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Quaderno n. 17

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Marco Cosconati, Viviana Medori

Agosto 2021

(decreto legge 6 luglio 2012 n. 95 convertito con legge 7 agosto 2012 n. 135}

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La serie è disponibile online nel sito www.ivass.it

ISSN 2421-4671 (online}

THE EFFECT OF UNCERTAINTY ON THE CAR INSURANCE MARKET: EVIDENCE FROM THE COVID-19 SHOCK†

MARCO COSCONATI⋆ AND VIVIANA MEDORI⋆⋆

Abstract. We leverage on a high-frequency (daily) panel data set covering the period 2014–Q2:2020 at the province level with information on auto insurance prices and claims to measure the effect of the COVID-19 (*Knightian*) uncertainty shock on the Italian car insurance market. With a difference-in-difference research design based on variation in the timing of mobility restrictions across Italian provinces we exploit exogenous price variation by sales agents to jointly identify the sign of selection and the lockdown effect on demand and (realized) cost curves. Controlling for pricing variables and seasonality, when compared to a day not subject to any mobility restriction the number of contracts underwritten during the lockdown experiences a short–term 25–28 percentage points reduction and no significant variation in the associated premiums; daily claims payouts gets reduced by about 76 percentage points. In light of the textbook model, we rationalize price rigidity and demand's contraction in terms of behavioral responses to the large uncertainty shock. The cost curve test implies that the market is adversely selected before and during lockdown days.

Keywords: COVID-19, auto insurance, uncertainty, adverse selection.
JEL classification: D82, G22, G52

1. Introduction

The relationships between economic shocks and uncertainty has been largely studied in the last decade. In particular, the rise of uncertainty in response to bad events such as wars and oil-price shocks has been largely documented: hiring, investments and consumers' spending are negatively affected by uncertainty (see Bloom (2014) for a summary of the available evidence). Because there exists a conceptual strong link between uncertainty and risk, the latter being what insurance markets provide hedging from, it is of direct interest to assess how insurance markets react to the COVID-19 shock to learn a more general lesson about plausible short-run responses to other unfortunate events—natural catastrophes—that are insurable and at the same time increase (Knightian) uncertainty.[1] In a recent paper, Harris, Yelowitz, and Coutermanche (2020) examine the COVID-19 effect on the US life insurance offerings; because, surprisingly, no significant effect on premiums has been detected, the authors argue that competition prevented insurers from increasing premiums in response to the higher mortality rates.

†All errors are ours; the views in this paper do not reflect the opinion of the Bank of Italy or IVASS.

⋆ Banca d'Italia and IVASS. Corresponding author: e-mail: marco.cosconati@gmail.com

⋆⋆ IVASS .

[1]In his 1921 book "Risk, Uncertainty, and Profit" the University of Chicago economist Frank Knight makes a distinction between risk and uncertainty. Risk is a situation in which the decision maker is uncertain about an outcome but is able to assign a probability to each event. In contrast, under uncertainty, the decision maker does not hold enough information to compute the odds of the events. Altig, Baker, Barrero, Bloom, Bunn, Chen, Davis, Leather, Meyer, Mihaylov, Mizen, Parker, Renault, Smietanka, and Thwaites (2020) provide evidence of the effect of the pandemic shock on economic uncertainty indicators for the US and UK.

In this paper we use the COVID-19 shock to ascertain the immediate effect of uncertainty on the Italian auto insurance.[2] This market represents an ideal laboratory because, among European countries, Italy has been the first country to be hit by the pandemic shock and strict mobility restrictions have been enforced to contain the virus. At the beginning of the pandemic crisis consumers in this market faced uncertainty about two relevant factors (for insurance decisions): (i) future income prospects and (ii) the intensity and duration of mobility restrictions enforced to contain the virus (see Immordino, Jappelli, Oliviero, and Zazzaro (2021)). Uncertainty about income/wealth affects the willingness to pay for insurance once we introduce liquidity constraints within a dynamic consumption–insurance models (see Ericson and Sydnor (2018)) while uncertainty about (ii) reduce the value of car usage and in turn of insurance. Uncertainty also affects the supply side in different ways. First, the inability to predict demand at any given price due to uncertainty can generate price rigidity (see Ilut, Valchev, and Vincent (2020)). Secondly, insurance rates are set *before* claims cost realize using predictions based on historical data and on expectations about the aggregate macro variables. In the absence of information on the new mobility patterns, traditional pricing models cannot deliver actuarially fair rates, leading risk neutral insurers to make pricing decisions under ambiguity.[3] In this situation a standard minimax criterion would intuitively suggest to set prices consistently with recent claims payout because decreasing premiums could lead to losses if the cost of accidents does not fall accordingly.[4] Finally, insurers might wonder whether the pre-COVID selection pattern remains unaltered; namely, it is possible that mobility restrictions change the composition of potential demand leading to a selection reversion effect, e.g. from adverse to advantageous selection.

We adopt the graphic approach by Einav, Finkelstein, and Cullen (2010) (EFC) to illustrate the mechanism through which mobility restrictions influence the equilibrium outcomes in the presence of uncertainty. The comparative statics of the textbook model imply that if insurers were to correctly anticipate claims payout reduction both the number of contracts and premiums would be reduced—not adjusting rates downward would lead to loose market shares—while the magnitude of these reductions depends on the (relative) slope of the cost curves and on the sign of selection. However, in the presence of adverse selection if insurers react to uncertainty by setting rates consistently with pre-COVID costs (equilibrium) premiums increase and the fraction of covered drivers gets reduced to a lower extent relative to a rational expectation situation. In the presence of advantageous selection a similar effect on the number of underwritten contracts arises but uncertainty leads to a price decrease. By exploiting novel price variations, we test for the presence of *market-wide* adverse/advantageous selection before and during the implementation of lockdown interventions and we evaluate these predictions—we estimate the (causal) lockdown effect of premiums, claims, and contracts—using rich data on auto insurance contracts underwritten in Italy

[2] Henceforth the term uncertainty is a shortcut for Knightian uncertainty or ambiguity.

[3] Auto insurance prices are pro-cyclical because during recessions consumers substitute car with public transportation thereby reducing accidents frequency. Traditionally, it is thought that insurers use observable risk factors to predict frequency and not the severity of accidents. If this is the case premiums should be reduced in response to mobility restrictions. The overall effect of mobility restrictions on per-contract claims payout is ex-ante ambiguous both qualitatively—fewer accidents were expected to occur during lockdown days but a lower number of circulating vehicles could lead to more severe accidents—and quantitatively.

[4] Sautua (2017) shows through an experiment that inertia—the tendency to keep the status quo—arises in the presence of ambigity.

in the period 2014–Q2:2020.

We exploit a large and representative micro data-set on auto insurance contracts that allows us to construct a surrogate panel dataset with information on the average premiums and on the prevalence of the most commonly priced risk factors (policyholder's age, car's characteristics) and contractual clauses at the *day–province* level. We also obtain from another dataset information at the day–province level on claims frequency and size. Our rich (derived) panel dataset, consisting of 257,496 observations, is complemented by indicators on the different interventions enforced by the Italian public authorities, such as school closures and suspension of public activities, as well as announcement indicators. At a descriptive level, our data display a downward trend in the number of underwritten contracts in March and April 2020, as well as a reduction in insurance rates and a dramatic drop in claims frequency after the nation-wide lockdown on March 9, 2020.

Our econometric analysis is articulated in two steps. First, through an event history analysis we measure the COVID-19 effect on prices, claims, and number of contracts. We isolate four critical periods, corresponding to the timing of various interventions during 2020, and we control for seasonality and composition effects. We find that (i) the reduction in the insurance rates observed in the raw data mostly comes from seasonality and composition effects; (ii) controlling for these factors mobility restrictions imply a 50 percent reduction in the number of transactions; and (iii) large reductions (up to 65 percent) in the number of claims took place during the critical periods.

We recognize that this analysis might be affected by correlated unobservables, and we address this problem by leveraging on a difference-in-difference panel data research design. Specifically, we leverage on the staggered adoption of mobility restrictions across Italian provinces and on rich price variations generated by sales' agents discounts to jointly identify the lockdown effect on the (conditional) slope and the intercept of the demand and cost curves. In order to separate out the effect of uncertainty from competition on premiums, we control for the Herfindahl concentration index at the quarter–province level.
We find that, once we control for observable and unobservable pricing variables, restrictions on mobility substantially reduce the overall number of underwritten contracts—the overall effect can be as large as 28 percent—with a 41 percent reduction of contracts covering new vehicles.[5] We find that the enforcement of a lockdown has an economically negligible effect on prices—consistent with the main empirical result by Harris, Yelowitz, and Coutermanche (2020)—and that it reduced accident frequency and claims size by 69 percentage points and 23 percentage points, respectively, translating into a 76 per-contract claims payout (at the day frequency) percentage points reduction.

The small price response coupled with the large claims cost reduction lends empirical support to the importance of *Knightian* uncertainty in shaping the short–run equilibrium outcomes in this market, and suggests that in relatively competitive adversely selected insurance market an uncertainty shock induces price rigidity.[6] The many initiatives by Italian and US insurers aimed at

[5]The larger reduction of new contracts is also due to the fall of sales in the automotive industry. We stress that this estimate represent a short-run response in the sense that policyholders might choose to postpone renewals.
[6]There exists a large body of macroeconomics literature on price rigidity, see Nakamura and Steinsson (2013) for a survey.

discounting ex-post insurance contracts represent direct evidence of the relevance of this channel. Along the same lines, the large negative effect on the number of underwritten contracts can be interpreted in terms of precautionary savings as well as evidence of liquidity constraints.

This paper is structured as follows. In section 2 we describe the evolution of the virus in Italy and the adopted restrictions on mobility, and we show descriptive evidence of their correlation with market outcomes. In section 3 we illustrate how market outcomes would change with and without uncertainty, depending on the sign of selection. In section 4 we describe our data and the institutional environment. In section 5 we describe the results of our event history analysis carried on time-series data at the day level. Section 6 contains our identification strategy and empirical results. Concluding remarks are in section 7.

2. The Spread of COVID-19 in Italy and Restrictions on Mobility

Italy was the first country in Europe to be massively contaminated by COVID-19 in early 2020, and the government intervened to contain the spread of the virus by introducing at its outbreak a nation-based lockdown. The timing of the various interventions, such as school closures and suspension of public activities, was heterogenous across provinces, reflecting differential contagion rates. The first contagion episodes happened in the region of Veneto—in the province of Vo'—and Lombardia. These regions were the first to experience a lockdown involving severe limitations to mobility. In particular, people were allowed to drive within cities only under certain conditions, such as for health or work-related reasons, and drivers were asked to carry a document self-declaring their departure and arrival locations and their reason for circulating. Subsequently, these limitations were removed and people were allowed to circulate within but not across regions. A synthesized description of the chronological sequence of events, taken from Briscese, Lacetera, Macis, and Tonin (2020) (henceforth BLMT), is reported in the appendix.[7] BLMT also contains a graphical description of the spread of the virus in Italy, which we update using recent data in figure 2.

We isolate four critical periods

(1) February 23– March 9: the period between the first lockdown in Veneto and Lombardia and the nation-wide lockdown
(2) March 9– April 1: the period between the first lockdown and the nation-wide first extension
(3) April 1– May 4: the period between the first extension and the beginning of phase 2
(4) after May 4: the beginning of phase 2 and onward

As can be observed in the graph 2 the outbreak of the virus took place in periods 2 and 3, with a peak of COVID-19 cases and related deaths.

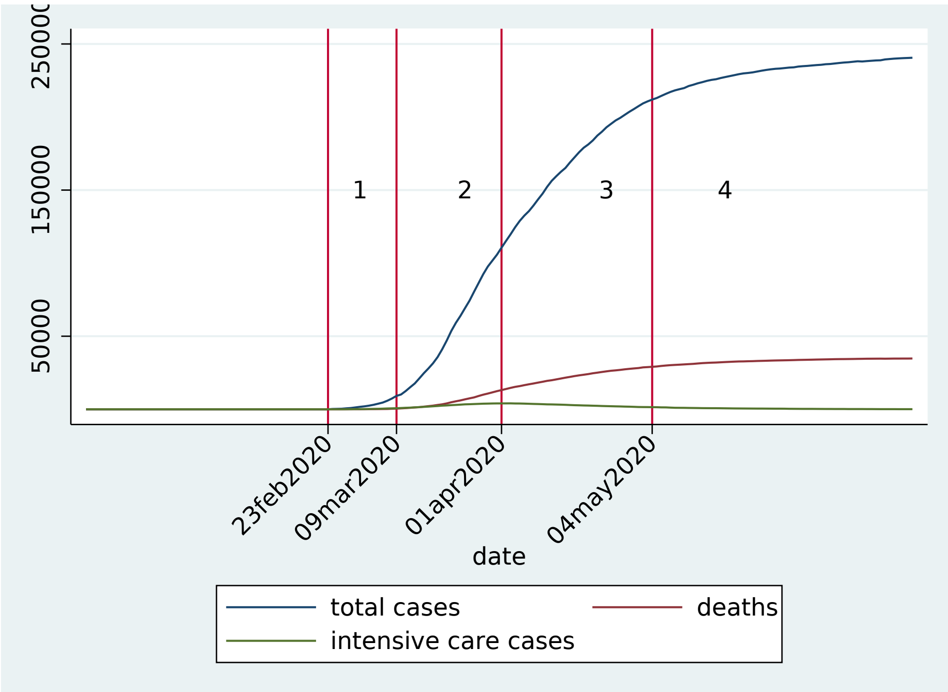
2.1. **Descriptive Evidence.**

We examine the nation-wide time trend of the number of transactions, paid premiums, and number of claims.

Transactions.— From figure 2 it appears that the number of contracts is rather stable from 2014 through 2019, with some seasonal peaks, such as on August 15.

[7]We also verified that the reported interventions coincide with those officially announced on the *Gazzetta Ufficiale*.

Figure 1. Pattern of Cases and Deaths



Note: This chart depicts the time trend of the total number, the number of intensive care cases, and deaths at the national level.

The pattern in 2020 is depicted in figure 3. The chart shows that the number of contracts underwritten drops in period 2 and 5.

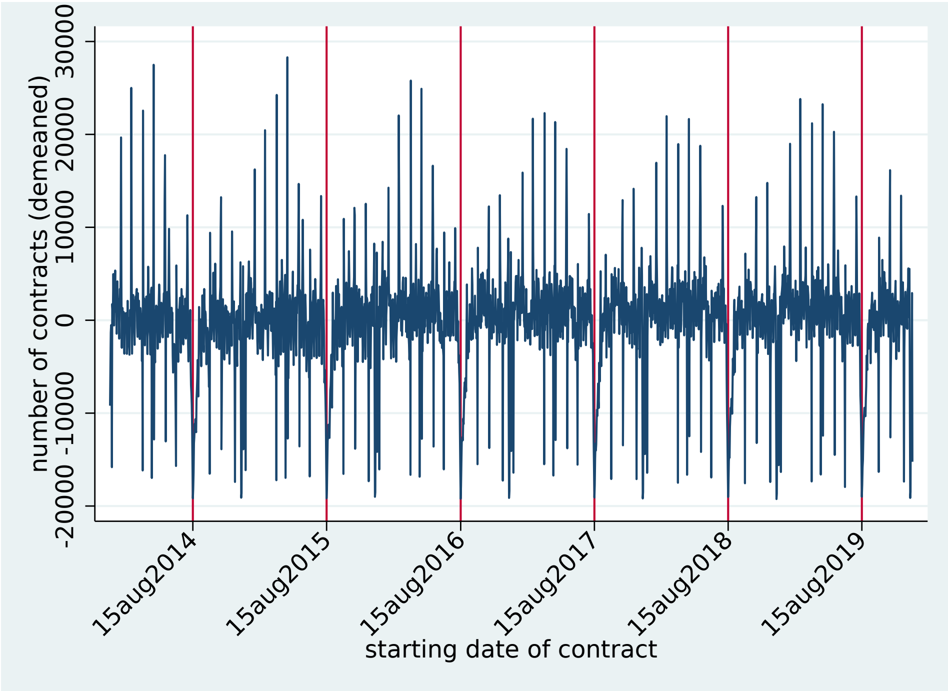
Premiums.— Figure 4 illustrates the pattern of the average auto insurance prices from 2014 through 2019. Insurance prices were curtailed over this period by about 100 euros, corresponding to 20 percent, although the bulk of the reduction happened in the period 2014–2017. There are clear structural changes in the average prices on January 1 and August 15, reflecting the revision of the pricing strategies made by insurers at the central level. Insurance prices display considerable fluctuations within consecutive days as a result of sample noise and sales agents' behavior.[8]

Figure 5 helps us visualize the response of insurance prices to the mobility restrictions by focusing on Q1–Q2:2020. In the very first part of the year, prices fluctuate around the mean until February 23. Premiums were subject to a reduction in period 1—during which some regions in the North suspended events, and a complete lockdown of outbreak areas in Lombardia and Veneto was enforced—and rapidly declined in period 2, when a nation-wide lockdown was enforced. Prices went down until April 1, when a lockdown was extended to the whole country (until April 13). After April 1, prices have been relatively stable with some fluctuation around the mean.

Claims.— As can be seen in figure 6, the number of accidents—we use the terms claim and accident interchangeably—drops by about 80 percentage points after March 9, the start date of the lockdown, until May 4, the beginning of phase two. The number of accidents increases after

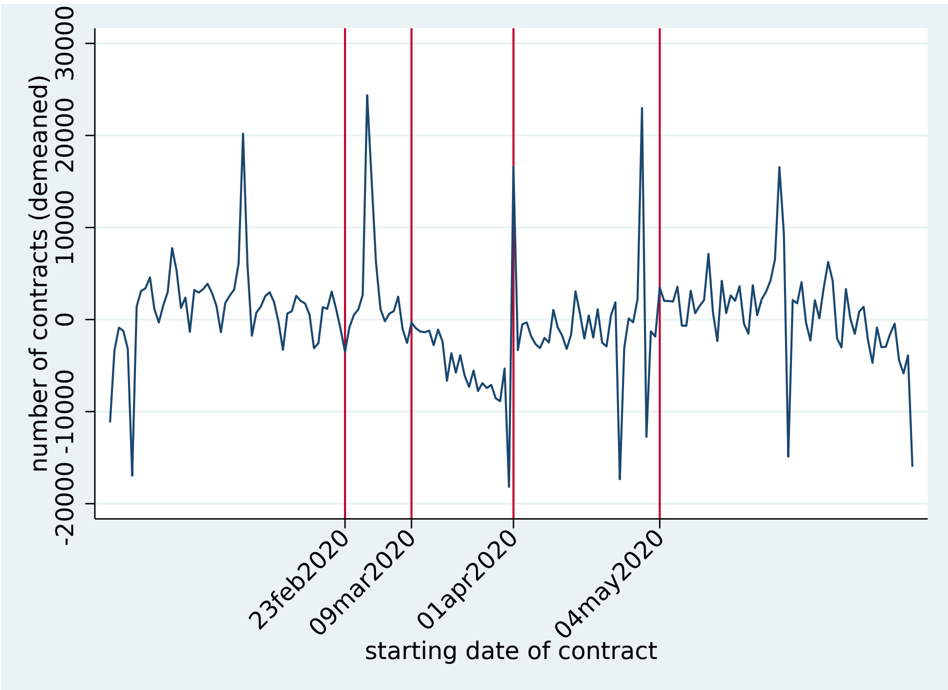
[8]About 90% of the contracts are sold through agents who enjoy a relative amount of discretion in giving discounts to meet sales targets.

Figure 2. Pattern of the Number of Contracts from 2014–2019



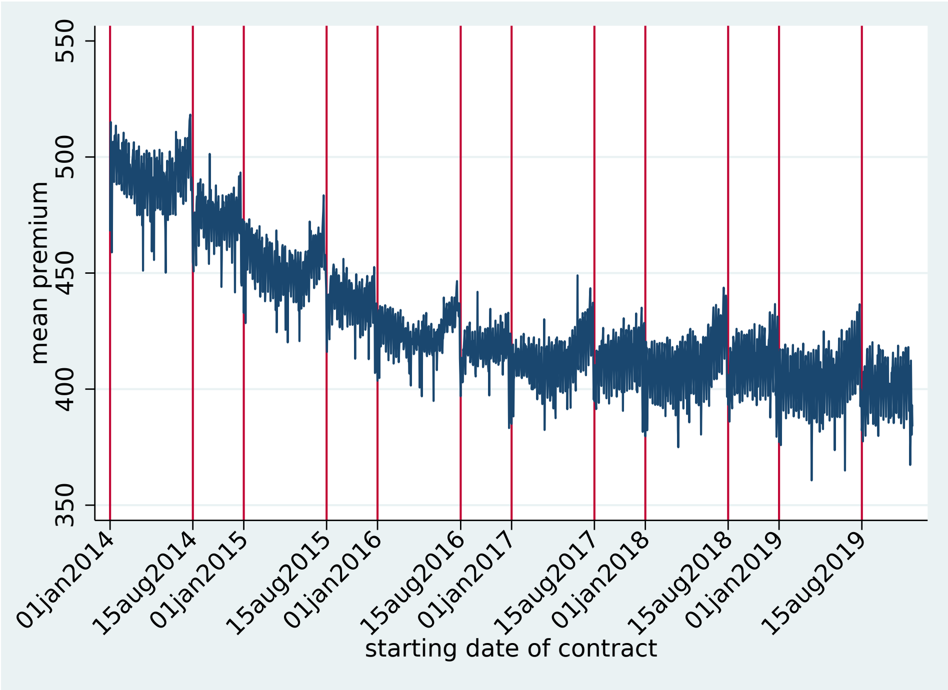
Note: This chart depicts the demeaned number of daily contracts underwritten from 2014-2019 at the national level.

Figure 3. Pattern of the Number of Contracts in 2020



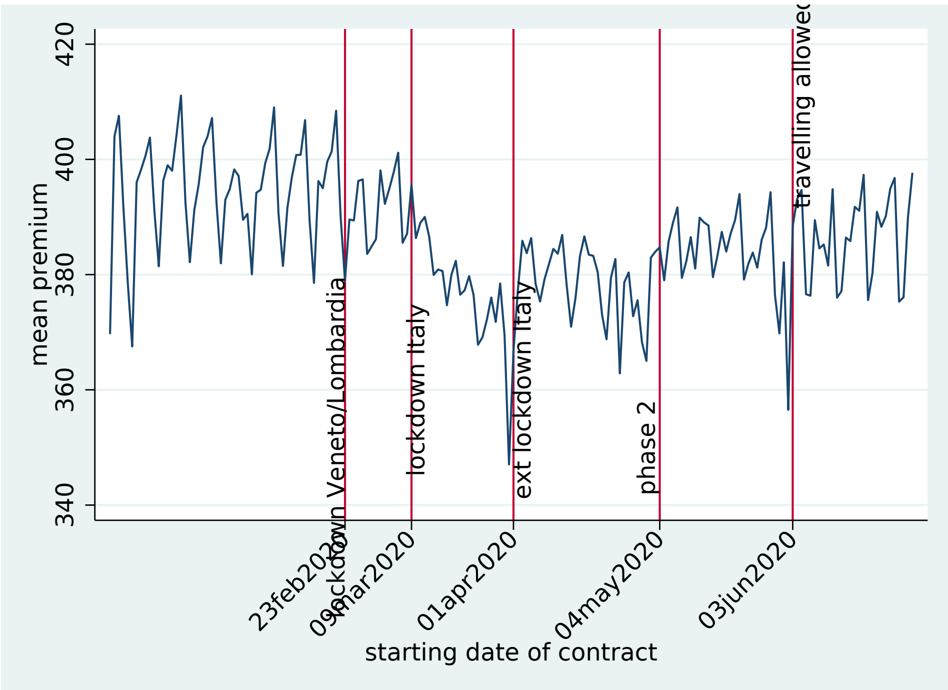
Note: This chart depicts the demeaned number of daily contracts underwritten in 2020.

FIGURE 4. Pattern of Prices from 2014-2019



Note: This chart depicts the average daily premium 2014-2019 at the national level.

FIGURE 5. Pattern of Prices in Q1–Q2:2020

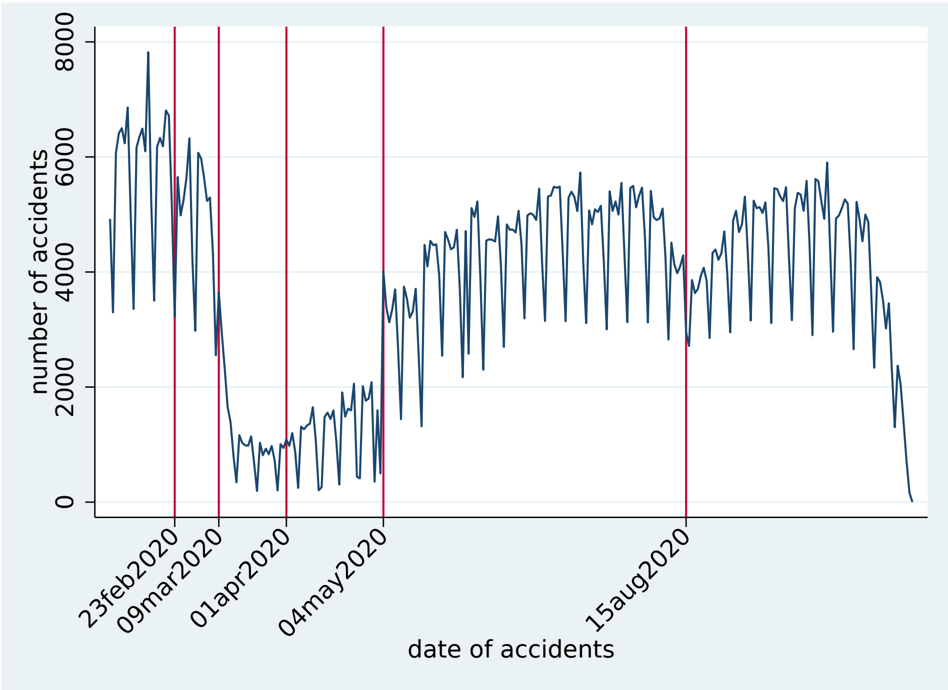


May 4 until August 15 but does not converge to the pre-lockdown period mean.[9] Such a drastic

[9]In order to construct homogeneous groups of claims we disregarded the so-called IBNR, claims filed much later relative to the date of accident.

reduction is not an artifact of the fact that fewer vehicles are insured: figure 7 shows that claims frequency—the number of accidents is normalized by the number of active contracts in the IPER sample—display a similar pattern.[10] These facts provide *prima facie* striking descriptive evidence on the effect of the reduced mobility on the realized claim cost and automatically imply that the unanticipated mobility restrictions generated extra profits on contracts expiring in the second quarter of 2020.

FIGURE 6. Pattern of the Number of Accidents from 2014–Q3:2020



Note: This chart shows the time series of the number of accidents at each date, obtained from the *Banca Dati Sinistri* (BDS), containing the universe of claims filed in the Italian market.

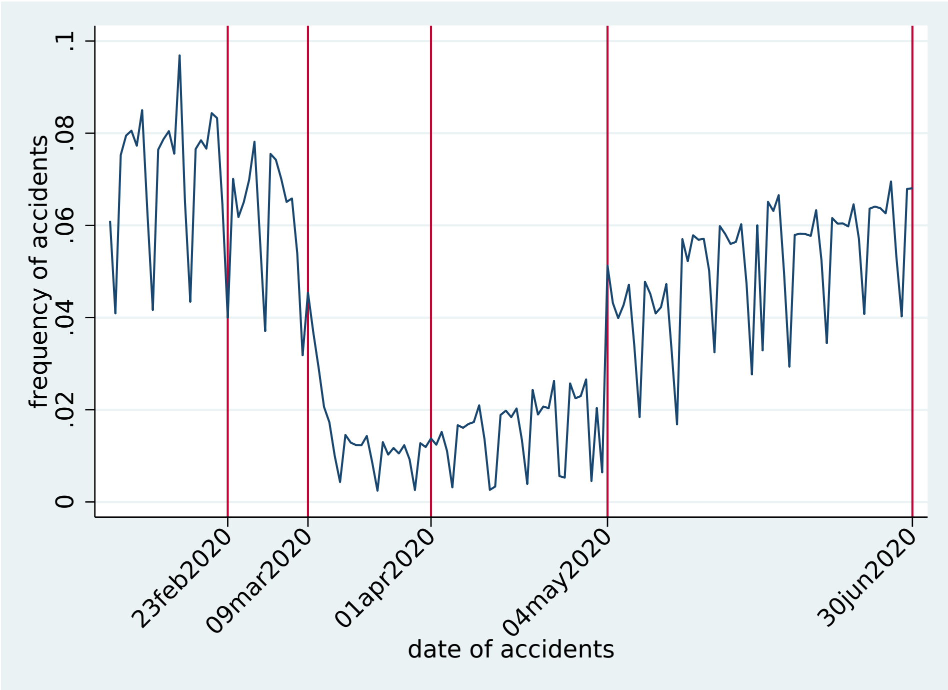
While these pictures illustrate striking variations related to the mobility restrictions, they do not tell us about their *causal* effect. Potential confounders are seasonality and pre-existing trends; moreover, composition effects—variation of the observable pricing variables—could explain the bulk of the observed effects. That is, mobility restrictions could only indirectly affect the share of insured drivers, transaction prices, and claims frequency, by altering demand's characteristics. Before investigating these issues econometrically, we present the textbook insurance model as a tool to elucidate the mechanism through which mobility restrictions affected the market.

3. Textbook Analysis

The graphical approach by Einav and Finkelstein (2011), henceforth EFC, is adopted to illustrate the mechanisms through which mobility restrictions impact the market's functioning. Consumers

[10]Because we use the number of contracts from a sample of about 30 percent of the universe to impute the number of active contracts while the number of claims is obtained from the *universe* of claims the resulting ratio overestimates the accident rate. Nevertheless, this imputation is likely to produce unbiased estimates of the accident rate time trend.

FIGURE 7. Pattern of the Frequency of Accidents from Q1–Q2:2020



Note: This chart shows the time series of the frequency of accidents at each date, obtained by normalizing the number of accidents by the number of active contracts at each date. The number of accidents is obtained from the *Banca Dati Sinistri* (BDS), containing the universe of claims filed in the Italian market.

face two options: no insurance (L)—whose cost is normalized to zero—and a full insurance contract (H). Following EFC, the population is described by a distribution $G(\zeta)$, where ζ captures individual risk factors and preferences. From the perspective of the insurance company, each type generates a claim cost $c(\zeta_i)$. Letting the relative price of insurance be denoted by p, $v^H(\zeta_i, p)$ and $v^L(\zeta_i)$ signify the utility a ζ_i-type receives from each option. Utility is decreasing in p, thereby generating a downward-sloping (individual) demand curve. Consumer i purchases insurance if and only if $v^H(\zeta_i, p) \geq v^L(\zeta_i)$. Consumer-$i$ willingness to pay for insurance (WTP) can be defined as $\pi(\zeta_i) \equiv \max\{p : v^H(\zeta_i, p) \geq v^H(\zeta_i)\}$. Aggregate demand is given by

$$D(p) = \int \mathbf{1}(\pi(\zeta) \geq p) dG(\zeta) \tag{1}$$

The average cost (AC) curve is written as

$$AC(p) = \frac{1}{D(p)} \int c(\zeta) \mathbf{1}(\pi(\zeta) \geq p) dG(\zeta) \tag{2}$$

corresponding to the overall cost of consumers choosing to be covered. The marginal cost (MC) curve at a given price p is given by the cost of consumers whose WTP equals p:

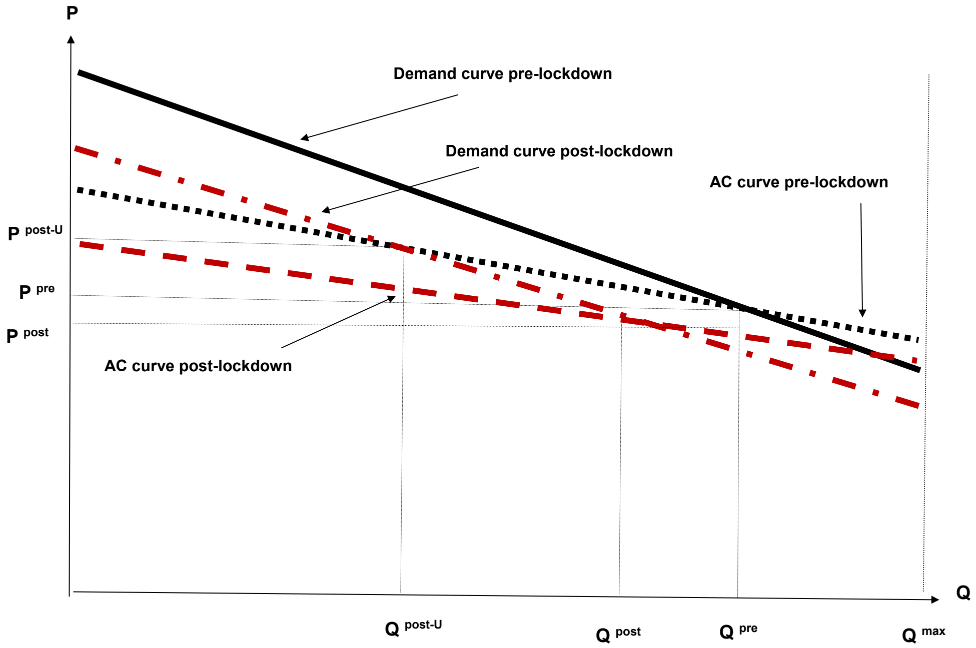
$$MC(p) = E(c(\zeta) | \pi(\zeta) = p) \tag{3}$$

Under some assumptions described by EFC, with perfect competition there exists a unique equilibrium (Q_{eqm}, P_{eqm}) determined by the intersection of demand and the AC curve. Because consumers can only decide whether or not to buy insurance, the equilibrium quantity Q_{eqm} represents the number of insured drivers. In the presence of adverse selection, the MC curve is decreasing because as the price decreases, the marginal consumer buying insurance has lower risk than the inframarginal consumer. For this same reason, the AC curve lies above the MC curve. Insurers cannot observe the individual cost of coverage $c(\zeta)$ due to asymmetric information and therefore use the average cost to price risk. In a perfectly competitive market, the equilibrium (Q_{eqm}, P_{eqm}) is socially inefficient, relative to the first best—a situation in which insurers can observe $c(\zeta_i)$—determined by the intersection of the MC and demand curve. With adverse selection, the well-known situation of under-insurance arises because some consumers with a low WTP and a low risk end up uninsured, while it would be socially efficient to cover them. A symmetric equilibrium outcome arises in the presence of advantageous selection— featuring increasing cost curves—characterized by overinsurance.

Lockdown effects.— Mobility restrictions reduce driving hours and/or the practical usefulness of car usage, as citizens are not allowed to perform certain activities such as shopping in malls and driving children to school. As a result, a natural consequence is that for every type ζ WTP $(\pi(\zeta))$ is reduced, i.e. the demand curve shifts down; it is also likely that the demand curve rotates, capturing the fact that the private valuation of insurance is heterogeneous in the population. An outward shift of demand could also arise due to a substitution effect—people could feel uncomfortable relying on public transportation, leading to increased car usage—or driving could become more enjoyable due to a lower (anticipated) congestion level. We are skeptical, however, about the quantitative importance of these channels, and mobility data on driving habits clearly show that distance driven dropped dramatically during lockdown periods.

We translate these arguments into action in figure 8. As a result of the downward shift of all three curves, the post-lockdown equilibrium features a lower number of insured drivers ($Q^{pre} > Q^{post}$) and a lower equilibrium premium ($P^{pre} > P^{post}$). Whether the new equilibrium generates a higher or lower deadweight loss—the area of the triangle CDE in figure I in EFC—is ambiguous ex-ante: the inefficiency from underinsurance could be exacerbated or ameliorated, depending on how much the demand curve shifts down (and rotates) relative to the AC curve. In this figure we analyze an analogous situation, and we focus on the extreme case in which the AC curve does not move, capturing insurers' *uncertainty.* This could happen because insurers are caught by surprise by the mobility restrictions and are unable to update their actuarial methods in response to this extreme event. In this situation—and in all cases in which the AC curve shifts down by little—the equilibrium price increases ($P^{pre} < P^{post-U}$) and the fraction of covered drivers decreases by a larger extent relative to the rational expectation situation ($Q^{post-U} < Q^{post} < Q^{pre}$). Again, it is ambiguous whether mobility restrictions are welfare improving: if $D(p)$ shifts down without rotating as much, the deadweight loss measured by the area CDEF shrinks, generating a welfare gain. If the slope of the demand curve also changes the deadweight loss could in principle decrease.
All in all, with adverse (advantageous) selection, the post-lockdown number of underwritten contracts unambiguously decreases (increases) while the effect on prices is undetermined and depends on the relative response of insurers' predicted claims costs to the lockdown.

FIGURE 8. Lockdown Equilibrium Effect with Adverse Selection

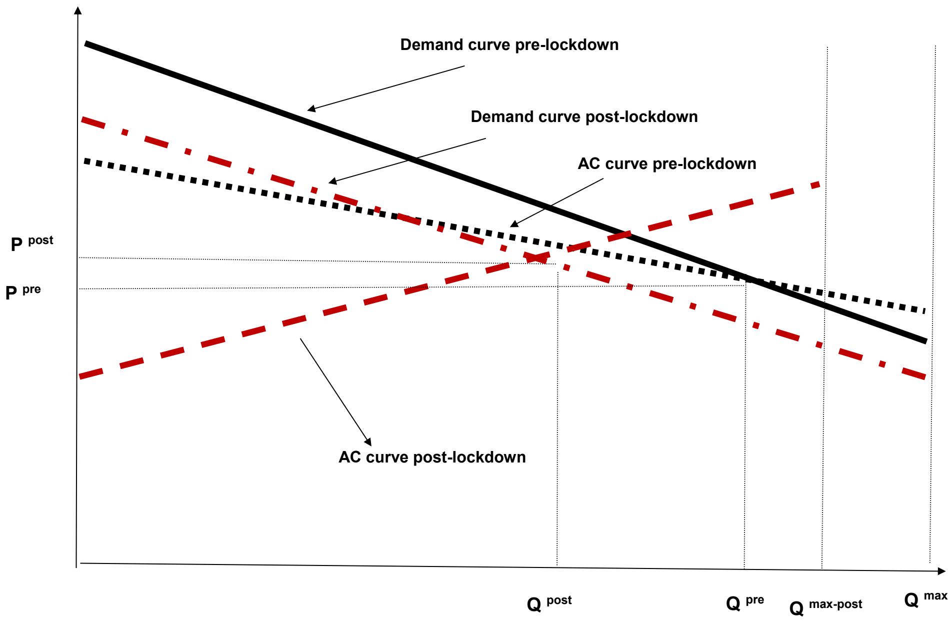


Selection reversion effects.— One intriguing possibility is that mobility restrictions change the sign of selection. As an extreme example, let the pre-lockdown market be adversely selected. Upon introducing mobility restrictions, only workers who cannot perform their activities from home need to use the car (commuters), while non-commuters decide not buy insurance regardless of the premium, namely they are perfectly inelastic. As a result of this selection effect, potential demand during the lockdown period is represented by a subset of consumers who are responsive to price variations. If advantageous selection is at play within commuters and cost curve monotonicity is preserved—this is a maintained assumption in EFC—mobility restrictions effectively change the sign of selection. This situation is depicted in figure 9: mobility restrictions reduce potential demand ($Q^{max} < Q^{max-post}$), the demand curve both rotates and shifts down, and the AC curve becomes increasing. Even if insurers anticipate this variation in demand's composition, the overall effect on prices and quantities is theoretically ambiguous. It seems implausible, however, that insurers are able to predict the distribution of risk preferences within the new post-lockdown potential demand and anticipate the selection reversion effect.

4. Data and Institutional Background

The original dataset we build our analysis on is called IPER, *"Indagine per la Garanzia Effettiva RC Auto"*, and it comprises information on about 58 million auto insurance contracts (at the individual level) underwritten in Italy over the period 2014-Q2:2020. This large administrative dataset consists of a sequence of 2 million contracts underwritten at each quarter, out of about 6 million contracts underwritten at each quarter in Italy. The unusually large sampling rate of about

Figure 9. Lockdown Equilibrium Effect with Reverse Selection Effect



30% and the size of the original sample allow us to obtain precise mean estimates of the variables at the province-day and nation-day level. The sampling scheme is described in the appendix.

The data give us information on the premium and its components, on several contractual clauses, on the policyholder's driving record, and on her personal/vehicle characteristics. Contracts feature a number of clauses that link the size of the indemnity and/or the current/future premium to the occurrence of specified conditions. The data provide information on the most common clauses, including the liability limits (see the appendix), and two omitted clauses indicators: insurers are asked to report whether the contract features clauses other than the ones explicitly reported that increase or decrease the premium. The increasing/decreasing clauses indicators act as a *sufficient statistic* for the presence of missing clauses. Furthermore, we augment the data with information on the Herfindahl concentration index (at the province–quarter level), on the market shares held by insurers selling contracts online/by phone and through banks, density of population, and the fraction of small and medium towns (at the province level).

From the micro data in IPER we construct two datasets at the nation-day level and at the province-day level covering the period 2014–Q2:2020. That is, at each starting date of the contract, we compute means of premiums, contractual clauses, and policyholder and car's characteristics. IPER does not contain direct information on claims. We complete the data by obtaining this information from the *Banca Dati Sinistri* (BDS), containing the universe of claims filed in the Italian market. We obtain information on the number of accidents that happened at each date, the indemnities received from accidents not at fault and the amount corresponding to third parties associated with accidents at fault.[11]

Italian law establishes that vehicles must be covered by basic *rc auto* insurance (*"Responsabilità Civile Auto"*), a mandatory motor third-party liability insurance contract covering damage to third parties' health and property in accidents where one is *not-at-fault*. An important aspect of the regulation has to do with the mandatory coverage even if a vehicle is permanently parked in the public road or in a garage.

The Italian insurance market–overseen by IVASS, the Italian supervising authority–is large: in 2018, about 31 million *rc auto* contracts were underwritten and over 4 million claims were filed. The Italian system follows the common tort (or fault-based) system in which, by definition, accidents are the result of someone's negligence.[12] All individuals involved in an accident who experience physical damages, with the exception of the liable driver, are compensated by the company covering the liable vehicle. It is possible to purchase comprehensive insurance contracts that cover your property damage ("*Kasko*") and physical damage ("*polizza infortuni*") for accidents when you are at-fault; in practice, however, because of the high prices, the vast majority of contracts only feature the compulsory coverage.

Accidents are characterized by a percentage of fault $x \in [0, 100]$. Someone holds "major" responsibility (*"responsabilità principale"*) if $x \geq 51$: there exists "equal responsibility" (*"responsabilità paritaria"*) and "minor responsibility" (*"responsabilità minoritaria"*) if $x = 50$ and $x < 50$, respectively, in which case the policyholder is not liable and the malus does not apply. Indemnities are proportional to x.[13] In Italy, as in many other countries, a uniform experience rating system relates the history of accidents to a class of risk, the so-called bonus-malus (BM) class. There are 18 classes, and BM class 1 is the best; youngsters without a driving history are assigned to BM class 14. The driving history at the beginning of a new contractual year is summarized by a public certificate, "*attestato di rischio*" (AR), a paper document that reports the BM class and the number of accidents over the previous five years with major and equal liability. In the case of an accident with major responsibility or if the sum of accidents with minor fault during the previous five years exceeds 51, the malus is applied and the BM class increases by two. If no accident occurs, the BM class decreases by one.

Almost all contracts last one year, consumers decide whether to renew the contract or change companies at the end of the year, and contracts are exclusive.

There are three types of contracts: bonus-malus, deductible, and mixed bonus-malus/deductible. The vast majority of contracts are bonus-malus (96%) or mixed bonus-malus/deductible (3.7%). Both for historical reasons and because of a peculiar law, only a negligible fraction of contracts feature a deductible. The law establishes a mandatory minimum of liability coverage (*"massimali"*):

[11]It is well known that, given the relatively long liquidation time, the indemnified amounts associated to more recent claims are smaller. Although this is also true in our data, we did not include the claims reserving amounts to avoid introducing bias from insurers' expectations. We hope that controlling for year, month, and day fixed effects the confounding mechanic claims reduction can be minimized.

[12]A major difference between at-fault and no-fault systems is that in the latter, insurers cover the damage regardless of who is at-fault. At-fault systems are based on a principle of fairness, while not-at-fault systems minimize litigation costs.

[13]If a driver is involved in an accident with damage D and holds percentage of fault x, the indemnity is $D(1 - x)$.

if the damage to third parties exceeds this amount, the policyholder is responsible for any amount exceeding this limit.[14]

5. Event History Analysis

Our first econometric exercise consists of a plain event history analysis. We construct four indicators for the critical periods previously isolated. We denote these indicators by d_t^i, taking value one if date t belongs to period i, and zero otherwise. We start by estimating the following OLS regression:

$$\log(o_t) = \beta X_t + \sum_{i=1}^{4} \gamma_i d_t^i + \alpha A_t + \mathrm{RT}_t + \text{day FE} + \text{month FE} + \text{year FE} + \text{month} \times \text{year FE} + \mathsf{p}_t \quad (4)$$

where $o_t = \{P_t, N_t, \pi_t)\}$. In this notation P_t signifies the premium at date t, N_t is the number of contracts underwritten at date t, and π_t denotes the claims frequency.[15] The vector X_t contains all of our pricing variables (policyholder/car characteristics, contractual clauses) and province-specific characteristics (penetration rates of companies selling on-line, etc,). The vector A_t contains announcement dummies taking value one at the dates at which relevant information has been released.[16]

Our focus is on the γ_i's coefficients that pool together the effect of various interventions on mobility within the critical periods. Seasonality is a potential confounder of the true lockdown effects because the restrictions might happen in periods of the year in which insurance rates usually change in response to the periodic revisions of pricing strategies. Seasonal weather precipitation is less of a concern because contracts cover a calendar year and therefore the premium incorporates future variations of the accident rates during the calendar year.[17] We take into account seasonality by controlling for day, month, year, and month×year fixed-effects, and we capture changes in pricing strategies at the central level by controlling for a dummy (RT_t), taking value one in days between January 1 and August 15. Finally, in an effort to proxy for expectations about the evolution of the virus that might affect future mobility patterns—Keane and Neal (2020) estimate the effect of the spread of the virus on panic across countries—we include in the control set the number of total daily cases, defined as the sum of deaths, newly infected people, and hospitalized people.

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[14] The liability limits are 1 million and 6 million euros for property and health damage to third parties, respectively. In June 2017, the minimum liability coverage increased to 1,220,000 and 6,070,000 euros.

[15] The denominator of the dependent variable—the number of active contracts at each date—is taken from a database accounting for about 30 percent of the universe of contracts, while the numerator—the number of claims in a province at each date—is taken from the universe of claims (BDS). In order to rescale our variables to the universe we multiplied by 3 the number of contracts in our sample and computed the claims frequency accordingly.

[16] The events we constructed announcement indicators for are as follows: state of emergency, school closure, national lockdown, extension of the first/second lockdown, and beginning/end of phase two. These events are described in section 9.1 of the appendix.

[17] Einav (2007) examines seasonality of demand for movies.

The results based on the period 2014–Q2:2020 are displayed in table 1.[18] By comparing the results in columns (1) and (2) of the table, it can be observed that not controlling for seasonality alters the sign and magnitude of the estimates of γ_i. For example, seasonality conflates the COVID-19 price reduction effect (panel A); once we control for the available pricing variables (columns (3)–(4)), we do not find any significant lockdown effect on premiums, as the associated coefficients are close to zero (column (3)). Moreover, the change in the coefficients when we add controls indicates that the observed price reduction is mostly driven by demand composition effects. Finally, perhaps because many of the announcement dates coincide with some of the spikes in figure 5, these coefficients are no longer significant when we add announcement indicators (column (4)).
The estimates in panel B of table 1 imply demand reductions are as large as 50 percent in periods 3–4, but as for prices, these effects are no longer significant when we add announcement indicators (column (4)). Finally, in panel C we report the lockdown effect on claims frequency. We find reductions as large as 65 percent in period 3, and the effect is even larger when we control for announcement indicators.

While these results provide *prima facie* evidence of the effect of the COVID-19 shock on the Italian auto insurance market, the absence of a treatment and control group(s) and the high sensitivity to the inclusion of the announcement indicators suggest caution in giving them a causal interpretation. To more credibly identity the lockdown causal effect and its welfare implications we now combine the idea of rich price variation with a research design based on the variation of the lockdown decisions across provinces.

6. Price Variations

The first step of our analysis consists of using rich price variations to infer the lockdown effect on demand and AC curves, following EFC. The price variation we rely on to estimate demand and cost curves is generated by the discounts given by sales agents. In the Italian market, as in many other auto insurance markets, the vast majority of contracts—about 90%— are underwritten by sales agents, who are given a total amount they use discretionarily to meet sales targets. Therefore, it is often the case that two similar policyholders covered by the same company and adopting the same insurance plan are charged different premiums.[19] Letting s_{it} denote the average discount in

[18] Recall that in a Poisson model and in models in which the dependent variable is log-transformed the coefficients can be interpreted in terms of a semi-elasticity. However, such an interpretation is valid only when the estimated coefficient is not too large, as it arises from a Taylor expansion of the conditional mean function around zero. Given the conditional expectation model

$$E[\pi|l, X] = \exp(\alpha l + \beta X) \tag{5}$$

the marginal effect of l is written as

$$ME_l = E[\pi|l = 1, X] - E[\pi|l = 0, X] = (\exp(\alpha) - 1) \times \exp(\beta x) \tag{6}$$

When $\alpha \approx 0$, it measures the percentage change in the outcome variable when $l = 1$. When α is not close to zero the marginal effect corresponds to the estimated value of $\exp(\alpha) - 1$, that is, the marginal effect at $x = 0$. From now on, we translate the estimated coefficients on discrete variables in Poisson and log-linear models in terms of marginal effects at $x = 0$. See Halvorsen and Palmquist (1980) for more details.

[19] As a way of quantifying price dispersion due to agents behavior, an OLS regression of the premium at the insuree-level on observable pricing variables and contractual clauses delivers an R-squared of about 0.5; however, when we restrict the sample to the set of contracts underwritten by the so-called direct companies—they subscribe contracts through the internet/by phone—the R-squared becomes 0.6. This type of variation has been used by Jeziorskiy, Krasnokutskaya, and Ceccarini (2017) to identify a model with moral hazard in the context of the Portuguese auto insurance market.

province i at date t, we estimate the following Poisson regression:

$$E[s_{it}|\text{observables}] = \exp\big(\alpha l_{it} + \iota I_{it} + \beta X_{it} + \mu M_{it} + \gamma HHI_{iqy} \tag{7}$$
$$+\text{RT}_t + \text{day FE} + \text{month FE} + \text{year FE} + \text{province FE} + \text{province} \times \text{month} \ \times \text{year}\ \big)$$

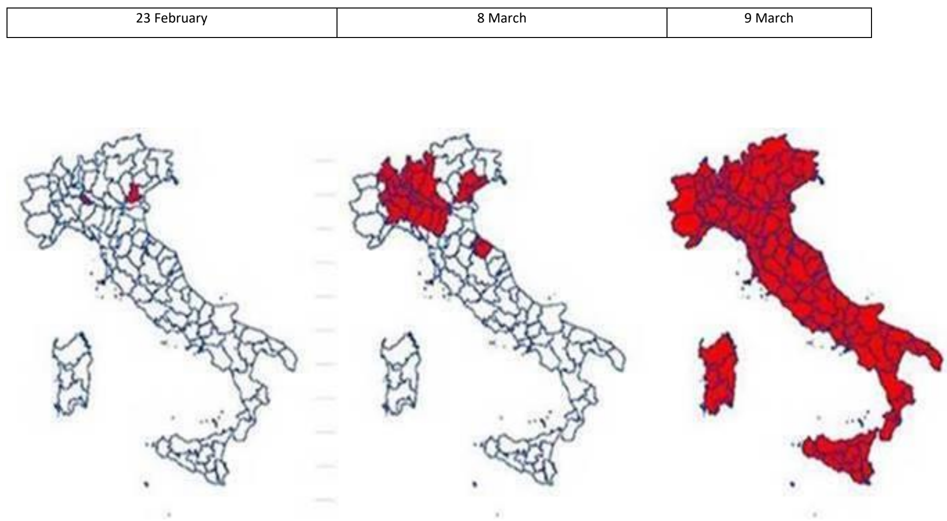
The vector X_{it} contains the mean pricing variables at a given date and province described in the appendix. The indicator l_{it} takes value of one if province i is subject to a lockdown at date t, the vector I_{it} contains dummy variables taking the value of one if a specific intervention—school closure, suspension of public activities, store closure, or phase two—is active at a given date in a province, and zero otherwise; the vector M_{it} contains the fraction of contracts underwritten at t by direct companies, as well as the fraction of contracts underwritten by sales agents/banks at the quarter–year–province level. In order to control for variation in market structure, we also include the Herfindahl-Hirschman concentration index in province i at year y in quarter q (HHI_{iqy}). We control for RT_t, an indicator taking the value of one if date t belongs to the period January 1—August 15, which mostly covers a period in which the pricing variables have been revised. This variable, together with the (calendar) day, month, and year fixed-effects accounts for common seasonal effects, while the province and province×month×year fixed effects absorb province-specific shocks.

Letting $\widehat{s}_{it}$ denote the predicted discount using specification (7), the instrument we use as a source of price variation is the estimated *residualized* discount $\widehat{\mathsf{p}}_{it} \equiv s_{it} - \widehat{s}_{it}$, namely the variation in the discount unrelated to pricing variables, seasonal effects, market structure, and province-specific factors. Within an OLS regression our rich set of controls explains most of the variability of s_{it} ($R^2 = 0.91$), suggesting that the variation of $\widehat{\mathsf{p}}_{it}$ is unlikely to be driven by unobservable factors. Also, notice that in our sample $\widehat{\mathsf{p}}_{it}$ takes 257,480 distinct values; moreover the ratio s_{it}/p_{it} varies from 0.11 to 0.51 with a standard deviation of 0.09, allowing us to precisely estimate the relationship between claims cost (demand) and (exogenous) prices. The richness of our data is then crucial to address the applicability of the price variation approach highlighted by several researchers.[20] As an alternative to this instrument, we considered as a source of exogenous variation the tax rates—the ratio between the fraction of the premium due to taxes and the premium itself—across time and provinces. However, such a measure exhibits a lower degree of variation (from 7 to 12.6 percentage points), making $\widehat{\mathsf{p}}_{it}$ a richer source of price variation.

Research Design.— We rely on a panel data difference-in-differences (DD) research design—the treatment(control) group is represented by the provinces in which the lockdown interventions are (not) implemented—to identify the effect of mobility restrictions on claims, number of contracts, and premiums. The identification is based on exogenous variation of l_{it} generated by the differential timing of the interventions across provinces. The map in figure 10 conveys information about the timing of the lockdown decisions across Italian provinces. Because much of the time variation took place between March 8 and 9, the DD identification of the lockdown effect is obtained by comparing "similar" provinces such that one became subject to a lockdown on March 9 (control

[20]As observed by Fang and Wu (2018): In empirical applications, the range of the exogenous price variations is often quite limited. For example, Einav, Finkelstein, and Cullen (2010) have a total of six price levels (or three price levels if one only considers those with somewhat large number of consumers)."

Figure 10. Timing of Lockdown Across Provinces



Note: Red provinces are subject to a lockdown.

group) and the other did not (treatment group). This argument based on intra-days comparisons justifies the construction of a panel at the daily frequency. As it is well-known, an important identification assumption underlying the validity of a DD research design is the so-called common trend assumption. When translated to our context, this means that provinces subject to the lockdown interventions would have experienced a common trend (in prices) when compared to the untreated provinces. There are reasons to believe this might not be the case because Northern provinces are typically characterized by a lower rate of price reductions relative to Southern provinces.[21] To mitigate the violation of the parallel trend assumption we include year×month×province fixed effects in our regressions to capture local shocks (see Angrist and Pischke. (2009)).

As is evident from the maps, because the dynamic required for a DD research design only took place within the Northern provinces, the Southern provinces do not provide treatment and control groups. Nevertheless, as in the traditional panel data fixed effect strategy, they convey information by comparing the same province before and after the lockdown. Obviously, to the extent that the spread of the virus is (conditionally) uncorrelated with risk factors affecting prices and claims and that we can fully control for province-specific factors, the identification of the lockdown effect also comes from cross-sectional variations across provinces.

[21] As observed by Keane and Neal (2020), with large T the so-called Nickell's bias in the presence of lagged outcome variables among the covariates is small. Our preferred specification will include one lag of the premium.

Claims cost and the cost curve test.— Let π_{it} denote the frequency of claims at the province level at a given date t and i_{it} denote the average indemnity corresponding to third parties associated with claims not-at-fault, we define the per-contract realized average cost of claims in province i at date t. as $c_{it} = \pi_{it} \times i_{it}$. c_{it} is the weighted average of the claims cost associated with contracts active at date t. In order to fix the ideas, suppose that contracts last for 3 days (t,$t+1$,$t+2$) and let one contract start at each date. Focusing on a given province and assuming out seasonality, the average cost curve at date $t+1$ for contracts underwritten at dates t and $t+1$ reads

$$c_{t+1}^{t} = \beta X_t + \alpha \widehat{\mathsf{p}}_t + u_{t+1}^{t}$$
$$c_{t+1}^{t+1} = \beta X_{t+1} + \alpha \widehat{\mathsf{p}}_{t+1} + u_{t+1}^{t+1}$$

where c_{τ}^{t} denotes the cost of claims that happened on date t As the ultimate goal is to implement the cost curve test (estimated α) and estimate the lockdown effect on the average cost of accidents that happened on date t (we do not have information on the cost/number of claims associated with date–specific contracts), we can average out these two equations:

$$\overline{c}_{t+1} = \beta \overline{X}_{t+1} + \alpha \overline{\widehat{\mathsf{p}}}_{t+1} + \overline{u}_{t+1}$$

where $\overline{x}_t$ denotes the mean of x over contracts active at date t. This expression highlights that the claims cost of accidents that happened at a given date reflects the composition of risk factors within contracts active at that date, we parsimoniously proxy for $\overline{X}_{t+1}$ using the average (over the previous 365 days) projected (log) premium associated with contracts active at $t+1$ ($\overline{p}_{t+1}$) and stipulated at some date during the year ending at $t+1$ Our average cost curve is modeled in terms of the following regression specification:

$$\log(c_{it}) = \beta \overline{p}_{it} + \gamma_0 l_{it} + \gamma_1 \widehat{\mathsf{p}}_{it} + \gamma_2 \widehat{\mathsf{p}}_{it} \times l_{it} + \iota I_{it} + \beta X_{it} + \mu M_{it} + \delta HHI_{iqy} + \quad (8)$$
$$\mathrm{RT}_t + \text{day FE} + \text{month FE} + \text{year FE} + \text{province FE} + \text{province} \times \text{month } \times \text{year FE } + u_{it}$$

Notice how the large sample size of the original data—over 52 million contracts—allows us to compute means of the variables at the day–province level, generating a panel with unusually large T(=2,496), allowing us to minimize the well-known bias arising in short panels.

Our interest is centered on the γ's: γ_0 captures the change in the intercept due to the lockdown, while γ_2 captures the lockdown effect on the slope relative to the baseline (γ_1). As the textbook analysis in section 3 elucidates, under adverse selection $\gamma_1 > 0$: as the discount increases (the price decreases), the realized claims payout of the insured drivers decreases. On the contrary, if γ_1 is estimated to be negative, the market is advantageously selected. The magnitude and sign of the coefficient on the interaction term $\widehat{\mathsf{p}}_{it} \times l_{it}$ tells us whether lockdown restrictions exacerbate or mitigate selection.

Our results are presented in table 2. In columns (1)–(2), (3)–(4), and (5)–(7), the dependent variables are the (logarithm of) π_{it}, i_{it}, and c_{it}, respectively. Separately analyzing the determinants of the average claims cost allows us to isolate counteracting effects on frequency and claims size. In the odd columns we do not include our sufficient pricing variables, allowing us to further infer how the pool of insured drivers changes by looking at the changes in γ_0, relative to when we include these controls (even columns and column (7)). Consistent with the pattern observed in the raw data, we find that lockdown negatively affects the number of accidents, generating a claim frequency reduction of $69(= \exp(-1.18) - 1)$ percentage points (column (2)). Interestingly, there appears to be no correlation between lockdown and observable risk factors because the coefficient on l_{it} remains unchanged if we do not control for composition effects $\bar{\bar{p}}$. The lockdown effect on the size of claims equals $-23.5(= \exp(0.268) - 1)$ percentage points (column (4)), while the average (per-contract) cost of claims (c_{it}) is reduced by 75.9 percentage points (column (6)), and cost reductions are also associated with the suspension of all activities (-76 percent) and store closure (-38 percent). Consistent with a large body of empirical literature in macroeconomics (see Gardner, Scotti, and Vega (2020)) and with recent findings by Keane and Neal (2020), we add several announcement indicators in column (7): the results are basically left unchanged.

The cost curve test implies that this market is *adversely* selected as the coefficient on $\widehat{\mathsf{p}}$ is significant at the 1 percent level: a 10 euro discount(premium) (p) increase(decrease) implies a 14 percent increase in claims frequency (defined as the ratio between the number of accidents and the number of active contracts at a given date), a 15 percent reduction in the per-contract payout costs (column (6)), while no effect on the size of claims is detected (column (4)). The interaction term $\widehat{\mathsf{p}} \times$ lockdown is not statistically significant, indicating that the sign of selection is left unchanged during lockdown days.[22]

Insurance Demand.— In order to estimate the lockdown effect on demand and on the elasticity to prices, we specify an analogous model to (8), and the dependent variable is the logarithm of the number of contracts underwritten at date t in province i (N_t). The results are reported in panel A of table 3. By comparing columns (1) and (2) we find that not controlling for our pricing variables leads to downward biased estimates, indicating that mobility restrictions alter the composition of insured drivers. The estimates of the (conditional) lockdown effect imply that the number of underwritten contracts is reduced by about 25 to 28 percentage points (the marginal effect implied by the coefficients on lockdown in columns (2) and (3)). Other mobility restrictions also generally decrease insurance demand, except school closure; interestingly, the COVID-19 shock seems to have long-lasting effects because demand is reduced by 6 to 8 percent even when mobility restrictions were eased (phase two). In column (4) we examine the effect on new contracts (covering new cars or cars that changed of ownership): we find a 41 percent lockdown reduction effect, a larger effect relative to old contracts. New contracts are also affected by other mobility restrictions and the sign of the coefficients is consistent with the effect we find within all types of contracts, with the exception of phase two, which increases new contract subscriptions by about 21 percent. Demand seems to be highly sensitive to insurance prices: a 1 percent increase in the (residualized) discount generates a 39 percent increase (column (3) of table 3), but there is no significant change

[22] Because the empirical distribution of the number of claims is left skewed we also tried a Poisson model, by applying a pseudo-maximum likelihood estimator for models with large number of fixed effects. The STATA command developed by Correia, Guimares, and Zylkin (2019) is PPMHLDFE. A Poisson model is appealing because even with a large number of fixed effects, the only requirement for the consistency of a pseudo-maximum likelihood Poisson estimator is the correct specification of the conditional mean, the data do not have to display a Poisson distribution or the dependent variable to be an integer (see Santos Silva and Tenreyro (2006)). Our results did not significantly change.

in the slope during lockdown days; furthermore, new contracts' elasticity is similar in magnitude to previously underwritten contracts.[23]
Top 5 Players.—Panel B of table 3 reports the results of these same analysis using the sample of contracts underwritten by the top 5 players, accounting for about 60 percent of total market shares. By comparing the estimates in column (3), it can be seen that mobility restrictions had a similar effect on insurance demand, although the lockdown effect is half of a percentage point smaller than the average market response. Moreover, demand elasticity within new contracts is roughly half that in the overall market (column(4)). This finding suggests a greater degree of inertia within policyholders covered by the top 5 players.

Coverage.— As a way of measuring how the intensive margin of insurance choices responded to mobility restrictions, we use a two-step approach aimed at circumventing the fact that multiple contractual clauses alter the indemnities in the case of an accident. First, we predict (out of sample) coverage during 2013–2019 using the regression model (8) in which the dependent variable is the indemnity to third parties in claims not-at-fault. Letting $\widehat{c_{it}}$ denote the predict coverage, we then estimate the following regression

$$\widehat{c}_{it} = \beta l_{it} + \iota I_{it} + v_{it}$$

The coefficients (β, ι) capture the effect of mobility restrictions on coverage, once the variation due to changes in pricing variables and seasonality has been netted out. From column (5) in panel A of table 3, it can be seen that mobility restrictions had an economically small effect on coverage, implying that much of the variation on the demand side is due to changes along the intensive margin.

Price Effects Consider our previous specification:

$$\log(P_{it}) = \beta X_{it} + \gamma l_{it} + \iota I_{it} + \beta X_{it} + \mu M_{it} + \delta HHI_{iqy} + \tag{9}$$
$$\mathrm{RT}_t + \text{day FE} + \text{month FE} + \text{year FE} + \text{province FE} + \text{province} \times \text{month } \times \text{year FE } + v_{it}$$

where P_{it} denotes the average premium in province i at date t. One concern in estimating this model has to do with the absence of pricing variables in X_{jt}, such as car value or education. We adopt the control function by Bajari, Fruehwirth, Kim, and Timmins (2012) in the context of hedonic price equation. First, we impose the following structure on the error term

$$v_{it} = v_i + \varepsilon_{jt} \tag{10}$$

$$\varepsilon_{jt} = \rho \varepsilon_{j,t-1} + u_{it} \tag{11}$$

where u_{it} represents an i.i.d. error term, assumed to be orthogonal to the pricing variables at time $t-1$. A more compact version of this equation is obtained by defining

$$L_{it} \equiv (l_{it}, I_{it})$$

[23] As this elasticity seemed too high, we experimented with a quadratic and a cubic (in $\widehat{\mathsf{p}}_{it}$) specification. The implied marginal effects were estimated at -17 and -25 percent, respectively. We still prefer the linear specification because it provides a better out of sample fit.

and

$$A_{it} = (M_{it}, HHI_{iqy}, \text{time and province FE})$$

We can then rewrite our hedonic price equation as

$$\log(P_{it}) = \beta X_{it} + \gamma L_{jt} + \alpha A_t + \rho(p_{it-1} - \beta X_{it-1} - \gamma L_{it-1} - \alpha A_{t-1}) + v_i + u_{it} \tag{12}$$

Under several orthogonality conditions—rational expectations—the error term u_{it} is uncorrelated with (X_{jt}, L_{jt}, A_t) and the province fixed-effect v_i can be eliminated by a first differencing or by a within-group transformation. In short, this approach solves the omitted variable problem based on the idea that past prices convey information about future realizations of the unobservable pricing variables and can be used to control for them.
A second concern is reverse causality: namely, there could be some feedback effects between insurance rates and lockdown decisions at the local level. For example, price reductions could lead to greater mobility, a key factor contributing to the spread of the virus that triggers lockdown interventions. However, it is unlikely that daily price variations across provinces can be large enough to determine a first-order contemporaneous response of the lockdown decisions.

Table 4 reports our results. In columns (1)–(2) we display the results from a plain within-group estimator applied to equation (9). When we only control for seasonality and province×year fixed effects (column (1)), we find a small and significant reduction of 2.6 percent; the lockdown effect becomes essentially zero when we control for pricing variables (column (2)). This pattern indicates that lockdown interventions are negatively correlated with risk factors that increase premiums, consistent with the evidence on advantageous selection effects we obtained through the cost curve test. We obtain similar results from the control function approach (CF-FE) (column (3)), and the results remain unchanged when we add announcement indicators (column (4)). In column (5) we restrict the sample to the contracts underwritten by the top 5 insurers and, again, we find little evidence of price responses.

We also investigate in table 5 the lockdown effects on the overall price distribution by estimating (9), the dependent variables being the logarithm of various percentiles (P10, P25, P50, P75, P90). The coefficient on lockdown is small in magnitude and only statistically significant within the lower part of the distribution, indicating a similar effect to the one we found on the conditional mean.

Geographical Variations.— In order to investigate the presence of heterogeneous lockdown effects across macro-regions, we interacted the lockdown coefficients with 5 macro-regions dummies (north-west, north-east, center, south, and islands). Table 6 shows the effects on the number of contracts, premiums, claims cost, and coverage. We adopt our baseline specification, controlling for pricing variables and the various time–province fixed effects. From column (1) we can observe a substantially larger demand contraction within the provinces located in the south and islands (-35 and -32 percent) relative to the center and northern provinces, in which the effect ranges from 16 to 20 percent. By scrolling the other columns, we do not see substantial differences across areas, indicating that claims cost, coverage, and premiums were affected equally across the macro-regions.

Sum-up of results and main takeaways.— Our results indicate that at initial outbreak of the pandemic (i) auto insurance premiums did not respond to the enforced mobility restrictions, (ii) the overall number of contracts experienced a substantial contraction and an even larger response within newly covered cars, (iii) a (per-contract) claims payout reduction as large as 76 percentage points during lockdown days, (iv) the presence of adverse selection and (v) evidence that only the extensive margin responded to the pandemic shock. We stress that these responses, taking place within the first two quarters of 2020, represent short-run effects plausibly capturing a large uncertainty shock.[24] We make the case that Italian insurers adopted a conservative approach in pricing contracts, generating price rigidity. The alternative explanation in terms of lack of competition—a risk-neutral insurer holding rational expectations would decrease premiums to conquer market shares in the presence of competition—seems a less convincing narrative because we control for competition by including the Herfindahl concentration index and taking into account the absence of a substantially different price response between small and large players. The large demand reduction can be a manifestation of (i) precautionary savings—this is consistent with the dramatic increase in savings—(ii) an income effect, or (iii) a change in behavior due to the risk of contagion. The more pronounced demand response in the southern provinces—characterized by lower income levels, high premiums—suggests a first-order effect of liquidity constraints and uncertainty about income/employment prospects.[25]

7. Concluding Remarks

Rather than summarizing the findings we previously illustrated, we conclude by arguing that the exercise in this paper can serve as a leading case–study to learn about short-run uncertainty effects on competitive insurance markets. Nevertheless, by changing living habits—the increase of working from home and the resulting reduction of commuting—the COVID-19 shock is likely to yield long-lasting effects on the auto insurance market. The change of the composition of insured drivers and driving habits might speed up the adoption of monitoring technologies that more closely relate premiums to actual car usage. The granular data we use in our analysis and the price variations we employ can be fruitfully exploited in the future to measure the long run effects of the pandemic shock.

[24]Recall that our analysis is based on data at the day–province level. As such, these reductions can be interpreted as a comparison between a day subject to the lockdown and a similar day not subject to any mobility restriction in the period 2014-2020.

[25]Individuals working in the black sector cannot be reached by COVID-19–specific welfare programs.

8. Tables

Table 1. The Effect of COVID-19 on Outcomes

	(1) No Seasonality		(2) Seasonality		(3) Control+Season.		(4) Control+Season.+Ann.	
				Panel A—Dependent Variable: Log of the Premium				
period 1	-0.091***	[0.004]	-0.012	[0.009]	-0.005**	[0.002]	-0.005**	[0.002]
period 2	-0.113***	[0.005]	-0.036***	[0.011]	-0.004	[0.003]	-0.004	[0.003]
period 3	-0.068***	[0.015]	-0.011	[0.014]	-0.023***	[0.005]	-0.015	[0.012]
period 4	-0.031	[0.020]	0.008	[0.016]	-0.022***	[0.006]	-0.014	[0.012]
R^2	0.131		0.905		0.993		0.993	
N	2,371		2,371		2,371		2,371	
				Panel B—Dependent Variable: Log of Number of Contracts				
period 1	0.147***	[0.053]	0.147	[0.114]	0.099	[0.109]	0.099	[0.110]
period 2	-0.058	[0.067]	-0.065	[0.139]	0.183	[0.117]	0.195	[0.119]
period 3	0.467	[0.300]	-0.488**	[0.199]	-0.730***	[0.170]	-0.314	[0.271]
period 4	0.725*	[0.433]	-0.120	[0.302]	-0.702***	[0.208]	-0.278	[0.280]
R^2	0.006		0.257		0.815		0.816	
N	2,371		2,371		2,371		2,371	
				Panel C—Dependent Variable: Log of Claims Frequency				
period 1	0.114	[0.073]	-0.011	[0.112]	0.038	[0.085]	0.038	[0.085]
period 2	-1.543***	[0.215]	-1.620***	[0.258]	-0.499**	[0.221]	-0.481**	[0.235]
period 3	-1.388***	[0.481]	-1.760***	[0.414]	-1.058***	[0.305]	-2.614***	[0.758]
period 4	-0.092	[0.654]	-0.528	[0.662]	-0.560	[0.547]	-2.074***	[0.685]
R^2	0.085		0.794		0.898		0.899	
N	2,371		2,371		2,371		2,371	

NOTES: This table reports OLS estimates of regression specification (4). The period covered is 2014-Q2:2020. *, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Robust standard errors are reported in parentheses.

Table 2. The Effect of Mobility Restrictions on the Average Cost Curve

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Claims Frequency		Size of Claims		Average Claims Cost		
	No Controls	Controls	No Controls	Controls	No Controls	Controls	Controls + Ann.
lockdown	-1.180***	-1.180***	-0.268***	-0.268***	-1.427***	-1.426***	-1.553***
	[0.074]	[0.074]	[0.047]	[0.047]	[0.083]	[0.083]	[0.085]
$\widehat{\mathsf{p}}$	0.013**	0.014**	-0.001	-0.000	0.014*	0.015**	0.016**
	[0.006]	[0.006]	[0.004]	[0.004]	[0.008]	[0.008]	[0.008]
$\widehat{\mathsf{p}}\times$lockdown	0.000	0.000	0.001***	0.001***	0.001**	0.001**	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
school closed	-0.005	-0.005	0.033	0.033	0.024	0.023	0.012
	[0.024]	[0.024]	[0.021]	[0.021]	[0.034]	[0.034]	[0.035]
susp. all activities	-1.354***	-1.354***	-0.120	-0.120	-1.445***	-1.445***	-1.419***
	[0.065]	[0.065]	[0.113]	[0.113]	[0.133]	[0.133]	[0.134]
closure stores	-0.434***	-0.434***	-0.063***	-0.063***	-0.491***	-0.491***	-0.391***
	[0.017]	[0.017]	[0.013]	[0.013]	[0.022]	[0.022]	[0.025]
phase two	-0.005	-0.005	-0.006	-0.006	-0.024	-0.024	-0.056
	[0.026]	[0.026]	[0.026]	[0.026]	[0.038]	[0.038]	[0.039]
$\overline{\widehat{p}}$		0.618***		0.096***		0.713***	0.713***
		[0.046]		[0.006]		[0.039]	[0.039]
day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province×month×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
announcement indicators	No	No	No	No	No	No	Yes
R^2	0.690	0.690	0.237	0.237	0.435	0.435	0.436
N	212,046	212,046	206,732	206,732	206,732	206,732	206,732

NOTES: This table reports estimates by the within-group estimator of regression specification (8). The dependent variables in columns (1)–(2), (3)–(4), and (5)–(7) are the (logarithm of) claims frequency (π_{it}), size of claims at-fault ($\imath_{it}$), and average claims cost (c_{it}), respectively.

Claims frequency is computed as the ratio between the number of claims filed and the number of active contracts at each date and province. Because the number of active contracts at each date is taken from a database comprising about 30 percent of the universe of contracts (IPER), while the numerator—the number of accidents happened in a province at each date—is taken from the *universe* of claims (BDS), this ratio has been rescaled.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Robust standard errors clustered at the province level are reported in parentheses.

Table 3. Demand Estimates and Lockdown Effects

	(1) No. Contracts	(2) No. Contracts	(3) No. Contracts	(4) No. New Contracts	(5) Coverage
	Panel A: All Players				
lockdown	-0.353***	-0.297***	-0.336***	-0.540***	0.024***
	[0.010]	[0.012]	[0.013]	[0.024]	[0.001]
$\widehat{\epsilon}$	0.330***	0.332***	0.332***	0.388***	
	[0.028]	[0.025]	[0.025]	[0.047]	
$\widehat{\epsilon}\times$lockdown	-0.051	-0.154	-0.181*	-0.686***	
	[0.115]	[0.105]	[0.103]	[0.242]	
school closed	0.100***	0.084***	0.091***	0.228***	-0.006***
	[0.017]	[0.015]	[0.015]	[0.027]	[0.000]
susp. all activities	-0.090***	-0.122***	-0.119***	-0.592***	0.008***
	[0.014]	[0.016]	[0.016]	[0.062]	[0.001]
closure stores	-0.101***	-0.055***	-0.037***	-0.161***	0.005***
	[0.005]	[0.006]	[0.006]	[0.013]	[0.000]
phase two	-0.075***	-0.064***	-0.082***	0.193***	0.010***
	[0.010]	[0.012]	[0.012]	[0.030]	[0.000]
R^2	0.798	0.835	0.835	0.735	0.016
N	257,480	257,480	257,480	240,830	257,496
	Panel B: Top 5 Players				
lockdown	-0.342***	-0.313***	-0.354***	-0.494***	
	[0.011]	[0.012]	[0.012]	[0.027]	
$\widehat{\epsilon}$	0.279***	0.280***	0.280***	0.154***	
	[0.020]	[0.017]	[0.017]	[0.026]	
$\widehat{\epsilon}\times$lockdown	-0.033	-0.063	-0.077	-0.189*	
	[0.080]	[0.084]	[0.083]	[0.109]	
school closed	0.093***	0.065***	0.072***	0.190***	
	[0.017]	[0.016]	[0.016]	[0.029]	
susp. all activities	-0.085***	-0.127***	-0.124***	-0.577***	
	[0.018]	[0.020]	[0.020]	[0.091]	
closure stores	-0.119***	-0.073***	-0.054***	-0.198***	
	[0.005]	[0.006]	[0.007]	[0.014]	
phase two	-0.034***	-0.040***	-0.059***	0.176***	
	[0.012]	[0.013]	[0.013]	[0.037]	
R^2	0.765	0.815	0.816	0.616	
N	257,341	257,341	257,341	224,310	
controls	No	Yes	Yes	Yes	No
day FE	Yes	Yes	Yes	Yes	No
month FE	Yes	Yes	Yes	Yes	No
year FE	Yes	Yes	Yes	Yes	No
province FE	Yes	Yes	Yes	Yes	Yes
province$\times$ year FE	Yes	Yes	Yes	Yes	Yes
announcement indicators	No	No	Yes	No	No
R^2	0.798	0.835	0.835	0.735	0.016
N	257,480	257,480	257,480	240,830	257,496

NOTES: This table reports estimates by the within-group estimator of regression specification (8); the dependent variable in columns (1)–(3) is the logarithm of the number of contracts underwritten at each date and province. The dependent variable in columns (4) and (5) is the logarithm of the number of new contracts and coverage (computed as described in the main text).
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Robust standard errors clustered at the province level are reported in parentheses.

TABLE 4. The Effect of Mobility Restrictions on Insurance Prices

	(1)	(2)	(3)	(4)	(5)
	FE Estimator			CF-FE Estimator	
	No Controls	Controls	Controls	Controls+Ann.	Controls
	All Insurers				Top 5
lockdown	-0.026***	-0.006***	0.003	-0.000	0.003
	[0.002]	[0.002]	[0.003]	[0.004]	[0.004]
school closed	-0.001	-0.003	-0.009**	-0.006	-0.010**
	[0.003]	[0.002]	[0.004]	[0.004]	[0.005]
susp. all activities	0.012**	0.018***	0.018***	0.018***	0.012***
	[0.005]	[0.003]	[0.003]	[0.003]	[0.004]
closure stores	-0.006***	-0.000	-0.003	-0.003	0.000
	[0.002]	[0.001]	[0.003]	[0.003]	[0.003]
phase two	-0.027***	-0.016***	-0.013***	-0.014***	-0.004
	[0.002]	[0.002]	[0.003]	[0.003]	[0.004]
controls	No	Yes	Yes	Yes	Yes
announcement indicators	No	No	No	Yes	No
day FE	Yes	Yes	Yes	Yes	yes
month FE	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes
province×month× year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.929	0.965	0.965	0.965	0.943
N	257,496	257,496	257,141	257,141	256,981

NOTES: Columns (1)–(2) report fixed-effect estimates of the regression specification (9). Columns (3)–(5) report fixed-effect estimates of regression specification (12). The dependent variable is the logarithm of the average daily premium at the province level. The period covered is 2014-Q2:2020.
*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.

Table 5. The Effect of Mobility Restrictions on Price Distribution

	(1) P10	(2) P25	(3) MEDIAN	(4) P75	(5) P90
lockdown	-0.008***	-0.005***	-0.003	-0.003	-0.009***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]
school closed	-0.001	-0.003	-0.003	-0.005*	-0.004
	[0.003]	[0.002]	[0.002]	[0.003]	[0.004]
susp. all activities	0.017***	0.015***	0.013***	0.025***	0.029***
	[0.006]	[0.004]	[0.004]	[0.005]	[0.007]
closure stores	-0.001	-0.000	-0.001	-0.000	-0.000
	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]
phase two	-0.007**	-0.008***	-0.011***	-0.012***	-0.024***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]
controls	Yes	Yes	Yes	Yes	Yes
announcement indicators	No	No	No	No	No
day FE	Yes	Yes	Yes	Yes	yes
month FE	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes
province×month× year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.905	0.947	0.954	0.937	0.880
N	257,496	257,496	257,496	257,496	257,496

NOTES: This table reports fixed effects estimates of the indicated (on top of the table) percentile price distribution. The dependent variable is the average daily premium at the province level. The period covered is 2014-Q2:2020. *, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.

Table 6. The Lockdown Effect on Outcomes Across Macro-Regions

	(1) Contracts		(2) Claims Cost		(3) Premium		(4) Coverage	
North-West	-0.229***	[0.015]	-1.777***	[0.09]	-0.005	[0.004]	0.017***	[0.001]
North-East	-0.180***	[0.015]	-1.788***	[0.11]	-0.005**	[0.002]	0.016***	[0.001]
Center	-0.286***	[0.019]	-1.752***	[0.13]	-0.015***	[0.003]	0.016***	[0.001]
South	-0.436***	[0.021]	-1.589***	[0.15]	-0.003	[0.003]	0.018***	[0.001]
Islands	-0.399***	[0.039]	-1.573***	[0.10]	0.000	[0.003]	0.016***	[0.001]
controls	Yes		Yes		Yes		No	
other interventions	Yes		Yes		Yes		Yes	
revise tariff	Yes		Yes		Yes		Yes	
total cases	Yes		Yes		Yes		Yes	
day FE	Yes		Yes		Yes		Yes	
month FE	Yes		Yes		Yes		Yes	
year FE	Yes		Yes		Yes		Yes	
province×year×month FE	Yes		Yes		Yes		Yes	
R^2	0.835		0.464		0.965		0.397	
N	257,480		234,756		257,480		257,496	

NOTES: This table reports fixed effects estimates of the indicated (on top of the table) percentile price distribution. The dependent variable is the average daily premium at the province level. The period covered is 2014-Q2:2020. *, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively. Standard errors are reported in parentheses.

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9. Appendix

9.1. Sequence of Chronological Events (from Briscese, Lacetera, Macis, and Tonin (2020).)

- 30-Jan-20: Italy closes flights from China
- 31-Jan-20: First two cases of COVID-19 diagnosed in Rome
- 31-Jan-20: Government declares state of emergency
- 21-Feb-20: First cases of community transmission reported in Lombardia and Veneto; first COVID-19 death (in Vo', Veneto)
- 23-Feb-20: Government imposes lockdown in Lombardia and Veneto
- 24-Feb-20: School closure in Northern Italy due to coronavirus
- 4-Mar-20: Closure of all schools and universities in Italy
- 8-Mar-20: Government announces lockdown in Northern Italy
- 9-Mar-20: Government extends lockdown nationwide
- 11-Mar-20: All commercial and retail businesses closed
- 19-Mar-20: Italy surpasses China in COVID-19 cases
- 22-Mar-20: All non-necessary businesses and industries shut down
- 1-Apr-20: Lockdown extended until April 13
- 10-Apr-20: Lockdown extended until May 3
- 26-Apr-20: Government announces Phase 2, a gradual easing of Italy's lockdown
- 4-May-20: Phase 2 kick off: traveling to permanent place of residence is allowed as well as meeting relatives who live in the same region. Construction, manufacturing, wholesale and real estate sectors are allowed to resume activity
- 13-May-20: School closure extended until September

- 16-May-20: Government announces the easing of some lockdown restrictions, including the reopening of all shops, bars, restaurants and hairdressers. Traveling within one's own region is allowed
- 3-Jun-20: All travel restrictions eased starting June 3

9.2. **Sampling Scheme.** From the universe of auto insurance contracts underwritten at each quarter—6 million contracts—300 strata are constructed from the combination of three variables: age groups (5 categories), city size (small, medium, and large), and region of residence. In practice only 240 strata are populated. The sampling scheme adopted is proportional: the number of contracts associated with each cell is proportional to the weight of that cell in the population. From each cell, 30 percent of contracts are randomly drawn.

9.3. **Description of the Variables.**

- premium (in euros): yearly premium paid
- discount (in euros): discount on the theoretical tariff applied by the agent/broker, if any. The theoretical tariff by definition equals premium+discount
- installments: number of chunks the premium is split in:
- age (in years): age of the subscriber at the time of underwriting date of the contract. The following age groups have been constructed: [18;25), [25;34), [35;44), [45;60), and ≥ 60.
- accidents on AR: number of accidents at fault (percentage of fault > 50) over the past five years reported on the AR ("*Attestato di Rischio*")
- bm class: bonus-malus class (1-18)
- man: indicator for whether the subscriber is a male
- clauses
  - repair: indicator taking value one if the clause "*risarcimento in forma specifica*" is active. The clause establishes that if an accident not at fault occurs, the vehicle has to be repaired by a specified list of body shops. Typically, companies have agreements with those body shops to minimize expenses.
  - black box: indicator for whether the so-called black box, a device able to record a variety of behaviors (e.g., km driven and whether there has been a "crash"), has been installed and guarantees a reduction in the base premium.
  - driving clauses: this clause conditions the indemnity on the identity of the driver. In particular, if restrictions on the drivers are present, if an accident is provoked and the restrictions are not met, the company refunds whoever is not at fault and recoups the damage from the subscriber of the contract. There are four mutually exclusive alternatives generating the following dummies
    * free driving: indicator taking value one if there is no restriction on the driver's identity
    * expert driving: indicator taking value one if only individuals with a certain driving experience can drive
    * exclusive driving: indicator taking value one if only individuals with a certain driving experience can drive
    * other: other types of driving clauses are present (the omitted category is "other")

  - protected bonus: indicator taking value one if the so called "*bonus protetto*" clause is active on the contract. Such a clause allows one to eliminate/diminish the increase in the premium in case of an accident.
- increasing clause: indicator taking value one if there are other clauses that (i) imply an increase in the premium, or (ii) are different than the ones listed that are active on the contract
- coverage (in euros): upper limit on the amount the company will pay for accidents at fault. The insured driver is responsible if the damage exceeds the specified liability limit
- car's characteristics:
  - type of fuel supply. The categories are diesel, fuel, electric, gpl, hybrid diesel/electric, hybrid petrol/electric, methane, mixture, particulate filter, petrol, petrol/ethanol, petrol/lpg, petrol/wank, and petrol/methane.

    Two dummies have been constructed, petrol and diesel, taking value one if the fuel supply is diesel or petrol, respectively, and zero otherwise. The omitted category is other types of fuel supply.
  - car's age: year of registry of the vehicle
  - cc: cubic cylinder of the vehicle, ranging from 1 to 100. I constructed dummies for the following groups: [10, 12), [12, 13), [13, 15), [15, 22), [22, 100]. The omitted category is [1, 10).
  - power of the vehicle (in KW) ranging from 1 to 585

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