



Government Interventions During the COVID-19 Pandemic, Culture, and Corporate Cost Behaviour

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Abstract

The COVID-19 pandemic triggered unprecedented government interventions, creating a unique setting to examine implications on corporate cost behaviour. This study explores the relationship between the stringency of government interventions during the pandemic and labour cost stickiness, as well as the moderating role of national culture, using 15,446 firm-year observations from 3,383 listed firms across 25 European countries from 2017 to 2022. A difference-in-differences regression analysis reveals that stringent interventions are related to increased labor cost stickiness, suggesting that managers view such measures as a signal of pandemic control which reduces their pessimism about future demand. Additionally, a median-based sample split shows that several dimensions of national culture moderate the relation between governmental stringency and labour cost stickiness, highlighting that culture influences how managers form future expectations based on stringent government interventions. The study connects formal institutions, i.e. governmental interventions, and informal institutions, i.e. national culture, with cost asymmetry as well as expands firm-level cost behaviour research in the context of the COVID-19 crisis.

Keywords: cost stickiness; COVID-19; culture; interventions

1. Introduction

In March 2020 the World Health Organization declared the outbreak of the novel coronavirus disease 2019 (COVID-19) a global pandemic (World Health Organization, 2020). In retrospective, this might have marked the beginning of a crisis which profoundly impacted the lives of millions and disrupted businesses worldwide. To ensure social distancing and curb the spread of the virus, most governments introduced unprecedented interventions, including travel restrictions, stay-at-home orders and school or workplace closures (Hale et al., 2021). Besides the detrimental effects on health, the pandemic, as well as governments' reactions to it, induced severe economic disturbances and confronted companies' decision-makers with extreme levels of uncertainty (Altig et al., 2020; Caggiano et al., 2020). A considerable stream of literature investigates the impact of the

outbreak of COVID-19 and subsequent government interventions on aggregate economic metrics like stock returns or exchange rate volatility (e.g. Aggarwal et al., 2021; Feng et al., 2021). However, until today, there is only little research on the microeconomic consequences, such as the relation between government interventions during COVID-19 and corporate cost behaviour.

Traditional cost models assume costs to behave proportionally and symmetrically to changes in activity, independent of the direction of the change (Noreen, 1991). More recent studies suggest an alternative model, arguing that costs are behaving asymmetrically – in other words “sticky” – because managers make the deliberate decision to retain some of the unused resources when activity declines (M. C. Anderson et al., 2003). Next to firm-specific factors, a company's operating environment is found to be associated with resource management decisions and, consequently, cost asymmetry (Banker et al., 2020; Bugeja et al., 2015). Among the various external factors influencing corporate cost behaviour, several studies have highlighted the relationship between

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cost stickiness and both formal and informal country-level institutions (Banker et al., 2013; Holzhaecker et al., 2015a; Kitching et al., 2016; Ma et al., 2021).

Given the exogenous nature of the COVID-19-induced changes in activity, along with the varying levels of government interventions' stringency across countries (Finne et al., 2024; Hale et al., 2021), the pandemic provides a unique opportunity to expand research on formal institutions and cost asymmetry. The COVID-19 crisis elicited profound reactions on the European labour market. For instance, the employment rate in the EU decreased by 2 percentage points and the total hours worked fell by 15 percent from the last quarter of 2019 to the second quarter of 2020 (Ando et al., 2022). This highlights why specifically management decisions during COVID-19 regarding labour should be investigated in more detail. Thus, this study leverages the pandemic context to examine the association between the stringency of government interventions during COVID-19 and labour cost stickiness. Although laws and governmental regulations provide the general boundaries for managers' decision-making, informal institutions such as culture impact the decision-making process as well, as they can unconsciously influence managers' values, attitudes, and behaviour (Kitching et al., 2016). Therefore, besides investigating the association between labour cost stickiness and a formal institution, namely government interventions during COVID-19, an additional analysis is conducted to examine the potential role of national culture in moderating this relation. In summary, this study aims at answering the following research questions: *how do government interventions during the COVID-19 pandemic relate to corporate cost behaviour, and does national culture moderate this relation?*

During COVID-19, decision-makers faced unparalleled uncertainty, as the duration of the crisis and its effects on the economy were largely unknown. Based on the findings of previous literature which identify managers' expectations about future sales under demand uncertainty as influencing cost asymmetry (M. C. Anderson et al., 2003; Banker et al., 2014), most authors argue and find that the outbreak of the COVID-19 virus is negatively related to cost stickiness (e.g. BenYoussef et al., 2023; Kwak et al., 2021). The authors claim that the uncertainty surrounding the pandemic increases managers' pessimism about the permanence of sales drops, thus lowering their future demand expectations and consequently also the level of cost stickiness.

Next to the outbreak of the virus itself, governmental reactions to curb its spread might be associated with cost stickiness as well. Government interventions are expected to be related to the level of corporate labour cost stickiness since they can induce managers to reassess their assumptions about the persistence of the crisis and thus change managerial expectations about future demand conditions. However, considering the contradictory argumentation and findings of the literature to date, the direction of this relation is unclear. On the one hand, government interventions might send the signal that the government is able to effectively control the pandemic and therefore reduce uncertainty (e.g. Kizys et al.,

2021). This could induce managers to be more optimistic about future demand and consequently to be more inclined to keep slack resources, resulting in increased levels of labour cost stickiness. On the other hand, government interventions might convey a perception of extended economic challenges (BenYoussef et al., 2023) and generate additional uncertainty regarding the interventions' effectiveness and impact (Ashraf, 2020). Thus, corporate decision-makers might be more pessimistic about future demand and therefore be more likely to remove unused resources, which leads to decreased levels of labour cost stickiness.

Moreover, it is expected that national culture leads to one argument predominating the other. National culture influences the understanding and acceptance of formal institutions (Helmke & Levitsky, 2006), which implies that cultural differences across countries may moderate the relation between stringent government interventions during COVID-19 and labour cost stickiness. Specifically, national culture is suggested to affect managers' acceptance of stringent interventions and their belief in the interventions' effectiveness. If managers perceive the stringent interventions as legitimate and effective in mitigating the adverse impacts of the COVID-19 crisis, they may adopt a more optimistic outlook on future demand. This optimism could, in turn, result in higher levels of labour cost stickiness, as managers are more inclined to retain resources in anticipation of a recovery in sales.

This study investigates the research questions using a sample of 15,446 firm-year observations from 3,383 listed firms across 25 European countries between 2017 and 2022. In an initial analysis, the full sample is tested for labour cost stickiness using a model based on the one developed by M. C. Anderson et al. (2003). Additionally, it is examined whether COVID-19 changes the result. Consistent with prior research, the findings indicate that, on average, labour costs exhibit stickiness. However, this stickiness significantly decreases after the outbreak of COVID-19, so that cost asymmetry can no longer be detected in the subsample covering the pandemic years 2020 to 2022. This aligns with the notion that the COVID-19 crisis heightens managerial pessimism, hence keeping corporate decision-makers from retaining unused resources when sales decline. Next, this study exploits the fact that the COVID-19 outbreak, and government interventions following it, can be considered an exogenous shock to firms (Finne et al., 2024). It employs a difference-in-differences (DiD) panel regression model to examine whether there is a relation between the stringency of government interventions during COVID-19 and firms' labour cost stickiness. This design allows comparing the difference in changes in labour cost stickiness from before to after the implementation of stringent government restrictions between countries with high versus low levels of governmental stringency, while controlling for known determinants of cost stickiness. This study finds evidence consistent with the conclusion that stringent government interventions during COVID-19 are associated with significantly higher labour cost stickiness. These results are in line with that stream of the literature, which argues that by introducing stringent interventions, governments

might signal that the pandemic is under control. This, in turn, decreases managerial pessimism and lead managers to retain slack resources during a sales drop. Lastly, to investigate whether an informal institution moderates the relation between a formal institution, namely the stringency of government interventions during COVID-19, and labour cost stickiness, national culture is used as a proxy. Like in other studies which examine cross-country differences in cost stickiness (e.g. Cannon et al., 2020), the sample is split based on the median value of the respective cultural dimension. The baseline model is re-estimated for both groups, and it is determined whether the DiD-coefficient differs between them. The regression estimations indicate that the relation between the stringency of government interventions during COVID-19 and labour cost stickiness varies between high- and low levels of several cultural dimensions, which provides evidence in line with national culture moderating, i.e. amplifying or attenuating, this association.

This study contributes to the existing literature in several ways. It is one of the few studies investigating the association between government interventions during COVID-19 and cost stickiness and it is the first one doing so in the European setting. Moreover, it is the first to examine the potential moderating role of national culture in this relation. Hence, this study adds to the literature on country-level determinants of asymmetric cost behaviour by showing how formal institutions are associated with labour cost stickiness and how informal institutions moderate this relation, in the context of COVID-19. In doing so, it addresses calls to expand research on the impact of governmental actions and cultural factors (Ibrahim et al., 2022) on cost asymmetry. Additionally, this study contributes to the growing research field examining the consequences of the COVID-19 crisis and government interventions related to it. Whereas most studies focus on aggregate, industry-level, or stock return analyses (Finne et al., 2024), this study deepens the research on firm-level consequences of the pandemic.

The remainder of this study is organized as follows. Initially, essential terms and concepts are defined, previous literature is reviewed, and the study's hypotheses are derived. Next, the sample and the research design are described. Subsequently, the results from the regression analyses are presented. In the final section, a discussion of the study's limitations, suggestions for future research, and a conclusion follow.

2. Theoretical perspective and hypotheses development

2.1. Key terms and concepts

2.1.1. Defining asymmetric cost behaviour

Costs are caused by resources that are needed to perform activities within a corporation (Cooper & Kaplan, 1992). In the short run, some resources are hardly adjustable whereas other resources can be flexibly adapted depending on the actual activity level. Accordingly, in the traditional model of corporate cost behaviour costs are classified as either fixed

or variable (Brüggen & Zehnder, 2014). It is assumed that fixed costs are constant, while variable costs move proportionally and symmetrically to changes in cost drivers such as production volume or sales (Banker & Byzalov, 2014). The assumption of proportionality and symmetry implies that if variable costs increase for example by 1% for a 1% incline in activity, they will decrease by 1% for an equivalent reduction in activity as well (Calleja et al., 2006). Thus, the average magnitude of the percentage change in cost for each percentage change in activity, i.e. the cost elasticity (Holzhacker et al., 2015a), is equivalent for activity increases and decreases. The traditional model has been extended to consider multiple cost drivers, for example in the activity-based costing (ABC) model¹, and non-linear effects such as economies of scale or learning effects. However, it still postulates a mechanistic relation between costs and cost drivers and does not consider how managerial decision-making may affect the resource adjustment process (Banker et al., 2018).

More recent empirical studies suggest an alternative model. Noreen and Soderstrom (1994, 1997) find initial, however weak, evidence for non-proportional and asymmetric cost behaviour by conducting a cross-sectional and time-series analysis of overhead costs in US hospitals. They conclude that the traditional model overstates the impact of changes in the activity level on concurrent costs. M. C. Anderson et al. (2003) were the first to present statistically and economically significant evidence that corporate cost behaviour is inconsistent with the traditional view of proportionally and symmetrically behaving costs. They show that SG&A costs in a sample of 7,629 US firms during the period 1979 to 1998 increase by 0.55% on average for a 1% sales increase but decrease by just 0.35% on average for a 1% sales decrease. The authors label this phenomenon “cost stickiness” and define costs correspondingly as sticky if “the magnitude of the increase in costs associated with an increase in volume is greater than the magnitude of the decrease in costs associated with an equivalent decrease in volume” (M. C. Anderson et al., 2003, p. 48). They claim that cost stickiness occurs because the resources underlying SG&A costs are not moving mechanistically with changes in sales volume but are actively managed by corporate decision-makers. The authors argue that if managers observe increasing demand, they have to deploy additional resources, as they otherwise would not be able to supply the required volume. However, if observing declining demand, it is at the discretion of the manager to either retain or reduce slack resources. In the case of sticky costs, managers deliberately decide to preserve idle resources because they perceive the retainment as less costly than the downward adjustment (M. C. Anderson et al., 2003). Summarizing, the cause of cost asymmetry is the deliberate management of corporate resources, and concurrent costs, by corporate decision-makers.

¹ In the ABC model costs are allocated to products based on multiple activities which are performed for example on the unit, batch, or product level (Noreen, 1991).

An extensive number of studies build on the seminal paper of M. C. Anderson et al. (2003). Subsequent researchers complement the model of asymmetric cost behaviour by adding the definition of cost anti-stickiness to it. According to Weiss (2010, p. 1142) costs are anti-sticky if “they increase less when activity rises than they decrease when activity falls by an equivalent amount”. Figure 1 summarizes the model of asymmetric cost behaviour and highlights the differences between symmetric, sticky, and anti-sticky costs.

If symmetric costs are assumed, the slope of the cost function (C) is linear and therefore identical for high (Y_H) and low activity levels (Y_L), for example sales increases and decreases. In the case of sticky costs, the slope is flatter for low activity levels (Y_L) than for high activity levels (Y_H). When the cost function exhibits anti-sticky behaviour, the slope is steeper for low activity levels (Y_L) than for high activity levels (Y_H). This implies that in the case of sticky (anti-sticky) costs, the cost elasticity is greater (lower) for sales increases than for sales decreases.

Subsequent research uses the regression model of M. C. Anderson et al. (2003) as a basis to provide evidence of asymmetric cost behaviour across different cost categories², countries³ and time periods. Whilst a comparably small number of authors investigates the consequences of asymmetric costs (for a summary see Ibrahim et al., 2022), a comprehensive stream of literature examines the determinants of cost asymmetry.

2.1.2. Characterizing determinants of asymmetric cost behaviour

The firm- and country-level determinants of asymmetric cost behaviour identified by prior literature can be classified into three main categories (Banker et al., 2018), namely, managers' expectations for future sales, resource adjustment costs and managerial opportunistic motives. They represent the channels through which cost asymmetry can be affected. As will be detailed in the following sections, it is assumed that the stringency of government interventions during COVID-19 is associated to cost asymmetry through the channel of managerial future expectations. Additionally, national culture is expected to moderate this relationship via the same channel. Therefore, the primary focus is on the channel of managerial future expectations. However, the literature on the channels of adjustment costs and opportunistic managerial motives is acknowledged for completeness.

Managerial decision-making and consequently cost behaviour is influenced not only by concurrent changes in demand but also by managers' expectations about future sales levels (Banker et al., 2018, 2020). Resource management

decisions are made under conditions of demand uncertainty (Banker et al., 2014), requiring managers to evaluate the permanence of a sales decline when deciding whether to retain or cut unused resources. Some authors argue that demand uncertainty is associated with increased cost stickiness. They suggest that managers purposely delay the resource adjustment decision and keep slack resources until they can gather more information about the permanence of the sales decline (e.g. M. C. Anderson et al., 2003; W. J. Lee et al., 2020). This materializes in an increased level of cost stickiness which reverses in subsequent periods when more information on the duration of the sales drop is known and uncertainty resolves. Other authors expand this argument and claim that the effect also depends on managerial *expectations* about the persistence of the demand uncertainty. If managers are optimistic and believe that the sales drop is temporary, they are more likely to keep unutilized resources, as the expected retention costs are smaller than the expected adjustment costs, resulting in greater cost stickiness. Conversely, if managers are pessimistic and believe the sales drop is permanent, the retention costs are expected to be higher than the adjustment costs, leading to the cutting of unused resources and, consequently, to less cost stickiness (Banker & Byzalov, 2014; Kama & Weiss, 2013). This reasoning applies to sales increases as well: optimistic managers are more willing to expand resources as they are more likely to classify the increase as permanent, while pessimistic managers are hesitant to commit resources due to the fear of having to reverse these commitments (Banker & Byzalov, 2014). The influence of managers' expectations on cost stickiness is first mentioned by M. C. Anderson et al. (2003). They show that the re-occurrence of declining sales in two consecutive periods is associated with increased pessimism about the permanence of the demand reduction and consequently decreasing SG&A cost stickiness, whereas macroeconomic growth is related to increased optimism about the duration of the sales decline and consequently increasing SG&A cost stickiness. Further empirical evidence is provided by Banker et al. (2014), who demonstrate that managers tend to extrapolate past trends, leading to more optimistic (pessimistic) expectations about future sales following a prior sales increase (decrease) and resulting in increased (decreased) cost stickiness accordingly. Their findings are reinforced and expanded by Ciftci and Zoubi (2019) who find that in addition to the sales change's direction, also the magnitude of the change influences managers' expectations and thus cost asymmetry.⁴ Next to rational, economic information about future sales, managers' optimism can also be based on psychological and behavioural biases like overconfidence (Banker & Byzalov, 2014). Literature suggests that overconfidence fosters excessive optimism about future sales, resulting in increased cost stickiness. As proposed, several studies find a positive rela-

² In addition to SG&A costs, operating costs (e.g. Kama and Weiss, 2013), costs of goods sold (e.g. Ibrahim, 2015), labour costs (e.g. Prabowo et al., 2018) and total costs (e.g. Subramaniam and Weidenmier Watson, 2016) are found to exhibit asymmetric cost behaviour.

³ Prior literature finds evidence for asymmetric cost behaviour in cross-country samples (e.g. Banker and Byzalov, 2014; Calleja et al., 2006), including developed as well as developing countries.

⁴ Their results show that cost stickiness is greater (smaller) for small (large) decreases in sales, as managers assess the permanence of the decline as temporary (permanent) and therefore are more optimistic (pessimistic) about future sales changes (Ciftci & Zoubi, 2019).

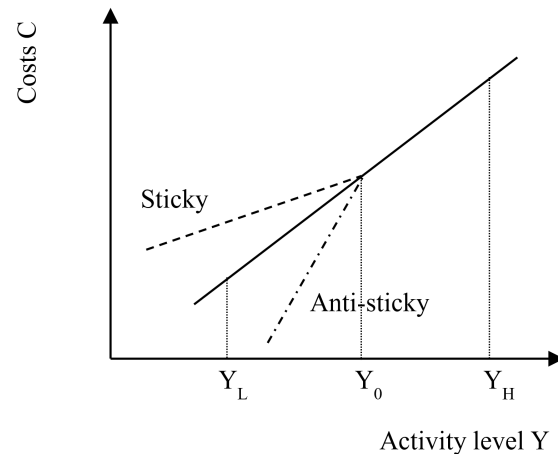


Figure 1: Graphical representation of the cost asymmetry model
(Own figure based on Weiss (2010, p. 1444).)

tion between proxies for managerial overconfidence and cost stickiness⁵.

Moreover, cost management decisions are influenced by resource adjustment costs, which are defined as costs “to remove committed resources and to replace those resources if demand is restored” (M. C. Anderson et al., 2003, p. 49). Adjustment costs include for example severance payments when cutting resources due to falling activity, or hiring costs, when replacing resources due to rising activity. However, they are not only of monetary nature, but also encompass implicit costs such as a loss of morale or efficiency if teamwork is disrupted (Banker & Byzalov, 2014). The higher the expected resource adjustment costs, the more reluctant managers are to cut excess resources when sales decline, and, in turn, the higher the level of cost stickiness. Several studies examine the relation between proxies for adjustment costs and cost stickiness. For example, Balakrishnan and Gruca (2008) provide department-level findings in showing that cost stickiness is higher for core functions than for ancillary and support services, since the adjustment costs are higher for core activities. M. C. Anderson et al. (2003) suggest that firms with higher asset or employee intensity incur higher adjustment costs as they lose more firm-specific investment when dismantling customized machinery or incur higher severance payments when dismissing employees, respectively. Accordingly, they find a positive association between asset or employee intensity and cost stickiness. Other studies show that country-level proxies for adjustment costs, such as the strictness of employment protection legislation, are related to higher levels of labour and SG&A cost stickiness (Banker et al., 2013).

Lastly, resource adjustment decisions are affected by managerial opportunistic motives. In contrast to studies from the

previously described categories, which assume that managers act in the firm’s best interest (Brüggen & Zehnder, 2014), this body of literature builds on the agency theory⁶ and conjectures that managers make self-interested decisions at the expense of firm value. As self-interested managers want to maximize their private benefit, they may engage in opportunistic behaviours like empire-building. These managers try to maximize the company’s size and consequently are more reluctant to cut slack resources, even if sales decline. Hence, the degree of cost stickiness is increased beyond its optimal level resulting from economic factors, i.e. adjustment costs and future expectations (C. X. Chen et al., 2012), resulting in deteriorating firm value (Banker et al., 2018). Authors substantiated this theory by showing that corporate governance diminishes the positive relation between empire-building incentives and cost stickiness as it reduces the agency problem through effective monitoring (Bugeja et al., 2015; C. X. Chen et al., 2012). Next to managers’ intrinsic motives, corporations can incentivize managers with performance compensation (Banker et al., 2018). For example, managers’ incentives to avoid losses or reach earnings targets (Dierynck et al., 2012; Kama & Weiss, 2013) are also found to be related to resource management decisions and consequently cost asymmetry.

2.1.3. Defining institutions

Managerial decisions “do not emerge independently of the social environment but are jointly shaped by formal and informal institutions” (Hartlieb et al., 2020b, p. 26). Thus, researchers acknowledge that cross-country differences in cost stickiness might exist due to regulatory or cultural aspects (Stimolo & Porporato, 2019) and express interest in

⁵ For example, C. X. Chen et al. (2022) find a positive association between CFO overconfidence, proxied by option-exercising behaviour, and cost stickiness. Additionally, D. Yang (2015) shows that CEO hubris is positively related to cost stickiness in examining overconfident bidder CEOs in merger events.

⁶ The agency theory assumes that, in a situation of separation of ownership and control, the principal (i.e. a corporation’s shareholders) and the agent (i.e. corporate managers) are both utility maximisers. Thus, an “agent will not always act in the best interests of the principal” (Jensen & Meckling, 1976, p. 308).

understanding the relation between cost management decisions and formal and informal country-level institutions (e.g. Banker et al., 2013; Kitching et al., 2016).

Institutions are defined as human-made “systems of established and embedded social rules that structure interactions” (Hodgson, 2006, p. 18) by “constraining and enabling actors’ behaviour” (Helmke & Levitsky, 2006, p. 5). They allow individuals to form stable expectations about the behaviour of others and thus make ordered human interaction possible (Hodgson, 2006). Both formal and informal institutions can be summarized under this definition (Redmond, 2005), yet they differ in how they are transmitted and enforced.

2.1.4. Characterizing government interventions during COVID-19 as formal institution

Redmond (2005, p. 666) defines formal institutions as “administered by a central authority” that has the power “to set rules which will direct the behaviour of many, as well as [...] to interpret and enforce the rules”. These explicit and codified rules and procedures are “communicated and enforced through channels that are widely accepted as official” (Helmke & Levitsky, 2006). Formal institutions comprise for example political and economic rules like laws and contracts (North, 1990) which set the boundaries for managerial decision-making, including resource and cost management decisions (Kitching et al., 2016).

Prior literature shows that cost behaviour varies with country-level formal institutions. For instance, Banker et al. (2013) investigate the impact of legal institutions on cost stickiness and report that cost stickiness is increasing in the strictness of employment protection legislation as the costs of firing employees, i.e. the downward adjustment costs, rise. Holzhacker et al. (2015a) and Belina et al. (2019) examine how changes in governmental healthcare regulations affect cost asymmetry and find that cost stickiness in German hospitals and US health insurers decreases due to rising operational risk and cost downward pressure introduced by the regulatory adjustments. The results of both Jin and Wu (2021) and W. J. Lee et al. (2020) reveal that political institutions moderate the relationship between political uncertainty and cost stickiness. Whilst the former show that high government spending, low property rights and low levels of labour regulation strengthen the proposed negative association between political uncertainty and cost stickiness, the latter report evidence that stable political and legal institutions reinforce cost stickiness in election years. Kuo and Lee (2023) show that strong political institutions are related to increased levels of cost stickiness, as they strengthen contract enforcement, corruption control and judicial independence.

This study utilizes government interventions implemented during the COVID-19 pandemic as a proxy for formal institutions, as they serve as a contemporary and globally relevant example of how formal institutions can exert influence across different countries. Governments during the pandemic acted as a central authority, setting up and enforcing codified rules to guide and constrain human behaviour. To

ensure social distancing and curb the spread of the virus, most governments introduced interventions, including for example school or workplace closings, travel restrictions or stay-at-home requirements. Though, the degree of individual governments’ interventions in Europe differed substantially, ranging from advisory measures to mandatory rules (Hale et al., 2021). For instance, some countries, including Italy and Germany, implemented mandatory stay-at-home requirements, while others, such as Sweden, only recommended working from home (Akter, 2020). This variance of stringency makes governmental interventions during COVID-19 a beneficial case to examine the relation between formal institutions and corporate cost stickiness. Although governments also issued health system policies, like testing or vaccination guidelines, and offered economic aid such as income support or debt reliefs (Hale et al., 2021), this study follows BenYoussef et al. (2023) and only considers non-pharmaceutical, non-financial government interventions in order to provide more nuanced insights.

2.1.5. Characterizing culture as informal institution

Informal institutions are defined as “socially shared rules, usually unwritten, that are created, communicated and enforced outside officially sanctioned channels” (Helmke & Levitsky, 2006, p. 3) and include for example “norms, conventions, customs and traditions” (Redmond, 2005, p. 666). They define acceptable or desirable behaviour which individuals comply to, as they try to avoid costs of deviant behaviour such as the feeling of embarrassment or shame (Sunstein, 1996).

Several studies show that various types of informal institutions are related to cost asymmetry. For instance, Ma et al. (2021) find that religion is negatively associated with corporate cost stickiness, as religious conservatism and ethicality tend to reduce managers’ (over-)optimism and empire-building tendencies. Hartlieb et al. (2020a) state that community social capital, i.e. cooperative norms and social networks, limits managers’ pursuit of opportunistic motives and therefore mitigates sticky cost behaviour. In another study, Hartlieb et al. (2020b) show that generalized trust has a positive effect on cost stickiness by increasing psychological adjustment costs and managerial optimism. Kitching et al. (2016) find that several dimensions of national culture, namely uncertainty avoidance, masculinity and long-term orientation, are related to operating cost stickiness through the managerial expectation channel and the adjustment cost channel. They argue that cost stickiness is less pronounced in firms located in countries being high in uncertainty avoidance and long-term orientation, as managers of such firms are more loss-averse and thrifty, respectively. Moreover, cost stickiness is attenuated in firms located in countries high in masculinity due to managers’ lower psychological downward adjustment costs.

The aforementioned definition of informal institutions also includes, but is not restricted to, national culture (Helmke & Levitsky, 2006; North, 1990). Given that managers frequently operate at corporate headquarters (Ma et

al., 2021), it is assumed that they are, to some extent, part of the national society of the country where the firm's headquarters is located. National culture is therefore expected to impact managerial resource decision-making by forming managers' values, beliefs, and assumptions (Kitching et al., 2016). Thus, this study uses national culture as defined by Hofstede et al. (2010) as a proxy for informal institutions. Hofstede et al. (2010, p. 6) refer to culture as "the collective programming of the mind that distinguishes the members of one group [...] from others". The authors explain that culture is learned through socialization processes and state that specifically nations are a "source of a considerable amount of common mental programming" (Hofstede et al., 2010, p. 21). They propose that national culture varies along six dimensions, namely power distance (PDI), individualism (IDV), masculinity (MAS), uncertainty avoidance (UAI), long-term orientation (LTO) and indulgence (IVR) and provide definitions for each of them. *Power distance* is defined as the degree to which unequal distribution of power, status and authority is accepted by lower status members of the society. In countries high in *individualism*, decisions are made based on individual needs, whereas in collectivistic countries, people are integrated into strong, cohesive groups and thus put a larger emphasis on protecting group interests. In societies characterized by high *masculinity*, social gender roles are clearly separated, meaning that "men are supposed to be assertive, tough, and focused on material success, whereas women are supposed to be more modest, tender, and concerned with the quality of life" (Hofstede et al., 2010, p. 140). Contrastingly, in feminine societies, social gender roles are suggested to overlap. *Uncertainty avoidance* is defined as "the extent to which the members of a culture feel threatened by ambiguous or unknown situations" (Hofstede et al., 2010, p. 191). While societies with a *long-term orientation* foster virtues oriented towards future rewards, like perseverance and thrift, short-term oriented societies support virtues related to the past and present, such as tradition and fulfilling social obligations. Lastly, *indulgence* is defined as "a tendency to allow relatively free gratification of basic and natural human desires related to enjoying life and having fun", whereas restraint is the "conviction that such gratification needs to be curbed and regulated by strict social norms" (Hofstede et al., 2010, p. 281).

2.2. Review of prior literature and hypothesis development

2.2.1. COVID-19 and asymmetric cost behaviour

On average, labour costs are expected to be sticky. This is confirmed for various samples in prior studies (e.g. Dalla Via and Perego, 2014; Dierynck et al., 2012; Prabowo et al., 2018). However, as Banker et al. (2018, p. 192) state: "costs that are sticky on average are not always sticky". Corporate cost stickiness indeed depends on various factors. In addition to firm-specific characteristic, the external environment, for example in terms of macroeconomic conditions, affects managers' operating decisions and hence the degree of cost stickiness (Banker et al., 2020; Bugeja et al., 2015). This study

focuses on examining the relationship between cost stickiness and formal institutions, i.e. government interventions, and the potential moderating role of informal institutions, i.e. national culture, in a specific context, namely the COVID-19 crisis. The pandemic caused unexpected macroeconomic disruptions, including severe demand drops⁷, which are likely to be related to resource management decisions. Hence, to delineate the setting and to establish the foundation for subsequent argumentations and analyses, the current state of research on cost stickiness and COVID-19 is reviewed and considered.

Prior research suggests that cost stickiness is decreasing during times of crisis. Banker et al. (2020) provides several reasons why the economic slowdown induced by a crisis is related to lower levels of cost stickiness. Firstly, as external financing becomes more expensive, managers may want to reduce costs to preserve cash. Furthermore, managers might have more pessimistic sales expectations, leading them to avoid preserving slack resources. Lastly, under the existential threat of dropping out of business, managers might be less resistant to operational changes which could improve organizational efficiency, thus being more inclined to adjust redundant resources downward. Additionally, literature suggests that managers are more likely to avoid committing contracts during periods of crisis to increase flexibility. For example, managers prefer hiring temporary workers which can be dismissed relatively easily (Ibrahim, 2015). Due to the contractual arrangement, firing costs for temporary employees are lower, resulting in less resource adjustment costs (Banker et al., 2013) and consequently decreasing cost stickiness. Economic downturns lower future adjustment costs as well, as it is easier to re-negotiate input costs such as wage rates (Jin & Wu, 2021).

The financial crisis of 2008 is found to induce cost anti-stickiness in samples of Egyptian firms (Ibrahim, 2015), UK Chemical firms (Hassanein & Younis, 2020) and municipalities in Spain (Karatzimas et al., 2022). Similarly, prior research shows that the COVID-19 pandemic is related to a decrease cost stickiness. COVID-19 confronted companies with unparalleled economic uncertainty, especially as the duration of the crisis was largely unpredictable in the absence of a similar historical event (Altig et al., 2020). As mentioned before, the level of cost stickiness depends on managers' expectations about the duration of the prevailing uncertainty and their optimism or pessimism about the permanence of a sales drop. In line with this argument, most studies in the field propose and find a negative association between COVID-19 and cost stickiness. The authors claim that the pandemic-induced un-

⁷ For completeness, it should be acknowledged that COVID-19 significantly affected both the demand and the supply side of businesses. Interpreting COVID-19 as a supply instead of a demand shock likely has different implications for cost stickiness. Scarcity of input resources may lead to higher adjustment costs, prompting managers to retain unused resources and resulting in increased cost stickiness. However, since firms generally perceive the pandemic primarily as a demand shock (Meyer et al., 2022), and this perspective is supported by prior literature, this study adopts the same viewpoint.

certainty caused managers to form pessimistic expectations about consumers' purchasing power and the prospect of sales rebounding in the short-term (Meyer et al., 2022). Therefore, managers are likely to assess the retention of resources to be more costly than the resource downward adjustment. Consistently, results show lower levels of cost stickiness during the pandemic. For example, Buchheim et al. (2022), although not directly examining cost stickiness, detect that firms who expect the duration of the shutdown to be longer than four months, cut significantly more resources, for example in terms of layoffs or the cancellation of investments. A negative association of the COVID-19 outbreak with cost stickiness is furthermore found in smaller samples of IT companies (Kwak et al., 2021) and healthcare firms (Ekici et al., 2024), as well as larger samples of American publicly listed companies (BenYoussef et al., 2023; Ghazy et al., 2024).

2.2.2. Government interventions during COVID-19 and asymmetric cost behaviour

When examining the consequences of COVID-19, it is important to differentiate between the effect of the pandemic itself and the government regulations implemented in response to it. This also applies when researching cost stickiness, as the study of Y. Yang and Chen (2024) shows. The authors investigate the influence of COVID-19 on cost stickiness in China and Australia and find the relation between the pandemic and cost stickiness to differ between both countries. They suggest that dissimilarities in policy responses to COVID-19 might explain this variation. Thus, to facilitate a clear distinction, this study focuses on the direct relation between the stringency of government interventions during COVID-19 and labour cost stickiness.

Literature examining government interventions during COVID-19 in the field of cost stickiness is scarce. The working papers by BenYoussef et al. (2023) and Ghazy et al. (2024) constitute notable exceptions. BenYoussef et al. (2023) examine SG&A cost behaviour in a North American sample and find a negative association between governmental stringency during COVID-19 and cost stickiness. Ghazy et al. (2024) investigate the relation between the strictness of workplace closures throughout the pandemic, as well as governmental economic support, and operating cost stickiness in US firms. Whereas their results show that cost stickiness exhibits a negative association with the strictness of workplace closure, economic support does not have a statistically significant effect. Due to the lack of theory regarding government interventions during COVID-19 in cost stickiness research, this study relies on argumentations and findings from another field, namely the finance literature. As Ashraf (2020, p. 1) states, stock markets "provide an incentivized survey of future expected outcomes". This makes the literature examining the impact of governmental stringency during COVID-19 on stock markets a suitable source for developing this study's theoretical framework, assuming that investors' and managers' future expectations are comparable.

Generally, the stringency of government interventions during COVID-19 is expected to be associated to labour

cost stickiness by changing managers' perception of the COVID-19-induced uncertainty and relatedly their expectations about the permanence of the economic downturn. In other words, it is suggested to be related to cost stickiness through the channel of managerial expectations about future demand, which was introduced in section 2.1.2. However, considering the results of the literature to date, the direction of the association between the stringency of government interventions during COVID-19 and cost stickiness remains unclear.

On the one hand, government interventions might send the signal that the pandemic is under control and therefore reduce uncertainty (Caggiano et al., 2020; Kizys et al., 2021). Several studies present evidence in line with this suggestion by showing a positive relation between government interventions and stock market return (Saif-Alyousfi, 2022; H. Yang & Deng, 2021). In addition to the research on stock markets, Feng et al. (2021) show that government non-pharmaceutical interventions are associated with decreasing exchange rate volatility as they send positive signals to markets and investors, thus effectively reducing panic and uncertainty. Like investors and markets in general, also corporate managers may interpret stringent government interventions as effectively reducing COVID-19-induced uncertainty. This might result in managers being more optimistic about demand recovery and consequently more inclined to keep slack resources, resulting in increased cost stickiness.

On the other hand, government interventions may give rise to additional uncertainty, for example regarding the interventions' duration and effectiveness (Altig et al., 2020; Ashraf, 2020). For instance, Zaremba et al. (2020) identify a positive association between the stringency of policy responses and stock market volatility. By accounting for country-specific factors and pandemic affectedness, their study demonstrates that the stringency of government interventions is an independent driver of increased volatility, distinct from the effects of the pandemic itself. Moreover, stringent government interventions might convey a perception of extended economic challenges (BenYoussef et al., 2023). Supporting this view, Ashraf (2020) finds that the announcement of stringent interventions is negatively related to stock market returns, as it leads to more pessimistic expectations due to the interventions' expected adverse impact on economic activity. In summary, stringent government interventions might as well lead corporate decision-makers to be more pessimistic about future demand. Hence, managers might be more likely to remove resources, which results in decreasing cost stickiness, as found by BenYoussef et al. (2023) and Ghazy et al. (2024).

Consistent with this double-sided argumentation, Aggarwal et al. (2021) show in the context of stock markets that the impact of government interventions' stringency during COVID-19 on investor behaviour is twofold. Their results suggest that more stringent government interventions positively influence the overall returns by making investors feeling more secure, as reflected in the declining equity risk premia demanded. On the other hand, the results also depict

that increased stringency of government interventions is negatively related to the overall return as it lowers investors' growth estimates. Since theory and prior literature do not clearly predict the direction of the association between stringent government interventions during COVID-19 and labour cost stickiness, it remains an open empirical question. Furthermore, it could also be the case that the proposed opposite effects of stringent government interventions might cancel each other out. Thus, the hypothesis is stated in a neutral form:

Hypothesis 1: There is no relation between the stringency of government interventions during COVID-19 and cost stickiness.

2.2.3. National culture as moderator

As prior research emphasizes, both formal and informal institutions influence decision-making, which highlights the importance of studying them in combination. For example, Graafland and Noorderhaven (2020, p. 1040) state that "[...] studies should not only look at both institutions and culture, but also at the interactions between these types of factors." Nevertheless, until today there are only few studies in the field of cost asymmetry research following this call. One exception is Cannon et al. (2020), who do not only examine the direct effect of takeover laws on SG&A cost stickiness, but also test whether culture, in terms of short-termism, moderates this relation. Their findings reveal that the negative relation between the passage of takeover laws and cost stickiness is more emphasized in short-term oriented countries.

Similarly, it is expected that national culture moderates the relation between the stringency of government interventions during COVID-19 and labour cost stickiness. National culture influences the understanding and acceptance of formal institutions (Helmke & Levitsky, 2006), which is why culture is also suggested to impact societal beliefs about the legitimacy of governments' mitigation measures (Wang et al., 2022). This view is supported by Dheer et al. (2021, p. 1873), who state that culture shapes "how individuals interpret and comply with stringent government measures". Generally, this might apply to all of the six cultural dimensions defined by Hofstede et al. (2010). For brevity, the reasoning is exemplary shown for only two of them.

For instance, individuals in collectivistic cultures might be more likely to acknowledge the legitimacy of stringent government interventions during COVID-19, as they are more willing to sacrifice individual freedom for the common good (Biddlestone et al., 2020; Dheer et al., 2021). This is supported by previous literature claiming that the state has a dominant role in collectivistic nations (Hofstede et al., 2010) and that individuals in collectivistic cultures derive satisfaction from fulfilling social obligations (Inglehart & Oyserman, 2004). In line with this, J. Lee et al. (2024) find that collectivistic cultures are more likely to endorse stringent government policies during COVID-19, whereas individualistic cultures are more prone to reject them.

In contrast, nations high in uncertainty avoidance might be less likely to accept stringent government interventions during COVID-19, as such measures are perceived as a source of additional uncertainty, for example regarding their economic impact (Altig et al., 2020; Ashraf, 2020). In addition, stringent interventions require people to profoundly change their everyday private and business life, due to measures like stay-at-home requirements or workplace closures. This can be particularly unsettling in uncertainty-avoidant cultures, where change is perceived as evoking unpredictability. Bakry et al. (2022) confirms this argument by showing that in emerging markets, which tend to have higher uncertainty avoidance scores, there is a positive association between the stringency of government interventions and stock volatility. Consistently, individuals from countries high in uncertainty avoidance are found to be less willing to comply to stringent interventions during COVID-19 (Dheer et al., 2021).

To summarize, the stringency of government interventions during COVID-19 is claimed to be related to labour cost stickiness in one of two opposing ways, as elaborated on in the previous section 2.2.2. Stringent measures might either increase managers' optimism about future demand and thus lead to rising levels of cost stickiness or lower managerial expectations about future demand, resulting in decreasing levels of cost stickiness. National culture is expected to be the factor determining which of both forces overweighs. In particular, culture is suggested to influence whether a national society, and thus also managers socialized within it, believes in the legitimacy of stringent government interventions during COVID-19. The acceptance or rejection of stringency is, in turn, believed to shape managers' future demand expectations. If managers accept stringent government interventions, they might believe in their effectiveness in reducing part of the COVID-19-induced uncertainty, which leaves them more optimistic about the temporary nature of declining sales. Ultimately, this materializes in higher levels of cost stickiness. Though, if managers reject stringent government interventions, they might doubt their usefulness in mitigating the adverse effects of the pandemic. They consequently are more pessimistic about future demand conditions, which results in lower cost stickiness. Thus, the extent to which managers' expectations about future demand are shifted due to government interventions during COVID-19 is likely to differ contingent on cultural factors (Buchheim et al., 2022).

Managers' likelihood to accept (reject) stringent government interventions, their resulting optimism (pessimism) about future demand and consequently the extent of cost stickiness exhibited, depend on the specific cultural dimension considered. Hence, the direction of the moderating role of culture in the relation between the stringency of government interventions during COVID-19 and cost stickiness differs between the various cultural dimensions. Therefore, the hypothesis is stated in a neutral form:

Hypothesis 2: National culture moderates the relation between government interventions during COVID-19 and cost stickiness.

3. Data and methodology

3.1. Sample construction

This study is based on panel data from the Thomson Reuters Eikon database, including observations of European publicly listed firms from 2017 to 2022⁸. The firm-level data is merged with country-level data on gross domestic product (GDP) growth obtained from the World Bank website⁹, data on the stringency of governmental interventions during COVID-19 from the Oxford Government Response Tracker website¹⁰ as well as data on national culture from Geert Hofstede's website¹¹. The sample construction procedure largely follows prior cost stickiness research and is summarized in Table 1. Only non-duplicate firm-year observations (S. W. Anderson & Lanen, 2007) from non-financial and non-utility firms¹² are considered (Hartlieb et al., 2020a). Observations with missing or negative labour costs or sales revenue in the current or two preceding years (Banker et al., 2013), as well as observations with missing values for control variables (Hartlieb et al., 2020a) and observations for which the ln-specification cannot be calculated, are deleted. In contrast to most prior studies (e.g. M. C. Anderson et al., 2003), observations in this study are not dropped if costs exceed sales revenue. The observations are only discarded if labour costs exceed sales revenue in the current *and* the prior year, following a suggestion of S. W. Anderson and Lanen (2007).¹³ Finally, observations are removed if there are fewer than 50 firm-year observations per country, to ensure that the model is reasonable for each country individually (Hartlieb et al., 2020b). To make the variables comparable between countries with differing currencies, the financial data is converted to euro¹⁴. All continuous variables are winsorized at the 1st and 99th percentile to weaken the impact of extreme outliers. The final sample contains 15,446 firm-year observations from 3,383 firms in 25 European countries¹⁵.

⁸ Constructing the control variable $SUC_DEC_{i,t}$ requires data from two additional years. However, the years 2015 and 2016 are excluded during the sample selection process, resulting in a symmetrical time span from 2017 to 2022, centred around the outbreak of COVID-19 in the beginning of 2020.

⁹ <https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG>.

¹⁰ <https://github.com/OxCGRT/covid-policy-tracker>.

¹¹ <https://geert-hofstede.com/national-culture.html>.

¹² Firms in the financial and utility industries are dropped to ensure comparability. The Standard Industrial Classification Code (SIC-Code) is used to assign firms to an industry.

¹³ Banker et al. (2014) suggest excluding observations where costs exceed sales, as these may reflect unusually high resource commitments. However, the COVID-19 pandemic caused significant declines in sales (Finne et al., 2024), which could result in labour costs exceeding sales as well – not due to excessive costs, but because of decreasing sales revenue. Consequently, removing these observations might bias the analysis. The empirical results remain similar, if observations with labour costs exceeding sales are not discarded at all, as suggested by Banker and Byzalov (2014).

¹⁴ The empirical results remain robust when adjusting for inflation by deflating the financial variables with country-specific GDP deflators.

¹⁵ Since data is not available for all firms over the entire sample period, the longitudinal panel is unbalanced. However, this is consistent with prior literature. For instance, the sample of M. C. Anderson et al. (2003) contains approximately 8.5 observations per firm in a sample period covering 20 years.

The sample distribution is presented in Panels A, B and C of Appendix 1. Although the number of observations per year rises, the distribution around the COVID-19 outbreak year 2020 is roughly symmetrical, with 43.9% of the observations being in the pre-COVID-19 period and 56.1% in the COVID-19 period. Most of the firms in the sample are headquartered in the United Kingdom (20%)¹⁶, followed by Germany (14%) and France (12%). This is consistent with these three countries being the largest in Europe resident-wise and speaks for the representativeness of the sample. Most of the firms belong to the manufacturing (44%) and the services industry (28%).

3.2. Variable measures

Stringency of government interventions during COVID-19

The stringency of government interventions during COVID-19 is captured by the stringency index (SI). The SI measures the level of non-pharmaceutical, non-financial actions that a government takes to contain the spread of the corona virus, mainly by reducing individuals' mobility.¹⁷ It is obtained from the publicly available Oxford COVID-19 Government Response Tracker (OxCGRT) database from the Oxford University's Blavatnik School of Government, which contains data on government responses during the pandemic for more than 150 countries from January 2020 to December 2022. The SI is based on the unweighted addition of nine closure and containment indicators¹⁸ and is scaled to vary from 0 to 100, with higher values indicating stricter government responses (Hale et al., 2021). It is assumed that only the stringency of government interventions in the country of a firm's headquarters is relevant for managers' decision-making, even if the company operates in other countries as well. As mentioned before, the SI varies significantly across European countries, which is illustrated by Appendix 2.

National culture

As the dimensions of national culture from Hofstede et al. (2010) are widely accepted and applied in empirics (Dheer et al., 2021; Kitching et al., 2016), the six dimensions power distance, individualism, masculinity, uncertainty avoidance, long-term orientation and indulgence are used in this study to measure national culture. Each country is assigned a score

¹⁶ According to Finne et al. (2024), it is common in the United Kingdom that the fiscal year ends in March. To examine whether this biases the analysis, a robustness check is conducted. Assigning all firm-year observations with a fiscal year end date before the 30th of June to the previous year does not change the results.

¹⁷ However, the stringency index contains no information on the effective implementation or the appropriateness of the interventions (Hale et al., 2021).

¹⁸ Namely school closings, workplace closings, cancellation of public events, restrictions on gathering size, closing public transport, stay-at-home requirements, restrictions on national movement, restrictions on international travel and public information campaigns (Hale et al., 2021).

Table 1: Sample selection

	Number of observations
Initial sample (2015-2022)	82,504
Less:	
(1) Observations with duplicate ISINs	8
(2) Observations of financial firms (2-digit SIC codes 60-69), public utilities (2-digit SIC code 49) or firms with non-specified industry (no SIC code)	37,536
(3) Observations with missing labour costs (sales revenue) in the current or (two) preceding year(s)	21,431
(4) Observations with negative labour costs (sales revenue) in the current or (two) preceding year(s)	42
(5) Observations where current labour costs exceed sales revenue of the current and the preceding year	2,420
(6) Observations with missing values for other required variables	5,445
(7) Observations from countries with less than 50 firm-year observations	176
Final sample (2017-2022)	15,446

between 0 and 100 for each dimension, with a higher score implying a stronger cultural parameter. Following Kitching et al. (2016), it is assumed that the national culture of the country in which the firm is headquartered is representative for the cultural values of its corporate decision-makers.

3.3. Model specification

Basic model

In a first step, an equation based on the ln-linear¹⁹ model established by M. C. Anderson et al. (2003) is employed to test for the presence of labour cost stickiness. Whereas M. C. Anderson et al. (2003) examine SG&A costs, this study focuses on labour costs, as they represent a significant proportion of total costs and are susceptible to managerial discretion (Pinnuck & Lillis, 2007). Furthermore, examining one specific type of cost potentially allows to locate in which cost category cost stickiness originates (Ibrahim et al., 2022). Following prior literature on labour cost stickiness, changes in the activity level are proxied by the *Net Sales or Revenues* item from Datastream, whereas changes in the labour cost level are operationalized using the *Salaries and Benefits Expenses* item from Datastream (Prabowo et al., 2018). Like Banker et al. (2013), Hartlieb et al. (2020a) and Ma et al. (2021), this study utilizes an extended version of the M. C. Anderson et al. (2003) model. Thus, the equation includes not only the three-way interaction terms of the control variables

with $\Delta \ln SALES_{i,t} \times DEC_{i,t}$, but also their two-way interactions with $\Delta \ln SALES_{i,t}$, as the control variables are found to be related to cost elasticity independent of a decrease in sales as well (Holzhacker et al., 2015a)²⁰. Model (1) shows the corresponding empirical regression equation:

$$\begin{aligned}
 \Delta \ln LABOUR_{i,t} = & \beta_0 + \beta_1 \Delta \ln SALES_{i,t} \\
 & + \beta_2 DEC_{i,t} \times \Delta \ln SALES_{i,t} \\
 & + \beta_3 \Delta \ln SALES_{i,t} \times SUC_DEC_{i,t} \\
 & + \beta_4 \Delta \ln SALES_{i,t} \times DEC_{i,t} \times SUC_DEC_{i,t} \\
 & + \beta_5 \Delta \ln SALES_{i,t} \times GDP_{n,t} \\
 & + \beta_6 \Delta \ln SALES_{i,t} \times DEC_{i,t} \times GDP_{n,t} \\
 & + \beta_7 \Delta \ln SALES_{i,t} \times AINT_{i,t} \\
 & + \beta_8 \Delta \ln SALES_{i,t} \times DEC_{i,t} \times AINT_{i,t} \\
 & + \beta_9 \Delta \ln SALES_{i,t} \times EINT_{i,t} \\
 & + \beta_{10} \Delta \ln SALES_{i,t} \times DEC_{i,t} \times EINT_{i,t} \\
 & + \varepsilon_{i,t}
 \end{aligned} \quad (1)$$

where $\Delta \ln LABOUR_{i,t}$ represents the ln-change in labour costs for firm i from year $t-1$ to year t and $\Delta \ln SALES_{i,t}$ displays the ln-change in net sales for firm i from year $t-1$ to year t . $DEC_{i,t}$ is an indicator variable which equals one if sales of firm i decrease from year $t-1$ to year t . Thus, the coefficient β_1 measures the percentage change in labour costs with a 1% increase in sales revenue, whereas the sum of the coefficients $\beta_1 + \beta_2$ measures the percentage change in labour costs with a 1% decrease in sales revenue. If labour costs display sticky behaviour, the change in labour costs for sales increases is

¹⁹ Prior studies state that using ratios and the ln-form provides several benefits, such as increasing the comparability of the variables between firms, reducing potential bias from heteroscedasticity, decreasing the model's sensitivity towards outliers and enabling an economically meaningful interpretation of the estimated coefficients as percentage changes (M. C. Anderson et al., 2003; Ibrahim et al., 2022).

²⁰ Additionally including the standalone control variables, i.e. estimating the fully interacted model, yields similar results (untabulated).

greater than the change in labour costs for sales decreases, implying that $\beta_2 < 0$, conditional on $\beta_1 > 0$ (M. C. Anderson et al., 2003). Consequently, if $\beta_2 > 0$ ($\beta_2 = 0$), labour costs would behave anti-sticky (symmetrical). The model includes the following firm- and country-level variables based on prior literature to control for economic determinants of asymmetric cost behaviour (M. C. Anderson et al., 2003; Cannon et al., 2020). $SUC_DEC_{i,t}$ is an indicator variable taking the value of one if sales of firm i decrease from year $t-2$ to year $t-1$ and from year $t-1$ to year t , i.e. in two consecutive periods. $GDP_{n,t}$ measures the percentage growth in GDP of country n during year t . Both $SUC_DEC_{i,t}$ and $GDP_{n,t}$ are employed as proxies for managerial expectations about future demand. To proxy the magnitude of adjustment costs, asset intensity ($AIN_{i,t}$) and employee intensity ($EINT_{i,t}$), measured as the ln of the ratio of assets or employees to sales of firm i in year t , are included as control variables. β_0 is the constant and $\varepsilon_{i,t}$ represents the error term. Appendix 3 provides detailed variable definitions.

The model is estimated using a random-effects generalized least squares (GLS) regression²¹ with robust standard errors clustered at the firm level, to account for the panel data structure and control for heteroscedasticity and autocorrelation. Given the inclusion of interaction terms, the model is tested for multicollinearity. The initial average variance inflation factor (VIF) exceeds the suggested cut-off value of 10 (VIF = 16.21). Mean-centring the continuous control variables (Banker et al., 2013; Cannon et al., 2020; Prabowo et al., 2018) reduces the VIF to 2.00 and thus effectively mitigates multicollinearity. Mean-adjusting additionally facilitates a straightforward interpretation of the main effects, implying that the coefficients on $\Delta \ln SALES_{i,t}$ ($\Delta \ln SALES_{i,t} \times DEC_{i,t}$) can be interpreted as the (incremental) change in labour costs for sales increases (decreases) of a firm that has average values of the continuous control variables (Cannon et al., 2020).

Difference-in-Differences model

The global and exogenous nature of the COVID-19-induced demand shock, as well as the broad cross-country variation in subsequent government interventions suggest the suitability of a difference-in-differences research design for investigating the relation between the stringency of government interventions and cost stickiness (Finne et al., 2024; Goodman-Bacon & Marcus, 2020). A DiD design can leverage quasi-experimental variation arising from the assumption of as-if random assignment to treatment and control and yields the advantage of reducing the likelihood that the estimated association is influenced by unobserved confounding factors. Therefore, an expanded model based on the DiD design of Cannon et al. (2020)²² is used to examine the

relation between the stringency of government interventions during COVID-19 and labour cost stickiness. The properties of the M. C. Anderson et al. (2003) model allow appending additional control variables as interaction terms (Ibrahim et al., 2022). Hence, the equation is complemented by the indicator variables $TREAT_n$ and $POST_t$, as well as the interaction term $TREAT_n \times POST_t$. The model includes the main effects, as well as two-, three- and four-way interactions²³. The following DiD regression specification is used to compare the changes in the degree of labour cost stickiness for firms subject to stringent government interventions from the pre- to the post-COVID-19-period (treatment firms) with the changes in the degree of labour cost asymmetry for firms not subject to stringent government interventions from the pre- to the post-COVID-19-period (control firms):

$$\begin{aligned} \Delta \ln LABOUR_{i,t} = & (\beta_0 + \beta_1 TREAT_n + \beta_2 POST_t \\ & + \beta_3 TREAT_n \times POST_t + \beta_4 CONTROLS_{i,t} / n,t) \\ & + (\gamma_0 + \gamma_1 TREAT_n + \gamma_2 POST_t + \gamma_3 TREAT_n \times POST_t \\ & + \gamma_4 CONTROLS_{i,t} \text{ or } n,t) \times DEC_{i,t} \\ & + (\delta_0 + \delta_1 TREAT_n + \delta_2 POST_t + \delta_3 TREAT_n \times POST_t \\ & + \delta_4 CONTROLS_{i,t} \text{ or } n,t) \times \Delta \ln SALES_{i,t} \\ & + (\theta_0 + \theta_1 TREAT_n + \theta_2 POST_t + \theta_3 TREAT_n \times POST_t \\ & + \theta_4 CONTROLS_{i,t} \text{ or } n,t) \times \Delta \ln SALES_{i,t} \times DEC_{i,t} \\ & + \lambda_i + \mu_t + \varepsilon_{i,t} \end{aligned} \quad (2)$$

$TREAT_n$ is an indicator variable that captures the degree of stringency of government interventions during COVID-19. Following an approach similar to the one used by Akter (2020), $TREAT_n$ equals one for observations from countries whose average stringency index over the COVID-19 period exceeds the median of all sample countries' average stringency indices during the same period²⁴. The treatment (control) group consequently consists of observations from countries with a comparably high (low) government stringency index. The assignment of firms to treatment versus control is assumed to be exogenous, as firms cannot choose to be treated or not, i.e. being headquartered in a country with higher or lower government stringency index during COVID-19, at least in the short-term. The indicator variable $POST_t$ is equal to one if the observation is from the COVID-19 period, i.e. 2020-2022, and is equal to zero if the observation stems from the pre-COVID-19 period, i.e. 2017-2019. The

²¹ Using an ordinary least squares (OLS) regression yields similar outcomes (untabulated).

²² Cannon et al. (2020) use a DiD analysis to examine the effect of a legislative shock, namely the enactment of M&A laws, on SG&A cost asymmetry.

²³ Cannon et al. (2020) include only $TREAT_n$ and $TREAT_n \times POST_t$, but do not consider the stand-alone variable $POST_t$ to avoid collinearity issues inherent in their setting. This study incorporates $POST_t$ and its corresponding interaction terms for completeness, thereby estimating the fully interacted model.

²⁴ One could claim that there is no 'true' control group, as all firms are exposed to the shock of government interventions during COVID-19. However, Atanasov and Black (2016) argue that DiD designs comparing strongly affected versus mildly affected firms are also valid.

outbreak of COVID-19 in 2020 thus constitutes also the point in time where the treatment comes into effect, although this represents a simplification of reality. $CONTROLS_{i,t} / n_{i,t}$ is a vector of the same conventional control variables as in Model (1), namely $SUC_DEC_{i,t}$, $GDP_{n,t}$, $AIN T_{i,t}$ and $EINT_{i,t}$.

Similar to the previously described Model (1), the coefficient on $\Delta \ln SALES_{i,t}$ (δ_0) captures labour costs' sensitivity towards sales increases, whereas the sum of the coefficient on $\Delta \ln SALES_{i,t}$ and $\Delta \ln SALES_{i,t} \times DEC_{i,t}$ ($\delta_0 + \theta_0$) displays labour costs' sensitivity towards sales decreases. θ_0 thus reflects the average degree of labour cost asymmetry in the full sample. The coefficient on $\Delta \ln SALES_{i,t} \times TREAT_n$ (δ_1) and the sum of the coefficients on $\Delta \ln SALES_{i,t} \times TREAT_n$ and $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times TREAT_n$ ($\delta_1 + \theta_1$) captures the difference in labour cost sensitivity towards sales increases and decreases, respectively, between the treatment and the control group. θ_1 thus reflects the average difference in the degree of labour cost asymmetry between firms headquartered in countries which initiated less versus more stringent government interventions during COVID-19. The coefficient on $\Delta \ln SALES_{i,t} \times POST_t$ (δ_2) and the sum of the coefficients on $\Delta \ln SALES_{i,t} \times POST_t$ and $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times POST_t$ ($\delta_2 + \theta_2$) measures the difference in labour costs' sensitivity towards sales increase and decreases, respectively, between the pre-treatment and the treatment period. θ_2 thus reflects the average difference in the degree of labour cost asymmetry between the pre-COVID-19 and the COVID-19 period. Finally, the coefficient on $\Delta \ln SALES_{i,t} \times POST_t \times TREAT_n$ (δ_3) and sum of the coefficients $\Delta \ln SALES_{i,t} \times POST_t \times TREAT_n$ (δ_3) and $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times POST_t \times TREAT_n$ ($\delta_3 + \theta_3$) captures the difference in changes in labour costs' sensitivity towards sales increases and decreases, respectively, from the pre-COVID-19 to the COVID-19 period, between the treatment and the control group. θ_3 thus represents the construct of interest. It displays the difference in the changes in labour cost stickiness from before to after the treatment year 2020 in firms headquartered in countries with stringent government interventions to the changes in labour cost stickiness from before to after the treatment year 2020 in firms located in countries with less stringent government interventions. As Hypothesis 2 is stated in a neutral form, there is no prediction on the sign of θ_3 . If θ_3 is positive (negative), there is a negative (positive) relation between the stringency of government interventions during COVID-19 and labour cost stickiness.

Following Cannon et al. (2020), a fixed effects model including firm- (λ_i) and year-fixed effects (μ_t)²⁵ is used to con-

trol for unobservable time-invariant firm characteristics and temporal factors. Robust standard errors are clustered at the country level²⁶ to reduce heteroscedasticity and autocorrelation. As in Model (1), the initial average VIF exceeds the threshold of 10 ($VIF = 23.15$) which indicates multicollinearity issues. After mean-centering the continuous control variables (Cannon et al., 2020), the VIF equals 8.80. Thus, the mean-centered variables are used in the following regression analysis.

The validity of a DiD design depends on the assumption of comparability of the treatment and the control group (Goodman-Bacon & Marcus, 2020) in the pre-treatment period. In other words, it depends on the fulfilment of the parallel pre-trends assumption, which requires that the difference in labour cost stickiness between firms in the treatment and the control group would remain constant in the absence of the treatment, i.e. stringent government interventions during COVID-19. To check this key assumption, a labour cost stickiness variable ($STICKY_t$) is created for each year for the treatment and the control group, respectively, and displayed graphically. The most common way to define a firm-level cost stickiness measure in the cost asymmetry literature is the approach of Weiss (2010). The author models $STICKY_t$ as the difference between the ratio of cost changes to sales changes of the most recent period with decreasing sales and the corresponding ratio of cost changes to sales changes of the most recent period with increasing sales, across the last four periods. As the sample of this study spans only six periods, i.e. years, in total, following the approach of Weiss (2010) is not feasible due to significant data loss. Thus, to create $STICKY_t$, this study uses an alternative, yet less common, model based on Zhang et al. (2022). Unlike Zhang et al. (2022) who do not include the main effect of $DEC_{i,t}$ and the two-way interaction term $\Delta \ln SALES_{i,t} \times SUC_DEC_{i,t}$, this study utilizes the following fully interacted model:

$$\begin{aligned} \Delta \ln LABOUR_{i,t} = & \beta_0 + \beta_1 \Delta \ln SALES_{i,t} + \beta_2 DEC_{i,t} \\ & + \beta_3 SUC_{i,t} + \beta_4 \Delta \ln SALES_{i,t} \times DEC_{i,t} \\ & + \beta_5 \Delta \ln SALES_{i,t} \times SUC_{i,t} \\ & + \beta_6 \Delta \ln SALES_{i,t} \times DEC_{i,t} \times SUC_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (3)$$

Consistent with Zhang et al. (2022), the model does not entail the control variables used by M. C. Anderson et al. (2003) with the exception of $SUC_DEC_{i,t}$ and defines $STICKY_t$ as the ratio of the coefficient on $\Delta \ln SALES_{i,t} \times DEC_{i,t}$ (β_4) to the coefficient on $\Delta \ln SALES_{i,t}$ (β_1)²⁷. For a more intuitive interpretation, the ratio of β_4/β_1 is multiplied by minus one (Zhang et al., 2022). Figure 2 indicates visually that the parallel pre-trends assumption can be confirmed²⁸.

The trends in labour cost stickiness between 2017 and 2019, i.e. in the pre-treatment period, are relatively paral-

²⁵ Including country-fixed effects likely results in removing variance related to the variable of interest $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times POST_t \times TREAT_n$, which is why this study refrains from doing so in the main analysis. It should be noted that omitting country-fixed effects raises the concern that treatment and control group differ in unobserved country-level characteristics which could confound the results. As expected, if country-fixed, industry-fixed, and year-fixed effects are included in the model as a robustness check like suggested by Cannon et al. (2020), the coefficient on $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times POST_t \times TREAT_n$ gets smaller ($\theta_3 = -0.153$, $p < 0.01$) and is only statistically significant in a regression specification without robust and clustered standard errors (untabulated).

²⁶ Unreported results confirm that the findings are robust to alternatively clustering standard errors at the firm-level.

²⁷ Zhang et al. (2022) argue that defining $STICKY_{i,t}$ as β_4/β_1 rather than β_4 on its own is beneficial because the ratio also accounts for labour costs' sensitivity to activity changes, i.e. cost elasticity, in general. However,

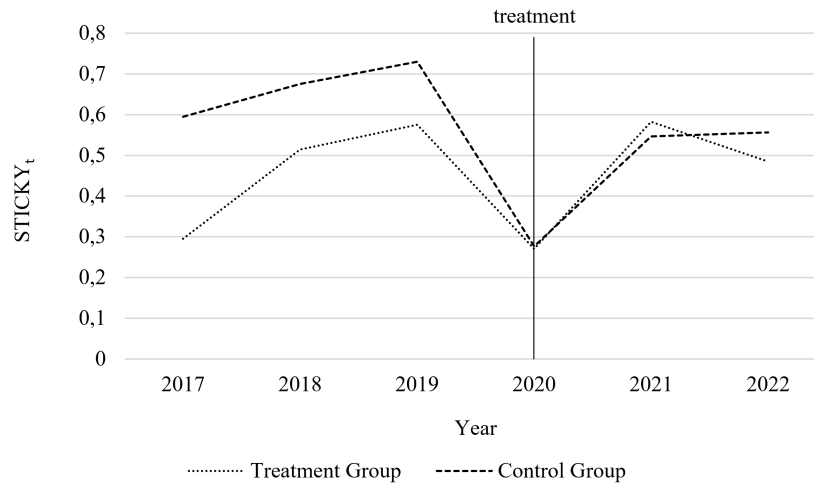


Figure 2: Graphical representation of the parallel pre-trends assumption

lel in the treatment and the control group until 2020. The graph indicates that the treatment group exhibits lower levels of labour cost stickiness compared to the control group before the outbreak of COVID-19 in 2020. With the outbreak of the pandemic, labour cost stickiness in both groups drops significantly. However, during the period from 2020 to 2021, the treatment group displays higher levels of cost stickiness, before falling below the cost stickiness level of the control group after 2021 once again.

Sample split

To test Hypothesis 2 and examine the potential moderating role of national culture in the relation between government interventions during COVID-19 and labour cost stickiness, Model (2) is re-estimated for various subsamples. Kitching et al. (2016) highlight that the six dimensions of national culture are highly correlated, which is also the case in this study's sample, as can be seen in Table 3. Thus, to avoid multicollinearity issues, the cultural dimensions are examined separately and not in a single model. Furthermore, including the cultural dimensions as control variables would involve using five-way-interaction terms, which complicates the interpretation of the coefficients (C. X. Chen et al., 2012). Therefore, based on prior research which uses the DiD methodology and examines moderation effects (e.g. Cannon et al., 2020; L. Chen et al., 2022), the sample is divided into two subsamples for each cultural dimension, using the dimensions' median. Observations with values greater

than or equal to the median represent the “high”-subsample, while observations with values less than the median make up the “low”-subsample. An indicator variable is used to assign the observations to either group. For example, PDI_high_n (PDI_low_n) is coded one if country n 's power distance score is above (below) the median value of power distance in the full sample, and zero otherwise. Subsequently, the DiD Model (2) is re-estimated for both groups in each of the six dimensions of national culture, namely PDI, IDV, MAS, UAI, LTO and IVR. To test Hypothesis 2, it is examined whether the coefficient on $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times POST_t \times TREAT_n$ (θ_3) varies between the high- and the low-subsample. To determine statistical significance, a z-test based on Clogg et al. (1995)²⁹ is used. If the difference between the coefficients $\theta_{3,high}$ and $\theta_{3,low}$ is statistically significant, this is an indication for national culture moderating the relation between the stringency of government interventions during COVID-19 and labour cost stickiness.

4. Results and discussion

4.1. Descriptive statistics and correlation results

Descriptive statistics

Panels A and B of Table 2 provide the descriptive statistics for the main firm- and country-level variables³⁰, including the respective mean, standard deviation, median and 25%- and 75%-percentiles.

Overall, the descriptive statistics are broadly similar to those of prior studies. However, since there is no study examining a current-period European sample, direct comparisons are hardly feasible. The mean value of labour costs

defining $STICKY_{i,t}$ as β_4 also yields similarly parallel pre-trends.

²⁸ Though, checking for covariate balance in the pre-treatment period reveals that the treatment and control groups' means of almost all variables differ statistically significantly, as can be seen in Appendix 4. By including the corresponding variables in the regression model, the baseline differences are adjusted for. However, even though the pre-treatment trends seem reasonably parallel, the covariate imbalance in the pre-treatment period might raise the concern that treatment and control might as well differ in unobservable characteristics, which would confound the results (Atanasov & Black, 2016).

²⁹ The z-Test following Clogg et al. (1995) is generally calculated as follows:

$$z = \frac{\hat{\beta}_1 - \hat{\beta}_2}{\sqrt{[s^2(\hat{\beta}_1) + s^2(\hat{\beta}_2)]}}$$

³⁰ For variable definitions see Appendix 3 The variables are presented without being mean-centered.

Table 2: Descriptive statistics

Panel A: Firm-level variables					
Variable	Mean	St. dev.	Q25	Q50	Q75
LABOUR _{<i>i,t</i>}	527.29	1,822.15	13.27	54.82	253.66
$\Delta \ln \text{LABOUR}_{i,t}$ [winsorized]	0.08	0.22	-0.02	0.06	0.15
SALES _{<i>i,t</i>}	2,980.00	12,400.00	59.16	251.52	1,273.63
$\Delta \ln \text{SALES}_{i,t}$ [winsorized]	0.09	0.31	-0.03	0.07	0.19
DEC _{<i>i,t</i>}	0.31	0.46	0.00	0.00	1.00
SUC_DEC _{<i>i,t</i>}	0.12	0.33	0.00	0.00	0.00
ASSETS _{<i>i,t</i>}	4,420.74	19,700.00	77.09	320.98	1,669.63
AIN _{<i>i,t</i>} [winsorized]	0.31	0.75	-0.17	0.20	0.66
EMPLOYEES _{<i>i,t</i>}	11,059	39,193	261	1,112	5,150
EINT _{<i>i,t</i>} [winsorized]	-5.43	0.87	-5.89	-5.37	-4.90
Panel B: Country-level variables					
Variable	Mean	St. dev.	Q25	Q50	Q75
GDP _{<i>n,t</i>} [winsorized]	1.83	4.32	1.12	2.29	4.35
SI _{<i>n</i>}	41.95	4.92	37.26	42.90	44.04
TREAT _{<i>n</i>}	0.66	0.48	0.00	1.00	1.00
POST _{<i>t</i>}	0.56	0.496	0.00	1.00	1.00
PDI _{<i>n</i>}	44.42	16.15	35.00	35.00	60.00
PDI_high _{<i>n</i>}	0.38	0.49	0.00	0.00	1.00
IDV _{<i>n</i>}	70.70	12.93	67.00	71.00	76.00
IDV_high _{<i>n</i>}	0.82	0.39	1.00	1.00	1.00
MAS _{<i>n</i>}	50.27	22.37	42.00	64.00	66.00
MAS_high _{<i>n</i>}	0.76	0.43	1.00	1.00	1.00
UAI _{<i>n</i>}	61.62	23.33	35.00	65.00	86.00
UAI_high _{<i>n</i>}	0.40	0.49	0.00	0.00	1.00
LTO _{<i>n</i>}	57.86	15.24	51.13	52.90	63.98
LTO_high _{<i>n</i>}	0.48	0.50	0.00	0.00	1.00
IVR _{<i>n</i>}	52.70	16.72	40.40	48.55	69.42
IVR_high _{<i>n</i>}	0.63	0.48	0.00	1.00	1.00
CASES _{<i>n</i>}	3,897.02	1,210.69	2,724.07	3,600.83	4,861.95
$\ln \text{CASES}_n$ [winsorized]	8.21	0.35	7.91	8.19	8.49
DEATHS _{<i>n</i>}	24.69	7.54	19.36	23.37	31.62
$\ln \text{DEATHS}_n$ [winsorized]	3.15	0.34	2.96	3.15	3.45
ES _{<i>n</i>}	48.96	13.40	35.15	56.14	56.80
$\ln \text{ES}_n$ [winsorized]	3.85	0.29	3.56	4.03	4.04

(LABOUR_{*i,t*}) is approximately 527.29 million euro. This corresponds to 17.7% of total sales revenue (SALES_{*i,t*}), which amounts to 2,980.00 million euro, on average. The pro-

portion of labour costs to sales is close to the one reported by Hassanein and Younis (2020), who present a ratio of 18.7% for chemical firms in the UK during the 2008 financial

crisis. The variables in monetary units are comparable to BenYoussef et al. (2023), who report average SG&A costs of 471.12 million dollar and average sales revenues of 2,669.08 million dollar for North American companies from 1999 to 2021. All variables reported in euro are heavily skewed to the right. However, this is again consistent with the descriptives of BenYoussef et al. (2023) and constitutes no issue as the ln-specification largely diminishes the skewedness. The average annual growth rate of ln-labour costs is 0.08 and the average annual growth rate of ln-sales is 0.09, which is comparable to the values reported by Cannon et al. (2020), who examine cost asymmetry in an international sample spanning the years 1984 to 2011³¹. $DEC_{i,t}$ has a mean value of 0.31, indicating that 31% of the firms in the sample experience a decrease in sales. Similarly, the mean value of 0.12 for $SUC_DEC_{i,t}$ shows that 12% of the sample firms experience a decrease in sales for two consecutive periods. This is roughly consistent with the descriptive statistics of Prabowo et al. (2018), whose sample entails firms from 22 European countries between 1993 and 2012. The firms included in the sample have on average 4,420.74 million euro in total assets ($ASSETS_{i,t}$) and employ 11,059 employees ($EMPLOYEES_{i,t}$), which is roughly equal to the sample firms in BenYoussef et al. (2023). The asset intensity ($AIN_{i,t}$) in this study is higher than in Cannon et al. (2020), whereas the employee intensity ($EINT_{i,t}$) is lower. This could, for example, reflect the high proportion of manufacturing firms in this study's sample, which exhibit high levels of fixed assets (Subramaniam & Weidenmier Watson, 2016) compared to service firms. Or it could indicate a shift toward increased automatization in the more recent sample, resulting in an increase in asset intensity and a decrease in employee intensity. The average annual GDP growth ($GDP_{n,t}$) is 1.83 percent, suggesting that even when considering the COVID-19 pandemic, the economic conditions in Europe in the sample period are generally positive. The countries in the sample have an average stringency index (SI_n) of 41.95, which is lower than the average SI of 62.66 for North America (BenYoussef et al., 2023). The mean of $TREAT_n$ indicates that 66% of the firms are in the treatment group, whereas the mean of $POST_t$ shows that 56% of the observations are from the COVID-19 period. This implies that the sample includes an adequately balanced number of observations from both treated and untreated firms, as well as from before and after the treatment, i.e. the year 2020. The statistics of the national culture dimensions are broadly consistent with Kitching et al. (2016) who examine an international sample in the period from 1990 to 2013³².

Correlation results

Panel A of Table 3 present the results of the Pearson correlation analysis, showing the relationships among the key variables from Model (1). Furthermore, it displays the correlations between the main variables and indicator variables for the years 2017 to 2020 in order to examine changes over time. Since the associations between the independent variables of interest and labour cost stickiness are not captured by standalone variables, but two-, three- and four-way interaction terms, no conclusions on Hypotheses 1 and 2 can be drawn from the correlation results.

As expected, $\Delta \ln LABOUR_{i,t}$ and $\Delta \ln SALES_{i,t}$ are significantly positively correlated (0.599, $p < 0.01$), indicating that a positive change in sales revenue is associated with a positive change in labour costs. $DEC_{i,t}$ and $SUC_DEC_{i,t}$ are negatively correlated to $\Delta \ln LABOUR_{i,t}$ (-0.416 , $p < 0.01$; -0.282 , $p < 0.01$), suggesting that a (successive) decrease in sales is negatively associated with labour cost growth. The correlation between some variables, such as $DEC_{i,t}$ and $\Delta \ln SALES_{i,t}$ is moderate to high (-0.602 , $p < 0.01$) which implies that multicollinearity should be controlled for to avoid issues related to it. The year indicators of the pre-COVID-19 period, i.e. $YEAR_2017_t$, $YEAR_2018_t$ and $YEAR_2019_t$, are not or only weakly correlated to $\Delta \ln LABOUR_{i,t}$, $\Delta \ln SALES_{i,t}$ and $GDP_{n,t}$. However, the indicator variable for the COVID-19 outbreak year 2020 ($YEAR_2020_t$), shows a moderate to strong negative correlation to those three variables and a positive correlation to $DEC_{i,t}$ and $SUC_DEC_{i,t}$. This might be an indication for the adverse economic effects induced by the COVID-19 pandemic, being reflected in declining average sales as well as falling GDP growth rates. Interestingly, the indicators for the years 2021 ($YEAR_2021_t$) and 2022 ($YEAR_2022_t$) depict a positive correlation with $\Delta \ln LABOUR_{i,t}$, $\Delta \ln SALES_{i,t}$, and $GDP_{n,t}$, suggesting that the overall economic condition rapidly resurged after the drop in 2020.

Panel B of Table 3 shows the associations between $TREAT_n$ and the various dimensions of national culture. All culture variables, except for long-term orientation (LTO_n) and individualism (IDV_n), are significantly correlated with each other, as stated by Kitching et al. (2016). It should be noted that all dimensions of national culture are significantly correlated to $TREAT_n$. This indicates an association between the various cultural dimensions and the likelihood of a country being in the treatment group, meaning its government imposing interventions more stringent than the median of all European countries' means in the sample. For example, as the correlation between LTO_n and $TREAT_n$ is positive and significant (0.328, $p < 0.01$), a government in a long-term oriented country is more likely to impose stringent interventions during COVID-19. In contrast, because the cor-

³¹ However, Cannon et al. (2020) examine SG&A cost stickiness instead of labour cost stickiness.

³² It should be noted that the means of the indicator variables for the cultural dimensions, for example PDI_high_n , differ from 0.5. This suggests that the number of observations with a PDI index higher than the median is unequal to the number of observations with a PDI index lower than the median. This disparity arises as some countries are more heavily represented than others, as can be seen in Appendix 2. Although restricting the

sample to countries with a similar number of observations would mitigate this imbalance, it would also result in significant data loss. Therefore, this study opts to retain the full dataset, acknowledging the unequal subsample sizes as a potential caveat.

relation between IVR_n is negative and significant (-0.149 , $p < 0.01$), a government in a country high in indulgence is less likely to impose stringent interventions. Thus, there is not just a potential moderating effect of national culture on the relation between stringency of government interventions and labour cost stickiness, but likely also a direct relation between national culture and governmental stringency during COVID-19. However, this is not the focus of this study and therefore not examined in further detail.

4.2. Analysis and discussion of the regression results

Basic model

In a first step, Model (1) is employed to assess whether labour costs in Europe are on average sticky, using the full sample which includes the years 2017 to 2022. Columns (I) and (II) of Table 4 present the regression results for the basic Model (1) with and without controls, respectively.

The results in column (I) show that labour costs in the sample behave sticky on average, as β_1 is positive and statistically significant ($\beta_1 = 0.431$, $p < 0.01$) and β_2 is negative and statistically significant ($\beta_2 = -0.110$, $p < 0.01$). This implies that labour costs increase by approximately 0.431% per 1% increase in sales and decrease by approximately $(0.431 - 0.110 =) 0.321\%$ per 1% decrease in sales. Moreover, the results are robust to controlling for determinants of cost stickiness used in prior studies, as shown in column (II). The significantly positive value of β_1 and the significantly negative value of β_2 continue to exist ($\beta_1 = 0.489$, $p < 0.01$; $\beta_2 = -0.084$, $p < 0.01$). However, the economic significance of the results could be questioned. Given the average sales of 2,980.00 million euro and the average labour costs of 527.29 million euro in the sample, a 29.8 million euro increase in sales (1% times 2,980.00 million euro) increases labour costs by 2.57 million euro (0.489% times 527.29 million euro), whereas a 29.8 million euro decrease in sales decreases labour costs by only 2.13 million euro ($(0.489 - 0.084 =) 0.405\%$ times 527.29 million euro), assuming that the company under consideration has average values for the continuous control variables. The difference of $(2.57 - 2.13 =) 0.44$ million euro between positive and negative labour cost changes in reaction to sales increases versus sales decreases is rather small, especially in comparison to the overall sales and labour cost figures. The potential lack of economic significance may be related to the magnitude of the coefficients being smaller than in prior studies. For example, Prabowo et al. (2018), who examine labour cost stickiness in a European sample with a similar model, report $\beta_1 = 0.673$ and $\beta_2 = -0.277$. The smaller magnitude of the coefficients could be attributed to the fact that this study's sample contains the COVID-19 pandemic, which prior research has found to decrease cost stickiness due to rising managerial pessimism about future demand.

The signs and magnitude of the control variables are largely consistent with theory and results of prior studies (e.g. M. C. Anderson et al., 2003; Prabowo et al., 2018). The

estimated coefficient on $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times SUC_DEC_{i,t}$ is positive and significant ($\beta_4 = 0.090$, $p < 0.01$), indicating that labour cost stickiness decreases when corporations experience declining sales in two consecutive periods. This is consistent with theory stating that managerial future expectations worsen if a sales drop continues to exist in the subsequent year. The coefficients on the interaction terms $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times GDP_{n,t}$ and $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times AINT_{i,t}$ are negative and significant ($\beta_6 = -0.005$, $p < 0.05$; $\beta_8 = -0.136$, $p < 0.01$), implying that cost stickiness increases in economic growth and asset intensity. Again, this is in line with previous research arguing that macroeconomic growth increases managers' optimism about future demand conditions and asset intensity rises adjustment costs, both of which result in higher levels of cost stickiness. In contrast to M. C. Anderson et al. (2003), this study finds a significantly positive coefficient on $\Delta \ln SALES_{i,t} \times DEC_{i,t} \times EINT_{i,t}$ ($\beta_{10} = 0.044$, $p < 0.05$). However, the fact that the sample period covers the COVID-19 pandemic might explain this result. Banker et al. (2020) claim that during an economic downturn, employment opportunities deteriorate, resulting in an oversupply of labour. This leaves firms in a good position to negotiate and allows them to increasingly rely on temporary workers, for which downward adjustments are less costly. Following the argumentation of C. X. Chen et al. (2012), corporations with greater labour intensity also employ a larger percentage of temporary workers, which might lead employee intensity to be negatively related to cost stickiness.

Although not shown in the tables, the inclusion of firm- and year- as well as country-, industry- and year-fixed effects to control for potentially unobserved factors yields similar results³³. The overall R-squared of Model (1) including control variables is similar to the adjusted R-squared reported by M. C. Anderson et al. (2003) and indicates that the model explains about 39.7% of the variance in labour cost changes.

To provide insights on whether there is a difference in labour cost stickiness before and during the COVID-19 pandemic and establish a starting point for further analysis, Model (1) is re-estimated for the pre-pandemic period and the pandemic period separately. Whereas observations from the years 2017 to 2019 constitute the pre-COVID-19 subsample, observations from the years 2020 to 2022 make up the COVID-19 subsample. This approach is based on prior literature that examines the influence of COVID-19 on cost stickiness (e.g. Liu and Jin, 2023). The regression results are reported in Table 5.

Column (I) shows the results for the sample which is restricted to the years prior to COVID-19, i.e. 2017-2019. They are qualitatively the same as the results reported for the full sample in Table 4. Most importantly, β_1 is positive and sta-

³³ Although the results of a Hausman (1978) test indicate that the fixed-effects model is more appropriate, this study reports the random effects model for consistency with M. C. Anderson et al. (2003). They used a random coefficient specification to test their regression model and report the fixed effects model only as a robustness check.

Table 3: Correlation results

Panel A: Main variables related to Model (1)													
	$\Delta \ln$ $LABOUR_{i,t}$	$\Delta \ln$ $SALES_{i,t}$	$DEC_{i,t}$	SUC_{-} $DEC_{i,t}$	$GDP_{n,t}$	$ANNT_{i,t}$	$EINT_{i,t}$	$YEAR_{-}$ 2017_t	$YEAR_{-}$ 2018_t	$YEAR_{-}$ 2019_t	$YEAR_{-}$ 2020_t	$YEAR_{-}$ 2021_t	$YEAR_{-}$ 2022_t
$\Delta \ln LABOUR_{i,t}$	1.000												
$\Delta \ln SALES_{i,t}$	0.599*	1.000											
$DEC_{i,t}$	-0.416*	-0.602*	1.000										
$SUC_{-}DEC_{i,t}$	-0.281*	-0.345*	0.560*	1.000									
$GDP_{n,t}$	0.125*	0.190*	-0.209*	-0.090*	1.000								
$ANNT_{i,t}$	-0.014	-0.178*	0.115*	0.089*	-0.024*								
$EINT_{i,t}$	-0.079*	-0.092*	0.107*	0.060*	-0.023*	0.134*	1.000						
$YEAR_{2017_t}$	-0.036*	-0.024*	-0.005	-0.024*	0.082*	-0.051*	0.013	1.000					
$YEAR_{2018_t}$	-0.027*	-0.025*	0.001	0.021*	0.019	-0.046*	0.012	-0.161*	1.000				
$YEAR_{2019_t}$	-0.005	-0.040*	0.010	0.006	0.000	-0.022*	0.012	-0.171*	-0.182*	1.000			
$YEAR_{2020_t}$	-0.137*	-0.187*	0.247*	0.111*	-0.807*	0.053*	0.039*	-0.179*	-0.190*	-0.203*	1.000		
$YEAR_{2021_t}$	0.029*	0.081*	-0.068*	0.006	0.511*	0.053*	-0.001	-0.188*	-0.199*	-0.213*	-0.222*	1.000	
$YEAR_{2022_t}$	0.162*	0.179*	-0.175*	-0.115*	0.182*	0.001	-0.068*	-0.193*	-0.204*	-0.218*	-0.228*	-0.240*	1.000
Panel B: Main variables related to Model (2)													
	$TREAT_{SI_n}$	PDI_n	IDV_n	MAS_n	UAL_n	LTO_n	IVR_n						
$TREAT_{SI_n}$	1.000												
PDI_n	0.116*	1.000											
IDV_n	0.263*	-0.422*	1.000										
MAS_n	0.498*	0.074*	0.212*	1.000									
UAL_n	0.108*	0.816*	-0.654*	0.221*	1.000								
LTO_n	0.328*	0.025*	-0.011	0.301*	0.191*	1.000							
IVR_n	-0.149*	-0.623*	0.541*	-0.318*	-0.804*	-0.251*	1.000						

* indicates two-tailed significance at the 1 percent level.

Table 4: Regression results Model (1) – basic model

Variables	(I)	(II)
	Without controls	With controls
$\Delta \ln SALES_{i,t} (\beta_1)$	0.431*** (0.014)	0.489*** (0.014)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} (\beta_2)$	-0.110*** (0.023)	-0.084*** (0.032)
$\Delta \ln SALES_{i,t} \times SUC_DEC_{i,t} (\beta_3)$		<i>omitted</i> (.)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} \times SUC_DEC_{i,t} (\beta_4)$		0.090*** (0.030)
$\Delta \ln SALES_{i,t} \times GDP_{n,t} (\beta_5)$		-0.001 (0.002)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} \times GDP_{n,t} (\beta_6)$		-0.005** (0.003)
$\Delta \ln SALES_{i,t} \times AINT_{i,t} (\beta_7)$		-0.087*** (0.014)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} \times AINT_{i,t} (\beta_8)$		-0.136*** (0.017)
$\Delta \ln SALES_{i,t} \times EINT_{i,t} (\beta_9)$		0.083*** (0.012)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} \times EINT_{i,t} (\beta_{10})$		0.044** (0.018)
Constant (β_0)	0.039*** (0.002)	0.037*** (0.002)
Number of observations	15,446	15,446
R^2 (overall)	0.364	0.397

Robust standard errors clustered at the firm-level are reported in parentheses.

*, **, *** indicate two-tailed significance at the 10 percent, 5 percent, and 1 percent levels.

tistically significant ($\beta_1 = 0.559$, $p < 0.01$) and β_2 is negative and statistically significant ($\beta_2 = -0.205$, $p < 0.01$), which implies that labour costs in the pre-COVID-19 period are on average sticky. The magnitude of both β_1 and β_2 is larger in the pre-COVID-19 sample than in the full sample and now more comparable to the coefficients reported in prior research (e.g. Prabowo et al., 2018). This confirms the previously made supposition that the full samples' coefficients on $\Delta \ln SALES_{i,t}$ and $\Delta \ln SALES_{i,t} \times DEC_{i,t}$ are smaller than those reported in previous studies due to the inclusion of the COVID-19 crisis in the sample period. Now economic significance is more likely given as well. Assuming average sales of 2,980.00 million euro and average labour costs of 527.29 million euro, a 29.8 million euro increase in sales (1% times 2,980.00 million euro) increases labour costs by 2.95 million

euro (0.559% times 527.29 million euro), whereas a 29.8 million euro decrease in sales decreases labour costs by only 1.87 million euro ((0.559 - 0.205 =) 0.354% times 527.29 million euro), assuming that the company under consideration has average values for the continuous control variables.

Column (II) reports the results for the sample which is restricted to the COVID-19 years, i.e. 2020 to 2022. The coefficient on $\Delta \ln SALES_{i,t}$ (β_1) remains positive and statistically significant ($\beta_1 = 0.482$, $p < 0.01$). Interestingly, its size is smaller compared to the pre-COVID-19 subsample, which indicates a decline in firms' cost elasticity for sales increases during the pandemic. A pairwise comparison of the coefficients of interest using a z-test based on Clogg et al. (1995) confirms the statistical significance of the difference between the coefficients (2.502, $p < 0.05$). This finding contrasts

Table 5: Regression results pre-COVID-19 versus COVID-19 period

Variables	(I) Pre-COVID-19 period	(II) COVID-19 period
$\Delta \ln SALES_{i,t} (\beta_1)$	0.559*** (0.026)	0.482*** (0.017)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} (\beta_2)$	-0.205*** (0.057)	-0.054 (0.039)
$\Delta \ln SALES_{i,t} \times SUC_DEC_{i,t} (\beta_3)$	<i>omitted</i> (.)	<i>omitted</i> (.)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} \times SUC_DEC_{i,t} (\beta_4)$	0.126** (0.061)	0.076** (0.035)
$\Delta \ln SALES_{i,t} \times GDP_{n,t} (\beta_5)$	0.000 (0.016)	-0.001 (0.002)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} \times GDP_{n,t} (\beta_6)$	-0.020 (0.025)	-0.004 (0.003)
$\Delta \ln SALES_{i,t} \times AINT_{i,t} (\beta_7)$	-0.134*** (0.025)	-0.068*** (0.015)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} \times AINT_{i,t} (\beta_8)$	-0.148*** (0.028)	-0.138*** (0.020)
$\Delta \ln SALES_{i,t} \times EINT_{i,t} (\beta_9)$	0.137 (0.024)	0.051*** (0.013)
$\Delta \ln SALES_{i,t} \times DEC_{i,t} \times EINT_{i,t} (\beta_{10})$	0.033 (0.031)	0.055*** (0.021)
Constant (β_0)	0.026*** (0.003)	0.036*** (0.003)
Z-Value (difference of β_1 between pre-COVID-19 and COVID-19 subsample)		2.502**
Z-Value (difference of β_2 between pre-COVID-19 and COVID-19 subsample)		-2.185**
Number of observations	6,786	8,660
R^2 (overall)	0.373	0.413

Robust standard errors clustered at the firm-level are reported in parentheses.

*, **, *** indicate two-tailed significance at the 10 percent, 5 percent, and 1 percent levels.

with previous studies that report increased levels of cost elasticity, interpreted as a lower proportion of fixed to variable costs, during periods of heightened risk and uncertainty (e.g. Holzhacker et al., 2015a). Firms with a cost structure characterized by a high proportion of fixed costs, or in other words lower cost elasticity, are argued to require higher levels of activity to break even, compared to firms with higher cost elasticity (Holzhacker et al., 2015b). Consequently, firms increase their cost elasticity in times of crises, to be in a better position to avoid economic losses. However, unlike studies

focusing on cost elasticity in general, this study distinguishes between cost behaviour for sales increases versus decreases. Therefore, the results are not directly comparable. Detached from the definition of cost elasticity as measuring the proportion of fixed to variable costs, the size of the coefficient on $\Delta \ln SALES_{i,t}$ can also be interpreted as reflecting the magnitude of managers' resource expansions in response to sales growth (e.g. Cannon et al., 2020; Ma et al., 2021). In this context, the findings could indicate that the COVID-19 pandemic increases managerial pessimism about future demand

expectations in general, and the uncertainty about the duration of the sales growth in particular. Managers might be more likely to take a cautious ‘wait and see’-approach and, for example, delay (re-)hiring employees, even if sales increase. Hence, the observed decrease in cost elasticity when sales rise and the increase of cost elasticity when sales fall (i.e., the decrease in cost stickiness) during the pandemic in this study can be reconciled with the cost elasticity literature’s view that firms adjust their resources to improve flexibility when uncertainty is high.

As can be seen in columns (I) and (II) respectively, the coefficient on $\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t}$ is negative and significant ($\beta_2 = -0.205$, $p < 0.01$) in the pre-COVID-19 sample, whereas it is close to zero and statistically insignificant ($\beta_2 = -0.054$, $p > 0.1$) in the COVID-19 sample. The statistical significance of the difference between the coefficients in the pre-COVID-19 and the COVID-19 subsample is confirmed by a z-test (-2.185 , $p < 0.05$). Hence, during the pandemic, there is no difference in the magnitude of labour cost changes between sales increases and decreases like in the pre-COVID-19 period. Consequently, the COVID-19 subsample shows no indication of labour cost stickiness, on average. This in line with theory and the findings of prior literature (e.g. Ghazy et al., 2024; Kwak et al., 2021) which suggest that the uncertainty during the pandemic increases managers’ pessimism about the duration of the sales decline and incentivizes corporate decision-makers to discard unused resources. These results on cost elasticity and cost stickiness before and during the COVID-19 pandemic constitute the starting point for further analyses and interpretations.

Difference-in-differences model

Table 6 presents the regression results for Model (2) which examines the relation between the stringency of government interventions during COVID-19 and labour cost stickiness.

Like in Model (1) the coefficients on $\Delta \ln \text{SALES}_{i,t}$ and $\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t}$ are significantly positive ($\delta_0 = 0.507$, $p < 0.01$) and negative ($\theta_0 = -0.262$, $p < 0.01$), respectively. Hence, the results reconfirm that labour costs in the full sample are on average sticky. This implies that labour costs increase by 0.507% per 1% increase in sales and decrease by ($\delta_0 + \theta_0 = 0.507 - 0.262 =$) 0.245% per 1% decrease in sales, on average.

The coefficient on $\text{TREAT}_n \times \Delta \ln \text{SALES}_{i,t}$ (δ_1) is not statistically significant ($\delta_1 = -0.108$, $p > 0.1$), showing that for sales increases, there is no significant difference in cost elasticity between treatment and control group, on average. The coefficient on $\text{TREAT}_n \times \Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t}$ is positive and statistically significant ($\theta_1 = 0.191$, $p < 0.1$). This implies that labour cost stickiness is, on average, significantly lower in the treatment group than in the control group over the full sample period, as can be seen in the graphical representation of STICKY_t in Figure 2 as well. However, the difference in the pre-treatment period is controlled for by utilizing the DiD design, assuming that parallel pre-trends exist. It should be

noted that the variable TREAT_n (β_1) is omitted when estimating the model due to the simultaneous inclusion of firm-fixed effects. The effect of TREAT_n is absorbed by the firm-fixed effects because a firm’s assignment to the treatment or control group is constant over the sample period, as long as the location of a firm’s headquarters remains the same, which is the case in this study. To avoid collinearity issues, TREAT_n is automatically dropped (Cannon et al., 2020).

The coefficient on $\text{POST}_t \times \Delta \ln \text{SALES}_{i,t}$ is negative, but insignificant ($\delta_2 = -0.039$, $p > 0.1$), implying that cost elasticity for sales increases during the pandemic is not significantly different than in the pre-COVID-19 period. However, the coefficient on $\text{POST}_t \times \Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t}$ is positive and statistically significant ($\theta_2 = 0.258$, $p < 0.01$) and hence supports the finding of prior literature that labour cost stickiness decreases with the outbreak of COVID-19. Thus, as of 2020, labour costs increase on average by approximately ($\delta_0 + \delta_2 = 0.507 - 0.039 =$) 0.468% per 1% increase in sales and decrease by approximately ($\delta_0 + \delta_2 + \theta_0 + \theta_2 = 0.507 - 0.039 - 0.262 + 0.258 =$) 0.464% per 1% decrease in sales. Consistent with the results shown in Table 5, this highlights that labour cost stickiness is no longer present following the outbreak of COVID-19. During the pandemic, labour costs behave symmetrically for sales increases and sales decreases. This supports the argumentation of prior authors who claim that COVID-19 induces uncertainty that, in turn, increases managerial pessimism about the duration of the decline in sales and is therefore negatively related to cost stickiness.

Hypothesis 1 states that there is no relation between the stringency of government interventions during COVID-19 and labour cost stickiness, as theory predicts opposing directions of the association. However, the coefficient on $\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t} \times \text{TREAT}_n \times \text{POST}_t$ is negative and statistically significant ($\theta_3 = -0.260$, $p < 0.05$), showing that treatment firms exhibit significantly higher levels of labour cost stickiness after the treatment, i.e. the implementation of stringent government interventions during COVID-19, than control firms, when holding everything else equal. Thus, for a 1% decrease in sales after the treatment, treatment firms exhibit a ($|\delta_3 + \theta_3| = |0.117 - 0.260| =$) 0.143 percentage point lower decrease in labour costs than the control firms, after accounting for pre-treatment trends. This indicates that treatment firms’ labour costs are less sensitive to negative sales changes after the treatment. Put into an economic context, this means that the difference in labour cost sensitivity to sales decreases after 2020 between treatment and control group is approximately half as large as the average labour cost sensitivity to sales decreases in the full sample ($58.37\% = 0.143\% / 0.245\% = (|0.117 - 0.260|) / (|0.507 - 0.262|) = (|\delta_3 + \theta_3|) / (\delta_0 + \theta_0)$). Additionally, the DiD coefficient on $\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t} \times \text{TREAT}_n \times \text{POST}_t$ (θ_3) is comparable in magnitude to DiD coefficients in previous studies which are deemed economically significant (e.g. Cannon et al., 2020; L. Chen et al., 2022).

The coefficient on $\Delta \ln \text{SALES}_{i,t} \times \text{TREAT}_n \times \text{POST}_t$ is positive and statistically significant ($\delta_3 = 0.117$, $p < 0.1$), im-

Table 6: Regression results Model (2) – difference-in-differences model

Variables	
<i>Main effects</i>	
<i>Constant</i> (β_0)	0.047*** (0.008)
<i>TREAT_n</i> (β_1)	<i>omitted</i> (.)
<i>POST_t</i> (β_2)	-0.0369* (0.020)
<i>SUC_DEC_{i,t}</i> ($\beta_{4,a}$)	-0.010 (0.008)
<i>GDP_{n,t}</i> ($\beta_{4,b}$)	-0.003 (0.002)
<i>AINT_{i,t}</i> ($\beta_{4,c}$)	0.014 (0.013)
<i>EINT_{i,t}</i> ($\beta_{4,d}$)	0.088*** (0.015)
<i>DEC_{i,t}</i> (γ_0)	-0.021** (0.010)
$\Delta \ln \text{SALES}_{i,t}$ (δ_0)	0.507*** (0.060)
<i>Two-way interaction terms</i>	
<i>TREAT_nxPOST_t</i> (β_3)	-0.008 (0.013)
<i>TREAT_nxDEC_{i,t}</i> (γ_1)	-0.003 (0.016)
<i>TREAT_nxΔ ln SALES_{i,t}</i> (δ_1)	-0.108 (0.084)
<i>POST_txDEC_{i,t}</i> (γ_2)	0.020 (0.012)
<i>POST_txΔ ln SALES_{i,t}</i> (δ_2)	-0.039 (0.047)
<i>SUC_{i,t}xDEC_{i,t}</i> ($\gamma_{4,a}$)	<i>omitted</i> (.)
<i>GDP_{n,t}xDEC_{i,t}</i> ($\gamma_{4,b}$)	0.000 (0.001)
<i>AINT_{i,t}xDEC_{i,t}</i> ($\gamma_{4,c}$)	0.010** (0.004)

Table 6 — continued

<i>EINT_{i,t}xDEC_{i,t}</i> ($\gamma_{4,d}$)	0.005 (0.006)
<i>SUC_DEC_{i,t}xΔ ln SALES_{i,t}</i> ($\delta_{4,a}$)	0.067 (0.043)
<i>GDP_{n,t}xΔ ln SALES_{i,t}</i> ($\delta_{4,b}$)	0.001 (0.003)
<i>AINT_{i,t}xΔ ln SALES_{i,t}</i> ($\delta_{4,c}$)	-0.099*** (0.015)
<i>EINT_{i,t}xΔ ln SALES_{i,t}</i> ($\delta_{4,d}$)	0.072*** (0.017)
$\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t}$ (θ_0)	-0.262*** (0.073)
<i>Three-way interaction terms</i>	
<i>TREAT_nxPOST_txDEC_{i,t}</i> (γ_3)	-0.004 (0.014)
<i>TREAT_nxPOST_txΔ ln SALES_{i,t}</i> (δ_3)	0.117* (0.066)
<i>TREAT_nxΔ ln SALES_{i,t}xDEC_{i,t}</i> (θ_1)	0.191* (0.096)
<i>POST_txΔ ln SALES_{i,t}xDEC_{i,t}</i> (θ_2)	0.258*** (0.081)
<i>SUC_DEC_{i,t}xΔ ln SALES_{i,t}xDEC_{i,t}</i> ($\theta_{4,a}$)	<i>omitted</i> (.)
<i>GDP_{n,t}xΔ ln SALES_{i,t}xDEC_{i,t}</i> ($\theta_{4,b}$)	-0.005 (0.003)
<i>AINT_{i,t}xΔ ln SALES_{i,t}xDEC_{i,t}</i> ($\theta_{4,c}$)	0.006 (0.020)
<i>EINT_{i,t}xΔ ln SALES_{i,t}xDEC_{i,t}</i> ($\theta_{4,d}$)	0.010 (0.031)
<i>Four-way interaction term</i>	
$\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t} \times \text{TREAT}_n \times \text{POST}_t$ (θ_3)	-0.260** (0.119)
Firm-fixed effects	Yes
Year-fixed effects	Yes
Number of observations	15,446
<i>R</i> ² (overall)	0.284

Robust standard errors clustered at the country-level are reported in parentheses.

*, **, *** indicate two-tailed significance at the 10 percent, 5 percent, and 1 percent levels.

plying that treatment firms, headquartered in countries with a higher stringency index, exhibit significantly higher levels of cost elasticity for sales increases after the treatment than control firms do. Hence, for an 1% increase in sales after the

treatment, i.e. after the outbreak of COVID-19, treatment firms exhibit a ($\delta_3 =$) 0.117 percentage point higher increase in labour costs than the control firms, after accounting for pre-treatment trends. This implies that treatment firms'

labour costs are more sensitive to positive sales changes than control firms' labour costs after the treatment.³⁴

Summarizing, the negative sign of θ_3 suggests a positive relation between the stringency of government interventions during COVID-19 and labour cost stickiness. Thus, Hypothesis 1 can be rejected. This result is in line with the strand of the finance literature which argues that stringent government interventions signal effective pandemic control to investors. Hence, also corporate decision-makers' perceived uncertainty is argued to be reduced, which leads them to form more optimistic expectations about future demand. Managers are consequently more inclined to expand labour resources, i.e. hire new employees or increase the existing employees' working hours, in response to sales increases as they believe in the permanence of the sales growth. At the same time, managers are less likely to divest labour resources, i.e. fire employees or reduce their working hours when sales decrease, because they expect sales drops to be only temporary. Consequently, the results indicate that stringent government interventions diminish the COVID-19 induced pessimism and the resulting decrease in labour cost stickiness to some extent.

It should be noted that the result contradicts the findings of Ghazy et al. (2024) and BenYoussef et al. (2023), who report that the stringency of government interventions during COVID-19 is positively associated to cost anti-stickiness, or in other words, negatively associated to cost stickiness. However, there are some differences between their research methodologies and the one of this study which might explain the differing results. BenYoussef et al. (2023, p. 14) use a different dependent variable, focusing on abnormal SG&A costs, which they define as the "discrepancy between the actual SG&A cost and an out-of-sample forecast from a benchmark model similar to the framework [...] proposed by M. C. Anderson et al. (2003) [...]", instead of the logarithmic change in labour costs. Ghazy et al. (2024) define the independent variable as strictness of workplace closure, a variable ranging from zero (no measures) to three (closure of all but essential workplace such as hospitals or grocery stores). Furthermore, Ghazy et al. (2024) do not attempt to proxy governmental stringency, but rather overall COVID-19-induced uncertainty. Both studies examine operating costs instead of labour costs. Moreover, they both analyse North American firms, whereas this study focuses on a European sample. Lastly, their sample periods span the years 2020 to 2021 (Ghazy et al., 2024) and 1999 to 2021 (BenYoussef et al., 2023) respectively, which

differs from the sample period examined in this study.

Robustness checks

To be considered valid, a DiD design must fulfil the only-through condition (Atanasov & Black, 2016, p. 217), implying that "the shock must be 'isolated' – there must be no other shock, at around the same time, that could also affect treated firms differently than control firms". However, it could be argued that this is not the case in this study's setting. Given that the treatment coincides with the outbreak of the COVID-19 pandemic in 2020, it is likely that additional shocks, which may differently affect the treatment and control group, occur simultaneously. To mitigate this endogeneity concern, two robustness checks are conducted. This study follows Akter (2020) and BenYoussef et al. (2023) in adding COVID-19 cases and COVID-19-related deaths, as well as the degree of governmental economic support during COVID-19 as additional variables³⁵ to Model (2).

Greater exposure to the pandemic, measured by COVID-19 cases and deaths, might be a confounding factor as it could lead governments to implement stricter interventions (Pulejo & Querubín, 2021) and simultaneously may induce declining cost stickiness resulting from increased managerial pessimism about future demand (Ghazy et al., 2024). Thus, the natural logarithm of country-level cumulated COVID-19 cases as well as COVID-19 related deaths per 10,000 population³⁶ over the entire COVID-19 period are added as controls (Akter, 2020).

The degree of governmental economic support should also be controlled for, as it is shown to be correlated with the stringency of governmental interventions and it is likely associated with managerial optimism about future demand, as managers might expect governmental economic support to mitigate potential negative effects of stringent measures on the economy (Alfano et al., 2022). Hence, a country's average economic support index over the entire COVID-19 period, measuring the degree of income support, debt and contract relief, fiscal stimuli and international support, is included in Model (2). Table 7 shows the results of the robustness checks³⁷.

As can be seen in column (I) and column (II), respectively, the coefficient of interest on the four-way interaction term

³⁴ The difference-in-difference estimators for cost elasticity and cost stickiness, i.e. δ_3 and θ_3 , can also be calculated based on the remaining coefficients (see for example Jiménez and Perdiguer, 2019). They are computed as follows: $\delta_3 = 0.117 = [(\delta_0 + \delta_1 + \delta_2 + \delta_3) - (\delta_0 + \delta_1)] - [(\delta_0 + \delta_2) - \delta_0] = [(0.507 + (-0.108) + (-0.039) + 0.117) - (0.507 + (-0.108))] - [(0.507 + (-0.039)) - 0.507]$ and $\theta_3 = -0.260 = [(\theta_0 + \theta_1 + \theta_2 + \theta_3) - (\theta_0 + \theta_1)] - [(\theta_0 + \theta_2) - \theta_0] = [((-0.262) + 0.191 + 0.258 + (-0.260)) - ((-0.262) + 0.191)] - [((-0.262) + 0.258) - (-0.262)]$. Hence, these estimators represent the difference in the change in labour cost sensitivity to sales increases and sales decreases, respectively, from the pre-treatment to the post-treatment period in the treatment group, relative to the corresponding change in the control group.

³⁵ For consistency, the additional control variables are mean-centred and transformed to the ln-form and are added to the model as main variables as well as two- and three-way interactions.

³⁶ Data on the number of COVID-19 cases and COVID-19 related deaths is obtained from the OxCGRT database. The population data used to scale cases and deaths is drawn from the World Bank website (<https://data.worldbank.org/indicator/SPPOPTOTL>).

³⁷ The additional control variables $\ln CASES_n$, $\ln DEATHS_n$ and $\ln ES_n$ are defined as cumulated ($\ln CASES_n$ and $\ln DEATHS_n$) or average ($\ln ES_n$) values over the entire COVID-19 period. This is done for consistency with the assignment of firms to the treatment or control group based on the mean value of their headquarter country's stringency index over the same period. However, as untabulated results show, including $\ln CASES_{n,t}$, $\ln DEATHS_{n,t}$ and $\ln ES_{n,t}$ based on yearly values yields similar outcomes.

Table 7: Regression results Model (2) with additional controls

Variables	(I) Including $\ln \text{CASES}_n$ and $\ln \text{DEATHS}_n$	(II) Including $\ln \text{ES}_n$
<i>Main effects</i>		
Constant(β_0)	0.054 (0.095)	-0.018 (0.036)
$TREAT_n$ (β_1)	omitted (.)	omitted (.)
$POST_t$ (β_2)	omitted (.)	omitted (.)
$SUC_DEC_{i,t}$ ($\beta_{4,a}$)	-0.010 (0.007)	-0.010 (0.007)
$GDP_{n,t}$ ($\beta_{4,b}$)	-0.003** (0.001)	-0.003** (0.007)
$AIN T_{i,t}$ ($\beta_{4,c}$)	0.014 (0.012)	0.014 (0.012)
$EINT_{i,t}$ ($\beta_{4,d}$)	0.089*** (0.014)	0.088*** (0.014)
$\ln \text{CASES}_n$ ($\beta_{4,e}$)	0.003 (0.017)	
$\ln \text{DEATHS}_n$ ($\beta_{4,f}$)	-0.003 (0.016)	
$\ln \text{ES}_n$ ($\beta_{4,g}$)		-0.030* (0.017)
$DEC_{i,t}$ (γ_0)	-0.113 (0.124)	0.063 (0.051)
$\Delta \ln \text{SALES}_{i,t}$ (δ_0)	0.519 (0.440)	0.793*** (0.180)
<i>Two-way interaction terms</i>		
$TREAT_n \times POST_t$ (β_3)	-0.008 (0.014)	0.002 (0.012)
$TREAT_n \times DEC_{i,t}$ (γ_1)	-0.003 (0.013)	-0.004 (0.013)
$TREAT_n \times \Delta \ln \text{SALES}_{i,t}$ (δ_1)	-0.109* (0.063)	-0.109* (0.063)
$POST_t \times DEC_{i,t}$ (γ_2)	0.181 (0.214)	-0.120 (0.086)
$POST_t \times \Delta \ln \text{SALES}_{i,t}$ (δ_2)	-0.052 (0.756)	-0.523* (0.302)
$SUC_{i,t} \times DEC_{i,t}$ ($\gamma_{4,a}$)	omitted (.)	omitted (.)
$GDP_{n,t} \times DEC_{i,t}$ ($\gamma_{4,b}$)	0.000 (0.001)	0.000 (0.001)
$AIN T_{i,t} \times DEC_{i,t}$ ($\gamma_{4,c}$)	0.009** (0.008)	0.010 (0.008)
$EINT_{i,t} \times DEC_{i,t}$ ($\gamma_{4,d}$)	0.004 (0.006)	0.004 (0.006)
$\ln \text{CASES}_n \times DEC_{i,t}$ ($\gamma_{4,e}$)	-0.019 (0.022)	
$\ln \text{DEATHS}_n \times DEC_{i,t}$ ($\gamma_{4,f}$)	-0.002 (0.022)	

Table 7 — continued

$\ln \text{ES}_n \times DEC_{i,t}$ ($\gamma_{4,g}$)		0.039* (0.023)
$SUC_DEC_{i,t} \times \Delta \ln \text{SALES}_{i,t}$ ($\delta_{4,a}$)	omitted (.)	0.068* (0.039)
$GDP_{n,t} \times \Delta \ln \text{SALES}_{i,t}$ ($\delta_{4,b}$)	0.001 (0.004)	0.000 (0.004)
$AIN T_{i,t} \times \Delta \ln \text{SALES}_{i,t}$ ($\delta_{4,c}$)	-0.099*** (0.021)	-0.096*** (0.021)
$EINT_{i,t} \times \Delta \ln \text{SALES}_{i,t}$ ($\delta_{4,d}$)	0.070*** (0.019)	0.071*** (0.019)
$\ln \text{CASES}_n \times \Delta \ln \text{SALES}_{i,t}$ ($\delta_{4,e}$)	-0.019 (0.080)	
$\ln \text{DEATHS}_n \times \Delta \ln \text{SALES}_{i,t}$ ($\delta_{4,f}$)	0.054 (0.072)	
$\ln \text{ES}_n \times \Delta \ln \text{SALES}_{i,t}$ ($\delta_{4,g}$)		0.133* (0.080)
$\Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ (θ_0)	0.329 (0.651)	-0.513** (0.262)
<i>Three-way interaction terms</i>		
$TREAT_n \times POST_t \times DEC_{i,t}$ (γ_3)	0.002 (0.021)	-0.016 (0.019)
$TREAT_n \times POST_t \times \Delta \ln \text{SALES}_{i,t}$ (δ_3)	0.107 (0.082)	0.071 (0.076)
$TREAT_n \times \Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ (θ_1)	0.194* (0.109)	0.191* (0.108)
$POST_t \times \Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ (θ_2)	-0.763 (1.119)	0.682 (0.439)
$SUC_DEC_{i,t} \times \Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ ($\theta_{4,a}$)	0.066* (0.038)	omitted (.)
$GDP_{n,t} \times \Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ ($\theta_{4,b}$)	-0.004 (0.005)	-0.004 (0.005)
$AIN T_{i,t} \times \Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ ($\theta_{4,c}$)	0.004 (0.032)	0.004 (0.032)
$EINT_{i,t} \times \Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ ($\theta_{4,d}$)	0.013 (0.032)	0.012 (0.030)
$\ln \text{CASES}_n \times \Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ ($\theta_{4,e}$)	0.143 (0.116)	
$\ln \text{DEATHS}_n \times \Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ ($\theta_{4,f}$)	-0.040 (0.113)	
$\ln \text{ES}_n \times \Delta \ln \text{SALES}_{i,t} \times DEC_{i,t}$ ($\theta_{4,g}$)		-0.116 (0.116)
<i>Four-way interaction term</i>		
$\Delta \ln \text{SALES}_{i,t} \times DEC_{i,t} \times TREAT_n \times POST_t$ (θ_3)	-0.306** (0.135)	-0.221* (0.120)
Firm-fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
Number of observations	15,446	15,446
R^2 (overall)	0.283	0.285

Robust standard errors clustered at the firm-level are reported in parentheses.

*, **, *** indicate two-tailed significance at the 10 percent, 5 percent, and 1 percent levels.

$\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t} \times \text{TREAT}_n \times \text{POST}_t$ remains negative and significant after controlling for pandemic affectedness ($\theta_3 = -0.306, p < 0.05$) and governmental economic support ($\theta_3 = -0.221, p < 0.1$). These results indicate that the positive association between stringent government interventions during COVID-19 and labour cost stickiness continues to exist after controlling for factors that change simultaneously with the treatment and hence could constitute alternative explanations for the change in labour cost stickiness. It should be noted that the variable POST_t is omitted from the model due to perfect collinearity with the additional controls, since their values are zero before the outbreak of COVID-19. Furthermore, the results reveal that the coefficient on $\ln \text{ES}_n \times \Delta \ln \text{SALES}_{i,t}$ is positive and statistically significant ($\delta_{4,g} = 0.133, p < 0.1$), indicating a positive relation between governmental economic support and cost elasticity for sales increases. This might be the case as managers expect economic support to enhance customers' purchasing power, which reduces their pessimism about future demand and thus results in increased resource extension, such as (re-)hirings, during periods of sales growth. All other additional control variables as well as their interaction terms, except for $\ln \text{ES}_n$ and $\ln \text{ES}_n \times \text{DEC}_{i,t}$ which cannot be interpreted economically meaningful, lack statistical significance.

Sample split

After analysing the association between a formal institution and labour cost stickiness, this study investigates whether an informal institution, namely national culture, has a moderating role in this relation. If evidence in line with national culture moderating the relation between the stringency of government interventions during COVID-19 and labour cost stickiness is found, this could also explain why the results in Table 6 show a positive association between stringent government interventions and cost stickiness, although theory provides contradictory predictions regarding the direction.

Model (2) is re-estimated for the high- and low-subsample for each dimension of national culture, i.e. PDI, IDV, MAS, UAI, LTO and IVR. Table 8 presents the results. Similarly to the findings shown in Table 4 and Table 6, the coefficients on $\Delta \ln \text{SALES}_{i,t}$ (δ_0) and $\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t}$ (θ_0) are significantly positive and negative, respectively, across both the high and the low subsample for most of the dimensions of national culture³⁸. This reconfirms the prior finding that labour costs are on average sticky. However, the size of the coefficient on $\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t}$ (θ_0) differs between the high- and the low-subsample for some dimensions of national culture, indicating that national culture is directly related to the level of labour cost stickiness. These findings are in line with Banker et al. (2014, p. 224) who state that while behavioural factors, such as culture, "do not affect the general structure of asymmetric cost behaviour, they can either accentuate or diminish its magnitude". The coefficients diverge most in terms

of absolute magnitude between the high- and low-subsample of the dimensions MAS ($\theta_{0, \text{high}} = -0.209, p < 0.05$ and $\theta_{0, \text{low}} = -0.366, p < 0.05$), UAI ($\theta_{0, \text{high}} = -0.230, p < 0.05$ and $\theta_{0, \text{low}} = -0.305, p < 0.05$) and LTO ($\theta_{0, \text{high}} = -0.072, p > 0.1$ and $\theta_{0, \text{low}} = -0.290, p < 0.01$). Thus, labour cost stickiness is found to be lower in firms headquartered in countries which exhibit high levels in masculinity, uncertainty-avoidance or long-term orientation. This aligns with the results of Kitching et al. (2016), who report a negative relation between cost stickiness and masculinity, high uncertainty avoidance, and long-term orientation as well. They explain the findings by stating that in masculine societies, managers tend to be "assertive, tough, and focused on material success" (Kitching et al., 2016, p. 406), which reduces psychological adjustment costs, such as those associated with firing employees, leading to lower levels of cost stickiness. Furthermore, decision-makers with high uncertainty avoidance are more loss-averse and prone to anticipating worst-case scenarios for future demand, resulting in decreased cost stickiness. Finally, Kitching et al. (2016) argue, that managers with a strong long-term orientation have a strong propensity for thriftiness (Hofstede et al., 2010) and are thus more inclined to cut costs when sales decline. However, it must be noted that the results of a z-Test, which assesses the statistical significance of the difference between the two coefficients $\theta_{0, \text{high}}$ and $\theta_{0, \text{low}}$, are only significant for the dimensions MAS and LTO and only if the regression is re-estimated without robust or clustered standard errors. Table 8 displays the z-values and the associated statistical significance based on a two-tailed p-value both for the regression with robust and country-clustered standard errors and the regression without them (in brackets). The limited statistical significance of the differences may indicate a low economic significance, which must be considered when interpreting the results.

Next to the direct association between national culture and cost stickiness, the results suggests that national culture might moderate the relation between stringent government interventions during COVID-19 and labour cost stickiness, in contrast to Hypothesis 2 that claims the absence of a moderating relationship. The coefficient on the interaction term of interest $\Delta \ln \text{SALES}_{i,t} \times \text{DEC}_{i,t} \times \text{TREAT}_n \times \text{POST}_t$ (θ_3) varies between the high- and the low-subsample for most of the dimensions of national culture. For example, whereas θ_3 is statistically significantly negative for the low-subsample of PDI ($\theta_{3, \text{high}} = -0.165, p > 0.1$ and $\theta_{3, \text{low}} = -0.378, p < 0.01$), UAI ($\theta_{3, \text{high}} = -0.163, p > 0.1$ and $\theta_{3, \text{low}} = -0.381, p < 0.01$), LTO ($\theta_{3, \text{high}} = -0.122, p > 0.1$ and $\theta_{3, \text{low}} = -0.299, p < 0.1$) and IVR ($\theta_{3, \text{high}} = -0.238, p > 0.1$ and $\theta_{3, \text{low}} = -0.328, p < 0.05$), it has a smaller magnitude and is statistically insignificant for the high-subsamples of these cultural dimensions. Hence, the results indicate that the positive relation of stringent government interventions during COVID-19 and labour cost stickiness is amplified in firms headquartered in countries with low levels of power distance, uncertainty avoidance, long-term orientation or indulgence, but attenuated in firms headquartered in countries with high

³⁸ Only in the high-LTO-subsample θ_0 is not statistically significant.

levels of the respective dimensions. For the MAS dimension, the situation is reversed. Whereas the positive relation between stringent government interventions during COVID-19 and labour cost stickiness holds for cultures high in masculinity, it does not for more feminine ones ($\theta_{3, high} = -0.264$, $p < 0.05$ and $\theta_{3, low} = -0.715$, $p > 0.1$). Lastly, for the IDV dimension, the relation between stringent government interventions during COVID-19 and cost stickiness is negative and significant for both the high- and the low-subsample. However, the coefficient is smaller for the individualistic subsample than for the collectivistic one ($\theta_{3, high} = -0.283$ $p < 0.1$ and $\theta_{3, low} = -0.389$, $p < 0.05$).

The results largely align with the findings of Dheer et al. (2021) and J. Lee et al. (2024)³⁹. Thus, they are also in line with the hypothesized argumentation that managers which accept stringent government interventions during COVID-19 as legitimate are more likely to have a positive outlook on future demand and are thus more inclined to keep resources in a situation of declining demand. In conclusion, managers' increased acceptance of governmental stringency results in increasing levels of cost stickiness. For the sake of brevity, not all dimensions of national culture are considered in detail, but an overview on the chain of argumentation is provided based on two dimensions⁴⁰. For instance, as J. Lee et al. (2024) state, masculine cultures tend to prefer assertiveness and directive leadership and are therefore more likely to accept stringent policies as a legitimate response to the COVID-19 outbreak. Consequently, managers in masculine cultures might interpret the stringency of governmental interventions during COVID-19 as a positive signal which increases their optimism about future demand expectations. This is reflected by the results, which show that stringent government interventions during COVID-19 are positively related to labour cost stickiness only in more masculine, but not in more feminine countries. Furthermore, people in high uncertainty avoidance cultures are more averse towards change and risk, which makes them less willing to accept stringent government interventions (Dheer et al., 2021), as they constitute severe incisions in peoples' lives but are uncertain to be effective. Thus, managers in firms which are headquartered in countries high in uncertainty avoidance might ques-

tion the inventions' legitimacy and thus draw less optimistic conclusions from stringent government interventions. Ultimately, this results in lower levels of labour cost stickiness, which is reflected in the coefficient of interests, θ_3 , being insignificant in the high UAI subsample, but significant in the low UAI subsample.

Again, the z-Test which measures the between-sample difference in coefficients is only statistically significant in a regression specification without robust and clustered standard errors and only for the dimension MAS and UAI. This might raise doubts about the economic significance of the findings. Consequently, the results should not be interpreted causally, but only as an indication for a moderating role of national culture on the relation between stringent government interventions during COVID-19 and labour cost stickiness, especially considering the unequal sizes of the subsamples. Nevertheless, as the magnitude and the significance of the coefficients themselves is unchanged in both specifications, i.e. with and without robust and clustered standard errors, this study argues that overall, the results still support the notion that national culture moderates the relationship between stringent government interventions during COVID-19 and labour cost stickiness. Hence, Hypothesis 2, which claims the lack of a moderating role, is rejected.

Interestingly, these findings might also explain, as previously suggested, why the relationship between stringent government interventions during COVID-19 and labour cost stickiness is positive in the full sample, although theory predicts two opposing directions which were hypothesized to potentially cancel each other out. For example, the overall sample tends to be lower in PDI, UAI and LTO with less than 50% of the observations having a score above the median. However, this study's sample is comparably high in MAS, with 76 percent of the observations having a score above the median (which can be seen in Table 2). Hence, the full sample contains a comparably large number of observations from firms headquartered in countries having national cultures that are associated with a positive moderating role on the relationship between stringent government interventions and COVID-19, which could be the reason for the overall positive relation in the full sample⁴¹.

5. Limitations and possibilities for future research

This study is subject to several limitations, most of them being related to the utilized DiD methodology. Firstly, the treatment variable is considered to be binary, despite being continuous in fact. Countries are assigned to either the treatment or the control group based on whether their average governmental stringency index during the COVID-19

³⁹ Whereas Dheer et al. (2021) examine the moderating effect of national culture on the relation between stringent government interventions and COVID-19 case growth, J. Lee et al. (2024) examine whether the six dimensions of culture strengthen or weaken the negative relation between stringent government interventions and mobility.

⁴⁰ It should be noted, that unlike for IDV, MAS, UAI and IVR, the results for the dimension PDI and LTO do not align with the expectations based on prior literature. Both Dheer et al. (2021) and J. Lee et al. (2024) argue that high power distance and long-term orientation is positively related to the acceptance of stringent government interventions. Oppositely, the findings of this study suggest that managers in low power distance countries and short-term oriented cultures derive more positive inferences from stringent government interventions, resulting in higher levels of labour cost stickiness. However, the results can be reconciled with Hofstede et al. (2010) who state that individuals in low power distance cultures are more inclined to pro-social acts like donating blood, and short-term oriented cultures put an emphasis on the fulfilment of social obligations.

⁴¹ It should be noted that the sample also tends to be comparably high in IDV and IVR, with more than 50% of the observations having a score above the respective median. Both IDV and IVR are found to diminish the positive relation between the stringency of government interventions and labour cost stickiness. However, this is expected to be outweighed by the relatively large number of observations from low PDI, UAI and LTO and high MAS countries.

Table 8: Regression results Model (2) high- versus low-subsample of various dimensions of national culture

Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
<i>Main effects</i>												
Constant (β_0)	0.036 ^{***} (0.009)	0.049 ^{***} (0.014)	0.050 ^{***} (0.010)	0.011 (0.015)	0.037 ^{***} (0.010)	0.064 ^{***} (0.013)	0.038 ^{***} (0.009)	0.047 ^{***} (0.014)	0.060 ^{***} (0.007)	0.034 ^{**} (0.013)	0.045 ^{***} (0.012)	0.042 ^{**} (0.016)
TREAT _n (β_1)	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
POST _t (β_2)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
SUC_DEC _t ($\beta_{4,d}$)	-0.028 (0.032)	-0.032 (0.024)	-0.030 (0.025)	-0.052 ^{**} (0.022)	-0.039 [*] (0.019)	-0.044 [*] (0.022)	-0.036 (0.026)	-0.031 (0.025)	-0.007 (0.014)	-0.054 [*] (0.028)	-0.047 (0.027)	-0.024 (0.023)
GDP _{n,t} ($\beta_{4,b}$)	-0.001 (0.020)	-0.017 ^{**} (0.006)	-0.010 (0.006)	-0.012 (0.037)	-0.017 [*] (0.009)	0.014 (0.016)	-0.005 (0.018)	-0.016 ^{***} (0.006)	-0.003 (0.011)	-0.019 (0.014)	-0.013 (0.008)	-0.005 (0.020)
AIN _{T_t} ($\beta_{4,c}$)	0.001 (0.002)	-0.005 ^{***} (0.001)	-0.003 (0.002)	-0.001 (0.002)	-0.003 (0.002)	0.001 (0.004)	0.001 (0.002)	-0.005 ^{***} (0.001)	0.002 (0.002)	-0.006 ^{**} (0.002)	-0.005 ^{**} (0.002)	0.001 (0.001)
EIN _{T_t} ($\beta_{4,d}$)	-0.015 (0.023)	0.021 (0.014)	0.022 [*] (0.012)	-0.037 (0.034)	-0.004 (0.013)	0.053 [*] (0.027)	-0.014 (0.021)	0.020 (0.015)	0.009 (0.011)	0.018 (0.020)	0.029 [*] (0.016)	-0.018 (0.021)
DEC _t (γ_0)	0.109 ^{***} (0.025)	0.071 ^{***} (0.016)	0.073 ^{***} (0.016)	0.120 ^{***} (0.029)	0.095 ^{***} (0.015)	0.051 (0.046)	0.111 ^{***} (0.024)	0.068 ^{***} (0.016)	0.087 ^{***} (0.023)	0.091 ^{***} (0.022)	0.075 ^{***} (0.017)	0.107 ^{***} (0.026)
$\Delta \ln \text{SALES}_{i,t}$ (δ_0)	-0.027 (0.023)	-0.020 [*] (0.010)	-0.018 (0.011)	-0.029 [*] (0.013)	-0.044 ^{***} (0.011)	-0.016 [*] (0.008)	-0.032 (0.022)	-0.018 (0.010)	-0.014 (0.023)	-0.022 ^{**} (0.008)	-0.017 (0.010)	-0.040 ^{**} (0.016)
$\Delta \ln \text{SALES}_{i,t}$ (δ_1)	0.403 ^{***} (0.071)	0.548 ^{***} (0.064)	0.566 ^{***} (0.062)	0.356 ^{***} (0.048)	0.389 ^{***} (0.042)	0.598 ^{***} (0.065)	0.400 ^{***} (0.068)	0.553 ^{***} (0.064)	0.424 ^{***} (0.022)	0.522 ^{***} (0.074)	0.549 ^{***} (0.064)	0.377 ^{***} (0.061)
<i>Two-way interaction terms</i>												
TREAT _n xPOST _t (β_3)	0.006 (0.021)	-0.014 (0.017)	-0.014 (0.012)	0.011 (0.027)	0.010 (0.017)	0.012 (0.029)	0.004 (0.021)	-0.012 (0.018)	-0.017 (0.014)	0.013 (0.015)	-0.005 (0.011)	-0.001 (0.022)
TREAT _n xDEC _t (γ_1)	0.017 (0.030)	-0.007 (0.013)	-0.010 (0.014)	0.066 ^{**} (0.027)	0.025 (0.017)	0.023 (0.015)	0.025 (0.029)	-0.009 (0.013)	0.004 (0.023)	-0.001 (0.018)	-0.016 (0.013)	0.039 [*] (0.018)
TREAT _n x $\Delta \ln \text{SALES}_{i,t}$ (δ_1)	0.132 (0.092)	-0.242 ^{***} (0.077)	-0.195 ^{**} (0.086)	0.253 ^{**} (0.091)	0.005 (0.071)	-0.067 (0.125)	0.137 (0.090)	-0.251 ^{***} (0.077)	0.009 (0.091)	-0.152 (0.107)	-0.187 ^{**} (0.078)	0.073 (0.122)

Table 8 — continued

$POST_{it}xDEC_{it}(\gamma_2)$	0.031 (0.022)	0.019 (0.012)	0.021* (0.011)	0.026 (0.022)	0.041*** (0.013)	0.006 (0.013)	0.031 (0.023)	0.019 (0.012)	0.008 (0.020)	0.028* (0.013)	0.021 (0.013)	0.042** (0.015)
$POST_{it}x\Delta\ln SALES_{it}(\beta_2)$	0.013 (0.045)	-0.061 (0.056)	-0.052 (0.058)	0.032 (0.047)	0.014 (0.025)	-0.079 (0.046)	0.009 (0.049)	-0.058 (0.056)	0.049 (0.031)	-0.056 (0.055)	-0.061 (0.056)	0.031 (0.045)
$SUC_DEC_{it}xDEC_{it}(\gamma_{4,d})$	omitted (.)	omitted (.)	omitted (.)	omitted (.)	omitted (.)	omitted (.)	omitted (.)	omitted (.)	omitted (.)	omitted (.)	omitted (.)	omitted (.)
$GDP_{it}xDEC_{it}(\gamma_{4,b})$	-0.002 (0.001)	0.002** (0.001)	0.001 (0.001)	-0.003* (0.001)	0.001 (0.001)	-0.005* (0.002)	-0.001 (0.001)	0.002* (0.001)	-0.000 (0.001)	0.001 (0.002)	0.001 (0.001)	-0.001 (0.002)
$AINT_{it}xDEC_{it}(\gamma_{4,c})$	0.013 (0.010)	0.007 (0.006)	0.009** (0.004)	0.007 (0.019)	0.009* (0.005)	0.011 (0.009)	0.009 (0.010)	0.010* (0.005)	0.005 (0.007)	0.009 (0.007)	0.008 (0.005)	0.013 (0.010)
$EINT_{it}xDEC_{it}(\gamma_{4,d})$	0.010 (0.012)	0.002 (0.007)	0.005 (0.006)	0.006 (0.018)	0.011 (0.007)	-0.007 (0.010)	0.011 (0.011)	0.002 (0.007)	0.018*** (0.005)	-0.004 (0.010)	0.002 (0.006)	0.009 (0.012)
$SUC_DEC_{it}x\Delta\ln SALES_{it}(\beta_{4,d})$	0.011 (0.050)	0.089 (0.070)	0.092* (0.051)	-0.026 (0.100)	0.020 (0.049)	0.241*** (0.038)	omitted (.)	omitted (.)	omitted (.)	0.035 (0.072)	0.059 (0.064)	0.071 (0.069)
$GDP_{it}x\Delta\ln SALES_{it}(\beta_{4,b})$	-0.003 (0.004)	0.005** (0.002)	0.002 (0.003)	-0.002 (0.004)	0.002 (0.003)	-0.009 (0.009)	-0.002 (0.004)	0.004** (0.002)	-0.003 (0.006)	0.002 (0.003)	0.002 (0.004)	0.001 (0.003)
$AINT_{it}x\Delta\ln SALES_{it}(\beta_{4,c})$	-0.108*** (0.032)	-0.092*** (0.014)	-0.111*** (0.017)	-0.079 (0.045)	-0.116*** (0.017)	-0.046** (0.019)	-0.109*** (0.031)	-0.087*** (0.015)	-0.147*** (0.017)	-0.071*** (0.016)	-0.097*** (0.015)	-0.109*** (0.034)
$EINT_{it}x\Delta\ln SALES_{it}(\beta_{4,d})$	0.084*** (0.027)	0.077*** (0.020)	0.085*** (0.021)	0.052*** (0.014)	0.065*** (0.018)	0.131*** (0.017)	0.075** (0.026)	0.083*** (0.021)	0.094*** (0.023)	0.064** (0.022)	0.079*** (0.024)	0.079*** (0.021)
$\Delta\ln SALES_{it}xDEC_{it}(\theta_0)$	-0.240** (0.092)	-0.292** (0.099)	-0.296** (0.102)	-0.276** (0.112)	-0.209** (0.074)	-0.366** (0.124)	-0.230** (0.092)	-0.305** (0.099)	-0.072 (0.176)	-0.290** (0.087)	-0.264** (0.102)	-0.256** (0.094)
Three-way interaction terms												
$TREAT_{it}xPOST_{it}xDEC_{it}(\gamma_3)$	-0.016 (0.026)	-0.003 (0.014)	-0.004 (0.012)	-0.039 (0.043)	-0.026* (0.012)	-0.018 (0.047)	-0.017 (0.026)	-0.005 (0.015)	0.001 (0.022)	-0.019 (0.016)	-0.004 (0.015)	-0.037* (0.019)
$TREAT_{it}xPOST_{it}x\Delta\ln SALES_{it}(\beta_3)$	-0.037 (0.058)	0.206** (0.066)	0.156* (0.075)	-0.129 (0.116)	0.073 (0.052)	-0.061 (0.221)	-0.034 (0.059)	0.205** (0.066)	-0.002 (0.069)	0.152 (0.085)	0.147 (0.084)	0.027 (0.078)
$TREAT_{it}x\Delta\ln SALES_{it}xDEC_{it}(\beta_3)$	0.012 (0.105)	0.339** (0.113)	0.251* (0.122)	0.226* (0.107)	0.155 (0.092)	0.674* (0.322)	0.011 (0.106)	0.348** (0.114)	-0.021 (0.194)	0.258* (0.121)	0.222 (0.237)	0.155 (0.088)

Table 8 — continued

$POST_{it} \times \Delta \ln SALES_{it} \times DEC_{it} (\theta_2)$	0.314*** (0.069) omitted	0.265** (0.097) omitted	0.268** (0.104) omitted	0.255*** (0.071) omitted	0.265*** (0.030) omitted	0.230** (0.095) omitted	0.308*** (0.061) 0.002	0.264** (0.097) 0.096	0.151 (0.098) 0.092** (0.035)	0.259** (0.094) omitted	0.267** (0.101) omitted	0.268** (0.102) omitted
$SUC_DEC_{it} \times \Delta \ln SALES_{it} \times DEC_{it} (\theta_{4,a})$	(.)	(.)	(.)	(.)	(.)	(.)	(0.050)	(0.071)	(0.035)	(.)	(.)	(.)
$GDP_{it} \times \Delta \ln SALES_{it} \times DEC_{it} (\theta_{4,b})$	-0.002 (0.006)	-0.003 (0.003)	-0.001 (0.003)	-0.014 (0.011)	-0.003 (0.003)	-0.015 (0.015)	-0.003 (0.006)	-0.002 (0.003)	-0.004 (0.007)	-0.003 (0.003)	-0.002 (0.003)	-0.013* (0.007)
$AMT_{it} \times \Delta \ln SALES_{it} \times DEC_{it} (\theta_{4,c})$	0.035 (0.037)	-0.018 (0.021)	0.011 (0.022)	-0.034 (0.041)	0.017 (0.022)	-0.040 (0.037)	0.033 (0.037)	-0.018 (0.021)	0.033 (0.032)	-0.009 (0.020)	0.003 (0.022)	0.014 (0.043)
$EINT_{it} \times \Delta \ln SALES_{it} \times DEC_{it} (\theta_{4,d})$	0.048 (0.038)	-0.028 (0.042)	-0.030 (0.038)	0.172** (0.032)	0.030 (0.027)	-0.097 (0.054)	0.063 (0.037)	-0.042 (0.045)	0.012 (0.038)	-0.001 (0.052)	-0.014 (0.044)	0.029 (0.048)
Four-way interaction term												
$\Delta \ln SALES_{it} \times DEC_{it} \times TREAT_{it} \times POST_{it} (\theta_5)$	-0.165 (0.134)	-0.378** (0.107)	-0.283* (0.142)	-0.389** (0.170)	-0.264** (0.096)	-0.715 (0.519)	-0.163 (0.128)	-0.381*** (0.107)	-0.122 (0.169)	-0.299* (0.141)	-0.238 (0.176)	-0.328** (0.108)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	5,864	9,582	12,618	2,828	11,791	3,655	6,144	9,302	7,365	8,081	9,774	5,672
R^2	0.268	0.305	0.311	0.264	0.266	0.378	0.264	0.310	0.266	0.296	0.308	0.250
Z-Value (difference of θ_0 between high and low subsample)	0.387 [0.521]	-0.131 [-0.180]			1.085 [1.642*]		0.551 [0.752]		1.116 [1.750*]		-0.059 [-0.079]	
Z-Value (difference of θ_3 between high and low subsample)	1.240 [1.630]	0.477 [0.593]			0.854 [2.026**]		1.309 [1.686*]		0.806 [1.186]		0.438 [0.671]	

Robust standard errors clustered at the country-level are reported in parentheses.

*, **, *** indicate two-tailed significance at the 10 percent, 5 percent, and 1 percent levels.

Z-values in brackets are based on a regression specification without robust and clustered standard errors.

period is higher than the median of all sample countries' average stringency indices. This approach creates only two groups – the 'higher stringency group' and the 'lower stringency group' – although the actual variation in the degree of stringency is much broader. Secondly, it is assumed that the degree of stringency remains constant over the entire COVID-19 period. However, the stringency of government interventions may also change over time. For example, governments might impose restrictions cautiously at early stages when infections are low but increase stringency as COVID-19 cases rise (Pulejo & Querubín, 2021). To address these caveat, future research could utilize more sophisticated models, such as continuous (Morris et al., 2023) or staggered (Mader & Rüttenauer, 2022) DiD designs. Furthermore, a typical limitation of multinational samples is cross-country heterogeneity, which introduces an increased risk of omitted variable bias, thus making the comparison of firm-level measures across countries more difficult (Cannon et al., 2020; Ma et al., 2021). As shown in *Appendix 4*, covariate balance between treated and control firms prior to the treatment is questionable. The results of the t-test and the Kolmogorov-Smirnov test reveal statistically significant differences in the means and distributions of most variables, indicating that treated and control firms differ significantly in several observable characteristics during the pre-treatment period. Thus, the concern arises that firms headquartered in countries with more stringent government interventions might differ from firms headquartered in countries with less stringent government interventions in unobserved characteristics as well. Consequently, the study might be subject to omitted variables which could confound the results. Future studies might perform matching methods prior to conducting the analyses to improve covariate balance⁴². Additionally, although the study controls for pandemic affectedness and governmental economic support in a robustness check, there might be further time-varying confounding variables that influence treatment and control group differently. In summary, the results do not allow to draw conclusions about causal effects. As it is acknowledged that certain methodological issues remain unsolved, this study cannot go beyond demonstrating evidence on associations.

There are limitations unrelated to the DiD design as well. One caveat inherent in using financial data for cost stickiness research is that labour expenses and sales are imperfect proxies for economic labour costs and activity levels, because they might also be affected by accounting rules or price changes (Brüggen & Zehnder, 2014). Moreover, the study assumes that only the stringency of interventions in the firm's headquarters country is relevant for managers' decision-making. Though, many firms conduct business Europe- or worldwide and rely heavily on geographically

expansive supply chains. Therefore, the stringency of government interventions in other countries could also influence managerial decision-making and, consequently, labour cost stickiness. To mitigate this issue, future research could apply this study's methodology to a sample of private instead of publicly listed firms, since they might operate more nationally. Furthermore, national culture may not necessarily influence managerial behaviour and decision-making in the assumed way. Neither is it clear that the managers' nationality or country of residence coincides with the location of the firm's headquarters, nor is it possible to rule out that managers' behaviour is also influenced by other factors such as corporate culture, education or past experiences (Kitcing et al., 2016). As BenYoussef et al. (2023) and Brüggen and Zehnder (2014) suggest, future research could aim at assessing cognitive processes underlying managerial decisions more directly by using methods such as surveys or laboratory experiments. Lastly, this study is only able to present an indication of the moderating role of culture on the relation between stringent government interventions during COVID-19 and labour cost stickiness, as the statistical significance of the differences between the cultural characteristics is not given in all regression specifications. Thus, the results should be treated cautiously and motivate future research to deepen research in this field, for example by investigating whether the positive association between stringent government interventions and labour cost stickiness also exists for other regions with different cultural backgrounds, such as America or Asia.

6. Conclusion

This study is conducted to examine how formal and informal country-level institutions are associated with corporate cost behaviour within the COVID-19 context. Specifically, it aims at answering the research questions of how the stringency of government interventions during COVID-19 is related to labour cost stickiness and whether national culture moderates this relation. To accomplish that, the study investigates a sample of 15,446 firm-year observations of 3,383 publicly listed firms from 25 European countries in the period 2017 to 2022. First, this study empirically tests for the existence of labour cost stickiness in the sample and finds, in line with prior literature, that labour costs are sticky on average. Next, the level of labour cost stickiness before and after the outbreak of the COVID-19 pandemic in 2020 is compared. This study finds that the sticky behaviour of labour costs disappears after 2020, aligning with theory as well as previous research findings which state that the COVID-19-induced uncertainty increases managerial pessimism about future demand. Furthermore, this study provides evidence of a positive association between stringent government interventions during COVID-19 and labour cost stickiness, while controlling for known economic determinants of cost asymmetry. Using a DiD model, the study shows that firms headquartered in countries with stringent government interventions during the pandemic exhibit higher labour cost sensitivity towards

⁴² This study refrains from employing matching methods due data availability constraints. As the sample is unbalanced and the sample period covers only six years, variance in the data is not large enough to compute a firm-level score for labour cost stickiness using Model (1) or Model (3) for a sufficiently high number of observations on which matching based on a labour cost stickiness score could be performed.

sales increases and lower labour cost sensitivity towards sales decreases after 2020, compared to firms headquartered in countries with less stringent government interventions during COVID-19. This is consistent with the argument that stringent government interventions signal the governments' ability to effectively manage the pandemic, which in turn increases managerial optimism about future demand conditions. Hence, managers from firms located in countries with stringent government interventions during COVID-19 are more likely to view sales growths as permanent and sales drops as temporary, resulting in increased levels of labour cost elasticity for sales increases and increased levels of labour cost stickiness for sales decreases. Finally, a sample split based on the median value of each of Hofstede's six dimensions of national culture, namely PDI, IDV, MAS, UAI, LTO and IVR, is conducted to examine whether culture moderates the relation between the stringency of government interventions during COVID-19 and labour cost stickiness. The results provide an initial indication for national culture indeed strengthening or weakening the association. This is consistent with the idea that depending on national culture, managers are more or less inclined to accept stringent government interventions, which in turn shapes their optimism about the future and consequently results in increased or decreased levels of labour cost stickiness. As such, the results of this study deepen the understanding of how managers make resource adjustment decisions in times of crises and why the level of labour cost stickiness varies across countries.

In addition to extending the academic literature on institutions and cost asymmetry, this study has practical implications as well. It provides governments with insights on how state-level interventions can influence managers' perceptions of the future, ultimately leading to operational firm-level consequences such as changes in labour resource management. Therefore, the results can offer guidance for governments when designing policy responses during potential future pandemics, allowing them to consider economic, next to health-related consequences. By leveraging the positive relationship between the stringency of interventions and the exhibited levels of corporate labour cost stickiness, governments might be able to mitigate costs related to layoffs and possible resulting social unrest to some extent (Gu et al., 2020). This supplies them with additional arguments to justify stringent interventions to businesses and citizens. The results of this study also show that governments should consider national culture when planning actions to combat the spread of viruses, as the cultural context might influence whether and to what degree stringent governmental interventions are able to shape managers' future expectations and, consequently, resource management decisions. Thus, accounting for cultural diversity by allowing variance in the degree of stringency is particularly crucial when developing transnational policies, such as EU-wide regulations.

Although causal relationships cannot be detected in this study's setting, it still provides valuable insights that can serve as a foundation for further academic discussions and practical considerations on firm-level cost implications of

stringent government interventions during pandemics in distinct cultural settings.

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