Occupational safety climate as a COVID-19 mitigant: a dynamic fractional response panel analysis

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Abstract

Introduction: A topic understudied in the literature is the effect of the safety climate on aspects of the firm not directly related to occupational safety. In this research, the relationship between safety climate and COVID-19 infections suffered by workers is analyzed as a case study.

Method: This relationship was analyzed by estimating a dynamic fractional response panel model, with microdata from 1,077 construction worksites for 34 weeks. The mechanisms by which this relationship may occur are through workers' behavior within their workstations, and through external factors such as the impact of the safety climate on the general behavior of workers.

Results: A negative and significant effect of the safety climate on the number of infections suffered by workers is observed. Using the entire period of the available data sample, a 10% safer safety climate, compared to an average company, implies a reduction in the contagion rate by 11.5%. If the period without the effect of population vaccination is considered, the decrease in the infection rate increases to 14.4%.

Conclusions: The safety climate of the construction firms had an effect on the COVID-19 infections suffered by the workers.

Practical Applications: Continuous monitoring and evaluation of the safety climate should be a priority for companies and national authorities to reduce possible negative spillover effects.

Keywords: Safety climate, Fractional response model, Construction, COVID-19

1. Introduction

Safety climate is one of the most studied concepts in the occupational safety literature in recent years (Hofmann et al., 2017). There is abundant evidence that safety climate has a significant impact on reducing accident rates (e.g., Siu et al., 2004; Vinodkumar and Bhasi, 2009; Cornelissen et al., 2017).

However, limited research has been done on the effects of safety climate on other performance measures of the company. A notable exception is presented by Pousette et al. (2017), who find a positive relationship between the safety climate of workers and the performance of healthcare institutions. A good climate influences workers to take fewer risks, comply with regulations and report incidents, all of which have an impact on better patient care.

The COVID-19 pandemic provides an opportunity to investigate whether the safety climate may have had an impact on the number of infections suffered by companies. Reverse causality has already been studied by De Oliveira Neto et al. (2021), who found that practices to combat the pandemic created a risk management and biohazard mitigation program that was associated with improved health and safety performance in companies.

The mechanisms by which this relationship between safety climate and worker contagion can be grouped into two channels: internal and external. The internal channel is related to the impact of the safety climate on the behavior of workers when adopting different safety or sanitary measures within their workplaces. The external channel takes into consideration the effects that the safety climate has on the general behavior of workers, which is transmitted to their daily lives outside working hours.

We conducted our empirical study in the construction sector, with one of the highest accident rates in the world (Kim, 2019). For such a reason, the occupational safety literature has paid special attention to it, as shown by the meta-analysis of Mohammadi, Tavakolan and Khosravi (2018).

Our main source of information is provided by the Chilean Chamber of Construction (CChC) on 1,077 construction sites[1]. This database contains the contagions and the number of workers per week reported by the construction sites between January and August 2021, together with other characteristics of the construction sites. We also use databases that contain the accident rate of 2019 for the companies of the analyzed construction sites and the weekly contagions of the general population of Chile by commune of residence. Given the nature of the data to be used, we develop a fractional response model for a dynamic

[1] The appendix describes the development of the COVID-19 pandemic in the construction sector in Chile.

data panel that allows us to obtain an average partial effect. Our results demonstrate the relevance of the safety climate on the COVID-19 infections suffered by construction workers. As an example, if a company was 10% safer before the pandemic than an average company, its infection rate was 11.5% lower. If the model is considered in the period when there was still no vaccination effect, the infection rate is 14.4% lower.

The availability of microdata on COVID-19 infections at the company level has been restricted to healthcare workers (e.g., Iversen et al., 2020; Sikkema et al., 2020). Research in other sectors is scarce, and in these the information is obtained through health systems rather than directly from companies (e.g., Kim et al., 2020; Murti et al., 2021), except for Waltenburg et al. (2020) which uses microdata from meat and poultry processing facilities. The construction sector is massive, between 7% and 9% of the workforce in Chile depending on the economic cycle, and in many respects similar to manufacturing and mining. Therefore, our conclusions could be generalized to the national level, and thus illustrate the importance of occupational health and safety in public policies.

The rest of the document is structured as follows. Section 2 presents the theoretical framework that supports the hypothesized relationship. Section 3 develops the econometric model used and describes the data. The results are presented and discussed in section 4. Finally, section 5 presents our conclusions.

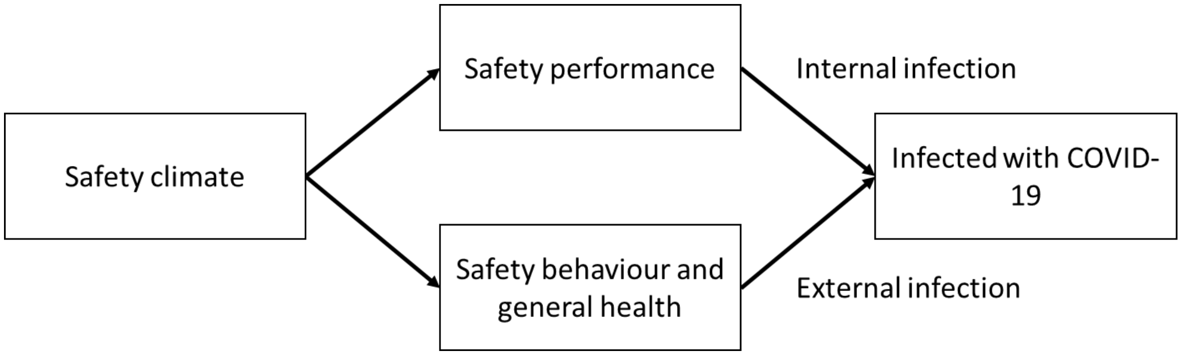
2. Theoretical framework

Safety climate is defined as employees' perception of the organization's safety policies and practices (Stackhouse and Turner, 2019). A good safety climate induces high levels of safety behavior and a lower accident rate (Agnew et al., 2013; Pousette et al., 2017; Smith et al., 2019). As a hypothesis, we propose that the safety climate, by affecting the general behavior of workers, also affects the effectiveness of preventive measures taken to avoid COVID-19, so it should have an impact on the level of contagions suffered by firms. The mechanisms by which this relationship could occur are shown in Figure 1.

Hypothesis. The safety climate has a negative impact on COVID-19 infections.

Figure 1

Relationship between safety climate and COVID-19 infections



The internal channel of this relationship occurs through the behavior of workers inside the workplace. Companies can implement, by will or mandated by the authorities, sanitary measures to minimize contagion. However, if workers do not carry them out, or as recommended, there is a possibility that there may be sources of contagion inside the workplace. Kim (2019) demonstrates that safety climate is a mediator for an effective general safety management system, and therefore should influence safety management in the case of COVID-19.

The external channel has to do with the vulnerability of the company's workers to infection outside the firm. The hypothesis is that the safety climate affects the behavior of workers in their non-working time, influencing the occurrence of accidents (in this case, infections). Salminen (2005) explains the existence of two theories that explain the relationship between accidents at work and accidents at home: 1) The accident-proneness theory proposes that there are individuals who are prone to accidents regardless of the environment in which they find themselves; and 2) The risk-taking theory proposes that individuals have an objective general level of risk, so that a decrease in risk in the work environment should lead to an increase in risk-taking in other aspects of the worker's life. A third theory, proposed by Lund and Aarø (2004), states that one of the factors that most influences the occurrence of accidents, both at work and at home, is the behavior of the individual, and this in turn is influenced by long-term factors such as social norms and the safety climate. Therefore, improvements in the safety climate of the company should lead to better behavior (and, therefore, fewer accidents) of workers not only at work, but also in their leisure time (Lund and Hovden, 2003).

Based on the theory of Lund and Aarø (2004), the hypothesis that supports the external channel proposed in our work is that the safety climate affects psychological aspects of the worker, which in turn affect the risk of infection with COVID-19 in their daily lives. The meta-analysis of Clarke (2010) indicates that the occupational safety climate can have an impact on personal aspects of workers, such as job stress and workers' physical and psychological well-being. Mohren et al. (2001) and Ghilotti et al. (2020) found that occupational stress can lead to an increased risk of respiratory infections due to an alteration of the worker's immune system, which can increase the risk of infection in their daily lives.

3. Materials and methods

3.1. Variables

3.1.1. Dependent variable

To analyze the effect of the safety climate on COVID-19 infections at construction sites, we used as a study variable the number of infected workers divided by the labor mass reported each week, which we call the "Infection rate" ($IR_{i,t}$). The available data are weekly and by construction site, although we do not have a balanced panel due to the nature of the information collection (detailed in section 3.3). Being a proportion, the domain of the variable is between 0 and 1, with extremes included.

3.1.2. Independent variables

Accident rate ($\boldsymbol{AR_i}$): To evaluate our hypothesis in a model it is necessary to use some indicator of the safety climate of a company. Several authors (e.g., Varonen and Mattila, 2000; Vinodkumar and Bhasi, 2009) have found that the accident rate is negatively correlated with the safety climate, so we will use this rate as a proxy for the safety climate (all studies find a negative correlation greater than 0.8 in absolute value).

The annual accident rate for each company is calculated as the sum of the days of sick leave divided by the average number of workers in the year. These data are at the company level and not at the construction site level, i.e., there are sites that share the same accident rate. For our research, this assumption is reasonable since the safety climate is mainly developed at the company level due to the transitory nature of the construction sites. For example, Choudhry et al. (2009) find that a relevant factor affecting the safety climate is management commitment.

As the objective of this variable is to have a proxy for the safety climate during the pandemic, in our model we consider the 2019 accident rate, i.e., it does not depend on t. Neal and Griffin (2006) and Bergman et al. (2014) found that a safety climate indicator has predictive power up to two years after its measurement, so it is a valid proxy. In addition, the 2020 accident rate is disrupted by several factors specific to the pandemic, including construction downtime due to quarantines and the disease itself (which in some cases may have been recorded as an occupational accident).

For a better interpretation of the results, the logarithm of this variable is used in the model. A drawback to consider are the observations with value 0, so it is necessary to perform a transformation of the variable. The method that we use was introduced by MaCurdy and Pencavel (1986) and consists of adding 1 to all the observations of the variable, that is, $ln(AR + 1)$. Another possibility is to use a very recently used method: the inverse hyperbolic sine transformation (Ravallion, 2017). Section 4.2 discusses whether the method used affects the estimation.

Active cases ($\boldsymbol{AC_{i,t-1}}$): Workers can become infected at their homes, so our model considers the existing viral load in the workers' communes of residence. This variable is constructed as the average of the active cases with COVID-19[2] in the commune of residence in the week t divided by the population of the commune. Since workers may reside in different communes, this variable was calculated as a weighted average of the different communes of residence.

Since the incubation period of the virus is six days (Elias et al., 2021), it is possible that the detection of a worker's infection is several days later than the actual date of infection at their place of residence. For this reason, we will assume that this variable affects the dependent variable in a lagged manner in a period $(t-1)$.

Although in our model we are omitting the vaccination rate of workers, which might have a significant effect on infections, we assume that $AC_{i,t}$ has a high correlation with this omitted variable

[2] Active cases are defined as all living persons with a positive COVID-19 sample who have been symptomatic for a maximum of eleven days.

because vaccination influences COVID-19 outbreaks (Moghadas et al., 2021). Consequently, the coefficient estimator of the accident rate coefficient, which is the effect that supports our hypothesis, should not be affected by the omission of the vaccination rate. Even so, in section 4.1 we consider a period in which vaccination in Chile was low.

3.2. Econometric model

Using the infection rate as the dependent variable has the disadvantage that linear functional forms cannot be used in the analysis, since they ignore the restricted nature of the rate in the unit interval. For example, a linear model for the conditional mean would ignore possible relevant nonlinearities (Papke and Wooldridge, 1996). Therefore, we use a "fractional response model", whose particularity is that the dependent variable is a proportion that takes values between 0 and 1, and observations can be found at these extremes (this point is an impediment that does not allow the use of a beta model or a logarithmic transformation for this type of variable).

Although this econometric literature has been prolific (Papke and Wooldridge, 2008), this technique is scarcely used in the field of occupational safety. Some works that have used this methodology in the area have analyzed the occupational safety climate in intensive care units (Seibert et al., 2020), and the exposure to risk and occurrence of occupational accidents according to the relationship of dependence with the company (Shin, 2021). A feature that contrasts our work from these two studies is that we use panel data instead of cross-sectional data, which requires that other relevant aspects must be considered for the estimates to be consistent, such as the individual effect of construction sites and the initial value problem.

The methodology for panel data to be used will be the one developed by Papke and Wooldridge (2008), called correlated random effects for strictly exogenous independent variables.

Data are available for i construction sites in T periods with a dependent variable $0 \leq IR_{i,t} \leq 1$ and a set $x_{i,t}$ of j independent variables (described in section 3.1.2). A static probit model will be assumed:

$$E\left(IR_{i,t} \middle| x_{i,t}, c_i\right) = \Phi\left(\beta x_{i,t} + c_i\right), \quad t = 1, \dots, T. \tag{1}$$

Here $\Phi(\cdot)$ is the standard normal cumulative distribution function (CDF) and c_i is the unobserved effect that appears additively in the model. While there are no theoretical difficulties in using a logit function, it is not known whether conditional logit estimation is consistent unless the dependent variable is binary (Papke and Wooldridge, 2008).

Since Φ is strictly monotonic, and ignoring index i, the partial effect of a change in the continuous variable $x_{t,j}$ is:

$$\frac{\partial E(IR_t|x_t, c)}{\partial x_{t,j}} = \beta_j \Phi(\beta x_t + c) \tag{2}$$

That is, the sign of the partial effect depends only on β. From equation (2) it follows that the partial effects depend on the level of the covariates and unobserved heterogeneity, so it is necessary to discuss these aspects. A common way to solve the first drawback is to average the partial effects over the distribution of c distribution, thus obtaining the average partial effect or APE (Papke and Wooldridge, 2008).

In order for the estimators and APE to be well identified, some additional assumptions need to be made. A common assumption of unobserved effects panel data models is to assume exogeneity of the independent variables such that:

$$E(IR_{i,t}|x_i, c_i) = E(IR_{i,t}|x_{i,t}, c_i), \quad t = 1, \dots, T. \tag{3}$$

Section 3.4 discusses the exogeneity of the explanatory variables, so that this assumption is plausible for our model. In addition, it is necessary to restrict the distribution of c_i given x_i, so Papke and Wooldridge (2008) use a convenient functional form assuming conditional normality:

$$c_i|(x_{i,1}, x_{i,2}, \dots, x_{i,T}) \sim Normal(\psi + \xi\overline{AC}_i + \mu F, \sigma_a^2) \tag{4}$$

Here $\overline{AC}_i$ is the mean of $AC_{i,t}$ over time. It is relevant to emphasize that the mean accident rate is not considered in this assumption due to the perfect collinearity that this would mean given the timeless nature of the variable. Because the estimator of the accident rate coefficient may be capturing firm characteristics unrelated to safety, our model includes firm dummy variables μF. It is necessary to briefly discuss why the incidental parameter problem described by Neyman and Scott (1948) does not exist in our model. According to Greene (2004), the bias caused by incidental parameters decreases rapidly as T is greater than or equal to 3, so that the $T = 33$ of our data allows this drawback to be reduced. Another relevant point to consider is that the dummy variables are at the firm level and not at the site level, so, given that a firm can have more than one site, the number of dummies per firm is less tan $N - 1$. To strengthen this point, in our model we will only consider the sites of those companies with more than one site (i.e., the number of dummies will be less than or equal to $\frac{N}{2} - 1$), so that the estimators of the coefficients of the dummies per firm are no longer incidental parameters. Assumption (4) leads to a direct estimation of β_j and consistent estimators of the APE. Diverse ways of relaxing (4) that are not addressed in this study are discussed in Papke and Wooldridge (2008).

For simplicity, we model (4) as $c_i = \psi + \xi\overline{AC}_i + \mu F + a_i$, where $a_i|x_i \sim Normal(0, \sigma_a^2)$. To reduce the possible contemporaneous correlation problem, time dummies ρ_t were included to reduce the overconfidence of the estimator (Certo and Semadeni, 2006).

Considering assumptions (1), (3) and (4), the static model is obtained:

$$E\left(IR_{i,t}|x_i, a_i\right) = \Phi\left(\psi + \beta x_{i,t} + \xi\overline{AC}_i + \mu F + \rho_t + a_i\right) \tag{5}$$

Due to the large number of observations of $IR_{i,t}$ with value 0 it is necessary to make an assumption about the existence of either one or two models for the data (one for the observed zeros and another for the rest of the cases). Ramalho et al (2011) state that this decision depends on the interpretation given to the observed zeros. If these are results of a maximization process or something similar, it is convenient to use a one-part model. An example of a two-part model given by Ramalho et al (2011) is the relationship between tobacco consumption and its price. If the price of tobacco decreases, it is possible that some individuals will increase their consumption (first model), but there are also other individuals who will never consume regardless of its price (second model). In our work we consider that the relevant specification is a one-part model since the observed zeros may be due to an adequate strategy of the companies to prevent contagions (captured by AR_i) and a good sanitary situation (captured by $AC_{i,t}$). In other words, the zeros and the positives are not two different populations. Section 4.2 discusses the possibility that a construction site may not systematically report infections, causing the most suitable model to be a two-part model.

Although the sanitary measures imposed to the construction sites make it possible to assume that internal contagions were minimized at the construction site, it is not possible to reject a priori the possibility of their existence, so it is necessary to extend model (1) to a dynamic version:

$$E\left(IR_{i,t} \middle| x_{i,t}, c_i\right) = \Phi\left(\beta x_{i,t} + \gamma \mathrm{IR}_{\mathrm{i,t-1}} + c_i\right), \quad t = 1, \dots, T. \tag{6}$$

The most used methods to solve the initial value drawback of a nonlinear dynamic panel are those proposed by Heckman (1987) and Wooldridge (2005). We use Wooldridge's method because its solution is implemented in a model like the one in (5). Akay (2012) performs a Monte Carlo experiment to compare the two solution methods and finds that both works equally well in panels with a long duration (15-20 periods), which is our case. Although Wooldridge (2005) only analyzes binary and ordinal probit models, there is no inconvenience in using his solution in a fractional response model (e.g., Loudermilk, 2007).

The Wooldridge (2005) method consists of including the initial value of the dependent variable in the unobserved error. From equation (4), it is modeled as:

$$c_i | \left(x_{i,2}, x_{i,3}, \dots, x_{i,T}\right) \sim Normal\left(\psi + \xi \overline{AC_i} + \mu F + \delta \mathrm{IR}_{\mathrm{i,1}}, \sigma_a^2\right) \tag{7}$$

This solution implies that the model is estimated from $T = 2$.

Wooldridge (2005) models the unobserved error conditionality of the explanatory variables through the row vector of $x_{i,t}$ instead of $\bar{x}_i$ (which is the way we model it in (7)). Rabe-Hesketh and Skrondal (2013) demonstrate through a Monte Carlo experiment that $\bar{x}_i$ produces a significant bias due to omitting the relevance of the coefficient of the initial explanatory variable. The solution they propose is to include to the unobserved error the initial value of the explanatory variables ($\bar{x}_i$ is still calculated over all T), so that:

$$c_i | \left(x_{i,2}, x_{i,3}, \dots, x_{i,T}\right) \sim Normal\left(\psi + \xi \overline{AC_i} + \mu F + \delta \mathrm{IR}_{\mathrm{i,1}} + \theta \mathrm{AC}_{i,1}, \sigma_a^2\right) \tag{8}$$

Given the structure of our panel data ($N \to \infty$, T fixed), a Harris-Tzavalis unit root test was performed to verify the stationarity of our dependent variable. With 1% significance the null hypothesis is rejected, so it can be stated that the panels are stationary. Replacing (8) in (6), and remembering the inclusion of the time dummies ρ_t, the dynamic econometric model to be estimated is:

$$E\left(IR_{i,t}\middle|x_i, a_i\right) = \Phi\left(\psi + \beta x_{i,t} + \gamma \mathrm{IR}_{\mathrm{i,t-1}} + \xi \overline{AC}_i + \delta \mathrm{IR}_{\mathrm{i,1}} + \theta \mathrm{AC}_{i,1} + \mu F + \rho_t + a_i\right) \tag{9}$$

As in Wooldridge (2005), it is assumed that the dynamics of the dependent variable is first order, i.e., infections within the construction sites depend on the infections reported in the previous week and not on earlier periods. This assumption is plausible in our model due to the sanitary measures carried out by the construction sites, which periodically performed COVID-19 tests to detect possible cases early (thus preventing the sick person from infecting the rest of the workers).

There are different consistent estimators for the coefficients of equation (9) (Papke and Wooldridge, 2008), but in this paper a generalized estimating equation or GEE will be used. As indicated by Ballinger (2004), this type of model is an extension of the generalized linear models (GLM) allowing for serial correlation between the data (although it still assumes the existence of heteroscedasticity), making it a more suitable methodology than GLM for longitudinal data. Another advantage of using the GEE estimator over other estimators is that it is consistent even when the covariance matrix is misspecified (Papke and Wooldridge, 2008). It should be noted that the GEE approach develops a model for the average population response, which is consistent with our objective to obtain the APE and not the per-site effect. An exchangeable work correlation matrix is used, as in Papke and Wooldridge (2008).

A drawback of the above methodology is that it imposes a restriction on the conditional distribution of heterogeneity based on the full history of covariates (Wooldridge, 2019), so an alternative is to make an additional assumption for an unbalanced panel of data called the "condition of ignorability of the selection". This assumption is that the selection of missing data is random, and the dependent variable is unconditional to it (Wooldridge, 2019). Section 3.4 discusses this assumption considering the nature of the data used.

3.3. Data

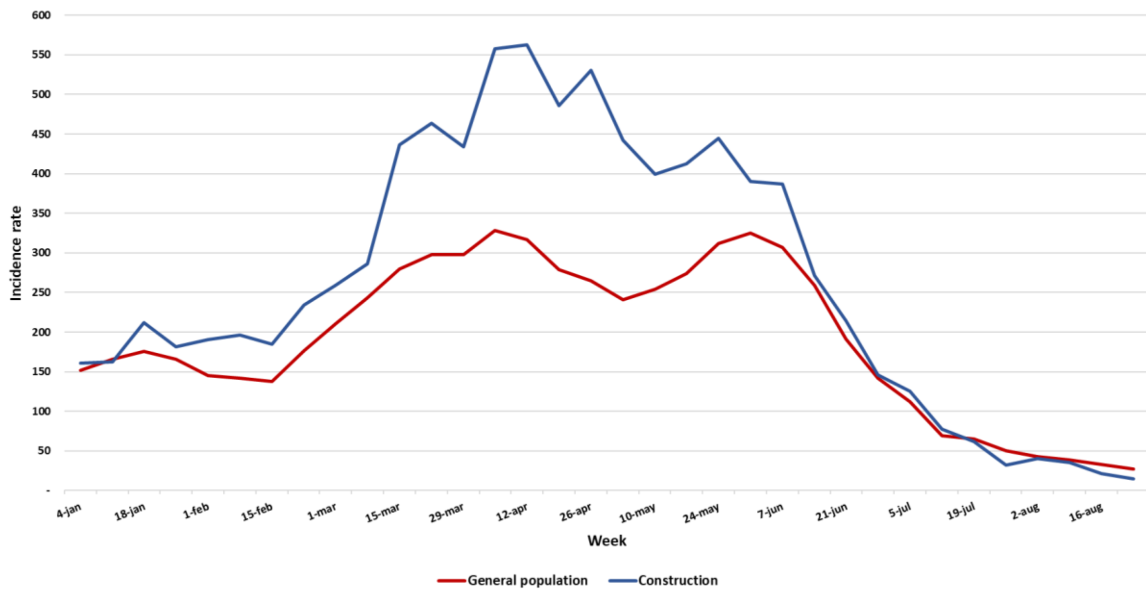
Our data on contagions and workers on construction sites in Chile come from the Chilean Chamber of Construction (CChC). This organization conducted a program called "Sanitary Commitment" whose purpose was that the registered construction sites committed themselves to comply with a sanitary protocol developed by the CChC together with the Chilean government, and to self-report weekly the number of infected workers and the total number of workers in the construction site. Adherence to this program was voluntary, although as of March 2021 sites wishing to operate in quarantined communities must be registered. Failure to comply with the self-reporting did not impose any sanction on the sites, although CChC analyzed the reports on a weekly basis and, if it considered that a site had a possible source of contagion, it carried out on-site inspections to rigorously corroborate the sanitary protocol, and if the sites were not complying, their quarantine operation permit could be revoked[3]. In turn, the CChC corroborated by telephone any information that might be erroneous (for example, that they recorded more infected people than workers). For this work we use weekly data collected between January and August 2021[4] (34 weeks) for the number of infections and the number of workers at construction sites. Figure 2 shows the evolution of the incidence rate, number of weekly infections per 100,000 inhabitants or workers, calculated with these data in comparison with the incidence rate for the general population reported by the Ministry of Science in conjunction with the Ministry of Health.

Figure 2

Evolution of national and construction contagions

[3] Between April and June 2021, 2,462 construction sitess were audited. Fifty sites had their operating permits revoked.

[4] Although there is information on self-reports since the week of September 14, 2020, these are composed of a low number of construction sites, in addition to the fact that the epidemiological situation of the country was different from that of 2021.



Fuente: Own elaboration with data from the Ministry of Science (2021) and CChC.

Since self-reporting was voluntary, not all sites reported in all weeks. This causes the panel data we used to be unbalanced. We subdivided the causes of non-reporting into two groups:

1) Due to an unknown deliberate or unintentional decision of the construction site. For example, the site may have failed to report because the manager forgot it, or he/she was on medical leave or vacation. Another probable reason is that the site did not report for fear that the authority would foreclose it. Although there was never a CChC or government regulation that contemplated this threat for not reporting, there was the possibility of revoking the operating permit if they did not comply with the sanitary protocol (in practice, fifty operating permits were revoked in a total of 2,462 inspections).

2) Because the site was not enrolled in the program: since adherence to the "Sanitation Commitment" was voluntary, the sites could enter or leave the program whenever they wanted. This means that there is no information on these sites before joining the commitment or after their exit (which they had to report to CChC). Sites that remain in the program at a certain date are referred to as "active".

The accident rate data for 2019 were provided by the two largest insurers of the occupational health system in Chile, the Asociación Chilena de Seguridad and Mutual de Seguridad. According to the

Superintendencia de Seguridad Social (2021), these institutions insured 84% of workers in the construction sector (28% and 56% respectively).

Data on active cases in the general population were obtained from the Ministry of Science (2021).

3.4. Validation of assumptions

This section discusses two of the assumptions made in the model: the exogeneity of the explanatory variables and the condition of ignorability of the selection.

Exogeneity of the explanatory variables: Since the accident rate AR_i used is from 2019, there is no endogeneity with the model. The exogeneity of the active cases $AC_{i,t}$ does need to be analyzed in more depth, since it can be argued that the sources of contagion at a construction site may have an impact on the active cases in their commune of residence.

Murti et al. (2021) analyzed outbreaks of infection in workers' residences following an outbreak of infection in their workplace. Of 1,245 outbreaks of occupational infection detected, only 339 outbreaks of infection in the home (27%) were related. Specifically, in the construction sector, three outbreaks were recorded at home after 44 outbreaks at work (7%). This allows us to assume that contagion at construction sites does not affect active cases in their communes of residence, so the variable is exogenous to the model.

Condition of ignorability of the selection: As described in section 3.3, there are two reasons for a site not to report its cases in each week: 1) Because of a decision that is unknown, and 2) Because the site was not enrolled in the program. We consider the first reason to be important to analyze since the construction sites may have the incentive not to report for fear that their permit to operate in quarantine may be revoked. One way to study this question is to test whether non-reporting is preceded by an outbreak of infection in the previous week. In Friesen and Gangadharan (2013) there is evidence that underreporting of accidents occurs more frequently if reporting is voluntary. Although the self-reporting of the construction sites was voluntary, in the case that the corresponding company was a member of CChC, it was pressured more intensely to report its cases. The probit model to be estimated is:

$$E\left(R_{i,t}=1\middle|x_{i,t},\epsilon_i\right)=\Phi\left(\alpha+\beta_1 IR_{i,t-1}+\beta_2 M_i+\epsilon_i\right),\quad t=1,\dots,T. \tag{10}$$

where $R_{i,t}$ is a dummy variable that takes the value 1 if the site i reported its cases in the week t, M_i is a dummy variable that takes the value 1 if the site i belongs to CChC, and ϵ is an unobserved effect. It was assumed to be a model with random effects for simplicity. The estimation is shown in model (1) in Table 1.

There is an effect of the infections reported in the previous week on the probability of reporting their cases, so the "condition of ignorability of the selection" cannot be assumed since the selection of missing data is not random. To solve this drawback, we will consider in our model the sites that have always reported their cases in the period analyzed, thus generating a balanced panel of data.

Table 1

Reason for not self-reporting [a]

	(1)		(2)		(3)	
Variables	**Coef**	**APE**	**Coef**	**APE**	**Coef**	**APE**
Infection rate (IR_{t-1})	-1.9167***	-0.1758***	-1.9287***	-0.1742***	-2.2227***	-0.1616***
	(0.3253)	(0.0304)	(0.3278)	(0.0302)	(0.3780)	(0.0282)
CChC member (M)	0.5338***	0.0490***	0.3844***	0.0347***	0.4282***	0.0311***
	(0.0410)	(0.0044)	(0.0454)	(0.0044)	(0.0499)	(0.0040)
Accident rate			0.0536***	0.0048***	0.0286*	0.0021*
($\ln(AR)$)			(0.0085)	(0.0008)	(0.0170)	(0.0012)
Number of sites	1,077		1,077		753	

a Notes: (i) Robust errors were used. (ii) Integration points (12) were checked.

* p < 0.10; ** p < 0.05; *** p < 0.01

Another analysis that can be performed with this model is to observe the effect of the accident rate on the probability that the site reports its cases. If the main hypothesis of our work is true, it should be expected that the rate of contagions and accidents are positively correlated, so the interpretation of the estimators is difficult due to the existence of multicollinearity. The estimation can be seen in model (2) in Table 1. A surprising result of this estimation is that the accident rate has a positive and significant effect on the probability of reporting, i.e., worksites with a worse safety climate have a higher probability of reporting their contagions. In model (3) of Table 1 we analyze whether this estimate holds if we consider only sites with an accident rate greater than zero. We observe that the accident rate is significant only at 10%. These two estimates allow us to argue that construction sites with an accident rate equal to 0 are likely to report less than others. Due to the different behavior of these groups, it reinforces the position of considering in our model only those construction sites that have systematically reported.

3.5. Descriptive statistics

The descriptive statistics of the model variables are presented in Table 2. Given the assumptions described in the previous sections[5], a subsample of the total data available is used for the estimation. Table 2 shows the statistics for both the complete database and the subsample to be used.

A relevant difference to consider is the decrease in the observed zeroes of the accident rate, which results in both the mean and the standard deviation increase. The main reason for the decrease in the observed zeros is the elimination of sites with unreported periods (observed zeros decrease from 30% to 3%), which is in line with the findings in section 3.4.

Table 2

Descriptive statistics

	Infection rate (IR)		Active cases (AC)		Accident rate (AR)[a]	
	Complete	**Model**	**Complete**	**Model**	**Complete**	**Model**
Minimum	0	0	0	0.00002	0	0
Maximum	1	1	0.0103	0.0071	3018.394	3018.394
Mean	0.0034	0.0026	0.0020	0.0019	290.3165	450.2389
S.D.	0.0273	0.0177	0.0012	0.0011	560.8825	679.3277
Observed zeros	86%	86%	0%	0%	30%	3%
Observed ones	0%	0%	0%	0%		

[5] It should be recalled that all sites with unreported periods and those belonging to companies with less than two sites were eliminated.

Number of observations	23,479	6,630	23,479	6,630		
Number of sites	1,077	195	1,077	195	1,077	195
Number of companies	443	55	443	55	443	55

a Note: Statistics were calculated from one observation per construction site since it is a timeless variable.

4. Results and discussion

4.1. Econometric estimates

Model (1) in Table 3 shows the estimation of the proposed model. The APE of the accident rate is 0.003, i.e., a 100% increase in the accident rate implies an increase of 0.3 percentage points in the rate of contagions in the sites. Considering that the mean contagion rate is 0.26%, this is a significant effect.

Using the accident rate as a proxy for safety climate has the drawback that it does not consider that there are industries that are riskier than others, and therefore with more accidents. For this reason, it is convenient to perform an analysis comparing companies within the same industry, as deviations compared to the industry average may be caused by a significant behavioral component (Marshall et al, 2018). To analyze these possible differences within the same industry, we estimate in model (2) of Table 3 the model only with the sites belonging to companies with an accident rate higher than the industry average (131.9). It should be taken into consideration that this average is different from the one proposed in section 3.5 because it considers companies that did not subscribe to the Sanitary Commitment. The APE of the accident rate indicates that a 100% increase in the indicator means an increase in the contagion rate by 0.36 percentage points, an effect higher than that estimated with the full model, which is consistent with the fact that the effect of the accident rate on the contagion rate is greater in companies with a worse rate.

An omitted variable that may be relevant to our model is the vaccination rate of workers, as discussed in section 3.1.2, but the lack of reliable data by construction site makes it difficult to incorporate. Vaccination programs around the world generate that contagion patterns in the population are modified through herd immunity (Randolph and Barreiro, 2020), which implies that the data generating process (DGP) prior to vaccination is different from the existing one when a high percentage of the inoculated population is reached. This is evidenced in our data in Figure 2, as from June onwards infections decreased rapidly while exceeding 50% of the Chilean population inoculated with the full COVID-19 vaccination scheme (Ritchie et al., 2020). To undertake this drawback with the DGPs, in model (3) of Table 3, data from construction sites up to the week of June 14 are considered, since at the end of this week the goal of 50% of the inoculated population was reached. The APE of the accident rate increases by 50% compared to model (1), i.e., a 100% increase in the indicator means an increase in the infection rate by 0.46 percentage points. This estimate, in addition to being evidence of a possible change in the DGP due to vaccination, corroborates the relevance of the safety climate on the COVID-19 infections suffered by workers.

The three models estimated in Table 3 allow us to ratify our hypothesis that the safety climate has a negative impact on COVID-19 infections.

Table 3

Estimation of the econometric model [a]

	(1)		(2)		(3)	
Variables	**Coef**	**APE**	**Coef**	**APE**	**Coef**	**APE**
Accident rate	0.3824**	0.0030**	0.4402***	0.0036**	0.4687***	0.0046**
(ln (AR))	(0.1797)	(0.0014)	(0.1661)	(0.0014)	(0.1787)	(0.0018)
Active cases (AC_{t-1})	101.2105***	0.7836***	115.1702**	0.9527**	104.2875***	1.0152***
	(32.4027)	(0.2485)	(44.6405)	(0.3727)	(34.2922)	(0.3285)
Infection rate (IR_{t-1})	2.2869***	0.0177***	3.4558**	0.0286**	2.6696***	0.0260***
	(0.8159)	(0.0060)	(1.4430)	(0.0120)	(0.8977)	(0.0081)
Working correlation	-0.0066		0.00004		-0.0067	
Mean IR	0.0026		0.0029		0.0032	
Number of sites	195		110		188	
Number of companies	54		33		51	
T	33		33		23	

[a] Notes: (i) Models contain time dummies. (ii) The models contain firm dummies. (iii) The estimation includes the

time average of the variable, and the initial values of IR and AC.

* p < 0.10; ** p < 0.05; *** p < 0.01

4.2. Robustness tests

To corroborate the results presented above, it is necessary to evaluate certain methodological assumptions made in this work. In section 3.1, a transformation to the accident rate variable was proposed considering that there are observations with value 0, which consisted of adding the constant 1 to all the observations of the variable. A second widely used method is called inverse hyperbolic sine transformation (Friedline et al., 2015): $\ln(AR + (AR^2 + 1)^{0.5})$. In model (4) of Table 4 the estimation with this transformation of the accident rate variable is performed and it is observed that there is no difference with model (1) of Table 3, so the method used does not influence the results.

In Section 3.2 we discussed the existence of one or two models for the data (it was assumed that it was relevant to use the one-part model). Our assumption may not be relevant for this data set due to the existence of firms that systematically reported zero contagions, which is called stable systematic reporting bias (af Wåhlberg and Dorn, 2015). One way to avoid the bias produced by these firms is to only consider the sites of firms that reported at least one contagion in all their sites in the whole period analyzed, which is done to estimate model (5) in Table 4. We observe an APE of the accident rate higher by 50% compared to model (1) in Table 3, so this first estimate should be considered as a minimal effect of the accident rate on the infection rate.

In section 2 it was argued that the safety climate has a long-term effect on the behavior of workers, so that the propensity to become infected cannot be circumstantial to a short period of one week. For this reason, in Table 4 the model (6) was estimated with monthly periods. It is observed that the estimated APE of the accident rate is approximately equal to a geometric progression of the APE of model (1) in Table 3: $(1 + 0.003)^4 - 1 = 0.0121 \cong 0.0130$. That is, the weekly estimate is consistent with the monthly estimate of the model.

Table 4

Robustness tests of the estimated model [a]

	(4)		(5)		(6)	
Variables	**Coef**	**APE**	**Coef**	**APE**	**Coef**	**APE**
Accident rate	0.3812**	0.0030**	0.4592***	0.0042***	0.4954**	0.0130**
(ln (AR))	(0.1792)	(0.0014)	(0.0700)	(0.0007)	(0.2149)	(0.0057)
Active cases (AC_{t-1})	101.2105***	0.7836***	117.7589***	1.0779***	133.3023**	3.5095**
	(32.4027)	(0.2485)	(37.8625)	(0.3465)	(56.4379)	(1.5075)
Infection rate (IR_{t-1})	2.2869***	0.0177***	2.9936**	0.0274**	0.5365	0.0141
	(0.8159)	(0.0060)	(1.3862)	(0.0126)	(0.5626)	(0.0148)
Working correlation	-0.0066		-0.0009		-0.0519	
Mean IR	0.0026		0.0031		0.0102	
Number of sites	195		132		194	
Number of companies	54		42		53	
T	33		33		7	

[a] Notes: (i) Models contain time dummies. (ii) The models contain firm dummies. (iii) The estimation includes the time average of the variable, and the initial values of IR and AC.

* p < 0.10; ** p < 0.05; *** p < 0.01

4.3. Limitations and ideas for future research

One of the limitations of the study is that the analysis was conducted in only one sector, which makes it impossible to exploit the differences that may exist in different sectors of the economy. As discussed in the introduction, the limited availability of epidemiological data at the firm level has made it impossible for researchers to analyze underlying factors that accentuated a global health problem. For this reason, this study is intended to be a precursor to the analysis of the effects of safety climate on other relevant aspects of the company beyond occupational health and safety.

5. Conclusion

The relevance of the safety climate in occupational safety practices has been studied in depth in the literature. A less intensely analyzed aspect is the effect of the safety climate on other aspects of the company, as could have been the COVID-19 infections suffered by workers in the pandemic that, as of the date of writing of this research, has not yet ended.

This research tested the hypothesis that the safety climate has a negative impact on COVID-19 infection. The mechanisms by which this relationship may occur are through the behavior of workers within their workplaces, and through external factors such as the impact of the safety climate on the general behavior of the workers. To corroborate our approach, a dynamic fractional response panel model was developed and estimated with microdata at the site level of the construction sector in Chile. The results were robust and verified a significant negative effect of the safety climate on worker infections. Using the entire sample period, a 10% safer safety climate, compared to an average company, implies a reduction of the contagion rate by 11.5%. In the case of companies with a worse safety climate this decrease increases to 12.4%. Using the period without the effect of vaccinating the population, the decrease in the infection rate is 14.4%.

6. Practical Applications

The relevance of these results should not be pigeonholed into the effects of the security climate on the pandemic, as we only use it as an case study. The conclusions of our findings could be extended to different business and, eventually, national issues. For this reason, continuous monitoring and evaluation of the safety climate should be a priority for companies and national authorities, as this can reduce the negative impacts on other aspects that are often not considered.

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Appendix: The pandemic in the construction sector in Chile

On March 3, 2020, the first person infected with SARS-CoV-2 coronavirus was registered in Chile. Up to that moment in the world, 92,980 people were infected and 3,160 died (Ritchie et al., 2020).

On March 21, the first death from COVID-19 was recorded in the country, by which time 537 people had already been infected in Chile (Ministry of Science, 2021). To contain this threat, the Chilean Chamber of Construction (CChC) distributed among its members an instructive called "Sanitary Protocol" in which a series of recommendations were given to mitigate the risks inside the construction sites that could have an impact on the spread of the infection among workers. Despite these efforts, on March 25 the first quarantines were announced, which prevented the construction sites and residents of the affected communities from working.

On June 14, the highest number of cases was detected in the first wave of infections in Chile, reaching an unemployment rate in the construction sector of 20%, compared to a rate close to 8% in the fourth quarter of 2019 (CChC, 2020).

By mid-July, 56% of the country's population was under quarantine, which led to a rapid decrease in the number of infections. On July 19, the government announced the implementation of the "Step by Step Plan", which consisted of a relaxation of some of the most restrictive measures. The CChC's efforts with the authorities led to the implementation of a pilot plan for the operation of construction sites in quarantined communities, which finally allowed the government to authorize the operation of the industry throughout the rest of the pandemic on November 2, regardless of the fluctuations in the number of infections that occurred in the country.

In December and January, the health authority authorized the emergency use of three vaccines in the country (Pfizer/BioNTech, Sinovac and AstraZeneca/Oxford). With this, the government implemented the "National Vaccination Plan" which sought to inoculate 80% of the country's target population. By the end of February, 17% of the population was inoculated with at least the first dose of the vaccine, making Chile the third country with the greatest progress in the vaccination of its population (Ritchie et al., 2020).

The overconfidence generated by the success of the vaccination plan led to a rapid increase in contagions in March 2021. For this reason, the CChC, together with the Ministry of Economy, agreed to increase the prevention measures to be complied with by the industry, which materialized in the obligatory signing of an affidavit and compliance with the "Sanitary Protocol" for all construction sites wishing to operate in quarantine.

During the week of May 10, the national vaccination plan was able to inoculate 56% of the target population with the first dose. This situation was not replicated in the construction industry, where only 37% of workers were vaccinated. This prompted the CChC to initiate a strong communications campaign to encourage vaccination in member companies.

On May 27, the highest number of daily infections of this second wave was recorded, 8,117 cases. One of the government's measures to combat this critical situation was to tighten the freedoms granted by the "Mobility Pass", a document that allowed those vaccinated with the full vaccination schedule to carry out activities that could not be carried out by unvaccinated people. On June 23, the authority announced that the goal of vaccinating 80% of the target population with the first dose had been achieved. In mid-July, the construction sector reached this goal and equaled the national vaccination rate. This good news was coupled with a decrease in daily infections, reaching levels in August that had not been seen since April 2020.