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THREE ESSAYS ON MANAGEMENT CONTROL

El Fassi Ismail

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FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT COMPTABILITÉ ET CONTRÔLE

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pour l'obtention du grade de
Doctorat en Management

par

Ismail EL FASSI

Directeur de thèse
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Jury

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Prof. Antonio Dávila, expert interne
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Three Essays on Management Control

sans se prononcer sur les opinions exprimées dans cette thèse.

Lausanne, le 10.01.2024

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TABLE OF CONTENTS

Synthesis Report

This dissertation analyzes three drivers of firms' long-term performance within the dynamic landscape of the contemporary business environment: stakeholder management, resource management and artificial intelligence (AI) tools management.

The debate concerning whether corporate social responsibility (CSR) activities are value-enhancing or value-destroying is very active in both academic and business words. In the first chapter we contribute to this academic debate by analyzing the relationship between corporate social performance (CSP) and corporate financial performance (CFP). We use the Covid-19 pandemic as an exogenous shock and use both stock returns and risk measures to examine this relationship across a sample of companies in the travel and leisure (T&L) industry, which were heavily impacted during this period. Consistent with stakeholder salience theory, our results indicate that CSP in salient CSR activities is associated with higher CFP. We also find that companies following a stakeholder salience approach outperform their peers adopting either a stakeholder approach (high-CSP for all CSR activities) or a shareholder-only approach (low-CSP for all CSR activities) and constitute the only group of companies that did not experience a significant decline in stock returns during the Covid-19 market downturn. Finally, we find that the CSP-CFP relationship has an inverted U-shape suggesting the existence of an optimal level of CSP that maximizes CFP.

This work has both theoretical and practical contributions. managers need to define effective and context-dependent CSR activities by focusing on salient CSR activities and defining the optimal CSP level. In can also be informative to regulators, NGOs and other stakeholders to understand the stakeholder-firm relationship. More specifically, it can help deduce when

pressures on managers are necessary – i.e., when it is not (or no longer) financially beneficial for firms to voluntarily address these issues – and deploy resources and measures accordingly.

In the second chapter, we empirically examine the relationship between asymmetric cost adjustments (i.e., costs stickiness) and capital structure and profitability. We develop a novel measure of cost stickiness and address endogeneity issues using instrumental variables. We first find that high-sticky-cost firms have lower financial leverage, shorter debt maturity, and higher cash holdings. Our findings imply that cost stickiness increases the risk of default, reducing the optimal leverage. They also suggest that cost stickiness increases financial constraints, leading managers to favor internal financing to pay for operational excess capacity and to sustain investments when sales are low. Moreover, we find that cost stickiness has a positive effect on profitability. Finally, we compare the effects of cost stickiness and the related concept of operating leverage. We observe that, while they have similar effects on capital structure, operating leverage has an overall negative effect on profitability unlike cost stickiness.

While extensive research has been conducted to document cost stickiness and the factors under which it is amplified, research on the effects of cost stickiness have been very limited. Therefore, by introducing an accounting topic (cost stickiness) as an important determinant of financial leverage, cash holdings, and debt maturity, we add to both the accounting literature by looking further at the financial consequences of asymmetric cost behavior and the corporate finance literature examining the firms' operating policies affecting capital structure.

In the third chapter, we examine the algorithm appreciation phenomenon and how gender and knowledge influence the level of trust humans place in AI. AI is increasingly utilized to provide real-time assistance and recommendations across a wide range of tasks, especially since the emergence of AI Chatbots such as ChatGPT. However, it is unclear how users perceive the

trustworthiness of these tools, more so given the publicized "hallucinations" that they may experience. We conduct a randomized field experiment to analyze how subject characteristics affect trust in AI versus human peers. We randomly assign students to two experimental groups receiving advice labeled to come from an AI system (treatment group) or labeled as coming from human peers (control group). Our results are in line with recent laboratory experiments documenting algorithm appreciation. However, we find that algorithm appreciation varies with subject knowledge and gender. Specifically, both male and high-knowledge subjects place considerably less weight on AI advice. Our results remain consistent even over an extended out-of-sample period and after providing subjects with performance information.

This highlights the need to tailor AI tools to subject characteristics to significantly enhance their effectiveness and ultimately also the adoption rates. A personalized approach to AI can enhance engagement and mitigate potential adoption barriers. Further research in technology management is needed to explore various factors influencing AI trust. For example, future experimental projects, in collaboration with current co-authors explore various related questions such as: how to build and restore trust in AI; identify the main subject characteristics influencing trust in AI; understand the drivers of gender differences in AI and peer trust; and exploring task characteristics affecting trust in AI.

From a managerial perspective, understanding the circumstances in which AI assistance is beneficial and determining effective control mechanisms is crucial. While literature explores the benefits and challenges of AI, the impact of controlling AI assistance on task performance remains relatively unexplored. One of our ongoing research projects focuses on investigating the effects of restraining and controlling AI assistance on task performance, considering potential trade-offs and implications for human-AI dynamics.

Chapter 1. Financial Implications of Stakeholder Saliency and Corporate Social Performance[1]

ABSTRACT

The Covid-19 pandemic represents a unique exogenous shock to test the relationship between corporate social performance (CSP) and corporate financial performance (CFP). We examine this relationship using both stock returns and risk measures across a sample of companies in the travel and leisure (T&L) industry, which Covid-19 impacted heavily. Consistent with stakeholder salience theory, our results indicate that CSP in salient corporate social responsibility (CSR) activities is associated with higher CFP. We also find that companies following a stakeholder salience approach (high-CSP only for salient CSR activities) outperform their peers adopting either a stakeholders approach (high-CSP for all CSR activities) or a shareholders-only approach (low-CSP for all CSR activities) and constitute the only group of companies that did not experience a significant decline in stock returns during the Covid-19 market downturn. Finally, we find that the CSP-CFP relationship has an inverted U-shape suggesting the existence of an optimal level of CSP that maximizes CFP.

Keywords: Corporate social responsibility; Stakeholder salience theory; Corporate social performance; Crisis; Corporate financial performance.

[1] This chapter is based on a working paper under the same name with Antonio Davila, Giovanni-Battista Derchi and Daniel Oyon.

INTRODUCTION

In the past decade, increasing pressure from multiple stakeholders has made corporate social responsibility (CSR) a strategic priority for organizations.[2] Recent crises have reinforced this trend, leading to a sharp increase in both governments' and market participants' attention to social and environmental considerations (Bae, El Ghoul, Gong, & Guedhami, 2021). Yet, the question of whether and under which conditions CSP benefits CFP is still open, and recent results regarding the CSP-CFP relationship are mixed (Albuquerque, Koskinen, & Zhang, 2019; Awaysheh, Heron, Perry, & Wilson, 2020; Flammer, 2015; Hwang, Titman, & Wang, 2021; Zhao & Murrell, 2016), leaving managers without a clear guidance on how to approach CSR activities.

We explore two contingency approaches to the CSP-CFP relationship that bring possible explanations to these mixed findings: first, we test whether the relationship between CSP and CFP is contingent on the firm's relationship with its stakeholders and address the first research question: which CSR activities are most associated with CFP? To do so, we adapt the stakeholder salience theory (SST) (Mitchell, Agle, & Wood, 1997). SST originally aims to predict managerial decisions regarding CSR activities based on stakeholder attributes of power, legitimacy, and urgency. However, it does not directly connect these attributes to CFP. Therefore, we start by adapting this theory to better analyze the CSP-CFP relationship by making one main adjustment, considering that for a claim to be financially relevant, both attributes of power and urgency must coexist, while the legitimacy attribute only indirectly effects CFP through the other attributes. Another adjustment is that we do not focus on the

[2] See Mckinsey 2014 survey 'Sustainability's strategic worth' https://www.mckinsey.com/business-functions/sustainability/our-insights/sustainabilitys-strategic-worth-mckinsey-global-survey-results.

absolute power and urgency attributes of the actors themselves (the firm and its stakeholders) but rather on the attributes of the firm-stakeholder relationship. Second, we test whether the CSP-CFP relationship is contingent on the level of CSP rather than linear, such that there is an optimal level of CSP as suggested by previous works (McWilliams & Siegel, 2001), by addressing the second research question: is there an optimal level of CSP in terms of CSP-CFP relationship?

To answer these research questions, we focus on the stock market performance of an international sample of Travel and Leisure (T&L) firms during the Covid-19 crisis.[3] This setting is suitable for several reasons. First, the Covid-19 shock is exogeneous to pre-crisis CSR activities; firms could not predict this event and anticipate it by adapting their CSR activities. Second, the short time frame examined (34 days) suggests that firms' overall CSP level is likely to remain unchanged during this period as CSR activities take time to activate (Derchi, Davila, & Oyon, 2023; Derchi, Zoni, & Dossi, 2021; Tang, Hull, & Rothenberg, 2012) and social performance to evolve (Albuquerque et al., 2020; Amiraslani, Lins, Servaes, & Tamayo, 2022). Third, travel and leisure (T&L) was one of the most impacted industries by the Covid-19 crisis (Huang, Makridis, Baker, Medeiros, & Guo, 2020)[4]. Fourth, T&L companies compete on the reputation and brand image that they project to their end consumers (Delgado & Mills, 2020), making them sensitive to CSR issues (Du, Bhattacharya, & Sen, 2007; Eccles, Ioannou,

[3] Similarly to other papers (e.g., Demers, Hendrikse, Joos, & Lev, 2021; Lins, Servaes, & Tamayo, 2017), we define the market crash period as delimited by the pre-crisis market capitalization peak (February 19th, 2020) and its lowest point during the pandemic (March 23rd, 2020) following the definition of Lins, Volpin, & Wagner (2013).

[4] Our sample includes five subindustries – Airlines, Casinos and Gambling, Hotels and Motels, Leisure Facilities; Restaurants and Bars. According to the S&P Global Market Intelligence, Airlines, Casinos and Gambling, and Leisure Facilities are the top three most impacted sub-industries during the Covid-19 market crash from a probability of default perspective. Last visited on February 15, 2023. https://www.spglobal.com/marketintelligence/en/news-insights/blog/industries-most-and-least-impacted-by-covid-19-from-a-probability-of-default-perspective-march-2020-update

Serafeim, & Hall, 2012; Lev, Petrovits, & Radhakrishnan, 2010; Servaes & Tamayo, 2013). Finally, focusing on large firms within one specific industry facilitates the comparison of stakeholders' salience as these firms face similar CSR opportunities and risks (Eesley & Lenox, 2006; Gianfelici, Casadei, & Cembali, 2018).[5]

We run a difference-in-differences model (Lins et al., 2017: 1805) with continuous treatment using the Covid-19 market crash as a quasi-experimental setting and pre-crisis levels of CSR activities to examine the effect of CSP on CFP. In line with recent papers (e.g., Albuquerque et al., 2020; Amiraslani et al., 2022), we measure CSP using Refinitiv ESG scores and identify five CSR dimensions associated to natural environment, product responsibility, employees, human-rights, and community relations. Based on prior literature, we use three different variables to measure CFP (stock returns, idiosyncratic volatility (IVOL), and total volatility) (e.g., Albuquerque et al., 2020; Becchetti, Ciciretti, & Hasan, 2015; Lins et al., 2017; Luo & Bhattacharya, 2009).

Our study contributes to the existing knowledge on the relationship between CSP and CFP as follows. First, our paper contributes theoretically to the development of the stakeholder salience theory (SST) and tests empirically its validity to explain the relationship between CSP and CFP. In fact, there isfew empirical evidence linking salience to CFP (Derry, 2012; Laplume et al., 2008) with the most prominent empirical paper finding no significant impact (Agle et al. 1999). Thus, we fill this void by showing that the CSP-CFP relationship depends on the salience of stakeholders' claims. More specifically, we find that, during the Covid-19 induced market

[5] In particular, Gianfelici et al. (2018) and Eesley & Lenox (2006) show that industry and firm size are primary determinants of the salience of stakeholders' claims. Thus, by focusing on large firms within a same industry, we reduce intrafirm differences in the level of claims' salience and increase the reliability of our identification.

crash, CSR activities related to salient claims are positively related to CFP unlike CSR activities related to non-salient claims.

Second, our paper also compares the effects of CSP on CFP across four different approaches to CSR activities: *Shareholders-only Approach*, *Stakeholders Approach*, *Stakeholder Salient (SST) Approach*, and *Stakeholder Non-Salient (Non-SST) Approach*. Firms following a *Shareholders-only Approach* show low CSP in every dimension (Becchetti et al., 2015; Friedman, 1962; Wright & Ferris, 1997). Firms following a *Stakeholders Approach* show high CSP in all dimensions, responding to all stakeholders' claims regardless of their salience (Freeman, 1984; Freeman & McVea, 2001). Firms pursuing an *SST Approach* report high CSP only for salient CSR activities (Mitchell et al., 1997). This is in contrast to firms pursuing a *Non-SST Approach* that focus their CSR activities on non-salient dimensions. We find that firms following an *SST Approach* show a stronger CSP-CFP relationship. In fact, companies with an *SST Approach* did not experience a decline in stock returns during the stock market crash induced by the Covid-19 crisis. Firms following a *Stakeholders Approach* are the second-best performing group. Finally, firms in the *Non-SST* group show worse financial performance than the other three groups.[6]

Finally, we challenge the linear assumption previously made in the literature regarding the relationship between CSP and CFP (e.g., Bae et al., 2021; Demers et al., 2021; Lins et al., 2017). Our findings reveal a more nuanced and complex relationship that sheds light on the weak and mixed findings reported thus far. Additionally, we observe that assuming an overall linear relationship can lead to erroneous conclusions regarding a neutral relationship. We find

[6] The fact that we observe the existence of other behaviors may explain other normative approaches. Managers have different cultural and ethical considerations that also motivate CSP. These questions are outside the scope of our work.

supporting evidence on the existence of an optimal level of CSP that maximizes CFP in accordance with McWilliams & Siegel (2001). In particular, we show that the CSP-CFP relationship displays an inverted U-shaped curve and observe that the optimal levels of CSP that maximize stock returns and minimize stock volatility is aligned with the third quartile of the CSP distribution in our sample and correspond to a 'B-grade' based on Refinitiv ratings.[7] Our study has various practical implications for organizations and stakeholders. We highlight the relative financial impact of different CSR activities. This differential effect can guide CSR investment decisions by firms as well as inform stakeholders how their efforts might influence the decisions at firms.

THEORY AND HYPOTHESES

CSP-CFP Relationship Based on SST

Explicit SST prediction. Shareholder salient theory argues that managers respond to stakeholders' claims based on their salience, defined as "the degree to which managers give priority to competing stakeholder claims" (Mitchell et al., 1997: 854). Salience defines which stakeholders' needs require more management attention. The SST framework predicts that the likelihood of responding to a stakeholder claim increases with the salience of the claim (Laplume et al., 2008; Mitchell et al., 1997). Salience depends on three attributes: power, legitimacy, and urgency (Etzioni, 1964). Power is defined as the extent to which a stakeholder group can use coercive, utilitarian, or normative means to influence the firm (Mitchell et al., 1997: 865). Stakeholder power depends not only on the stakeholder's resources, but also, on the firm's dependence to these resources (relative power) (Eesley & Lenox, 2006; Frooman,

[7] According to Refinitiv, scores between 50 and 75 are considered above average and range from B- (up to 58) to B+ (if above 67). cf. Refinitiv methodology report of May 2022 https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf).

1999). Legitimacy refers to the perception that the claims of a stakeholder group are desirable or appropriate from a normative point of view (Suchman, 1995). Finally, urgency exists only when a claim is both time-sensitive and critical to the stakeholder (Mitchell et al., 1997: 867). The salience of a claim is enhanced by the combined effect of all attributes as perceived by managers.

Implicit SST prediction. SST primary objective is to predict managerial actions and the theory as is do not link salience attributes directly to CFP. Some papers suggest that the financial impact of a claim may depend on its saliency (Agle et al., 1999; Barnett, 2007; Peloza & Papania, 2008; Winn, 2001).[8] While this is an implicit prediction based on the fact that managers focus on issues that are instrumental to CFP, there is little theoretical and empirical support for this prediction linking the three attributes of salience to CFP. In fact, few empirical studies have explored the effect of salience on CFP (Derry, 2012; Laplume et al., 2008), with the most prominent empirical paper finding no significant impact (Agle et al. 1999)[9]. This may be explained by the poor development around the theoretical reasoning linking salience attributes to CFP. In fact, most papers focus on the theoretical arguments linking salience in general to CFP, with the overall logic that focusing on important stakeholder claims ultimately leads to financial gains (e.g., Peloza & Papania, 2008; Barnett, 2007) rather than focusing on how its attributes may affect CFP.

For a claim to be financially relevant (second SST prediction), we argue that two attributes of power and urgency should hold together. Otherwise, stakeholders will not take action (or be

[8] This argument is in accordance with Agle et al. (1999: 507) stating that "the salience-performance link is implicit" in Mitchell et al. (1997) theory.

[9] "The importance of stakeholders can be determined by their relative power, legitimacy, and urgency (Mitchell, Agle, & Wood, 1997). The overall logic is that CSR increases the trustworthiness of a firm and so strengthens relationships with important stakeholders (e.g., increases employee satisfaction), which decreases transaction costs and so leads to financial gains (e.g., decreased employee turnover)" (Barnett, 2007: 796).

willing to do so) to reward or punish the firm. In fact, in order to affect financial performance, not only stakeholders need to have the means to pressure managers (i.e., power) but they also need to know and care about the issue (i.e., urgency) (Mitchell et al., 1997).

We argue that an urgent claim stemming from stakeholders possessing substantial power always holds financial relevance, irrespective of its legitimacy. In fact, legitimacy does not have a direct instrumental effect on CFP (Schoon, 2022)[10]. Yet, legitimacy can moderate the effect of power (Lammers, Galinsky, Gordijn, & Otten, 2008), therefore, affecting the CSP-CFP relationship indirectly through power (or possibly by triggering urgency, making the claim more time sensitive in the eyes of managers). In line with this argument, Frooman (1999) questions the importance of the legitimacy attribute and argues that "from a firm's strategic planning standpoint […] [t]he appropriateness of a stakeholder's claim [i.e., its legitimacy] may not matter nearly as much as the ability of the stakeholder to affect the direction of the firm." For instance, if there exists a non-negligible risk of a temporary facility shutdown, be it the result of an employee strike or a terrorist attack, all else being equal, the legitimacy of the threat would not discernibly impact the ensuing financial consequences.

Unlike in Mitchell et al. (1997), we do not focus on the absolute attributes of the actors (the firm and its stakeholders) but rather on the firm-stakeholder relationship by focusing on the power balance in the stakeholder-firm relationship (relative power) (Frooman, 1999; Rowley, 1997)[11] and the urgency of the claims. In fact, given that stakeholders might have multiple claims with different urgency levels, we focus on claims as a level of analysis instead of

[10] According to Schoon (2022), legitimacy is not an attribute with financial performance effects but reflects a relationship between a legitimacy object (the CSR level being valued) and the source evaluating the object (stakeholders) that affects other outcomes.
[11] Following Frooman, we view power as "an attribute of the relationship between the actors-not of the actors themselves" (Frooman, 1999: 192).

stakeholders (Durand, Hawn, & Ioannou, 2019; Eesley & Lenox, 2006). For instance, we determine the salience of product responsibility instead of salience of customers, as customers might also value other environmental and social actions that may have different urgency levels, therefore, different levels of salience.

Power refers to the stakeholder's ability to influence the firm through various means. Stakeholders with significant power can exert pressure on the firm to make specific financial decisions or changes in their corporate social responsibility (CSR) practices. For instance, powerful stakeholders may be able to influence investment decisions, strategic directions, or resource allocation within the firm. As a result, their critical demands and concerns (i.e., urgent claims) are more likely to translate into tangible financial impacts on the firm's bottom line. For example, when a powerful stakeholder group, such as a major shareholder or a government regulatory agency, demands that a company invest in cleaner and more sustainable production processes, the company is more likely to comply. This compliance can lead to increased production costs initially but may result in long-term financial benefits through improved public perception, regulatory compliance, and operational efficiency. Let's consider another situation where a powerful stakeholder group highlights a safety issue in one of the company's products, and this issue poses an imminent threat to public safety. If the firm doesn't address this issue urgently, it could face product recalls, lawsuits, reputational damage, and a significant drop in stock prices. Therefore, urgent claims, especially when related to critical matters, are more likely to translate into immediate financial consequences. Claims lacking in either of the two attributes may not result in significant financial consequences for the firm; if stakeholders lack power to pressure the firm or are not aware or do not care about such claim (lack urgency).

Based on the above arguments, we posit that salient claims are instrumental to the relationship CSP-CFP in line with the second prediction of SST (Agle et al., 1999; Mitchell et al., 1997; Peloza & Papania, 2008). More specifically, we predict that CSR activities related to salient claims are positively related to CFP unlike CSR activities related to non-salient claims. To test this prediction, we propose the following hypotheses:

Hypothesis 1a. Corporate social performance (CSP) of salient CSR activities is positively associated with corporate financial performance (CFP).

Hypothesis 1b. Corporate social performance (CSP) of non-salient CSR activities is unrelated to corporate financial performance (CFP).

Multiple Approaches to Address Stakeholders' Claims

Companies choose different approaches to invest in CSR activities. In this section, we argue that, from an instrumental point of view, companies following an *SST Approach* overperform companies pursing alternative approaches. Managers using an *SST Approach* simultaneously focus on salient CSR activities that increase CFP (unlike the *Shareholders-only Approach*) and reduce their effort on non-salient ones that can decrease CFP (unlike the *Stakeholders Approach*).

Shareholders' versus SST Approach. A *Shareholders' Approach* indicates that managers' primary responsibility is to respond to shareholder claims to maximize the value of their investment (cf. Friedman, 1962, 1970). Investing in other stakeholders' interests such as CSR activities is interpreted as detrimental to CFP and therefore inconsistent with this economic goal. Prior empirical studies support this argument and find that managers destroy firm value when implementing strategies focused on non-relevant stakeholders' claims (Becchetti et al., 2015; Cordeiro & Sarkis, 1997; Wright & Ferris, 1997; Zhu & Sarkis, 2004). For instance, Zhu & Sarkis (2004: 270) comment on how environmental activities can have a negative impact on

CFP through "increase of investment, increase of operational cost, increase of training cost and increase of costs for purchasing environmentally friendly materials." Wright & Ferris (1997) document that financial markets reacted negatively to firms divesting in South Africa in response to Apartheid. More recently, Becchetti et al. (2015) find a positive association between CSP and stock price idiosyncratic volatility concluding that CSR activities reduce shareholder value by decreasing managers' ability to react to negative productivity shocks through a reduction of stakeholders' well-being.

A major limit of the *Shareholders' Approach* is that it interprets stakeholders' claims as conflicting with shareholders' value maximization, ignoring the financial benefits that salient claims might have (Barnett, 2007; Jones, 1995). A *Shareholders' Approach* often focuses on short-term profit maximization, neglecting how salient stakeholder claims affect long term CFP (Benabou & Tirole, 2010). As a result, managers destroy value while trying to maximize short-term profits at the expense of other stakeholders' interests associated with long-term value (Freeman, 1984). To test this prediction, we propose the following hypothesis:

Hypothesis 2a. Firms following an SST Approach show higher CFP than firms following a Shareholders-only Approach.

Stakeholders versus SST Approach. Based on Freeman (1984), the *Stakeholders Approach* to CSR activities entails meeting the multiple needs of all stakeholders to build trust, strengthen cooperation, and ultimately foster financial performance. Stakeholder theory identifies a positive link between CSP and CFP, suggesting that firms with strong stakeholder relationships generate new business opportunities, reduce the costs of opportunistic behavior, and gain a competitive advantage over firms not being stakeholder oriented (Jones, 1995; Porter & Kramer, 2006).

A first limit of this approach is that it neglects the costs of creating and maintaining relationships with stakeholders, which can be higher than the costs associated with opportunistic behavior, resulting in no added value or even negative value from investing in such CSR activities (Jones et al., 2018). In addition, CSR goals and actions often conflict with firms' core strategies aimed at profit maximization and creating a competitive advantage (Hengst, Jarzabkowski, Hoegl, & Muethel, 2020). Indeed, focusing on non-salient claims such as those of low- and non-specific-skilled workers can be particularly costly in crisis periods, where revenues decline sharply and companies cut costs and focus on value enhancing activities to cope with short-term financial challenges (Becchetti et al., 2015; Flammer & Ioannou, 2015). Therefore, we argue that, in periods of crisis, the benefits of addressing non-salient claims to build long-term relationships with certain stakeholders may not compensate for the short-term costs to implement the related CSR activities.

A second limit is associated with scarcity of company's resources. Even if we assume that all CSR activities generate a positive return on investment, firms have limited financial, human, and technical resources preventing them to address all stakeholders' claims, at least in the short term (Tang et al., 2012). Therefore, managers must choose among which claims to respond to, prioritizing those that bring higher value to both shareholders and stakeholders. Addressing non-salient claims seldom rank at the top of value generation.

In line with these arguments, Freeman and McVea (2001: 10) state that the "idea that all stakeholders, defined widely, are equally important has been a barrier to further development" of stakeholder theory. Based on SST, salience would help managers determine which stakeholders are more important and, therefore, which CSR claims to prioritize in terms of CFP impact. We test this prediction through the following hypothesis:

Hypothesis 2b. Firms following an SST Approach show higher CFP than firms following a Stakeholders Approach.

Non-SST versus SST Approach. Finally, based on our argument that salient activities are the only value enhancing activities (see hypotheses 1a and 1b), a *Non-SST Approach,* where a company focuses only on non-salient activities might lead to a lower CFP than all other approaches. In fact, while both *Stakeholders Approach* and *Non-salient Approach* focus on non-salient activities the later does not focus on salient value enhancing activities. A *Shareholders-only Approach* might also outperform a *Non-SST Approach* as it focuses on salient activities that are value enhancing. Therefore, ultimately, the *SST Approach* might outperform the *Non-SST Approach* as well. We test this prediction through the following hypothesis:

Hypothesis 2c. Firms following an SST Approach show higher CFP than firms following a Non-SST Approach.

Optimal Level of CSP

In this section, we investigate the shape of the CSP-CFP relationship during the Covid-19 market crash. Prior literature shows that, in crisis time, CFP is more sensitive to CSR activities (Amiraslani et al., 2022; Lins et al., 2017). Therefore, identifying the level of CSP that maximizes CFP becomes crucial.

We test the existence of an optimal level of CSP by relaxing the assumption of linear relationship between CSP and CFP during crisis adopted in prior literature (e.g., Bae et al., 2021; Demers et al., 2021; Lins et al., 2017).

CSP effect on CFP depends not only on claims' salience but also on the feasibility of addressing them (Durand et al., 2019). In fact, the higher the CSP level, the costlier and more complex and challenging it gets to further address these claims, reducing the marginal contribution of additional investment. This supports the existence of an optimal level of CSR

activities that maximize CFP (McWilliams & Siegel, 2001) and beyond which desirable CSR does not result in the expected financial results. This is also consistent with what Pierce & Aguinis (2011) refer to as the "Too-Much-of-a-Good-Thing effect," where an excessive amount of a desirable managerial and organizational behavior leads to negative outcomes or consequences once the optimal point is reached. Higher levels of CSP indicate lower marginal benefits of further increasing CSP (e.g., Serafeim, 2021). Both the increase in costs and reduction in benefits suggest that firms face diminishing returns on their investments in social and environmental activities (Marom, 2006; Sun, Yao, & Govind, 2019). Accordingly, we predict that the relationship between CSP and CFP is nonlinear as it varies with different levels of CSP and propose the following hypothesis:

Hypothesis 3. The marginal effect of CSP on CFP diminishes for higher CSP levels, such that there is an optimal level of CSP.

DATA AND METHODOLOGY

Sample and Data

We test our hypotheses using an international sample of listed T&L firms based on the MSCI Global Industry Classification Standard (GICS) for the two-year period 2019 to 2020. The final sample with available data for our main CSP and CFP variables includes 200 firms corresponding to 19,596 firm-week observations. We obtain market and accounting data from Compustat and Fama-French datasets. The sample includes 35 firms in the Airline sub-industry, 49 in Casinos and Gambling, 21 in Hotels and Motels, 39 in Leisure Facilities, and 56 in Restaurants and Bars. Finally, we gather information on CSR activities from Refinitiv ESG database.

Determining Salient and Non-Salient Claims for our sample

Stakeholders' claims and their saliency are context-dependent. The relationship between CSP and CFP depends on changing contextual characteristics (Barnett, 2007; Jones, Harrison, Felps, & Felps, 2018; Mitchell et al., 1997; Rivoli & Waddock, 2011). In this section, we determine the salience of stakeholders' claims for our sample of T&L listed firms during the Covid-19 market crash. We do so by identifying five CSR dimensions consistent with the Refinitiv ESG dataset[12]: Environment, Product-responsibility, Community, Workforce, and Human-rights. Given that stakeholders can have multiple claims with different salience levels, we determine the salience of the claims rather than the salience of its stakeholders (Durand et al., 2019; Eesley & Lenox, 2006).

Environment. Environmental activities have become increasingly important for firms[13] with pressing demands for improved green management coming from multiple stakeholders, such as customers, social activists, governments, and shareholders (Murillo-Luna et al., 2008; Wright & Nyberg, 2016). As a result, these shared behavioral expectations regarding environmental issues makes it more difficult for the firm to resist stakeholders' pressures (Rowley, 1997).

Indeed, the importance of environmental claims is seen as particularly high across companies in consumer-facing industries, like T&L firms, where customers are increasingly sensitive to environmental issues and can exercise utilitarian power by adapting their consumption (Currás-Pérez et al., 2018). In addition, these companies are highly sensitive to

[12] cf. Refinitiv methodology report of May 2022 https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf).

[13] On this regard, the World Economic Forum Global Crisis report (2022) sees the most critical current risks for businesses to be environmental (World Economic Forum, 2022).

compelling claims from NGOs and environmental activists that can damage their reputation through normative power in public media (Graafland, 2018). Governments, powerful stakeholders in the ecosystem, have also implemented policies to address environmental issues (e.g., European Green Deal)[14] (Gago & Antolín, 2004; Monasterolo & de Angelis, 2020). Finally, shareholders have showed strong interest on environmental activities given their direct effect on CFP through mitigation of idiosyncratic risks (Bansal & Clelland, 2017), lower cost of capital (Sharfman & Fernando, 2008), and higher long term financial performance especially in consumer-facing industries (Eccles et al., 2012; Hart, 1995). To sum up, the combination of both climate and Covid-19 crises (Phelan, 2022) has changed firms' external conditions making environmental claims more salient[15], especially in consumer-facing industries such as T&L.

Product responsibility. Product-related activities –including management of product quality, responsible marketing, and protection of customer data privacy– are often highly valued by customers (Peloza & Shang, 2011). In the T&L industry, it also includes additional dimensions like safety management of leisure services, and public health issues such as obesity and pathological gambling.[16] Prior research has showed that customers are powerful

[14] After the presentation of the European Green Deal in December 11, 2019, additional steps were taken during the Covid-19 induced market crash to consolidate the commitment to carbon neutrality of Europe by 2050 (e.g., European climate law proposal in March 4, 2020 and the adoption of the Circular Economy Action Plan in March 11, 2020) (see the European Commission website, last visited on July 26, 2022 https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en#timeline)

[15] We posit that power and urgency are the only salient attributes having a direct effect on the CSP-CFP relationship. In fact, despite being an important driver of managerial behaviors (Mitchell et al. 1997), legitimacy does not have a direct instrumental effect on CFP (Schoon, 2022). However, legitimacy can moderate the effect of power (Lammers, Galinsky, Gordijn, & Otten, 2008), therefore, affecting the CSP-CFP relationship indirectly through power. In line with this, Frooman (1999) questions the importance of the legitimacy attribute and argues that "from a firm's strategic planning standpoint […] [t]he appropriateness of a stakeholder's claim [i.e., its legitimacy] may not matter nearly as much as the ability of the stakeholder to affect the direction of the firm."

[16] For further examples, see the relevant issues for T&L subindustries in the materiality finder in the Sustainability Accounting Standards Board (SASB) website, last visited on September 1, 2022 https://www.sasb.org/standards/materiality-finder/find/ and Refinitiv website (May 2022 report), last visited on July 29, 2022 https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

stakeholders in consumer-facing industries (like T&L) where companies compete on reputation and brand image (Eccles et al., 2012; Lev et al., 2010) and customer satisfaction represents a primary driver of financial performance (Gianfelici et al., 2018; Miles, 1987).

During Covid-19 crisis, managers of T&L companies were forced to implement urgent measures for customer safety (e.g., infection prevention and control such as physical distancing and special hygiene protocols, extended natural or mechanical ventilation, isolation, and distancing).[17] As a result, product responsibility claims gained more importance, becoming essential for the survival of T&L companies. In sum, we argue that claims on product responsibility were salient for T&L companies during Covid-19 market crash.

Workforce. Due to seasonality and the nature of services, a large range of T&L activities depends on low-skilled employees (Ioannides & Debbage, 1997; Krakover, 2000). Low-skilled employees do not represent powerful stakeholders especially when firms can dismiss and replace them at reduced costs and constraints (Ioannides & Debbage, 1997; Krakover, 2000). In addition, non-specific jobs require standard sets of skills, making alternatives easy to find (Hill & Jones, 1992; Williamson, 1979). In general, employment contracts with low and non-specific skilled employees include fast and inexpensive termination (Hill & Jones, 1992), lowering the power of their claims. Moreover, in industries with low knowledge-intensity, such as T&L, the benefits of developing long-term relationships with employees and contractors are low (Jones et al., 2018).

Therefore, in T&L firms, claims from workforce for better employment conditions and improved labor protection are likely to remain largely unanswered. This is more so in times of

[17] The European Commission communication "EU Guidance for the progressive resumption of tourism services and for health protocols in hospitality establishments – COVID-19". From the website of the European Union, last consulted on July 29, 2022.
https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52020XC0515%2803%29

crisis, when decline in activity level leads to both decrease of cash inflows and increase of unused capacity, making reduction of workforce often financially necessary. Accordingly, most T&L companies addressed the challenges caused by Covid-19 pandemic by dismissing significant numbers of employees.[18] For instance, Marriott International "laid off or furloughed a significant percentage of their workforce, jeopardizing employees' healthcare benefits when they were arguably needed the most" (Bae et al., 2021). Similarly, the Hilton Group dismissed many employees including top executives such as the vice president of global diversity.[19]

Finally, the less a firm is dependent on a stakeholder, the more managers can resist pressure coming from it (Oliver, 1991). Market supply of a specific company resource plays a crucial role in determining the power of stakeholders that provide it. Managers in the T&L industry do not perceive the supply of workforce as a major constraint due to the large available market (Ioannides & Debbage, 1997; Krakover, 2000). During the first part of the Covid-19 crisis, labor supply became exceptionally larger than demand because of the massive layoffs and reduced firm activity, leading to a temporal increase in the relative power of T&L firms over its workforce.[20] In sum, we contend that claims from employees were non-salient during Covid-19 market crash for T&L companies.

Human rights.[21] Human rights constitute 'taken-for-granted' minimal universal standards for any corporate activity (Kendrick, 2017; Nickel, 1987; Shue, 1980). If most firms comply

[18] According to the Congressional Research Service (CRS) report on unemployment rates during the COVID-19 Pandemic (2021), "Workers whose last job was in the leisure and hospitality sector experienced a higher peak in unemployment (39.3% in April 2020) than did workers who were previously employed in any other sector". Updated report on august 20, 2021 https://sgp.fas.org/crs/misc/R46554.pdf

[19] See https://www.businessinsider.com/hilton-laid-off-vice-president-of-global-diversity-jon-muoz-2020-6 last visited on July 26, 2022.

[20] Cf. Congressional Research Service (CRS) report on unemployment rates during the COVID-19 Pandemic (2021). Updated report on august 20, 2021 https://sgp.fas.org/crs/misc/R46554.pdf

[21] Following the United Nations (UN) definition, "Human rights are rights inherent to all human beings, regardless of race, sex, nationality, ethnicity, language, religion, or any other status. Human rights include the right

with these standards, a firm cannot gain a competitive advantage over peers. In fact, a CSR activity focused on protecting human rights cannot create a competitive advantage unless it is difficult to imitate it (Jones et al., 2018). According to this argument, Paine states that "[t]he typical argument, which relies on the purported marketing benefits of respecting human rights, is shaky at best" (Paine, 2000: 324).

Pressing claims for human rights protection have been issued by a variety of stakeholders including regulators, shareholders, employees, NGOs, and activists reaching large audiences through social media and other channels (Spar, 1998). Nevertheless, managers in the T&L industry do not perceive them as urgent for three main reasons: (1) addressing human rights issues (e.g., child labor and forced labor) is considered a minimum accepted norm rather than a value added activity; (2) addressing human rights issues often does not require implementing activities that need a substantial amount of resources in accordance with sustainability standard setters not considering human rights as a material financial risk for this industry;[22] (3) T&L firms are less exposed to human rights scandals than other firms in industries such as oil, mining or manufacturing that are more at the center of attention of human right activists (e.g., Blanton & Blanton, 2009).

Moreover, T&L firms did not face growing human rights issues during Covid-19 crisis as both activity levels and consequently potential violations were reduced (e.g., displacement from

to life and liberty, freedom from slavery and torture, freedom of opinion and expression, the right to work and education, and many more. Everyone is entitled to these rights, without discrimination." UN website, visited on July 26, 2022
https://www.un.org/en/global-issues/human-rights#:~:text=Human%20rights%20include%20the%20right,to%20these%20rights%2C%20without%20discrimination

[22] These issues are reported to be non-significant for any of T&L sectors according to the Sustainability Accounting Standards Board (SASB). See the materiality finder in SASB website, last visited on February 28, 2022 www.sasb.org/standards/materiality-finder/find/

home for tourism development, lowered access to natural resources, human trafficking, sex tourism) (Baum & Hai, 2020). In line with these arguments, we contend that claims for human rights-related activities were non-salient for T&L companies during Covid-19 market crash.

Community relations. Claims for adequate community relations refer to a firm's commitment towards local communities by being a good citizen, protecting health and safety of local residents, and respecting business ethics principles (e.g., avoiding tax fraud, money laundering or anti-competitive behaviors).[23]

Local communities generally have relatively low power and means to exert pressure on T&L multinationals, which are diversified across multiple locations and can deploy extensive resources to lobby and fend claims (Darnall et al., 2010; Eesley & Lenox, 2006; Meznar & Nigh, 2017).[24] For example, managers of international hotel chains often consider many requests from local residents as neither urgent nor coming from powerful stakeholders, thus, not worth to be answered (Sripun et al., 2017). This argument is consistent with prior research measuring salience based on the notion of relative power between a firm and its stakeholders; the larger the firm size, the more power and resources it has to face and resist the pressure from a given stakeholder (Eesley & Lenox, 2006).[25] Darnall et al. (2010) show that enforcement actions and litigations are more costly against larger organizations, with authorities inclined to impose lower constraints and sanctions. Moreover, local communities have strong interests in

[23] Refinitiv ESG scores methodology document, updated on may 2022 https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

[24] "Firms with larger asset bases are more likely to have dedicated legal and public relations staff to fend off requests by secondary stakeholders" (Eesley & Lenox, 2006: 770)

[25] "The greater the resource-base of the stakeholder group relative to the resource- base of the targeted firm (Relative Power), the greater the likelihood that the firm responds to the stakeholder request (Saliency)" (Eesley & Lenox, 2006: 768).

having large T&L firms operate in their geographical area. To do so, they can make concessions by damping their claims. On the contrary, the relationship is more balanced with smaller firms as they depend more on local community acceptance and face higher community-related risks (Russo & Perrini, 2010; Russo & Tencati, 2009).

Furthermore, during Covid-19 crisis, managers of T&L companies turned most of their attention on urgent social issues, such as customer safety and product responsibility, rather than strengthening their community relations. Indeed, the pandemic caused an increased need to comply with emerging health and safety requirements. The combined effect of these factors diminished the relative urgency of local community claims, leading to both management effort and resources to be deployed elsewhere during Covid-19 crisis. In sum, we contend that community-related claims were non-salient during Covid-19 market crisis for T&L companies.

Empirical support of our salient classification based on Tweets. Based on SST, Gómez-Carrasco, Guillamón-Saorín, & García Osma (2021) argue that social media represent a channel where legitimate stakeholders address urgent claims which in turn lead to an increased power to pressure the firm. Specifically, they find that external stakeholders predominantly concentrate on core CSR issues (that are directly related to firm's value creation rather than non-core issues such as philanthropic and cultural actions) on social media and more specifically on Twitter. Moreover, Saxton, Ren, & Guo (2021) show that firm interactions on Twitter are influenced positively by stakeholders' relative power to the firm and the urgency of stakeholders' claims.

Hence, to empirically substantiate our categorization of salient and non-salient claims, we conducted an analysis of tweets by webscrapping the Twitter pages content of firms within our sample during the market crash period.

Following (Gómez-Carrasco et al., 2021), we focus on stakeholders' interactions with CSR related tweets to determine which categories represent core CSR issues and therefore more likely to be salient issues. We gathered a total of 704 tweets from 71 firms that had an active Twitter account during that timeframe (the remaining firms in our sample either did not have a tweeter account or did not post any tweet during that period). These tweets were manually categorized based on their content into three categories[26]: salient-CSR, non-salient-CSR, or non-CSR. Our analysis revealed that 33.24% of the tweets were related to CSR issues. Two-thirds of them are related to salient issues and only one-third to non-salient issues which aligns with the findings of Saxton, Ren, & Guo (2021).

Using t-tests[27], we observe that non-salient-CSR posts generated a moderate level of engagement, with an average of 68.29 likes, 10.26 reposts, and 1.73 replies/quotes per tweet. In contrast, salient-CSR posts garnered significantly higher levels of engagement, indicating heightened interest and relevance. On average, these tweets received 53.75 more likes ($p= 0.076$) which is 78.70% more compared to the interactions with non-salient posts, 14.35 more reposts ($p= 0.009$) which is 139.87% more, and 4.74 more replies/quotes which is 273.70% more. This increased engagement suggests that legitimate stakeholders, likely including employees, customers, and shareholders, demonstrated greater interest in salient CSR issues during this critical period deeming them more urgent (Gómez-Carrasco et al., 2021). This heightened engagement might have also contributed to increased media scrutiny and the accumulation of more influence, thereby increasing the power these stakeholders hold relative to the firm (Gómez-Carrasco et al., 2021). Consequently, our examination of tweet engagement

[26] This categorization was made by one teaching assistant and one PhD student and double checked based on the definition and descriptions of the CSR dimensions by Refinitiv.

[27] We first winsorized the likes, replies and reposts variables at at the 1st and 99th percentiles to avoid outliers effect.

substantiates our classification of salient and non-salient claims, affirming that salient CSR initiatives garner significantly more attention from stakeholders expressing their concerns through social media.

Dependent Variables

We measure corporate financial performance (CFP) using stock market measures of return and risk in line with economic and social arguments on CSR activities affecting both financial returns and risk exposure (Albuquerque et al., 2019; Eccles, Ioannou, & Serafeim, 2014; Flammer & Ioannou, 2015; Harjoto & Laksmana, 2018; Kim, Li, & Li, 2014; Mcguire, Sundgren, & Schneeweis, 1988). We use weekly stock market *Raw Returns*, which incorporate expected future adjustments and actions not necessarily captured by accounting measures (Fahlenbrach, Rageth, & Stulz, 2021). We proxy stock market risk using total stock *Volatility* computed on a weekly basis (similarly to Albuquerque et al., 2020; Becchetti et al., 2015; Mishra & Modi, 2013). In line with previous work (e.g., Goyal & Santa-Clara, 2003), we measure idiosyncratic volatility (*IVOL*) of stock *I* in week *t* as the standard deviation of residuals from the following least-squared regression, in accordance with Fama-French three-factor model (Fama & French, 1992):

$$Excess\_return_{i,t} = b_0 + b_1 Market\_excess\_return_t + b_2 SMB_t + b_3 HML_t + e_{i,t}$$

where $Excess\_return_{i,t}$ is the daily excess return of stock *i* over the risk free rate which is the monthly U.S. Treasury bill rate; $Market\_excess\_return_t$ is the daily return of the value-weighted market index minus the risk-free rate; SMB_t is the daily premium of the size factor; HML_t is the daily premium of the market-to-book factor (Fama & French, 1992).

Independent Variables

We measure corporate social performance (CSP) using the firms' environmental pillar score (*Environment*) and the scores for social categories – *Product-responsibility*, *Community*, *Workforce*, and *Human-rights* – from Refinitiv ESG database. We also derive the combined CSP for *Salient* (*Non-Salient*) CSR activities as the average score of *Environment* and *Product-responsibility* (*Community*, *Workforce*, and *Human-rights*). Finally, we calculate the average of all environmental and social scores (*ES score*) to capture firms' overall CSP (Albuquerque et al., 2020; Amiraslani et al., 2022).

We create three dummy variables to identify firms' different approaches to address stakeholders' claims. *SST Approach* takes the value of one if the average score of salient (non-salient) CSR activities is above (below) the median of their subindustry group and zero otherwise (30 firms). *Stakeholders Approach* takes the value of one if the average scores of both salient and non-salient CSR activities are above the subindustry median and zero otherwise (56 firms). *Shareholders-only Approach* takes the value of one if the average scores of both salient and non-salient CSR activities are below the subindustry median and zero otherwise (83 firms). We label the remaining firms as *Non-SST Approach*.

Similarly to recent papers analyzing the CSP-CFP relationship during crisis (e.g., Demers et al., 2021; Lins et al., 2017), we control for firms' main financial characteristics. *Size* is measured as the natural logarithm of the firm's market capitalization. *Profitability* as the ratio of operating income to total asset. *Cash Holding* as the ratio of cash and short-term investments to total assets. *Long-Term Debt* as the ratio of long-term debt to total assets; *Short-Term Debt* as the ratio of debt in current liabilities to total assets. *Book-to-Market* ratio at the end of the fiscal year. *Negative Book-to-Market* is a dummy variable taking the value of one if a firm's

book to market ratio is negative. We also control for Fama-French three factors model plus momentum, namely, *Market Excess Return, High-minus-Low* premium, *Small-minus-Big* premium and *Up-minus-Down* (winners minus losers premium) (based on Carhart's extended Fama-French model (1997)). We also add *Tangible Assets* using the net property, plant, and equipment to assets ratio as a proxy for firms' level of intangible assets, *Inventory* as the ratio of total inventory to total assets, and *Dividend* as the ratio of total dividends to net income. Finally, we include firm fixed effects to control for time invariant unobservable drivers.

Model Specifications

Based on Lins et al. (2017: 1805), we run a difference-in-differences model using Covid-19 market crash as exogeneous shock and pre-crisis environmental and social scores as continuous treatments to identify the effect of CSP on CFP. We distinguish three distinct periods to isolate the effect of CSP during the exogenous crisis: (1) *Pre-Crisis*, from January 1st, 2019 to February 18th, 2020; (2) *Crisis* from February 19th, 2020 to March 23rd, 2020, which covers the 34 days (24 working days) of the stock market crash induced by the Covid-19 pandemic, from its peak until it reached its lowest point during the crisis (Lins, Volpin, & Wagner, 2013); and (3) *Post-Crisis* from March 24th, 2020 to December 31st, 2020, covering the stock market recovery.

To avoid the effect of outliers on estimated coefficients, we winsorize at the 1st and 99th percentiles the dependent and control variables (e.g., Lins et al., 2017). Standard errors are clustered at the week level, therefore, robust to time-series interdependences.

To test hypotheses H1a and H1b on the positive (non-positive) association of CSP of salient (non-salient) claims and CFP, we interact firms' CSP with two binary indicators (*Crisis* and *Post-Crisis*). Equation (1) provides the specification.

$$(1)\ CFP_{i,t} = b_0 + b_1 Crisis_t + b_2 Post\ Crisis_t + b_3' CSP'_{i,2018}\ x\ Crisis_t + b_4' CSP'_{i,2018}\ x\ Post\ Crisis_t + b_5' X_{i,t-1} + b_6' Fama\ French\ Factors_t + b_7' Firm\ Fixed\ Effects_i + e_{i,t}$$

Where CFP is either Raw Return, Volatility, or Idiosyncratic Volatility. Similar to prior research measuring CSR activities at least one year before the crisis (Albuquerque et al., 2020; Lins et al., 2017), CSP is a vector of each firm's environmental and social scores measured at year-end 2018 (namely, Environment Score, Product-responsibility Score, Community Score, Workforce Score, and Human-rights Score).

Equation (2) interacts the dummy variables for *SST Approach, Stakeholders Approach*, and *Shareholders-only Approach* with the time period binary indicators to test for hypotheses H2a and H2b: firms following an *SST Approach* outperform firms following either a *Shareholders-only Approach* (H2a) or a *Stakeholders Approach* (H2b).

$$(2)\ CFP_{i,t} = b_0 + b_1 Crisis_t + b_2 Post\ Crisis_t + b_3 SST\ Approach_{i,2018}\ x\ Crisis_t + b_4 Stakeholders\ Approach_{i,18}\ x\ Crisis_t + b_5 Shareholders\ Approach_{i,2018}\ x\ Crisis_t + b_6 SST\ Approach_{i,2018}\ x\ Post\ Crisis_t + b_7 Stakeholders\ Approach_{i,2018}\ x\ Post\ Crisis_t + b_8 Shareholders\ Approach_{i,2018}\ x\ Post\ Crisis_t + b_9' X_{i,t-1} + b_{10}' Fama\ French\ Factors_t + b_{11}' Firm\ Fixed\ Effects_i + e_{i,t}$$

Finally, equation (3) includes the interactions of CSP and its quadratic term with the periods dummy variables to test for hypothesis H3: the relationship between CSP and CFP is inverted U shaped.

$$(3)\ CFP_{i,t} = b_0 + b_1 Crisis_t + b_2 Post_t + b_3 CSP_{i,2018}\ x\ Crisis_t + b_4 CSP^2_{i,2018}\ x\ Crisis_t + b_5 CSP_{i,2018}\ x\ Post\ Crisis_t + b_6 CSP^2_{i,2018}\ x\ Post\ Crisis_t + b_7' X_{i,t-1} + b_8' Fama\ French\ Factors_t + b_9' Firm\ Fixed\ Effects_i + e_{i,t}$$

Where CSP is the firm average environmental and social score (ES Score).

RESULTS

Descriptive Statistics

Table 1 presents descriptive statistics and pairwise correlations. We observe that CSP dimensions vary significantly across firms in our sample with mean values between 32.93 and 56.74 and standard deviations ranging from 22.48 to 33.09 for the various CSP scores. Moreover, CFP measures during crisis indicate that firms were heavily impacted by the crisis – e.g., *Crisis Raw Returns* have a mean and median of respectively -8.71% and -8.72%, while *Raw Returns* have a 0.08% mean and 0.13% median over the whole period.

Insert TABLE 1 about here

CSP-CFP Relationship based on SST

Table 2 reports the results from equation (1). The findings are consistent with the predictions of hypotheses H1a and H1b. The CSP-CFP relationship is positive for activities that benefit salient claims from stakeholders but non-significant for non-salient ones. Indeed, the coefficient for interaction *Crisis x Environmental Score* is positive for the *Raw Returns*' model ($\beta = 0.05$, $p < .01$), negative for *IVOL* ($\beta = -0.01$, $p < .01$), and also negative for *Volatility* ($\beta = -0.01$, $p < .05$). A one-standard-deviation increase in the *Environmental Score* (28.95) corresponds to a 1.35% increase in weekly stock returns during crisis, a 0.29% decrease in *IVOL*, and a 0.40% decrease in *Volatility*. The coefficient for *Crisis x Product Responsibility* is also positive and significant for the *Raw Returns*' regression ($\beta = 0.01$, $p < .05$), and negative for *IVOL* ($\beta = -0.003$, $p < .01$) and *Volatility* ($\beta = -0.01$, $p < .01$). A one-standard-deviation increase in the *Product Responsibility* score (29.15) corresponds to a 0.29% increase in *Stock Returns*, a 0.06% decrease in *IVOL*, and a 0.13% decrease in *Volatility* during crisis. Overall, these results indicate

that salient activities (i.e., environment and product responsibility) enhance firm value during the stock market crash period, in accordance with hypothesis H1a.

Conversely, we find that the coefficient for *Crisis x Community Score* is significantly negative for the *Raw Returns*' regression (β = -0.03, p < .01), and positive for *IVOL* (β = 0.01, p < .05) and *Volatility* (β = 0.02, p < .05). A one-standard-deviation increase in *Community Score* (28.48) corresponds to a 0.96% decrease in *Stock Returns*, a 0.46% increase in *IVOL*, and a 0.23% increase in *Volatility*. The coefficient for *Crisis x Human-Rights Score* is significantly negative for the *Raw Returns'* regression (β = -0.02, p < .01), positive but non statistically significant for *IVOL* (β = 0.01, t=1.52) and significantly positive for *Volatility* (β = 0.01, p <.1). A one-standard-deviation increase in *Human-Rights Score* (33.09) is associated with a 0.56% decrease in stock raw returns and a 0.24% increase in *Volatility*. Finally, our results suggest the presence of a neutral relationship between *Workforce Score* and CFP as none of the interaction coefficients with *Crisis* are significant. Overall, these findings suggest that CSR activities related to less salient stakeholders' claims are not value-enhancing during the stock market crash period, in accordance with hypothesis H1b.

Insert TABLE 2 about here

Multiple Approaches to Address Stakeholders' Claims

Table 3 reports the results for our tests of hypotheses H2a and H2b. Consistent with our prediction for H2a, firms that follow an *SST Approach* have a higher CFP than firms following a *Shareholders-only Approach*. Consistent with H2b, firms that follow an *SST Approach* have a higher CFP than firms following a *Stakeholders approach*. Firms following an *SST Approach* report a 2.85% higher weekly *Raw Returns* (p= 0.01), a 0.72% lower weekly *IVOL* (p= 0.03),

and a 1.31% lower weekly *Volatility* (p= 0.01) compared to firms following a *Shareholders-only Approach*, further supporting H2a. Furthermore, firms following an *SST Approach* show a 2.76% higher *Raw Returns* (p= 0.0), 0.67% lower *IVOL* (p= 0.03) and 0.89% lower *Volatility* (p= 0.08) during crisis than firms pursuing a *Stakeholders Approach*, consistent with H2b.

Second, we analyze the effect of the Covid-19 market crash on each of the four groups of firms. The *Crisis* coefficient of -6.07% in the *Raw Returns'* regression represents the estimated effect of *Crisis* on firms of the control group (i.e., following the *Non-SST Approach*). The estimated effect of *Crisis* on firms following the *SST Approach* is the sum of *Crisis* coefficient and *SST Approach* x *Crisis* coefficient. The resulting coefficient is not statistically significant in the *Raw Returns*' regression suggesting that the *Raw Returns* of firms following an *SST Approach* were not affected negatively by the stock market crash induced by the pandemic. Conversely, *Crisis* + *Crisis* x *Shareholders-only Approach* and Crisis + *Crisis* x *Stakeholders Approach* are both significantly negative (-4.41%, p= 0.01 and -4.50%, p= 0.02 respectively).

Interestingly, both firms following a *Shareholders-only Approach* and a *Stakeholders Approach* outperformed those who follow the *Non-SST Approach*. We find that, during the *Crisis*, firms following a *Shareholders-only Approach* report higher *Raw Returns* ($\beta = 1.58$, $p < .01$), lower *IVOL* ($\beta = -0.27$, $p < .05$), and lower *Volatility* ($\beta = -0.28$, $p < .01$) than the control group (*Non-SST Approach*). Firms following a *Stakeholders Approach* also display higher *Stock Returns* ($\beta = 1.67$ $p < .05$) , lower *IVOL* ($\beta = -0.32$, $p<.05$) and lower *Volatility* ($\beta = -0.70$, $p < .01$) than the control group.

Insert TABLE 3 about here

Optimal Level of CSP

Table 4 reports results from equation (3) analyses consistent with H3a. CSP has a concave (inverted-U-shaped) relationship with CFP. Results show a significantly positive association between *Raw Returns* and *Crisis x ES Score* ($\beta = 0.09$ $p<.05$), yet a significantly negative association with the interaction between crisis and the score's quadratic term *Crisis x ES Score*^{2} ($\beta = -0.0007$ $p<.05$). The direction and significance of these linear and quadratic coefficients indicate that an increase in *ES Score* leads to higher *Raw Returns* during the *Crisis* period until an optimal level is reached.[28] The estimated optimal *ES Score* is 62, with a 90% confidence interval from 45 to 79. This level corresponds to an 'above-average score' or a 'B-grade' based on Refinitiv ratings and also compared to the *ES Score* mean for firms in our sample of 45 and the third quartile of 62.

Our results also indicate the existence of a convex relationship between CSP and CFP using market risk measures. We observe that both relationships between *ES Score* and *IVOL* and *Volatility* are significantly U-shaped during the *Crisis* period. In particular, the association between *Crisis x ES Score* and *IVOL* is significantly negative ($\beta = -0.02$, $p<.05$) while the relationship between *Crisis x ES Score* ^{2} and *IVOL* is significantly positive ($\beta = -0.0001$, $p<.10$). The association between *Crisis x ES Score* and *Volatility* is also significantly negative ($\beta = -0.05$, $p<.01$) while the relationship between *Crisis x ES Score*^{2} and *Volatility* is significantly positive ($\beta = 0.0004$ $p<.01$). This evidence suggests that CSP leads to lower *IVOL* and *Volatility* until a firm reaches an optimal *ES Score* of 68, with a 90% confidence interval of [50, 86] for

[28] This point is found by calculating the derivative of the CFP regression with respect to CSP and setting it equal to zero: $dCFP/dCSP = \beta1 + 2*\beta2*CSP = 0$. Hence, Optimal CSP = $-\beta1 / (2*\beta2)$ where $\beta1$ is the coefficient of CSP x Crisis and $\beta2$ = CSP2 x Crisis

IVOL and 67, with a 90% confidence interval of [61, 74] for *Volatility*. Beyond these levels, an increase in CSP increases the firm risk level.

Insert TABLE 4 about here

Finally, we remove the quadratic terms from our regressions in Table 4 and test the linear relationship between overall *CSP* (without distinguishing salient from non-salient CSR activities) and CFP in accordance with prior studies (see Appendix A). We find that the association between overall CSP (measured as *ES Score*) and *Raw Returns* during the Covid-19 market crash is statistically not significant, which is in line with recent findings from Demers et al. (2021) and Bae et al. (2021). This suggest that assuming a linear relationship may lead to an erroneous conclusion that the relationship is neutral. We also find that *ES Score* relates negatively to *IVOL* and *Volatility* (at respectively 10% and 5% levels), which is consistent with Albuquerque et al.'s (2020) findings.[29]

Robustness Tests

Similarly to Demers et al. (2021) and Bae et al. (2020), we run the *Raw Returns* model using a sample of US-listed companies excluding financial companies (SIC codes 6000-6999), Utilities (4900-4999), and small capitalizations (< $250 Millions). In line with their findings, we find a positive but non-significant relationship between *ES Score* and *Raw Returns* during the Covid-19 financial crisis. Next, we replicate our *IVOL* and *Volatility* models using a sample of US-listed companies (similarly to Albuquerque et al., 2020) to verify that our results are not driven by methodological differences with these previous studies or by potential measurement

[29] Finding similar results to these recent studies when analyzing the overall CSP-CFP relationship also indicates that our results do not suffer from sampling bias.

errors in our empirical models. In line with Albuquerque et al. (2020), we find a significantly negative relationship at a 5% (1%) level between *ES Score* and *IVOL* during (and post-) Covid-19 financial crisis, and a significantly negative relationship at a 1% level between *ES Score* and *Volatility* post-crisis.

In following analyses, we relax our model specification that includes firm fixed effects to control for other time-varying confounding factors. We use firms' pre-crisis governance score (*Governance Score*) from ESG Refinitiv, based on evidence that well governed firms perform better in crisis periods (Lins et al., 2013). We include the variation in CSP that occurs between 2020 and 2021 (as the difference in all ESG Refinitiv scores: *Environment Variation; Product-responsibility Variation*, *Community Variation*, *Workforce Variation*, *Human rights Variation;* and *Governance Variation*) to control for the effect of any firms' unobserved reaction to crisis by changing their CSR activities during or just right after the crisis period. In addition, to control for other unobservable external drivers of stock returns such as government aids, we include both country and sub-industry fixed effects. Finally, we add *Pre-Crisis Average Raw Return* and *Pre-Crisis Average IVOL* measuring, respectively, the pre-crisis stock return over a three-year period and the pre-crisis idiosyncratic volatility over a three-year period (Lins et al., 2017).[30] Overall findings are very consistent with primary results showing even stronger and more significant coefficients for the main interaction variables.

Furthermore, we test whether our results are robust to other measures of stock risk and find that they are not affected by potential measurement errors related to *IVOL* using the four-factor model (Carhart, 1997). In fact, we find similar results employing the *IVOL* measure based on the market model and using the extended Fama-French model proposed by Carhart, by adding

[30] These variables are absorbed by firms fixed effects in our main regression specification.

the momentum factor. We also conduct additional tests by measuring *CSP* using environmental and social scores of 2019 instead of 2018 and find very consistent results. Following Fahlenbrach et al. (2021), we alternatively define a wider market crash period, from February 3, 2020 until March 23, 2020, and find consistent results. Finally, we run a normal difference-in-differences model using firms with scores lower than the industry median as a control group to test for H1a and H1b and find robust results – salient activities are positively related to *CFP* while non-salient ones are not.

DISCUSSION AND CONCLUSION

The debate concerning whether CSR activities are value-enhancing or value-destroying is very active in both academic and business words. Using a sample of T&L firms, we analyze the financial implications of addressing CSR activities' salient and non-salient issues during the Covid-19 exogenous shock. Our main findings suggest that an absolute positive or negative relationship between CSP and CFP may not exist, and it is more a matter of *which CSR activities should managers focus on* and *to what extent*, rather than *if they should invest* in CSR.

Consistent with stakeholder salience theory (e.g., Agle et al., 1999), we observe that the effect of CSP on CFP is contingent on the salience of claims from the stakeholders involved. CSR activities considered as salient (i.e., relating to product-responsibility and the natural environment for T&L firms during the Covid-19 market crash) are associated with higher stock returns and lower market risk. On the contrary, non-salient activities (i.e. relating to workforce, community, and human rights dimensions) do not have a positive effect on CFP. In addition, we find that firms following a *Stakeholders* or a *Shareholders-only Approach* to address their stakeholders' claims underperformed as compared to firms pursuing an *SST Approach*. This evidence suggests that the *SST Approach* is a more effective instrumental approach to CSR

activities than the other approaches investigated[31]. Interestingly, we document that the group of firms following an *SST Approach* was the only one not being significantly impacted by the stock market crash.

Finally, we find evidence of a concave relationship between CSP and CFP suggesting the existence of an optimal level of CSR activities that maximize financial performance and beyond which desirable CSR inputs do not result in desirable financial outputs. For all three CFP measures, the overall CSP score (*ES Score*) that maximizes CFP corresponds to a 'B-grade' score based on Refinitiv ESG rating (e.g., the score that maximizes *Raw Returns* is 62 with a 90% confidence interval from 45 to 79). Beyond this level, higher CSP is likely to lead to lower CFP. Therefore, there might be no financial incentives for firms to target excellent overall environmental and social performances. This result is consistent with what Pierce & Aguinis (2011) refer to as the "Too-Much-of-a-Good-Thing effect", where an excessive amount of a desirable managerial and organizational behaviors can lead to negative outcomes or consequences.

These findings have several practical implications. First, they are informative to managers responsible to define optimal CSR levels. As the effect of CSR activities on CFP is conditional on changing external conditions (Barnett, 2007; Durand, Hawn, & Ioannou, 2019; Rivoli & Waddock, 2011), managers need to define effective and context-dependent CSR activities. Corporate risk managers might need to focus on salient claims and, more importantly, recognizing the probability of a claim to become salient if contextual changes trigger one or

[31] We analyze CSP from an instrumental point of view. But, based on our findings, if financial performance was the only managerial incentive, we should not observe other approaches than the salient one. The fact that other behaviors exist (especially a fourth group of firms with a more 'altruistic' choice of CSR activities, overinvesting into non-salient CSR activities and underinvesting in salient CSR activities) may explain the existence of normative approaches. Managers have different cultural and ethical considerations that also motivate their decisions and therefore, drive CSP. These questions are outside the scope of our work.

more attributes (e.g., customer safety becoming more salient during the Covid-19 crisis). Second, our work is also useful to regulators, NGOs and other stakeholders to understand the stakeholder-firm relationship and influence the salience of their claims. More specifically, by estimating the optimal CSP level of a claim, they can deduce when pressures on managers are necessary – i.e., when it is not (or no longer) financially beneficial for firms to voluntarily address these issues – and deploy resources and measures accordingly.

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TABLES AND FIGURES

Table 1. Descriptive Statistics and Correlation Matrix

	Stats	SD	Mean	p50	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Raw Return**	6.27	0.08	0.13														
2	IVOL**	1.94	2.31	1.73	0.01													
3	Volatility**	2.38	2.59	1.84	-0.01	**0.91**												
4	Crisis Raw Return**	7.65	-8.71	-8.72	**1.00**	**-0.51**	**-0.58**											
5	Crisis IVOL**	2.69	3.57	2.74	**-0.51**	**1.00**	**0.85**	**-0.51**										
6	Crisis Volatility**	3.56	4.52	3.31	**-0.58**	**0.85**	**1.00**	**-0.58**	**0.85**									
7	ES Score	23.59	44.70	42.92	**-0.02**	**-0.05**	**-0.06**	0.07	**-0.09**	**-0.13**								
8	Environmental Score	28.95	39.32	37.57	**-0.03**	**-0.06**	**-0.07**	0.09	**-0.11**	**-0.15**	**0.96**							
9	Product Responsibility Score	29.15	50.82	53.95	-0.01	**-0.03**	**-0.04**	0.07	-0.07	**-0.11**	**0.65**	**0.50**						
10	Workforce Score	26.42	56.74	56.97	-0.02	**-0.03**	**-0.06**	0.06	-0.08	**-0.16**	**0.79**	**0.74**	**0.45**					
11	Community Score	28.48	55.22	57.93	0.01	-0.02	**0.03**	-0.07	0.02	0.08	**0.48**	**0.39**	**0.15**	**0.19**				
12	Human Rights	33.09	32.93	25.66	-0.01	**-0.02**	**-0.02**	0.01	-0.03	-0.05	**0.72**	**0.62**	**0.36**	**0.58**	**0.34**			
13	Governance Score	20.75	51.37	50.54	0.00	**-0.02**	**-0.03**	0.01	-0.05	-0.06	**0.47**	**0.45**	**0.20**	**0.43**	**0.28**	**0.37**		
14	Salient Score	25.20	45.07	45.22	**-0.02**	**-0.05**	**-0.06**	**0.09**	**-0.11**	**-0.15**	**0.93**	**0.87**	**0.87**	**0.68**	**0.31**	**0.57**	**0.37**	
15	Non-Salient Score	22.48	48.30	46.23	-0.01	**-0.03**	**-0.02**	0.00	-0.04	-0.05	**0.86**	**0.76**	**0.42**	**0.76**	**0.66**	**0.86**	**0.47**	**0.68**
16	Firm Size	1.32	14.95	14.85	0.01	**-0.13**	**-0.08**	**0.10**	**-0.13**	-0.06	**0.46**	**0.48**	**0.19**	**0.31**	**0.32**	**0.28**	**0.28**	**0.39**
17	Long-Term Debt	0.31	0.40	0.36	0.02	**0.03**	**0.07**	0.00	0.01	0.08	**-0.08**	**-0.13**	-0.02	**-0.18**	**0.20**	-0.02	**-0.02**	**-0.08**
18	Short-Term Debt	0.04	0.04	0.02	**-0.03**	**0.04**	**0.03**	0.06	0.00	-0.05	**0.12**	**0.12**	**0.10**	**0.18**	**-0.11**	**0.11**	**0.05**	**0.13**
19	Cash Holdings	0.14	0.14	0.10	0.01	**-0.04**	**-0.07**	**0.11**	-0.08	**-0.10**	**-0.14**	**-0.09**	**-0.12**	**-0.10**	**-0.18**	**-0.14**	**-0.10**	**-0.12**
20	Book-to-Market	0.44	0.43	0.33	**-0.03**	0.00	**-0.04**	0.00	0.00	**-0.09**	**0.19**	**0.22**	**0.08**	**0.28**	**-0.09**	**0.14**	-0.02	**0.17**
21	Negative Book-to-Market	0.30	0.10	0.00	0.02	**-0.03**	0.00	0.03	-0.03	0.03	**-0.05**	**-0.08**	**-0.05**	**-0.13**	**0.18**	0.01	**0.04**	**-0.08**
22	Profitability	0.08	0.09	0.07	**0.03**	**-0.10**	**-0.08**	**0.12**	**-0.12**	-0.05	**-0.14**	**-0.14**	**-0.06**	**-0.17**	**-0.05**	**-0.10**	**-0.02**	**-0.11**
23	Tangible Assets	0.27	0.46	0.51	-0.02	**0.04**	**0.06**	-0.04	0.00	0.01	**0.19**	**0.21**	**0.12**	**0.03**	**0.16**	**0.06**	**0.07**	**0.19**
24	Inventory	0.03	0.02	0.01	0.00	**-0.07**	**-0.06**	**0.09**	-0.05	-0.04	**-0.11**	**-0.09**	**-0.11**	**-0.08**	**-0.08**	**-0.07**	**-0.10**	**-0.12**
25	Dividends	1.05	0.43	0.27	0.00	**-0.06**	**-0.08**	0.07	**-0.10**	**-0.10**	0.00	0.01	-0.01	**0.04**	**-0.03**	**-0.04**	**0.11**	0.00

		15	16	17	18	19	20	21	22	23	24
14	Firm Size	**0.39**									
15	Long-Term Debt	0.01	**0.03**								
16	Short-Term Debt	**0.08**	**-0.06**	**-0.02**							
17	Cash Holdings	**-0.18**	**0.06**	**-0.15**	**-0.08**						
18	Book-to-Market	**0.14**	**-0.18**	**-0.39**	**0.22**	**-0.10**					
19	Negative Book-to-Market	**0.03**	**0.07**	**0.67**	**-0.06**	-0.01	**-0.47**				
20	Profitability	**-0.14**	**0.18**	**0.37**	**-0.25**	**0.34**	**-0.53**	**0.46**			
21	Tangible Assets	**0.11**	**0.03**	**0.08**	0.01	**-0.35**	**0.17**	**-0.07**	**-0.17**		
22	Inventory	**-0.10**	**-0.05**	**-0.05**	**0.17**	**-0.07**	**0.04**	**-0.03**	**0.05**	**-0.10**	
23	Dividends	**-0.01**	0.01	0.06	-0.04	**0.07**	**-0.08**	**0.12**	**0.12**	**-0.11**	**0.03**

N = 18'010 for the main analyses, except for the CFP during crisis variables (Crisis Raw Return, Crisis IVOL, Crisis Volatility) for which N = 835

Correlations that are significant at a level below 1 percent (two-tailed) are in bold.

** The values of the dependent variables are disclosed in percentage points.

Table 2. Relationship between CSP of Salient and Non-Salient Activities and CFP

		(1) Raw Return			(2) IVOL			(3) Vola-tility		
Crisis		-3.70	*	(-1.98)	1.98	**	(2.18)	2.72	**	(2.29)
Post-Crisis		0.46		(0.94)	1.40	***	(7.62)	2.09	***	(8.26)
Crisis x Environmental Score	(H1a)	0.05	***	(3.67)	-0.01	***	(-2.76)	-0.01	**	(-2.30)
Crisis x Product Responsibility Score	(H1a)	0.01	**	(2.24)	0.003	***	(-3.01)	-0.01	***	(-2.66)
Crisis x Community Score	(H1b)	-0.03	***	(-2.75)	0.01	**	(2.27)	0.02	**	(2.09)
Crisis x Human-Rights Score	(H1b)	-0.02	***	(-4.40)	0.01		(1.52)	0.01	*	(1.72)
Crisis x Workforce Score	(H1b)	-0.01		(-1.28)	0.00		(-0.29)	-0.01		(-1.53)
Post-Crisis x Workforce Score		-0.01		(-0.85)	0.00		(1.14)	-0.01	***	(-3.49)
Post-Crisis x Environmental Score		-0.01		(-1.62)	0.00	***	(-2.65)	-0.01	***	(-2.78)
Post-Crisis x Product Responsibility Score		0.00		(0.28)	0.00	***	(-3.80)	-0.01	***	(-4.72)
Post-Crisis x Community Score		0.01		(1.52)	0.00	*	(1.90)	0.01	***	(3.36)
Post-Crisis x Human-Rights Score		0.00		(-0.86)	0.01	***	(6.66)	0.01	***	(8.00)
Firm Controls										
Firm Size		-0.15		(-0.36)	-0.76	***	(-6.94)	-0.79	***	(-6.09)
Long-Term Debt		-0.50		(-0.55)	0.77	***	(4.21)	1.48	***	(5.46)
Short-Term Debt		0.89		(0.35)	-1.24	**	(-1.98)	-1.57	**	(-2.20)
Cash Holdings		-0.56		(-0.46)	0.72	**	(2.13)	1.06	***	(2.84)
Book-to-Market		0.50		(0.77)	-0.81	***	(-3.96)	-1.22	***	(-5.29)
Negative Book-to-Market		0.23		(0.46)	-1.07	***	(-7.32)	-1.24	***	(-7.52)
Profitability		-5.83	*	(-1.97)	1.96	**	(2.41)	1.92	**	(2.17)
Tangible Assets		0.28		(0.25)	-0.35		(-1.24)	-1.41	***	(-3.73)
Inventory		-8.40		(-0.79)	-5.55	**	(-2.46)	-8.09	***	(-3.32)
Dividends		0.08		(1.27)	-0.05	***	(-3.10)	-0.10	***	(-5.03)
Fama-French Factors										
Market Excess Return		0.81	***	(6.69)				-0.05		(-0.59)
Small-minus-Big		0.28		(1.58)				-0.16		(-1.26)
High-minus-Low		0.07		(0.37)				-0.39	**	(-2.32)
Up-minus-Down		-39.14	**	(-2.53)				-31.45	***	(-2.65)
Constant		2.65		(0.41)	13.12	***	(7.85)	13.95	***	(7.05)
Firm Fixed Effects		YES			YES			YES		
R^2		27%			29%			36%		
Number of observations		18'008			17'999			17'999		

Standard errors are clustered by week and reported in parentheses. Two-tailed significance tests for coefficients.

* p<.10; ** p<.05; *** p<.01

Table 3. Responses to Stakeholders' Claims

		(1) Raw Return			(2) IVOL			(3) Volatility		
Crisis		-6.07	***	(-3.58)	2.30	**	(2.48)	2.85	**	(2.49)
Post-Crisis		0.24		(0.52)	1.82	***	(7.75)	2.41	***	(8.19)
Shareholders-only Approach x Crisis		1.58	***	(4.23)	-0.27	**	(-2.33)	-0.28	***	(-2.85)
Stakeholders Approach x Crisis		1.67	**	(2.60)	-0.32	**	(-2.55)	-0.70	***	(-2.91)
SST Approach x Crisis		4.43	***	(4.32)	-0.99	**	(-2.40)	-1.58	**	(-2.21)
Control Variables		YES			YES			YES		
Firm Fixed Effects		YES			YES			YES		
Group Comparison:										
Crisis x (SST Approach - Shareholders-only Approach)	(H2a)	2.85	***	[0.01]	-0.72	**	[0.03]	-1.31	**	[0.05]
Crisis x (SST Approach - Stakeholders Approach)	(H2b)	2.76	***	[0.00]	-0.67	**	[0.03]	-0.89	*	[0.08]
Crisis x (Stakeholders Approach - Shareholders-only Approach)		0.09		[0.88]	-0.06		[0.48]	-0.42	**	[0.04]
The effect of Crisis on each group:										
Crisis + SST Approach x Crisis		-1.64		[0.30]	1.31	**	[0.02]	1.26	**	[0.04]
Crisis + Stakeholders Approach x Crisis		-4.41	**	[0.01]	1.98	**	[0.02]	2.15	**	[0.02]
Crisis + Shareholders-only Approach x Crisis		-4.50	**	[0.02]	2.04	**	[0.02]	2.57	**	[0.02]
R^2		28%			29%			36%		
Number of observations		18'528			18'519			18'519		

Standard errors are clustered by week and reported in parentheses. Two-tailed significance tests for coefficients.

Prob > F for the Wald test is in square brackets.

* p<.10; ** p<.05; *** p<.01.

Control variables include Post-crisis interactions with CSP measures, Firm Size, Long-Term Debt, Short-Term Debt, Cash Holdings, Book-to-Market, Negative Book-to-Market, Profitability, Tangible Assets, Inventory, Dividends, Market Excess Return, Small-minus-Big, High-minus-Low, Up-minus-Down, and the Constant term.

Coefficients can be interpreted in percentage points.

Table 4. Optimal Level of CSP

		(1) Raw Return			(2) IVOL			(3) Volatility		
Crisis		-6.36	***	(-2.72)	2.45	**	(2.54)	3.58	**	(2.51)
Post-Crisis		0.93		(1.61)	1.69	***	(7.41)	2.49	***	(7.71)
Crisis x ES Score	(H3)	0.09	**	(2.17)	-0.02	**	(-2.01)	-0.05	***	(-2.73)
Crisis x ES Score^2	(H3)	-0.0007	**	(-2.34)	0.0001	*	(1.75)	0.0004	***	(2.98)
Control Variables		YES			YES			YES		
Firm Fixed Effects		YES			YES			YES		
Hypothesis 3: *Optimal Score*		*62*			*68*			*67*		
90% Confidence Interval		*[45, 79]*			*[50, 86]*			*[61, 74]*		
R^2		27%			29%			36%		
Number of observations		18'008			17'999			17'999		

Standard errors are clustered by week and reported in parentheses. Two-tailed significance tests for coefficients.

Prob > F for the Wald test is in square brackets.

* p<.10; ** p<.05; *** p<.01.

Control variables include Post-crisis interactions with CSP measures, Firm Size, Long-Term Debt, Short-Term Debt, Cash Holdings, Book-to-Market, Negative Book-to-Market, Profitability, Tangible Assets, Inventory, Dividends, Market Excess Return, Small-minus-Big, High-minus-Low, Up-minus-Down, and the Constant term.

Coefficients can be interpreted in percentage points.

Appendix A. The linear relationship between the ES Score and CFP

	(1) Raw Return			(2) IVOL			(3) Volatility		
Crisis	-5.19	**	(-2.44)	2.22	**	(2.42)	2.98	**	(2.38)
Post-Crisis	0.72	*	(1.77)	1.45	***	(6.92)	2.06	***	(7.47)
Crisis x ES Score	0.02		(1.25)	-0.006	*	(-1.97)	-0.02	**	(-2.18)
Control Variables	YES			YES			YES		
Firm Fixed Effects	YES			YES			YES		
R^2	27%			29%			36%		
Number of observations	18'008			17'999			17'999		

Standard errors are clustered by week and reported in parentheses. Two-tailed significance tests for coefficients.

Prob > F for the Wald test is in square brackets.

* p<.10; ** p<.05; *** p<.01.

Control variables include Post-crisis interactions with CSP measures, Firm Size, Long-Term Debt, Short-Term Debt, Cash Holdings, Book-to-Market, Negative Book-to-Market, Profitability, Tangible Assets, Inventory, Dividends, Market Excess Return, Small-minus-Big, High-minus-Low, Up-minus-Down, and the Constant term.

Coefficients can be interpreted in percentage points.

Chapter 2. Asymmetric Cost Behavior, Capital Structure and Profitability

ABSTRACT

We examine how asymmetric cost adjustments (i.e., costs stickiness) may affect capital structure and profitability. We develop a novel firm-level measure of cost stickiness and address endogeneity issues using instrumental variables. We first find that high-sticky-cost firms have lower financial leverage, shorter debt maturity, and higher cash holdings. Our findings imply that cost stickiness increases the risk of default, reducing the optimal leverage. They also suggest that cost stickiness increases refinancing risks and financial constraints, leading managers to favor internal financing to pay for operational excess capacity and sustain investments when sales are low. Moreover, we find that cost stickiness has a positive effect on profitability. Finally, we compare the effects of cost stickiness and the related concept of operating leverage. We observe that, while they have similar effects on financial leverage and cash holdings, operating leverage has an overall negative effect on profitability unlike cost stickiness.

Keywords: Asymmetric cost behavior; Cost stickiness; Capital structure; Cash holdings; Profitability.

INTRODUCTION

Managing resource capacity is a critical managerial decision as it significantly influences a company's cost structure, its capacity to generate revenue, and ultimately, make profit. Managers, on average, make asymmetric decisions adjusting more costs to revenue increases than they do for revenue decreases. This cost stickiness phenomenon, documented by Anderson et al. (2003), contrasts with the traditional cost management perspective assuming a symmetric adjustment of costs to changes in the volume of activity. This asymmetry arises because managers adjust resources upward when demand increases, yet carefully weigh the costs and benefits of adjusting and maintaining resources when demand drops. Extensive research has been conducted to document this phenomenon and examine the multiple firm-specific, managerial, and contextual factors under which cost stickiness is amplified (e.g., Banker et al. 2013; Calleja et al. 2006; Chen et al. 2012; Kama and Weiss 2013).

The magnitude of this asymmetry is economically significant for firms[32] and, therefore, might lead to important organizational and financial consequences. Yet, research on the effects of cost stickiness have been very limited in contrast to studies of its determinants[33]. In particular, the impact of cost stickiness on capital structure remains unexplored, and we attempt to fill this void by analyzing its relationship with financial leverage, cash holdings, and debt maturity. At this stage, it is unclear how cost stickiness affects the way firms are financed. On one hand, prior work highlighting a substitution effect between operating and financial leverage (e.g., Ferri and Jones 1979; Mandelker and Rhee

[32] Anderson et al. (2003) observe that SG&A costs increase by 0.55% on average when revenues increase by 1% while they decrease only by 0.35% when revenues decrease by 1%.
[33] Notable exceptions are Weiss (2010) showing that cost stickiness reduces the accuracy of analysts' earnings forecasts. More recently, Agarwal (2022) reports that cost stickiness delays stock price adjustment because of higher information asymmetry between managers and investors, and He et al. (2020) observe that high-sticky-cost firms pay lower dividends than their peers.

1984) suggests that higher operating leverage and fixed costs reduce the level of debt[34] (e.g., Kahl et al. 2019; Serfling 2016). On the other hand, other studies may imply a positive relationship. For example, Petacchi (2015) finds that information asymmetry, as a relevant driver of cost stickiness (Agarwal, 2022), leads to higher debt levels, while MacKay (2003) provides supporting evidence that lower operating leverage leads to lower financial leverage. In addition, Agrawal and Matsa (2013) show that higher unemployment insurance benefits, another relevant determinant of cost stickiness (Banker et al. (2013), is associated with larger financial leverage. Therefore, we address empirically the following research question: (RQ1) *Does cost stickiness influence financial leverage?* In line with the literature, cost stickiness might lead to a higher risk of default due to reduced operational flexibility when revenues decline compared to when revenues increase. Consequently, high-sticky-cost firms need a more conservative debt-to-equity level to mitigate their risk of default (Ferri & Jones, 1979; Kahl et al., 2019; Lev, 1974; Mauer & Triantis, 1994; Tan, 2013)[35].

To explore further the relationship between cost stickiness and capital structure, we break down net financial leverage into high- and low-maturity debt, and (negative) cash-holdings. Ceteris paribus, firms with lower operational flexibility to revenue decreases (i.e., high-sticky-cost firms) face higher cash-flow risks in case of revenue declines (He, Tian, Yang, & Zuo, 2020), leading to higher cash holdings (Gamba & Triantis, 2008; Kahl et al., 2019; Opler, Pinkowitz, Stulz, & Williamson, 1999; Serfling, 2016). In addition, high-sticky-cost firms are subject to higher refinancing costs due to greater information asymmetry between managers and investors (He et al., 2020), resulting in both higher cash

[34] Cost stickiness means higher operating leverage when revenue drops compared to when revenue increases, resulting in more fixed costs to finance.

[35] "Higher production flexibility (due to lower costs of shutting down and reopening a production facility) enhances the firm's debt capacity" Mauer & Triantis (1994 : 1253).
"High fixed costs expose firms to the risk of low cash flows if sales are low. The most common argument in the literature is that high fixed cost firms have a greater risk of default for a given financial leverage ratio, because fixed costs are another fixed financial obligation that is similar to debt." (Kahl et al. 2019: 1)

holdings (Harford, Klasa, & Maxwell, 2014) and lower debt maturity (Barclay & Smith, 1995; Custódio, Ferreira, & Laureano, 2013; Flannery, 1986), leading to two subsequent research questions: (RQ2) *Does cost stickiness influence cash holdings?* and (RQ3) *Does cost stickiness influence debt maturity?*

We also analyze the link between cost stickiness and profitability. In that respect, the body of knowledge provides mixed findings regarding whether cost stickiness has a positive effect on profitability through the creation of intangible assets (e.g., Banker et al., 2019, 2006; Baumgarten et al., 2010) or a negative effect due to inefficient cost adjustment to revenue decreases (e.g., Chen et al., 2012; Dierynck et al., 2012; Kama and Weiss, 2013; Lopatta et al., 2020). In fact, Janakiraman (2010) and Baumgarten et al. (2010), studying the association between cost stickiness and future earnings, document contradictory results. Hence, we address empirically the following research question: (RQ4) *Does cost stickiness influence profitability?*

Finally, we explore to what extent cost stickiness have similar financial effects to the related concept of operating leverage. In fact, cost stickiness can be defined as the asymmetric variation of the operating leverage ratio to revenue changes. Operating leverage is driven by high adjustment costs to revenue changes and can be proxied by the proportion of fixed costs in the cost structure. Cost stickiness on the other hand is driven by the difference in adjustment costs when revenues decrease compared to when they increase. Hence, operating leverage exists whether costs are sticky or not. In fact, it is common in investment and financial decisions models to assume that adjustment costs are symmetrical for simplicity, meaning the existence of operating leverage and absence of cost stickiness (e.g., Mauer and Triantis, 1994). This leads us to the subsequent research question: (RQ5) *To what extent cost stickiness and operating leverage have similar effects on financial leverage, cash holdings, and profitability?*

We analyze these multiple effects of cost stickiness using a sample of U.S. non-financial listed firms from 1980 to 2021. To analyze these relationships listed above, we use a sample of U.S. non-financial listed firms from 1980 to 2021 and compute a novel measure of cost stickiness at the firm level. We do so by subtracting the average SG&A to sales variation (from year t-3 to t+3 excluding t) during revenue decreasing (increasing) periods from SG&A to sales variation for period t when revenues increase (decrease). Unlike other recent papers (e.g., Agarwal 2022), we did not use Weiss's (2010) firm-level measure of stickiness. In fact, by logging the SG&A to sales ratio, their method discards all the observations for which the two variables do not evolve in the same direction, which might bias the results[36] (cf. Banker and Byzalov 2014: 25).

To mitigate endogeneity concerns[37] we use an instrumental variable (IV) approach based on a two-stage least squares (2SLS) model. We instrument the *Stickiness* variable using two instruments. The first one is *Stickiness COGS* computed using SG&A to COGS (cost of goods sold) variation instead of SG&A to SALES variation. Unlike SG&A costs, COGS behave proportionally with SALES[38]. This measure results in a strong instrument (see the identification tests in the method section), and thus satisfies the first condition for a valid instrument. We argue that the second condition related to the exclusion restriction is also supported given that it is unlikely that financial leverage drives the ratio of SG&A to COGS or the opposite, except through SG&A to sales ratio. Like Agarwal (2022) and Ciftci and Salama (2018) we use industry average stickiness (*Industry Stickiness*) as a second instrument.

[36] These observations account for 25.3% in our sample.
[37] Previous research analyzed the effect of debt intensity on cost stickiness (e.g., Subramaniam & Weidenmier, 2003; Calleja et al., 2006; Via & Perego, 2013) and find evidence of a negative relationship, arguing that higher debt level pressures managers to meet payments and, therefore, save on excess capacity by adapting costs to revenue decreases, reducing cost stickiness.
[38] The quantity of COGS needed to produce one unit of output remains usually stable, unless there is a variation in the price of inputs or a strategic change leading to a variation of the quality of the outputs for example. In fact, they have an extremely high correlation of 0.97 with sales in our sample.

First, we observe that a one-standard-deviation increase in cost stickiness (2.16) is associated with a 3.5% increase in gross book leverage ratio and a 12.0% decrease in cash holdings ratio. When we combine gross book leverage and cash holdings, we find that a one-standard-deviation increase in cost stickiness is associated with a 5.1% increase in net book leverage ratio. These results are economically significant given that the average net (gross) book leverage ratio in our sample is 10.5% (24.5%). Second, we find that cost stickiness affects mature debt holdings. More specifically, we provide evidence that, high-sticky-cost firms hold more long-term debt compared to low-sticky-cost firms, but we do no observe significant differences for short-term debt.

Third, we test how cost stickiness is related to profitability. Our results are strong and suggest that cost stickiness have a significantly positive effect on profitability both during revenue increasing and decreasing periods.

Fourth, we compare the effects of cost stickiness and operating leverage on capital structure, and profitability. In line with previous findings (e.g., Chen et al., 2019; Kahl et al., 2019), we find that operating leverage is negatively associated with financial leverage after controlling for cost stickiness. However, we observe that operating leverage is negatively related to profitability on average, unlike cost stickiness, which is driven by the negative relationship during periods of negative profitability. These results contradict Chen et al. (2019) who find that this negative relationship in revenue declining periods is offset by the positive relationship during periods of positive profitability.

Finally, in line with previous findings, we observe that financial leverage is negatively related to profitability (e.g., Chen et al. 2019). This brings a potential explanation to the negative relationship between financial leverage and financial performance, a well-documented limitation of the trade-off theory model (e.g., Chen et al., 2019; Graham, 2000; Myers and Majluf, 1984): to improve financial performance, managers may prefer financing

operational rather than financial obligations when facing declines in revenue. To ensure that our results are not affected by the stickiness measure, dependent variables' measures, or sample selection bias, we conduct a series of robustness checks (cf. end of section III).

We contribute to two streams of literature. First, by introducing an accounting topic (cost stickiness) as an important determinant of financial leverage, cash holdings, and debt maturity, we add to both the corporate finance literature examining the firms' operating policies affecting capital structure (e.g., Bhojraj et al., 2021; Chen et al., 2019; Serfling, 2016; Yehuda et al., 2023) and the accounting literature by looking further at the financial consequences of asymmetric cost behavior, beyond earnings forecasts, earnings predictions, dividend payouts and stock price adjustments (Agarwal, 2022; Banker & Chen, 2006; Baumgarten et al., 2010; He et al., 2020; Weiss, 2010). Second, we add also to the body of knowledge on asymmetric cost behavior by developing a novel firm-level measure of cost stickiness. This measure allows us to analyze the consequences of cost stickiness and avoid the selection bias caused by using the logarithm of the cost adjustment ratio (Banker & Byzalov, 2014). Third, we participate to the accounting debate on the effect of cost stickiness on financial performance (e.g., Baumgarten et al., 2010; Janakiraman, 2010) by observing that higher stickiness is related to higher profitability in both revenue declining and revenue increasing periods. Fourth, we distinguish between the two related concepts of cost stickiness and operating leverage and find that, while they have both a negative and positive relationship respectively with financial leverage and cash holdings, our results suggest that, unlike cost stickiness, operating leverage is negatively associated with profitability.

RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

Cost Stickiness

The traditional cost theory suggests two types of behavior: costs are either variable with respect to the cost driver or fixed, meaning that they do not depend on the level of activity, up to a certain capacity threshold (e.g., production capacity) (Noreen, 1991). According to this classification, cost variations are independent of managerial decisions and simply adapt "mechanically" to the level of activity either linearly or by step. Based on this assumption, total costs adapt symmetrically to the level of the cost driver (activity volume), with variable costs adjusting proportionally and fixed costs remaining unchanged for a range of capacity. This traditional cost behavior is questioned by Noreen and Soderstrom (1994, 1997) and Jaramillo et al. (1993) who find respectively evidence of non-proportional and non-symmetric cost adjustments. Anderson, Banker, and Janakiraman (2003) introduce the notion of sticky costs, defined as costs whose adjustment to the activity volume is conditional on the direction of change. Costs are sticky (anti-sticky) if they adjust less to decreases (increases) in activity levels than to increases (decreases).

Cost stickiness is due to higher adjustment costs (e.g., firing costs, losses when selling specific assets, opportunity costs due to lack of capacity) when revenues drop than when they increase (e.g., hiring costs or buying specific assets), leading managers to deliberately maintain the level of resources even if it creates excess capacity in the short-term.[39]

[39] The accounting literature shows that they are multiple firm-, manager, and context- drivers of asymmetric cost behavior (e.g., Anderson et al., 2003; Banker et al., 2013; Calleja et al., 2006; Chen et al., 2012; Kama and Weiss, 2013). For example, Anderson et al. (2003) report that costs are stickier for asset intensive firms compared to firms relying more on external resources giving them more flexibility to scale down. Governance issues such as executives' empire-building incentives can also increase cost stickiness (Chen et al., 2012)

Cost Stickiness and Financial Leverage

Based on the trade-off theory of capital structure, managers trade off the benefits of debt with its costs. In the base theoretical model, the tradeoff relates to tax benefits of debt versus costs of default. Previous studies such as Fischer et al., 1989; Mauer and Triantis, 1994; Strebulaev, 2007) extend this model by including refinancing costs as an important determinant of capital structure choices.

Cost Stickiness and Risk of Default. Cost stickiness means higher resource commitment when revenues drop. A direct consequence of a lower operational flexibility to revenue decreases is an increased level of risk of not meeting financial obligations, including debt obligations (i.e., higher probability of default). Mauer and Triantis (1994) argue that low operational flexibility (e.g., high costs of shutting down and reopening a production facility) reduces the firm's debt capacity. Chen et al. (2019: 370) also argue that failing to reduce costs when revenues drop reduces the firm's "ability to pay their debt and increases their future probability of default, which causes firms to choose lower financial leverage ex ante".

Corporate finance literature shows that high operating leverage (high fixed costs) affects negatively financial leverage (e.g., Ferri and Jones, 1979; Kahl et al., 2019; Serfling, 2016; van Horne, 1971). A central argument is that fixed costs are fixed financial obligations similar to debt (Reinartz and Schmid, 2016). Hence, for a given debt ratio, higher fixed costs increase the probability of default (Kahl et al., 2019). Cost stickiness is the result of a company's choice to not adapt the level of resources to revenue declines, as much as it adjusts them to revenue increases. It exposes firms to higher cash flow needs when sales are low, increasing the solvency risk. Therefore, cost stickiness – operational (un)flexibility when revenues drop compared to when they increase – affects negatively the optimal financial leverage. In other words, considering that operational expenses when revenues are

low are similar obligations to interest expenses, higher cost stickiness leads to higher risk of default just like higher financial leverage.

Another direct consequence of higher resource commitment when revenues drop is an increase in cash flow volatility (Weiss, 2010). This leads to increases in cash flow risks, resulting in higher risk of default (e.g., Lemmon et al., 2008).

Cost Stickiness and Net Tax Shield. Mauer and Triantis (1994) trade off the tax benefits of debt with both refinancing and financial distress costs. Under a net tax shield perspective, they find that operational and financial flexibility (costs of raising and paying debt) are to some extent substitutes. Therefore, a decrease in operational flexibility when revenues drop (i.e., low stickiness) lowers the net tax shield benefits. Although they model operational flexibility as being proportional to increases and decreases in revenues, cost stickiness has no effect on tax benefits unless the firm experiences operating losses (Mauer and Triantis, 1994), in which case, a higher operational flexibility and lower adjustment costs allow the firm to support a greater debt level. Thus, the higher the stickiness, the lower the operational flexibility to decreases in revenues, and the lower the tax benefits.

In sum, higher cost stickiness leads to a higher risk of default offsetting the tax benefits of debt financing and reducing the optimal financial leverage ratio. Thus, we formulate the following hypothesis:

Hypothesis 1. High-sticky-cost firms have lower financial leverage.

Cost Stickiness and Cash Holdings

Due to cash flow risks and costs of refinancing, cash cannot be seen only as negative debt (Acharya, Almeida, & Campello, 2007; Harford et al., 2014; Opler et al., 1999), and partly explain why firms hold simultaneously cash and debt.

In line, we first argue that cost stickiness increases cash-flow risks, leading to higher cash holdings. In fact, Acharya, Almeida, and Campello (2007) argue theoretically and find

empirical support that holding more cash is a better solution to face cash flow risks than reducing the level of financial debt (i.e., unused debt capacity). Moreover, following previous literature, firms with higher cash flow risks behave as if they were more financially constrained, and thus, hold more cash (Gamba & Triantis, 2008; Kahl et al., 2019; Opler et al., 1999).

Ceteris paribus, firms with lower operational flexibility to revenue decreases (i.e., high-sticky-cost firms) face higher cash flow risks in case of future revenue declines (He et al., 2020). In other words, high-sticky-cost firms need to finance their excess capacity (i.e., more cash outflows) while cash inflows derived from revenues drop, exposing them to higher cash flow risks. Therefore, the less managers are willing to adjust costs when revenues decrease, the higher the cash flow risk, leading to more cash holdings (to remain independent from external financing). In line with this argument, Ghaly et al. (2017) find empirical evidence that firms with more skilled employees (i.e., less operational flexibility) hold more cash.

Second, we argue that cost stickiness increases information asymmetry leading to higher cash holdings. Because cost stickiness results from managerial decisions based on private information, higher stickiness leads to higher information asymmetry between managers and investors (Agarwal, 2022; Weiss, 2010). This information asymmetry increases the gap between cost of internal financing versus cost of external financing (i.e., higher financial constraints, cf. Fazzari et al. (1987)). Hence, the higher the cost stickiness, the higher the liquid assets of the firm since the low return on liquid assets offsets the high cost of refinancing (Harford et al., 2014; Kim, Mauer, & Sherman, 1998; Myers & Majluf, 1984; Opler et al., 1999; Stein, 2003). For example, high-sticky-cost firms are tempted to retain more cash to avoid external financing for unused resources when revenues drop.

According to Opler et al. (1999) saving on refinancing costs is one of the two main reasons why firms hold cash.

Third, we argue that cost stickiness increases financial constraints leading to higher cash holdings (e.g., Almeida et al., 2004; Opler et al., 1999). According to Opler et al. (1999), the second reason why firms hold cash is to overcome temporary restrictions (unavailability or high costs) in external financing through debt or equity. In line with this explanation, high-sticky-cost firms may retain more cash to maintain investments when facing strong cash flow reductions in periods of revenue decreases. In fact, retaining unused resources may be perceived negatively by external capital providers and therefore limits access to external capital.

To sum up, high-sticky-cost firms face higher cash flow risks, financial constraints, and cost of capital, leading them to hold more cash to cope with declines in revenues. Thus, we formulate the following hypothesis:

Hypothesis 2. High-sticky-cost firms have higher cash holdings.

Cost Stickiness and Debt Maturity

Building upon previous research findings, it is well-established that information asymmetry between corporate managers and providers of both debt and equity can lead to a reduction in the proportion of long-term, mature debt holdings (Barclay & Smith, 1995; Custódio et al., 2013; Flannery, 1986; Harford et al., 2014). This reduction is often attributed to the higher information costs associated with long-term debt. This choice is also driven by the anticipation of securing more favorable financing terms in the future, thereby avoiding the long-term commitment associated with such debt.

Drawing from the argument that cost stickiness is a result of managerial decisions driven by private information, it follows that higher cost stickiness can diminish the quality of information available to investors (e.g., Agarwal, 2022; Weiss, 2010). Therefore, due to

higher information asymmetry, managers of high-sticky-cost firms may favor debt with shorter maturities. Thus, we posit the following hypothesis:

Hypothesis 3. High-sticky-cost firms hold less mature debt.

Cost Stickiness and Financial Performance

Finally, we argue that higher cost stickiness means higher risk-taking, therefore, higher profitability. According to previous work, cost stickiness is partly driven by agency problems (e.g., Chen et al., 2012, 2013; Dierynck et al., 2012; Kama and Weiss, 2013; Lopatta et al., 2020; Xue and Hong, 2016) resulting in a negative relationship with profitability (Janakiraman, 2010), but might be negligeable compared to the benefits of maintaining costs sticky. In fact, previous papers show that the main drivers of cost stickiness are contextual and structural attributes (e.g., future economic growth, Anderson et al. (2003)) and, thus, intended by managers to generate future revenues (Baumgarten et al., 2010). Therefore, under the assumption that managers make decisions in line with shareholders profit maximization, they maintain excess capacities when revenues drop in view of higher future demand. Moreover, cost stickiness may protect intangible assets and therefore could be positively associated to future earnings (Banker et al., 2019). This leads us to the following hypothesis:

Hypothesis 4. High-sticky-cost firms have higher profitability.

RESEARCH DESIGN

Sample Selection, Model Specification and Variable Measurement

To form our sample, we start with all U.S. firms appearing in Compustat between 1980 and 2021 (230,526 firm-year observations). We, then, exclude financial firms (with a SIC code between 6000-6999) and small capitalizations (firms with a market capitalization lower than $10 million). We exclude observations with sales variations exceeding an absolute value of 50% as a proxy for large mergers and acquisitions (Banker, Basu, Byzalov,

& Chen, 2016; Banker et al., 2013). We use Compustat annual data in line with most sticky cost papers. Although some papers used quarterly data (e.g., He et al., 2020; Weiss, 2010), we argue that annual data is more appropriate given that macroeconomic changes during a short time frame of one quarter is, in most cases, likely not long enough to allow managers to make important production capacity adjustments.[40] The final sample, discarding observations with missing data for the main variables, contains 8,945 firms with 74,355 firm-year observations[41]. We winsorize all variables at the first and 99th percentile to mitigate outliers' effects.

Explanatory Variable. We compute a novel measure of cost stickiness at the firm level by subtracting the average SG&A to sales variation (from year t-3 to t+3 excluding t) during revenue decreasing (increasing) periods from SG&A to sales variation in period t if revenues increase (decrease) compared to t-1.[42]

We drop R&D and advertising expenses as they represent value-enhancing investments that drive future sales (Banker & Chen, 2006; Banker, Ciftci, & Mashruwala, 2012; Xue & Hong, 2016)[43].

Equations 1:

$$\boldsymbol{Stickiness_{i,t}} = \Delta SG\&A/\Delta Sales_{i,t} - AVG^{-}(\Delta SG\&A_{i,t-n}/\Delta Sales_{i,t-n}) \;\; if\; \Delta Sales_{i,t} > 0$$

$$\boldsymbol{Stickiness_{i,t}} = \Delta SG\&A/\Delta Sales_{i,t} - AVG^{+}(\Delta SG\&A_{i,t-n}/\Delta Sales_{i,t-n}) \;\; if\; \Delta Sales_{i,t} < 0$$

Where $AVG^{+(-)}$ represents the average adjustment to revenue increases (decreases) in a +/- three-year window ($3 \geq n \geq -3$).

[40] Anderson et al. (2003) and other follow-up papers analyze cost-stickiness in the mid-term between one and four years.
[41] Excluding labor force variable, our sample increases to 88,500 firm-year observations and 9,082 firms.
[42] Like most sticky cost papers, we use sales variation to proxy for activity change as the latter is usually unobserved.
[43] If these expenses are missing, we assume that they are equal to zero (Chen et al., 2012; Banker et al., 2012).

Anderson et al.'s (2003) stickiness measure is useful for analyzing the determinants of cost stickiness. However, to measure the effects of cost stickiness we need a firm-year specific measure. Prior research (Anderson, Banker, Huang, & Janakiraman, 2007; Baumgarten et al., 2010) examines separately the SG&A variation effect on earnings per share when revenues increase and when revenues decrease using a cross sectional regression. However, this does not allow to measure the direct effect of cost stickiness.

Finally, we use Weiss's (2010) firm-level measure of stickiness as a baseline and introduce two modifications. First, we remove the log specification (cf. Weiss, 2010: 1447) as it leads to dropping all negative values of costs to sales ratio which represents a significant portion of observations. Negative values occur if costs decrease in revenue-increasing periods due to unobserved reasons, which represents 13.7% of our observations. Negative values occur also when costs increase in revenue-decreasing periods, which also happens very frequently (11.6% of our observations). These observations represent 25.3% of our overall sample and dropping them will probably lead to biased results (Banker & Byzalov, 2014)[44]. Second, we subtract from the SG&A to sales variation, the average variation in the opposite direction within a six-year interval instead of using the closest past variation in opposite direction. We argue that this is a more precise proxy and result in a smoother stickiness measure. It is, in fact, arbitrary to deduce the closest past or future observation in the opposite direction as both of them are unperfect proxies for what would have been the unobservable adjustment in the opposite direction in time t.

Validity of our cost stickiness measure. To make sure that our measure really captures cost stickiness, we test its validity by regressing it on the main sticky cost drivers

[44] "[Weiss's (2010) stickiness measure] can be computed only for firms that had both a sales increase and a sales decrease in the last four periods, and the sample has to be restricted to observations for which sales and costs change in the same direction. This leads to substantial data loss. Further, it is essential to examine whether this pattern of data loss is correlated with the dependent variable, because that can lead to significant selection bias in some applications." (Banker and Byzalov, 2014: 25)

following the cost stickiness literature (Anderson et al., 2003; He et al., 2020). As expected, we find that our measure of cost stickiness is significantly positively related to asset intensity, employee intensity and GDP growth and negatively related to successive revenue decreases (cf. Anderson et al., 2003). It is also significantly positively associated with the lagged sales increase dummy and lagged free cash flows (He et al., 2020) (see appendix 1). We also observe high similarities between the associations of our cost stickiness measure with these different variables and the associations of He et al's cost stickiness measure with these same variables (cf. He et al., 2020: 998), suggesting that the two measures are similar and are appropriate proxies for this asymmetric cost behavior.[45]

Model Specifications. Some papers analyzed this reverse causality, namely, the effect of debt intensity on cost stickiness (e.g., Subramaniam and Weidenmier 2003; Calleja et al. 2006; Dalla Via and Perego 2014), and find evidence of a negative relationship, arguing that higher debt level pressures managers to meet payments and, therefore, save on excess capacity by adapting costs to revenue decreases, reducing cost stickiness.

In order to address this reverse causality issue and capture the effect of cost stickiness on financial leverage, we estimate a two-stage least square system of equations (2SLS). In the first stage of the 2SLS, we regress the endogenous variable *Stickiness* on both instruments (*Stickiness COGS* and *Industry Stickiness*) and all endogenous (control) variables (Larcker & Rusticus, 2010).

Instrumental Variables. We instrument *Stickiness* using *Stickiness COGS* (by substituting SG&A to Sales with SG&A to cost of goods sold (COGS) ratio in the above equations 1) and *Industry Stickiness* (using the industry average *Stickiness* in year t, excluding the concerned firm i as our two instrumental variables.

[45] We have not used their measure given the 2SLS approach we have chosen for our model.

Dependent Variables. To test for the first hypothesis (i.e., high sticky cost firms have lower financial leverage ratios), we use net book leverage and net market leverage as the dependent variables. Based on previous research, we measure *Net Book Leverage* as the ratio of total debt (long-term debt (*dltt*) plus debt in current liabilities (*dlc*)) minus cash and short-term investments (che) divided by total book value of assets (*at*) and *Net Market Leverage* as the ratio of total debt minus cash and short-term investments divided by total debt plus market value of equity (*prcc_f*csho*) (e.g., Lemmon et al., 2008; Serfling, 2016).

To test for the second hypothesis (i.e., high sticky cost firms hold more cash) we use *Cash Holdings* and *Net Cash Holdings,* measured as the natural logarithm of cash and short-term investments divided by, respectively, the book value of assets (Harford et al., 2014) and book value of assets minus cash and short-term investments (Opler et al., 1999).

To test for the third hypothesis (i.e., high sticky cost firms hold less mature debt) we use *Short-term Leverage* as the ratio of debt in current liabilities (due within one year) divided by total debt (Huang, Tan, & Faff, 2016), *Long-term Leverage* as the ratio of long-term debt divided by total debt (Huang et al., 2016), and *Debt due in one year* as the ratio of debt due in one year to total debt ratio (Harford et al., 2014).

To test for the fourth hypothesis (i.e., high sticky cost firms have higher profitability), we use *Profitability* which is the ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total assets.

Control Variables. In financial leverage regressions (that test for hypotheses 1 and 3), we control for variables typically included in the literature on the determinants of capital structure (e.g., Rajan and Zingales 1995; Lemmon et al. 2008) and, more specifically, in analyses of the relationship between financial leverage and investment and operating decisions (e.g., Kahl et al. 2019; Serfling 2016). We control for firm size using the logarithm of sales (*Log(Sales)*); for tangible assets using net property, plant, and equipment to assets

ratio to control for potential collateral (*Tangible Assets*) (tangible assets increase both cost stickiness (Anderson et al., 2003; Banker et al., 2019) and optimal debt level (Myers, 1984)); for *Market-to-Book* ratio to proxy for potential growth and labor force signal (as the annual change in sales per employee); for *Profitability* to proxy for the availability of internal funds; *Cash-Flow Volatility* to proxy for financial distress risk, measured using the standard deviation of profitability;[46] and industry median book leverage (*Industry Median Leverage*) based on two-digits sic codes. Finally, we control for industry and year fixed effects[47]. All explanatory and control variables are one-year lagged relative to the dependent variables (Kahl et al., 2019; Lemmon et al., 2008; Serfling, 2016). Finally, we adjusted standard errors of the coefficients by clustering observations at the firm level. Statistics are also robust to heteroscedasticity.

We also control for asset and employee intensity and economic growth as they can affect both cost stickiness and financial leverage. Higher asset specificity translates into higher cost stickiness (Anderson et al. 2003). These specific assets have usually low liquidation values (Williamson, 1979). This increases the cost of debt, leading to lower optimal debt ratios following the trade-off model (Aivazian & Berkowitz, 1998). Another major driver of cost stickiness is employee intensity and employees' power (Anderson et al., 2003; Banker et al., 2014). Serfling argues that greater labor cost and rigidity raise the operating leverage, thus lowering the optimal debt ratio (Serfling, 2016). We control for DGP growth to proxy for macroeconomic factors that may affect simultaneously cost stickiness and capital structure. We also control for *Operating Leverage* – a closely related concept to cost stickiness (cf. section 2) – using SG&A to Sales ratio (Chen et al., 2019).

[46] It is measured over the last ten years, firms are required to have at least three years of data (similarly to Serfling, 2016 and Lemmon et al., 2008)

[47] We do not use Firm fixed effects given that the dependent variable is measured based on firm-level SG&A costs averages. Therefore, we cannot identify the effect of SG&A variation from the effect of firm fixed costs.

For the cash holdings regressions (H2), we add relevant controls used by Opler et al. (1999) and have been widely considered in previous papers analyzing drivers of cash holdings (e.g., Almeida et al., 2004; Harford et al., 2014). Namely, capital expenditures to total assets ratio; dividend dummy equals to one if the firm distributed dividends during the year, zero otherwise; and net working capital to total assets ratio. For the profitability regressions (H4), we use the same set of control as in the financial leverage regressions, add net book leverage and, remove profitability from the controls.

Insert TABLE 1 about here

RESULTS

Validity of The Instrumental Variables

Appropriateness of the Instruments. First, we test for the appropriateness of the instruments under the assumption that at least one of them is valid by testing over-identifying restrictions (Hausman, 1978; Larcker & Rusticus, 2010). The Sargan-Hansen overidentification tests are validated. Their p-values for all ten regressions except one[48] in tables 2 to 5 are non-significant which shows that the instruments are overall uncorrelated with the error term. Hence, the exogeneity condition, namely that the instrument needs to be exogenous to our dependent variables is also validated. Theoretically also, it is unlikely that financial leverage or cash holding drives the proportion of SG&A costs compared to COGS or the opposite, except through SG&A to sales ratio. The relationship between SG&A to COGS ratio and profitability is also not very straightforward and we could not

[48] Regression 2 in Table 5 analyzing the relationship between cost stickiness and profitability shows a significantly low p-value of Hansen J statistic. However, this p-value is non-significant for the other two profitability regressions (i.e., subsample analyses: profitability when revenues increase (regression 4) and profitability when revenues decrease (regression 6)).

find theoretical groundings from previous literature.[49] Therefore, we argue that the second condition (exclusion restriction) is also valid (i.e., *Stickiness COGS* drives our dependent variables exclusively through the effect of cost stickiness). In addition, as argued in Agarwal (2022) and Ciftci and Salama (2018), it is also unlikely that the industry average cost stickiness is endogenous to our dependent variables as managers or a single firm's financial attributes (capital structure and profitability) are unlikely to influence the cost behavior of the entire industry (Agarwal, 2022).

Second, we run a regression-based test for the existence of an endogeneity problem in our regressions[50] and thus whether a 2SLS approach is more appropriate than an OLS regression (Hausman, 1978; Larcker & Rusticus, 2010). Results are reported for each regression in Tables 2 to 5 and suggest the existence of endogeneity. Indeed, all but one[51] regression-based test p-values reject the null hypothesis of exogeneity as a confidence level of at least 10%[52].

Underindentification and Weak Identification Tests. To ensure instrument validity, two key conditions must be met: relevance (strength) and exogeneity. We conduct a series of endogeneity tests from both an econometric and theoretical perspective to support our instrument choices.

The weak identification tests are validated for all the regressions (see the F statistics for weak identification tests in Tables 2 to 5). This is not surprising given the that sales (SALES) and cost of goods sold (COGS) exhibit an exceptionally high correlation (0.97) in our sample. Unlike discretionary costs included in SG&A costs, COGS show a proportional

[49] We found little evidence on this relationship. One exception would be Lévesque et al. (2012) who document that SG&A and COGS play as substitutes to generate revenues.
[50] We perform this test instead of Wu-Hausman test as the latter assumes that the error term is i.i.d. while we use robust standard errors. In addition, we do not perform Wooldridge's (1995) score test as it is not amenable to clustering (while we cluster by firms).
[51] Out of the ten regressions, the only one where exogeneity is not rejected is the one with short-term debt as the dependent variable.
[52] Exogeneity is reject at a 1% level for the Net Book Leverage, Long-Term Debt, and all three Profitability regressions.

relationship with sales as demand for a certain product reflects proportionally on both SALES and COGS[53]. Indeed, we test for the stickiness of COGS in our sample and find no evidence of sticky COGS[54] as the coefficient reflecting the difference between COGS adjustment to decreases in sales compared to increases in sales is very small (0.055%) compared to COGS adjustment to increases in sales (73.1%) and statistically non-significant (0.0055; t= 0.72) suggesting no cost stickiness. The coefficient reflecting the percentage of adjustment of COGS to sales' increases is high and significantly positive (0.731; t= 31.62) suggesting that COGS are, to a large extent, variable costs to revenue variation and non-sticky (see appendix 2).

For the underidentification test, we use the Lagrange multiplier (LM) test of whether our equations are identified (i.e., the instruments are highly correlated to our endogenous *Stickiness* variable, meaning they are "strong", "relevant") (tests are reported in table 2). We also validate the weak identification tests – whether the instruments are jointly significant in explaining the endogenous variable *stickiness* –. The F-statistics of excluded instruments (Kleibergen-Paap Wald rk F statistic) for all three models are above 90, higher than the 'rule of thumb' for a strong instrument proposed by Staiger and Stock (1997), namely the first-stage F-statistic should be at least equal to ten.

Main Results

H1 Results: Cost Stickiness and Financial Leverage. We test and find supporting results for our first hypothesis (H1), namely, high-sticky cost firms have lower financial

[53] COGS typically include direct costs related to the production of goods and services (including raw materials and labor costs used in the production process). The quantity of COGS needed to produce one unit of output remains stable on average unless there is a variation in the price of inputs or a strategic change leading to a variation of the quality of the outputs for example. Therefore, COGS adjustment to sales should be symmetrical.

[54] Some previous research finds evidence of sticky COGS or sticky operating costs (i.e., the sum of SG&A and COGS) for various samples. For example, Subramaniam and Watson (2016) find that COGS are sticky for financial firms (excluded from our sample) but not sticky for firms in service and merchandising industries. We do not attempt to explain the differences in findings. As long as COGS variable does not behave asymmetrically in our sample, we can use it to instrument SG&A costs' stickiness.

leverage. Results in Table 2 show that cost stickiness is significantly negatively associated with net book leverage ratio (Table 2, regression 2: $\beta = -0.0195$, $p < .01$) and net market leverage (Table 2, regression 4: $\beta = -0.0128$, $p < .01$). In term of economic significance, we find that a one-standard-deviation increase in cost stickiness (2.16) is associated with a 4.22% percentage points decrease in net book leverage and a 2.77% decrease in net market leverage.

Insert TABLE 2 about here

H2 Results: Cost Stickiness and Cash Holdings. We test and find supporting results for our second hypothesis (H2), namely, high-sticky cost firms have higher cash holdings. Results in table 2 show that cost stickiness is significantly positively associated with cash holdings ratio (Table 2, regression 2: $\beta = 0.0435$, $p < .05$) and net cash holdings (Table 2, regression 4: $\beta = 0.0520$, $p < .05$). A one-standard-deviation increase in cost stickiness (2.16) is associated with a 9.42% percentage points increase in cash holdings and a 11.26% increase in net cash holdings.

Insert TABLE 3 about here

H3 Results: Cost Stickiness and Debt Maturity. We find that cost stickiness is significantly negatively related to long-term debt (Table 4, equation 2: $\beta = -0.0118$, $p < .01$). However, we observe a non-significantly relationship with short-term debt (Table 4, equation 4: $\beta = -0.00205$, $p = -1.19$). Moreover, we observe that cost stickiness is significantly negatively related to the ratio of debt due in one year (Table 4, equation 2: $\beta = -0.117$, $p < .01$). These results are in line with the argument that cost stickiness increases

financial constraints through higher information asymmetry leading to a preference for less mature debt (Custódio et al., 2013; Hackbarth & Mauer, 2012; Harford et al., 2014).

Insert TABLE 4 about here

H4 Results: Cost Stickiness and Profitability. Finally, we test our fourth hypothesis (H4) regarding whether cost stickiness is positively associated with profitability (Table 5). For this analysis, we use the same controls as the ones for our main tests and include net financial leverage and cash flow volatility as additional controls. We find supporting evidence that high-sticky-cost firms have higher profitability (Table 5, equation 2: $\beta = 0.0164$, $p < .01$). A one-standard-deviation increase in cost stickiness is associated with a 3.55% increase in profitability. Subsample analysis shows that this holds for both revenue increasing periods (Table 5, equation 4: $\beta = 0.0132$, $p < .01$) and revenue decreasing periods (Table 5, equation 6: $\beta = 0.0119$, $p < .01$).

Insert TABLE 5 about here

Supplementary Analysis

Cost Stickiness and Operating Leverage. Operational leverage has a very similar relationship with financial leverage and cash holdings compared to cost stickiness. A one-standard-deviation increase in operational leverage (cost stickiness) is associated with a 3.3% (4.2%) reduction in net book leverage, a 3.1% (2.8%) reduction in net market leverage, a 10.3% (9.4%) increase in cash holdings, and a 11.0% (11.3%) increase in net cash holdings. Hence, after controlling for cost stickiness, we observe that operating leverage has also a negative effect on financial leverage and a positive effect on cash holdings, similarly to previous findings (e.g., Chen et al., 2019; Kahl et al., 2019). However, unlike cost stickiness, we observe that operational leverage has a positive effect on debt maturity. While

a one-standard-deviation increase in cost stickiness is associated with a reduction in the share of debt due in one year by 25.3%, a one-standard-deviation increase in operational leverage is associated with an increase of 8.8%.

Moreover, we observe that operating leverage has an overall negative effect on profitability, unlike cost stickiness, and this is the case during both periods of revenue increases and revenue decreases (see Table 5). A one-standard-deviation increase in operational leverage is associated with a 2.7% reduction in profitability, driven by a 1.7% reduction during revenue increases and a sharper reduction of 3.3% during revenue decreases.[55]

Financial Leverage and Profitability. We find that, not only profitability (ROA) is positively related to stickiness, but it is also negatively related to net financial leverage (Table 3, regression 4: $\beta = -0.0252$, $p < .01$). These results are consistent with previous literature on the relationship between financial leverage and financial performance (e.g., Chen and Zhao, 2005; Chen et al., 2019; Hennessy and Whited, 2005; Strebulaev, 2007b).

Robustness Tests

We next address several econometric concerns by performing a series of robustness tests. We perform a series of checks to ensure that our results are not affected by the stickiness measure. We first use a measure of stickiness including R&D and advertising expenses. Second, we use a non-lagged measure of stickiness instead of the one-year lagged measure.

In additional tests, we also control for *CEO ownership* to proxy for agency issues. Previous finance and accounting literature show that agency issues may drive both financial leverage (Agrawal & Mandelker, 1987; John & John, 1993; Leland, 1998; Morellec, 2004;

[55] These results conflict with Chen et al. (2019) who found a positive relationship overall. We detail these differences in the robustness tests.

Morellec, Nikolov, & Schürhoff, 2012) and cost stickiness (Chen et al., 2012, 2013; Dierynck et al., 2012; Kama & Weiss, 2013; Lopatta et al., 2020; Xue & Hong, 2016). Agency costs may also drive cash holdings (Harford, 1999; Jensen, 1986). We drop this variable from our main tests as it reduces significantly the number of observations (to about 12'000 observations).

To ensure that both instruments independently lead to the same conclusions we run our first model using only the first instrument (*Stickiness COGS*) and obtain consistent results for all three dependent variables. We also run the model using only the second industry average stickiness Industry *Stickiness* (similar to Agarwal, 2022) and obtain once again consistent results for all three dependent variables.

We ran subsample analyses using post-2008 crisis observations and find that our results hold for more recent periods. We also run the analysis using a subsample of firms excluding those with zero-leverage policy and find consistent results.

Finally, to test whether the difference between our operating leverage results and those of Chen et al. (2019) are driven by the inclusion of cost stickiness measure or because of methodological or sample selection differences. We ran an OLS regression using our sample and the same set of control variables and found similar results as they did; namely, a significantly positive relationship between operating leverage in revenue increasing periods and a significantly negative relationship in revenue decreasing periods (Appendix 3). Coefficients of the control variables are also similar. However, once we control for cost stickiness and the main drivers of cost stickiness (asset intensity, employee intensity and GDP growth), operating leverage becomes negatively associated to profitability in both revenue decreasing and revenue decreasing periods (for both our entire sample and for and subsample that includes years covered in their paper) (Table 5).

CONCLUSION

We study the financial implications of cost stickiness for firms, an accounting phenomenon that attracted two decades of research around its drivers, to offer valuable insights for both theory and practice. Our paper contributes to the accounting and corporate finance literature by introducing cost stickiness as a critical determinant of financial decisions and providing a novel firm-level measure of cost stickiness, addressing selection bias issues. We find that higher cost stickiness is associated with increased leverage and reduced cash holdings, with significant economic implications. Moreover, it affects the maturity of debt holdings, favoring short-term debt in high-sticky-cost firms. Notably, cost stickiness positively influences profitability, even during periods of declining revenue, distinguishing it from operating leverage, which has a nuanced impact on financial performance. Furthermore, we observe a negative relationship between financial leverage and financial performance. Hence, managers may prefer financing operational obligations over financial ones during revenue declines to enhance financial performance while managing risk.

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TABLES AND FIGURES

Table 1A. Descriptive Statistics

The table presents variable number of observations *N*, Mean, standard deviation *SD*, first quartile *p25*, *Median* and third quartile *p75* for our entire sample.

Stats	N	Mean	SD	p25	p50	p75
Stickiness	79'019	0.22	2.16	-0.12	0.07	0.37
Stickiness COGS	79'019	0.46	4.68	-0.21	0.10	0.64
Industry Stickiness	79'019	0.32	1.42	-0.12	0.17	0.58
Net Book Leverage	78'765	0.10	0.32	-0.09	0.13	0.31
Net Market Leverage	78'765	0.12	0.32	-0.06	0.11	0.32
Long-term Debt	78'828	0.20	0.20	0.02	0.16	0.30
Short-term Debt	78'958	0.05	0.09	0.00	0.02	0.06
Debt Due In One Year	65'342	0.50	2.17	0.01	0.07	0.23
Cash Holdings	78'585	-2.68	1.44	-3.59	-2.47	-1.59
Net Cash Holdings	78'585	-2.50	1.62	-3.56	-2.39	-1.36
Profitability	79'019	0.05	0.12	0.02	0.07	0.11
Cash-Flow Volatility	79'019	0.07	0.06	0.03	0.05	0.09
Operating Leverage	79'019	0.28	0.24	0.11	0.22	0.38
Log(Sales)	79'019	5.99	2.05	4.49	5.87	7.41
Tangible Assets	79'019	0.29	0.22	0.12	0.23	0.41
Market-to-Book	79'019	2.36	3.78	1.03	1.66	2.78
Industry Median Lev.	79'019	0.17	0.20	0.04	0.15	0.25
Asset Intensity	79'019	0.01	0.66	-0.42	-0.05	0.38
Employee Intensity	79'019	-5.32	0.91	-5.83	-5.27	-4.74
GDP Growth	79'019	2.56	1.94	1.84	2.85	3.80
Dividends Dummy	79'019	0.43	0.49	-	-	1.00
CAPEX	78'574	0.06	0.06	0.02	0.04	0.07
Working Capital	77'375	0.10	0.20	-0.01	0.09	0.22
Gross Book Leverage	78'767	0.25	0.22	0.07	0.22	0.37

Table 1B. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12
1	Stickiness	1											
2	Stickiness COGS	0.09	1										
3	Industry Stickiness	0.06	0.01	1									
4	Net Book Leverage	-0.02	-0.04	-0.05	1								
5	Net Market Leverage	-0.01	-0.03	-0.05	0.88	1							
6	Long-term Debt	-0.02	-0.03	-0.05	0.8	0.7	1						
7	Short-term Debt	0.00	-0.01	-0.01	0.37	0.33	-0.03	1					
8	Debt Due In One Year	0.00	0.00	-0.01	-0.07	-0.07	-0.22	0.33	1				
9	Cash Holdings	0.01	0.02	0.03	-0.66	-0.64	-0.35	-0.18	0.05	1			
10	Net Cash Holdings	0.01	0.02	0.03	-0.70	-0.67	-0.36	-0.19	0.05	0.99	1		
11	Profitability	-0.02	0.03	-0.01	-0.02	0.00	0.01	-0.17	-0.12	-0.03	-0.04	1	
12	Cash-Flow Volatility	0.01	0.00	0.04	-0.21	-0.23	-0.16	0.07	0.12	0.20	0.22	-0.41	1
13	Operating Leverage	0.04	0.04	0.04	-0.21	-0.21	-0.24	0.05	0.11	0.15	0.15	-0.21	0.31
14	Log(Sales)	-0.04	-0.02	-0.09	0.24	0.23	0.22	-0.05	-0.11	-0.13	-0.15	0.28	-0.44
15	Tangible Assets	-0.01	-0.02	-0.03	0.37	0.36	0.30	0.01	-0.07	-0.33	-0.34	-0.01	-0.1
16	Market-to-Book	0.00	0.01	0.01	-0.08	-0.08	-0.04	-0.02	0.00	0.08	0.08	0.08	0.07
17	Industry Median Lev.	-0.02	-0.01	-0.12	0.20	0.20	0.17	0.05	-0.02	-0.16	-0.16	0.01	-0.05
18	Asset Intensity	0.00	0.01	0.02	0.02	0.02	0.17	-0.06	-0.04	0.08	0.10	-0.13	-0.03
19	Employee Intensity	0.04	0.01	0.04	-0.02	-0.02	-0.07	0.04	0.02	-0.02	-0.02	-0.04	-0.03
20	GDP Growth	0.02	0.01	0.07	0.02	0.03	-0.03	0.03	0.00	-0.08	-0.08	0.03	0.03
21	Dividends Dummy	0.00	0.00	-0.02	0.06	0.05	0.01	-0.08	-0.10	-0.10	-0.12	0.29	-0.35
22	CAPEX	0.03	0.00	0.03	0.16	0.13	0.11	-0.01	-0.04	-0.16	-0.17	0.00	0.05
23	Working Capital	0.02	0.01	0.07	-0.10	-0.06	-0.12	-0.34	-0.16	-0.15	-0.15	0.21	-0.1
24	Gross Book Leverage	-0.01	-0.03	-0.05	0.89	0.77	0.90	0.40	-0.06	-0.39	-0.4	-0.07	-0.11

		13	14	15	16	17	18	19	20	21	22	23	24
13	Operating Leverage	1											
14	Log(Sales)	-0.26	1										
15	Tangible Assets	-0.34	0.09	1									
16	Market-to-Book	0.10	0.01	-0.07	1								
17	Industry Median Lev.	-0.12	0.06	0.22	-0.03	1							
18	Asset Intensity	-0.52	-0.03	0.26	-0.02	0.04	1						
19	Employee Intensity	0.15	-0.29	-0.02	-0.03	-0.03	-0.14	1					
20	GDP Growth	0.06	-0.13	0.02	0.00	0.06	-0.11	0.17	1				
21	Dividends Dummy	-0.18	0.44	0.14	0.02	0.06	-0.02	-0.04	0	1			
22	CAPEX	-0.12	-0.05	0.59	0.00	0.10	0.12	0.02	0.09	0.02	1		
23	Working Capital	0.07	-0.16	-0.25	-0.08	-0.11	-0.28	0.12	0.11	0.05	-0.14	1	
24	Gross Book Leverage	-0.19	0.17	0.27	-0.05	0.18	0.13	-0.05	-0.01	-0.03	0.10	-0.27	1

Table 2. Cost Stickiness and Financial Leverage

	First Stage Stickiness	Second Stage Net Book Leverage	First Stage Stickiness	Second Stage Net Market Leverage
	(1)	(2)	(3)	(4)
Stickiness COGS	0.0404***		0.0405***	
	(10.75)		(10.74)	
Industry Stickiness	0.0914***		0.0909***	
	(8.61)		(8.56)	
Stickiness		-0.0195***		-0.0128**
		(-2.87)		(-1.97)
Profitability	-0.100	-0.381***	-0.105	-0.332***
	(-0.81)	(-15.88)	(-0.84)	(-17.64)
Cash-Flow Volatility	-0.720**	-0.513***	-0.718**	-0.637***
	(-2.37)	(-9.37)	(-2.36)	(-12.39)
Operating Leverage	0.377***	-0.138***	0.375***	-0.130***
	(3.59)	(-8.40)	(3.56)	(-8.36)
Log(Sales)	-0.0294***	0.0250***	-0.0298***	0.0220***
	(-3.44)	(15.15)	(-3.49)	(13.61)
Tangible Assets	-0.0426	0.397***	-0.0458	0.411***
	(-0.50)	(22.78)	(-0.53)	(23.50)
Market-to-Book	0.00142	-0.000455	0.00184	-0.00122***
	(0.44)	(-0.74)	(0.57)	(-2.94)
Industry Median Lev.	-0.0798	0.0344***	-0.0752	0.0611***
	(-1.25)	(4.31)	(-1.18)	(8.21)
Asset Intensity	0.109***	-0.0408***	0.110***	-0.0360***
	(3.80)	(-6.76)	(3.81)	(-5.67)
Employee Intensity	0.0555***	0.0209***	0.0555***	0.0199***
	(3.26)	(5.48)	(3.27)	(5.14)
GDP Growth	0.0103**	0.0101***	0.0102**	0.0119***
	(2.37)	(15.94)	(2.33)	(18.06)
Industry FE	YES	YES	YES	YES
Cluster by Firm	YES	YES	YES	YES
F statistic for weak identification		97.39		96.92
LM test statistic for underidentification		184.6		183.9
Hansen J statistic (overindentification)		1.163		0.0383
p-value of Hansen J statistic		0.281		0.845
r2		0.105		0.108
r2_a		0.104		0.107
Number of Firms	8939	8939	8919	8919
N	74123	74123	73930	73930

The t-statistics, based on standard errors clustered by week and firm, are presented in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Two-tailed significance tests for coefficients.

Table 3. Cost Stickiness and Cash Holdings

	First Stage Stickiness (1)	Second Stage Cash Holdings (2)	First Stage Stickiness (3)	Second Stage Net Cash Holdings (4)
Stickiness COGS	0.0397***		0.0397***	
	(10.48)		(10.48)	
Industry Stickiness	0.0874***		0.0874***	
	(8.07)		(8.07)	
Stickiness		0.0435*		0.0520*
		(1.66)		(1.77)
Profitability	-0.240*	0.903***	-0.240*	1.102***
	(-1.85)	(11.05)	(-1.85)	(11.70)
Cash-Flow Volatility	-0.686**	2.210***	-0.687**	2.656***
	(-2.21)	(12.18)	(-2.21)	(12.89)
Operating Leverage	0.413***	0.424***	0.413***	0.456***
	(3.93)	(7.01)	(3.93)	(6.76)
Log(Sales)	-0.0246***	-0.0238***	-0.0246***	-0.0449***
	(-2.69)	(-3.31)	(-2.69)	(-5.53)
Tangible Assets	-0.285***	-1.648***	-0.285***	-1.936***
	(-2.94)	(-21.10)	(-2.94)	(-22.56)
Market-to-Book	0.00105	-0.000255	0.00105	-0.000490
	(0.32)	(-0.14)	(0.32)	(-0.24)
Industry Median Lev.	-0.0658	-0.0578**	-0.0658	-0.0527*
	(-1.01)	(-2.12)	(-1.01)	(-1.67)
Asset Intensity	0.143***	0.333***	0.143***	0.402***
	(4.92)	(13.53)	(4.92)	(14.71)
Employee Intensity	0.0419**	-0.0463***	0.0419**	-0.0684***
	(2.38)	(-3.11)	(2.38)	(-4.18)
GDP Growth	0.00734*	-0.0439***	0.00734*	-0.0474***
	(1.65)	(-16.33)	(1.65)	(-16.02)
Dividend Dummy	0.0584**	-0.0417*	0.0584**	-0.0452*
	(1.96)	(-1.76)	(1.96)	(-1.72)
CAPEX	1.770***	-0.657***	1.770***	-0.804***
	(7.91)	(-3.97)	(7.91)	(-4.50)
Working Capital	0.277***	-1.894***	0.277***	-2.235***
	(3.25)	(-31.17)	(3.25)	(-32.68)
Net Book Leverage	0.0269	-2.122***	0.0269	-2.441***
	(0.38)	(-37.11)	(0.38)	(-38.22)
Industry FE	YES	YES	YES	YES
Cluster by Firm	YES	YES	YES	YES
F statistic for weak identification		90.11		90.11
LM test statistic for underidentification		171.2		171.2
Hansen J statistic (overindentification)		5.942		4.732
p-value of Hansen J statistic		0.0148		0.0296
r2		0.224		0.246
r2_a		0.223		0.245
Number of Firms	8752	8752	8752	8752
N	71857	71857	71856	71856

The t-statistics, based on standard errors clustered by week and firm, are presented in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Two-tailed significance tests for coefficients.

Table 4. Cost Stickiness and Debt Maturity

	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
	Stickiness	Long-Term Debt	Stickiness	Short-Term Debt	Stickiness	Debt Due In One Year
	(1)	(2)	(3)	(4)	(5)	(6)
Stickiness COGS	0.0404***		0.0405***		0.0412***	
	(10.75)		(10.82)		(9.48)	
Industry Stickiness	0.0917***		0.0910***		0.0974***	
	(8.63)		(8.58)		(8.12)	
Stickiness		-0.0118***		-0.00205		-0.117**
		(-2.94)		(-1.19)		(-2.54)
Profitability	-0.0986	-0.101***	-0.106	-0.146***	-0.196	-1.478***
	(-0.79)	(-6.96)	(-0.85)	(-20.81)	(-1.33)	(-9.46)
Cash-Flow Volatility	-0.719**	-0.131***	-0.732**	0.0153	-0.622*	1.469***
	(-2.37)	(-4.02)	(-2.42)	(1.14)	(-1.75)	(4.67)
Operating Leverage	0.378***	-0.0528***	0.379***	-0.0184***	0.477***	0.363***
	(3.59)	(-5.19)	(3.60)	(-4.27)	(3.78)	(3.79)
Log(Sales)	-0.0294***	0.0159***	-0.0291***	-0.00139***	-0.0280***	-0.0757***
	(-3.45)	(15.65)	(-3.40)	(-3.05)	(-2.97)	(-10.49)
Tangible Assets	-0.0447	0.163***	-0.0427	0.0159***	-0.0288	-0.408***
	(-0.52)	(13.92)	(-0.50)	(3.69)	(-0.31)	(-5.94)
Market-to-Book	0.00133	0.000359	0.00138	0.000227	0.000434	-0.00593*
	(0.41)	(0.80)	(0.43)	(1.45)	(0.13)	(-1.93)
Industry Median Lev.	-0.0789	0.0220***	-0.0793	0.00625***	-0.00131	0.155*
	(-1.24)	(4.80)	(-1.25)	(2.82)	(-0.02)	(1.76)
Asset Intensity	0.110***	0.0285***	0.111***	-0.0111***	0.0880***	-0.0893***
	(3.82)	(7.78)	(3.83)	(-6.84)	(2.85)	(-3.23)
Employee Intensity	0.0560***	-0.00305	0.0558***	0.00582***	0.0468**	-0.0462***
	(3.29)	(-1.27)	(3.29)	(5.19)	(2.52)	(-2.70)
GDP Growth	0.0104**	0.00304***	0.0102**	0.00261***	0.00699	-0.00118
	(2.39)	(7.37)	(2.33)	(13.02)	(1.52)	(-0.25)
Industry FE	YES	YES	YES	YES	YES	YES
Cluster by Firm	YES	YES	YES	YES	YES	YES
F statistic for weak identification		97.66		98.01		80.96
LM test statistic for underidentification		185.2		185.8		151.4
Hansen J statistic (overindentification)		2.162		0.0509		4.165
p-value of Hansen J statistic		0.142		0.821		0.0413
r2		0.0662		0.0386		0.00954
r2_a		0.0653		0.0377		0.00842
Number of Firms	8945	8945	8945	8945	8213	8213
N	74191	74191	74315	74315	61531	61531

The t-statistics, based on standard errors clustered by week and firm, are presented in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Two-tailed significance tests for coefficients.

Table 5. Cost Stickiness and Profitability

Regression (2) shows the relationship between cost stickiness and profitability using the whole sample, while Regression (4) analyzes the sub-sample for periods of increasing revenues and regression (6) analyzes the sub-sample for periods of decreasing revenues (Chen et al., 2019)

	First Stage Stickiness (1)	Second Stage Profitability (2)	First Stage Stickiness (3)	Second Stage Profitability (4)	First Stage Stickiness (5)	Second Stage Profitability (6)
Stickiness COGS	0.0402***		0.0446***		0.0336***	
	(10.70)		(10.18)		(6.51)	
Stickiness Industry Avg.	0.0914***		0.0971***		0.0832***	
	(8.61)		(7.65)		(6.16)	
Stickiness		0.0164***		0.0132***		0.0119***
		(6.31)		(5.45)		(2.63)
Cash-Flow Volatility	-0.669**	-0.478***	-0.983***	-0.261***	-0.267	-0.685***
	(-2.28)	(-22.35)	(-2.93)	(-12.48)	(-0.71)	(-23.49)
Operating Leverage	0.389***	-0.111***	0.453***	-0.0721***	0.284**	-0.135***
	(3.83)	(-15.07)	(4.02)	(-9.36)	(2.17)	(-15.37)
Log(Sales)	-0.0279***	0.00901***	-0.0297***	0.00697***	-0.0266**	0.0127***
	(-3.23)	(16.07)	(-3.26)	(12.41)	(-2.34)	(18.49)
Tangible Assets	-0.0103	-0.00706	0.0510	0.00625	-0.102	-0.0227***
	(-0.11)	(-1.37)	(0.51)	(1.23)	(-0.92)	(-3.48)
Market-to-Book	0.000778	0.00327***	0.00566	0.00271***	-0.00657	0.00213***
	(0.24)	(13.11)	(1.54)	(9.96)	(-1.45)	(6.17)
Industry Median Lev.	-0.0710	0.00570*	-0.0379	0.00166	-0.141	0.00774
	(-1.12)	(1.79)	(-0.48)	(0.54)	(-1.63)	(1.41)
Asset Intensity	0.113***	-0.0429***	0.135***	-0.0485***	0.0843**	-0.0416***
	(4.07)	(-24.17)	(4.46)	(-25.60)	(2.27)	(-18.94)
Employee Intensity	0.0585***	0.000703	0.0612***	-0.00621***	0.0574**	0.00212
	(3.45)	(0.60)	(3.28)	(-5.24)	(2.41)	(1.44)
GDP Growth	0.0103**	-0.00105***	0.0110**	-0.000175	0.00873	-0.00273***
	(2.38)	(-4.18)	(2.07)	(-0.68)	(1.29)	(-6.60)
Net Book Leverage	-0.0631	-0.0321***	-0.0823	-0.0301***	-0.0401	-0.0219***
	(-1.29)	(-9.26)	(-1.47)	(-8.30)	(-0.67)	(-5.32)
Industry FE	YES	YES	YES	YES	YES	YES
Cluster by Firm	YES	YES	YES	YES	YES	YES
F statistic for weak identification		96.88		84.11		41.54
LM test statistic for underidentification		183.8		160.8		81.11
Hansen J statistic (overindentification)		12.10		1.626		3.758
p-value of Hansen J statistic		0.000504		0.202		0.0525
r2		0.0669		0.0455		0.192
r2_a		0.0661		0.0440		0.190
Number of Firms	8941	8941	8063	8063	7841	7841
N	74151	74151	44759	44759	29392	29392

The t-statistics, based on standard errors robust to heteroscedasticity and clustered by firm, are presented in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Two-tailed significance tests for coefficients.

Appendix 1. Validity of The Cost Stickiness Measure

The first regression uses the four main drivers of stickiness following Anderson et al. (2003). The second and third regression uses the same variables used by He et al. (2020) to test for their own cost stickiness measure.

	(1) Stickiness	(2) Stickiness	(3) Stickiness
Asset Intensity	0.0781***	0.0246	0.0805***
	(3.22)	(1.22)	(3.12)
Employee Intensity	0.0946***		
	(5.97)		
GDP Growth	0.0147***	0.0307***	
	(3.55)	(5.85)	
Successive Decrease	-0.256***	-0.173***	-0.175***
	(-11.08)	(-6.05)	(-5.91)
Increase Dummy t-1		0.0577***	0.0421**
		(3.11)	(2.11)
FCF t-1		0.507***	0.561***
		(4.33)	(4.63)
Constant	0.734***	0.0690***	0.150***
	(8.30)	(2.84)	(6.77)
Industry FE	YES	NO	NO
Industry x Year FE	NO	NO	YES
r2	0.00587	0.00263	0.0284
Number of Firms	10606	9218	9214
N	93026	76228	76176

The t-statistics, based on standard errors robust to heteroscedasticity and clustered by firm, are presented in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Two-tailed significance tests for coefficients.

Appendix 2. Stickiness of COGS

	(1) COGS	(2) COGS
SALES	0.718***	0.731***
	(40.45)	(31.62)
Decrease x SALES	-0.000568	0.00550
	(-0.04)	(0.72)
Constant	-174.4***	-213.0***
	(-5.38)	(-3.62)
Firm FE	NO	YES
Year FE	NO	YES
r2	0.941	0.979
N	204584	202318

The t-statistics, based on standard errors robust to heteroscedasticity and clustered by firm, are presented in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Two-tailed significance tests for coefficients.

Appendix 3. Operating Leverage and Profitability

The first regression uses the complete sample. The second one (2) is for a subsample of firms with positive profitability while the third one (3) is for a subsample of firms with negative profitability.

	Profitability (1)	Profitability (2)	Profitability (3)
Operating Leverage	-0.0494***	0.0308***	-0.0764***
	(-10.55)	(8.57)	(-12.43)
Log(Sales)	0.00759***	0.00227***	0.0120***
	(17.95)	(6.57)	(15.83)
Tangible Assets	-0.0257***	-0.00430	-0.0146**
	(-5.80)	(-1.13)	(-2.06)
Market-to-Book	0.00393***	0.00481***	-0.000189
	(18.81)	(22.13)	(-0.71)
R&D	-0.290***	-0.175***	-0.0562***
	(-19.40)	(-12.58)	(-3.06)
R&D dummy	0.00209	-0.00154	0.00586*
	(1.15)	(-1.06)	(1.72)
Cash-Flow Volatility	-0.427***	-0.0769***	-0.423***
	(-25.64)	(-5.64)	(-18.06)
Industry Median Lev.	0.00277	-0.00525***	0.0267***
	(1.24)	(-3.19)	(4.66)
Dividend	-0.0000774	0.00519***	-0.00725*
	(-0.06)	(4.40)	(-1.94)
Dividend dummy	0.0288***	0.0183***	0.0245***
	(19.23)	(14.86)	(7.99)
Cash Holdings	0.00773***	0.00737***	-0.00108
	(16.20)	(18.08)	(-1.22)
Constant	0.0593***	0.0662***	-0.0615***
	(16.53)	(21.75)	(-10.14)
r2	0.197	0.167	0.125
r2_a	0.197	0.167	0.123
N_clust	15550	13859	8493
N	154440	124032	30408

The t-statistics, based on standard errors robust to heteroscedasticity and clustered by firm, are presented in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Two-tailed significance tests for coefficients.

Chapter 3. Gender, Knowledge, and Trust in Artificial Intelligence: A Classroom-Based Randomized Experiment[56]

ABSTRACT

Artificial intelligence (AI) is increasingly utilized to provide real-time assistance and recommendations across a wide range of tasks in both education and workplace settings, especially since the emergence of AI Chatbots such as ChatGPT. However, it is unclear how users perceive the trustworthiness of these tools, more so given the publicized "hallucinations" that they may experience. We conduct a randomized field experiment in an undergraduate class setting where students perform periodic tests through a digital platform. We analyze how subject characteristics affect trust in AI versus peers' advice. Students are randomly assigned to either a treatment group receiving advice labeled to come from an AI system or a control group receiving advice labeled as coming from human peers. Our results are in line with recent laboratory experiments documenting algorithm appreciation. However, we find that algorithm appreciation varies with subject gender and knowledge. Specifically, male and high-knowledge participants place considerably less weight on AI advice. Our results remain consistent even over an extended out-of-sample period and after providing subjects with performance feedback.

Keywords. Algorithm aversion; Algorithm appreciation; AI Chatbots; Advice-taking; Trust; Gender.

[56] This chapter is based on a working paper under the same name, co-authored with Antonio Davila, Daniel Oyon and Nicolas Rudolf.

INTRODUCTION

The COVID-19 pandemic has triggered the rapid digitalization of education and workplace communications that have led to a profound shift in the ways in which humans interact with technology. New AI tools based on large language models, such as ChatGPT, are increasingly employed in educational settings. However, adoption patterns among users remain diverse, raising questions about the psychological underpinnings that shape human-AI interactions, such as trust towards AI systems[1,2,3,4]. Understanding the determinants of user trust in AI systems is essential to understand varying adoption and usage behaviors. To examine individuals' trust in AI, we conduct a randomized field experiment within an educational context in an undergraduate class where students take online tests regularly on a digital platform.

In our experiment we focus on the question whether individuals are more inclined to rely on AI-generated advice or human (peer), a question debated in the academic literature, particularly in decision-making contexts. More than four decades of research suggests algorithm aversion, where people prefer human advice over algorithmic recommendations (Burton, Stein, & Jensen, 2020; Castelo, Bos, & Lehmann, 2019; Dawes, 1979; Dietvorst & Bharti, 2020; Dietvorst, Simmons, & Massey, 2015; Einhorn, 1986). However, recent laboratory experiments indicate a shift in preferences towards algorithmic appreciation, particularly for more complex and more objective tasks (Bogert, Lauharatanahirun, & Schecter, 2022; Bogert, Schecter, & Watson, 2021; Castelo et al., 2019; Logg, Minson, & Moore, 2019). At the same time, early and largely anecdotal evidence suggests subject characteristics, including knowledge, experience, and personality traits may contribute to variations in AI appreciation (Abeliuk, Benjamin, Morstatter, & Galstyan, 2020; Logg et al., 2019).

Our research focuses on two primary factors affecting trust in AI. First, we explore gender differences towards AI appreciation. Existing economic literature yields mixed results regarding gender differences in trusting behaviors, although most studies indicate that women trust their peers less than men (Buchan, Croson, & Solnick, 2008; Croson & Buchan, 1999; Croson & Gneezy, 2009; Dittrich, 2015). However, it remains an open question whether this pattern extends to trust in AI versus peer advice. Second, we examine subject knowledge as a driver of AI appreciation. Prior evidence indicates that subjects with greater knowledge and expertise generally exhibit lower levels of trust in advice, irrespective of the source of advice (human or AI) (Buchan et al., 2008; Logg et al., 2019). Knowledgeable individuals often dismiss peer advice, as they consider it as inferior to their own knowledge and understanding (Abeliuk et al., 2020). Empirical evidence also indicates that knowledgeable individuals also reject AI advice more frequently (Allen & Choudhury, 2022). However, it is unclear whether these people trust AI to a larger extent than peer advice.

Recent studies exploring AI appreciation rely exclusively on 'one-shot' laboratory settings (Bogert et al., 2022, 2021; Logg et al., 2019). However, previous research highlights the external validity limitations of such environments, noting that many effects documented in laboratories do not extend to real-world settings (Beshears, Choi, Laibson, & Madrian, 2017; Harrison & List, 2004; Levitt & List, 2007). Moreover, trust is a learning process and individuals may behave differently once they learn about and get used to the source of advice. Thus, while these experiments capture the dispositional aspect of trust, they cannot capture the dynamic nature of trust (learned trust) (Hoff & Bashir, 2015; Marsh & Dibben, 2003). Therefore, it is unclear whether individuals trust AI advice in real-life settings to the same extent as they do in the laboratory. To address this question, we conduct a randomized field experiment over a four-week period, divided into two distinct phases. The first phase

captures the initial exposure to both peer and AI advice to ensure internal validity (i.e., the one-shot experiment). The second phase extends over the next three weeks, allowing students to communicate. Furthermore, we provide students with performance feedback after the second week of this phase. This research design allows us to assess the persistence of AI appreciation over time and after providing subjects with performance feedback.

For our study, we enlisted undergraduate students enrolled in a management course. Students perform tests on an online platform during their weekly lecture, offering a significant bonus to their final grade as an incentive for participation. We assign students randomly to our treatment group that receives advice labeled as AI or to our control group receiving advice that is labeled peer advice. Through this design, we aim to address the following research questions: Do subjects demonstrate AI appreciation by relying more on AI than peer advice? (RQ1); Is AI appreciation moderated by subject gender and knowledge? (RQ2); Do these biases (AI aversion or appreciation) hold over time and post-feedback? (RQ3). We find that subjects trust more AI relative to peers' advice measured using Weight on Advice (WOA). However, we find that algorithm appreciation varies with subject knowledge and gender. Specifically, male, and high-knowledge participants place considerably less weight on AI advice. These results are consistent over time and after providing subjects with performance feedback.

METHODOLOGY

Experimental Design, Context, Subjects, and Incentives

Summary of the experiment. Our field experiment setting is a face-to-face undergraduate management course that meets once a week and includes a digital quiz every meeting. We randomly assign students to either a treatment group, receiving AI-labeled advice, or the control group, receiving peer-labeled advice. These groups remain constant

throughout the entire experimental period, and the only difference between them is the label on the advice provided (AI or peer).

The experiment lasts four weeks (four sessions). The first week represents our controlled 'one-shot' experiment that allows us to confirm AI appreciation bias observed in recent studies (Bogert et al., 2021; Logg et al., 2019). To explore whether AI appreciation is persistent over time, we continued the experiment during the remaining three weeks of the course and gave performance feedback to students after the second week. Finally, in the last session, we switched the source of recommendations to capture within subject differences.

In all analyses, we manipulate question difficulty and type including both conceptual and numerical questions. We control for question difficulty and question type as prior literature indicates that the nature of the task moderate trust in AI, with individuals potentially relying more on advice in tasks of higher difficulty (Bogert et al., 2021) or lower subjectivity (Castelo et al., 2019).

To explore trust differences between AI and peer advice, we utilize the Judge–Advisor System (JAS) (Bogert et al., 2022, 2021). In this system, subjects can view the advice after their initial answer to a question. After seeing the advice, subjects have the option to revise their answer without any penalty. We then compute the Weight on Advice (WOA), common dependent variable in experiments using JAS, to quantify the extent to which an individual adjusts their response towards the received advice.

Context. Participants are enrolled in the management course that is compulsory in the undergraduate program. Students perform short quizzes (tests) throughout the semester on an online platform during the regular lecture (an example is shown in the appendix 1). Student participation in the quiz is voluntary. However, students have strong incentives to participate as above median performance in the quizzes provides students with a substantial

bonus on their final grade (0.5 out of 6 points). Due to these strong incentives, 98% of students participate regularly.

While the observations of the first quiz session (week 1) represent the 'one-shot' experiment, we continued the experiment over the following three weeks and performed two additional manipulations. First, after the second week, subjects received feedback on their overall performance. Second, in the last week, we divided the test into two parts. We switched the recommendation source (label) for each subject in the second part of the test to observe within-subject differences. Therefore, subjects initially in the control (treatment) group received AI (peer) recommendations instead of peer (AI) recommendations in the second half of the test. This within subject comparison concerns only the final part of the experiment and (table 3) is excluded from the main analyses (tables 1 and 2) in order to keep the advice as between subjects' treatment.

Subjects and Incentives. At the end of the semester, students above the median performance in the tests receive a 0.5 out of 6 bonus on the final grade. Students pass the final exam if they receive a grade of at least 4. Therefore, the bonus represents a high incentive and 94% (98%) of all students participated in the quizzes in the first week (four-week period).

Out of 84 enrolled students, 79 participated in the one-shot experiment, 17 of which chose not to access the provided advice (number of observations: 868). Furthermore, we continued with the same experimental setup during three additional sessions with quizzes to provide evidence whether our findings are stable over time. After the first two weeks, we provide subjects with performance feedback covering their initial attempt performance and their post-advice performance. All subjects either maintained or improved their scores in the second attempt, thus receiving a nudge towards trusting the advice, independent of the

advice source. Our dataset for the first session includes 868 observations and the full dataset including the three additional sessions includes 3,667 observations.

Task and Advice

All subjects received 14 (66) independent questions in the first week (in the four-week period), which were provided in a random order and answered consecutively. Out of these questions, 9 (54) were numerical requiring a numerical answer and 5 (12) were conceptual questions that included four short statements in the first week (in the four-week period). For conceptual questions, subjects needed to determine the correct statements and provide a yes/no answer to each one (between zero and four correct statements).

We implemented the Judge Advisor System, where participants initially respond to a question, subsequently decide whether to view the advice, and finally, provide a second answer without any deduction of points or penalty for viewing the advice or changing their answer.

Subjects were randomly assigned to either the group receiving advice labeled as coming from an AI system (treatment group) or the group receiving advice labeled as peer advice (control group). This grouping remained consistent for all questions during the first three weeks, representing a between-subjects condition. In the instructions, participants in the control group saw an advice source that read: “A frequent answer to this question given by a group of management accounting students was: [Advice]”. Participants in the treatment group saw an advice an advice source that read: “The answer provided by an artificial intelligence*: [Advice]. *An artificial intelligence with various capabilities (such as ChatGPT or BARD) and trained on similar problems.”

Students were not aware that they were divided in two groups receiving different types of advice. We set the accuracy of the advice to 50%. Correct advice was randomly

distributed across questions. The advice was the same for both groups, only the labeling of the source of the advice (AI or peers) was different.

Model

We employ ordinary least squares (OLS) regressions to analyze the effects of advice type, gender, and subject knowledge on weight on advice. We control for the type of task (conceptual or numerical) and task difficulty. We cluster standard errors by subject and question in the multiple period analysis and use robust standard errors within the one-shot experiment (Abadie, Athey, Imbens, & Wooldridge, 2023; Colin Cameron & Miller, 2015). The average (median) WOA by subjects is 21.0% (14.3%). To mitigate the influence of outliers we trimmed the data at the 1% level based on subjects' WOA. This helps to address scenarios in which a subject blindly follows most of the advice given, indicating that the subject may not be taking the task seriously. This procedure results in the exclusion of two participants from our sample. Our main model (see Table 1) is the following:

$$WOA_{ij} = \beta_0 + \beta_1\, AI\ advice + \beta_2\, Gender + \beta_3\, High\text{-}Knowledge + \beta_4\, AI\ advice \times Gender + \beta_5\, AI\ advice \times High\text{-}Knowledge + \beta X_{ij} + e_{ij}$$

Where, X_{ij} is the vector of control variables (Task Difficulty and Conceptual Task).

Dependent Variable

WOA is the weight on advice. This variable takes the value of '1' if the subject changes their first attempt answer to follow the advice, '0' if the subject did not change their answer and 0.5 if the subject took the average of the advice given and their initial answer. For instance, the subject chose answer A in the initial response. After receiving the advice that recommends answers A, B and C, the subject changes the answer to A and B, thus taking the advice only partly into account.

Explanatory Variables

Gender is a dummy variable that takes the value of '1' if the subject is male and '0' if the subject is female. *High-knowledge* is a proxy for subject overall knowledge and is

measured using subject's overall first attempt performance in the tests. The variable Knowledge takes the value of '1' if the performance is above the median (i.e., high-knowledge) and '0' otherwise (i.e., low-knowledge).

Control Variables

Task Difficulty is measured on the question level. It represents the average points achieved by all subjects for a question during the first attempt (thus, exogenous to the advice). We find that subjects are 42% less accurate when answering difficult questions (questions for which the difficulty is above the median) during the first attempt (ß = -0.420; p-value < 0.001). Subject accuracy is on average 69.9% for easy tasks and 27.9% for difficult tasks. *Conceptual Task* is a binary variable, equal to '1' for conceptual questions and '0' for numerical questions.

RESULTS

Task Validation and Randomization Check

We do not find significant performance differences across our treatment and control groups in the quizzes during the pre-experimental period of six weeks (t = 0.22; p-value = 0.826). Furthermore, we document no statistically significant difference in performance across gender in the pre-experimental period (t = 1.26; p-value = 0.213). The gender distribution across our treatment and control groups is balanced. Specifically, out of 41 subjects in the treatment group, 23 are female, while in the control group of 42 subjects, 24 are female. In addition, there is no significant difference across treatment and control groups in their performance on the first attempt answers before providing the advice (t = -1.21; p-value = 0.229). There is also no significant difference across gender in their performance on the first attempt answers before providing the advice (t = 1.38; p-value = 0.170).

We measure knowledge based on subjects' answers during their first attempts and therefore exogenous to the treatment. To validate this measure, we examine whether high-

knowledge subjects outperformed their counterparts in both the pre-experimental phase and the final exam. Notably, high-knowledge participants exhibited an average performance 8.1 percentage points superior to low-knowledge subjects before the experiment (ß = 0.0805; p-value = 0.042), demonstrating a 66.5% accuracy compared to 58.5% for the latter. Furthermore, in the subsequent final exam conducted about one month post-experiment, high-knowledge subjects demonstrated a performance 39.45% higher than their low-knowledge counterparts. On average, low-knowledge subjects scored 33.5%, while those with high knowledge scored 46.7%, signifying a 13.2% difference (ß = 0.1320; p-value = 0.003).

Main Analyses

We first analyze whether subjects rely differently on AI versus peed-labeled advice. Table 1, column 1, documents that subjects change their answers more often when they receive AI-labeled advice, after controlling for factors that can affect a subject's reliance on advice (ß = 0.072; p-value < 0.001). Subjects who receive AI-labeled advice revise their responses 7.2% more than subjects receiving advice from peers, consistent with AI appreciation. We also find a significantly positive effect of difficulty on WOA (ß = -0.387; P < 0.001). That is, subjects follow the advice 17.7% more often if task difficulty is high (higher task difficulty means students scoring less points on average for a given question in the first attempt). We also observe that high-knowledge subjects rely on advice to a lesser extent (ß = -0.152; P < 0.001). Finally, subjects follow more advice when the task is conceptual (ß = -0.079; P = 0.030).

Table 1, column 2 includes the interaction between gender and AI-labeled advice. We find a significantly positive main effect for female subjects' weight on AI advice (ß = 0.146; P = 0.002). That is, female subjects who receive AI advice revise their responses 14.6% more than female subjects receiving advice from peers. In contrast, we find that male

subjects rely on average 12.1% less on AI advice than female subjects (ß = -0.121; p-value = 0.031).

Table 1, column 3 includes an additional interaction between high-knowledge and AI advice. We find that low-knowledge subjects who receive AI advice revise their responses 16.1% more often than low-knowledge subjects receiving advice from peers (ß = 0.161; p-value < 0.001). In contrast, high-knowledge subjects rely 16.8 % less on AI advice compared to low-knowledge subjects (ß = -0.168; p-value = 0.001). Column 4 includes both interactions in a complete model and is consistent with these findings.

Insert TABLE 1 about here

Insert Figures 1 & 2 about here

Table 2 explores whether AI appreciation and the moderating effects of gender and knowledge are persistent over time. We test whether our findings hold during the two periods of the experiment and find consistent results regarding all three research questions (i.e., AI appreciation bias, the moderating effect of gender and knowledge). Table 2, Column 1 documents that subjects change their answers 6.1% more often (compared to 7.2% during the first week) than subjects receiving advice from peers (ß = 0.061; p-value = 0.056), consistent with AI appreciation being persistent over time. The interaction between AI advice and gender in Column 2 also supports the results obtained during the first period: male subjects rely 12.8% less (compared to 12.1% in the first week) on AI advice compared to female subjects (ß = -0.123; p-value = 0.053). Finally, Column 3 confirms that high-knowledge subjects rely 16.4% less (compared to 16.4% in the first week) on AI advice (ß = -0.164; P = 0.007).

Insert TABLE 2 about here

Finally, we analyze how subjects in the treatment (control) group who are used to AI (peer) advice react when receiving peer (AI) advice after we switch the label of the source of advice within subjects in the last test of the four-week sequence. By switching the source of advice, we explore whether AI appreciation persists after the switch. If it persists, then we expect AI exposed subjects to discount peer advice to a larger extent. Table 3, Column 1, reports both the coefficient of the switch dummy variable and the coefficient of the combination switch + AI advice x switch to be significantly negative (ß = -0.238; p = 0.074 and ß = -0.228; p = 0.031, respectively), indicating that subjects in both the treatment and control group reduce their trust in advice after the switch in the source of advice.

We explore this result in greater detail by performing a subsample analysis for female (Table 3, Column 2) and male subjects (Table 3, Column 3). Results indicate that female subjects trust more AI than peer advice before the switch (i.e., female show AI appreciation) (ß = 0.143; p = 0.043). After the switch in the advice source, female subjects in the treatment group (that were receiving AI advice pre-switch) follow peer advice significantly less (ß = -0.280; p-value < 0.001). Therefore, the overall effect of the advice source for female participants on the weight on advice is almost exactly mirroring the pre-switch magnitude of AI appreciation (0.143-0.28 =-0.137 WOA for peer advice post switch vs. 0.14 WOA for AI advice pre-switch.

In contrast, we observe that male subjects trust less AI than peer advice before the switch (ß = -0.121; p = 0.059). We also observe that male subjects in the control group (that were receiving peer advice) trust 45.6% less the advice after the switch to AI advice (ß = -0.456; p = 0.010). However, the coefficient of the AI advice x switch interaction is significantly positive (ß = 0.267; p-value < 0.001) indicating that male subjects in the treatment group

(that were receiving AI advice) decrease significantly less their reliance on advice after the switch to peer advice compared to the control group that switch from peer to AI advice.

Insert TABLE 3 about here

Robustness Tests

We test the robustness of our findings regarding the following three empirical design choices. First, our results are robust to using a binary WOA measure that takes the value of one if the subject changes the answer to match exactly the recommendation and zero otherwise.

Second, our results are robust to multiple combinations of control variables (e.g., without including other interactions when analyzing gender and knowledge effects; excluding task difficulty and/or conceptual task dummy; and using a binary measure of task difficulty).

Third, we test whether our results are robust to other measures of knowledge. Our conclusions remain unchanged if we substitute our knowledge variable by a numeracy dummy variable by measuring subjects' performance on numerical questions, as they may particularly affect subjects assessment of algorithmic advice taking (Bogert et al., 2021; Logg et al., 2019).

Fourth, for the entire experiment period, we employ alternative clustering and regression methods, including the wild bootstrapping method, multilevel mixed-effects linear regression with random intercept, and other regression methods (Logit, Probit) including clustering at the subject level. Our results remain largely statistically and economically unchanged (gender coefficients are even slightly more significant).

Finally, when we conduct subsample analyses by gender instead of fully interacted regression models, we find no evidence of AI appreciation among males in either the one-

shot experiment or the entire experiment. This confirms that AI appreciation may exist only in the female subsample. Similarly, subsample analyses using high-knowledge and low-knowledge groups show no evidence of AI appreciation in the high-knowledge subsample for both the one-shot experiment and the entire experiment. In contrast, we document AI appreciation in the low-knowledge subsample.

DISCUSSION

In light of the accelerated digital transformation that was partly induced by the COVID-19 pandemic, our study offers timely insight into the psychology of digitalization, particularly in an educational setting. We employ a randomized field experiment to explore how the availability of AI advice on digital platforms shapes trust. Our first set of results is consistent with recent laboratory findings on algorithm appreciation in real-world settings, thereby contributing to an understanding of digital adoption and trust dynamics. Furthermore, our analyses reveal that two key demographic variables—knowledge and gender— moderate trust in AI. This highlights the need to tailor AI tools to subject characteristics to significantly enhance their effectiveness and ultimately also adoption rates. Therefore, a more personalized approach to AI can enhance subject engagement and mitigate potential barriers to the adoption of digital resources.

We use a randomized field experiment for two reasons. First, a controlled field experiment typically provides higher external validity compared to online experiments while keeping internal validity largely comparable to a laboratory environment (Harrison & List, 2004). In our ‘one-shot’ experiment, subjects were randomly assigned to treatment or control groups, they were in a ‘test’ mode where they were not allowed to communicate with each other, helping to avoid spillovers between groups. In our setting, subjects were unaware of the experiment and should therefore not be influenced by the perception of being in an experiment. Furthermore, subjects have a substantial incentive to perform the task

voluntarily and seriously. Nevertheless, we find strong differences when comparing the average weight on advice in our setting to the online experiment of Bogert et al. (2021). We find that WOA is more than 50 percentage points higher their experiment than in our real-world setting (75% compared to 21% on average in our setting) (Bogert et al., 2021). This suggests that subjects may not have been sufficiently incentivized to perform the task with the same commitment as in our high-stake field experiment.

Second, our findings demonstrate that AI appreciation bias, observed in one-shot lab experiments, remains persistent over time and even after subjects receive performance feedback (after the second week). This suggests that the source of advice not only influences dispositional trust – the inherent inclination of a subject (psychological disposition or personality trait) to trust or not trust – captured in one-shot experiments, but also influences learned trust – the tendency to trust as a result of experience –, referring to the dynamic relationship where trust can evolve based on experience, which can be captured over time in our four-week experiment (Hoff & Bashir, 2015; Marsh & Dibben, 2003).

In addition, our findings support Logg et al's (2019) conclusions when comparing AI to a group of peers, as opposed to comparing AI to the advice of a single individual (Logg et al., 2019). Consequently, we can infer that AI advice is not only more highly valued than advice from a single peer but also more highly valued than advice from a crowd of peers. Furthermore, our findings document that algorithm appreciation depends on subject knowledge. We find that high knowledge individuals trust AI advice less than subjects with lower knowledge. Second, we document a difference in algorithm appreciation between genders. Female subjects are more likely to trust AI advice compared to peer advice.

Our study also has certain limitations. First, the relatively low number of subjects reduces the statistical power of our results, especially after clustering the standard errors on the individual subject level to account for correlations in the error terms within individuals

over time (Petersen, 2009). Second, our sample is composed of undergraduate students, therefore our results may not generalize to older populations. Third, although we observe the influence of gender on AI appreciation, we do not have access to data on other personality traits or characteristics that could further elucidate the factors driving trust in AI and peers. These unobserved characteristics such as risk-taking attitudes, confidence in own judgement, group affiliation, or previous experiences with technology might offer a more detailed understanding of the gender effect.

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Ethics Information

This study was approved by the University of Lausanne ethical committee. Subjects gave written consent. All methods were carried out in accordance with relevant guidelines and regulations.

Data Availability

The dataset analyzed during the current study, as well as code to conduct analyses, are available from the corresponding author on request.

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Competing interests

The authors declare no competing interests.

TABLES AND FIGURES

Table 1. The effect of gender and knowledge on AI appreciation in the first week 'one-shot' experiment.

		(1)	(2)	(3)	(4)
		WOA	WOA	WOA	WOA
AI advice	RQ1	0.072***	0.146***	0.161***	0.214***
		(2.73)	(3.10)	(3.64)	(3.86)
Gender		-0.056**	-0.008	-0.041	-0.003
		(-2.08)	(-0.23)	(-1.56)	(-0.09)
High-knowledge		-0.152***	-0.141***	-0.081**	-0.078**
		(-5.82)	(-5.48)	(-2.46)	(-2.39)
AI advice x Gender	RQ2		-0.121**		-0.099*
			(-2.16)		(-1.77)
AI advice x High-knowledge	RQ2			-0.168***	-0.155***
				(-3.21)	(-2.94)
Task Difficulty		-0.387***	-0.387***	-0.387***	-0.387***
		(-4.88)	(-4.83)	(-4.92)	(-4.88)
Conceptual Task		-0.056	-0.056	-0.056	-0.056
		(-1.63)	(-1.62)	(-1.64)	(-1.63)
Constant		0.534***	0.501***	0.487***	0.463***
		(11.46)	(10.29)	(10.09)	(9.35)
r2		0.121	0.127	0.132	0.136
Adjusted r2		0.116	0.120	0.126	0.128
N		826	826	826	826

The dependent variable is the Weight on Advice (WOA), with values between 0 and 1. Our main explanatory variables (Gender, AI advice and High-knowledge) are binary; thus, the coefficients can be interpreted in percentage terms. The table reports OLS coefficient estimates and (in parentheses) standard errors based on robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 2. The effect of gender and knowledge on AI appreciation in the four-week experiment.

		(1)	(2)	(3)	(4)
		WOA	WOA	WOA	WOA
AI advice	RQ3	0.0611*	0.134**	0.142***	0.196***
		(1.95)	(2.36)	(2.73)	(3.23)
Gender		0.0787**	0.0761**	0.0754**	0.0732*
		(2.13)	(2.06)	(2.04)	(1.83)
High-knowledge		-0.0248	0.0309	-0.00984	0.0354
		(-0.74)	(0.77)	(-0.31)	(0.93)
Feedback		-0.205***	-0.193***	-0.132***	-0.129***
		(-5.94)	(-5.56)	(-3.09)	(-3.09)
AI advice x Gender	RQ2		-0.128*		-0.107*
			(-1.98)		(-1.79)
AI advice x High-skilled	RQ2			-0.164***	-0.149**
				(-2.82)	(-2.58)
AI advice x Feedback					0.000765
					(0.01)
Task Difficulty		-0.374***	-0.378***	-0.377***	-0.380***
		(-4.88)	(-4.94)	(-4.93)	(-4.95)
Conceptual Task		0.0613*	0.0599*	0.0605*	0.0594
		(1.72)	(1.68)	(1.70)	(1.67)
Constant		0.441***	0.409***	0.399***	0.376***
		(7.41)	(6.68)	(6.63)	(6.38)
r2		0.135	0.141	0.144	0.148
Adjusted r2		0.134	0.139	0.143	0.146
N		3667	3667	3667	3667

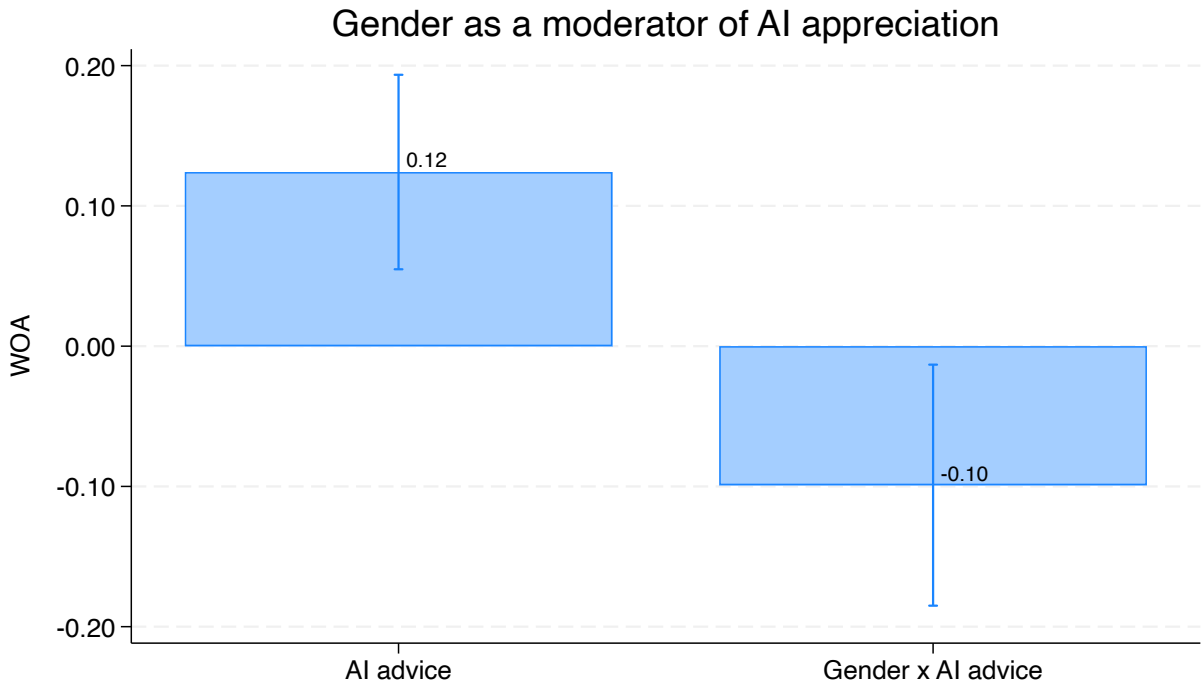
The dependent variable is the Weight on Advice (WOA), with values between 0 and 1. Our main explanatory variables (Gender, AI advice and High-knowledge) are binary; thus, the coefficients can be interpreted in percentage terms. Feedback is a binary variable that takes the value of '1' for observations after the second week. The table reports OLS coefficient estimates and (in parentheses) standard errors based on robust standard errors two-way clustered by subject and question. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3. The effect of gender and knowledge on AI appreciation in a within subject comparison.

	(1) Last week only	(2) Male subsample	(3) Female subsample
	WOA	WOA	WOA
AI advice	0.003	-0.121*	0.143**
	(0.05)	(-1.89)	(2.03)
Switch	-0.238*	-0.456***	-0.001
	(-1.79)	(-2.59)	(-0.01)
AI advice x Switch	0.010	0.267***	-0.280***
	(0.17)	(3.55)	(-3.35)
Task Difficulty	-0.384	-0.526	-0.221
	(-1.39)	(-1.40)	(-0.56)
High-knowledge	-1.340***	-1.471***	-1.328***
	(-15.29)	(-10.24)	(-11.14)
Gender	0.053**		
	(2.20)		
Constant	0.963***	1.200***	0.794***
	(6.65)	(6.16)	(3.81)
r2	0.189	0.178	0.249
Adjusted r2	0.184	0.171	0.242
N	1150	620	530

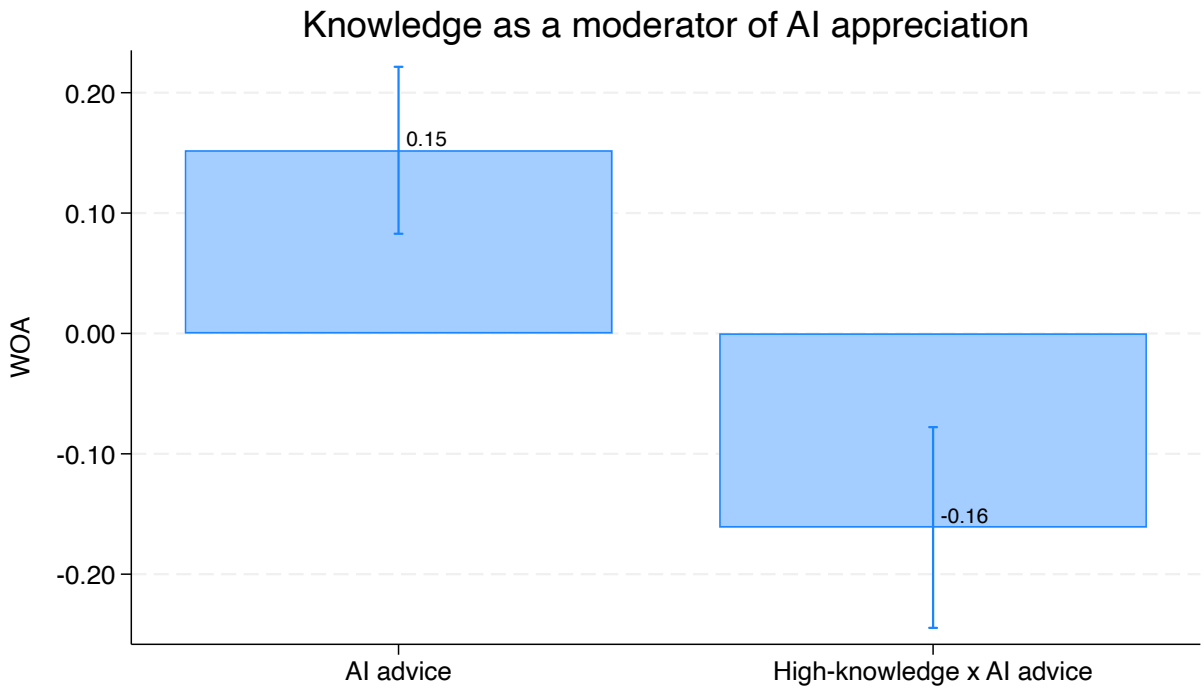
The table shows a regression analysis of the last week only (pre- and post-switching the source of advice). The dependent variable is the Weight on Advice (WOA), with values between 0 and 1. Our main explanatory variables (Gender, AI advice and High-knowledge) are binary; thus, the coefficients can be interpreted in percentage terms. Switch is also a dummy variable that takes value of one for observations after the second part of this last session (once we switch the advice source within subjects). The table reports OLS coefficient estimates and (in parentheses) standard errors based on robust standard errors two-way clustered by subject and question. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Figure 1. Week 1 results of the 'one-shot' experiment by regressing WOA on treatment dummy, Gender, their interaction plus controls (826 obs.).



The left bar (AI advice) represents the treatment effect on the reference group (female subjects). The difference is significant ($p < 0.01$). The right bar (Gender x AI advice) represents the moderating effect of being a male on the treatment effect (AI advice) compared to being a female. The difference across conditions is significant ($p < 0.05$). The confidence interval level is set at 90%.

Figure 2. Week 1 results of the 'one-shot' experiment by regressing WOA on treatment dummy, High-knowledge, their interaction plus controls (826 obs.).



The left bar (AI advice) represents the treatment effect on the reference group (low-knowledge subjects). The difference is significant ($p < 0.01$). The right bar (High-knowledge x AI advice) represents the moderating effect of being in the high-knowledge group on the treatment effect (AI advice) compared to the reference group for the interaction (low-knowledge subjects). The difference across conditions is significant ($p < 0.01$).

Appendix 1. Example of a question and advice given to subjects.

Experimental design, one example of a question where the student answers "1" while the advice suggests "45'000". The left screenshot shows the question and first attempt answer. The screenshot on top-left shows the advice shown to students in the treatment group (AI advice). The screenshot on bottom-left shows the advice shown to students in the control group (peer advice).

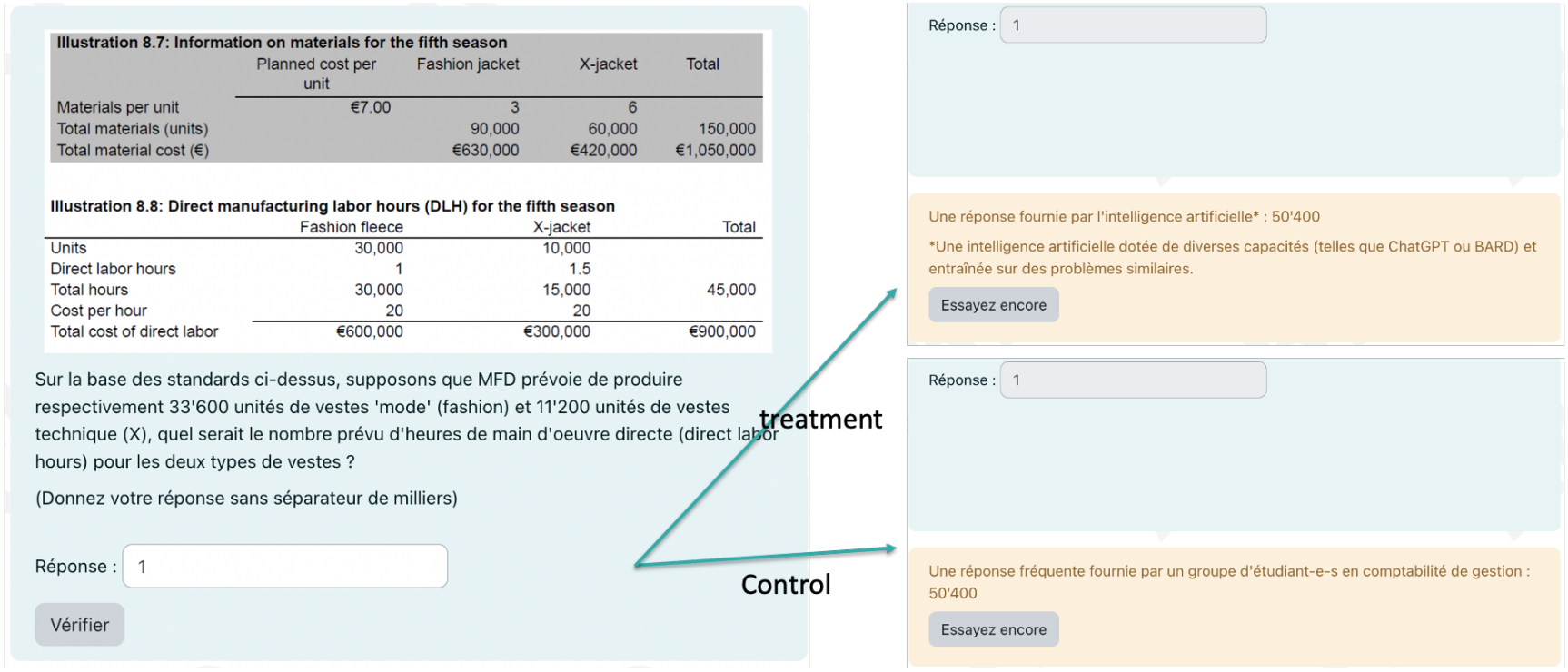


Illustration 8.7: Information on materials for the fifth season

	Planned cost per unit	Fashion jacket	X-jacket	Total
Materials per unit	€7.00	3	6	
Total materials (units)		90,000	60,000	150,000
Total material cost (€)		€630,000	€420,000	€1,050,000

Illustration 8.8: Direct manufacturing labor hours (DLH) for the fifth season

	Fashion fleece	X-jacket	Total
Units	30,000	10,000	
Direct labor hours	1	1.5	
Total hours	30,000	15,000	45,000
Cost per hour	20	20	
Total cost of direct labor	€600,000	€300,000	€900,000

Sur la base des standards ci-dessus, supposons que MFD prévoie de produire respectivement 33'600 unités de vestes 'mode' (fashion) et 11'200 unités de vestes technique (X), quel serait le nombre prévu d'heures de main d'oeuvre directe (direct labor hours) pour les deux types de vestes ?

(Donnez votre réponse sans séparateur de milliers)

Réponse : 1

Vérifier

treatment

Control

Réponse : 1

Une réponse fournie par l'intelligence artificielle* : 50'400

*Une intelligence artificielle dotée de diverses capacités (telles que ChatGPT ou BARD) et entraînée sur des problèmes similaires.

Essayez encore

Réponse : 1

Une réponse fréquente fournie par un groupe d'étudiant-e-s en comptabilité de gestion : 50'400

Essayez encore