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Financial distress in the hospitality industry during the Covid-19 disaster

Rafel Crespí-Cladera, Alfredo Martín-Oliver, Bartolomé Pascual-Fuster [*]

Departament d'Economia de l'Empresa, Universitat de les Illes Balears, Cra. de Valldemossa km 7.5, 07122 Palma, Illes Balears, Spain

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ABSTRACT

We implement the stress test methodology of the banking industry in conjunction with a Logit model of bankruptcy with parameters estimated with data from the Great Recession (2008–2013) to predict which firms would face financial distress among Spanish hospitality firms during 2020 due to the Covid-19 disaster. The predictions from both methods rely on the last accounting data available and on the expected revenue drop for 2020. Both methods coincide to predict that 25% of these firms will face a financial distress situation if revenues drop 60%. This forecast raises up to 32% of firms if revenues drop 80%. Financial distress will affect mainly small firms. Most of the firms in financial distress will face solvency problems, with total assets being insufficient to pay all debts.

1. Introduction

The tourism industry is specially affected by health emergences (Chien & Law, 2003; Dahles & Susilowati, 2015; Dombey, 2003; Mckercher & Chon, 2004; Novelli, Gussing Burgess, Jones, & Ritchie, 2018). For example, in China, the SARS crisis in 2003 strongly affected the tourism industry compared to other industries (Dombey, 2003). The Covid-19 crisis is much stronger— not only for its effect on the tourism industry, reducing total activity by 60–80% in 2020 according to the United Nations World Tourism Organization (UNTWO), but also because it is widespread around the globe, collapsing the world economy. In Spain, where tourism's relevance to the GDP is close to 15%,[1] the overall impact to the economy is devastating. In such situations, recent studies are finding that the financial strength of firms is becoming especially relevant: stock market prices are less affected by the crisis in firms with more cash holdings, lower leverage and more profits (Acharya & Steffen, 2020; Ding, Levine, Lin, & Xie, 2020; Pagano, Wagner, & Zechner, 2020; Ramelli & Wagner, 2020). A natural interpretation of this finding is that investors do not expect financial markets to provide the financial resources firms will need to resist this crisis period (Ramelli & Wagner, 2020). The financial markets also predict this issue to be more relevant in industries where it is more problematic to maintain social distance measures, like in the hotel industry (Pagano et al., 2020).

In a stable or growing period, cash holdings are of little value since firms may easily access financial markets to obtain funds, when required. Furthermore, due to the agency conflict between managers and shareholders, cash holdings may generate negative incentives to executives and reduce shareholder value (Jensen, 1986). However, in the Covid-19 crisis stock market prices anticipate the difficulty many firms face to obtain the financial resources to survive this crisis period. Firms with low cash holdings, high financial leverage and with a history of low profits are at a disadvantage (Acharya & Steffen, 2020; Ramelli & Wagner, 2020). Past research in the hotel industry found that the financial structure of firms is irrelevant for the probability tourism firms' survival (Gémar, Moniche, & Morales, 2016). Indeed, little attention has been paid to the financial strength of hospitality firms in past literature which studies their performance (Claver-Cortés, Molina-Azorín, & Pereira-Moliner, 2006; Sainaghi, Phillips, & Zavarrone, 2017). Other characteristics of firms, such as the geographical location or the type of service attracted more attention (Assaf & Tsionas, 2018). However, a period with little revenues generates a strong need for financial resources in hospitality firms to survive and pay fixed costs, which are quite relevant in these firms (Nicolau, 2005). This situation could be easily solved in many firms if they had access to bank loans and/or financial markets operated properly, providing these firms with the needed financial resources to survive. This is something that changed in the Covid-19 crisis and that the previous literature on hospitality firms does not consider.

In this article, we analyze the relevance of the financial strength of hospitality firms to explain differences in resilience to the Covid-19 crisis and any global disaster that might cause a fall in operating

* Corresponding author.
E-mail addresses: rafel.crespi@uib.es (R. Crespí-Cladera), alfredo.martin@uib.es (A. Martín-Oliver), tomeu.pascual@uib.es (B. Pascual-Fuster).

[1] Data extracted from INE, the National Institute of Statistics.

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income of tourism firms together with the freeze of financial markets and inability to access to bank financing. We analyze these firms in Spain, where public debt is above 100% of GDP (European Central Bank), and, therefore, where financial markets expect a shortage of public injections of liquidity (Gerding, Martin, & Nagler, 2020). Furthermore, the high relevance of the tourism industry in Spain is key to explain the growth of the Spanish economy (Perles-Ribes, Ramón-Rodríguez, Rubia, & Moreno-Izquierdo, 2017). Spain is among the most relevant countries in international tourism, with more than 80 million foreign visitors in 2019 (UNTWO).

Additionally, in Spain the Covid-19 crisis has been especially prevalent. The first cases of Covid-19 were diagnosed in January 2020, and the number of affected people began to rise until the end of March, when the Spanish health system collapsed. The government decision to the confinement of the population restricted the economic activity to basic survival activities. Travel, tourism and hospitality activities were forbidden until the middle of May, when a three-phase approach was established to return to the "new normal". During the quarantine period, only a few hotels remained open to isolate the infected people and under strict health security measures. After the confinement, in June 2020, the tourism industry was able to operate. However, borders were closed to foreign visitors and almost all hotels remained closed. A few weeks later, borders opened to European Union citizens and to a small group of non-European countries, generating some activity in the Spanish hospitality sector. During the January to August period in 2020, the estimated occupancy rate of Spanish hospitality firms was at 30% of the level achieved during the same period in 2019 (INE).

This situation devastated the activity of hospitality firms, which have to cope with considerable fixed costs. We analyze the survival chances of hospitality firms in different scenarios of revenue generation during 2020. Our findings suggest that cash holdings and a strong financial structure play an insurance role in hospitality firms, helping them to hedge global risks that are otherwise difficult to hedge. Our empirical strategy includes two methodologies. First, we implement the stress testing methodology commonly applied to the banking industry. To do so, we simulate a relevant drop in revenues and estimate the operating costs that firms have to bear, given their particular structure of fixed costs versus variable costs. We analyze whether the firm has enough cash funds or equity funds to cope with the potential negative net income. Second, we complement this traditional stress test methodology with an empirical model that predicts default in hotel firms. The estimation period used to obtain the parameters of the model is the Great Recession (2008–2013), when financial markets dried up and firms were subject to financial constraints similar to those faced in the Covid-19 crisis. Then, using the most recent available accounting data and the predicted revenue drop for 2020, we apply this model to predict the failure of hospitality firms during the Covid-19 crisis. The model predicts that the probability of failure increases for firms with low levels of cash, high leverage and a higher proportion of fixed costs with respect to variable costs.

With the combination of both the stress test methodology and the probabilistic model of failure, we detect which firms could face financial distress situations during the Covid-19 crisis, thus requiring additional funds to avoid failure. Our results indicate that almost 25% of hospitality firms could experience a financial distress situation, most of them related to solvency (with total assets being lower that total debt) when revenues drop 60%. This adverse situation would especially affect smaller firms, those providing about 11% of total employment in the industry. If revenues drop 80%, financial distress could affect to 32% of firms. These magnitudes of the revenue drop in 2020 are consistent with the occupancy rate of Spanish hospitality firms from January to August (INE), and with the estimations of Exceltur (a specialized consulting service on the Spanish hospitality firms). These situations could result in firms filing for bankruptcy if financial resources are unavailable. There are instruments and mechanisms that could reduce the impact of the predicted financial distress situations, such as off-balance sheet financial resources (i.e., credit lines), the reduction of some non-vital expenses in the short run, and/or support from public authorities. Indeed, half of the firms with data available on credit lines would not be in a financial distress situation given the resources provided by this financial instrument, according to our estimations. Also, around 5% of firms suffering a financial distress situation would solve it by eliminating the maintenance investments. Besides, the Spanish Government is actually providing some support to the tourism industry, paying the salary to inactive employees due to the Covid-19 crisis.

Our analysis provides a contribution to the tourism literature, showing the relevance of financial strength and its different components in a crisis period that devastates revenues, with an expected shortage of financial resources, to generate liquidity and solvency financial distress situations. Previous literature found little relevance of the financial structure of firms to explain the survival of tourism firms (Gémar et al., 2016), and their performance (Assaf & Josiassen, 2012; Assaf & Tsionas, 2018; Chen, 2007; Claver-Cortés et al., 2006; Prayag, Chowdhury, Spector, & Orchiston, 2018; Sainaghi et al., 2017; Saito & Romão, 2018; Stauvermann & Kumar, 2017). The findings in this literature are consistent with a situation where the financial system (basically financial markets and banks) provides the financial resources to survive transitory periods with little revenue for firms. We also expand the literature by analyzing the operational leverage of hospitality firms (Nicolau, 2005), showing its relevance in a crisis situation to survive. We also extend the crisis literature in the hospitality industry with a detailed analysis of different dimensions of financial strength and its relation to survival probability. Previous studies focused the analysis on strategies to survive, paying almost no attention to financial factors (e.g. Li, Nguyen, & Coca-Stefaniak, 2020; Novelli et al., 2018; Ritchie, 2004). Our results suggest that firms should consider different aspects of their financial strength in the overall strategy to survive a crisis period. The investment in financial strength is like insurance against crises as the Covid-19 one. Finally, we expand the finance literature analyzing the Covid-19 crisis with a detailed analysis of its impact on the financial stability of hospitality firms (e.g. Acharya & Steffen, 2020; Ramelli & Wagner, 2020). While the previous financial literature focuses their attention on stock prices, we focus our attention on the effect of revenue drop on firms' financial statements, including the analysis of non-listed firms.

We review the related literature in the next section. In the third section, we describe our data. The methodological approach is described in section four. Section five presents the results, section six provides a discussion of our results, and in the seventh section we conclude.

2. Related literature

There is abundant literature studying crisis and disasters in the tourism industry (Dombey, 2003; Faulkner, 2001; Israeli & Reichel, 2003; Mckercher & Chon, 2004; Novelli et al., 2018; Ritchie, 2004). Any phenomenon affecting the security of travelers and tourists, such as wars, terror attacks, natural disasters (e.g., earthquake) and health crises have a devastating impact on the tourism industry (e.g., Chien & Law, 2003). Faulkner (2001) and Ritchie (2004) analyze the tourism industry in such situations, distinguishing crises from disasters depending on the capacity of firms to control such situations. According to them, the situation generated by Covid-19 should be classified as a disaster, as it is out of the control of firms. There are also previous articles studying health crises since the SARS outbreak in 2003, which devastated the tourism industry in Asia (Chien & Law, 2003; Mckercher & Chon, 2004). Some articles on crises in tourism are focused on the strategies of firms to survive, such as diversification (Chien & Law, 2003) or changing foreign to national tourism (Israeli & Reichel, 2003), even lobbying the political power to obtain funding and adapted regulation. However, the consequences of a global health crisis affecting all countries and all industries, much stronger than SARS, are still to be explored. In the Covid-19 disaster, all destinations should focus on health security to obtain competitive advantage as the number of tourists is expected to decrease strongly everywhere. Some recent papers already analyzed different aspects of the Covid-19 disaster in the tourism industry (Dolnicar & Zare, 2020; Li et al., 2020; Wen, Kozak, Yang, & Liu, 2020; Yang, Zhang, & Chen, 2020; Zenker & Kock, 2020). These articles focus on the initial effects on the demand of tourism services (Li et al., 2020), on modifications in the services that hospitality firms offer (Dolnicar & Zare, 2020), and also on the global effects on the tourism industry, such as Yang et al. (2020), using a general equilibrium model. Some articles also discuss how research in tourism should analyze the Covid-19 crisis, demanding deeper analyses (Zenker & Kock, 2020). Our article expands this literature with a deep analysis of the role of the financial strength of firms in the hospitality industry to survive the disaster period, with an overpassed financial system, to quantify how different dimensions of financial strength contribute to the survival of hospitality firms, and also to quantify the magnitude of the disaster in terms of the number of otherwise profitable firms which may default without a proper injection of financial resources. To this end, we use a new methodology in the tourism literature, the stress test methodology, commonly used by banking authorities.

In the finance literature, the current articles analyzing the Covid-19 crisis study the effects on the financial markets, especially the stock market reactions (e.g., Pagano et al., 2020; Ramelli & Wagner, 2020). Since stock prices are the present value of the expected cash flows generated by the firm in the future, a transitory and short period of reduced activity should only have a moderate effect on prices. However, stock markets declined quite low (34% drop of the S&P500 stock market index from February to March 2020, while the drop was only around 23% the first month after the Lehman Brothers default in the Great Recession in 2008). Ramelli and Wagner (2020) find that prices decline less in firms with strong financial structure, suggesting a shortage of financial resources in the financial system. The public agencies and the central banks could intervene, providing the financial resources that many firms would need to survive the Covid-19 disaster. However, the stock market discounts that the most indebted countries will be unable to obtain the necessary financial resources (Gerding et al., 2020). Indeed, by July stock market prices recovered their 2019 level in the US (S&P500), while remaining low in Spain (a highly indebted country) with around 23% loss in 2019 by the Ibex-35 stock market index (even after the approval of a large budget at the European Union level to support the economic recovery, July 21). In sum, the stock market prices expect shortages of financial resources in some countries, even for what were profitable firms just before the Covid-19 crisis, and therefore expect that cash holdings and financial strength of firms will be relevant to survive the Covid-19 crisis.

In the tourism industry, the literature has paid attention to a number of aspects away from the financial structure of firms to explain firms' performance (Assaf & Josiassen, 2012; Assaf & Tsionas, 2018; Chen, 2007; Claver-Cortés et al., 2006; Prayag et al., 2018; Sainaghi et al., 2017; Saito & Romão, 2018; Stauvermann & Kumar, 2017). However, the financial strength of firms may become especially relevant during the Covid-19 disaster since the crisis is global and the financial system is disrupted. The decline in revenues is expected to be especially relevant in industries where it is difficult to maintain the proper social distance, such as the hotel industry (Pagano et al., 2020). In addition, it is well known that operational leverage is large in hospitality firms (Nicolau, 2005), generating a special need for financial resources to pay fixed costs. Indeed, stock market prices declined more in firms with large operational leverage (Fahlenbrach, Rageth, & Stulz, 2020). All these results suggest that hospitality firms will be especially affected by the Covid-19 disaster. Consistently, the stock price of Melia Hotels International (the largest Spanish hospitality firm) declined around 50% from 2019 to July 2020, while the overall Spanish Stock market (Ibex-35) declined only 23%. In stable, growing periods with the financial system operating effectively, previous literature found firms' financial structure to be non-significant to explain the survival probability of tourism firms (Gémar et al., 2016). We show that financial strength may be crucial to survive the Covid-19 disaster in the hospitality industry. It is expected to be only a transitory period until Covid-19 is under control, and cash is fundamental to survival. Firms with financial strength already have this cash or have an advantage to obtain it.

3. Data sample

Our firms' financial data comes from the SABI database (Bureau van Dijk) which contains data of all Spanish and Portuguese firms. We obtain the financial data of all Spanish hospitality firms (NACE code 5510) from 2006 to 2019, with 69,182 firm-year observations.[2] Table 1 shows the descriptive statistics of the main variables. We analyze the main magnitudes of the balance sheet, and of the income statement of the firms. The number of observations varies due to restrictions in data availability, such as for cash holdings, available for 50,691 observations. On average, total assets amount to almost ten million euros and almost sixteen million euros for the ten percent of firms representing the largest organizations. Shareholder funds represent, on average, one third of total assets, showing a considerable financial leverage of hospitality firms (about two-thirds), where debt form other firms in business groups represent only around 1% of total assets. There is considerable variability in financial leverage with around 90% of debt (10% of shareholder funds) in the quartile of firms with more debt. The operating income grows substantially during our sample period, above 15% per year. Cash holdings represent on average around 15% of total expenses, ranging from double the amount of cash in the decile of firms with more cash, to less than 1% in the decile of firms with less cash. Labor expenses are the most relevant, reaching on average more than one million euros per year, followed by other expenses (i.e., rentals, insurances, supplies, legal fees, property taxes). Finally, in Table 1 we show two location dummy variables. These variables distinguish among hospitality firms in Madrid (where the most relevant attraction for tourism is culture), and firms located in the Mediterranean coast, where the "sun and beach" type of tourism is predominant. Almost one third of Spanish hospitality firms is located on the Mediterranean coast.

4. Methodology

4.1. Cost structure: fixed versus variable costs

Splitting the expenses of hospitality firms into variable costs and fixed costs depends on their sensitivity to the volume of the firm activity. Our assumption is that firms with a higher proportion of variable costs with respect to fixed costs will be better able to adjust their costs to the fall of activity derived from the Covid-19 disaster. Different types of operating costs show a different structure of fixed versus variable costs. On the one hand, we assume that financial interests are fixed costs and do not depend on the firm's operating activity. The logic is that interests are to be paid to the lender, independently of the level of activity. Similar logic can be applied to the depreciation costs, which are an estimation of the capital investment that the hospitality firm has to face to maintain the fixed assets ready to produce. On the other hand,

[2] Firms publish their accounting data of 2019 during 2020 and then SABI incorporates this data gradually. To perform our simulations for 2020, we use the last available data of 2019. In the case of data not being available, we use the information of 2018. This would be a reasonable approximation if data during the years prior to the outburst of the Covid-19 crisis behaved as in a steady-state scenario. We checked with yearly data of 2016–2019 and find that the main accounting magnitudes for our analysis are relatively stable over time (operating income, cash holdings, and shareholders' funds). Therefore, we do not expect that our assumption introduces relevant variations in our main results.

Table 1
Descriptive statistics.

	# Obs.	MEAN	SD	P10th	P25th	P50th	P75th	P90th
ASSETS	69,182	9898	74,891	149.0	501.9	1623	5459	15,933
GROWTH OPERATING INCOME	50,902	15.80%	92.99%	−22.40%	−8.65%	2.23%	12.26%	31.30%
CASH/TOTAL EXPENSES	50,691	0.146	0.235	0.005	0.018	0.059	0.165	0.369
OWN FUNDS/ASSETS	69,182	0.362	0.388	−0.123	0.096	0.370	0.682	0.883
INTERMEDIATE INPUTS	62,723	785.7	8062	11.62	56.3	195.5	497	1153
LABOR EXPENSES	64,582	1285	9903	37.61	125.0	358.7	854	1993
OTHER OPERATING EXPENSES	63,657	1242	14,069	17.77	62.76	226	700	1798
DEPRETIATION	62,392	357	2701	5.306	19.11	66.50	209	561
INTERESTS	69,043	125	2489	−6.668	0	7.214	44.01	188
DEBT FROM GROUP/ASSETS	69,182	0.011	0.058	0	0	0	0	0
Id (MADRID)	69,182	0.054	0.227	0	0	0	0	0
Id (MEDITERRANEAN COAST)	69,182	0.331	0.471	0	0	0	1	1

Note. All the variables are expressed in thousands of Euros, except GROWTH OPERATING INCOME which is in percentage, CASH/TOTAL EXPENSES, OWN FUNDS/ASSETS, and DEBT FROM GROUP/ASSETS which are in unit terms, and Id(MADRID) and Id(MEDITERRANEAN COAST) that are dummy variables. Data for 2006–2019.

Intermediate inputs, Labor and Other operating expenses, have a fixed component and a variable component. We estimate such a cost structure for every firm with the following model for each type of cost:

$$\ln Cost^j_{it} = \alpha + \beta^j \ln Operating\ Income_{it} + \eta_i + \varepsilon_{it} \quad (1)$$

Where sub-indexes i and t identify the firm and year, j identifies the type of cost, $j = \{\text{Intermediate, Labor, Other}\}$, ε_{it} is the error component and η_i is a firm fixed effect. We estimate the model using all the sample period data (2006–2019) to obtain a more accurate estimate of the fixed cost of each firm. Since the sum of the intercept, α, and the fixed effect, η_i, are the components of the cost of the firm that do not depend on the firm's operating income, we can obtain an estimate of the cost structure (CS^j_{it}) for each firm and each type of cost as $CS^j_{it} = \frac{\alpha+\eta_i}{\beta^j \ \ln\ Operating\ Income_{it}}$.

The estimate of the coefficient β^j does inform about the sensitivity of each type of cost to changes in the operating income. That is, since both the dependent variable (operating cost) and the explanatory variable (income) are in logs, we may compute directly the expected variation of the operating cost given any expected variation in operating income as $\frac{\Delta Cost^j_{it}}{Cost^j_{it-1}} = \beta^j \frac{\Delta Income^j_{it}}{Income^j_{it-1}}$. We will use this expression to estimate the relative change in each type of cost in each firm for a given change in the operating income.

Table 2, panel A, shows the estimation of (1). As expected, the variable component of intermediate inputs expense is larger than in the rest of expenses. For example, a drop of 60% in operating income would imply a drop of 53.1% (60%*0.885) in Intermediate inputs expense, a drop of 40% (60%*0.667) in Labor costs, and a drop of 32% (60%*0.532) in Other operating expenses. These results are consistent with the high operating leverage found in the hospitality firms by previous literature (Nicolau, 2005).

Panel B of Table 2 shows the descriptive statistics of the measures of cost structure, CS, for each type of cost j. We observe that the operational leverage due to intermediate input expenses is comparatively much lower than the operational leverage due to the rest of expenses. To obtain an overall measure of operational leverage due to these expenses, we obtain the weighted average of these measures where the weight comes from the value of these expenses. Table 1 shows that Labor expenses and Other operating expenses are the most relevant ones, and consistently, the weighted average of the operational leverage takes a value between the operational leverage of labor and of other operational expenses.

4.2. *Stress test*

The stress tests analysis consists of simulating different scenarios of negative shocks that affect the operating income of firms, estimates the expected loss of the firm given the assumptions on the evolution of operating costs, and assess whether this loss might imply problems in terms of liquidity and solvency that might compromise the viability of the firm. This methodology follows the spirit of the stress tests performed periodically by the bank regulatory authorities to assess the strength of the banking sector. To do so, we depart from the situation reflected in the accounting statements as of 2019, which are quite stable in last recent years, and simulate a fall in the operating income of X%, with respect to that level. Firms will not be able to adjust all their

Table 2
Sensitivity of expenditures to operating income.

PANEL A: SENSITIVITY OF EACH TYPE OF EXPENDITURE WITH RESPECT TO OPERATING INCOME			
Dependent variable:	ln INTERMEDIATE INPUTS	ln LABOR COSTS	ln OTHER OP. EXPENSES
ln OPERATING INCOME	0.885***	0.667***	0.532***
	(0.022)	(0.019)	(0.014)
Firm Fixed Effects	YES	YES	YES
# Obs.	61149	63311	59969

PANEL B: OPERATING LEVERAGE. DESCRIPTIVE STATISTICS	MEAN	SD	P10th	P25th	P50th	P75th	P90th
WEIGHTED AVERAGE$_{it-1}$	0.315	0.137	0.148	0.229	0.313	0.394	0.486
INTERMEDIATE INPUTS$_{it-1}$	0.001	0.006	0.000	0.000	0.000	0.000	0.000
LABOR$_{it-1}$	0.251	0.124	0.018	0.209	0.281	0.332	0.370
OTHER$_{it-1}$	0.464	0.237	0.000	0.363	0.511	0.617	0.710

Note. Panel A presents the results of the estimation of a fixed-effect regression in which the dependent variable is the log of the corresponding expense and the explanatory variable is the log of the operating income, using all the sample period (2006–2019). Panel B presents descriptive statistics of each measure of operating income. They are computed as the ratio of the absolute value of the firm fixed effect estimated in the regressions of Panel A with respect to the estimate of beta times the log of operating income. Weighed Average of operating leverage is the weighted average of each operating leverage computed as weighted the book value of intermediate input, labor and other operating expenses.

operating costs to the fall of activity, since there are components that are fixed and are not dependent on the level of activity. In our setup, interests and depreciation are assumed to be constant, and the rest of operating costs j can adjust up to $X\% \times \hat{\beta}^{j}$ (from equation (1)) of the total fall of X% in operating income. Then, we estimate the expected loss of firm i in 2020 as:

$$EL_{i,2020} = \min\{0, (1-X)Income_{i,2019} - Cost_{i2019}^{Depreciation} - Cost_{i2019}^{Interests} - (1-X)\hat{\beta}^{Labor} Cost_{i2019}^{Labor} - (1-X)\hat{\beta}^{Interme} Cost_{i2019}^{Interme} - (1-X)\hat{\beta}^{Other} Cost_{i2019}^{Other}\} \quad (2)$$

If $EL_{i,2020} < 0$, we are predicting that firm i will present negative cash flows during 2020. We identify firms that are likely to be in financial distress during 2020 as those that generate a negative cash flow that is larger in absolute terms than their own funds (capital plus reserves). In such a situation, the outstanding asset value of the firm becomes lower than the actual value of the debt and, thus, the firm might end up by filing for bankruptcy. We call this situation a Solvency financial distress situation.

As well as solvency problems as those in banks' stress tests, we also assume that firms might face liquidity problems, if they do not have enough liquid assets to cover the negative cash flows derived from the fall of activity. In this sense, the context of financial constraints during the coronavirus crisis might imply that firms are not able to raise fresh funds from the financial system or obtain liquidity from other alternative sources. If this was the case, liquidity problems of firms might become solvency problems, since they might be forced to liquidate fixed assets at fire-sale prices to cover negative cash flows or, in the worst case, be obliged to file for bankruptcy. We call this a Liquidity financial distress situation. We identify firms with potential liquidity problems as those whose predicted negative cash flows are larger in absolute terms than the cash amount available in the balance sheet. These firms are candidates to face liquidity constraints, though not all of them will necessarily fail because they might have access to other sources of liquidity, such as credit lines contracted prior the coronavirus crisis.

The Solvency financial distress situation allow us to detect firms with weak financial structure that would have difficulties to survive the Covid-19 crisis given the expected scarcity of financial resources in the Spanish economy. The Liquidity financial distress situation would be relevant in a more severe environment in 2020, where no external financial resources are available at all, and only firms with sufficient cash holdings would be able to pay their expenses whenever operating income is not sufficient. Being in any of these situations would imply bankruptcy only if the scarcity of financial resources is sufficiently strong, and the firm is not able to find alternative ways to overcome with the liquidity and/or capital shortages.

4.3. Logit bankruptcy model

To complement the stress test approach, we estimate an empirical model of bankruptcy using information from the financial crisis of the period 2008 to 2013 (Great Recession), and use the estimated parameters to predict default in 2020. This prediction relies on the data of the explanatory variables in 2019 and the expected drop in revenues for 2020. Our hypothesis is that firms during the mentioned recession were subject to a situation of scarce financial resources that could be similar to the Covid-19 disaster. That is, the failure of firms during the Great Recession might also relate to the same problems (liquidity, leverage and cost structure) as those that we predict in the Covid-19 period. If this is the case, the estimates of the parameters of the probabilistic model for the Great Recession might be a powerful tool to predict firm failures in 2020. In both periods, the financial system was not able to provide financing to all profitable firms, although during the Covid-19 crisis hospitality firms suffered a much larger drop in revenues.

We estimate the following logit model;

$$\Pr(y_{it}=1) = f\left(GrOpIncome_{it}, \frac{Cash_{it}}{OpCosts_{it}}, \frac{Capital_{it}}{Assets_{it}}, CS_{it}^{j}, Control_{it}\right) \quad (3)$$

where the dependent variable is a dummy variable identifying firms filing for bankruptcy. We include the growth of operating income as an explanatory variable to account for the sensitivity of firm failure to changes in operating activity. To capture liquidity, leverage and cost structure, we include cash holdings divided by total expenses, shareholder funds divided by total assets, and the measures of fixed versus variable costs for Intermediate inputs, Labor costs and Other operating expenses. We expect a larger probability of bankruptcy the lower cash holding are in comparison to total expenses and the lower the shareholder funds are in relation to total assets. Also, we expect that firms with a lower proportion of fixed costs will be able to better adjust their costs to a potential fall of their activity and, thus, they will be less likely to file for bankruptcy.

We also include control variables that might affect the probability of failure, $Control_{it}$. In this sense, we include total assets to account for the

Table 3
Logit model of bankruptcy during 2008–2013.

$DEPENDENT_{it} = 1$ if the firm files for bankruptcy during 2008–2013, and 0 otherwise	MARGINAL EFFECTS			
	(1)	(2)	(3)	(4)
GROWTH OPERATING $INCOME_{it}$	−0.014**	−0.016**	−0.016**	−0.015**
	(0.007)	(0.006)	(0.006)	(0.006)
CASH/TOTAL $EXPENSES_{it-1}$	−0.018**	−0.018**	−0.015*	−0.015*
	(0.009)	(0.008)	(0.009)	(0.009)
OWN FUNDS/ $ASSETS_{it-1}$	−0.026***	−0.022***	−0.022***	−0.022***
	(0.003)	(0.003)	(0.003)	(0.003)
$ASSETS_{it-1}$	−0.004***	−0.005***	−0.005***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
OPERATING LEVERAGE				
WEIGHTED $AVERAGE_{it-1}$		0.056***		
		(0.008)		
INTERMEDIATE $INPUTS_{it-1}$			0.120	0.125
			(0.197)	(0.197)
$LABOR_{it-1}$			0.021*	0.021*
			(0.011)	(0.011)
$OTHER_{it-1}$			0.037***	0.041***
			(0.008)	(0.008)
DEBT FROM GROUP/ $ASSETS_{it-1}$			0.013	0.013
			(0.013)	(0.013)
Id $(MADRID)_i$				−0.007
				(0.004)
Id $(MEDITERRANEAN\ COAST)_i$				−0.004*
				(0.002)
Whald Chi^2	166.36***	248.36***	222.17***	222.60***
Log Pseudolikelihood	−3170.5	−3147.4	−3150.4	−3148.6
Pseudo R^2	0.0283	0.0353	0.034	0.035
# Observations	23378	23378	23378	23378

Note: Logit estimation with data of hotel firms operating during 2008–2013. Robust standard errors clustered at firm level, in parentheses. *** statistical significance at 1% level, ** statistical significance at 5% level, * statistical significance at 10% level.

firm size to capture differences in the access to finance. For example, an easier access to new financial resources by larger firms that are listed in a stock exchange. Finally, we consider geographical location variables to consider any difference in probability of bankruptcy related to the geographical location of hospitality firms, as found in previous literature analyzing the survival probability of hotels (Gémar et al., 2016).

4.3.1. Estimation of the logit model

We estimate the parameters of the Logit model (3) with robust standard errors (Huber, 1967; White, 1980, 1982) clustered at the firm level (Petersen, 2009) with data of the Spanish hospitality firms. We present in Table 3 the average marginal effects of the variables to the probability of bankruptcy, for different model specifications. In column 1, we present the results when we include leverage and liquidity as the main determinants of the probability of bankruptcy, as well as the growth of operating income to account for the fall of activity. As expected, we find that firms that had lower levels of liquid assets and higher leverage were more likely to go bankrupt during the Great Recession. This result supports our hypothesis that leverage and liquidity are key determinants to explain the probability of firm survival during a period of financial constraints. Indeed, the magnitude of the average marginal effects suggest that an increase of 1 percentage point in the ratios of $\frac{Cash_{it}}{OpCosts_{it}}$ and $\frac{Capital_{it}}{Assets_{it}}$ decrease the average probability of filing for bankruptcy by 1.8 and 2.6 percentage points, respectively. Next, operating income is also a key determinant for firm survival, since a decrease in 1 percentage point of the growth rate of income increases the probability of failure by 1.4 percentage points. As for the size control, we also observe that larger firms also show a lower probability of bankruptcy.

In Column 2 and Column 3 we include our estimated measures of cost structure, CS^j_{it}. Column 2 includes the weighted average of the different measures of CS^j_{it}. We observe that firms with a higher proportion of fixed costs are more likely to file for bankruptcy. On average, an increase by 1 percentage points of the weighted average of CS_{it} increases the probability of firm failure by 5.6 percentage points. This suggests that the capability to adjust the operating costs to the changes of operating income will be a key determinant for the survival of the firm.

Column 3 presents the results introducing the cost structure CS^j_{it} for each type of cost. We observe that the positive effect of the operating leverage on the probability of failure comes from Labor Expenses and Other operating expenses. The coefficient of $CS^{Interme}_{it}$ is not statistically significant, which could be expected because we already observed in Table 2 that these costs can be (almost) perfectly adjusted to the level of activity of the hospitality firm. Additionally, in column 3 we include debt from group firms, finding no special effect of this debt on the probability of bankruptcy. Finally, in column 4 we include dummies that identify hospitality firms in Madrid and in the Mediterranean Coast, to account for potential differences in the probability of survival explained by the location of the firm. We find a lower probability of bankruptcy in hospitality firms located in the Mediterranean coast.

Overall, these results show the relevance of financial strength (i.e., leverage and liquidity) to survive during a period where the financial system collapsed and financial resources were scarce. Also, we have found evidence that the higher the capacity to adjust operating costs to the activity of the firm, the higher the probability of survival.

5. Results

This section presents the results of the predictions of failure for tourism firms based on the methodology presented above. We first analyze whether the Logit model and the stress tests posited in this paper, based on the leverage, liquidity and cost structure, are good instruments to predict failures of hospitality firms during the Great Recession. To do so, we do not simulate drops in operating income (as we will do in the Covid-19 crisis), but take the actual value of income and operating costs observed during those years. If the models are good instruments to predict defaults during the 2008–2013 period, we could extend this methodology to predict failures during the Covid-19 crisis under different scenarios of stress, since we expect that hospitality firms are affected by problems of the same nature (i.e., shutting down of financial markets, lack of liquidity) during Covid-19 and during the Great Recession. The common problem in both crises is that long-term viable companies are not able to obtain resources from the financial system.

5.1. Predictions of failure in 2008–2013 and goodness of the fit

During this crisis (2008–2013) there are 4808 hospitality firms in our sample and 1789 of them did not survive. We now analyze whether the estimated Logit model and the stress test methodology posited for hospitality firms are useful tools to identify those firms that go bankrupt.

5.1.1. Logit model

For the Logit model, we use the specification presented in Column 3 of Table 3. Fig. 1 shows the ROC curve, with an area under the ROC curve close to 70%, which implies a good prediction capacity. We identify firms that are likely to go bankrupt as those whose probability of default predicted by the model is higher than a predefined threshold value. We set this threshold using the distribution of predicted probabilities of default, in such a way that the number of predicted failures equals the number of observed failures, that is, 1789 firms (27.12% of the operating firms in 2008).

In panel A of Table 4, we present a classification table that compares the number of predicted and observed failures and non-failures. The Pearson tests clearly rejects that the rows and columns in the two-way table are independent. Almost 80% of firms that survived this crisis period are predicted to survive by the Logit model, and more than 40% of firms which failed are predicted to fail by the Logit model (788 firms). In terms of the observed surviving and failing firms, Type I error (model predicts failure and firm survives) arises to 20.82% and Type II error (model predicts survival and the firm goes bankrupt) is equal to 55.95%, respectively. Overall, the model does provide a reasonable fit to predict defaults, given the limited number of determinants included in the analysis (i.e., liquidity, solvency and cost structure).

5.1.2. Stress test

To assess the predictive power of the stress test methodology, we consider firms that presented negative values in their net income during

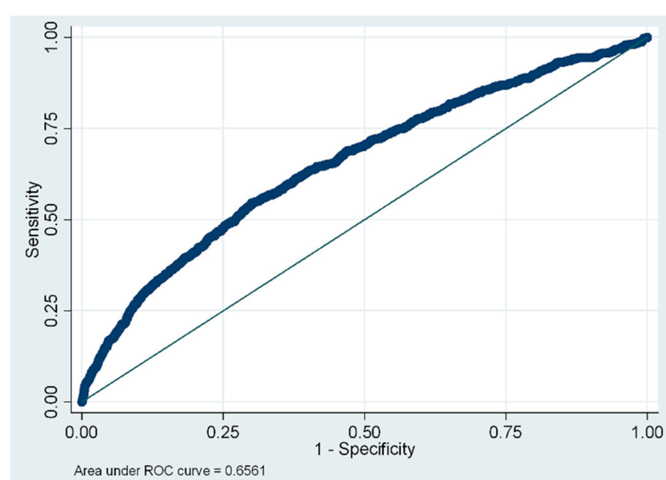

Fig. 1. ROC Curve. Note: ROC Curve to evaluate the prediction capacity of survival and failure during the financial crisis, 2018–2013, of the Logit model of column 1 in Table 3.

Table 4
Firm survival and failure for 2008–2013.

PANEL A							
		PREDICTION LOGIT MODEL					
		COUNT			% (in terms of OBSERVED)		
		Survive	Failure	Total	Survive	Failure	Total
OBSERVED	Survive	3807	1001	4808	79.18%	20.82%	100%
	Failure	1001	788	1789	55.95%	44.05%	100%
	Total	4808	1789	6597	72.88%	27.12%	
Pearson chi^2 (1) = 353.64							
p-value = 0.000							
PANEL B							
		PREDICTION FROM FINANCIAL STRENGTH (SOLVENCY)					
		COUNT			% (in terms of OBSERVED)		
		Survive	Failure	Total	Survive	Failure	Total
OBSERVED	Survive	3626	1182	4808	75.42%	24.58%	100%
	Failure	967	822	1789	54.05%	45.95%	100%
	Total	4593	2004	6597			
Pearson chi^2 (1) = 281.36							
p-value = 0.000							
PANEL C							
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY)					
		COUNT			% (in terms of OBSERVED)		
		Survive	Failure	Total	Survive	Failure	Total
OBSERVED	Survive	2271	2537	4808	47.23%	52.77%	100%
	Failure	561	1228	1789	31.36%	68.64%	100%
	Total	2832	3765	6597			
Pearson chi^2 (1) = 134.13							
p-value = 0.000							
PANEL D							
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY & SOLVENCY)					
		COUNT			% (in terms of OBSERVED)		
		Survive	Failure	Total	Survive	Failure	Total
OBSERVED	Survive	2069	2739	4808	43.03%	56.97%	100%
	Failure	448	1341	1789	25.04%	74.96%	100%
	Total	2517	4080	6597			
Pearson chi^2 (1) = 178.84							
p-value = 0.000							

Note: We use firms during the period 2008–2013 for which we have observations of the prediction of survival under the logit model and under the stress test model, for comparison. We also report the Pearson's chi-squared for the hypothesis that the rows and columns in a two-way table are independent. Failure in logit model is determined as those observations whose predicted probability of default is above a threshold, defined in such a way that the number of predicted failures is adjusted to the actual number of failures.

the sample period and compare the magnitude of such losses with the liquidity and capital stocks as defined above. In Panels B and C of Table 4, we present the classification tables of observed and predicted failure using the stress test methodology of solvency and of liquidity, respectively. In Panel B, we observe that the stress test based on solvency provides similar predictions than the Logit model, in terms of number of predicted failures and surviving firms. In panel C, the number of predicted failures in the liquidity stress test is substantially larger compared to the observed number of failures (3765 versus 1789). However, as stated above, this approach was likely to overestimate the number of potential failures, since firms could have access to alternative liquidity sources (i.e., credit lines) and do not necessarily have to face liquidity problems. In Panel D, we combine the predictions of the solvency and the liquidity approach of the stress test. In this case, we are able to identify 1341 out of the 1789 firms that go bankrupt (74.95%). However, this improvement in the identification of failures partly responds to the increase in the predicted number of defaults, which amounts to 61.84% of the sample, higher than the 27.12% of observed failures.

5.1.3. Discussion of the predicting power of stress test and logit model

The combination of the solvency stress test and the Logit model provide similar predictions in both the number and the identification of the firms that are predicted to fail and to survive. From non-tabulated data, we see that both approaches coincide in predicting the default of 1371 firms (76.6% of the 1789 predicted defaults in the logit model). In terms of success in the prediction, both approaches correctly predict the default of 613 firms during the Great Recession. This figure represents around 45% of the predicted defaults by both approaches (1,371) and 35% of the firms that finally go bankrupt (1,789). If we also consider the predictions from the liquidity stress test, the number of predicted defaults in both methodologies increases to 1604 cases (89.66% of the 1789 predicted defaults in the logit model), and the number of correct default predictions to 714 (44.5% of the predicted defaults in both methodologies).

Overall, combining the results from the two methodologies provides a tool that is able to predict a high percentage of defaults and identify firms with potential liquidity problems during the Great Recession. Assuming that hospitality firms might face a similar (or even worse) situation in terms of financial disruptions in the markets, although a stronger fall of economic activity, we now extend our methodology to make predictions about defaults due to solvency and liquidity problems in the Covid-19 disaster period.

5.2. The Covid-19 disaster period

In this section, we present the predictions of defaults under different, plausible scenarios of stress in 2020. Our database contains 3327 active firms and the challenge is to identify which are candidates to go bankrupt because of a weak financial situation.

Table 5 presents the predictions of defaults and non-defaults derived from the Logit model and the stress test methodology for a drop in the operating income of firms equal to 60%. These predictions rely on the most recent available accounting data. The Pearson tests clearly rejects the hypothesis that the rows and columns in all the two-way tables are independent. The Logit model predicts the failure of 843 firms (around 25% of firms alive) and the solvency stress test predicts the failure of 730

Table 5
Firm survival and failure for 2020. Drop in operating income: 60%.

PANEL A							
		PREDICTION FROM FINANCIAL STRENGTH (SOLVENCY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	2374	110	2484	95.57%	4.43%	100%
	Failure	223	620	843	26.45%	73.55%	100%
	Total	2597	730	3327	78.06%	21.94%	
Pearson chi^2 (1) = 1754							
p-value = 0.000							
PANEL B							
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY)					
		COUNT			% (in terms of LOGIT		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	1148	1336	2484	46.22%	53.78%	100%
	Failure	61	782	843	7.24%	92.76%	100%
	Total	1209	2118	3327			
Pearson chi^2 (1) = 396.03							
p-value = 0.000							
PANEL C							
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY & SOLVENCY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	1122	1362	2484	45.17%	54.83%	100%
	Failure	17	826	843	2.02%	97.98%	100%
	Total	1139	2188	3327			
Pearson chi^2 (1) = 501.63							
p-value = 0.000							

Note: We also report the Pearson's chi-squared for the hypothesis that the rows and columns in a two-way table are independent. Failure in logit model is determined as those observations whose predicted probability of default is above a threshold, defined in such a way that the number of predicted failures is adjusted to the actual number of failures in 2008–2013.

firms, 620 of them are predicted to fail also by the Logit model (see panel A of Table 5). Therefore, around 73% of the firms that are expected to default, according to the Logit model, are firms that present a weak situation in terms of leverage.

If we compare the predictions of the Logit with the liquidity stress test (Panel B of Table 5), the number of coincidences in the prediction of default increases to 782, but also because the prediction of failures increases from 730 in the solvency stress test to 2118 in the liquidity stress test, as discussed above for the Great Recession.

Comparing the predictions of the Logit model and the joint predictions of liquidity and solvency stress tests (Panel C, Table 5), we identify 826 firms that are predicted to default by both methodologies. This represents an increase of 206 firms compared with Panel A, which would go bankrupt because of liquidity problems. If our predictions of failure with this methodology had the same level of success as in the Great Recession, we would be identifying 367 firms (44.5% of 826) that are going to default during 2020 (11% of the operating firms). The remaining firms that we consider candidates to default are, nonetheless, firms with potential solvency and liquidity problems that might lead to default if the economic and financial conditions become harder.

Overall, this analysis predicts a large percentage of failures during the Covid-19 disaster period if no sufficient injections of liquidity are provided to the hospitality industry. Almost 25% of firms are predicted to fail by the logit model and by the stress test when solvency and liquidity problems are considered, providing almost 11% of the total employment in the Spanish hotel industry. This reveals that failures related to financial weakness are predominantly among small firms. Furthermore, In Table 6 we split the firms in our sample into three groups according to their total assets: small (below percentile 33th), medium, and large firms (above percentile 66th). A much larger number of firms would suffer a financial distress situation in 2020 the smaller the size of firms is.

All the previous estimations are based on a 60% drop in operating revenues. With a larger drop, a larger percentage of firms would fail. In Table 7, we compare the predicted number of failures by the logit model and the stress tests if revenues drop 80% instead. Then, around one thousand firms are predicted to fail by both methodologies, 32% of the firms alive.

6. Discussion

Our analysis predicts a large proportion of firms in financial distress, up to 32% of firms when revenues drop 80% and the logit model coincides with the solvency or the liquidity stress tests to predict failure (panel C of Table 7). Three main factors could mitigate the magnitude of the disaster. One factor is the availability of financial resources out of the balance sheet. We were able to detect the availability of credit lines for 396 firms. These credit lines would alleviate the liquidity problem of firms, providing the financial resources necessary to pay the predicted negative net income in 2020. In Table 8 we show how many of these firms would survive or fail before and after considering the credit line, adding the credit line to the cash holding of these firms. If operating revenues decrease 60%, 270 firms would suffer a liquidity financial distress situation, and 133 of them (almost 50%) would be able to obtain the needed financial resources from their credit lines (panel A). If operating revenues decrease 80%, only one third of firms will be able to solve the liquidity problem with their credit lines (panel B).

The second factor that might help to mitigate the disaster is to cut some expenses that would not generate serious damage to the business, at least in the short run (the expected duration of the Covid-19 crisis). This requires an effort by managers to identify these non-vital expenses, for the short run, that may reduce the operating leverage of the firm. We repeated the analysis when operating revenues drop 60%, assuming that investments in maintenance are not necessary. Table 9 shows that around 5% of firms that would suffer financial distress situations (solvency or liquidity) in Table 5 could avoid these situations without

Table 6
Firm size, survival and failure for 2020. Drop in operating income: 60%.

SMALL FIRMS

PANEL A

		PREDICTION FROM FINANCIAL STRENGTH (SOLVENCY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	479	50	529	90.55%	9.45%	100%
	Failure	119	415	534	22.28%	77.72%	100%
	Total	598	465	1063	56.26%	43.74%	
Pearson chi2 (1) = 501.15							
p-value	0.000						

PANEL B

		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	244	280	524	46.56%	53.44%	100%
	Failure	46	488	534	8.61%	91.39%	100%
	Total	290	768	1058			
Pearson chi2 (1) = 189.6							
p-value	0.000						

PANEL C

		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY & SOLVENCY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	237	287	524	45.23%	54.77%	100%
	Failure	16	518	534	3.00%	97.00%	100%
	Total	253	805	1058			
Pearson chi2 (1) = 266.1							
p-value	0.000						

MEDIUM-SIZED FIRMS

PANEL A

PREDICTION FROM FINANCIAL STRENGTH (SOLVENCY)

		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	867	27	894	96.98%	3.02%	100%
	Failure	87	140	227	38.33%	61.67%	100%
	Total	954	167	1121	85.10%	14.90%	
Pearson chi2 (1) = 484.4							
p-value	0.000						

PANEL B

PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY)

		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	432	462	894	48.32%	51.68%	100%
	Failure	11	216	227	4.85%	95.15%	100%
	Total	443	678	1121			
Pearson chi2 (1) = 138.98							
p-value	0.000						

PANEL C

PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY & SOLVENCY)

		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	425	469	894	47.54%	52.46%	100%
	Failure	5	222	227	2.20%	97.80%	100%
	Total	430	691	1121			
Pearson chi2 (1) = 155.70							
p-value	0.000						

LARGE FIRMS

PANEL A

PREDICTION FROM FINANCIAL STRENGTH (SOLVENCY)

		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	1028	48	1076	95.54%	4.46%	100%
	Failure	17	65	82	20.73%	79.27%	100%
	Total	1045	113	1158	90.24%	9.76%	
Pearson chi2 (1) = 511.4							

(continued on next page)

Table 6 (*continued*)

p-value	0.000							
PANEL B								
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY)						
		COUNT			% (in terms of LOGIT)			
		Survive	Failure	Total	Survive	Failure	Total	
LOGIT	Survive	472	604	1076	43.87%	56.13%	100%	
	Failure	4	78	82	4.88%	95.12%	100%	
	Total	476	682	1158				
Pearson chi2 (1) = 47.33								
p-value	0.000							
PANEL C								
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY & SOLVENCY)						
		COUNT			% (in terms of LOGIT)			
		Survive	Failure	Total	Survive	Failure	Total	
LOGIT	Survive	457	619	1076	42.47%	57.53%	100%	
	Failure	1	81	82	1.22%	98.78%	100%	
	Total	458	700	1158				
Pearson chi2 (1) = 54.72								
p-value	0.000							

Table 7

Firm survival and failure for 2020. Drop in operating income: 80%.

PANEL A							
		PREDICTION FROM FINANCIAL STRENGTH (SOLVENCY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	2137	106	2243	95.27%	4.73%	100%
	Failure	273	811	1084	25.18%	74.82%	100%
	Total	2410	917	3327	72.44%	27.56%	
Pearson chi2 (1) = 1754							
p-value	0.000						
PANEL B							
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	764	1479	2243	34.06%	65.94%	100%
	Failure	35	1049	1084	3.23%	96.77%	100%
	Total	799	2528	3327			
Pearson chi2 (1) = 396.03							
p-value	0.000						
PANEL C							
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY & SOLVENCY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	742	1501	2243	33.08%	66.92%	100%
	Failure	12	1072	1084	1.11%	98.89%	100%
	Total	754	2573	3327			
Pearson chi2 (1) = 501.63							
p-value	0.000						

Note: We also report the Pearson's chi-squared for the hypothesis that the rows and columns in a two-way table are independent. Failure in logit model is determined as those observations whose predicted probability of default is above a threshold, defined in such a way that the number of predicted failures is adjusted to the actual number of failures in 2008–2013.

expenses in maintenance (fixed cost in Table 5). Therefore, in most firms managers should focus on deeper modifications of the production process, to modify the operating leverage to avoid the financial distress situation.

The third factor is the support provided by public authorities. Indeed the central government provided firms with support to maintain their labor force during the crisis. Workers of firms affected by the Covid-19 crisis were paid a salary by the central government while their firms remained inactive. This increased substantially the labor flexibility of firms, reducing their operational leverage due to labor fixed costs, avoiding the need to fire workers which could imply the payment of compensations to many of them. This program is expected to last in January 2021.

However, our analysis is based on the impact of the crisis for year 2020. Other factors out of the scope of our analysis will determine the duration of the Covid-19 crisis, especially the availability of a vaccine, cheap and fast diagnostic tests, and of an effective medical treatment. Our methodology could easily provide predictions for longer horizons, but they would be less accurate because we would have to introduce assumptions about the evolution of the economy, availability of a vaccine, and the impact of potential bailout programs financed by national and supranational authorities. If the duration of the crisis is larger the number of firms facing financial distress will probably be much larger than what we predicted, also the probability of filing for bankruptcy.

Table 8
Credit lines to solve liquidity problems.

PANEL A: Drop 60% operating costs				
		Including Credit Lines COUNT		
		Survive	Failure	Total
Not Including Credit Lines	Survive	126	0	126
	Failure	133	137	270
	Total	259	137	396
Pearson chi2 (1) = 105.88				
p-value	0.000			
PANEL B: Drop 80% operating costs				
		Including Credit Lines COUNT		
		Survive	Failure	Total
Not Including Credit Lines	Survive	88	0	88
	Failure	103	205	308
	Total	191	205	396
Pearson chi2 (1) = 121.44				
p-value	0.000			

Another relevant aspect to discuss is that to implement the stress test methodology we assumed the same drop in operating revenues in all hospitality firms. However, the duration and the intensity of the crisis of specific hospitality firms may vary depending on the type of tourists they serve, the selling channels they use, or the geographic places where they are located, among others. For instance, differences in the purchasing power of the customers (i.e., tour operators versus individual final customers) or the hotel business model (i.e. all-inclusive versus high quality) could affect the level of income and/or restrictions that tourism firms could face. The geographical location and transportation limitations may also be relevant. In our dataset, hotels located in the islands (Canarias and Balearic) depend on the airlines' activity, where social distance is a relevant issue. Spanish airport authority reports a reduction of almost 70% in the number of passengers in August 2020 compared to 2019. This is consistent with Wen et al. (2020), who show that Chinese travelers changed their consumption patterns avoiding situations where it is difficult to maintain the social distance. On the other side, these archipelagos were especially successful to isolate from the pandemic in its first wave. Therefore, summarizing, some hospitality firms might recover their operating revenue sooner, or even might be less affected by the overall drop of activity.

Additionally, the parameters of the empirical model of bankruptcy we use to complement the predictions of the stress test are computed with data from the Great Recession (2008–2013), the most recent period where the financial system collapsed. During this period, as during the Covid-19 disaster, many firms were unable to obtain financial resources to survive a transitory low revenue period. Under these circumstances is when financial strength variables are expected to be relevant for firm survival. However, there might exist specific characteristics of the bankruptcy processes in the Covid-19 disaster. Then, future research would be needed to obtain estimations of the parameters of the bankruptcy model reflecting these characteristics, using accounting data from 2020, which will be released by firms during the first semester of 2021.

Finally, it is worth discussing that our article is focused on the financial characteristics of firms that would facilitate to survive crises like the Covid-19 one. These characteristics will help to survive crises where operating revenue suffers a transitory substantial drop. Such as in the event of wars, terrorist attacks, or health emergencies. However financial strength may be costly (e.g., cash holdings generate a low return, and production processes with lower fixed costs may produce at a higher cost or with lower quality). Hospitality firm managers should use financial strength as insurance against this type of crisis and could select the financial characteristics that generate the best insurance for each firm considering also its cost. The overall design of the strategy of

Table 9
Firm survival and failure for 2020. Drop in operating income: 60%. No maintenance expenses.

PANEL A								
		PREDICTION FROM FINANCIAL STRENGTH (SOLVENCY)						
		COUNT			% (in terms of LOGIT)			
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	2389	95	2484	96.18%	3.82%	100%
	Failure	266	577	843	31.55%	68.45%	100%
	Total	2655	672	3327	79.80%	20.20%	
Pearson chi^2 (1) = 1789							
p-value = 0.000							
PANEL B							
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	1500	984	2484	60.39%	39.61%	100%
	Failure	122	721	843	14.47%	85.53%	100%
	Total	1622	1705	3327			
Pearson chi^2 (1) = 435.03							
p-value = 0.000							
PANEL C							
		PREDICTION FROM FINANCIAL STRENGTH (LIQUIDITY & SOLVENCY)					
		COUNT			% (in terms of LOGIT)		
		Survive	Failure	Total	Survive	Failure	Total
LOGIT	Survive	1479	1005	2484	59.54%	40.46%	100%
	Failure	61	782	843	7.24%	92.76%	100%
	Total	1540	1787	3327			
Pearson chi^2 (1) = 583.32							
p-value = 0.000							

Note: We also report the Pearson's chi-squared for the hypothesis that the rows and columns in a two-way table are independent. Failure in logit model is determined as those observations whose predicted probability of default is above a threshold, defined in such a way that the number of predicted failures is adjusted to the actual number of failures in 2008–2013. No maintenance expenses are considered in the stress test.

hospitality firms to survive this type of crisis should consider the collection of relevant information to predict them. Therefore, data on geopolitics and on heath emergencies is relevant to hospitality firm managers.

7. Conclusions

Our study points out the relevance of the financial strength of hospitality firms to survive the Covid-19 disaster. These firms are especially vulnerable to health crises as tourism decreases substantially in such situations (e.g., Chien & Law, 2003). Furthermore, current research analyzing the Covid-19 disaster shows that hospitality firms are also suffering more than other firms also due to their difficulties to maintain social distance measures (Pagano et al., 2020) and to the structural operating leverage of these firms (Fahlenbrach et al., 2020). This leverage implies a large amount of fixed costs that must be paid even with low or no revenues (Nicolau, 2005). In normal circumstances financial resources are not an issue since firms may obtain these resources from the financial system. However, current research on the Covid-19 crisis predicts a shortage of financial resources, which would probably be needed by too many firms (e.g., Ramelli & Wagner, 2020). Additionally, we analyze the hospitality firms in Spain, a highly indebted country, and financial markets expect countries in such a situation to not secure the needed financial resources to support their firms (Gerding et al., 2020).

Our results suggest that financial strength of firms will be crucial for hospitality firms to survive the Covid-19 disaster. We identify the nature of the financial distress situation that firms may suffer (solvency and liquidity) and the specific relevant financial characteristics that might contribute to survival. Furthermore, those firms with lower operational leverage (lower relevance of fixed costs) will be in a better position to survive the crisis. We also identify the relevant sources of operational leverage to achieve a safer position. Two different approaches, a Logit model of bankruptcy with parameters estimated with the data in the Great Recession (2008–2013) and the stress test methodology (usually used by banking regulators), both using the most recent accounting data available and the predicted drop of revenues for 2020, coincide in predicting that almost 25% of Spanish hospitality firms will face a financial distress situation when operational income decreases 60%. Most of these firms would suffer solvency problems (with total assets lower than debt) and would affect mainly smaller firms providing around 11% of the total employment provided by the hospitality industry in Spain. If revenues drop 80%, financial distress would reach 32% of firms. Financial distress does not imply bankruptcy, since firms may obtain the financial resources to survive. Indeed, in the Great Recession only 44.5% of the firms predicted to fail by the Logit and the Stress test methods end up filing for bankruptcy. As discussed in the previous section, off-balance financial resources (i.e., credit lines), reduction of non-vital expenses in the short run, and support by public authorities could ameliorate the predicted financial distress situations.

Our article contributes to the tourism literature by showing that financial strength variables are relevant to survive in a crisis period where the financial system is disrupted. Previous literature shows that in normal circumstances financial strength variables are not relevant to explain the survival probabilities of hotels (Gémar et al., 2016), and that aspects other than financial strength are more relevant to explain the financial performance of hospitality firms (e.g., Assaf & Josiassen, 2012; Sainaghi et al., 2017; Stauvermann & Kumar, 2017). These articles assumed a well-functioning financial system. Our results also contribute to the literature on crisis in the hospitality industry (Faulkner, 2001; Ritchie, 2004), suggesting that financial strength variables should be considered in the overall strategy to survive a crisis period. Finally, we enlarge the finance literature studying the Covid-19 disaster with an analysis of the consequences in the financial statements of firms and its survival probability, for listed and non-listed firms. These articles focus on stock prices only, leaving most of the firms in the economy, the non-listed firms, out of focus (e.g., Pagano et al., 2020; Ramelli & Wagner, 2020).

In disaster periods with low revenue and scarcity of financial resources, such as Covid-19, our results are relevant for hospitality managers and for regulators. For managers our results show that liquidity, solvency and operational leverage should be considered in the overall strategy of these firms to survive crisis periods. Financial resources are like an insurance hedging a risk, which is otherwise difficult to hedge. For regulators, we provide a methodology to anticipate which firms would have a financial distress situation and the nature of these situations, liquidity versus solvency, which might require different actions to keep firms alive.

Credit author statement

The three authors of this manuscript participated in all the processes to develop this research.

Impact statement

Hospitality firms represent a great proportion of the GDP of many countries (15% in Spain). These firms are especially sensitive to the Covid-19 disaster due to the difficulties to maintain social distance measures and to the relevance of fixed costs, which have to be paid even without revenues. In such a situation, different dimensions of the financial strength of hospitality firms become especially relevant. Using the stress test methodology of the banking industry and an empirical model of bankruptcy estimated using data from the Great Recession (2008–2013), we can identify which hospitality firms will probably face financial distress situations and the nature of these situations. Regulators could use our results to identify which hospitality firms may need help and the appropriate measures to keep them alive in the Covid-19 disaster. Managers could use our results to design their overall strategy to survive Covid-19 and any similar crisis.

Declaration of competing interest

None.

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Rafel Crespí-Cladea is full Professor at the Business Economics Department at Universitat de les Illes Balears. He also holds the Banca March Family Business Chair. His research is on Corporate Governance, Family Business, Strategy and has headed a number of projects on Tourism and Service Industries. The research has been published in Strategic Management Journal, Family Business Review, Journal of Corporate Finance, Corporate Governance International Review and Journal of World Business among others. He has also served as consultant in a number of project on strategic viability of hotel investments.

Alfredo Martín-Oliver is Associate Professor at the Business Economics Department at Universitat de les Illes Balears, since 2011. Previously, he worked as a research economist at Bank of Spain (2003–2010), currently on leave. He has published in international journals such as Corporate Governance: An International Review, Review of Corporate Finance Studies, Journal of Financial Intermediation, Regional Studies, Journal of Financial Stability, Review of Industrial Organization, Economics Letters, among others. Principal investigator of several research projects granted by public and private institutions; he has contributions in books and has presented papers in national and international conferences. Teaching experience in graduate and postgraduate courses.

Bartolomé Pascual-Fuster is Associate Professor at the Business Economics Department at Universitat de les Illes Balears. He is the head of the department since 2016. His current research interests are mainly: crises, corporate governance, firm productivity, tourism, and business groups. He has published in international journals such as Corporate Governance: An International Review, Journal of World Business, Journal of Corporate Finance, Journal of Financial Markets, and Journal of Accounting and Public Policy, among others. He has contributed to books and has presented papers at national and international conferences.