSis	0.00753***	0.00303	0.00653***	0.00430*
	(0.0008)	(0.004)	(0.0008)	(0.002)
Mortality rate	−0.122**	0.0979**	−0.195***	0.113***
	(0.0542)	(0.0495)	(0.0497)	(0.0386)
Percentage of employment in manufacture	0.0332***	0.0297***	0.0495	0.0557**
	(0.0026)	(0.002)	(0.044)	(0.028)
log GDP per capita	1.023***	0.945***	0.958*	1.215***
	(0.0899)	(0.0662)	(0.569)	(0.302)
log Pop. density	−0.0127	−0.00870	−0.267	0.0129
	(0.0187)	(0.0138)	(0.213)	(0.119)
log population	0.960***	0.969***	0.933	1.037**
	(0.0208)	(0.0156)	(0.633)	(0.417)
Tw_1	0.0132**	−0.00979	0.0279***	−0.00626
	(0.006)	(0.0071)	(0.005)	(0.0048)
Tw_2	−0.000513***	0.000136	−0.000881***	−0.00000108
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Tw_3	0.00000498***	0.000000706	0.00000695***	0.00000123
	(0.000001)	(0.000001)	(0.000001)	(0.0000008)
Constant	−17.72***	−17.52***	−16.52	−22.49**
	(0.983)	(0.843)	(14.61)	(9.264)
Fixed-effects	No	Time	Province	Province and time
N	2247	2247	2247	2247
Adjusted_R2	0.758	0.854	0.853	0.950
ATET	.204	.0217	.167	−.145

SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.
GDP per capita, population density and population were log-transformed.

Table 12
Regression results for non-essential vacancies.

	(1) Log of number of vacancies	(2) Log of number of vacancies	(3) Log of number of vacancies	(4) Log of number of vacancies
Treatment	0.296***	0.0616	0.244***	−0.158***
	(0.035)	(0.066)	(0.029)	(0.048)
Unemployment rate	−0.0292***	−0.0328***	0.00774	−0.00940
	(0.0051)	(0.0039)	(0.011)	(0.0074)
Percentage of college graduates	0.00851	0.00691	0.112*	−0.0248
	(0.016)	(0.013)	(0.068)	(0.044)
ItSis	0.00770***	0.00420	0.00657***	0.00666**
	(0.00097)	(0.0047)	(0.00096)	(0.0029)
Mortality rate	−0.137**	0.0146	−0.169***	0.0607
	(0.06)	(0.058)	(0.053)	(0.043)
Percentage of employment in manufacture	0.0456***	0.0422***	0.0631	0.0582*
	(0.0030)	(0.0023)	(0.048)	(0.033)
log GDP per capita	1.227***	1.167***	1.466**	1.772***
	(0.101)	(0.073)	(0.598)	(0.354)
log pop. density	0.0212	0.0248*	−0.176	0.0949
	(0.0209)	(0.0151)	(0.222)	(0.138)
log population	1.068***	1.070***	1.464**	1.310***
	(0.0233)	(0.0169)	(0.704)	(0.496)
Tw_1	0.0259***	−0.00694	0.0392***	−0.01000*
	(0.00682)	(0.00882)	(0.00604)	(0.00589)
Tw_2	−0.000754***	0.000122	−0.00112***	0.0000452
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Tw_3	0.00000616***	0.000000345	0.00000837***	0.000000998
	(0.000001)	(0.000001)	(0.000001)	(0.0000009)
Constant	−22.00***	−21.88***	−30.32*	−32.73***
	(1.102)	(0.972)	(16.05)	(10.95)
Fixed-effects	No	Time	Province	Province and time
N	2247	2247	2247	2247
Adjusted_R2	0.775	0.858	0.866	0.951
ATET	.349	.0561	.314	−.2064

SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.
GDP per capita, population density and population were log-transformed.

Table 13
Regression results for all vacancies, essential and non-essential vacancies without controls.

Log of number of vacancies	(1) Log of number of vacancies	(2) Log of number of essential vac.	(3) Log of number of non-essential vac.
Treatment	−1.027***	−1.003***	−1.111***
	(0.0498)	(.0501)	(.0623)
Tw_1	−0.0171***	−0.0151***	−0.0216***
	(0.00383)	(0.00383)	(0.00463)
Tw_2	0.000155*	0.000131	0.000187
	(0.0000840)	(0.0000837)	(0.000101)
Tw_3	0.000000371	0.000000487	0.000000329
	(0.000000654)	(0.000000643)	(0.000000779)
Constant	8.439***	7.818***	7.666***
	(0.0405)	(0.0408)	(0.0436)
Fixed-effects	Province and time	Province and time	Province and time
Adjusted_R2	.95	.94	.95
N	2568	2568	2568
ATET	−1.057849	−1.29	−1.152422

Robust SE in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.7. Correlation between variables

In this section, we display a correlation analysis between our variables of interest for the models with total, essential and non-essential vacancies (see Table 15).

A.8. ISTAT division of areas

To perform the heterogeneous effect by Italian macro areas we grouped the provinces following ISTAT criteria. For the analysis, we classify the islands within the Southern area. Therefore, our three macro areas are North, Center and South (see Table 16).

Table 14
Regression results for different thresholds.

Level	(1) 5th	(2) 10th	(3) 15th	(4) 20th	(5) 30th
Treatment	−0.300***	−0.258***	−0.162***	−0.110***	−0.0232
	(0.0585)	(0.0512)	(0.045)	(0.04)	(0.042)
ItSIs	0.00618*	0.00560*	0.00548**	0.00542**	0.00519**
	(0.0024)	(0.0024)	(0.002)	(0.002)	(0.002)
Mortality rate	0.0749	0.0451	0.0436	0.0502	0.0374
	(0.0404)	(0.04)	(0.0402)	(0.0402)	(0.0409)
Tw_1	−0.0159***	−0.0106*	−0.00918*	−0.00798	−0.00209
	(0.004)	(0.004)	(0.00469)	(0.00533)	(0.00642)
Tw_2	0.0001	0.000026	0.00003	0.00002	−0.00007
	(0.00009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Tw_3	0.0000004	0.000001	0.000001	0.000001	0.000001
	(0.00000071)	(0.00000078)	(0.0000008)	(0.0000009)	(0.000001)
Constant	6.980***	7.059***	7.053***	7.032***	7.063***
	(0.223)	(0.225)	(0.229)	(0.233)	(0.233)
Fixed-effects	Province and time	Province and time	Province and time	Province and time	Province and time
Adjusted_R2	0.957	0.957	0.9595	0.9594	0.9592
N	2247	2247	2247	2247	2247
ATET	−.327	−.295	−.201	−.150	−.044

Robust SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table 15
Correlation between variables.

	logvac	lvcessen	lvnonessen	ItSIs	Mortality rate	Treatment	Contagion rate
logvac	1.0000						
lvcessen	0.9953	1.0000					
lvnonessen	0.9918	0.9756	1.0000				
ItSIs	0.0751	0.0849	0.0599	1.0000			
Mortality rate	−0.1043	−0.1065	−0.0982	0.3495	1.0000		
Treatment	0.2049	0.1818	0.2306	−0.4520	−0.0358	1.0000	
contagion rate	0.2095	0.1865	0.2350	−0.4582	−0.0407	0.9995	1.0000

Treament corresponds to the transformed contagion rate.

Table 16
Area division.

Area	Region code	Region
Center	ITI4	Lazio
	ITI3	Marche
	ITI1	Toscana
	ITI2	Umbria
Islands	ITG2	Sardegna
	ITG1	Sicilia
North	ITH5	Emilia-Romagna
	ITH4	Friuli-Venezia Giulia
	ITH1	Provincia Autonoma Bolzano/Bozen
	ITH2	Provincia Autonoma Trento
	ITH3	Veneto
	ITC3	Liguria
	ITC4	Lombardia
	ITC1	Piemonte
	ITC2	Valle d'Aosta/Vallée d'Aoste
South	ITF1	Abruzzo
	ITF5	Basilicata
	ITF6	Calabria
	ITF3	Campania
	ITF2	Molise
	ITF4	Puglia

A.9. Results from the difference between the logarithm of essential and non-essential vacancies

As an additional exercise, we use as a dependent variable the difference in the logarithm of essential and non-essential vacancies. As mentioned, our main coefficient did not show statistically significant changes between vacancies.

Table 17
Regression results.

	(1) Log of diff. vacancies	(2) Log of diff. vacancies	(3) Log of diff. vacancies	(4) Log of diff. vacancies
Treatment	−0.206***	−0.416***	−0.115***	0.048
	(0.016)	(0.02)	(0.013)	(0.03)
ItSis	−0.00266***	0.0021	−0.00008	−0.002
	(0.0004)	(0.002)	(0.0003)	(0.00192)
Mortality rate	0.083***	0.208***	−0.0107	0.0696**
	(0.028)	(0.034)	(0.026)	(0.034)
Tw_1	0.00675**	−0.0215***	−0.0116***	0.003
	(0.003)	(0.004)	(0.002)	(0.003)
Tw_2	−0.000325***	0.000108	0.000251***	−0.00003
	(0.00009)	(0.0001)	(0.00007)	(0.00008)
Tw_3	0.0000027***	0.00000057	−0.0000015**	7.52e−08
	(0.0000007)	(0.0000007)	(0.0000006)	(0.00000066)
Constant	0.494***	−0.082	0.235***	0.355**
	(0.0350)	(0.209)	(0.0577)	(0.181)
Fixed-effects	No	Time	Province	Province and time
N	2247	2247	2247	2247
Adjusted_R2	0.113	0.205	0.510	0.552
ATET	−.219	−.547	−.148	.0708

Robust SE in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

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