Research paper

Targeted policies and household consumption dynamics: Evidence from high-frequency transaction data[☆]

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ABSTRACT

The COVID-19 pandemic shock heavily affected households and prompted governments to design policies supporting household consumption. Differentiated strategies were among the most commonly adopted policies, targeting territories and economic activities with a stringency consistent with the severity of the contagion. Leveraging a unique dataset of over 1 billion household payment transactions, which captures digital and physical consumption, we provide a retrospective analysis of targeted restrictions in Italy during the fall of 2020. We show that territories implementing less stringent policies exhibit a smaller reduction in consumption and that differentiated restrictions are effective in limiting the spread of infections. Furthermore, in our analyses we account for common factors limiting household consumption choices such as disposable income, liquidity constraints and fear of contagion. Our results demonstrate the effectiveness of targeted restrictions in balancing between economic and public health objectives and call for data-driven and evidence-based policymaking during crises.

1. Introduction

The response of household consumption to income shocks represents a fundamental topic of analysis for policy makers. In fact, appropriate variations in the marginal propensity to consume (MPC) of the average household are connected to the effectiveness of expansionary fiscal policies implemented against fluctuations in income associated with recessions (Oh and Reis, 2012). Several studies, however, have found considerable deviations between the observed households' MPC and the one that should be expected according to consumer theory (Fuchs-Schündeln and Hassan, 2016). This discrepancy has prompted further research highlighting the role of households' liquidity constraints (Zeldes, 1989; Johnson et al., 2006) and expectations (Reis, 2006; Parker, 2017) in determining the reason for differentiated responses to income shocks.

The COVID-19 pandemic represents an interesting case study to analyze household consumption responses because it constituted an unexpected and generalized external shock to incomes. In fact, during the first waves of infections, strict and generalized policies, such as national lockdowns, were introduced to control the spread of COVID-19 (Chinazzi et al., 2020; Kraemer et al., 2020; Badr et al., 2020; Brauner et al., 2020). These policies were effective in containing the contagion, but they also entailed a significant socioeconomic impact, affecting jobs (+20% global unemployment rate, ILO Monitor 2020), business activities (−3.1% in global world output, IMF 2021) and consumption patterns (−12% 2020Q2 quarter-on-quarter variation across the European Union, −8%

in the United States according to national accounts).[1] As a consequence, several studies have analyzed the dynamics of household consumption in response to generalized restrictions (Bounie et al., 2023; Baker et al., 2020; Sheridan et al., 2020).

Importantly, the trade-off between the positive containment impact and the negative economic effect of generalized policies in the first phase of the pandemic pushed governments to modify their containment strategies along two directions. On the one hand, extraordinary fiscal measures were introduced to compensate for the negative economic impact of the pandemic: for example, among advanced economies the average discretionary fiscal response to COVID-19 devoted to all non-health sectors was 7.84% of 2019 GDP (IMF Fiscal Affairs Department, 2021).[2]

On the other hand, several countries differentiated their containment strategy. When infections started to rise again in the fall of 2020, governments adopted targeted territorial approaches allowing restrictions to vary across territories depending on the severity of contagion. The implementation of differentiated restrictions has been widespread,[3] however only a few empirical works have focused on the impact of these policies on consumption (Carvalho et al., 2020; Shin et al., 2021).

Moreover, relevant issues regarding targeted restrictions remain unaddressed in the extant literature. First, several studies lack the scale or the granularity to properly evaluate the overall impact of these interventions. Second, studies evaluating the consumption-health trade-off for households in the context of targeted restrictions are still missing. Instead, as we show in the related literature section, policy recommendations to boost household consumption should not disregard the impact of targeted interventions on the diffusion of contagion. In fact, the effectiveness of these interventions may be highly reduced if fear of contagion or limitations to consumption interact with households' behavior (Parker et al., 2022). Finally, the evaluation of households' response to shocks should also account for other confounding variables affecting the variation in consumption patterns, such as liquidity constraints (Christelis et al., 2020) and the economic condition of households (Chetty et al., 2020).

The present work aims to contribute to the literature on household consumption behavior with a case study on the consequences of targeted restrictions in Italy during the second wave of COVID-19. As discussed in Banca d'Italia (2021), the year 2020 in Italy saw a percentage reduction of households' consumption expenditure and real disposable income of 10.72% and 2.66%, respectively. As a result, the household saving ratio sharply increased from 10.06 in 2019 to 17.52 in 2020.

This translated into changes in consumption and propensity to save of −12.6% and 8.5% in 2020, more intensely than in the Euro area (−8.0% and 6.8%, respectively). Similarly, the general consumer confidence index declined from 108.57 in December 2019 to 99.10 in December 2020. The impact of the pandemic also affected the use of payment cards at points of sale, with a drop in cash withdrawals and a sharp increase in card transactions also favored by the diffusion of digital technologies (*e.g.*, contactless payment and e-commerce). As an example, Banca d'Italia (2021) reported that in 2020 27% of respondents utilized payments cards more frequently and 32.3% answered that their use of cash declined. Interestingly, for supermarkets and retail purchases in 2020 the use of cash or credit cards was almost equivalent in terms of the number of transactions, while a year earlier cash represented almost four times as much as credit cards.

With regard to this, our contribution is particularly relevant for two reasons. First, because we leverage an unprecedented large-scale data collection of aggregated transactions from a major Italian bank, Intesa Sanpaolo. This dataset is composed of 1.2 billion operations with a total associated value of 62 billion euros, capturing both digital and physical daily transactions made during the period 2019–2020, over the entire Italian country. All in all, the dataset is unique in frequency, time span, and geographic coverage, allowing us to depict a very detailed picture of consumption patterns for territories with heterogeneous features.

Second, because the Italian case constitutes an ideal setting to investigate the outcome of differentiated policies on consumption, as they were implemented on the 6th of November 2020 with a three-tier risk framework targeting specific business sectors with different intensity depending on the severity of the contagion. Payment data thus help us evaluate the effectiveness of these competing restrictions on both consumption patterns and contagion outcomes. Furthermore, the Italian government stimulus package amounted to 6.2% of 2019 national GDP (below the average of advanced economies) and provided only mild measures to support households' incomes, accounting for only 2.4% of the 2019 national GDP (IMF Fiscal Affairs Department, 2021).[4] Hence, we expect that targeted mobility restrictions constituted one of the main policy interventions that shaped household consumption behavior during the second wave of the pandemic.

Through the integration of empirical analyses combining both economic and epidemic aspects, we offer a thorough assessment of the overall impact of containment policies differentiated by territory and sector. Our main research objective is to evaluate the impact of targeted restrictions on the consumption behavior of households, testing two hypotheses. Our first hypothesis is that the impact of targeted restrictions on household consumption has been consistent with their stringency. This means that household consumption has decreased less in low-risk territories (*i.e.*, less affected by restrictions) compared to high-risk ones. Our second hypothesis concerns the health-consumption trade-off. We want to assess whether targeted restrictions have been effective in limiting

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[1] In addition to this, generalized restrictions exacerbated existing socioeconomic inequalities among territories (Adams-Prassl et al., 2020; Hacıoğlu-Hoke et al., 2021; Iacobucci, 2020; Bonaccorsi et al., 2020; Chang et al., 2020; Perry et al., 2021; Giansante et al., 2023), leading to protests (Pavlik, 2020) and weak compliance with imposed restrictions (Bargain and Aminjonov, 2020; Gollwitzer et al., 2020; Wright et al., 2020).

[2] In line with the literature developed after the first phase of restrictions, several contributions have investigated household consumption behavior in response to the introduction of COVID-19 stimulus packages (Parker et al., 2022; Kubota et al., 2021; R. Baker et al., 2023). See Yannelis and Amato (2023) for a complete review.

[3] These types of NPIs were introduced *e.g.* by Brazil (Castro et al., 2021), China (Chinazzi et al., 2020) and the US (Haffajee and Mello, 2020) already during the first wave of the pandemic, and by Australia (Moloney and Moloney, 2020), Canada (Long et al., 2021-09-20), France (Allain-Dupré et al., 2020), Germany (Hattke and Martin, 2020), India (Salvatore et al., 2020), Italy (Bertuzzo et al., 2020), South Korea (Shin et al., 2021), Spain (Carvalho et al., 2020) and the UK (Davies et al., 2021) in the following waves.

[4] See Section 5.1.2 for more details on this.

the contagion. If both hypotheses hold, this means that targeted restrictions are preferable to generalized lockdowns since they entail better consumption levels while controlling for contagion diffusion.

We base our evaluation of socioeconomic effects on the evidence that restrictions targeting the mobility of individuals simultaneously affect their patterns of consumption and their interpersonal interactions. For this reason, the use of transaction data is instrumental for the joint assessment of economic and epidemic effects, as they carry information about both movements and consumption of individuals. However, we integrate transaction data with official statistics to account for other variables that are missing in our main dataset. In particular, we control for other motivations that are well-known in the literature for driving consumption behavior, such as disposable income, fear of contagion and liquidity constraints.

On the economic side, we employ a panel data approach to study the variation in the daily total value of transactions. From an epidemiological perspective, on the other hand, we build the mobility network of individuals jointly moving and consuming, and, following Chang et al. (2020), we use a SEIR epidemiological model based on this network to fit the observed dynamics of infected individuals.

Our analysis provides several takeaway messages that can be informative for the design of policies supporting household consumption during future crisis management. First, we show that sectors targeted by restrictions and heavily dependent on mobility and interpersonal interactions suffer from a consumption reduction that is consistent with the stringency of the policy. For instance, in the Restaurants sector, experiencing the strongest contraction of economic activities, the most stringent restrictions reduce the Year-on-Year variation in economic consumption by −82.1% compared to a baseline period when policy interventions are absent, while the same figure is −80.9% and −47.8% for medium- and low-level stringency restrictions. The same pattern also applies to the Retail sector, albeit with a smaller magnitude (−7.0%, −11.5% and −16.6% for low, medium and high levels of stringency). The low impact of restrictions on Retail can likely be explained by the fact that it comprises mostly essential business activities. We also notice that economic variables related to the local level of wealth significantly affect household consumption behavior. Indeed, liquidity constraints mainly curtail consumption in essential business sectors, where cash shortfall issues arose for less wealthy individuals. Conversely, territories characterized by larger income per capita and lower liquidity constraints experienced higher consumption reduction across other non essential sectors, due to restrictions predominantly focused on non-primary goods and services. We thus contribute to the debate on the impact of restrictions on household consumption behavior during the COVID-19 pandemic. In line with Carvalho et al. (2020), Chetty et al. (2020) and Cox et al. (2020), we confirm that a stronger contraction of consumption was experienced by high income households. Furthermore, we expand their studies, by disentangling the impact of targeted restrictions with heterogeneous stringency levels and by performing an analysis with a higher level of temporal and spatial resolution.

Second, we find that targeted restrictions are effective in containing the contagion compared to a counterfactual scenario in which mobility is not constrained. At the regional level, for instance, we estimate that the most stringent restrictions contribute to a −10.49% reduction in the total number of confirmed cases in the Lombardia region, while the least stringent regime results in a −8.62% reduction in the region of Lazio. Furthermore, we assess the contribution of territories and sectors to the virus transmission. We find that most populated areas become less relevant to the contagion under more stringent policies. We also highlight the role of the Retail sector in driving the number of new cases, even though it had a reduced importance under regimes of less stringent policies.

The period of targeted restrictions during the COVID-19 pandemic offers an interesting example of the impact of policies on household financial decisions. We show how households are interdependent agents that take consumption decisions based on the evolution of the infections and the complex and heterogeneous conditions of the territories where they live and work (additional results are presented in the Supplementary Information — SI). Overall, our study provides actionable insights for achieving a better trade-off between economic and public health objectives, calling for data-driven and evidence-based analyses when designing economic policies during crisis periods.

2. Related literature

As reported in Yannelis and Amato (2023), the availability of novel data in quasi real-time has been one of the distinctive features of the COVID-19 pandemic. This has led to the development of new academic research using these data to explore the impact of the pandemic across several dimensions, especially regarding households' behavior.

Among these studies, our work aims to contribute to the strand of literature using high-frequency transaction data to analyze the variation in household consumption during the pandemic. Similarly to Bounie et al. (2023) for France, Andersen et al. (2022) for Denmark, Chetty et al. (2020) for the US and Hacıoğlu-Hoke et al. (2021) for the UK, also in our work we document the steep reduction in consumption following the first phase of generalized restrictions and the shift in the composition of the set of consumed goods towards essential sectors and non-durables commodities.

Furthermore, similarly to Shin et al. (2021) and Carvalho et al. (2020), we focus our analysis on the consumption response following restrictions targeted to specific territories and sectors. The former find that when restrictions target specific city clusters, consumption reduction is limited to a 300 m distance radius from them, with different degrees of persistence over time according to the cluster characteristics. The latter perform a larger scale study, more similar to our work, and demonstrate that the reopening of specific sectors (retail and hospitality), even though with a limited capacity, contributed to a strong recovery in consumption in the first phases of lockdown easing.

One limitation of both works is that they do not assess the impact of targeted restrictions on contagion,[5] hence their policy recommendations are limited to the economic impact of these NPIs. In our work we analyze both sides of the health-economics trade-off, assessing the effectiveness of targeted restrictions in both aspects and therefore providing robust policy recommendations. Finally, contrary to Shin et al. (2021) we perform a large scale analysis at the national level, and contrary to Carvalho et al. (2020) we perform a more granular analysis since our territorial units of analysis are municipalities while their units are provinces.[6] The granularity of our data allows us to follow a bottom-up approach through which we reconstruct more accurately the economic aggregate fluctuations at a finer geographical resolution (Gabaix, 2011; Buldyrev et al., 2020).[7]

Besides assessing the magnitude of the variation in household consumption in response to the COVID-19 crisis, the literature has focused on investigating the factors associated with different household reactions. In our work we contribute to the strands of literature exploring the role of three factors: income, fear and liquidity constraints.

Among the set of papers addressing the first factor, a large number of studies ((Chetty et al., 2020; Kubota et al., 2021; Parker et al., 2022; Cox et al., 2020; R. Baker et al., 2023) to name a few), use stimulus payments from governments as natural experiments to measure the reaction of household consumption to expected (and often fixed) variations in income (Fuchs-Schündeln and Hassan, 2016). They find that, in general, COVID-19 stimulus programs have been less effective than past programs, *i.e.*, they elicited a weaker positive variation in the marginal propensity to consume (MPC) of recipients. A plausible explanation for this can be found in consumer theory: the pandemic, either through fear of contagion or through restrictions, has negatively affected the marginal utility of consumption making current consumption less valuable than future consumption and causing a shift toward the latter (*i.e.*, an increase in savings) (Andersen et al., 2022; Parker et al., 2022; Guerrieri et al., 2020).

Contrary to these works, we do not have data on the Italian government stimulus payment program (which has, however, been less sizeable than in other countries). Nevertheless, we contribute to this strand of literature by adding income to the set of covariates in our analysis and, similar to Carvalho et al. (2020), Hacıoğlu-Hoke et al. (2021), Chetty et al. (2020), Chronopoulos et al. (2020), Cox et al. (2020), we also find a stronger reduction in consumption among territories with more high-income earners.

The second stream addresses the issue of fear of contagion as a determinant of the reduction in consumption (Andersen et al., 2022; Goolsbee and Syverson, 2021; Farboodi et al., 2021; Immordino et al., 2022). We address this issue in our analyses by adding the lagged number of deaths to our covariates to account for the risk of infection.

Finally, a third issue addressed in the literature is the role of liquidity constraints. A common finding in the literature connected to stimulus payments (Kubota et al., 2021; Parker et al., 2022; R. Baker et al., 2023) is that the MPC of households receiving stimulus packages is greater for liquidity-constrained households. For instance, using data from a representative consumer survey across six European countries, Christelis et al. (2020) find that financial concerns amplify the negative effect of income losses after controlling for several covariates. Furthermore, the effect is stronger for younger, liquidity-constrained households and for the unemployed. Interestingly, they also control for health concerns related to contagion and find that "the precautionary saving motive behind the financial concern is a much stronger independent driver of spending behavior than the health-related concern per se" (Christelis et al. 2020, pp. 15). Simulating data for US workers' earnings, Catherine et al. (2020) demonstrate that cutting future old-age Social Security benefits in favor of present earnings by just 1% reduces significantly households' liquidity constraints and is preferable to other policies enacted by US Government such as the stimulus check. Finally, using the Special Survey of Italian Households (SSIH) from Bank of Italy, Guglielminetti and Rondinelli (2021) analyze multiple reasons behind consumption reduction including income expectations, fear of contagion and liquidity constraints. Overall, they find that economic reasons account on average for reduction in consumption in 55% of the cases, fear of contagion to 20% of the cases and restrictive measures and economic uncertainty to 12%–15% each. Furthermore, economic reasons are stronger for liquidity-constrained households.

The work of Guglielminetti and Rondinelli (2021) is the one closest to our analysis, since it analyzes Italian households during the period of differentiated restrictions in the fall of 2020. Similarly to their work, we will use the results of the SSIH to motivate our analysis and we will introduce a measure of liquidity constraints among our covariates. However, our measure of targeted restrictions allows us to obtain a clearer measurement of the impact of these policies since we have data at a more granular level in time and space. Furthermore, the work of Guglielminetti and Rondinelli (2021) does not contain any evaluation of the health effects of restrictions.

A common finding across these literature streams is that consumer responses are heavily dependent on both the diffusion of contagion and the content of government restrictions. This affects the effectiveness of any policy aimed at improving household conditions, since consumption for several categories of goods will be either considered too risky or not allowed according to government interventions. For these reasons, similarly to what is done in the recent literature on eco-epidemic modeling (Alvarez et al., 2020; Fernández-Villaverde and Jones, 2020), we integrate economic analyses with careful consideration regarding the epidemic consequences of restrictions. In particular, we contribute to the recent research pointing to targeted approaches as a sustainable policy response for prolonged periods of containment, as opposed to generalized lockdowns that are more suitable for shorter time frames when the contagion is out of control (Farboodi et al., 2021; Haffajee and Mello, 2020; Janiak et al., 2021).

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[5] An econometric analysis on the impact of consumption on the number of infected individuals is provided in Carvalho et al. (2020), but it is limited to the city of Madrid.

[6] Municipalities are the smallest administrative areas in Italy. According to the NUTS (Nomenclature des unités territoriales statistiques) classification Spanish provinces belong to the NUTS3 category (population between 800k and 150k) while Italian municipalities belong to Local Administrative Units (LAU) (population below 150k).

[7] Our work shares many similarities also with Bonaccorsi et al. (2023) where a subset of our data is used to analyze reopening scenarios for a single Italian territory (Lombardia). However, the focus of the authors is on simulations of alternative scenarios and not on the estimation of the actual impact of restrictions on household consumption and contagion.

Table 1

Differentiated restrictions. Specific content of the differentiated restrictions in Italian regions in the period from November 6th to December 7th, 2020.

Category	NACE	Description	Risk		
			High	Medium	Low
Transport	490,510	Public transport capacity is reduced by 50%	✓	✓	✓
Retail	470	Retail activities closed during weekdays[a]	✓		
		Retail activities closed during the weekend[a]	✓	✓	✓
Restaurants	560	Restaurants and bars closed all day	✓	✓	
	550	Restaurants and bars closed after 6 p.m.	✓	✓	✓
		Food delivery allowed until 10 p.m.	✓	✓	✓
Accommodation	560	Activity allowed without restrictions	✓	✓	✓
Human Health Activities	860,870,880	Activity allowed without restrictions	✓	✓	✓
Mobility		Mobility within the municipality is forbidden	✓		
		Mobility between municipalities is forbidden	✓	✓	
		Mobility is forbidden between 10 p.m. and 5 a.m.	✓	✓	✓

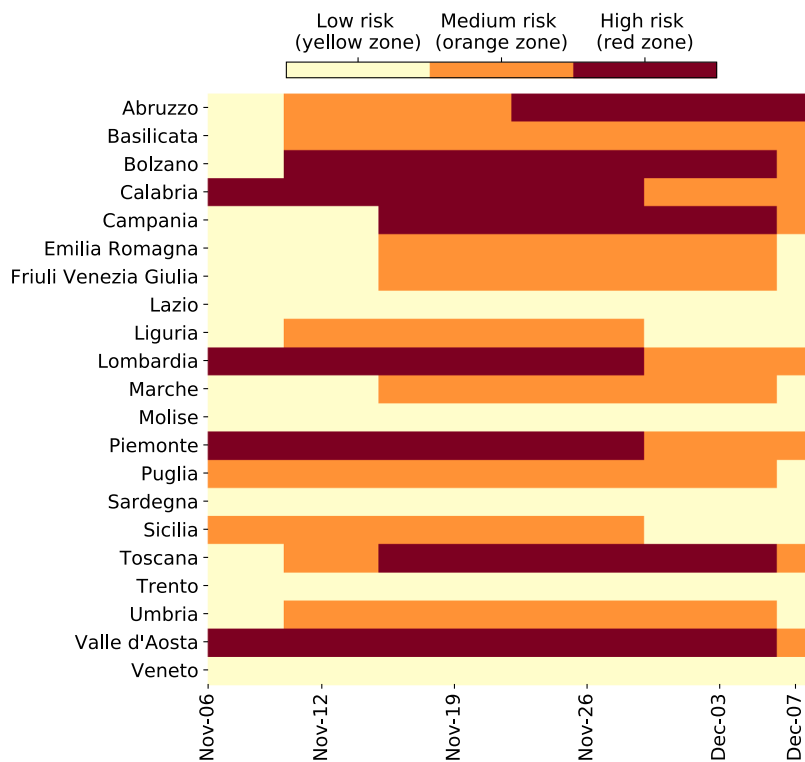[a] With the exception of essential sectors.

Fig. 1. The evolution of restrictions. Classification of Italian regions according to risk tiers, on a daily basis.

Finally, our work is also connected to the stream of research regarding the effectiveness of COVID-19 restrictions, in particular those related to mobility (Kraemer et al., 2020; Badr et al., 2020; Adriani and Ladley, 2021). Similarly to the work of Chang et al. (2020), we employ a SEIR metapopulation model based on empirical observations of individuals moving between residential and shopping locations. However, while they infer movements of individuals based on mobile phone data, our transactions provide information about the number and value of transactions that actually took place, thus allowing us to measure more precisely movements associated with consumption and track the economic impact of specific restrictions. In addition, we adapt their framework to accurately model differentiated restrictions by territory and sector similar to what we have done in previous analyses Bonaccorsi et al. (2023).

3. Background: Non-pharmaceutical interventions in Italy

This work focuses on targeted restrictions issued in Italy to contain COVID-19, for which we propose an empirical strategy precisely reflecting their content. In fact, similarly to other countries, the Italian government adopted two different approaches in the design of NPIs in 2020. First, a national lockdown with generalized restrictions on mobility started on 9th March 2020, imposing closure on all commercial and business activities, with the exception of essential services only (Ministero dello Sviluppo Economico, 2020). Such restrictions held until 4th May 2020 when they were gradually lifted.

Then, due to the resurgence of the contagion, new restrictive measures were implemented on 6th November 2020. These restrictions accounted for the heterogeneous severity of the pandemic across Italian regions (the largest administrative units in Italy) and adopted a differentiated approach. More specifically, regions were classified into 3 colored tiers (namely yellow, orange, and red) corresponding to increasing levels of ascertained risk and restriction stringency (see Table 1). The classification was based on weekly reports of the Istituto Superiore della Sanità (National Healthcare Institute), which evaluated the local severity of the contagion through multiple indicators, including the basic reproduction index and the saturation of hospitals and other healthcare infrastructures.

More specifically, each restriction tier imposed an increasing level of stringency, targeting specific sectors and activities. The low-risk tier allowed individuals to move across different municipalities and regions, except during the hours between 10 pm and 5 am. Retail activities were closed only during the weekend, with the exception of essential sectors, while restaurants and bars were open until 6 pm only, allowing food delivery until 10 pm. The medium risk tier applied more stringent restrictions by forbidding movements between municipalities. Moreover, restaurants were fully closed, while food delivery was still allowed. Finally, the high-risk tier prohibited all movements, with the exception of work or health-related reasons. Besides, it enforced a full closure of Retail activities. In all tiers, a 50% reduction in public transport capacity was enforced, while no explicit restriction was applied to Accommodation and Human Health sectors. Although the three risk tiers were characterized by different stringency levels of restrictions, penalties were homogeneous across territories and entailed pecuniary and administrative fines.[8] We report additional sectors that were required to be fully or partially closed in Tables S3–S7 in the SI.

Following the new policies, Italian regions entered into stricter or lighter restriction regimes at different times, as summarized in Fig. 1. We notice high variability across territories, with several regions never entering the higher risk tier (Lazio, Molise, Sardegna, Prov. Trento) and others never reaching the lower risk tier (Calabria, Lombardia, Piemonte, Valle d'Aosta). This suggests that the contagion was not equally distributed across the country, motivating the choice of a localized and differentiated containment strategy, and highlighting the necessity of data with detailed time and geographic granularity.

To assess the effectiveness of targeted policies, our work analyzes the period of tiered restrictions from 6th November to 7th December. This period is particularly relevant for our study because restrictions were applied without exceptions to all regions, and uniformly to administrative areas inside them.

Although our data capture individuals' daily transactions until the end of 2020, we exclude the period from 8th December to 31st December from our analysis for two main reasons. First, the government implemented on 8th December a policy package providing cashback for household consumption to stimulate private demand, thus significantly affecting the purchasing behavior of individuals. Second, during weekends and holidays of the Christmas period, stricter and uniform restrictions were implemented across territories, regardless of the local severity of the pandemic.

4. Data and methodology

4.1. Data

Our data cover aggregated daily transactions of clients of Intesa Sanpaolo, a major Italian bank, during 2019 and 2020. Transactions are recorded at the level of the smallest Italian administrative units, municipalities, without missing days.

Our basic unit of observation is the aggregate daily number and associated monetary value of transactions made in all Points-of-Sale (POSs) within a specific merchant category in a given municipality, by Italian cardholders. Physical (offline) sales contain geographical information about both cardholders and POSs, whereas digital (online) transactions only contain the location of cardholders. Therefore, we focus our main analysis on offline transactions, and we provide a complementary analysis of the online channel in a later section and in the SI.

Our data cover the entirety of the Italian territory, where Intesa Sanpaolo owns at least a 15% market share in each region. Nevertheless, we tested the representativeness of our sample. First, we checked that the number of payment cards covered in our sample remained almost constant over time, with only a 0.2% increase in our sample between the start and the end of our period of observation. This ensures that comparisons between 2020 and 2019 are between similar samples.

Following Scotti et al. (2023), in section 2 of the SI we checked the matching between our data and publicly available information on the Italian population. We observe a strong correlation between the share of total consumption in our dataset and the share of national GDP and national income at the province and municipality levels. Furthermore, regarding the evolution of consumption

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[8] The mobility reduction observed in our data highlights a significant and stable change in behaviors, signaling a generalized compliance to policies by the Italian population that is mainly affected by the content of restriction tiers. However, it is possible that differentiating penalties across tiers could have led to a stronger reaction from Italian citizens (*i.e.*, a greater reduction in consumption and movements). Hence, these additional effects of differentiated penalties should reinforce our conclusions regarding differentiated restrictions.

during 2020, we observe a good match between our data and data from Italian national accounts regarding household expenditures for final goods (ISTAT). This is consistent both at the level of aggregate consumption and at the level of subcategories of consumed goods.

Furthermore, information on the geographic location of purchases allows us to measure the movements of individuals associated with consumption. This includes both aggregated movements originated exclusively for consumption reasons, *i.e.*, individuals moving toward a specific POS to shop, and movements initiated for other reasons and in which consumption is contextual, for instance, food consumption near the workplace. Similar proxies of the actual mobility of individuals have been employed during the COVID-19 pandemic. They include social network data from Facebook to approximate commuting patterns (Maas et al., 2019; Bonaccorsi et al., 2020), GPS data from mobile phone devices to approximate visits to specific POSs collected by SafeGraph (Chang et al., 2020) or by Google (Fernández-Villaverde and Jones, 2020). Other studies (Gatto et al., 2020), however, have followed a different approach to model the role of mobility in COVID-19 contagion, employing publicly available surveys on the mobility of Italian individuals (Istituto Nazionale di Statistica, 2019). Despite their reliability, the latter data are available only for the year 2011 and do not allow for real-time analyses.

To assess the comparability of our mobility data to those from other sources, we filtered the data in two ways. First, for privacy reasons, we excluded daily observations below a threshold of 5 (similarly to what is done in mobility datasets from social networks, Maas et al. 2019). Secondly, we employed a filter to match our mobility observations with public surveys, pruning movements that were not likely to be observed in the public data. Details on the procedure are available in the SI. As a result, the correlation between our data and the data from public surveys is 0.75. Furthermore, we achieve an extremely good fit between our data and mobility data from Google Mobility reports with a correlation between 0.89 and 0.93, significant at the 0.01 level (see Figure S14 in the SI).[9]

4.2. Methodology

4.2.1. Econometric model: Policy effects on consumption

To test our first research hypothesis, concerning whether the economic impact of targeted restrictions has been consistent with their stringency, we perform a retrospective analysis of consumption patterns in Italy in the second half of 2020, when differentiated and targeted restrictions were implemented across Italian regions.

In particular, we estimate a set of linear panel regression models in which our main variable of interest is the year-on-year (Y-o-Y) growth rate of daily consumption in Italian municipalities. Formally, we define $Y_{i,t,k}$, the daily Y-o-Y variation of economic consumption in municipality i, on day t, in sector k as follows:

$$Y_{i,t,k} = \frac{Spending_{i,t,k} - Spending_{i,t-364,k}}{Spending_{i,t-364,k}}, \tag{1}$$

Here $Spending_{i,t,k}$ is a rolling average of daily economic consumption over a time window of 7 days in municipality i, in sector k on day t and $Spending_{i,t-364,k}$ is the corresponding value obtained 364 days before (one year before, with correspondence of week days), coherently with Sheridan et al. (2020).

Our main covariate of interest, *Differentiated Policy*$_{i,t}$, is a categorical variable stating the type of policy restrictions implemented on day t in municipality i. We consider four categorical levels: *uniform restrictions*, which consisted of weak limitations applied indistinctly to all regions in the period 24th October–5th November, and the three risk tiers (*yellow*, *orange*, *red*) described in Section 3. We consider as a baseline the period with almost no restrictions from 10th October 2020–23th October 2020, thus coefficients of *Differentiated Policy* can be interpreted as the excess percentage variation of municipality expenditure with respect to a period with almost no limitations.

Furthermore, we include two vectors of time-varying ($X_{i,t}$) and time-fixed (Z_i) control variables, including additional covariates that could affect the consumption variation. In particular, $X_{i,t}$ accounts for *Policy Persistence*, representing the number of days since the current policy framework applied in administrative unit i on day t was implemented, to investigate whether a longer duration of a specific restriction regime is associated with a reduction or reinforcement of the effect of the restriction. Moreover, we consider the daily lagged number of deaths (lag equal to 14 days) since a stronger economic contraction might have been experienced in areas with a higher contagion intensity. Finally, Z_i considers a set of variables related to the local level of wealth since households' economic conditions and liquidity constraints may affect the consumption behavior of individuals, especially in periods of uncertainty (Zeldes, 1989; Catherine et al., 2020; Coibion et al., 2021). In particular, we plug into the model the *Cash shortfall*, representing the percentage of families at the regional level with high or very high liquidity issues. This variable is based on data collected by the national statistical office according to the EU statistics on income and living conditions (EU-SILC), aiming

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[9] In particular, we examined the year-over-year changes in the Retail sector and compared it to the category labeled "Supermarket and pharmacy" in Google's mobility reports. Similarly, we analyzed the year-over-year fluctuations in the Restaurant sector and compared it to the "Retail and recreation" category. The correlation coefficients obtained were 0.89 and 0.93 respectively, both highly significant at the 0.01 level. The "Supermarket and pharmacy" category is defined in the Google mobility reports as "Mobility trends for places such as supermarkets, food warehouses, farmers markets, specialty food shops and pharmacies", while the "Retail and recreation" category is defined as "Mobility trends for places such as restaurants, cafés, shopping centers, theme parks, museums, libraries and cinemas".

to provide a representative overview of income, poverty, social exclusion, and living conditions in a certain country.[10] Furthermore, since income constitutes a main determinant of consumption, we consider the Income per capita (*Income pc*) and its squared value (*Income pc squared*) at the municipal level, to model linear and non-linear relationships between the variation of consumption and the local economic wealth, in line with Christelis et al. (2020), Coibion et al. (2021) and Guglielminetti and Rondinelli (2021).

The full panel model specification is the following:

$$Y_{i,t,k} = \alpha_0 + \beta * Differentiated\ Policy_{i,t}$$
$$+ \gamma * X_{i,t} + \delta * Z_i + \epsilon_{i,t} \tag{2}$$

We estimate different panel models analyzing the impact of restrictions on the variation of economic consumption in a set of relevant sectors for the Italian economy, namely Accommodation, Restaurants, Retail, Transport and Human Health activities. Moreover, we analyze the economic variation of aggregated consumption across all sectors of the economy and in the case where we exclude only the Retail sector, due to its peculiar behavior during lockdown with lower restrictions compared to other sectors.

4.2.2. Econometric model: The impact of consumption on COVID-19 contagion

We obtain some preliminary evidence on the impact of economic consumption on contagion by applying a panel negative binomial model in which the dependent variable is the number of new daily infections in a province over the period 25th October–7th December 2020. Let $y_{i,t}$ be the number of new daily COVID-19 cases in province i on day t. We use the model $y_{i,t} \mid \gamma_{i,t} \sim \text{Poisson}(\gamma_{i,t})$, where $\gamma_{i,t} \mid \delta_i \sim \text{gamma}(\lambda_{i,t-l}, \delta_i)$ with $\lambda_{i,t-l} = \exp(x_{i,t-l}\beta)$ and δ_i is the overdispersion parameter. This yields the model (for further details, see *e.g.* Hausman et al. 1984):

$$Pr(Y_{i,t} = y_{i,t} | x_{i,t-l}, \delta_i) =$$
$$\frac{\Gamma(\lambda_{i,t-l} + y_{i,t})}{\Gamma(\lambda_{i,t-l})\Gamma(y_{i,t} + 1)} \left(\frac{1}{1+\delta_i}\right)^{\lambda_{i,t-l}} \left(\frac{\delta_i}{1+\delta_i}\right)^{y_{i,t}} \tag{3}$$

where $x_{i,t-l}$ is the set of explanatory variables observed in province i on day $t - l$. In terms of regressors we consider the aggregate economic consumption across all sectors, the specific consumption in the Retail sector, and aggregate consumption across all sectors when only Retail is excluded, performed in each province. Moreover, we include the variable *Policy Persistence* representing the number of days since the current policy framework applied in each province. We consider a setting where all regressors are lagged by 14 days ($l = 14$). In this way, we ensure that new cases are imputed to transactions occurring 2 weeks before.

4.2.3. Epidemiological framework

The intuition driving the previous analysis is that consumption, especially in the Retail sector, might drive the contagion, suggesting that transaction data may contain considerable information to explain the spread of COVID-19 and the effectiveness of targeted restrictions. We build on such intuition to test our second research hypothesis, namely that targeted restrictions have been effective in limiting the contagion.

In particular, we employ a SEIR metapopulation epidemic model where the spatial distribution of contagion is based on the bipartite network of mobility community-POS constructed from transaction data. An illustrative visualization of the model is provided in Fig. 2E.

Our epidemiological framework is based on the Susceptible–Exposed–Infected–Recovered (SEIR) model, which has been extensively employed to study the spread of COVID-19 (Davies et al., 2020; Kucharski et al., 2020; Prem et al., 2020). We extend the basic model with two main modifications. First, we move from a uniform population to a metapopulation model (Chinazzi et al., 2020; Chang et al., 2020; Lai et al., 2020). Adapting the framework presented in Chang et al. (2020) to the Italian case, we assume that individuals are distributed in separate and homogeneous communities where the epidemic process takes place simultaneously. Specifically, communities represent Italian municipalities (the smallest administrative unit in Italy) inside the same region (the largest administrative unit in Italy). In each community we divide the population into four separate compartments: susceptible (S), exposed (E), infected (I) and removed (R) individuals. Contagion takes place independently in each community and it regulates how individuals transition between compartments when interactions occur between individuals of the same community.

As a second modification, we introduce a mechanism through which contagion may then spill across communities. Susceptible individuals can travel from their community toward other specific locations – Points-of-Sale (POSs) –, and interact with infective individuals from other communities, thus becoming exposed to the virus. This will in turn affect the contagion dynamics in their own community. Furthermore, the introduction of targeted restrictions will decrease the possibility of individuals visiting specific POS categories on the territory, hence reducing the probability of individuals becoming exposed or infecting others through the POS channel. For this reason, we consider only movements associated with consumption, as they were impacted by differentiated policy restrictions in Italy during the period of analysis.[11]

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[10] Detailed information on the EU statistics on income and living conditions (EU-SILC) is available at the following link: https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions. Additional details on the implementation of the survey in Italy are disclosed by the national statistical office at the following link: https://www.istat.it/it/archivio/5663.

[11] A similar model has also been employed in Bonaccorsi et al. (2023) but limited to a single Italian region and with the aim of simulating counterfactual reopening scenarios.
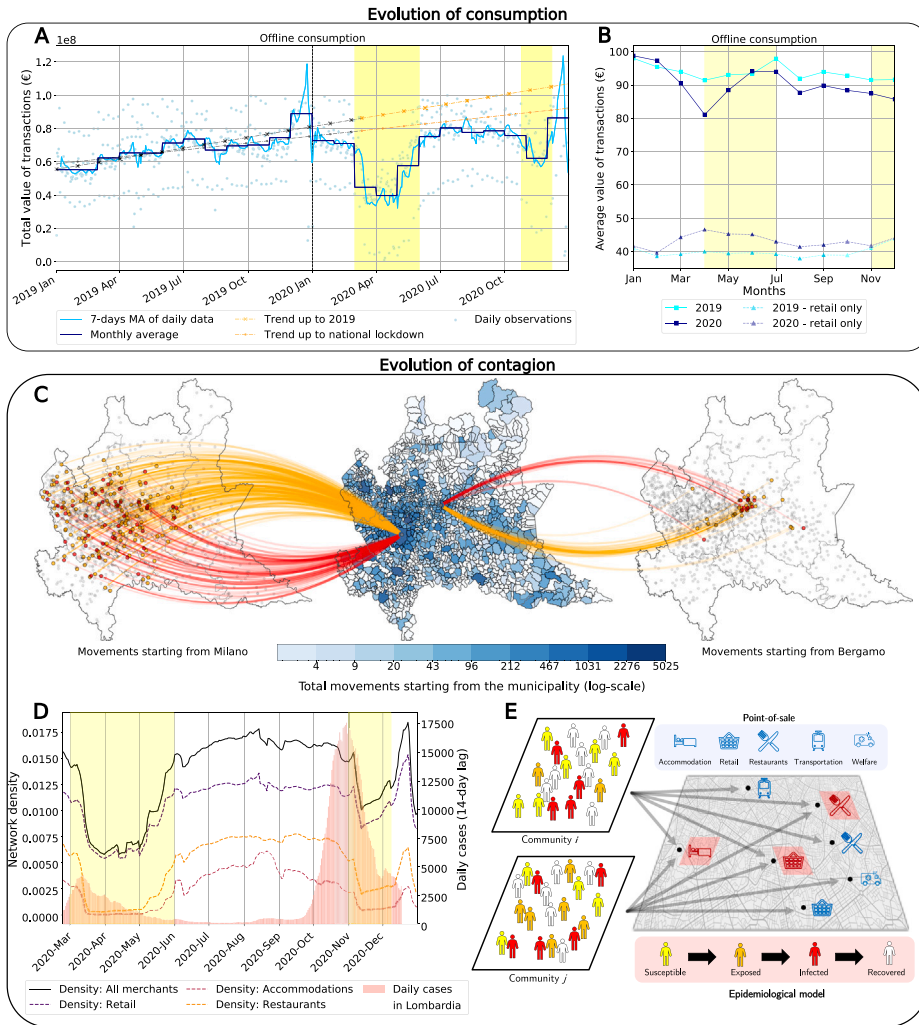
Fig. 2. Panel A: total value of daily consumption for 2019 and 2020 with long-run trends. Trends are computed with a linear regression model fitted on previous observations. Yellow areas refer to the lockdown phase (4th March–2nd June 2020) and to the period of targeted restrictions that we analyze in our empirical setting (6th November–7th December 2020). **Panel B**: average monthly value of transactions. **Panel C**: the bipartite network of movements associated with consumption in two sectors (Restaurants in red, Retail in orange) for two Italian municipalities: Milano (left-hand side), Bergamo (right-hand side). Middle panel reports the total number of movements by municipality, for the entire region. The colormap is in a logarithmic scale. **Panel D**: time series of network statistics and the number of confirmed cases in the Lombardia region. Solid lines correspond to the density of the mobility network for four specific sectors reported as a 7-day moving average. Orange bars correspond to daily confirmed cases as reported by ICPD shifted by 14 days. Correlation coefficients between network densities and the number of confirmed cases are all significant at $\alpha = 5\%$ significance level and positive for both phases of restrictions: All merchants (0.45, 0.48), Retail (0.45, 0.41), Accommodation (0.50, 0.49), Restaurants (0.48, 0.56). **Panel E**: schematic diagram of the epidemiological model. Individuals reside in communities (left) and travel to POSs (right) of different merchant categories to make purchases. Each community is located in a specific municipality, and each municipality has several POSs to which individuals can travel (they cannot move between communities). Contagion dynamics is regulated by a SEIR metapopulation model, which is detailed in Section 4.2.4. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2.4. Mobility based metapopulation SEIR model

We assume that the total population N^{c_i} of each community c_i is large and constant during the period, due to the rapid diffusion of the virus with respect to the natural birth/death processes. Accordingly, at each time t, the population of a community is described by the equation: $N^{c_i} = S_t^{c_i} + E_t^{c_i} + I_t^{c_i} + R_t^{c_i}$.

Transitions among states happen at each step t according to the following set of equations[12]:

$$\frac{dS^{c_i}}{dt} = -\lambda_t^{c_i} S_t^{c_i} - \Lambda_t^{c_i} \frac{S_t^{c_i}}{N^{c_i}} \tag{4}$$

$$\frac{dE^{c_i}}{dt} = \lambda_t^{c_i} S_t^{c_i} + \Lambda_t^{c_i} \frac{S_t^{c_i}}{N^{c_i}} - \mu_e^{c_i} E_t^{c_i} \tag{5}$$

$$\frac{dI^{c_i}}{dt} = \mu_e^{c_i} E_t^{c_i} - \mu_i^{c_i} I_t^{c_i} \tag{6}$$

$$\frac{dR^{c_i}}{dt} = \mu_i^{c_i} I_t^{c_i} \tag{7}$$

We overlay the SEIR metapopulation model on a temporal weighted community-POS network $G = (C, P, E)$. This is a bipartite network described by two disjoint sets of nodes, communities (C) and POS (P), in which edges represent the number of individuals moving for which a transaction has been registered. Nodes in both sets are characterized by a given municipality, and P nodes also possess a specific unique merchant category. An edge exists at time t between two nodes c_i, p_j if individuals travel from community c_i to make a purchase at POS p_j at time t. The network is bipartite because connections among nodes of the same type are not allowed, i.e., two communities c_i and c_j are never directly connected, and their members can only come in contact by visiting the same POS at the same time. Susceptible individuals can thus be exposed to the virus both in their community or when traveling to a POS of another municipality, each of which has its own rate of infection.

As a consequence, Eqs. (4)–(5) reflect two sources of exposure. The first source of exposure are the contacts inside the community and the transition from exposed to infected is governed by the parameter $\lambda_t^{c_i}$, i.e., the mean number of infections in the susceptible population of community c_i when exposed to infected individuals. We assume homogeneous mixing inside the community, hence $\lambda_t^{c_i} = \beta^{c_i} \gamma_t^{c_i} = \beta^{c_i} \frac{I_t^{c_i}}{N_t^{c_i}}$, i.e., the product of the base transmission rate β^{c_i} and the probability of interacting with infected individuals in the community $\gamma_t^{c_i}$. $\gamma_t^{c_i}$ is the proportion of infected individuals in the community at time t. Finally, $\mu_e^{c_i} = \frac{1}{\delta_e^{c_i}}$ is the inverse of the mean latency period and $\mu_i^{c_i} = \frac{1}{\delta_i^{c_i}}$ is the inverse of the mean infectious period.

The second source of exposure is visits to POSs. New infections arising from this source are sampled from a Binomial distribution with a number of trials equal to $w_t^{ij} \frac{S_t^{c_i}}{N^{c_i}}$ and success probability equal to $\lambda_t^{p_j}$. Since the first parameter is sufficiently large and the rate of infection is sufficiently small we can approximate the Binomial distribution with a Poisson distribution with rate equal to $w_t^{ij} \frac{S_t^{c_i}}{N^{c_i}} \lambda_t^{p_j}$ and obtain the sum of all new cases from POS exposures as a single sample from a Poisson with parameter: $\eta_{c_i} = \Lambda_t^{c_i} \frac{S_t^{c_i}}{N^{c_i}} = \frac{S_t^{c_i}}{N^{c_i}} \sum_{j=1}^{P} w_t^{ij} \lambda_t^{p_j}$ where $\lambda_t^{p_j}$, is the product of the transmission rate and the probability of encountering infected individuals in the population. However, both terms now depend on the specific POS visited by the individual, with a POS-specific transmission rate $\beta_t^{p_j}$ and a share of infected individuals encountered depending on the total number of visitors from all municipalities: $\lambda_t^{p_j} = \beta_t^{p_j} \frac{I_t^{p_j}}{\sum_{i=1}^{M} w_t^{ij}}$.

In addition, similarly to the original model presented in Chang et al. (2020), we model $\beta_t^{p_j}$ as a function of the structural characteristics ϕ^{p_j} of each POS, which depend on the number of visitors and a base transmission constant τ, equal for all POSs: $\beta_t^{p_j} = \tau \phi^{p_j} \sum_{i=1}^{M} w_t^{ij}$. The structural characteristic parameter is defined as $\phi^{p_j} = \frac{l^{p_j^2}}{a^{p_j}}$, i.e., the ratio of two factors affecting the density of visitors in the POS. The first factor is the average duration of a visit at the POS, l^{p_j} which has a quadratic effect on ϕ^{p_j} since it affects both the probability of two visitors being simultaneously in the same POS and the period in which visitors remain exposed to each other. The second factor is the surface area of the POS, a^{p_j}, which affects the closeness of visitors and hence has an inverse effect. Therefore, smaller POSs where visitors spend a longer time are characterized by higher transmission rates. Hence, the probability $I_t^{p_j}$ of a random visitor encountering an infectious individual, depends on the proportion of infected visitors coming from all communities: $I_t^{p_j} = \sum_{k=1}^{M} w_t^{kj} \frac{I_t^{m_k}}{N_t^{m_k}}$. Finally, for a given community c_i, the number of individuals becoming exposed due to visits to POSs can be modeled as a Poisson distribution with parameter:

$$\eta_{c_i} = \frac{S_t^{c_i}}{N^{c_i}} \Lambda_t^{c_i} = \frac{S_t^{c_i}}{N^{c_i}} \tau \sum_{j=1}^{P} w_t^{ij} \phi^{p_j} \sum_{k=1}^{M} w_t^{kj} \frac{I_t^{m_k}}{N_t^{m_k}} \tag{8}$$

4.2.5. Model initialization and calibration

We analyze transaction data at the finest granularity available, i.e., at the municipality level, which allows us to perform the analysis at different geographical aggregations. Furthermore, since restrictions were applied at the regional scale, we model three separate Italian regions, namely Lombardia, Lazio and Campania, which account for a total population of 19.07 million (approximately 32.09% of the Italian population in 2019). We chose these regions to cover three different areas of Italy (north, center and south Italy, respectively), and because they experienced diverse patterns of restrictions, which are summarized in Fig. 1. Although it is important to consider also movements between regions, the share of these movements with respect to overall mobility was negligible during the period of analysis and can be disregarded. Hence we ran a separate model for each region over the period

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[12] Notice that each transition is equivalent to sampling from a Binomial distribution where the number of trials is equal to the size of the starting compartment and the success rate is equal to the transition parameter.

10th October to 7th December which includes almost a month before the introduction of differentiated restrictions put in place on 6th November.

In each region, we set the initial number of infected individuals equal to the official measurement released by the ICPD. Furthermore, we allow the initial share of exposed individuals p_0 to be a non-zero percentage, and we initialize their compartment with a sample from a Binomial with size equal to the municipality population and a success rate of p_0. We assume no lag in the detection of cases to account for both the increase in public awareness of the virus and the improvement in testing capacity during this second phase of restrictions.

We calibrate the model with parameters from previous studies, when available (see Table S10 in the SI). Therefore, similarly to Chang et al. (2020), we are only required to calibrate three parameters in the model for which we run a grid search on plausible intervals: (1) the POS-specific transmission constant, (τ; equal for all POSs); (2) the base transmission rate in communities, (β^{c_i}); and (3) the initial proportion of exposed individuals at time $t = 0$, namely p_0.

We run a grid search over three intervals of plausible values, and select combinations of parameters that lead to better predictions of daily confirmed cases (as measured by the root mean squared error, RMSE), discarding those with an RMSE more than 20% greater than the best model. Each combination is replicated 30 times to control for stochastic variation in the simulations. The fitting of each combination is checked against official data on the total number of COVID-19 cases obtained from the ICPD repository. Table S11 in the SI reports the results of the grid search.

This procedure selects an ensemble of parameter combinations that identifies multiple best models. We use the results of these models to further investigate the different roles of territories and sectors in driving the contagion.

4.2.6. Robustness

To test the validity and robustness of our results we also provide in the SI a replication of the main results for the economic and epidemic analyses during the lockdown phase (see Sections 3, 4 and 9 of the SI).

5. Results

5.1. Motivating evidence

5.1.1. The evolution of transactions during the pandemic

Fig. 2A shows the daily value of offline transactions during the years 2019 and 2020. We show that during the two periods when mobility restrictions were put in place (highlighted in yellow in Fig. 2), the reduction in household consumption levels was stronger compared to the other periods. As expected, the most severe impact can be observed during the first phase of restrictions, when a full lockdown heavily constrained household consumption patterns: the monthly year-on-year variation in the total value of consumption reached a minimum of −39.19% in April 2020. This reduction is consistent with similar estimates of the variation in consumption observed in other countries: −29% in Denmark (Andersen et al., 2022), −30% in the US (Chetty et al., 2020), −40% in the UK (Hacıoğlu-Hoke et al., 2021) and −60% in Spain (Carvalho et al., 2020). However, a considerable variation in household consumption can also be observed during the phase of targeted restrictions: the monthly year-on-year variation during November 2020 was −16.66%.

An opposite pattern is observable in households' online consumption behavior. The overall share of purchases made online was 31.11% and 28.88% of the total value of household consumption in April and November 2020, respectively. This accounted for a monthly year-on-year variation in the total value of consumption made through the online channel of 36.77% in April 2020 and 44.59% in November 2020 (see Figure 11 in the SI). Similar shifts to online purchases have also been shown by Bounie et al. (2023) in France and Carvalho et al. (2020) in Spain.

We show in Fig. 2B the monthly average value of transactions considering all sectors (square solid lines), and for the Retail sector in particular (triangle dotted lines). The average monthly value of transactions ranges between a minimum of about 80€ and a maximum of about 98€, when all sectors are considered. Moreover, during 2020 the average value of transactions decreased compared to the corresponding value in 2019: the average difference in the monthly value between the two years is −3.47€ with a minimum in April (−10.34€). Instead, the Retail sector exhibits a positive growth in the value of transactions for all months of 2020: the average difference in the monthly value between the two years is 3.32€ with, again, a peak in April (6.55€). This shows the presence of sector-specific differences, suggesting that aggregate evidence may hide heterogeneous effects at the local level.

To highlight differences in the impact of restrictions across sectors, Fig. 3 shows the impact of targeted restrictions disaggregating the total value of consumption by sector for years 2019 and 2020. On the one hand, Retail registered an increase in the share of the total transaction value during restrictions (+10.07% average variation compared to 2019), since it includes several essential activities that were exempted from restrictions. On the other hand, some sectors suffered severe reductions in consumption because they were directly targeted by restrictions, such as Restaurants (−52.85%), Land (−71.29%) and Air (−82.18%) Transport, and Travel (−90.67%). Moreover, even sectors with open business activities, but that were strongly dependent on social interactions, were negatively affected, such as Accommodation (−78.00%).

Consumption patterns shown in Fig. 3 provide evidence of a differentiated impact of targeted restrictions among sectors. In addition, such a heterogeneous impact reveals a new dimension relevant to the analysis: the peculiar productive structure of Italian territories. In fact, among all regions classified with the same risk tier, a different concentration of targeted sectors at the local level might have generated different economic impacts due to restrictions. We address this aspect in the next analyses by taking into account the sectoral composition of the local economy.
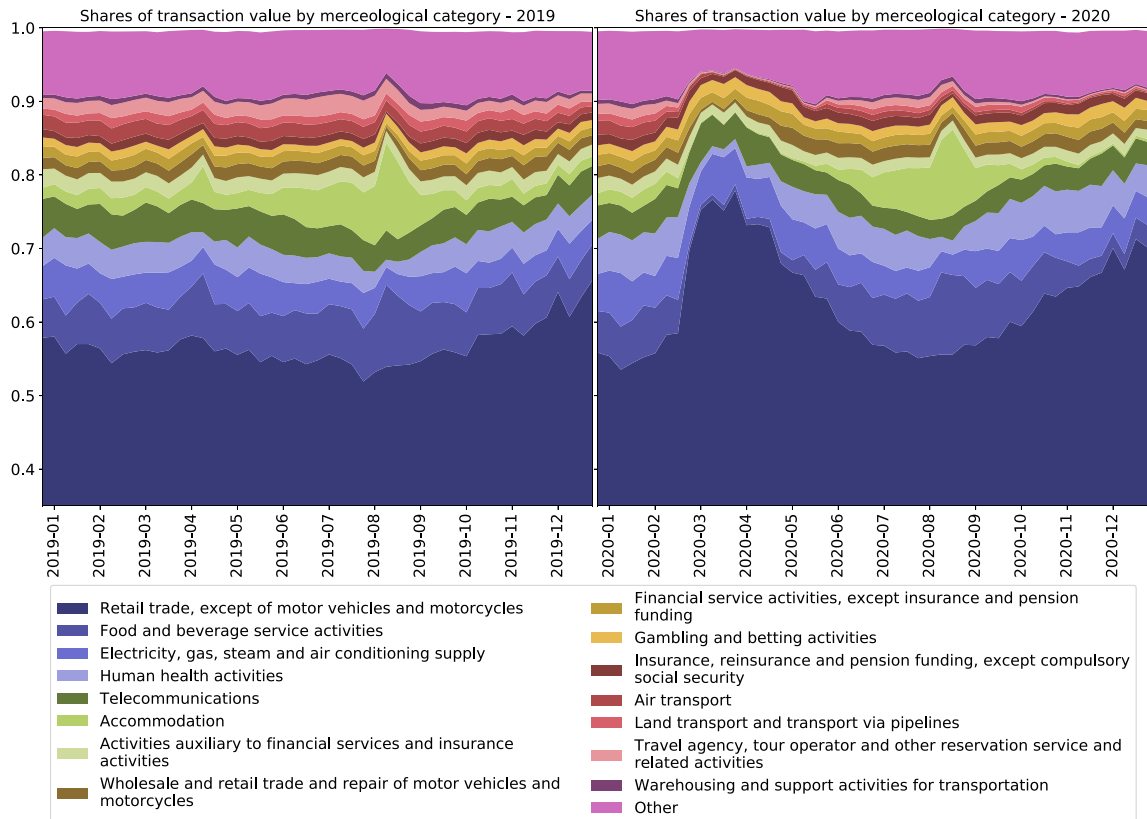
Shares of transaction value by merceological category - 2019   Shares of transaction value by merceological category - 2020

Fig. 3. Distribution of the total weekly value of consumption by sector in 2019 and 2020. Total weekly value is calculated on both online and offline channels.

Specifically, we focus on sectors that were directly targeted by restrictions, namely Restaurants, Retail and Transport. In addition, we include Accommodation, which experienced relevant economic losses even though its activities were partially allowed. Finally, we take into account Human Health Activities, which captures expenditures in healthcare services (+43.44% average variation compared to 2019), as well as consumption for residential care (+11.41% variation) and social work activities (−4.10% variation) that were relevant during the pandemic.

5.1.2. The factors affecting the household consumption response

As highlighted in the "Related literature" section, there are several factors that may affect the response of household consumption to targeted policies. In this section we complement the information available from our transaction data with information obtained from the Special Survey of Italian Households (SSIH) from the Bank of Italy (Rondinelli and Zanichelli, 2020), similarly to what has been done in Guglielminetti and Rondinelli (2021). The SSIH has been conducted by the Bank of Italy in multiple waves during 2020 and 2021 to collect information on the financial conditions and economic expectations of Italian households during the COVID-19 pandemic for a representative sample of Italian households. Results are provided at the level of macro-areas (*i.e.*, NUTS1) and we are mainly interested in the third wave of the survey that interviewed 2.077 households and ended in November 2020, *i.e.*, just at the beginning of the period of targeted restrictions that we are covering.

Following the literature on liquidity constraints, we are interested in exploring the financial conditions of surveyed households. In particular, we focus on the ease of making ends meet for a household as a target variable, following Guglielminetti and Rondinelli (2021), Coibion et al. (2021), and Christelis et al. (2020).[13]

According to the SSIH, for 18.8% of surveyed households making ends meet was difficult or very difficult in 2019. There was instead some difficulty for 35.1% of households, it was quite easy for 30.05% of them, and it was easy or very easy for the remaining 15%.

In particular, we are interested in how making ends meet affected the frequency of expenses for households. First, between 70% and 80% of all households declared they have reduced or eliminated shopping in restaurants, clothing and furniture shops,

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irrespective of their ability to make ends meet. Second, we find differences across household categories for two categories of sectors. In fact, nearly 60% of households having difficulties in making ends meet during 2019 decreased the frequency of their expenses in groceries and essential sectors, while for households finding it easy or very easy the percentage is only 39%. Similarly, the frequency of expenses related to personal services was reduced or eliminated by more than 70% of households having difficulties while 57% of households making ends meet easily or very easily eliminated or decreased their expenses. Hence, the SSIH provides evidence that the variation in consumption across sectors is also affected by liquidity constraints as captured by the capacity of households to make ends meet.

The SSIH elicited responses regarding the reasons behind the reduction in household expenses. We find that the harder it was for households to make ends meet in 2019 the greater was the percentage of them citing a reduction in available income as a reason behind reduced expenses: 76.45% for households having great difficulties, 59.75% for those having some difficulties, 28.51% for those finding it quite easy, and 15.4% for those finding it easy or very easy.[14] For households citing other motivations for a reduction in expenses, fear of contagion represented the stronger motivation (an assigned share between 39% and 44% on average across household categories), followed by restrictions limiting expenses in certain sectors (between 28% and 34%) and precautionary motives (between 25% and 31%).[15]

All in all, these responses signal the necessity to account for additional drivers in our analysis. In particular, precautionary savings may be accounted for by the shift of consumption from non-durable commodities to essential ones (*i.e.*, by differentiating the analysis across sectors), while we control for fear of contagion by checking if territories where COVID-19 deaths were higher had a stronger negative consumption reaction. Finally, with regard to restrictions, responses in each SSIH wave cannot capture their evolution over time and across territories due to their high spatial and temporal aggregation, and therefore they cannot be used to appropriately measure the impact of restrictions.[16] By using high-frequency transactions data, we are able to overcome these relevant limitations of the SSIH data and provide a more accurate analysis.

One last piece of evidence from the SSIH supporting the contribution of our work regards the relevance of government support among Italian households. According to the survey, nearly 25% of households received a form of government support in 2020. However, only one third of households having difficulties making ends meet in 2019 received a form of government support, with lower shares among the other categories (between 20% and 25%). Furthermore, among the recipients of any form of support, 47.64% declared that their income had decreased during 2020 and 38.66% of them were planning to reduce consumption in essential sectors, a share greater than that among non-recipients (30.92%). All in all, this last set of responses highlights that government support initiatives, while not completely absent, did not avoid a significant reduction in consumption among Italian households.

5.1.3. The evolution of mobility during the pandemic

The aggregated daily flow of transactions can be modeled with a bipartite network of mobility where nodes are of two types, namely, the municipality of residence of cardholders and the municipality in which POSs are located. Connections represent the number of individuals for whom, after traveling from a specific municipality toward a specific POS, a transaction has been registered. As an example, Fig. 2C represents the mobility network of one specific region, Lombardia. We show the municipalities where cardholders reside in the middle plot, and the municipality of POSs in the left and right plots. Specifically, on the left-hand side, we highlight the number of transactions (*i.e.*, movements associated with consumption) made by cardholders in the municipality of Milano towards merchants in the entire regional territory for the Retail and Restaurants sectors (in orange and red colors, respectively), in the period before restrictions. On the right-hand side, instead, we show the same measures for Bergamo, which is the second municipality in the region by the number of transactions in the same two sectors. It is immediate to observe that movements associated with consumption from Milano are more numerous and widely spread across the entire regional territory than those from Bergamo. This confirms that our data can capture the unequal distribution of movements by territory and sector that would be impossible to observe with aggregate mobility data or with the assumption of a homogeneous mixing population.

The patterns shown in Fig. 2C highlight that transactions data are able to capture differences in mobility by territory and sector. This shows another advantage in using movements associated with consumption instead of data from commuting patterns (for instance from Facebook (Kissler et al., 2020; Bonaccorsi et al., 2020; Maas et al., 2019) or from official surveys (Gatto et al., 2020)): they reflect the content of specific restrictions targeting sectors, allowing us to disentangle their heterogeneous impact. In Fig. 2D, we measure the evolution over time of the mobility network in Lombardia for 3 sectors (Retail, Accommodation, Restaurants), and the totality of the sectors combined. More specifically, we select every link going from all municipalities in which cardholders reside (*i.e.*, municipalities in the middle plot of Fig. 2C) to POSs relative to a specific sector (for instance, all orange or red links in Fig. 2C). We visualize the density of such networks, *i.e.*, the percentage of existing edges in the network with respect to the maximum number of edges allowed (Barabási et al., 2016). We report three findings. First, restrictions have a considerable effect on the density of the four networks, with a stronger effect during the first phase of restrictions, similarly to the daily value of transactions shown in Fig. 2A. Secondly, there are relevant differences among sectors, as Retail exhibits a greater level of density compared to the other sectors over the entire period. Finally, the pink bar plot in Fig. 2D shows the daily number of confirmed COVID-19 cases as reported

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[14] A similar pattern can be found if instead of making ends meet we use a survey question regarding variation in income during 2020.

[15] While the ranking of motivations is roughly comparable across household categories we find that the percentage of households assigning a weight greater than the median to each motivation is different across household categories.

[16] In their analysis, Guglielminetti and Rondinelli (2021) found a statistically insignificant impact of targeted restrictions employing a variable constructed from the macro-area information in the SSIH survey. However, as we showed in Section 3 the geographic level of targeted restrictions is at the regional level, which cannot be recovered from the SSIH data.

Table 2

Impact of policy restrictions on aggregated and sectoral consumption during the period of differentiated restrictions. We estimate random effects models, with data winsorized at 5th and 95th percentiles.

	Dependent variable: daily Y-o-Y variation of economic consumption (7-days rolling mean)						
	(All)	(Retail)	(Transportation)	(Accommodation)	(Restaurants)	(Human Health)	(Ex-Retail)
Differentiated restrictions:							
Uniform	−0.113***	−0.009*	−0.174***	−0.340***	−0.393***	0.131***	−0.109***
	(0.006)	(0.005)	(0.020)	(0.014)	(0.006)	(0.030)	(0.004)
Tier risk yellow	−0.213***	−0.070***	−0.282***	−0.470***	−0.478***	−0.070*	−0.179***
	(0.007)	(0.006)	(0.024)	(0.018)	(0.009)	(0.038)	(0.006)
Tier risk orange	−0.326***	−0.115***	−0.321***	−0.707***	−0.809***	−0.157***	−0.262***
	(0.007)	(0.006)	(0.022)	(0.017)	(0.007)	(0.034)	(0.005)
Tier risk red	−0.392***	−0.166***	−0.393***	−0.733***	−0.821***	−0.200***	−0.301***
	(0.008)	(0.006)	(0.022)	(0.017)	(0.008)	(0.034)	(0.006)
Policy persistence	0.006***	−0.002***	−0.001	−0.004***	−0.006***	0.0005	−0.002***
	(0.0003)	(0.0002)	(0.001)	(0.001)	(0.0003)	(0.001)	(0.0002)
Lagged deaths	−0.002	0.002	0.003	−0.003	−0.002	−0.010*	0.0001
	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.005)	(0.001)
Cash shortfall	−0.001	−0.001***	0.003*	−0.003***	−0.002***	0.015***	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.003)	(0.0004)
Income pc	0.014	−0.139***	0.087	0.087	0.091***	−0.283**	−0.080***
	(0.040)	(0.033)	(0.066)	(0.070)	(0.035)	(0.135)	(0.024)
Income pc squared	−0.071*	0.064**	−0.059	−0.101	−0.109***	0.076	0.018
	(0.039)	(0.031)	(0.061)	(0.070)	(0.035)	(0.122)	(0.023)
Constant	0.439***	0.367***	−0.257***	0.145***	0.262***	0.985***	0.267***
	(0.013)	(0.014)	(0.035)	(0.023)	(0.013)	(0.067)	(0.010)
Observations	240,181	230,990	70,952	137,333	214,312	149,827	236,686
R^2	0.025	0.053	0.092	0.203	0.428	0.010	0.137
Adjusted R^2	0.025	0.053	0.091	0.202	0.428	0.010	0.137

Notes: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors in parentheses. The regressor *Differentiated restrictions$_{i,t}$* is a categorical variable stating the type of policy restriction implemented (*i.e.*, uniform restrictions, tier risk yellow, tier risk orange, tier risk red). We consider the baseline as the period with almost no restrictions (10th October 2020–23th October 2020), thus coefficients of *Differentiated restrictions* can be interpreted as the excess percentage variation of municipality expenditure compared to a period with almost no limitation.

for provinces by the Italian Civil Protection Department (ICPD). We can observe a positive relationship between the evolution of mobility in transaction data and the daily number of COVID-19 cases, with infections dropping after the introduction of restrictions (with a two week lag): the correlation coefficient for all series depicted is positive and significant at $\alpha = 5\%$ significance level during both lockdown (average coefficient: 0.4726) and the phase of targeted restrictions (average coefficient: 0.4902).

These findings suggest the primary role of mobility in driving the contagion, highlighting the opportunity to exploit movements of individuals in our epidemiological model. Fig. 2E shows a schematic representation of our approach.

5.2. Effects of targeted restrictions on consumption

Our estimates of the effect of targeted restrictions on consumption are reported in Table 2. We show results for seven distinct models aggregating consumption at different sectoral levels: transactions from all sectors (*All*), from all sectors excluding Retail (*Ex-Retail*) and from five specific sectors (namely, *Retail*, *Transportation*, *Accommodation*, *Restaurants*, *Human Health Activities*).

We find a negative and significant effect of uniform restrictions across all models (β between −0.009 and −0.393). The negative coefficient in the Retail model ($\beta = -0.009$, S.E. = 0.005) suggests a reduction of economic activity even in a sector characterized by a large portion of essential business activities. The only exception is the Human Health sector ($\beta = 0.131$, S.E. = 0.030), where the growth of economic consumption is justified by a rise of expenditures for health reasons due to the resurgence of the contagion.

Stronger contraction of economic activities is observed in response to tiered restrictions on specific sectors. In particular, we find a negative impact on consumption that is largely coherent with the stringency of the policy, in line with our hypothesis (see also Fig. 4). For instance, focusing on the Transportation sector, a stronger contraction of consumption is associated with stricter levels of restrictions. Indeed, in this sector the least stringent policy ($\beta = -0.282$, S.E. = 0.024) allowed for inter-regional mobility, with movements forbidden only between 10 pm and 5 am. Instead, the moderately stringent policy ($\beta = -0.321$, S.E. = 0.022) permitted only intra-municipality mobility, while the most stringent policy ($\beta = -0.393$, S.E. = 0.022) allowed movements for work and health reasons only (see Table 1 for details).
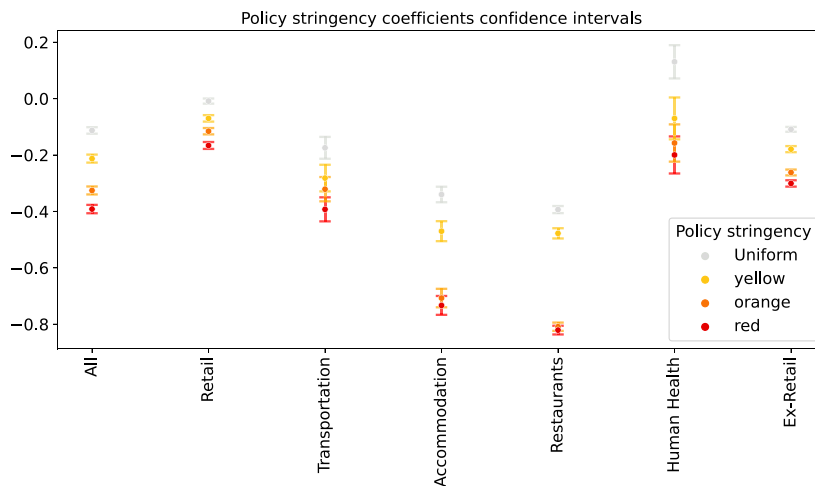
Fig. 4. We show the Confidence Intervals (CI) of the coefficients of categorical levels of the *Differentiated restrictions* variable shown in Table 2. Through a t-test we compare whether the impact of different levels of policy stringency applied to the same sector is statistically different. For all sectors we observe that coefficients of stricter restrictions are statistically lower (meaning stronger consumption reduction) than for less stringent interventions at a level of confidence of 99.9%. The only exceptions are the yellow vs orange risk tiers in the Transportation and the orange vs red risk tiers in the Accommodation, Restaurants, and Human Health sectors. More details on the t-tests are discussed in Section 11 of the SI. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The same ranking of effects is found in the Accommodation and Restaurants sectors, where we observe a stronger penalty corresponding to progressively more stringent restrictions. Note how these two sectors account for the largest reduction in economic activity with differences in coefficients between low ($\beta = -0.470$, S.E. = 0.018; $\beta = -0.478$, S.E. = 0.009) and medium ($\beta = -0.707$, S.E. = 0.017; $\beta = -0.809$, S.E. = 0.007) risk tiers being larger than the difference between medium and high ($\beta = -0.733$, S.E. = 0.017; $\beta = -0.821$, S.E. = 0.008) risk tiers. These results are consistent with the policies imposed by the Italian government. Indeed, for the Accommodation sector, despite not being targeted by explicit restrictions, these findings can be justified by the heterogeneity of mobility limitations, with individuals allowed to move across different regions in the low-risk tier and forced to stay within their municipality in medium and high-risk tiers. Similarly, restaurants and bars were open until 6 pm in the lower-risk tier, while these business activities were forced to stay closed every day, with only food delivery allowed until 10 pm, in the medium and high-risk tiers.

We observe a lower magnitude of the impact in the Retail sector, consistent with the large portion of essential activities within this sector. The stronger contraction in the high risk ($\beta = -0.166$, S.E. = 0.006) tier might be explained by the fact that these territories implemented the closure of retail activities even during weekdays, whereas it was applied only during the weekend in the low ($\beta = -0.070$, S.E. = 0.006) and medium ($\beta = -0.115$, S.E. = 0.006) risk tiers.

Similar patterns are observed in models that aggregate sectors (*All* and *Ex-Retail*). Interestingly, the effect is larger than in the Retail sector due to the lower presence of essential activities. However, the magnitude of the economic contraction is lower than in sectors targeted by specific restrictions such as Transportation, Accommodation, Restaurants. This is consistent with the fact that some sectors within these aggregate models were not subject to differentiated restrictions. We highlight that consumption in Human Health activities experiences a magnitude of reduction that is consistent with the policy stringency and the intensity of the contagion.

We further investigate whether the impacts of different levels of policy stringency applied to the same sector are statistically different. In particular, through a set of unilateral t-tests, we show that, across all analyzed sectors, the economic contraction of more stringent restrictions is statistically stronger than in lower risk tiers at a confidence level of 99.9% (see section 11 in SI). The only exceptions are the yellow vs. orange risk tiers in Transportation and the orange vs. red risk tiers in Accommodation, Restaurants and Human Health sectors.

We also noted that a longer implementation of specific policies (*Policy persistence*) tends to reinforce the contraction of consumption in the Retail, Accommodation, Restaurants sectors and when excluding Retail activities. We observe a statistically non-significant impact for the Transportation and Human Health sectors, whereas the coefficient is positive and significant when considering all sectors. This result unveils how restrictive policies targeting specific sectors and implemented over longer periods are generally more effective in limiting business activities and reducing consumption, although some possible heterogeneous responses to policy interventions emerge across economic sectors.

The number of deaths marginally affects the variation of economic consumption, being weakly statistically significant only for the Human Health sector ($\beta = -0.010$, S.E. = 0.005). Notice how such findings are different from previous evidence showing how, during the first wave of the pandemic, the fear of the virus constituted a relevant determinant of household consumption behavior (Farboodi et al., 2021). For instance, Andersen et al. (2022) find that individuals exposed to higher health risk reduced their consumption by 13% more than less-exposed individuals during lockdown and 3% after reopening. Similarly, Goolsbee and Syverson (2021) show

that fear of contagion is a strong determinant of the decrease in visits to businesses, accounting for nearly 30% of the total reduction, while Immordino et al. (2022) find that fear of contagion together with fear of job loss are two significant drivers of consumption reduction. We may obtain different results from these studies for different reasons. First, we rely on the lagged number of deaths as a proxy for the pandemic intensity since we do not have a direct measurement of the level of fear in Italy as in Immordino et al. (2022). Second, these studies mainly refer to the lockdown period, whereas our analysis focuses on the period of differentiated restrictions in fall 2020. Indeed, our results are more coherent with such literature when we consider the lockdown period (see Table S1 in SI).

We identify a stronger relationship between the local level of wealth and the variation of consumption. In line with Christelis et al. (2020), we observe that cash shortfall may reduce consumption in the Retail sector ($\beta = -0.001$, S.E. = 0.001). Note how this effect is economically significant since the Retail sector mainly encompasses essential business activities which are likely to be less elastic to liquidity constraints. Nevertheless, the same relationship also holds for the Accommodation ($\beta = -0.003$, S.E. = 0.001) and the Restaurants ($\beta = -0.002$, S.E. = 0.0005) sectors. Hence, cash shortfall represents a relevant driver of consumption patterns for both essential and non-essential goods. However, in aggregate, we identify a statistically non-significant relationship when focusing on all economic sectors or just excluding Retail activities. Such results may be justified by the fact that these sectoral aggregates include several non-essential activities, where consumption was mainly reduced by high-income households without liquidity constraints (Carvalho et al., 2020; Chetty et al., 2020; Chronopoulos et al., 2020; Cox et al., 2020). In addition, we find a weakly statistically significant and positive relationship between cash shortfall and consumption in Transportation ($\beta = 0.003$, S.E. = 0.001) and a strong positive relationship in the Human Health sector ($\beta = 0.015$, S.E. = 0.003). The latter is particularly interesting since it suggests that primary needs related to healthcare expenditures may be driven by the pandemic intensity more than liquidity constraints.

To complement previous findings on liquidity constraints, we also analyze the relationship between income levels and economic consumption. Our findings suggest that households reduced their economic activities more in areas with lower material deprivation, although in a non-linear way. In particular, we find a negative quadratic relationship when considering all economic activities and a negative linear and statistically significant relationship for both the Retail and Human Health sectors and when excluding Retail activities. Such results are consistent with previous evidence obtained by Carvalho et al. (2020) and Chetty et al. (2020), who highlight how the strongest contraction in consumption concentrated in the wealthier areas since rich individuals were unable to consume their normal goods basket due to restrictions.

However, we find a positive quadratic relationship between income per capita and consumption variation in the Retail sector, meaning that above a certain threshold of local wealth, a smaller decline in economic activity was experienced in areas with richer households. This result strengthens our previous finding of a negative coefficient of the cash shortfall regressor in the Retail sector, thus supporting that a stronger contraction of consumption for less wealthy areas emerges in those essential sectors where people concentrated their spending even before the pandemic. Interestingly, the opposite pattern characterizes the Restaurants sector, confirming that wealthier territories tended to penalize this type of consumption.

All in all, we find strong support for our first research hypothesis, *i.e.*, that the economic impact of targeted restrictions has been consistent with their stringency. Economic sectors played a relevant role in driving the reduction of consumption, with effects that are consistent with the requirements of policies imposed by the Italian government. Furthermore, we observe that the local level of wealth tends to affect household consumption behavior. Indeed, areas experiencing higher income per capita and lower liquidity constraints tend to strongly reduce their consumption level, due to restrictions mainly targeting non-primary goods and services. Conversely, a cash shortfall contributes to limiting consumption even in essential business sectors, where material deprivation issues clearly emerge for poorer individuals.

5.3. The impact of consumption on COVID-19 contagion

In the previous section, we tested the effectiveness of differentiated restrictions on consumption. Here, we analyze the interplay between consumption and contagion, which is further developed in the epidemiological modeling framework presented in the next section.

We apply a panel negative binomial regression model in which the dependent variable is the number of new daily infections in each province as a function of *Policy Persistence* and *Consumption*. In Table 3, model (1) considers aggregate consumption across all sectors, models (2) and (3) exclude or consider only the Retail sector, while model (4) includes both Retail and aggregate consumption across all other sectors. Our estimate shows that, during the period of differentiated restrictions, a generalized increase in consumption significantly contributes to contagion ($\beta = 0.261$, S.E. = 0.017). This first relevant finding unveils the importance of consumption patterns when studying the dynamics of contagion.

Interestingly, when only the Retail sector is considered, the impact of consumption is stronger (model 3, $\beta = 0.289$, S.E. = 0.020) than when excluding such expenditures from aggregate consumption (model 2, $\beta = 0.198$, S.E. = 0.009), indicating how highly frequent human interactions occurring in retail activities are likely to impact new infections. This result underlines the importance of controlling for the dynamics of consumption at the sectoral level. Model (4) corroborates the pivotal role of Retail, which exhibits a positive and significant impact on contagion ($\beta = 0.275$, S.E. = 0.053). Notice that the coefficient of aggregate consumption across all other sectors is still positive but not statistically significant ($\beta = 0.069$, S.E. = 0.046).

As a robustness check, we have also tested the relationship between the number of new daily infections and consumption by sector with a cross-section of observations at the province level, adding several controls to capture the specific features of the economy at the local level as in Pierri et al. (2023). The analysis confirms the results of Table 3 and is reported in Table S12 in the SI.

Table 3
Impact of aggregate consumption on daily COVID-19 cases.

	Dependent variable: new daily cases			
	(1)	(2)	(3)	(4)
Constant	0.079*	−0.020	0.122 ***	0.224***
	(0.032)	(0.028)	(0.042)	(0.047)
Policy persistence	0.001	0.004	−0.001	0.000
	(0.003)	(0.003)	(0.004)	(0.006)
Consumption	0.261***			
	(0.017)			
Consumption no Retail		0.198***		0.069
		(0.009)		(0.046)
Retail			0.289***	0.275***
			(0.020)	(0.053)
N	4699	4699	4699	4699
AIC	59 382.15	59 812.99	59 220.41	58 600.52
BIC	59 401.52	59 832.36	59 239.78	58 626.34

Notes: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Standard errors in parentheses.

5.4. Effects of targeted restrictions on contagion

We study the evolution of contagion with a SEIR metapopulation model: susceptible individuals are exposed to the virus, eventually becoming infected and spreading contagion inside their own communities (Italian municipalities) until recovery. The introduction of restrictions reduces or eliminates the movements of individuals, isolating the communities. However, movements for consumption reasons are allowed in specific sectors, as depicted in Fig. 2C, leading to a spread of contagion across communities from individuals shopping in the same places (red squares on the map in Fig. 2E).

To assess the role of targeted restrictions in reducing contagion, we first report the results of fitting the epidemiological model with the observed data. Fig. 5 reports results for the region of Lombardia, while results for the regions of Lazio and Campania are reported in Figures S7 and S8 in the SI. By comparing the week before the introduction of restrictions and the last week of our sample, we observe a considerable reduction in the total number of weekly cases: in Lombardia they decrease from 56.4k to 23.2k (a −58.78% decrease), in Lazio they shift from 17k to 12.1k (−29.21%), and in Campania they move from 27.0k to 11.6k (a −57.54%).

In Fig. 5A we observe the performance of the model when using the full sample of observations (we report results for the out-of-sample evaluation in the SI) to predict the daily number of confirmed cases. We notice that the model obtains a good fit across regions, with 66.67% of daily observed cases within the 95% confidence interval of the simulations in Lombardia, and likewise for Lazio and Campania (76.67% and 75.00% observations inside 95% CIs, respectively). The key lesson learned here is the remarkable effect of restrictions across regions, which provides support to our second research hypothesis. As a robustness test, in the SI we replicate these results for also two more Italian regions, Veneto and Tuscany, confirming these findings (see Figure 10 in the SI).

5.4.1. The role of mobility

The findings in Fig. 5A show that our model accurately fits the evolution of confirmed cases using mobility flows as the only input. We further explore the interplay between mobility and contagion by simulating several counterfactual scenarios, for which we provide results in Fig. 5B. We run separate models where mobility flows are rescaled by different percentages. Specifically, we consider scenarios where mobility is 10%, 50%, 150% and 200% of the actual mobility level in 2020, as well as a model that uses mobility observations from 2019. We observe that in the absence of restrictions (*i.e.*, using 2019 movements as a counterfactual) mobility in Lombardia would have been close to 150% of the observed 2020 levels, while for the regions of Lazio and Campania the ratio is below 150%, signaling a milder effect of less stringent restrictions in line with what is shown in Fig. 1. We find that changes in mobility directly affect the cumulative number of confirmed cases, even though not linearly. In Lombardia, for instance, restrictions were more stringent than in the regions of Lazio and Campania, and they prevented up to 10.49% of the infections that would have occurred with the same levels of mobility as 2019 at the end of the analyzed period. Nevertheless, in spite of less stringent restrictions, the region of Lazio avoided up to 8.62% of the infections and the region of Campania up to 6.71% (see Figures S7B and S8B in the SI). On the other hand, a scenario where the central government would have enacted even more stringent restrictions than those actually applied in 2020 (*e.g.* relying on a 90% reduction of mobility), would have led to a contraction of infections of 23.29% in Lombardia (around 26.28% in the region of Lazio and 16.68% in the region of Campania, see Figures S7B and S8B in the SI), confirming the nonlinear relationship between mobility and new cases.

Overall, such results reveal the importance of targeted mobility restrictions for effective pandemic control, corroborating our second research hypothesis and providing further evidence in favor of data-driven decision-making.

5.4.2. The role of territorial differences

Before the implementation of restrictions specifically targeting regions, the diffusion of contagion exhibited pronounced territorial differences at higher geographical granularity (see Fig. 5D for Lombardia). For this reason, we test the validity of the model at a lower scale in two of the most populous provinces of Lombardia, namely Milano and Brescia (Fig. 5C). We find a performance that is consistent with the regional results: 70.00% of observations are inside 95% CIs for Milano and 83.33% for Brescia. This underlies that our epidemiological model is able to explain the dynamics of contagion at different levels of geographic detail, with no significant loss of precision.

We then use the simulated outcomes of the best models to analyze the role of all provinces within each region. We decompose the predicted number of new cases by province in Fig. 5E. We observe a gradual reduction in the heterogeneity of new cases per province. In particular, by checking the difference between the initial and final percentages of daily infections, the provinces of Milano and Monza show a decrease in their composite share shifting from 65.22% to 45.37% (a −30.44% growth rate). All other provinces instead exhibit an increase with respect to their initial shares, especially Brescia, Mantova and Sondrio. Their composite share shifts from 34.77% to 54.62% (a 57.10% growth rate). These results confirm that territorial differences are indeed addressed by restrictions, which balance the relative contribution of provinces within regions.

The results for the other two regions confirm the precision of the model in predicting contagion at the province level (see Figures S7C and S8C in the SI): 91.67% and 80.00% of observations are inside 95% CIs for Roma and Latina, and 90.00% and 91.67% of observations are inside 95% CIs for Napoli and Salerno. Furthermore we find that in the region of Lazio, similarly to Lombardia, restrictions have reduced the contribution to contagion of the provinces that were initially more important (Roma and Viterbo, whose total share shifts from 77.06% to 67.36%) in favor of the other provinces (Frosinone and Rieti, from 22.94% to 32.64%) (see Figure S7E in the SI). In the region of Campania we observe a slightly lower reduction in the contribution to contagion of the most important provinces (Napoli and Caserta, whose total share shifts from 74.63% to 71.12%) compared the other provinces (from 25.37% to 28.88%) (see Figure S8E in the SI).

5.4.3. The role of spending categories

Previous analyses have highlighted the relevant role of sectors in explaining the heterogeneous economic impact of restrictions. The effect on contagion of NPIs targeting specific sectors, however, is not immediately evident due to the fact that the virus in our model spreads through two different channels, a local contagion inside communities and an external contagion through visits to POSs. As a consequence, the effect of targeted restrictions will not be exactly equal to the variation in movements reaching specific POS categories and should be assessed separately. Fig. 5F shows the contribution of different sectors to the contagion in the Lombardia region. We immediately observe that the Retail sector accounts for the large majority of the infections, with percentages above 85% in all observations.

Furthermore, we can see an evolution in the contribution of sectors to new infections that is consistent with regions entering or exiting targeted restrictions (see Fig. 1). For instance, as of the 6th of November, Lombardia is immediately classified in the high-risk regime (red) and experiences a steep reduction in the contribution of all sectors excluding Retail: other sectors accounted for 6.77% of infections before restrictions and their contribution is reduced to 3.46% after restrictions. However, in the last week of November the region shifts towards a less stringent tier (orange), which coincides with a reduction of the contribution of Retail in favor of other sectors whose contribution increases from 3.46% to nearly 4%. A slightly increasing pattern in the contribution of Retail is observed in the Campania region from 96.25% to nearly 97% (see Figure S8F in the SI), corresponding to a shift from the yellow to the red tier in mid-November. Finally, the Lazio region stays in the yellow tier for the entire period, consistently maintaining the same distribution of cases by sector over time (see Figure S7F in the SI) with a contribution to new cases of the Retail sector around 94%. Such patterns may be justified by the high concentration of essential activities within the Retail sector.

On the contrary, when considering sectors different from Retail, regions exhibit a heterogeneous sectoral contribution to new infections. Given that all three Italian regions were subject to a reduction in contagions after the 6th of November, such a result confirms that the differentiation of restrictions is effective in reducing the spread of contagion, independently of the local economic structure.

5.5. The role of online consumption

We analyze two main aspects of online transactions. First, as shown in Figure S2 of SI, the contribution of sectors to the overall consumption differs between the online and offline channels, and variations exhibited in 2020 are stronger and more persistent in the online channel. This suggests that the shift from in-person to digital purchasing is not limited to Retail.

Fig. 6A shows the variation in online consumption, compared to 2019, both in the number (left-hand side) and the value (right-hand side) of transactions, for several sectors. All of them exhibit an increase in the share of transactions made online (average variation: +175.00%) and their value (average variation: +165.07%), with a few exceptions.

The significant shift from offline to online consumption indicates a relevant change in consumers' behavior due to the COVID-19 pandemic, which has not only economic implications but also epidemiological consequences. In fact, digital purchases should reduce movements and physical interactions, reducing the overall risk of contagion.

However, in practice, two factors may hinder this phenomenon. First, several online purchases might still require physical interactions (see for instance Human health activities in Fig. 6A). Secondly, not all services can afford to transition entirely online without suffering costs and losing customers. The growth of online consumption is indeed a consequence of stringent mobility restrictions. Since targeted policies aim to contain the spread of the virus without disrupting consumption habits of individuals, it
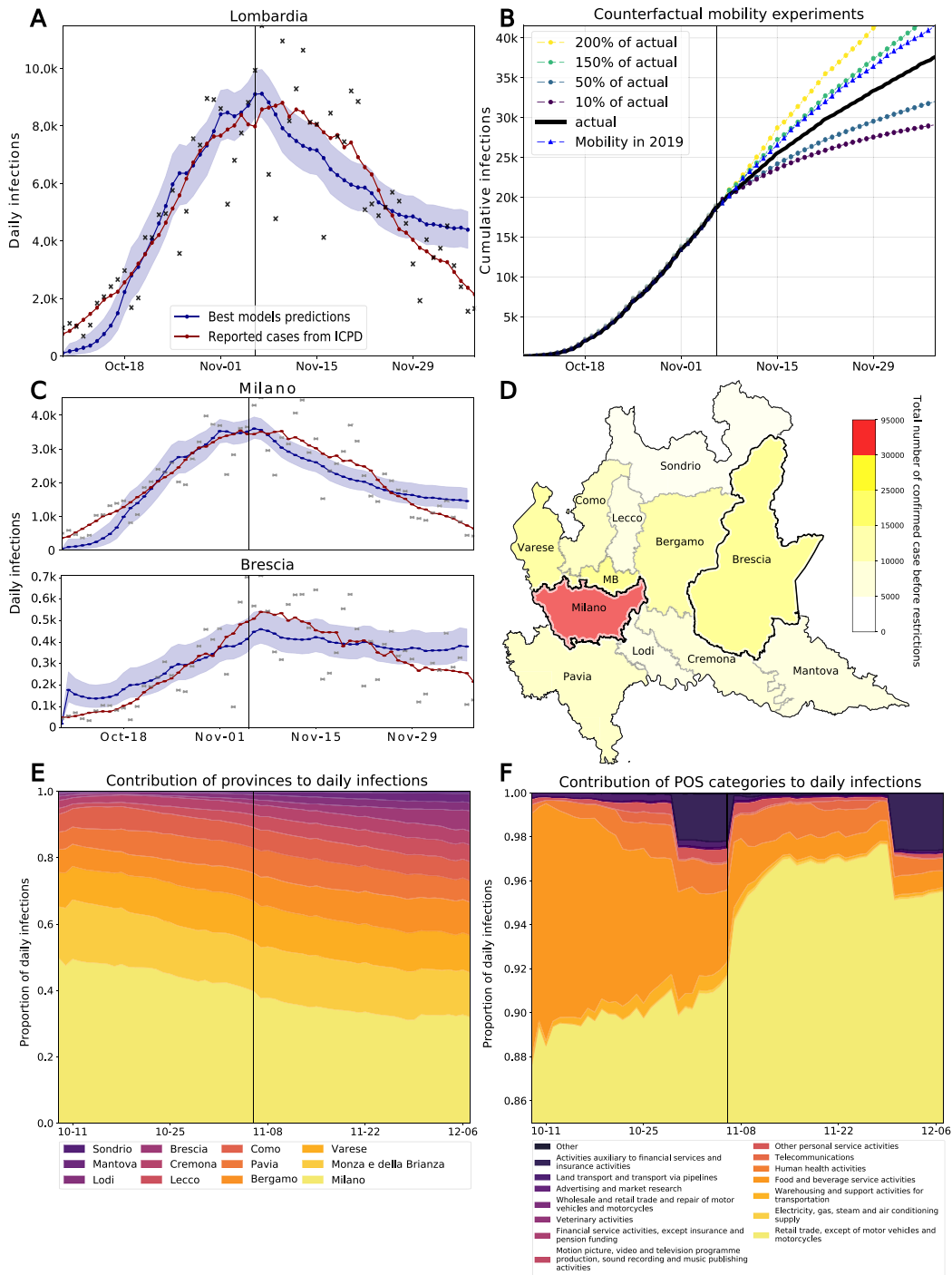
Fig. 5. A: performance of the epidemic model in predicting the number of daily confirmed cases reported by ICPD during the targeted restriction phase for the region of Lombardia. Scatter plot reports observed cases, red line reports the 7-day moving average of reported cases, blue line reports the average of all best models with their confidence interval. **B**: cumulative number of new cases for counterfactual mobility scenarios where mobility flows for the period post-restrictions have been replaced with rescaled flows or with the 2019 flows. MB: Monza e della Brianza. **C**: performance of the epidemic model during the targeted restriction phase for the two most populous provinces inside the region of Lombardia. **D**: distribution of the cumulative number of cases by province in Lombardia at the start of restrictions. **E**: percentage contribution of the provinces in Lombardia to the daily number of new cases for the period of consideration, 7-day moving average. **F**: percentage contribution of specific sectors to the daily number of new cases for the period of consideration, 7-day moving average. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

is reasonable to assume that physical transactions progressively return to values close to their pre-pandemic level. For instance, the Italian Government adopted in December 2020 a cashback policy for in-person purchases only, providing a partial reimbursement to physical transactions made with credit/debit cards.

Therefore, we investigate how a return to in-person purchases contributes to the contagion by means of several counterfactual experiments. Specifically, we increase the mobility of sectors shown in Fig. 6A by 10% and 50%, simulating less stringent policies that reopen only specific sectors while maintaining the same level of restrictions for the others. To assess the epidemiological impact of this strategy, we measure the difference in the number of new confirmed cases compared to a baseline in which mobility does not change. We show results separately for Retail, Human Health activities, and all other sectors but Retail and Human Health activities (Other Sectors) in Fig. 6B. In all regions, we notice that the number of confirmed cases is only slightly affected by the reopening of Human Health activities or Other Sectors. On the contrary, the reopening of Retail entails a significant increase in newly confirmed cases both for a +10% (average median value across regions: 932.94) and +50% change (average median value across regions: 4724.62).

Finally, comparing panels A and B of Fig. 6, we obtain a clear picture of the interplay between online consumption and mobility restrictions. Given that some sectors exhibit a reduced propensity for online consumption and, at the same time, an increase in their physical transactions does not lead to a resurgence of new cases, policymakers might encourage a return to in-person purchases through less stringent restrictions. On the other hand, the good propensity for online purchases in Retail, a relevant sector for the spread of the contagion, suggests that regulators could apply more stringent restrictions to limit the spread of the virus without incurring economic losses.

6. Discussion

The scientific and political debate surrounding the introduction of NPIs against COVID-19 has drawn increasing attention to the need for mitigating the socioeconomic impact while preserving public health objectives. As a consequence, national governments differentiated their approach by calibrating the stringency of interventions according to the severity of contagion in specific territories and sectors.

We contribute to this debate with a retrospective analysis that demonstrates the effectiveness of targeted restrictions through a combined estimation of the economic and epidemic consequences they entail. Our findings provide a set of lessons learned that can inform the design of policies supporting household consumption during future crises management.

Using Italy as a case study, we show that the alignment of the stringency of containment with the severity of contagion penalizes to a lower extent the working and consumption habits of individuals in areas less affected by the virus, contrary to one-size-fits-all approaches (Bonaccorsi et al., 2020; Pierri et al., 2023). We find that, in areas moving from more to less stringent restrictions, the Y-o-Y variation in economic consumption shifts from −31.5% to −21.9% in the Transportation sector, from −60.7% to −44.0% in the Accommodation sector and from −74.1% to −44.6% in the Restaurants sector. A smaller reduction in the Y-o-Y variation in economic consumption is observed in the Retail sector (between −25.0% and −12.1%), which is likely due to the high proportion of essential business activities.

At the same time, we demonstrate that targeted interventions are effective in stopping the spread of the virus and do not jeopardize public health objectives in favor of economic outcomes, contrary to "laissez-faire" strategies (Acemoglu et al., 2021; Alvarez et al., 2020; Farboodi et al., 2021). We find that targeted restrictions are generally effective, with a −10.49% reduction in the total number of cases in the region experiencing the most stringent policies (Lombardia) and a −8.62% reduction in the region experiencing the least stringent regime (Lazio). In general, the impact of these restrictions is lower than the one estimated during generalized lockdowns (Gatto et al., 2020). However, the direct comparison between the two impacts is complicated by several factors. First, the content of restrictions in the two phases does not coincide: on the one hand, there is partial overlap between lockdown and the most stringent regime of the differentiated restrictions phase, while, the official definition of infected individuals has been updated over time affecting the intervention criteria. Second, the awareness of individuals has changed after the first phase of generalized restrictions, due to the greater diffusion of information regarding contagion and as a reaction to previous restrictions. Finally, the timing of interventions has changed, with targeted interventions being implemented in a more developed phase of contagion.

Our analysis leverages a unique dataset of granular transaction data, provided by a major Italian bank, which covers the specific dimensions targeted by NPIs, namely territories and economic sectors. The novelty of our approach lies in extracting information both on individuals' consumption and mobility behavior under restrictions, with high-frequency and multiple levels of geographical aggregation.

Measuring individuals' movements in near real-time provides a strategic source of information to policymakers during public crises. Granular mobility data enhance the predictive capability of epidemic models, allowing them to depart from inaccurate assumptions on the mixing behavior of individuals (Bansal et al., 2007; Balcan et al., 2009; Brockmann and Helbing, 2013) and helping to design effective policy interventions. Indeed, during the COVID-19 crisis mobility data have become a fundamental tool for pandemic monitoring and management (Grantz et al., 2020). This was fostered by the increasing availability of mobility measurements from different data providers: national governments (Gatto et al., 2020), mobile phone companies (Schlosser et al., 2020; Badr et al., 2020), social networks such as Baidu (Kraemer et al., 2020) and Facebook (Kissler et al., 2020; Scotti et al., 2022; Maas et al., 2019) and finally other companies collecting geolocalized data from their users such as Google (Fernández-Villaverde and Jones, 2020), Apple (Nouvellet et al., 2021), SafeGraph (Chang et al., 2020) and Cuebiq (Aleta et al., 2020).
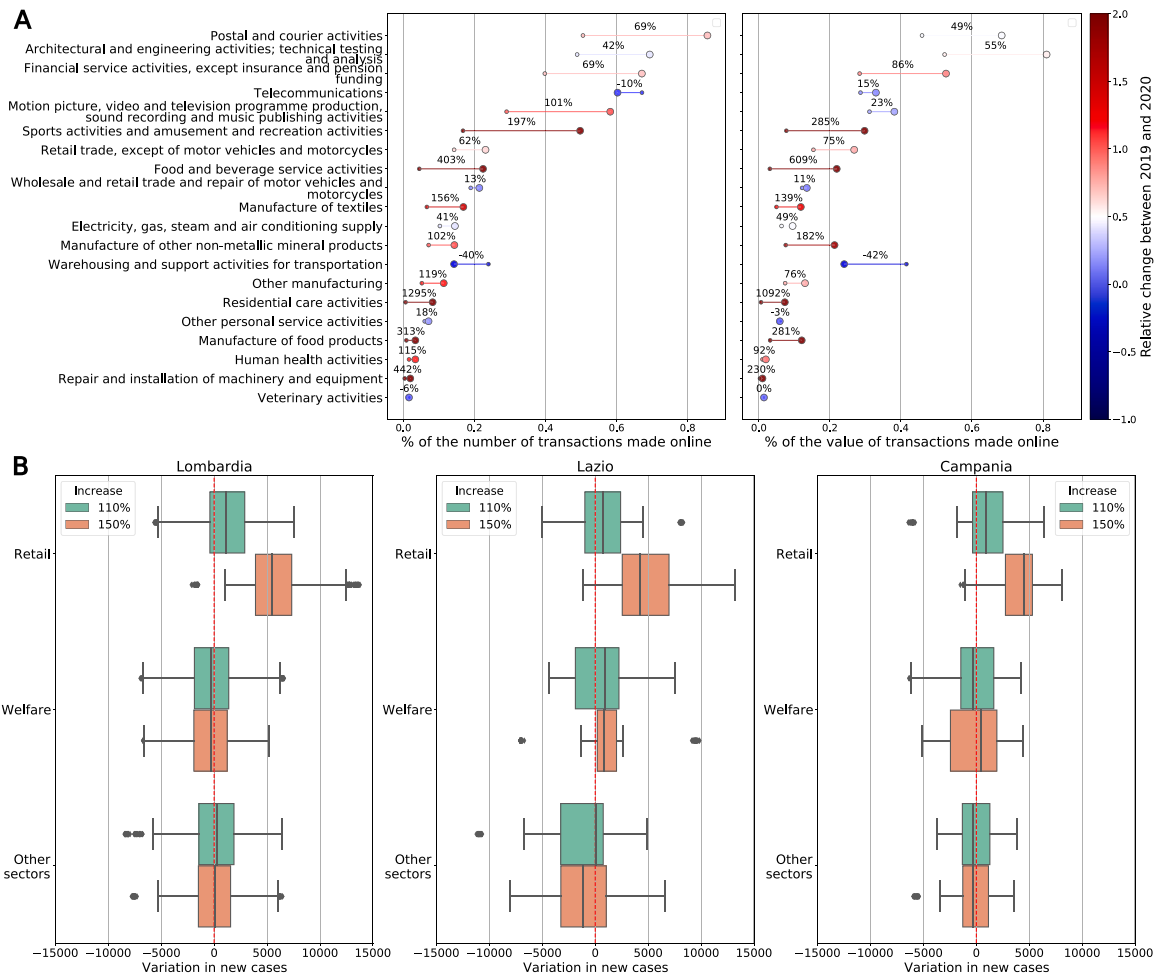
Fig. 6. Panel A: evolution in the share of total consumption made online compared to 2019, by category. Left plot: total value of transactions, right plot: total number of transactions. Each line represents the variation in the share of online consumption for a certain sector from 2019 (smaller sized points) to 2020 (bigger sized points). The line color is mapped to the relative growth of the share which is reported above the line. **Panel B**: boxplot of the impact on the number of new cases of an increase of 10% (green boxes) or 50% (orange boxes) in mobility in selected sectors. Since results are calculated for all best models selected via grid search and analyzed in Fig. 5 we do not obtain only a single value of newly confirmed cases but a distribution of estimates. The difference between the 10% and 50% boxes are evaluated with a Kruskal–Wallis test and are statistically significant at a significance level of 1% only for the Retail sector. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Notwithstanding the relevance of these results, our findings indicate that human mobility should be integrated with detailed observations on the socio-economic implications of such events. On the one hand, having access to individuals' movements and socio-economic characteristics allows better estimation of the effect of restrictions on limiting the contagion, as suggested in recent literature (Badr et al., 2020; Buckee et al., 2021). On the other hand, measurements of economic activities enact complementary analyses on the trade-off between epidemic and socio-economic consequences. In this work, we employed a proxy of interpersonal contacts data measuring movements associated with consumption instead of relying on commuting mobility flows (provided by Facebook (Maas et al., 2019) or from official statistics (Gatto et al., 2020), for instance). This reduced our capacity to precisely measure individuals moving to workplaces, but at the same time it allowed us to better track the evolution of consumption and contagion in response to interventions targeting specific economic sectors.

Our work has some limitations. First, our epidemiological framework is tailored to model individuals' movements, and it does not explicitly account for NPIs that do not impact directly human mobility, such as mask mandates and vaccinations. Second, our data describe movements associated with consumption and cover only partially mobility for other purposes, *e.g.*, commuting to school and work or leisure activities. Third, we only evaluate the short-run effects of restrictions, thus neglecting long-term implications. Fourth, due to the lack of data on the positivity rate during the period of analysis, we cannot exclude the presence of measurement error in the official number of infected individuals due to the partial coverage of epidemic testing. Finally, our data allow us to measure the impact of restrictions on consumption without accounting for potential reductions in the income of individuals. Further work should extend our framework to investigate the interplay between income and consumption in response to targeted restrictions.

Overall, we provide a valuable and flexible tool for policymakers to understand behavioral changes of individuals from an economic and epidemic perspective, underlining the advantage of data-driven and evidence-based analyses during crises.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgments

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2024.05.017.

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