Stockholm School of Economics
Department of Finance
Master Thesis in Finance, Fall 2020

No Place like Home: Work from Home Ability and the Impact of the COVID-19 Pandemic on Asset Prices Across European Countries

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Abstract: Social distancing during the COVID-19 pandemic has given rise to Work from Home (WfH). This paper explains why the WfH-ability of firms could entail a return differential between industries with high and low WfH-abilities (WfH-differential). Industry-level WfH-abilities impact risk premia of assets differently depending on correlations with labour income. Studying stock markets of 26 countries and sorting firms by WfH-ability we find a WfH-differential for the majority of countries. In contrast to prior literature with a descriptive approach towards the WfH-differential, our cross-country study allows us to analyze its driving forces. The WfH-differential relates positively to the respective countries' pandemic severity and workplace disruptions while it relates negatively to legal labour protection. In an additional analysis, we reaffirm and apply our results by identifying a negative relationship between the WfH-differential and GDP growth in early 2020.

Keywords: Asset Pricing, Social Distancing, Work from Home, COVID-19, Pandemic, European Stock Markets, Labour Income Risk

Acknowledgements: We would like to thank our supervisor Jungsuk Han sincerely for his advice, guidance, and unwavering support throughout our work on this thesis. We would also like to thank our friend Finn Aretz for providing valuable comments on our draft.

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1 Introduction

"We're not going back to the same economy [...] but to a different economy and it will be one that is more leveraged to technology, and I worry that it's going to make it even more difficult than it was for many workers." (Jerome Powell, 2020).

The COVID-19 pandemic did not only pose a major challenge for healthcare systems with more than 1 million fatalities globally but also impacted economies and financial markets profoundly. In Europe alone 5.1 million people lost their jobs and GDP contracted by roughly 12 percent in the second quarter of 2020, the sharpest decline since the start of data collection in 1995 (Eurostat, 2020). However, the pandemic[1] did not affect all sectors equally but impacted businesses that require physical presence of employees most severely (Mas and Pallais, 2020). In contrast, industries in which Work from Home (hereinafter "WfH") is possible are more resilient to the COVID-19 pandemic and consequential interventions by governments (Mongey et al., 2020). We hence argue that the WfH-ability of an industry might ultimately impact its risk profile and stock market performance. Therefore, we examine whether stocks of companies with a high WfH-ability (hereinafter "remote") experienced a positive price-adjustment while stocks of companies with a low WfH-ability (hereinafter "physical") experienced a negative price-adjustment. If that was the case, we expect to observe that "remote" stocks generated higher returns than "physical" stocks during the COVID-19 pandemic. Throughout the paper this return differential is referred to as the "WfH-differential". We raise the question about the prevalence of the WfH-differential as a starting point to examine whether it is a persistent phenomenon across countries and investigate country-level factors that influence its magnitude.

Examining data from 26 European countries that vary in their industry-level stock market composition, capital market size and institutional factors, we first show that the WfH-differential occurs across a majority of countries. The return differential cannot be adequately explained by differences in risk captured by the Fama and French (1992) three-factor model (hereinafter "FF3") and is even more pronounced after controlling for market risk, firm-size and the book-to-market ratio. We observe that the WfH-differential is particularly high between the first lockdown in Wuhan, China and the first European lockdown in Italy. While it is positive for a majority of countries in our sample, it differs significantly in its magnitude and persistence. In line with our theoretical framework, we identify a strong relationship between the size of the WfH-differential and the degree of workplace disruptions. Further, we show that particularly the digital and institutional environment of a country matters in explaining the WfH-differential. Lastly, we demonstrate that the WfH-differential is closely related to the

[1] Hereinafter, we use the terms "the COVID-19 pandemic" and "the pandemic" interchangeably.

health of the economy overall by reporting a negative relationship between the WfH-differential and quarterly GDP growth.

We base our analysis on the idea that if the WfH-differential occurs across countries during the pandemic, we should be able form a portfolio that exploits it. Therefore, we create a portfolio that buys “remote” stocks and sells “physical” stocks based on the WfH-ability measure of Dingel and Neiman (2020). We refer to this portfolio as the “remote minus physical portfolio”, short “RMP”, for the remainder of this paper. First, we investigate whether a WfH-differential occurs across different stock markets as observed for the US by Pagano et al. (2020). Second, we employ cross-country differences in pandemic severity and institutional factors to identify determinants of the WfH-differential. Based on empirical evidence provided by Eiling (2013), we relate our findings to the correlation between the return on risky assets and labour income.

Our assumptions regarding determinants of the WfH-differential are based on the notion of undiversifiable labour income risk, which varies across industries (Eiling, 2013). We argue that industries’ WfH-ability can be viewed as a form of undiversifiable labour income risk. As it can not be diversified, labour income risk should be reflected in asset prices. In our framework, agents’ portfolio returns are determined by their returns on risky assets as well as their returns on labour income. We formally explain how agents’ undiversifiable labour income risk impacts the risk premium of risky assets that are highly correlated with labour income. As returns and prices are inversely related, this reduces the prices of those assets. On the other hand, assets that show a low correlation with the agents’ labour income require a lower risk premium which increases the price of these assets. We argue that the WfH-ability of industries first became a significant driver of labour income risk and correlations with risky assets during the COVID-19 pandemic. Unlike past crises, the WfH-ability now determined whether employees could continue exercising their work and whether firms could continue their operations (Baker et al. 2020).

According to our framework, “remote” stocks should require a lower risk premium since they show lower correlations with the labour income of agents. On the other hand, “physical” stocks that show a high correlation with the agents’ labour income should require a higher risk premium. Based on this reasoning, the framework expects “remote” stocks to generate higher returns than “physical” stocks during the COVID-19 pandemic. If the price of “remote” stocks indeed increased and the price of “physical” stocks decreased due to the change in the respective risk premia, the RMP portfolio should be able to exploit this price-adjustment process. Notably, we would expect an opposite return pattern to emerge as soon as the WfH-ability has been priced. As "physical" stocks should offer a higher risk premium than "remote" stocks due to the higher correlation with labour income, the WfH-differential should become negative after the price- adjustment process is completed.

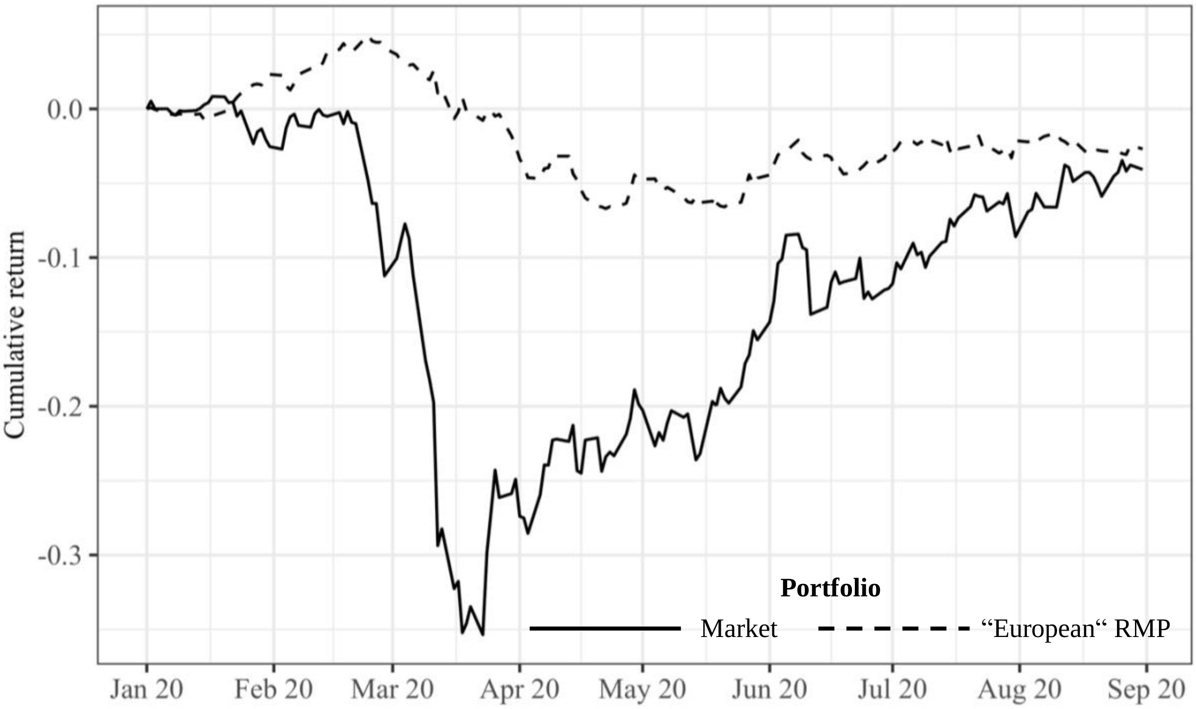

Figure 1: **Cumulative Return of the "European" RMP Portfolio Against Market**

Figure 1 plots the cumulative return of the "European" RMP portfolio aggregated over 20 European countries, as well as the European market portfolio retrieved from French (2020) between the 1st of January and the 31st of August 2020. Countries with less than 10 stocks per group were excluded for this representation.

Figure 1 above illustrates one of the main findings of our paper. Beginning with the first COVID-19 related lockdown on the 23rd of January 2020, the RMP portfolio outperforms the European market portfolio retrieved from French (2020). This finding becomes even more pronounced after controlling for the co-movement with the market return, firm size and book-to-market value by applying the Fama and French (1992) FF3. Particularly in the period between the first COVID-19 related lockdown in Wuhan, China on the 23rd January 2020 and the first lockdown in Europe on the 9th of March in Italy, we find a pronounced WfH-differential. Although we observe this differential throughout the sample on an aggregate level, we find differences between countries. In the empirical tests we determine potential factors that influence the magnitude of the WfH-differential across countries.

Consistent with our framework, we find that countries that implemented stricter government interventions causing widespread workplace disruptions show a higher WfH-differential compared to countries in which government interventions were more lenient. This supports the argument that a higher degree of workplace disruptions has a stronger impact on agents' labour income risk as well as on correlations with risky assets.

We further show that the WfH-differential is positively related to the increase in new COVID-19 related deaths as this might drive agents' sentiments about future workplace disruptions. The WfH-differential is significantly related to country-level characteristics: While the broadband speed in a country has a positive impact on the WfH-differential, the differential is inversely related to the institutional quality and the level of digital skills in a country. Even after controlling for these factors, the main parameter of interest, workplace disruptions resulting from government interventions, remains significantly positive and even increases in its magnitude.

We extend our framework by considering the implicit insurance of labour income in the form of legal labour protection as a country-level factor. According to Lucas (1994) labour income insurance disincentivises employees to smooth consumption by saving in the good state of the economy. Employees might not view the COVID-19 pandemic as an imminent threat to their labour income as they are aware of the implicit insurance. Hence, their labour income risk and correlation with risky assets is not affected to the same extent as in countries that are less protective. This results in a lower change of the required risk premium for risky assets. In line with this argument, we find that countries with stricter legal labour protection show a lower WfH-differential.

We incorporate our findings in an additional analysis of the impact of WfH-ability on the real economy. Our results show that the magnitude of the WfH-differential coincides with quarterly GDP decline in the first quarter of 2020. Further, we find that the WfH-differential can improve the predictive power of short-term GDP prediction models. Apart from revealing a possible application of the WfH-differential, our findings reassure us in our hypothesis of higher WfH-differentials in countries that were impacted more severely by the pandemic.

The results of this paper are in line with previous studies on the impact of the COVID-19 pandemic on asset prices which provide support for the prevalence of return differentials driven by resilience towards the pandemic (Cf. Pagano et al., 2020; Papanikolaou et al., 2020; Shen and Zhang, 2020). However, in contrast to these studies our paper uses asset pricing theory to demonstrate the risk premium channel through which the WfH-ability impacts stock prices. Furthermore, our paper is not limited to one within-country sample but covers multiple countries across the European continent. To our knowledge, our paper is the only one so far using country-level characteristics regarding the pandemic severity and institutional factors to explain variations of the WfH-differential across countries. We thereby contribute not only by providing support for the prevalence of a WfH-differential across countries but also by offering insight on its underlying driving forces.

The paper is structured in the following way. In section 2 we discuss the relevant literature and highlight potential gaps that we aim to address. In section 3, we develop our theoretical framework and construct corresponding hypotheses that are tested at a later stage. In section 4, we outline our data collection approach and the methodology used to test our hypotheses followed by a presentation of our findings in section 5. We apply our findings in section 6. A discussion of our findings in in a broader context and potential areas of further research are presented in section 7. Section 8 concludes this paper.

2 Literature Review

The year 2020 has produced a vast amount of economic literature on the impact of the COVID-19 pandemic. Brodeur et al. (2020) note that from March to May 2020, NBER publications alone grew to over 100, not accounting for the sizable amount of other working papers in the field. Our paper broadly relates to the equally fast-growing literature on the stock market reaction to the outbreak of the pandemic.

Baker et al. (2020) point out that the US stock market showed an unparalleled reaction to the COVID-19 pandemic, manifesting both in a steep rise in volatility and a historically high amount of large daily stock market movements[2]. The authors find that no pandemic before, despite entailing greater excess mortalities, even lead to the occurrence of a *single* large return. Pointing to a globalized economy as an amplifier of stock market reactions to COVID-19, Ding et al. (2020) conclude that the embeddedness of firms into international supply chains negatively impacted stock returns. In this vein, Ramelli and Wagner (2020) find that companies' supply chain exposure to China negatively impacted stock returns during the Chinese lockdown. The authors further indicate that, even within industries, highly levered and liquidity constrained firms incurred a more negative impact on returns. Albuquerque et al. (2020) show that firms with stronger environmental and social policies (ES) achieved significantly higher returns than firms with relatively weaker ES during the first three months of 2020.

Baldwin (2020) argues that policy responses to COVID-19 have "directly and massively reduced the flow of labour to businesses" leading to an abrupt negative impact on economic growth overall. The author acknowledges that industries are affected to very different extents in that government lockdowns affect service industries less than industries that produce goods. According to Baldwin (2020) this difference is largely driven by the extent to which employees can perform tasks from home.

Our paper contributes to the literature on stock market reactions to the COVID-19 pandemic at large by expanding the view to the cross-country perspective towards the matter of WfH-ability. A number of labour economics publications has focused on quantifying industry-level WfH-ability. Adams-Prassl et al. (2020) point out that during the COVID-19 pandemic the *capacity* to perform tasks at home, not the *past occurrence* of the latter, is decisive. Alipour et al. (2020) argue that the COVID-19 pandemic will drive the actual share of WfH to the level of WfH-capacity across industries. The researchers construct a survey-

[2] The authors define a large stock market move as one exceeding +/- 2.5% (Baker et al., 2020)

based industry measure for WfH-capacity in Germany. The style of the German "BIBB/BauA"-employment survey favours their research as employees are asked whether they *could* perform their tasks at home regardless of whether the employer allows it. Hensvik et al. (2020) apply a similar approach. The authors employ the "American Time Use Survey" (ATUS) to calculate a WfH-measure. This measure captures the lower-end of WfH-ability as the ATUS captures WfH-prevalence only. Hence, the finding of Hensvik et al. (2020), that 15% of working hours in the US are performed at home, does not capture the untapped WfH-potential that became important during the pandemic. To capture industry-level workplace disruptions, Koren and Petö (2020) employ survey data from the "Occupational Information Network" (O*NET). The authors use task descriptions of the O*NET survey to determine communication-intensity and the need for physical proximity of jobs in order to estimate the degree to which industries are negatively impacted by workplace disruptions. Although their research allows for cross-industry comparisons, the authors do not offer insight regarding the possible change of industries' communication-intensity and need for physical proximity during the pandemic. Dingel and Neimann (2020) follow a different approach utilising the O*NET data. The authors classify about 1,000 occupations binarily as either "WfH-able" or "WfH-unable" and aggregate their findings to industries. For the US, the authors find that 37% of jobs can be done for home. Interestingly, these jobs account for 46% of US wages indicating that WfH-ability is more prevalent in higher-paid jobs. As the Dingel and Neimann (2020) measure provides an estimate for the *ability* to WfH, the authors acknowledge that there is a notable discrepancy to the status quo of *actual* WfH. The study also extends the analysis beyond the US by providing a crosswalk from the US Standard of Occupational Classification (SOC) to the International Standard of Occupational Classification (ISCO). Within our paper, we use the Dingel and Neimann (2020) measure by aggregating country-level WfH-ability estimates to occupational employment structures across the 26 sample countries. Although the Dingel and Neimann (2020) measure (hereinafter "DN") has been used in cross-country studies for macroeconomic analyses (See for example Gottlieb et al. (2020)[3]), to our knowledge we are the first to use DN across countries for stock portfolio selection.

Some of the current literature on the stock market impact of the COVID-19 pandemic focuses on the cross-section of stock returns in the context of WfH-ability. Sorting US industries according to the measure of Koren and Petö (2020), Pagano et al. (2020) build a long-short portfolio and find that industries with high WfH-ability outperformed those with low

[3] The authors analyse the country-level impact of income-levels on the ability to WfH as well as the role of the WfH-ability within agriculture on overall country-level WfH.

WfH-ability. The authors further find that the return differential between these industries might have already been prevalent before the crisis. Based on option prices, Pagano et al. (2020) further anticipate that stocks within high (low) WfH-ability industries will generate lower (higher) returns after the COVID-19 pandemic due to a lower (higher) exposure to workplace disruptions.

Papanikolaou et al. (2020) find that analyst forecasts for both negative revenue growth and probability of default are associated with lower WfH-ability. Further, the authors analyse the stock market reaction across US industries and find that industries which are more exposed to workplace disruptions through low WfH-ability experienced significantly larger stock return declines even after adjusting for critical industries[4].

Shen and Zhang (2020) distinguish between "stay-at-home" (e.g. online services) stocks and "go-outside" stocks (e.g. travel) based on their criterion capturing whether firms' job tasks experience disruptions during lockdowns. By applying an event study approach, the authors find that the two groups are correlated while negative returns are more pronounced for "go-outside"-stocks. On the 23rd of January, the date of the Wuhan lockdown, "stay-at-home" stocks did not incur significant negative abnormal returns while "go-outside" did. Over the event window, "stay-at-home"-stocks achieved a cumulative abnormal return of over 6% while "go-outside" stocks incurred a cumulative abnormal return of about -3.9%.

Our paper is linked to the three aforementioned papers and adds to the discussion through three channels. First, prior literature on the cross section of asset prices and WfH-ability focuses on single countries: By expanding the view on 26 European countries we aim at offering a wider perspective on asset prices driven by WfH-ability. Second, apart from identifying that differences in WfH-ability cause a return differential, the cross-country setting of our paper provides possible explanations for the driving forces behind return differences of "remote" and "physical" industries. In this vein, we offer a view on the relationship among pandemic-severity, workplace disruptions and the cross section of stock returns driven WfH-ability across countries. Third, we show that countries with high WfH-differentials experience economic consequences to a distinctly different extent. Thereby we point to the future importance of WfH-ability in the light of the pandemic resilience of countries at large.

[4] The authors reclassify sub-sectors of certain industries according to the Commonwealth of Pennsylvania (2020) following the "Guidance On The Essential Critical Infrastructure Workforce" (CISA, 2020). Hereby, sub-sectors of industries with a low WfH-ability are reclassified as government intervention shelters companies in these sectors from workplace disruptions. This applies, inter alia, to the sectors " Fishing", "Coal Mining, and "Grocery Stores".

3 Theoretical Framework and Hypotheses

3.1 Undiversifiable Labour Income Risk and Asset Prices

According to Eiling (2013), factors that impact undiversifiable labour income risk include the degree of unionisation, transferability of labour from one occupation to another, and the risk that an agent's labour becomes obsolete due to technological advancement. We extend the list of factors by including WfH-ability as a potential driver of undiversifiable labour income risk.

If agents could fully diversify their labour income risk, merely aggregate labour income risk would matter for asset prices in addition to market risk as implied by the Human Capital CAPM (Jagannathan and Wang, 1996). However, agents face distinctly heterogenous labour environments across industries and therefore experience differences in both labour income risk and correlations of the latter with risky asset returns. As agents cannot diversify labour income risk, it should be reflected in asset prices. As classic asset pricing models like the Fama and French (1992) FF3 do not capture labour income, however, it is not adequately priced and thus ends up in the error term. Therefore, it appears as if agents were being compensated for diversifiable risk while this component is in fact at least partially due to labour income.

We show formally through which channel agent-specific labour income risk impacts asset prices by drawing on a static trading model with a representative agent in line with the CAPM according to Sharpe (1964), Lintner (1965) and Mossin (1966). For simplicity, we initially assume only one risky asset to exist, which we denote as asset i, with a return of r_i. The mean and variance are denoted by μ_i and σ_i^2 respectively. The risk-free rate is denoted by r_f and exogenously fixed. The representative agent maximizes her mean-variance utility as follows:

$$EU(r) = E[r] - \frac{a}{2}Var(r) \tag{1}$$

Where a is the risk aversion parameter. Hence, the agent trades off mean and variance of the optimal portfolio solely based on her risk aversion parameter. In addition to her risky asset the agent receives labour income with the respective return denoted by r_l, with a mean and variance of μ_l and σ_l^2 respectively. We denote the correlation between the risky asset and the labour income by ρ_{il}.

The expected return and variance of the return of the agent's portfolio of the financial asset and labour income are given by

$$E[r] = r_f + w_i(\mu_i - r_f) + \mu_l \tag{2}$$

and

$$Var[r] = w_i^2\sigma_i^2 + w_i\rho_{il}\sigma_i\sigma_l \tag{3}$$

where w_i is the portfolio weight on asset *i*. Solving this optimisation problem according to the first order condition (FOC) yields the optimal portfolio weight:

$$w_i^* = \frac{\mu_i - r_f}{a\sigma_i^2} - \frac{\rho_{il}\sigma_l}{a\sigma_i} \tag{4}$$

The above equation illustrates that the optimal share in the risky asset depends on two components. The optimal share in the risky asset is increasing in $\mu_i - r_f$ and decreasing in $a\sigma_i^2$. However, the optimal share in the risky asset also depends negatively on the correlation with the agent's labour income and the respective risk in labour income $\rho_{il}\sigma_l$.

In a clearing market equilibrium, where the agent holds all shares in the risky asset thereby equaling demand and supply, i.e. $w_i^* = 1$, the equilibrium risk premium should satisfy:

$$\mu_i - r_f = a\sigma_i^2 + \rho_{il}\sigma_i\sigma_l \tag{5}$$

Thus, from this expression it can be derived that the risk premium is increasing in the risk-aversion parameter *a*, and the covariance between the risky asset and the agent's labour income $\rho_{il}\sigma_i\sigma_l$. The covariance in turn depends on the correlation between the risky asset and the agent's labour income ρ_{il}. We therefore derive:

Proposition 1. The risk premium of a risky asset *i* is increasing in the correlation ρ_{il} between its return and an agent's labour income.

An agent that faces a higher correlation ρ_{il} between her risky-asset and labour income, requires a higher risk premium $\mu_i - r_f$ ceteris paribus. On the other hand, a risky asset with lower correlation ρ_{il} with the agent's labour income should require a lower risk premium $\mu_i - r_f$ and therefore trade at a higher price. By allowing for multiple agents who are employed in various industries we next derive the impact of the COVID-19 pandemic on labour income risk σ_l and asset prices through the channel of WfH-ability.

3.2 Undiversifiable Labour Income Risk, Asset Prices and the COVID-19 Pandemic

We argue that the impact of labour income risk on asset prices becomes particularly pronounced during the COVID-19 pandemic as adverse shocks to labour income risk are not equally spread across occupations and industries and are more severe in "physical" industries. This is due to the fact that "physical" industries face higher risk of workplace disruptions during the COVID-19 pandemic (Milasi et al., 2020). Hence employees' labour income risk increases through the threat of layoffs or working hour reductions inter alia (Bartik et al., 2020). While the risk of a pandemic is systematic and affects every stock in the economy, the magnitude of the shock depends on the degree of workplace disruptions which is unobserved by agents at the onset of the pandemic. Although agents do not know about the degree of workplace disruptions, they are aware of the impact of a labour income shock on their respective industry and thus adjust their expectations about changes in labour income more drastically if they are working in a "physical" industry that is disproportionately impacted by workplace disruptions. Furthermore, agents know that the correlations between their expected labour income and returns on risky assets are inversely related to WfH-ability.

Following Proposition 1, agents employed in "physical" industries require a higher risk premium for risky assets since their labour income is affected more by COVID-19-related workplace disruptions. This results in a higher volatility of these agents' labour income. At the same time their labour income becomes more correlated with risky assets due to the lower resilience of their labour income to workplace disruptions. The higher risk premium in turn results in lower prices for "physical" assets. On the other hand, agents employed in "remote" industries require a lower risk premium for risky assets since their labour income is less affected by workplace disruptions resulting in a lower volatility of their labour income. At the same time their labour income becomes less correlated with risky assets due to the higher resilience of their labour income to workplace disruptions. The lower risk premium in turn results in higher prices for "remote" assets. From this argumentation it follows that:

Hypothesis 1. We expect to observe a positive WfH-differential during the COVID-19 pandemic.

Since agents form their expectations of industry-level labour income risk in absence of any certainty about workplace disruptions at the early stage of the pandemic, we expect the WfH-differential to occur across all countries. As the framework suggests, prices adjust through higher risk premia for "physical" assets and lower risk premia for "remote" assets. This gives rise to a positive WfH-differential. After the materialization of this price adjustment, however, the changed risk premia entail that returns of "physical" assets should be higher than returns of "remote" assets. Furthermore, we expect government interventions to decrease market uncertainty. Hence, the overall volatility of risky assets should diminish. For "physical" assets this effect is more pronounced due to the higher correlation with labour income. This reasoning is consistent with volatility spikes in the first quarter of 2020 that flattened after the implementation of government interventions.[5] Taken together, the decrease in market uncertainty and stock prices that have adjusted for WfH-ability should result in a lower WfH-differential after government interventions. Therefore, we derive:

Hypothesis 2. The WfH-differential occurs across countries in the first quarter of 2020 before government interventions and decreases afterwards.

In the next section, we extend our framework to account for country-level government interventions. These vary in the degree of imposed workplace disruptions which in turn influence agents' expectations of industry-level labour income risk.

3.3 Undiversifiable Labour Income Risk, Asset Prices and Workplace Disruptions

As outlined previously, we expect agents to form their expectations across countries based on an expected change in industry-level labour income in the absence of workplace disruptions. However, it remains in question how differing degrees of workplace disruptions due to government interventions impact the WfH-differential. To this day there is no clear consensus regarding the optimal degree of interventions among policymakers in the European Union. While countries like Spain and Italy nearly experienced a standstill of public life in attempts to slow down infection rates, others focused on the importance of voluntary social distancing with Sweden being at the forefront of this policy approach.

Hence, changes of expectations about future labour income do not only appear on the industry-level but also on the country-level. Agents adjust their expectations about potential adverse changes to their labour income based on the severity of government interventions. More specifically, if agents in a country observe interventions to result in a higher degree of workplace disruptions, this drives up their labour income risk as well as correlations with risky assets. Following this logic, we expect to observe lower WfH-differentials in countries like Sweden, where agents incur less workplace disruptions. Due to the lower degree of workplace disruptions, correlations between labour income and risky assets are affected less, resulting in a less pronounced change in the risk premium. On the other hand, we expect higher WfH-

[5] For illustrative purposes, Appendix 1 shows the 25-day rolling volatility of the RMP portfolio.

differentials in countries like Italy or Spain, as agents observe a severe shock to their labour income risk which increases correlations with risky assets due to drastic workplace disruptions. Hence, we derive:

Hypothesis 3. As agents adjust their expectations about changes in labour income based on the observed degree of workplace disruptions, the WfH-differential depends on the country-level strictness of government interventions.

3.4 Undiversifiable Labour Income Risk, Asset Prices and Legal Labour Protection

So far, we have implicitly assumed that undiversifiable labour income risk is uninsurable, that is, agents face a real threat of unemployment that drives their labour income risk. We now extend our framework by including implicit insurance against unemployment in the form of legal labour protection. We argue that this can be seen as a form of insurance for which agents pay a premium through their national tax regime. As pointed out by Lucas (1994), the existence of insurance against unemployment disincentivises agents from consumption smoothing by saving in the good state of the economy while dissaving in the bad state.

If government-induced insurance of labour income indeed matters for agents, we would expect to see a lower WfH-differential in countries with stricter legal labour protection which raises the legal barrier for employers to lay off employees. In those countries, the COVID-19 pandemic might have a less pronounced impact on agents' required risk premium as the labour income risk of agents and the correlation with risky assets increases to a lower extent. We thus hypothesise:

Hypothesis 4. Stricter legal labour protection reduces the WfH-differential.

In Appendix 2 we present a schematic representation of the established framework leading up to the hypotheses.

4 Data and Methodology

4.1 Industry-level Measure of WfH-ability

To obtain industry-level estimates of WfH-ability we apply the Dingel and Neimann (2020) measure ("DN"). We choose this approach as this measure is the only one that directly estimates WfH-ability based on job tasks. Furthermore, the authors provide a replication package[6] that allows us to retrieve employment-level estimates on the ISCO-08 level.

Our methodology to translate the retrieved occupational-level measure to the industry-level is based on the following steps: We apply the Dingel and Neimann (2020) replication package and obtain WfH-ability estimates for the ISCO-08 two-digit occupation-level for all sample countries. By following this approach, we assume that occupational-level WfH-ability is constant across countries while cross-country differentials in WfH-ability arise through different occupational employment structures within industries.[7] Next, we match the obtained estimates with country-level occupational employment structures for the year 2019 which we retrieve from the International Labour Organization (ILO). The ILO dataset[8] provides a breakdown of employment for each NACE[9] section-level industry into ISCO-08 employment shares, i.e. shows the share of ISCO-08 two-digit occupations constituting total employment in a specific industry. We then calculate the weighted average DN for the NACE section-level industries based on total employees within each occupation in the respective industries.

Next, we repeat this step for all sample countries and calculate the cross-country median of DN. We use the cross-country median of DN to sort industries into either the "remote" group if DN lies above the cross-country median or the "physical" group if DN lies below the cross-country median. Our choice to use the cross-country median of DN is based on our aim to create a distinction between high and low WfH-ability relative to the whole sample, not relative to the country-level WfH-ability. Thereby, we account for relative cross-country differences in the industry-level WfH-ability. Notably, our approach allows us to classify the same NACE section-level industries in different countries into different portfolios, which reflects different industry-level WfH-abilities due to cross-country differences in the industry-level occupational employment structure. Table I below summarises the DN on an aggregate industry-level across

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[6] The Dingel and Neimann (2020) replication package is retrievable at: https://github.com/jdingel/DingelNeiman-workathome

[7] For a discussion on these assumptions Cf. Adams-Prassl et al. (2020)

[8] The data is retrievable at: https://www.ilo.org/shinyapps/bulkexplorer10/?lang=en&segment=indicator&id=EMP_TEMP_ECO_OCU_NB_A

[9] Short for the French term "nomenclature statistique des activités économiques dans la Communauté européenne", the industry classification system applied in the European Union.

our sample of 26 European countries. A summary of DN estimates by sample countries is presented in Appendix 3.

Table I:
WfH Estimates for Industry-level Aggregates

	NACE Section	Industry (NACE Section-level)	DN Estimate
Remote	J	Information and communication	0.67
	M	Professional, scientific and technical activities	0.65
	K	Financial and insurance activities	0.64
	P	Education	0.62
	U	Activities of extraterritorial organizations and bodies	0.61
	R	Arts, entertainment and recreation	0.53
	O	Public administration and defence, social security	0.51
	L	Real estate activities	0.48
	Q	Human health and social work activities	0.47
	D	Electricity gas, steam and air conditioning supply	0.46
Physical	S	Other service activities	0.33
	G	Wholesale and retail trade repair of motor vehicles	0.30
	S	Administrative and support service activities	0.27
	H	Transportation and storage	0.27
	C	Manufacturing	0.25
	E	Water supply sewerage and waste management	0.24
	I	Accommodation and food service activities	0.23
	F	Construction	0.19
	A	Agriculture forestry and fishing	0.09
	T	Activities of households as employers	0.09
	B	Mining and quarrying	0.02
	X	Not elsewhere classified	0.43
Median			0.38

Table I depicts the industry-level aggregated Dingel and Neimann (2020, "DN") estimates for the WfH-ability aggregated over all countries in our sample. For each NACE section-level industry we calculate the mean DN estimate from the industry-level estimates we obtained for each country in the sample. The thick line between NACE sections D and S indicates the break between the "remote" and "physical" groups. On a country-level, all industries with a DN estimate below the cross-country median are sorted into the "physical" group while all industries with a DN estimate are sorted into the "remote" group.

4.2 Stock Market Data

We obtain prices for all stocks listed in European countries for which we can create DN. This leaves us with stock market data for 26 countries. We retrieve data for an observation period from the 1st of January 2020 until the 31st of August 2020. Stock market data is obtained from the global database of daily prices from Compustat[10]. Since we observe cross-listings in currency-denominations other than those of the focal country, we apply filters to ensure that stocks are actually traded in local currencies. Furthermore, we apply strict filters to exclude stocks that either miss price data or lack data on shares outstanding. In addition, we exclude stocks of which prices lie in the lowest 1% country-level percentile as we observe a variety of pricing irregularities and see a common pattern of low trading volumes and market capitalisations in that percentile. By applying the aforementioned filters, we reduce the initial sample size from 7,352 stocks to 6,929 stocks across all countries. Our approach is in line with prior literature that reports biased results when including these so-called "microcaps" in the analysis (Fama and French, 2008). As prices obtained from Compustat are not adjusted for stock splits and dividend payments, we adjust prices for such events using the Cumulative Price Adjustment Factor obtained from Compustat:

$$Adjusted\ Price_{i,t} = \frac{Price_{i,t}}{Cumulative\ Price\ Adjustment\ Factor_{i,t}} \tag{6}$$

Based on these adjusted prices, we calculate simple daily returns in excess of the risk-free rate (RF) obtained from French (2020) for all stocks in our sample that survived the filter criteria.

$$Excess\ Return_{i,t} = Return_{i,t} - RF\ Rate_{i,t} \tag{7}$$

For the sake of brevity, we refer to the excess return in equation (7) as "return" for the remainder of this paper. Although logarithmic returns are often employed instead of simple returns due to their properties of time additivity and normality, they have one important drawback in that they are not asset-additive (Miskolczi, 2016). Therefore, they are impractical to use for our portfolio formation process. Hence, we employ simple daily returns for the purpose of this paper.

Finally, we match the stock return data with DN for each country by industry based on a concordance-crosswalk[11] from the NACE section-level to the NAICS (North American

[10] The data is retrievable at: https://wrds-web.wharton.upenn.edu/wrds/ds/compd/g_secd/index.cfm?navId=73

[11] The applied NACE to NAICS crosswalk is published by the US census bureau and retrievable at: https://www.census.gov/eos/www/naics/concordances/2017_NAICS_to_ISIC_4.xlsx

Industry Classification System) letter-level. Applying this crosswalk step is necessary as we obtain the stock data from the Compustat database with a NAICS classification only.

4.3 Portfolio Formation

Based on the classification of an industry in a country as either having a DN value above or below the cross-country median DN, we sort stocks into two groups. “Remote” stocks comprise all stocks that have an above median DN, thus resembling all industries with a high WfH-ability, while the group of “physical” stocks includes all stocks with a below median DN, thus resembling all industries with a low WfH-ability. Individual stocks within each group are value weighted. To avoid drifts in the composition of groups due to changes in the market capitalisation of stocks and resulting weights, we conduct a monthly rebalancing which is particularly important during a crisis like COVID-19 where we observe substantial changes in companies’ equity values. Plysakha, Uppal and Vilkov (2014) show that the result of asset pricing tests is significantly driven by the choice of the rebalancing employed. The authors suggest that a major share of excess returns in equally weighted portfolios actually occurs due to rebalancing to maintain constant weights. Hence, we use value weighted portfolios for the purpose of this paper.

The “physical” and “remote” groups are thus created in the following way: Every first day of the month we classify each stock for which we have price data on that day as “remote” or “physical” and allocate them to the respective groups.[12] Next, we calculate the total market capitalisation for the two groups on the respective day and each stock’s weight based on its respective market capitalisation. We keep these weights constant until the next re-formation day one month later. After assigning weights to each stock in the two groups, we calculate the daily weighted returns and aggregate them for each group.

Finally, we combine the “remote” and “physical” stocks to a single portfolio, the “remote minus physical” (RMP) portfolio. The RMP portfolio takes a long position in the “remote” group and a short position of equal weight in the “physical” group so that the total weight equals zero. The daily return of the RMP portfolio therefore equals the daily return of the “remote” group minus the daily return of the “physical” group.

In Table II below we report summary statistics for the “remote” and “physical” groups for 2020. For comparison, we report the analysis for the year 2019 in Appendix 4.

[12] With the repeated classification, we account for the possibility that the sample composition may change over time, i.e. new listings, delistings, changes in industry-classifications throughout the period.

Table II:
Summary Statistics of the Returns of the "Remote" and "Physical" Groups for 2020

	2020									
	Physical					Remote				
		Returns					Returns			
Country	No. Stocks	Ø Daily	Min Daily	Max Daily	Vola	No. Stocks	Ø Daily	Min Daily	Max Daily	Vola
Austria	44	-0.14	-13.82	10.98	2.42	26	-0.14	-11.43	8.68	2.22
Belgium	70	-0.11	-13.44	8.43	2.46	63	-0.08	-12.73	5.56	1.93
Switzerland	122	0.00	-7.22	4.85	1.36	111	-0.04	-9.94	9.30	1.77
Czechia	1	-0.12	-10.35	5.01	1.74	4	-0.11	-9.50	5.58	1.59
Germany	375	-0.01	-11.63	10.59	2.20	351	0.03	-11.26	9.22	1.87
Denmark	77	0.08	-7.21	4.03	1.46	68	0.06	-9.45	4.69	1.63
Spain	98	-0.13	-11.82	8.62	2.17	104	-0.07	-13.91	7.79	2.18
Estonia	11	-0.12	-11.17	4.66	1.56	5	0.05	-7.86	4.65	1.45
Finland	86	0.07	-8.80	6.78	1.89	72	-0.02	-13.08	8.38	2.31
France	402	-0.05	-10.89	8.73	2.07	258	-0.11	-13.05	8.68	2.31
United Kingdom	585	-0.08	-10.02	7.90	1.90	832	-0.11	-9.99	8.49	2.00
Greece	104	-0.15	-11.81	7.28	2.34	63	-0.14	-12.32	7.29	2.65
Croatia	58	-0.06	-5.87	3.36	0.99	18	-0.05	-6.36	3.97	1.28
Hungary	10	-0.13	-8.68	8.10	2.23	20	-0.17	-14.57	10.06	2.61
Ireland	27	-0.03	-7.19	6.46	2.18	15	0.04	-10.94	8.61	2.48
Italy	169	-0.13	-15.45	7.90	2.32	158	-0.06	-16.59	7.50	2.33
Lithuania	20	-0.01	-8.44	5.18	1.13	8	0.05	-6.24	3.38	0.83
Latvia	17	0.04	-7.93	7.05	1.02	2	0.61	-39.26	55.02	6.84
Netherlands	79	0.03	-9.68	6.77	1.95	57	-0.02	-13.13	8.42	2.17
Norway	103	-0.05	-10.98	7.13	2.10	89	-0.01	-9.02	5.58	1.86
Portugal	22	-0.15	-9.71	10.04	1.91	23	-0.04	-11.21	8.37	2.00
Romania	52	-0.07	-9.97	4.18	1.72	23	-0.04	-9.25	6.95	1.79
Slovakia	2	-0.16	-25.00	36.79	3.94	6	-0.07	-6.11	2.85	0.93
Slovenia	9	0.07	-9.25	6.29	1.67	12	-0.15	-8.41	4.43	1.44
Sweden	469	0.05	-10.38	8.15	2.00	271	0.04	-12.31	6.66	2.10
Turkey	234	0.17	-8.53	6.72	1.88	144	0.10	-9.74	6.88	2.65

Table II presents descriptive statistics of the "remote" and "physical" groups for 26 countries for 2020. The groups are constructed for each country individually and weighted based on the market capitalisation of the stocks. Each group is held for all existing trading days during 2020 and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. "Remote" and "physical" stocks are defined as having an above and below median Dingel and Neiman (2020) value for their respective industry. The table shows for every country the number of stocks in each group, the average daily return of the respective group, the maximum and minimum daily return, and the volatility the respective portfolio.

4.4 Fama and French (1992) Three Factor Risk Adjustment

In order to assess whether the WfH-ability of companies is captured by "classic" asset pricing models like the Fama and French (1992) FF3 during the pandemic we calculate risk adjusted returns for all observed stocks, based on the methodology of Ramelli and Wagner (2020). We focus solely on this asset pricing model, since related previous research reveals no significant difference in results when instead using four- or five factor models (Pagano et al., 2020). In a first step, model parameters are calibrated by running OLS regressions of individual stocks' daily returns in 2019 on Fama and French (1992) FF3 specifications.[13] Next, those parameters are employed to derive expected daily returns from 1st of January 2020 to 31st of August 2020 by multiplying the respective coefficient with its factor return for the period. In a last step, we subtract the expected daily returns from the actual observed stock returns to arrive at the risk adjusted excess return:

$$AR_{i,t} = R_{i,t} - \beta_{i,Mkt} * Mkt_t - \beta_{i,SMB} * SMB_t - \beta_{i,HML} * HML_t \tag{8}$$

where:

$R_{i,t}$ = Excess return of stock i at day t
$\beta_{i,Mkt}$ = Market beta of stock i
Mkt_t = Market excess return at day t
$\beta_{i,SMB}$ = Small minus big (SMB) factor beta of stock i
SMB_t = SMB excess return at day t
$\beta_{i,HML}$ = High minus low (HML) factor beta of stock i
HML_t = HML excess return at day t

For the sake of brevity, we refer to the risk adjusted excess return in equation (8) as "risk adjusted return" for the remainder of this paper. In a similar fashion to the unadjusted stock returns, we next sort the stocks into the "remote" and "physical" groups depending on their DN and calculate daily value weighted risk adjusted returns. We also aggregate the risk adjusted returns for all countries with more than 10 stocks per group to a "European" RMP portfolio.[14] This is done by weighting the daily risk adjusted returns of each country based on its share of the total sample market capitalisation on the 1st of January 2020. Since monthly changes in the weight of each country in our "European" RMP portfolio are negligible over the course of 8 months, we are not conducting any rebalancing here. Hence on the aggregated European level, the portfolio should be viewed as a "buy and hold"-portfolio throughout the entire observation period.

[13] The data can be retrieved at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[14] The applied restriction on the minimum number of stocks per group leads to the exclusion of Estonia, Latvia, Lithuania, Slovakia, Slovenia and Czechia.

4.5 Country-level Regressions

To test the impact of country-level characteristics on the risk adjusted return of the RMP portfolio between 1st of January 2020 and 31st of August 2020 we employ various panel regression techniques. From our initial dataset of 26 European countries only 15 survive our filter criteria to be included in this part of the analysis. The omitted 11 countries[15] either lack sufficient stock market data of at least 10 stocks in both the “remote” and “physical” groups or lack the necessary data quality to form a meaningful vector of regressors.

In a first step, we test whether a simple pooled ordinary least square (OLS) model produces estimates that are consistent as well as efficient by checking our panel for individual effects u_i that are either time-specific or cross-sectional. Pooled OLS only produces consistent and efficient estimators if those individual effects u_i are equal to zero (Park, 2011). Formally, we first plot the mean risk adjusted return of the RMP portfolio for every country as well as across countries for every day to examine time-specific and individual-specific effects. We test whether the individual or time-specific variance components are zero by applying Breusch and Pagan’s (1979) Lagrange multiplier (LM) test. Supporting our visual findings (See Appendix 5), the LM test indicates that there are significant random effects and that a random effects model is better able to deal with those than a pooled OLS model.

In order for us to employ a random effects model, the individual effects need to be uncorrelated with any regressor, $x_{i,t}$, in the model. Otherwise, the model produces estimators that are inconsistent and biased. In this case, a fixed effects model is more suitable to capture the individual variation in the panel data. Formally, we test whether the estimates of Least Square Dummy Variables (LSDV) are significantly different from estimates produced by General Least Square (GLS) by employing the Hausman test (Hausman, 1978). Under the null hypothesis the estimators should not differ significantly. With a p-value close to 1 we cannot reject the null hypothesis that individual effects, u_i, are significantly correlated with any regressor, $x_{i,t}$. Therefore, we are able to employ a random effects model for our analysis.

In a last step, we test our model for heteroskedasticity by running the Breusch-Pagan test (1979) under the null hypothesis of homoscedasticity. Since the test turns out highly significant, indicating heteroskedasticity in the error terms, we employ heteroskedasticity consistent covariance estimates (White, 1980).

[15] We exclude Switzerland, Czechia , Estonia, Croatia, Ireland, Lithuania, Latvia, Romania, Slovakia, Slovenia and Turkey. Appendix 6 shows the country-level return time series illustrating return irregularities.

5 Results

5.1 The WfH-differential

To examine whether there is a WfH-differential during the COVID-19 pandemic, we plot the daily risk adjusted returns of the RMP portfolio for every country individually in Figure 2 as well as aggregated for all countries in Figure 3. If we are able to observe a WfH-differential which is not explained by the Fama and French (1992) FF3, the risk adjusted returns should not only be non-zero but significantly positive.

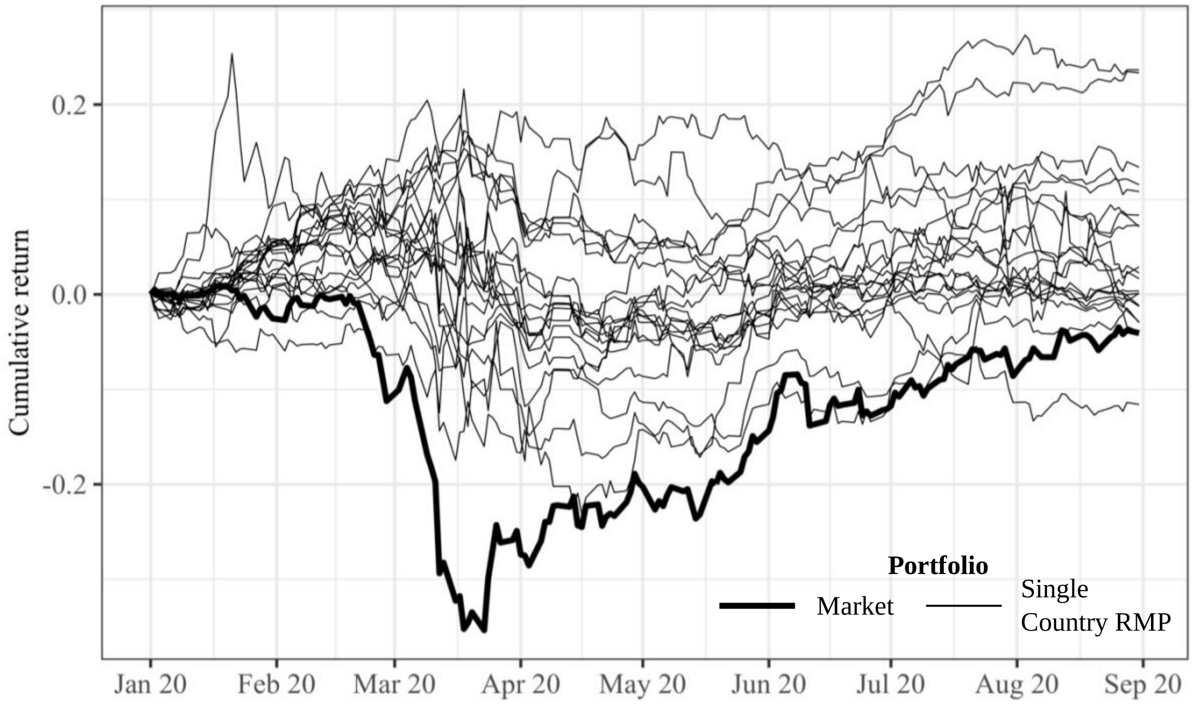

Figure 2: **Cumulative Risk Adjusted RMP Returns of Single Countries Against Market**

Figure 2 plots the cumulative risk adjusted return of the RMP portfolio for a sample of 20 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded.

Figure 2 above clearly indicates abnormal risk adjusted returns varying over time as well as across countries. While cumulative risk adjusted returns of the RMP portfolio fluctuate around zero in the beginning of 2020, they increase significantly from late January onwards coinciding with the first COVID-19 case in Europe on the 21st of January and the announcement of the lockdown in Wuhan on the 23rd of January. For most countries in our sample, the WfH-differential is rather driven by an outperformance of the "remote" stocks than of an underperformance of the "physical" stocks. As COVID-19 developed into a serious health crisis, with Italy implementing lockdown restrictions on the 9th of March and the World Health Organisation declaring it as a pandemic on the 11th of March, the cumulative risk adjusted returns of both "physical" and "remote" stocks started to deteriorate rapidly. Nonetheless, the cumulative risk adjusted return of the RMP portfolio remains positive for a majority of countries in our sample and grows again in mid-April, after markets absorbed the first COVID-19 shock. Interestingly, countries that were impacted most severely by the first wave of the COVID-19 pandemic such as Italy and Spain show a clearly diverging trend in the performance of “remote” and “physical” stocks from May onwards. In Appendix 6, we show the time series of cumulative returns and cumulative risk adjusted returns of the RMP portfolio and “remote” and “physical” groups separately for each sample country.

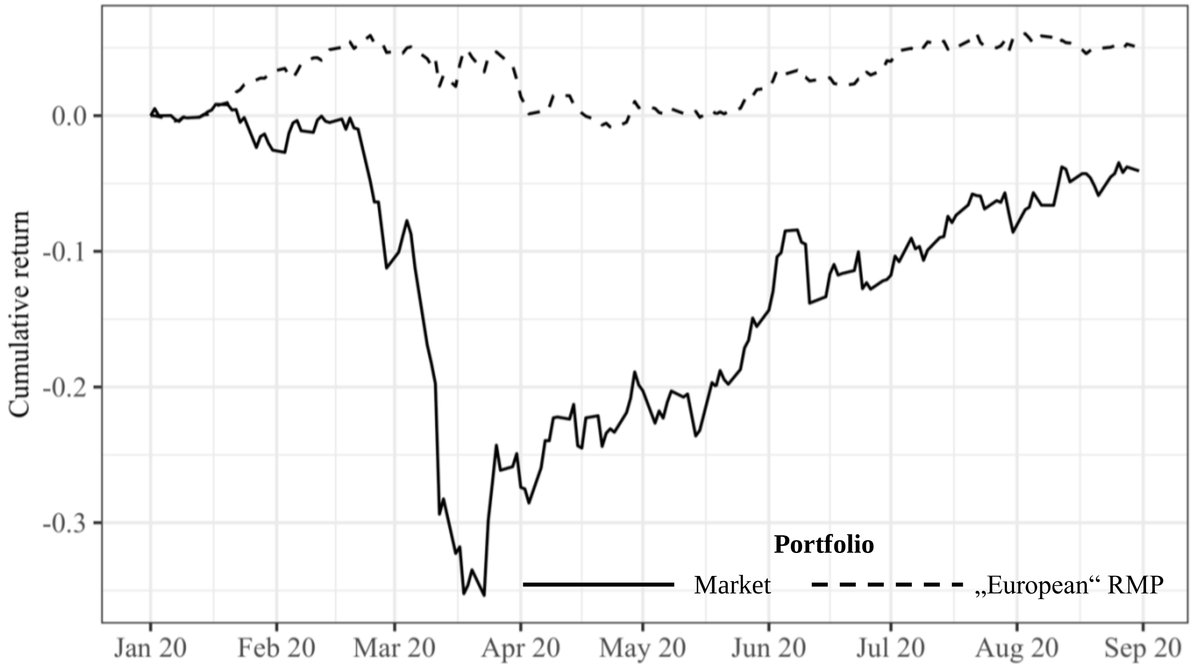

Figure 3: **Cumulative Risk Adjusted Return of the “European” RMP Portfolio Against Market**

Figure 3 plots the cumulative risk adjusted return of the “European” RMP portfolio aggregated over 20 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded.

The magnitude of the cumulative risk adjusted returns of the RMP portfolio becomes even more pronounced when aggregated across countries and compared with the performance of the European market excess return retrieved from French (2020). Figure 3 above shows that aggregated cumulative risk adjusted returns of the RMP portfolio start to accumulate in mid-January and reach their peak in the beginning of March. Even when lockdown measures were implemented in individual countries at the beginning of March, the WfH-differential, as shown in the cumulative risk adjusted RMP return, remained positive until April. While the market excess return incurred losses of up to 35.4% percent over the same period, the “European” RMP portfolio incurs maximum losses of 0.9% in May and achieves cumulative risk adjusted returns of 5% at the end of the observation period.

To test whether the daily average risk adjusted RMP returns are significant we apply a one-sided t-test, i.e. $H_0: \underline{AR_t} > 0$. We find evidence that risk adjusted daily returns of the

"European" RMP portfolio are indeed significant and positive for the first quarter of 2020. However, looking over the entire observation period from 1st of January until 31st of August 2020 we do not find significantly positive risk adjusted daily returns. Looking at the countries in our sample individually, we find significant positive daily risk adjusted returns over the entire observation period only for Spain and Italy while they are significantly positive for seven countries over the first quarter of 2020. Regardless of their significance, daily risk adjusted returns are positive for a majority of countries and we find positive cumulative risk adjusted returns for 20 out of 26 countries in our sample. Table III below presents the results.

Overall, we find support for our hypothesis of a positive WfH-differential although findings differ significantly across time and countries. In particular, positive daily risk adjusted returns seem to be concentrated in the time period before government interventions in Europe and in countries that were more severely impacted by the first wave of the pandemic. Our finding of varying WfH-differentials raises the question about its driving forces across countries. We examine this matter in greater detail in the sections to follow.

Table III:
Average Daily Risk Adjusted Return and Cumulative Risk Adjusted Return for the RMP Portfolio During Entire- and Pre-lockdown Period

	Whole Period			**Pre-european Lockdowns**		
Country	**Mean return**	**T stat.**	**Cum. RMP**	**Mean return**	**T stat.**	**Cum. RMP**
Spain	*0.13%	1.37	23.6%	0.15%	0.879	7.2%
Italy	***0.12%	2.05	23.3%	***0.30%	2.899	15.4%
Belgium	0.00%	0.91	13.4%	0.38%	2.968	20.5%
Portugal	0.07%	0.64	10.8%	0.09%	0.672	4.5%
Switzerland	0.07%	1.24	11.5%	*0.10%	1.451	4.9%
Greece	0.05%	0.69	8.3%	0.09%	0.687	4.4%
Denmark	0.05%	0.54	7.1%	-0.02%	-0.132	-1.1%
Netherlands	0.05%	0.62	7.3%	-0.10%	-1.147	-4.8%
Ireland	0.03%	0.24	2.9%	-0.23%	-1.487	-10.8%
Hungary	0.02%	0.12	-1.2%	0.18%	0.840	8.6%
Sweden	0.02%	0.23	2.3%	0.11%	0.854	5.4%
Austria	0.02%	0.19	1.7%	***0.28%	2.411	14.7%
Croatia	0.01%	0.08	0.1%	**0.26%	1.689	13.1%
United Kingdom	0.00%	0.08	0.4%	*0.09%	1.537	4.7%
France	0.00%	0.06	0.1%	0.09%	1.178	4.3%
Germany	0.00%	-0.07	-1.3%	0.08%	0.784	3.8%
Turkey	-0.01%	-0.05	-3.9%	0.28%	0.888	13.6%
Norway	-0.01%	-0.11	-3.0%	0.13%	1.089	6.4%
Romania	-0.01%	-0.13	-2.9%	*0.17%	1.554	8.4%
Finland	-0.06%	-0.58	-11.6%	-0.06%	-0.476	-3.2%
European RMP	**0.03%**	**0.88**	**5.0%**	****0.08%**	**1.930**	**4.2%**

Table III depicts the average daily risk adjusted return (Mean return) and cumulative risk adjusted return (Cum. RMP) of the RMP portfolio for 20 countries. The portfolio is constructed for each country individually and weighted based on the market capitalisation of the stocks. The portfolio is held for all existing trading days during the observation period and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. "Remote" and "physical" stocks are defined as having an above and below median Dingel and Neiman (2020) value for their respective industry. The table shows for every country the daily risk adjusted excess return and the cumulative risk adjusted excess return for the full observation period from the 1st of January until the 31st of August 2020 as well as the subperiod from the 1st of January until the first European lockdown in Italy on the 9th of March, 2020. In addition, the table also includes t-statistics from one-sided tests for whether the daily portfolio returns are greater than zero.
, **, and * represent significance at the 10%, 5% and 1% levels, respectively.*

5.2 The WfH-differential and Government Interventions

We argue that the first lockdown in the Chinese province of Wuhan might have shifted investors' sentiment towards disaster prevalence. As seen in an unprecedented volatility in financial markets (Baker et al., 2020, Baek et al. 2020) the extreme strictness of the lockdown measures in China might have sparked fear and uncertainty about the degree to which particular industries will suffer after global contagion. We posit that in this uncertain period higher risk premia for "physical" stocks compared to "remote" stocks should be prevalent. Further, we suggest that the first European government interventions, particularly the first Italian lockdown on the 9th of March might have reduced stock market uncertainty. This might have emerged as investors were now able to more accurately estimate the actual consequences of government interventions on their labour income. In addition, we argue that already before government interventions, WfH-ability was reflected in risk premia and prices adjusted accordingly. We hence expect lower WfH-differentials after government interventions.

To test this, we study the cumulative stock returns of the RMP portfolio in the 46 day-period from the 23rd of January, when the first lockdown was announced in Wuhan, until the 9th of March, the announcement date of the first lockdown in Italy ("period 1"). The cumulative returns for period 1 are compared with those of the following 46-day period from the 10th of March until the 24th of April ("period 2"). Our aim is to shed light on whether the first introduced government interventions led to a significant change in returns. Our results strongly support our hypothesis. First, we observe positive cumulative returns of the RMP portfolio before government interventions. Second, we observe a decrease of cumulative returns of the RMP portfolio after government interventions.

In period 1, we find the cumulative RMP return of 18 countries in our sample to be positive while negative in 8 countries. The median cumulative RMP return lies at 6.6%. Notably, countries in which the cumulative RMP return was positive experienced a higher median cumulative return amounting to 8.5% while countries in which the cumulative RMP return was negative incurred a median decline of the cumulative RMP return amounting to 3.4%. Further, we find support for the hypothesised reversal of the cumulative RMP return with the median cumulative RMP return declining to -8.3% in period 2. To formally test our hypothesis, we first employ the Shapiro-Wilk test (Shapiro and Wilk, 1965) testing differences of the sample periods for normal distribution. We find that the differences in cumulative RMP returns are not normally distributed with the p-value of 0.01 rejecting the null-hypothesis of normal distribution. Hence, in comparing the periods, we apply the Wilcoxon signed rank test that allows for non-normal distribution (Wilcoxon, 1945). We find the cumulative RMP returns in period 1 to be significantly higher from those in period 2 on a 1%-confidence level.

In section 3 we extended our hypothesis and argued that the cumulative RMP returns in the first period should be significantly higher than in the second even after accounting for the Fama and French (1992) FF3 risk factors. Interestingly, we find that after the adjustment, 21 countries show a positive cumulative risk adjusted RMP return. As supported by the findings reported in section 5.1, the WfH-ability might not be captured by the risk factors of the Fama and French (1992) FF3. We find further support for this hypothesis: Similar to our initial test of unadjusted returns we find the cumulative risk adjusted RMP returns in period 1 to be significantly higher than those in period 2 on a 1%-confidence level.

We summarise the results in Table IV below. As the results in the table indicate, for some countries we can only allocate low numbers of stocks into the “remote” and “physical” groups. The results are robust to applying a threshold of a minimum of 10 stocks per group. For the reduced sample analysis please refer to Appendix 7.

Table IV:
Cross-country RMP Returns for Pre- and Post-lockdown Windows

	Ø Number of Stocks		Ending 09. March		Ending 24. April	
			Cum. returns		Cum. returns	
Country	Remote	Physical	Unadjusted	Risk adj.	Unadjusted	Risk adj.
Slovakia	6	2	37.7%	40.8%	-39.9%	-40.7%
Belgium	63	70	17.3%	15.4%	-6.4%	-2.6%
Austria	26	44	14.0%	12.2%	-16.0%	-17.3%
Italy	150	177	12.3%	13.2%	-12.6%	-9.3%
Norway	87	105	11.3%	4.7%	-13.8%	-18.2%
Sweden	253	489	10.2%	3.6%	-6.8%	-8.3%
Germany	345	384	10.2%	1.3%	-0.6%	-6.3%
Latvia	2	17	8.7%	8.5%	32.5%	27.0%
Spain	105	98	8.6%	4.8%	-8.1%	-6.4%
Estonia	5	11	8.3%	9.9%	11.9%	14.5%
Romania	21	55	8.2%	7.4%	-5.9%	-8.0%
Portugal	22	23	7.8%	1.9%	-8.4%	-12.8%
Hungary	20	10	6.9%	9.4%	-29.9%	-27.1%
Croatia	19	60	6.3%	7.7%	-7.0%	-5.9%
Lithuania	8	20	5.9%	6.7%	-1.3%	-1.3%
Finland	69	90	1.3%	-3.4%	-13.3%	-13.2%
Slovenia	10	11	1.0%	1.8%	-23.1%	-22.6%
Czechia	4	1	0.4%	4.6%	-10.5%	-7.2%
United Kingdom	782	639	-0.5%	4.6%	-6.7%	-1.3%
Greece	54	114	-1.1%	5.4%	-10.5%	-7.1%
France	251	411	-1.3%	1.8%	-16.0%	-9.9%
Ireland	14	28	-3.4%	-5.0%	8.5%	6.7%
Switzerland	100	134	-3.4%	3.1%	-11.4%	-1.5%
Denmark	68	77	-5.6%	-3.6%	-10.0%	-4.0%
Turkey	135	246	-8.0%	-6.5%	0.7%	3.1%
Netherlands	56	82	-9.5%	-6.3%	-6.5%	0.8%
# Positive			18	21	4	5
# Negative			8	5	22	21
Median			6.6%	4.6%	-8.3%	-6.7%
Difference					-14.9pp	-11.4pp
Shapiro-Wilk W (p-value)					0.89 (0.010)	0.85 (0.002)
Wilcoxon signed rank test						
V					310	304
p-value					0.0003***	0.0006***

*Table IV depicts the cumulative returns of the RMP portfolio for all 26 sample countries for two consecutive 46-day windows. The first window "Ending 9.March" spans the period from 23rd January, the day of the lockdown announcement in the Chinese province of Wuhan, until the 9th of March, the day of the first European lockdown announcement in Italy. The second window "Ending 24. April" spans the period from March 10th until April 24th. The columns Ø Remote and Ø Physical denote the average number across the two periods of stocks in the "remote" and "physical" groups respectively. Columns "Unadjusted" denote the unadjusted cumulative return. Columns "Risk adj." denote the returns after adjusting for the Fama and French (1992) three-factor model (FF3) risk factors. The rows # Positive and # Negative denote the number of sample countries with positive and negative cumulative returns respectively. The row "Difference" denotes the percent point difference in the equally weighted median returns for both "Unadjusted" and "Risk adj.". W denotes the Shapiro Wilk (1965) test statistic for normality with the Null Hypothesis "The data is normally distributed". V denotes the test statistic for the Wilcoxon (1945) signed rank test. The null hypothesis amounts to "the medians of both samples are equal". *** denotes statistical significance at the 1%-level.*

In order to control for factors unrelated to COVID-19 that could be influencing the WfH-differential, we apply the same methodology to two identical control windows in 2019. By taking this step, we intend to provide support for our argument that the cumulative RMP returns are actually associated with the COVID-19 pandemic and the resulting importance of WfH-ability.

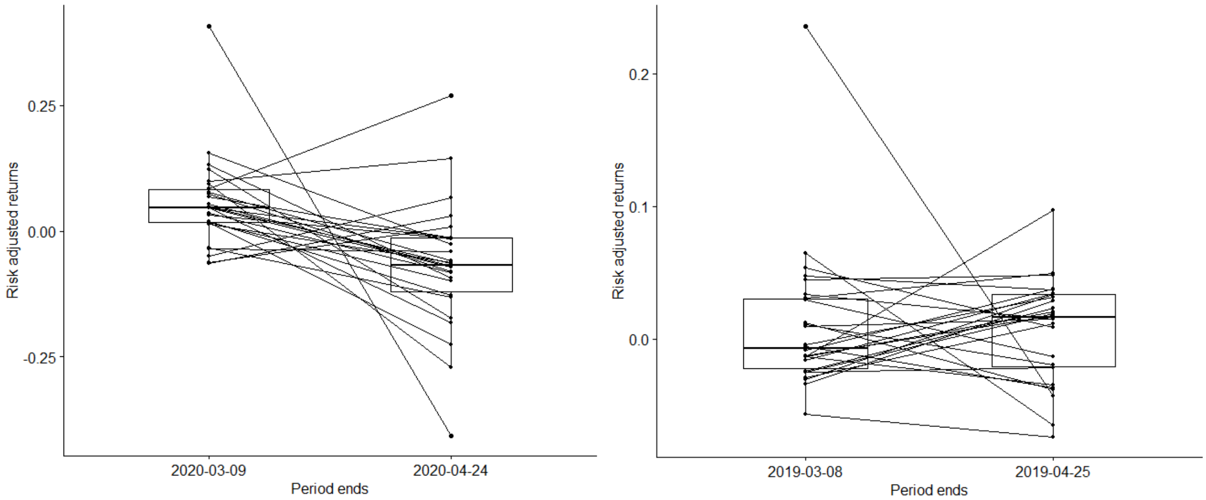

Figure 4: **Boxplot Comparison of Periods 1 and 2 in 2020 and 2019 Control Window**

Figure 4 shows two paired boxplots of countries cumulative risk adjusted returns of the RMP portfolio. In each figure, the left boxplot reflects the 46-day window beginning on the 23rd of January. Each figure's right boxplot reflects the 46-day window beginning from the 10th of March. Window end dates are shown on the x-axis. The left figure refers to the focal year 2020 while the right figure refers to the control year, 2019. Dots indicate the countries' cumulative risk adjusted RMP return while lines are used to indicate changes among the windows.

We find additional support for our hypothesis as the Wilcoxon signed rank test does not indicate significantly different cumulative RMP returns for the control windows. Furthermore, studying the control windows reveals no clear patterns that point to the prevalence of a WfH-differential. As the boxplots above illustrate, there is no sizable difference in mean returns in the control windows. We report the table of results for the analysis of control windows in 2019 in Appendix 8.

From our results, we conclude that there was indeed a pronounced WfH-differential at the onset of the COVID-19 pandemic which decreased significantly after government interventions. Findings presented in the following section provide further support that government interventions might indeed explain the magnitude of the WfH-differential.

5.3 The WfH-differential and Country-level Characteristics

According to our theoretical framework, an asset's risk premium depends on the volatility of the asset as well as the covariance between the asset and labour income. While the COVID-19 pandemic is a market-wide shock that influences the volatility of risky-assets, workplace disruptions influence the covariance between risky assets and labour income. To test these two channels empirically, we use the daily change in new deaths due to the COVID-19 pandemic as a proxy for the market-wide shock and the workplace closure value as a proxy for workplace disruptions that impact the labour income risk.[16]

In Figure 5 below we plot the countries' average daily risk adjusted RMP return in percent, the respective average country benchmark index returns[17] as well as the average closure index over the observation period from 1st of January to 31st of August. The figure shows a consistent pattern a high degree of workplace disruptions in associated with more negative average returns for benchmark stock indices as well as a better average performance of the RMP portfolio.

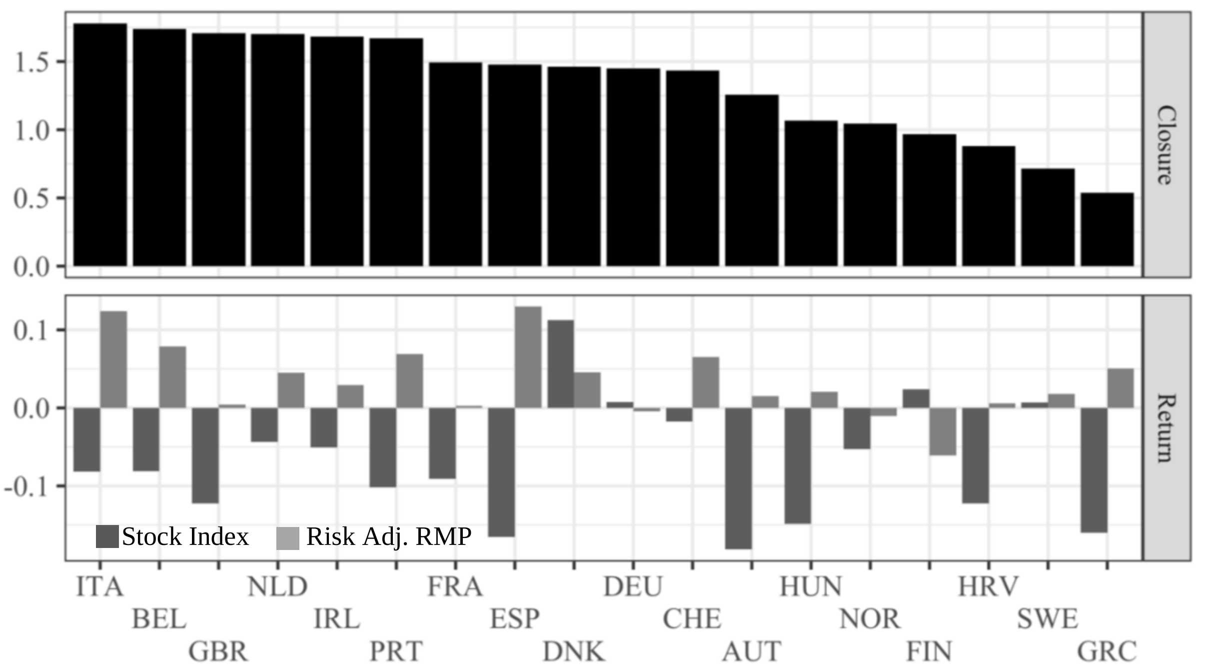

Figure 5: **Average Risk Adjusted Return of the RMP Portfolio Against Country Stock Market Indices and Average Workplace Closure Index**

Figure 5 shows the average risk adjusted return of the RMP portfolio for a sample of 18 European countries against the return of the respective stock market index. The top plot shows the corresponding average workplace closure value for the country. Romania and Turkey have been excluded due to limited stock market data and extreme outliers respectively. Countries with less than 10 stocks per group were excluded.

[16] We obtain the workplace closure index from the Oxford Covid-19 Government Response Tracker and the new COVID-19 related deaths variable from the data repository of the Center for Systems Science and Engineering (CSSE) at the Johns Hopkins University.

[17] For a list of the applied country stock indices, please refer to Appendix 9.

To test the magnitude of this relationship we establish two quasi-between panel regression models by averaging the RMP portfolio risk adjusted returns as well as the countries’ workplace closure value and new deaths of COVID-19 per million inhabitants. Workplace closure is an ordinal variable ranging from 0 to 3, with 0 for “no workplace restrictions” and 3 for “complete workplace closures for all but essential workers”. Below, we show the relationship between the variables and the average risk adjusted RMP portfolio return.

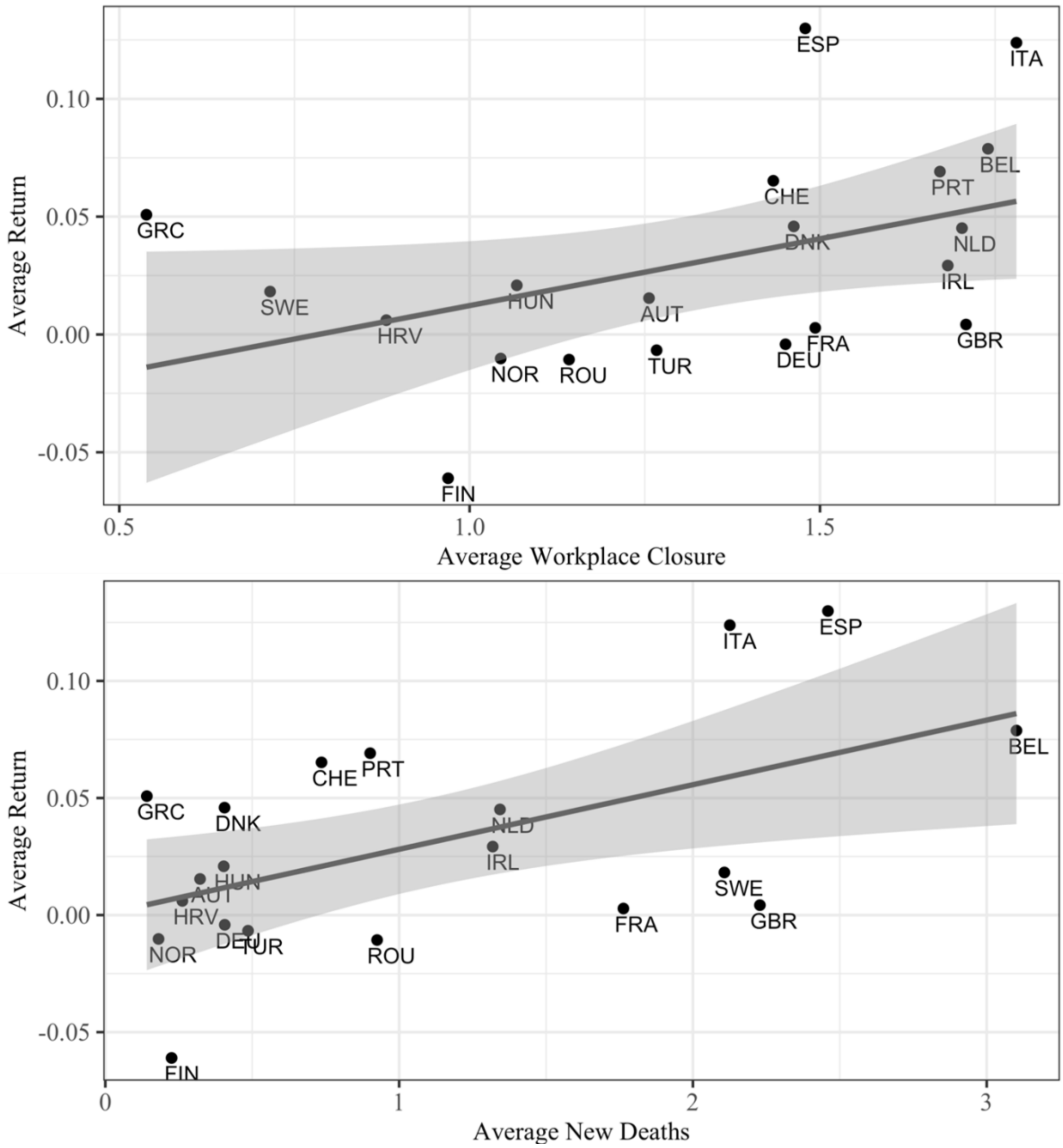

Figure 6: **Average Risk Adjusted Return of the RMP Portfolio Against Average Workplace Closure and Average New COVID-19 Related Deaths**

Figure 6 plots the average risk adjusted return of the RMP portfolio for a sample of 20 European countries against the respective average workplace closure (top chart) and average new deaths (bottom). Countries with less than 10 stocks per group were excluded. The graph includes a linear trendline with its corresponding 95% confidence interval.

Formally, we test this relationship by applying OLS and regressing the average risk adjusted RMP portfolio return on *Average closure* and *Average new deaths per million inhabitants* respectively. Both models show significant positive effects at the 10%- and 5%-level respectively providing evidence for our hypothesis that workplace disruptions and the pandemic severity positively impact the magnitude of the RMP portfolio.

Table V:
Cross-country Regression Analysis of the Average RMP Returns on COVID-19 Pandemic Characteristics.

	Dependent variable:	
	Average RMP risk adjusted return	
	(1)	(2)
Average closure	0.057*	
	(0.027)	
Average change in new deaths		0.028**
		(0.010)
Constant	-0.044	0.001
	(0.037)	(0.014)
Observations	20	20
R^2	0.196	0.287
Adjusted R^2	0.151	0.248
Residual Std. Error (df = 18)	0.043	0.040
F Statistic (df = 1; 18)	4.383*	7.259**

Table V shows the results from panel regression tests of the pandemic characteristic variables for the period from 1st January to 31st August 2020. We take the time-series average of the daily risk adjusted RMP return of each country and regress it on the time-series average of the respective characteristics. The portfolios are constructed for each country individually and weighted based on the market capitalisation of the stocks. Each portfolio is held for all existing trading days during the observation period and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. "Remote" and "physical" stocks are defined as having an above and below median Dingel and Neiman (2020) value for their respective industry. The pandemic characteristics included are the ***Average change in new deaths*** *as well as the* ***Average closure*** *which is an ordinal variable ranging from 0 to 3. Due to a lack of sufficient stock market data, we restrict our sample to 20 countries for which we observe at least 10 companies in each group trading continuously. *,** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.*

A drawback of this approach is that we omit the variability in our dataset by averaging observations. In order to better exploit the high frequency nature of the daily portfolio returns and the detailed real-time information on COVID-19 developments, we run a random effects model for our panel data after confirming the applicability through a Hausman (1978) test as outlined earlier.

Table VI below illustrates the findings. In the first model specification we include the two aforementioned variables of *Change in new deaths* which is the percentage change in daily new deaths due to COVID-19 and a dummy variable *Closed* for countries that show a higher degree of workplace disruptions than the cross-country median as well as an interaction term between *Closed* and *Change in new deaths.* The regression coefficients for the variable *Closed* and *Change in new deaths* turn out positive and significant at the 1%-level and 10%-level, respectively. These findings are in line with our framework, since we expect a higher degree of workplace disruptions and pandemic severity to have a positive impact on the RMP portfolio return. Interestingly, the interaction term between the *Closed* dummy variable and *Change in new deaths* has a negative coefficient. This implies that in countries with a higher degree of workplace disruptions due to government interventions, an increase in COVID-19 severity has a lower impact of the WfH-differential.

In the second model specification we further add the variable *Market capitalisation weight* which measures the ratio of a country's stock market capitalisation in relation to the market capitalisation of our entire sample on the 1st of January 2020. We include this variable to account for the size of country stock markets which could be a significant driver of stock returns due to resulting differences in liquidity and information dissemination to market participants (Amihud and Mendelsohn, 1986). Even after controlling for the size of the country stock market, the regression coefficient of the *Closed* dummy variable remains positive and significant. Similarly, the regression coefficients of *Change in new deaths* and the interaction term with the *Closed* dummy are robust after controlling for the size of the stock market.

The third model specification includes a set of control variables aimed to capture additional country-level characteristics that potentially have an impact on asset prices. Of particular interest are a country's level of digital infrastructure and its institutional quality. Esfahani and Ramirez (2003) highlight the importance of countries' infrastructure by establishing a positive relationship between infrastructure investments and GDP growth. La Porta, Lopez-de-Silanes, Shleifer and Vishny (1997) argue that law enforcement and legal systems have a significant impact on the size of the capital market. In the context of WfH-ability, the former plays an important role in enabling the shift to WfH by providing the necessary environment to work remotely such as sufficient internet speed while the latter captures a country's ability to actually enforce its imposed interventions. We control for a country's digital infrastructure by including a control variable for *Broadband*[18] speed as well

[18] The data on Broadband Speed is obtained from the SpeedTest Global Index.
The data is retrievable at: https://www.speedtest.net/global-index#mobile

as *Digital skills* which captures the digital literacy of the workforce.[19] The *Average institutional quality*[20] comprises three dimensions: government effectiveness, regulatory quality and rule of law similar to the measure employed by La Porta, Lopez-de-Silanes, Shleifer and Vishny (1997). While particularly the regression coefficients of *Average institutional quality* and *Broadband* speed turn out highly significant, the regression coefficients of the parameters of interest *Closed* and *Change in new deaths* remain highly significant and do not change direction. In fact, the regression coefficient of the *Closed* dummy becomes even more significant after controlling for country-level characteristics.

[19] The data on digital skills is obtained from EUROSTAT, applying the indicator "isoc_sk_dsl_i" which captures the percentage of individuals having basic or above basic overall digital skills. The data is retrievable at: https://ec.europa.eu/eurostat/web/products-datasets/product?code=tepsr_sp410

[20] The data on Average Institutional Quality is obtained from the Worldwide Governance indicators of the World Bank. The data is retrievable at: https://databank.worldbank.org/embed/Institutional-Quality/id/98e680fc

Table VI:
Random Effects Model of the Remote Minus Physical (RMP) Returns on COVID-19 Pandemic and Country-level Characteristics.

	Dependent variable:			
	RMP Risk-Adjusted Return			
	(1)	(2)	(3)	(4)
Closed dummy	0.049***	0.091***	0.349***	0.797***
Change in new deaths	0.0005*	0.0005*	0.001***	0.001***
Average institutional quality			-0.002	-0.001***
Digital skills			-0.001	-0.0005**
Broadband			0.00001	0.0004***
Market capitalisation weight		0.410***	0.986**	-1.260***
Legal labour protection				0.159***
Closed dummy x Change in new deaths	-0.001**	-0.001**	-0.001***	-0.001***
Closed dummy x Average institutional quality			-0.007***	-0.008***
Closed dummy x Digital skills			0.005**	0.004***
Closed dummy x Broadband			0.001***	0.001***
Closed dummy x Market capitalisation weight		-0.833***	-1.275***	0.960***
Closed dummy x Legal labour protection				-0.165***
Constant	0.006	-0.003	0.184***	-0.253***

Table VI shows the results from a random effects model of the COVID-19 pandemic and country-specific characteristic variables for the period from 1st January to 31st August 2020. We regress the daily ***RMP risk adjusted returns*** *for each country on the COVID-19 pandemic and country-specific characteristics. To account for differences between countries we use a random effects estimator. The portfolios are constructed for each country individually and weighted based on the market capitalisation of the stocks. Each portfolio is held for all existing trading days during the observation period and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. "Remote" and "physical" stocks are defined as having an above and below median Dingel and Neimann (2020) value for their respective industry. The pandemic characteristics included are the daily* ***Change in new deaths*** *as well as the* ***Closed dummy*** *based on the workplace closure variable which is an ordinal variable ranging from 0 to 3. The country-specific characteristics are the* ***Market capitalisation weight*** *on 1st January 2020, the* ***Average institutional quality****,* ***the Broadband*** *speed , the* ***Digital skills*** *of employees and* ***Legal labour protection****. Due to a lack of sufficient stock market and country-specific data, we restrict our sample to 15 countries for which we observe at least 10 companies in each portfolio trading continuously and have complete data for the regressors. In the first model specification we only include the COVID-19 pandemic characteristics. The second model further controls for the size of the capital market while the third model also incorporates other country-specific characteristics. The last specification tests our hypothesis of labour regulation effects on the RMP risk adjusted returns. The table reports coefficient estimates that have heteroskedasticity robust standard errors. We do not report adjusted R^2-measures since standard errors are assumed to be heteroskedastic. Therefore, the sum of squared errors does not follow a Chi-square distribution. *,** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.*

5.4 The WfH-differential and Legal Labour Protection

In a last step, we test the hypothesis of legal labour protection reducing the WfH-differential. Intuitively, we expect better legal labour protection of a country's workforce to entail an implicit insurance of labour income. This should result in lower labour income risk which reduces the WfH-differential as outlined earlier in this paper.

We therefore include the time-invariant variable *Legal labour protection* in our fourth model specification that captures the legal protection of employees from being laid-off.[21] Additionally we include an interaction term to test whether the degree of workplace disruptions had an impact on the significance of this factor. As we are interested in the mitigating effect of legal labour protection in the face of workplace disruptions during the pandemic, this interaction term is our main parameter of interest. The results in table VI show that the regression coefficient of the interaction term *Closed Dummy x Legal labour protection*, is negative and highly significant. Stricter legal labour protection indeed seems to have a detrimental effect on the WfH-differential in countries with a high degree of workplace disruptions. Thus, we find evidence for the negative relationship between legal labour protection and the WfH-differential. However, our results are mixed since, by itself, the legal labour protection has a positive impact on the RMP portfolio returns across countries. Although a detailed analysis of this unexpected finding is beyond the scope of this paper, one reason could be an omitted variable bias in the estimates as the *Legal labour protection* variable could serve as a potential instrument variable for other factors beyond the regulatory environment in the country itself.

5.5 Robustness Tests

5.5.1 Reclassification of Critical Industries "Pennsylvania List Robustness Test"

During the COVID-19 pandemic, government interventions leading to workplace disruptions have often exempted industries deemed to be "critical". To test our results for robustness, we reclassify critical industries as "remote" industries. According to the guidance by the US Cybersecurity and Infrastructure Security Agency, CISA (2020), "critical" in this sense refers to "conduct[ing] a range of operations and services that are typically essential to continued critical infrastructure viability". Under the guidance these span "medical and healthcare, telecommunications, information technology systems, defense, food and agriculture, transportation and logistics, energy, water and wastewater, and law enforcement." (CISA, 2020). It is important to note that sorting critical industries into the "remote" group extends the

[21] The data is obtained from the OECD based on the Employment Protection Legislation (EPL) that measures the protection from collective and individual dismissal along 21 dimensions aggregated to a synthetic index. The data can be retrieved from: https://www.oecd.org/employment/emp/oecdindicatorsofemploymentprotection.htm

notion of WfH-ability to a measure for resilience towards workplace disruptions at large. This notion now spans industries that either have a high WfH-ability or can continue operations despite a low WfH-ability because they have been classified critical by regulators and hence can continue to operate. With the "Pennsylvania list of lifesaving industries" ("Pennsylvania List", Commonwealth of Pennsylvania, 2020), we apply one of the first published accounts for critical industries. The underlying assumption of this approach is that those industries classified as critical according to the Pennsylvania List are also those deemed critical across our sample. Although this might not be true on a granular level, the resulting reclassified industries indeed have "critical" character. As the Pennsylvania list is structured at a more granular level than our NACE-section level industry classification, we first match the industry classification to the NACE-section level classification and observe the share of each industry corresponding to the NACE-section-level that has been classified as critical. If the share lies above 80%, we classify the whole industry as critical. This results in the industries "Agriculture", "Mining and Quarrying", "Water Supply" and "Transportation and Storage" to be reclassified from the "physical" group to the "remote" group. Note that these industries are clearly not "remote" in a sense of exhibiting high WfH-ability. Certainly, however, their regulatory classification as critical makes them resilient to workplace disruptions. For all analyses regarding our hypotheses conducted under the "Pennsylvania List Robustness Test" we find similar results than before the reclassification. This provides support for the view that the WfH-differential might not solely be driven by WfH-ability but by resilience towards workplace disruptions at large.

5.5.2 WfH-ability of Top- and Bottom Percentiles "Top and Bottom Robustness Test"

As a next step, we draw on an approach proposed by Kaniel et al. (2007). We omit the centre of the WfH-ranked industries in order to only capture industries with very high or very low WfH-ability respectively. Stocks with top 30% DN are classified "remote" while stocks with bottom 30% DN are classified "physical". We thereby test our results for a classification that captures only unambiguously high or low WfH-ability. This test leads to a smaller number of stocks in the countries' RMP portfolios. However, as we apply a reduced sample in the panel regression that excluded countries with low numbers of stocks, the respective RMP portfolios remain sufficiently large. For all analyses regarding our hypotheses conducted under the "Top and Bottom Robustness Test" we find similar results than before the reclassification. We report a summary of our results under assumptions of both robustness tests in the Appendix 10.

6 Application: The WfH-differential and GDP Growth

We have found support for our hypothesis that countries with a more severe COVID-19 trajectories, higher degrees of workplace disruptions as well as looser legal labour protection will experience a higher WfH-differential. We suggest that these factors might also impact future economic growth of the focal economy directly. This raises the question about the predictive power of the WfH-differential as represented by the RMP return during the pandemic.

To draw conclusions about this, we first look at the contemporaneous relationship between the cumulative risk adjusted RMP return and quarterly GDP growth. Next, we test whether the cumulative risk adjusted RMP return at the end of the first quarter of 2020 predicts the quarterly GDP growth of the following quarter. We gather quarterly GDP data for the sample countries from the OECD.[22] Specifically, we apply the OECD CQRSA measure. We follow Fama (1990) in using seasonally adjusted quarterly GDP data as we are interested in drawing conclusions on the predictive power of the RMP spread that are not driven by seasonal- and cyclical fluctuations. Based on the quarterly GDP data we calculate the quarter-on-quarter GDP growth as well as the year-on-year GDP growth until the second quarter of 2020 for all sample countries. Furthermore, we obtain quarterly stock index data for the leading country indices of our sample from the Compustat database. To calculate the cumulative stock index growth, we use the quarter-end closing figures.

6.1 The Contemporaneous Relationship of the WfH-differential and GDP Growth

As Figure 7 below suggests there might be a negative relationship between the cumulative risk adjusted RMP return and the quarterly GDP growth in the first quarter of 2020. In our sample of 25 countries[23], 21 incur quarterly GDP decline in Q1 2020. Further, we observe that for the first quarter of 2020 19 out of 25 countries exhibit a negative relationship between quarterly GDP growth and the cumulative RMP return.

[22] The data is retrievable at: https://data.oecd.org/gdp/quarterly-gdp.htm

[23] For this analysis, we excluded Slovakia from the sample as its RMP return figure appears to be an extraordinarily high outlier.

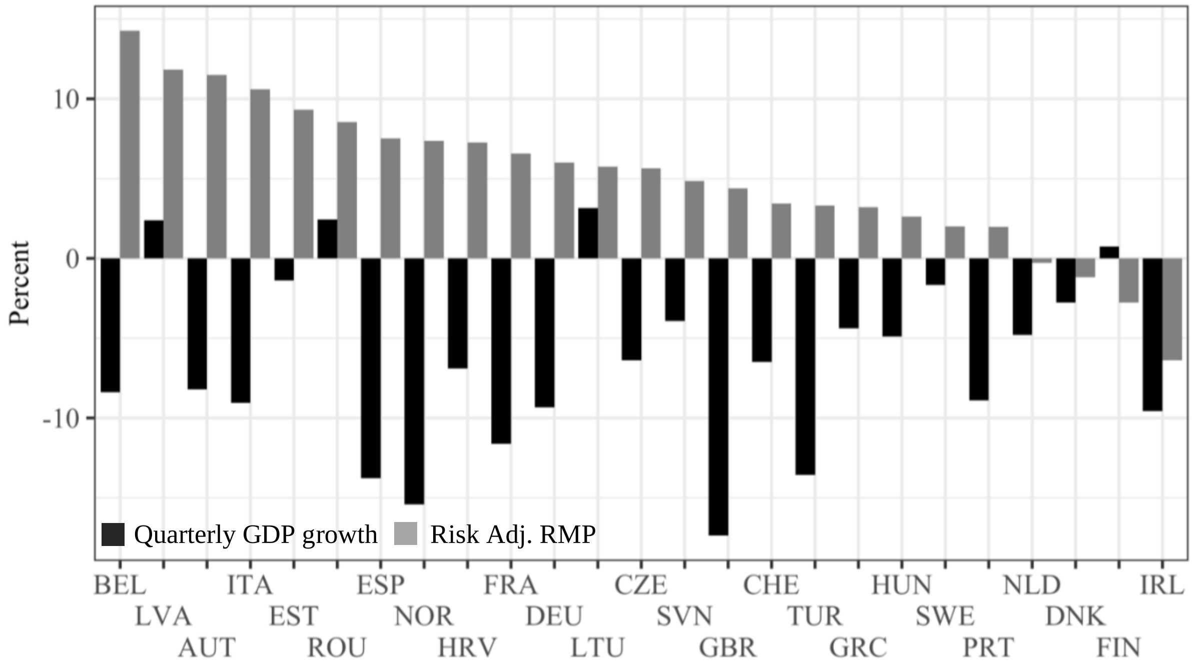

Figure 7: **Cumulative Risk Adjusted Return of the RMP Portfolio Against Change in GDP**

Figure 7 shows the cumulative risk adjusted RMP portfolio return in the first quarter of 2020 for a sample of 25 European countries against the quarterly GDP growth in the first quarter of 2020. Slovakia has been excluded due to an outlier value in the risk adjusted RMP return.

To test the contemporaneous relationship between the cumulative RMP return and quarterly GDP growth, we conduct OLS regressions of the quarterly GDP growth for the first quarter of 2020 on the cumulative risk adjusted RMP return at the end of Q1 2020. The results are reported in Table VII. A negative coefficient for the cumulative risk adjusted *RMP* return, significant at the 5% level indicates support for our argument of a negative relationship between the cumulative risk adjusted RMP return and quarterly GDP growth.

To rule out the possibility that not the cumulative risk adjusted RMP return, but the respective country's stock market itself explains the quarterly GDP growth, we include the Q1 cumulative return of national stock market indices as a control variable. We find no significance for the corresponding coefficient. Furthermore, the lower adjusted R-squared of the "Control" model indicates that including leading stock market indices does neither override nor improve the explanatory power of the cumulative risk adjusted RMP return regarding the quarterly GDP growth. Results are shown in Table VII on the following page.

Table VII:
Contemporaneous Relationship Between Quarterly GDP Growth and Risk Adjusted RMP Returns

	Dependent variable:	
	QGDP - 2020 Q1	
	Base	Control
	(1)	(2)
RMP	-0.610^{**}	-0.587^{**}
	(0.266)	(0.280)
STOCKINDEX		0.067
		(0.195)
Intercept	-0.067^{***}	-0.052
	(0.018)	(0.047)
Observations	25	25
R^2	0.185	0.190
Adjusted R^2	0.150	0.116
Residual Std. Error	0.062 (df = 23)	0.063 (df = 22)

Table VII depicts regression coefficients of the Q1 2020 quarterly GDP growth on the cumulative risk adjusted return of the RMP portfolio. The portfolios are constructed for each country individually and weighted based on the market capitalisation of the stocks. Each portfolio is held for all existing trading days during the observation period and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. "Remote" and "physical" stocks are defined as having an above and below median Dingel and Neimann (2020) value for their respective industry. The model base includes only the risk adjusted return of the RMP portfolio as an independent variable ***RMP*** *. The model control includes the risk adjusted return of the RMP portfolio, and the control variable* ***STOCKINDEX*** *as the cumulative return of the national stock index in Q1 2020. In both specifications the dependent variable is the Q1 2020 quarterly GDP growth, denoted* ***QGDP -2020 Q1*** *. Slovakia is excluded from the sample due as its RMP value is an outlier.*
, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively*.

6.2 The Predictive Relationship Between the WfH-differential and GDP Growth

To test if the cumulative risk adjusted RMP return offers insight into future economic growth we construct a simple OLS model regressing the Q2 quarterly GDP growth on the cumulative RMP return at the end of Q1. We do not find statistical support in applying this model. Although we argue that there is an economic relationship and the resulting coefficient is indeed negative, the magnitude of RMP returns alone can not explain the next quarter's GDP growth within this model specification.

Although the WfH-differential does not seem to predict quarterly GDP growth during the pandemic it might be able to explain GDP growth compared to pre-pandemic periods. Hence, we next investigate the year-on-year changes in GDP. Figure 8 shows the relationship between the Q1 cumulative risk adjusted RMP return and the year-on-year GDP growth until

Q2 2020. The figure suggests a negative relationship with a higher cumulative risk adjusted RMP return in Q1 entailing a steeper year-on-year GDP decline until Q2 2020.

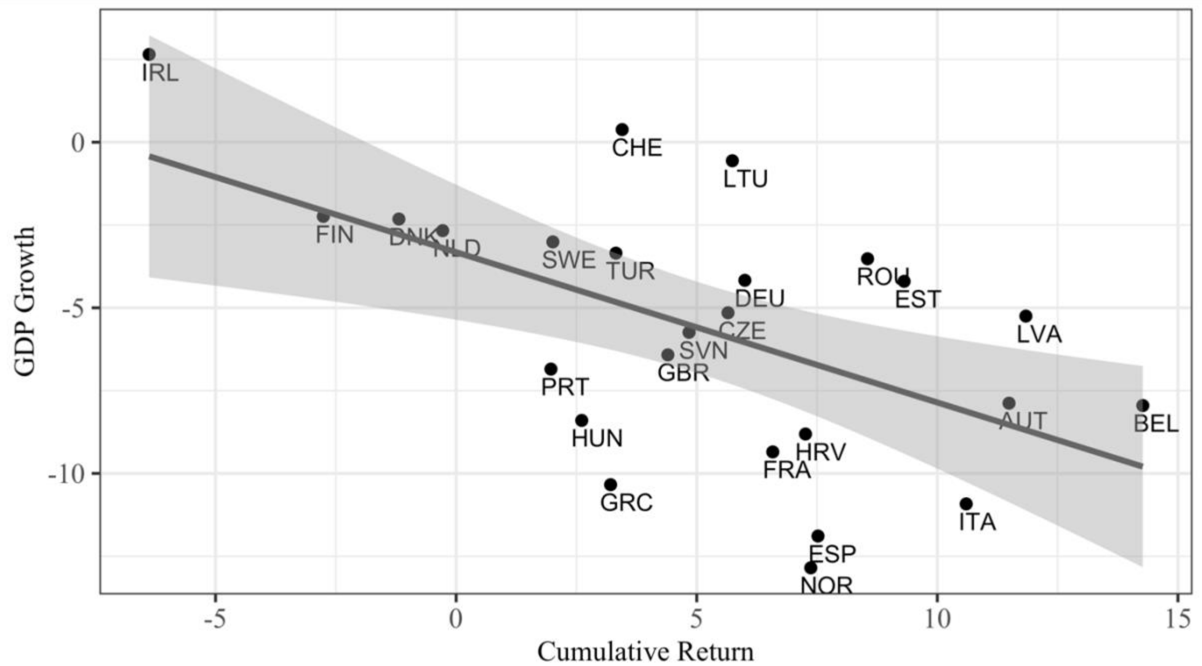

Figure 8: **Cumulative Risk Adjusted Return of the RMP Portfolio Against Year-on-Year Change in GDP until the Second Quarter**

Figure 8 plots the cumulative risk adjusted return of the RMP portfolio for a sample of 25 European countries against the respective year-on-year growth in the first half of 2020 compared to 2019. Slovakia has been excluded due to an outlier value in the risk adjusted RMP return.

To test the relationship, we regress the year-on-year GDP growth until Q2 2020 on the cross section of cumulative risk adjusted returns of the RMP portfolio at the end of Q1 2020. We report results in table VIII on the following page. The results indicate support for the negative relationship between the year-on-year GDP growth and the Q1 cumulative risk adjusted RMP return. In the base specification we find the coefficient for the Q1 cumulative risk adjusted RMP return to be negative and significant at the 1% level. Nevertheless, the R-squared of 0.05 indicates that the cumulative risk adjusted RMP return itself does not possess large explanatory power. Therefore, we next combine it with short term GDP predictors that have been established in the literature. By taking this step, we intend to offer insight on whether the cumulative risk adjusted RMP return can improve prior models.

Table VIII:
Predictive Relationship Between Year-on-Year GDP Growth Q2-2020 and Risk Adjusted RMP Returns

	Dependent variable:		
		YoY-GDP-Q2	
	RMP only	RMP and Controls	Controls only
	(1)	(2)	(3)
RMP	-0.439***	-0.292*	
	(0.146)	(0.157)	
QSTOCKINDEX- 2020 Q1		0.301***	0.368***
		(0.092)	(0.089)
QSTOCKINDEX- 2019 Q4		0.124	0.366*
		(0.219)	(0.186)
QGDP- 2019 Q4		0.069	-0.019
		(0.128)	(0.126)
QGDP- 2019 Q3		0.203*	0.179*
		(0.098)	(0.102)
Intercept	-0.034***	0.015	0.005
	(0.010)	(0.023)	(0.024)
Observations	25	25	25
R^2	0.281	0.606	0.535
Adjusted R^2	0.250	0.503	0.442
Residual Std. Error	0.034 (df = 23)	0.028 (df = 19)	0.029 (df = 20)

Table VIII depicts regression coefficients of the year over year GDP growth until Q2. That is the growth of the year-to-date GDP until the last day of Q2 in 2020 (30th of June) compared to the year-to-date GDP until the last day of Q2 in 2019. This is the independent variable denoted by ***YoY-GDP-Q2****. The model "RMP only" includes the cumulative risk adjusted return of the RMP portfolio for Q1 2020, the variable is denoted* ***RMP****. The portfolios are constructed for each country individually and weighted based on the market capitalisation of the stocks. Each portfolio is held for all existing trading days during the observation period and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. "Remote" and "physical" stocks are defined as having an above and below median Dingel and Neimann (2020) value for their respective industry. The model "RMP and Controls" includes* ***RMP*** *as well as the cumulative quarterly national stock index return for the first quarter of 2020,* ***QSTOCKINDEX – 2020 Q1*** *and the last quarter of 2019,* ***QSTOCKINDEX – 2019 Q4*** *furthermore quarterly GDP growth for 2019 Q4 and Q3 are included* ***QGDP -2019 Q3*** *and* ***QGDP - 2019 Q4****. The model "Controls only" comprises the same specification as "RMP and Controls" but omits the variable* ***RMP*** *in order to allow for comparisons of the adjusted R^2 in specifications with and without the variable RMP.*
, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.*

We control for leading factors for forecasting short-term GDP growth rates that the literature has named. Fama (1990) lays out the argument that information about the GDP development is contained in previous periods and hence formulates a model in which prior periods' stock returns explain GDP growth. To control for the impact of lagged stock market returns, we include the lagged cumulative returns (Q4 2019) of quarterly national index returns as a control variable. Furthermore, we control for the extremely volatile first quarter of 2020 by including the Q1 2020 national index returns as a control variable. We also include quarterly lags of GDP growth as control variables following Choi et al. (1999), who posit that not only the stock market but also lags of past GDP growth itself can explain future short term GDP growth rates. We find that the coefficient of the cumulative risk adjusted RMP return remains significant, although at the 10% level while the Q1 2020 cumulative national index returns are highly significant. We now remove the focal variable *RMP* as a regressor to compare whether the model that included the latter constitutes an improvement in explaining the variability of the year-on-year growth of GDP until Q2. Indeed, we find both a higher R-squared and adjusted R-squared when the cumulative risk adjusted RMP return is included. Observing a higher adjusted R-squared indicates that the improvement is not arbitrarily achieved by adding the regressor.

To conclude, we can not establish a relationship between quarterly GDP growth and the cumulative risk adjusted RMP return but find partial support for the predictive power of the cumulative risk adjusted RMP return for year-on-year changes in GDP. Notably, the cumulative risk adjusted RMP return itself does not possess strong predictive power. Nevertheless, our findings show that including it could improve the explanatory power of established models of short-term GDP growth prediction during the COVID-19 pandemic. Furthermore, these findings reaffirm our prior results by establishing that high WfH-differentials are present in countries that incur high economic decline during the COVID-19 pandemic.

7 Discussion

Within our paper we aimed at shedding light on WfH-ability and its impact on stock returns during the COVID-19 pandemic. We focused on the cross-country perspective and divided national stock markets into firms who by the nature of tasks performed can or cannot easily shift to WfH. Our analyses showed that the outbreak of the COVID-19 pandemic led to a varying stock return response throughout Europe between “remote” and “physical” stocks. As hypothesised, stock prices of “remote” firms seem to suffer less than those of “physical” firms. “Remote” firms appear to be able to respond better to social distancing measures by shifting to remote work and vice versa. We went further and argued that workplace disruptions arising from government interventions and the degree of legal labour protection impact the WfH-differential across countries.

Our results underline the key role of firms’ ability to shift to WfH, particularly in times of disasters that require social distancing. Our finding that WfH-ability can provide a shield against negative stock price reactions can be interpreted in different ways: The results indicate that the ability or inability to WfH adds a layer to labour income risk that should be taken into account both in asset pricing studies but also from a managerial perspective and in the political sphere. For asset pricing studies, because viewing WfH-ability as a driver of both labour income and financial income risk might improve the ability to explain asset prices in the future.[24] For managers, because a firm infrastructure that enables WfH can be a key determinant of success, in times of global health crises but also beyond (Baig et al., 2020). In this vein, Barker et al. (2020) surveying about 1,000 executives found that 74% plan to broaden WfH or at least maintain it. With regard to the political sphere our findings show that government responses impact the degree to which WfH-ability leads to financial market reactions. We argue that our findings also point to a discussion about heterogeneity in legal labour protection. In the light of WfH-ability as a driver of labour income risk, governments could reflect upon heterogeneous labour protection, identifying jobs that are impossible to be performed at home, e.g. restaurant staff and introduce specific labour protection plans to count for the labour income risk arising from low WfH-ability.

Our findings about workplace disruptions and legal labour protection indeed indicate that lenient government interventions and the legal labour protection environment play some

[24] While one strain of literature argues that only aggregate labour income risk matters for asset prices (Jaganathan and Wang, 1996), Eiling (2013) and others stress the importance of idiosyncratic differences in labour income risk to explain asset prices.

mitigating role. However, factors such as increased voluntary social distancing[25] and spillovers through foreign trade ingrainedness[26] of firms can not be entirely offset by governments' efforts to keep economies running as normal by relying on loose regulation or strict labour protection laws.

The example of Sweden illustrates this point. For Sweden, as a country with lenient government interventions and high labour protection, we find a persistent RMP return differential before adjusting for the Fama and French (1992) FF3 risk factors. After the Fama and French (1992) FF3 factor adjustment, we find that, although the differential turns negative from March to early July, at the end of our observation period the differential is positive at around 3%. More factors seem to interplay which underlines that the labour income risk can not be tackled by policymakers alone.

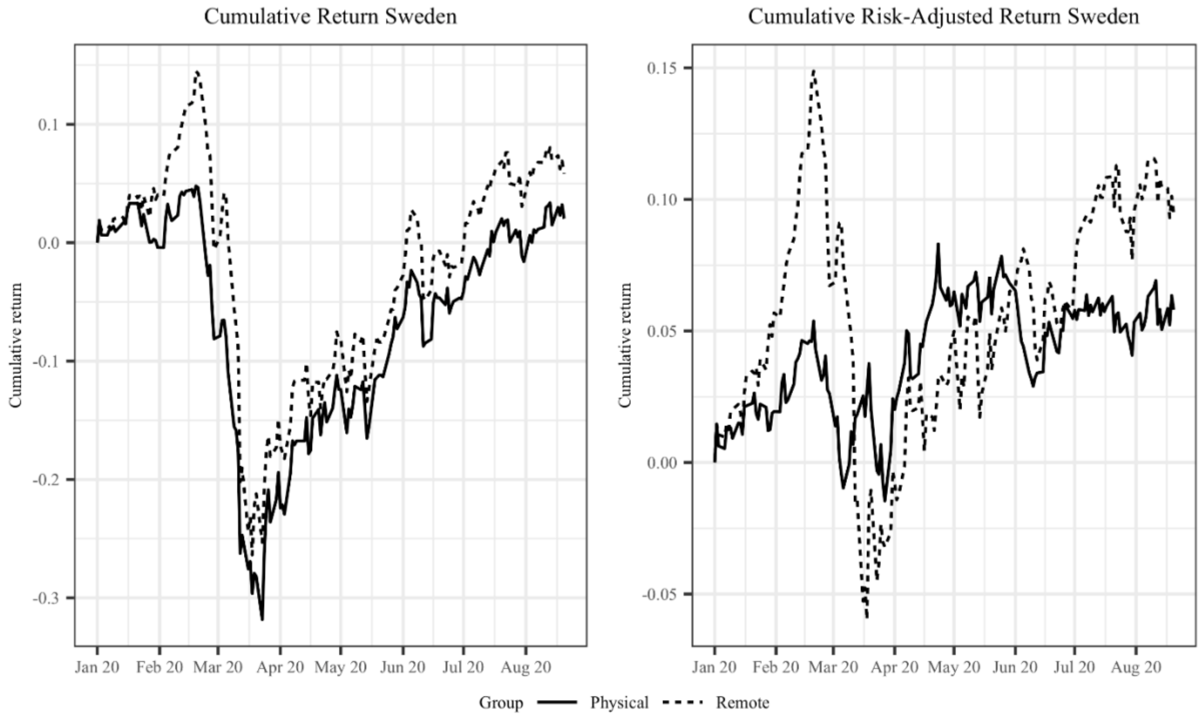

Figure 9: **Sweden - Cumulative Return and Cumulative Risk Adjusted Return for "Remote" and "Physical" Groups**

Figure 9 shows the returns of the cumulative returns of the "remote" and "physical" groups. The left chart depicts unadjusted cumulative returns. The right chart depicts risk adjusted cumulative returns.

[25] Maloney et al. (2020) find that the decrease in personal mobility during the COVID-19 pandemic, i.e. leisure travel, work commute, social gatherings, visits to restaurants, retail stores and other businesses is at least as much driven by voluntary social distancing as by government social distancing directives. The authors find that information about first cases in countries leads to pronounced increases in voluntary social distancing.

[26] Baker et al. (2020) note that one particular explanation for the stock market reaction to COVID-19 could be the dependence of firms on global supply chains that suffered severely during the COVID-19 pandemic. In this vein, a country with a laissez-faire government response to COVID-19 might still be heavily impacted depending on the degree that its economy produces goods that are supplied to countries that introduce mandatory business closures.

As we have shown in the last part, the WfH-differential and quarterly economic growth showed a negative relationship. This might point to the importance of a country-wide WfH-ability. Interestingly, countries like Spain or Italy for which we observe a high WfH-differential, and which all suffered severe economic downturn also exhibit clearly below average scores for the country-aggregated WfH-measure. We acknowledge that the aforementioned countries were impacted with particular severity by the COVID-19 pandemic. Nevertheless, our results indicate that a higher country-level WfH-ability might increase the resilience of countries at large when it comes to health crises like the COVID-19 pandemic.

Within our paper, we aimed at explaining the WfH-differential through the risk premium channel that is driven by undiversifiable labour income risk. Notably, there might be different explanation channels. Most prominently, a case could be made that it is not actually the risk premium changing more unfavourably for firms unable to shift to WfH but the *observed* lower cash flows or dividends itself which in turn lead to lower stock prices. Although we can not invalidate this reasoning, our results suggest that the risk premium channel is meaningful. First, our finding of a high WfH-differential prior to any government interventions suggests a changed risk premium. Second, as suggested by Heaton and Lucas (2000) and Lustig et al. (2010), labour income constitutes a sizable share of total wealth of investors. Therefore, retail investors are certainly exposed to the labour income risk of their respective industry although they are not necessarily exposed to the stock returns of their respective firms. On an aggregate level however, we argue that the risk premium channel should hold.

7.1 Future Research

Concluding the discussion of findings, we lay out potential areas for future research. For a detailed discussion on data and methodology limitations of our paper, which give rise to future research areas, please refer to Appendix 11.

First, we suggest future research to examine WfH-ability and asset prices within a longer data span across countries. Extending the data span could yield insight regarding the question of whether the WfH-ability became priced initially due to COVID-19. Notably, the cross-country perspective would enrich the discussion as it could provide the basis for identifying antecedents of the WfH-differential. In this vein, findings by Pagano et al. (2020), who suggest that WfH-ability might have been priced in US markets before COVID-19, could be complemented with a discussion on conditions that led to WfH-risk being priced.

Next, painting WfH-ability with a finer brush by investigating it on the firm-level instead of the industry-level might prove important in future research. We hence suggest conducting empirical analyses comparable to those within this paper with a more granular, firm-level WfH-measure. A promising side-effect of this style of research could be to reveal firm-level characteristics that increase WfH-ability and hence pandemic-resilience. Particularly the managerial implications arising from this approach could prove valuable.

Furthermore, we suggest extending the notion of working from home as a driver of labour income risk to a concept of pandemic-resilience at large. Arguably, WfH-ability is one driver of pandemic resilience in the context of social distancing. Nevertheless, further research could develop a broader view on factors driving labour income risk differences during the pandemic. This could comprise a discussion on firm level characteristics, such as ESG practises (Albuquerque et al. 2020) and solvency characteristics (Ramelli and Wagner, 2020). Furthermore the question of whether industry characteristics beyond WfH-ability drive disaster resilience should be addressed. We suggest developing a measure that captures a broader span of possible resilience drivers. Next, a replication of our research results could be useful, replacing the RMP portfolio with a long-short portfolio that could be named "Resilient minus Non-resilient" based on the broader measure of resilience. Such a study could shed light on the comparative magnitude of pandemic-resilience drivers.

8 Conclusion

This paper aimed at investigating whether high WfH-ability firms outperform low WfH-ability firms across European stock markets during the COVID-19 pandemic. By using the Dingel and Neimann (2020) measure of WfH-ability, we studied stock returns across 26 European countries. Our results clearly point towards the prevalence of return differentials arising from different WfH-abilities: The cumulative return for "remote" stocks exceeded that of "physical" stocks for the majority of countries in our sample even after adjusting for the Fama and French (1992) three factor model. Raising the question about antecedents of this WfH-differential, we find that countries' pandemic severity and degrees of workplace disruptions impact WfH-differentials positively while strict legal labour protection has a mitigating effect. In line with prior research, we further find the WfH-differential to be more pronounced before European governments introduced interventions to fight the spread of COVID-19. The findings are consistent with the presented framework: Agents require higher risk premia for "physical" stocks as low WfH-ability of "physical" industries renders them less resilient to workplace disruptions while increasing the correlation of "physical" labour income with risky assets. The opposite is true for "remote" industries. This leads to a price adjustment process that our "remote minus physical" portfolio seeks to exploit.

Broadly translated, our findings indicate that social distancing during the COVID-19 pandemic made WfH-ability a driver of risk. Our results on the impact of government interventions underline that the degree of imposed workplace disruptions drives the return differential between industries who are resilient and those who are not. This gives rise to the question whether WfH-ability as a driver of risk is here to stay. As the pandemic is ongoing as we write the paper this question can only be answered by future research.

Overall, the applied methodology proves effective in answering the questions we raise. In employing the Dingel and Neimann (2020) measure, we adjusted the returns of "remote" and "physical" firms for the Fama and French (1992) three-factor model and found that WfH-ability seems not to be captured by its risk factors. Extending the analysis to more risk factors proposed by the asset pricing literature could deepen the understanding of WfH-ability as a driver of risk. During our analyses, the Dingel and Neimann (2020) measure appears to capture WfH-ability sufficiently well although we argue that applying a finer brush by assessing WfH-ability on individual firm level might lead to more pronounced findings. Lastly, by comparing the WfH-differential before and after government interventions we find support for changes in risk premia as our proposed channel of explanation. We are aware that actual changes in cash flows driven by WfH-ability differences might offer an alternative explanation to the WfH-spread. Nevertheless, finding that the WfH-return differential emerged and was more pronounced ahead of social distancing directives points to the risk premium as a preferred channel of explanation.

A notable result of this paper is that not all countries show a positive WfH-differential. We suggest this to be a matter for future research as various antecedents might be at play. Perhaps, a more granular measure would eradicate negative WfH-differentials. More interestingly however, extending the analysis to other potential explanations of the WfH-differential could prove important in the understanding of the impact of WfH-ability on asset prices.

To conclude, this paper contributes to the fast-emerging body of literature on stock market reactions to the COVID-19 pandemic in several ways: We show that there is a WfH-differential for a considerable number of countries in Europe. Thereby we support findings of prior studies (Pagano et al, 2020, Shen and Zhang, 2020, Papanikolaou et al, 2020) that focused on single countries. Apart from reporting the prevalence of the WfH-differential, to our knowledge we are the first to study its antecedents. We confirm the intuitive notion that the severity of the COVID-19 pandemic drives the WfH-differential. Perhaps more interestingly however, our paper contributes to a deeper understanding of the WfH-differential by showing how government interventions and countries' legal labour protection settings impact the degree to which "physical" stocks are outperformed by "remote" stocks. By studying the relationship between economic growth and the WfH-differential, our study further contributes by pointing to possible improvements of established short term GDP prediction models.

As we pointed out, the possibility of WfH-ability being a short-lived factor, only prevalent during the COVID-19 pandemic, warrants further investigation once this global health crisis has been overcome. Nevertheless, our research offers insight on the interplay of WfH-ability and asset prices that could prove interesting for asset pricing research, management and the political sphere alike. As sentiments among researchers, employers and policy makers suggest that Work from Home is here to stay the implications of our paper might well range beyond the current pandemic.[27]

[27] For a discussion of the future of WfH from the academic, employer- and policy perspective, please refer to Bai et al. (2020), Kaufman et al. (2020), and Tschierse (2020), respectively.

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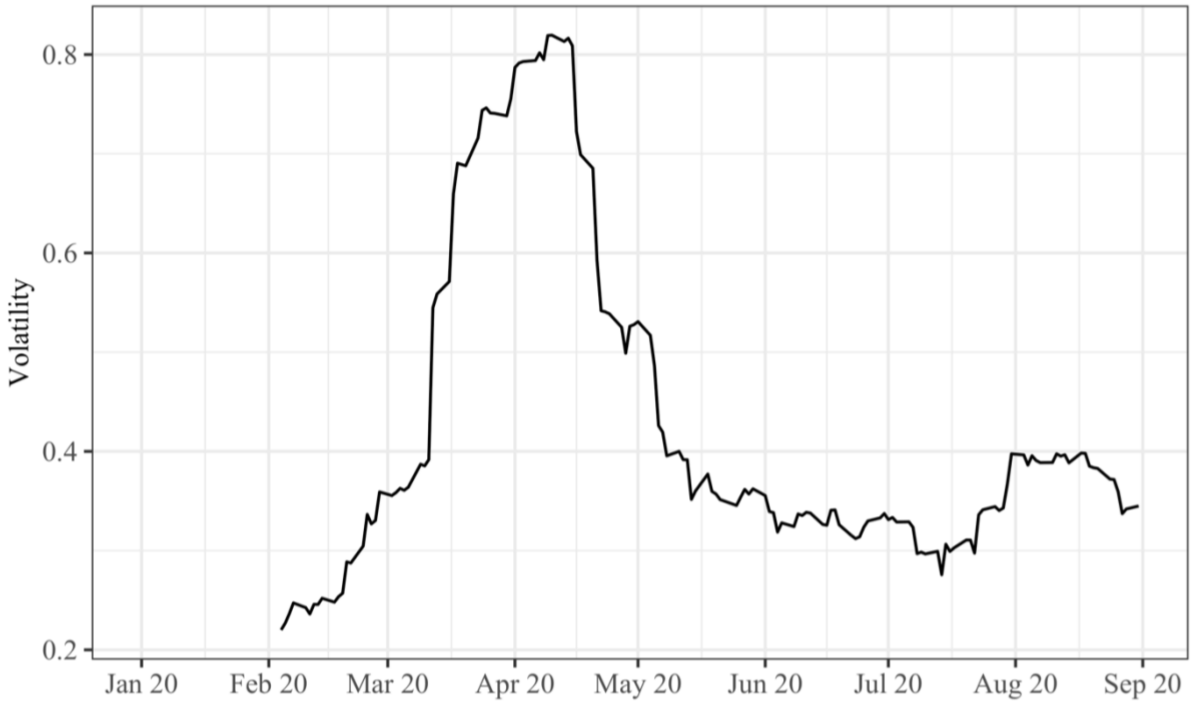
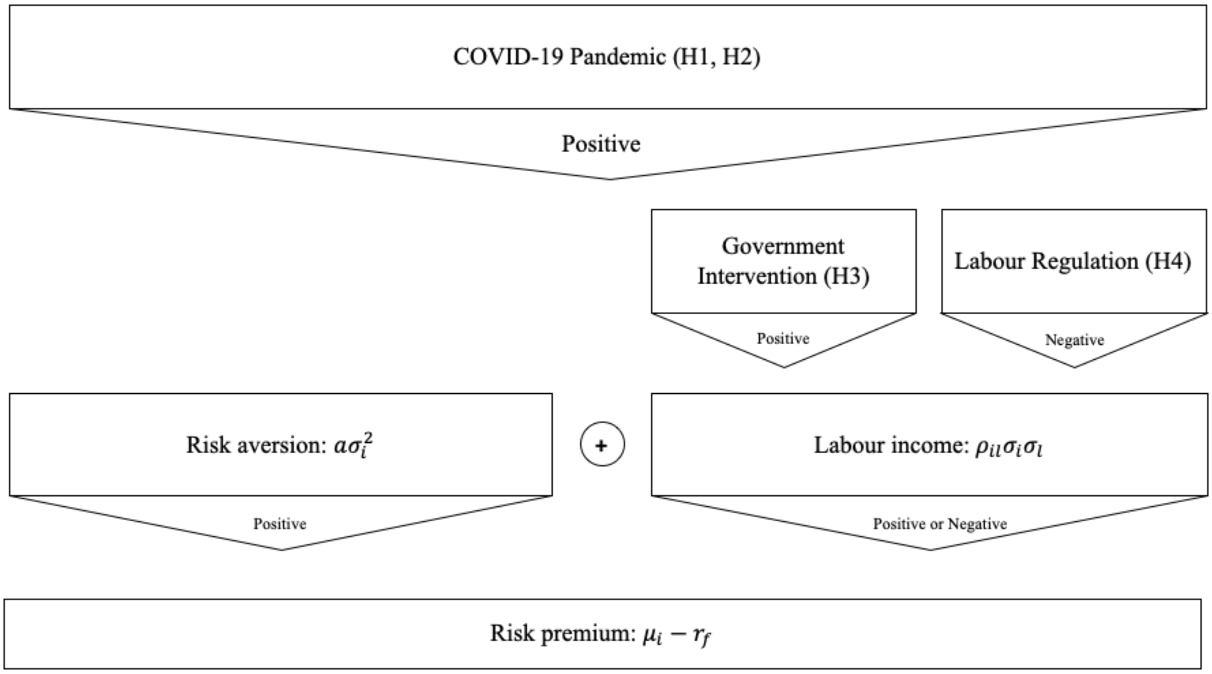
Appendix 1: Rolling Volatility of the RMP Portfolio



Appendix 1 – Figure 1: **25 Day Rolling Volatility of the RMP Portfolio**

Figure 1 plots the 25-day rolling volatility of the RMP portfolio aggregated for 20 countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded.

Appendix 2: Schematic Representation of the Theoretical Framework



Appendix 2 - Figure 1: **Schematic Representation of the Theoretical Framework**

Figure 1 summarises our established framework. Hypothesis 1 and Hypothesis 2 relate to the impact WfH-ability in context of the COVID-19 pandemic on asset prices by assuming that agents initially require a higher risk premium for all stocks due to a higher volatility level explained by the risk aversion channel. In addition, investors require a higher risk premium for "physical" stocks due to a higher correlation with labour income through the labour income risk channel. Hypothesis 3 relates to the impact of government interventions on the risk premium by establishing that countries that experienced a higher degree of workplace disruptions might show a higher risk premium for "physical" stocks through the labour-income risk channel. In a last step we argue that the implicit insurance of labour income risk through countries' level of legal labour protection mitigates the impact of social distancing interventions through the labour-income risk channel.

Appendix 3: Summary of DN Estimates by Sample Countries

Appendix 3 - Table I:
WfH Estimates for Country-level Aggregates

Country	DN Estimate
Sweden	0.443
Switzerland	0.440
United Kingdom	0.438
Norway	0.435
Belgium	0.434
Denmark	0.433
Slovenia	0.406
Netherlands	0.391
Finland	0.366
Estonia	0.365
Croatia	0.357
Austria	0.343
Germany	0.343
France	0.333
Lithuania	0.322
Ireland	0.318
Latvia	0.317
Portugal	0.309
Czechia	0.302
Italy	0.283
Greece	0.282
Hungary	0.260
Spain	0.257
Romania	0.255
Slovakia	0.253
Turkey	0.216

Table I depicts the Dingel Neimann (2020) country aggregates for estimates of WfH-ability. We aggregate the NACE section-level industry estimates by calculating the equally weighted median across all industries for each country to obtain country-level estimates. The table shows countries in descending order by the Dingel Neimann (2020) measure.

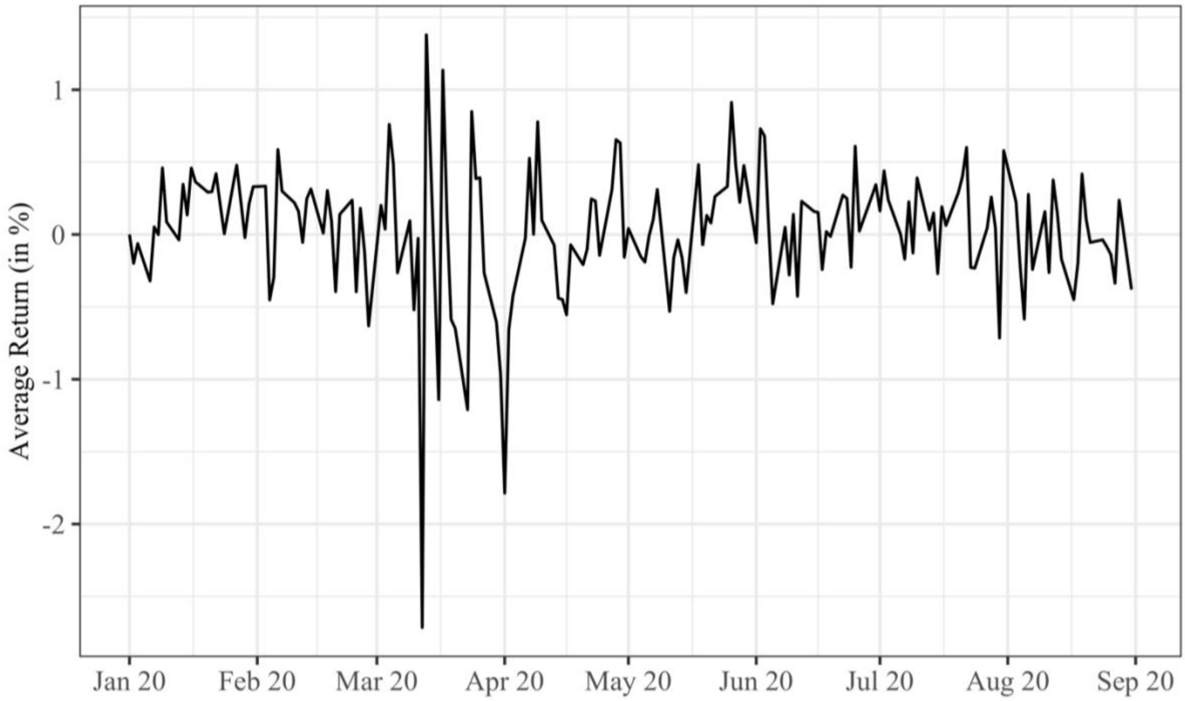
Appendix 4: Summary Statistics “Remote” and “Physical” Groups 2019

Appendix 4 - Table I:
Summary Statistics of the Returns of the “Remote” and “Physical” Groups for 2019.

	2019									
	Physical					Remote				
		Returns					Returns			
Country	**No.**	**Ø**	**Min**	**Max**	**Vola**	**No.**	**Ø**	**Min**	**Max**	**Vola**
Austria	45	0.05	-2.33	2.72	0.81	25	0.05	-2.10	2.57	0.75
Belgium	71	0.07	-6.45	4.20	1.09	64	0.05	-2.47	2.61	0.63
Switzerland	122	0.08	-2.10	1.91	0.62	116	0.05	-1.89	1.65	0.59
Czechia	1	-0.01	-2.95	4.47	0.81	4	-0.02	-2.13	1.52	0.59
Germany	378	0.06	-3.04	3.36	0.90	353	0.06	-2.01	2.82	0.67
Denmark	79	0.08	-2.85	3.34	0.93	68	0.08	-2.84	2.32	0.73
Spain	100	0.08	-2.62	2.65	0.86	109	0.03	-2.46	1.87	0.67
Estonia	11	-0.01	-3.10	1.59	0.44	4	0.07	-2.23	4.52	0.68
Finland	89	0.04	-2.57	3.58	0.93	74	0.03	-3.89	2.38	0.79
France	408	0.08	-3.34	2.36	0.80	266	0.06	-2.57	2.41	0.75
United Kingdom	611	0.05	-3.10	2.22	0.69	867	0.05	-2.74	3.36	0.73
Greece	109	0.08	-3.62	4.34	0.87	64	0.18	-4.57	6.28	1.29
Croatia	64	0.03	-2.54	1.64	0.43	19	0.04	-3.88	3.73	0.62
Hungary	10	0.00	-2.76	2.84	0.95	21	0.10	-3.06	3.16	0.92
Ireland	27	0.11	-2.97	2.70	0.80	17	0.13	-3.95	4.03	1.03
Italy	170	0.04	-3.01	2.40	0.79	162	0.09	-3.36	2.88	0.87
Lithuania	20	0.00	-1.60	2.14	0.53	8	0.04	-1.67	1.53	0.37
Latvia	18	0.02	-1.82	2.44	0.49	2	0.09	-9.06	11.02	1.37
Netherlands	80	0.12	-3.19	2.41	0.83	59	0.06	-3.60	3.16	0.87
Norway	102	0.02	-3.26	3.54	0.95	93	0.03	-2.01	1.99	0.72
Portugal	23	0.04	-3.35	2.89	0.91	24	0.02	-2.92	2.97	0.76
Romania	53	0.12	-2.90	5.77	0.93	23	0.10	-4.94	5.02	0.88
Slovakia	2	-0.13	-18.81	13.88	1.97	6	-0.05	-6.41	8.59	0.99
Slovenia	9	0.05	-3.77	2.31	0.64	12	0.03	-2.59	2.27	0.51
Sweden	475	0.12	-2.62	3.16	0.90	278	0.08	-2.31	2.11	0.65
Turkey	238	0.10	-4.62	2.93	1.06	143	0.19	-4.43	4.83	1.55

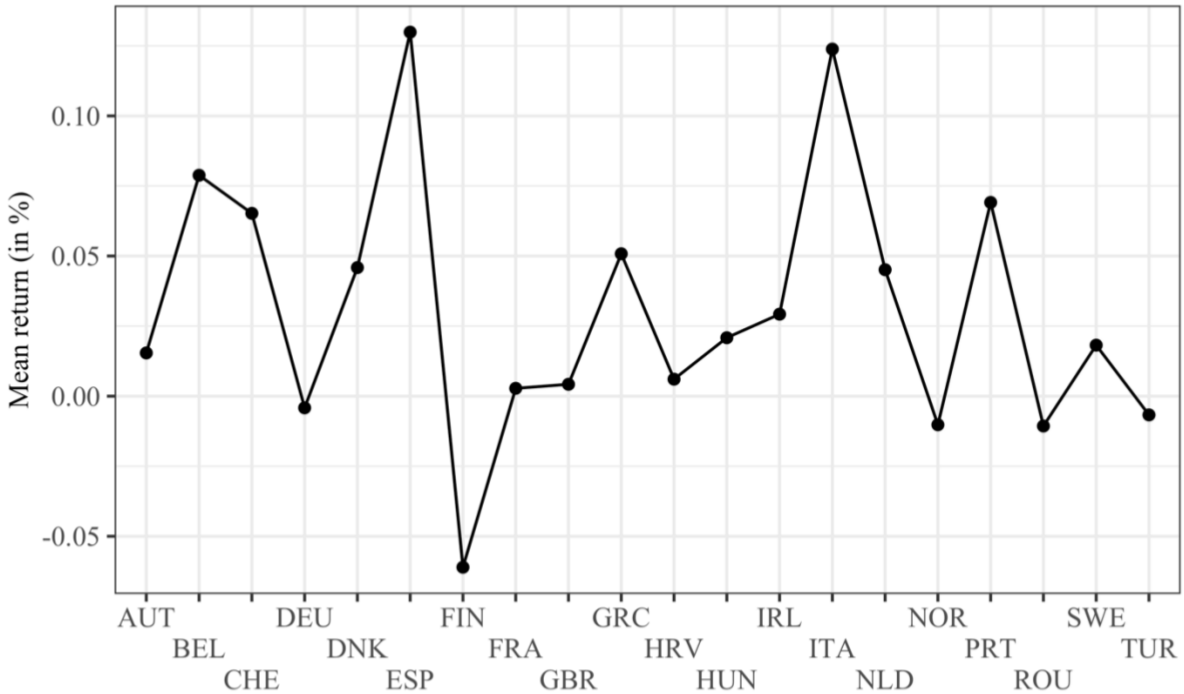
Table I presents descriptive statistics of the "remote" and "physical" groups for 26 countries for 2019. The groups are constructed for each country individually and weighted based on the market capitalisation of the stocks. Each group is held for all existing trading days during 2019 and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. "Remote" and "physical" stocks are defined as having an above and below median Dingel and Neiman (2020) value for their respective industry. The table shows for every country the number of stocks in each group, the average daily return of the respective group, the maximum and minimum daily return, and the volatility the respective portfolio.

Appendix 5: Time- and Individual-specific Effects Across Sample Countries



Appendix 5 – Figure 1: **Daily Risk Adjusted Return of the RMP Portfolio Averaged Across Countries**

Figure 1 shows the average daily risk adjusted return of the RMP portfolio averaged across 20 countries in our sample. Countries with less than 10 stocks per group were excluded.



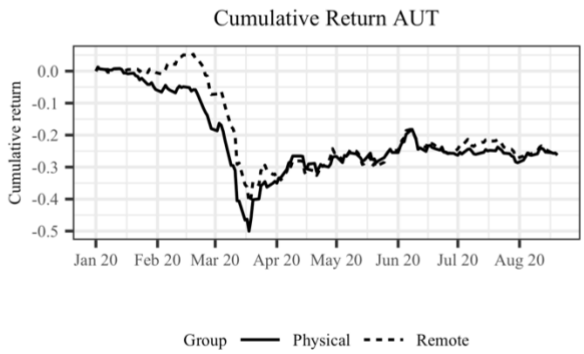
Appendix 5 – Figure 2: **Average Risk Adjusted Return of the RMP Portfolio Across Countries**

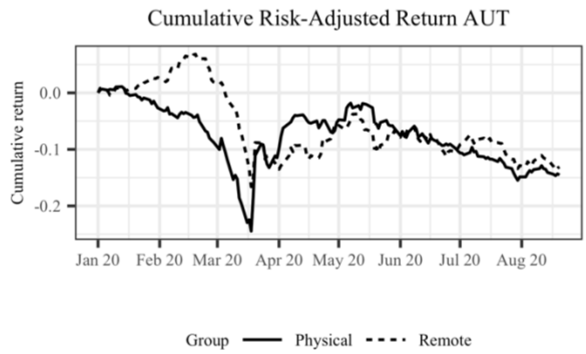
Figure 2 shows the average daily risk adjusted return of the RMP portfolio for each country individually. Countries with less than 10 stocks per group were excluded.

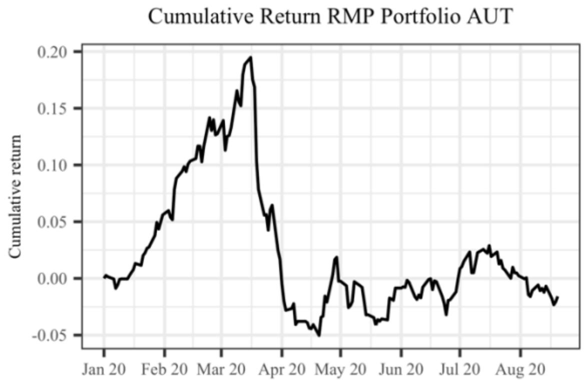
Appendix 6: Sample Country Time Series of Cumulative Returns and Cumulative Risk Adjusted Returns of the RMP Portfolio and the “Remote” and “Physical” Groups

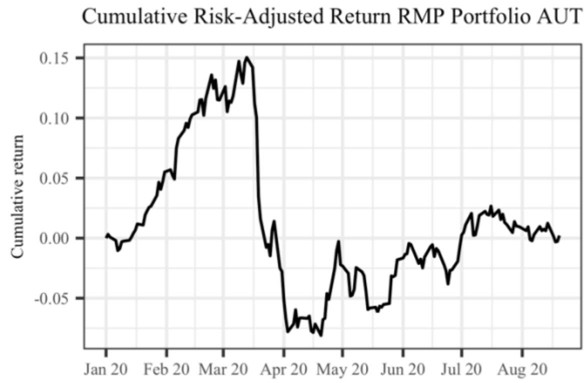
The figures plot the country-level cumulative return of portfolios formed based on the measure of Dingel and Neiman (2020) between the 1st of January and 31st of August 2020. We classify a stock as “remote” if its industry has a Dingel and Neimann (2020) value above the cross-country median. Likewise, we classify a stock as “physical” if its industry has a Dingel and Neimann (2020) value below the cross-country median. Each portfolio is held for all existing trading days during the observation period and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. The left two plots show the cumulative unadjusted returns per group and for the “remote minus physical” (RMP) portfolio while the right two plots adjust returns for Fama and French (1992) three factors (FF3).

6.1 Country-level returns: Austria

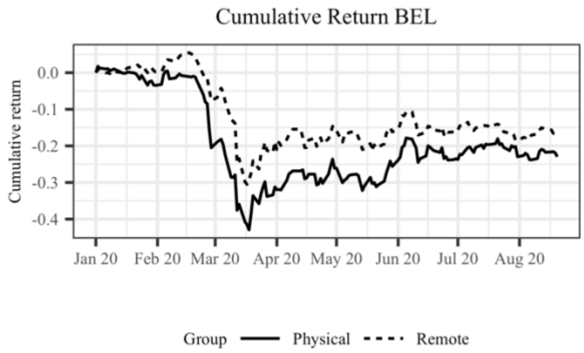


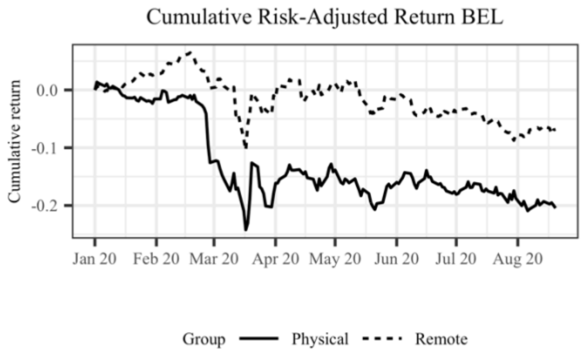


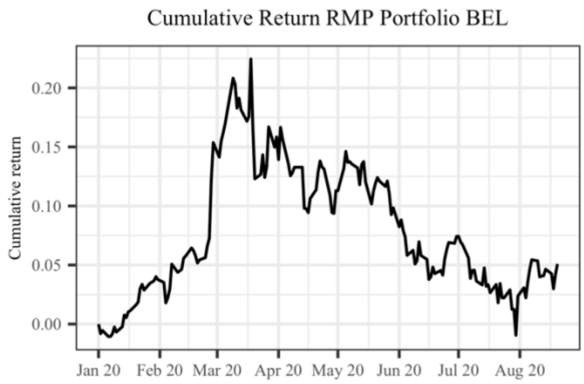


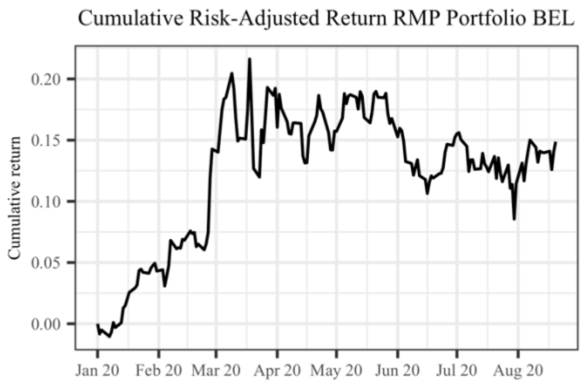


6.2 Country-level returns: Belgium

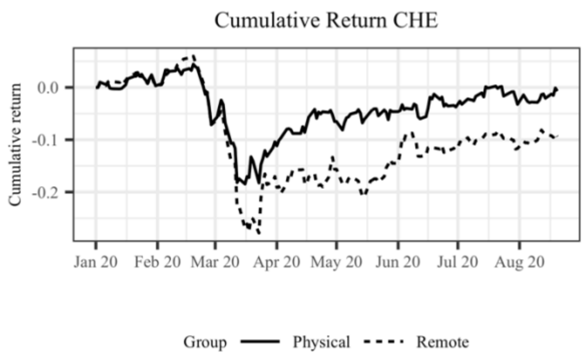


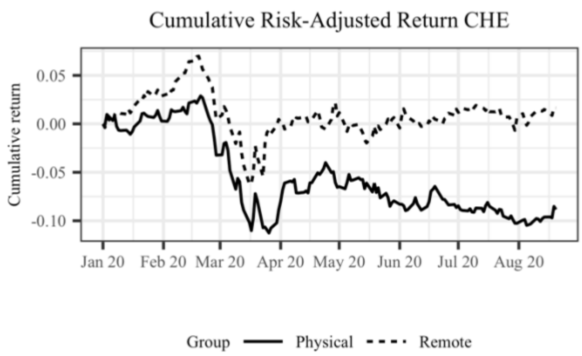


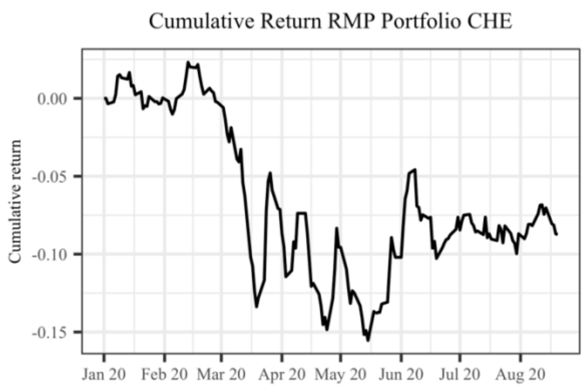


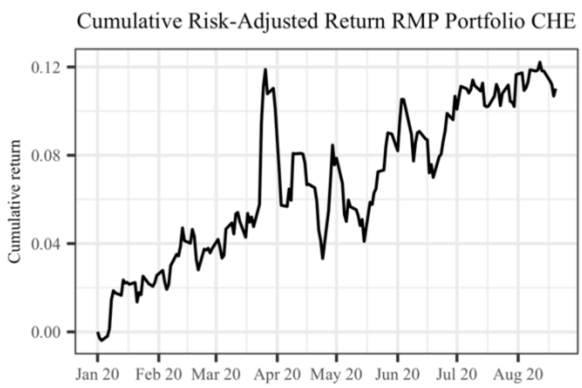


6.3 Country-level returns: Switzerland

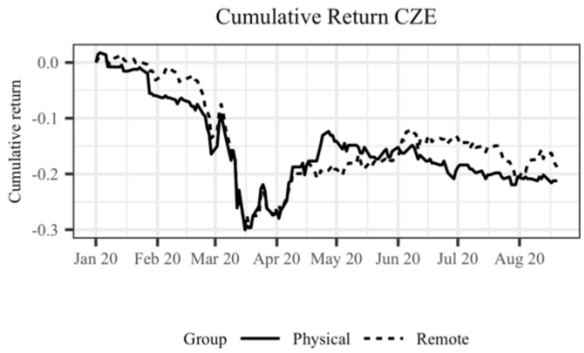


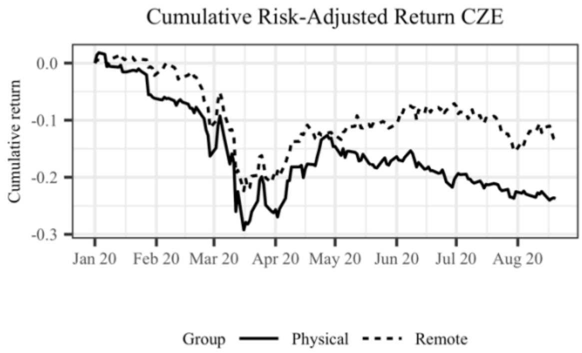


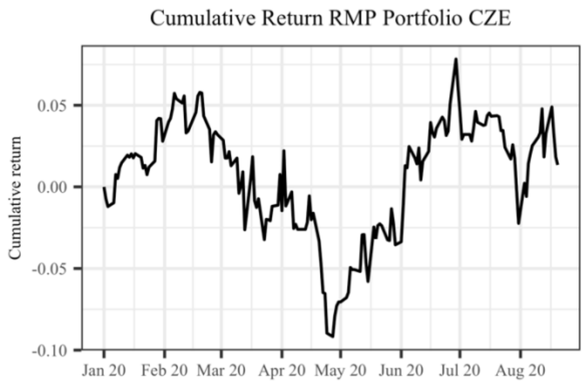


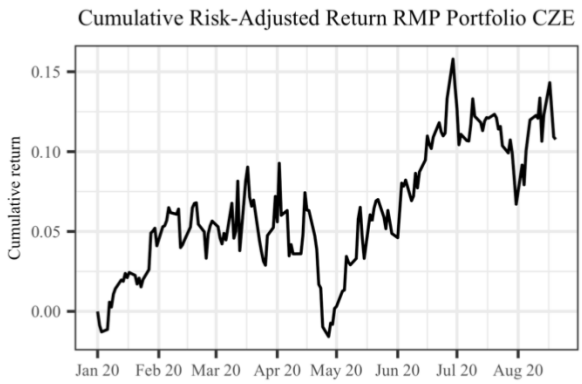


6.4 Country-level returns: Czechia

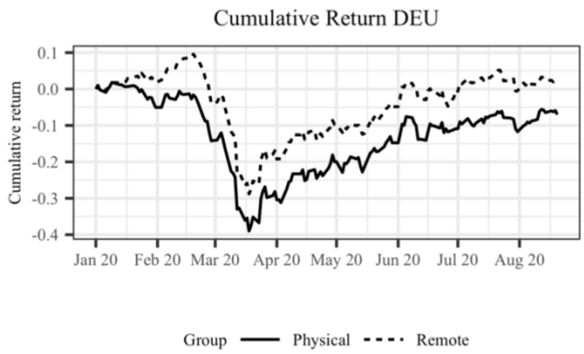


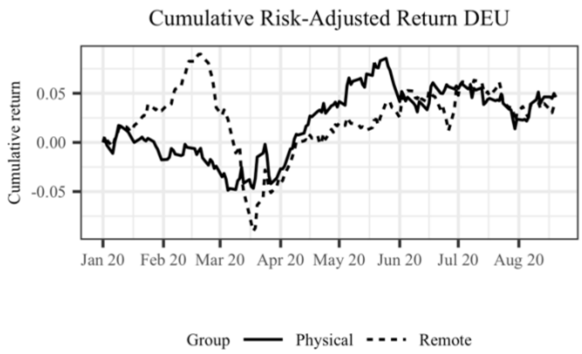


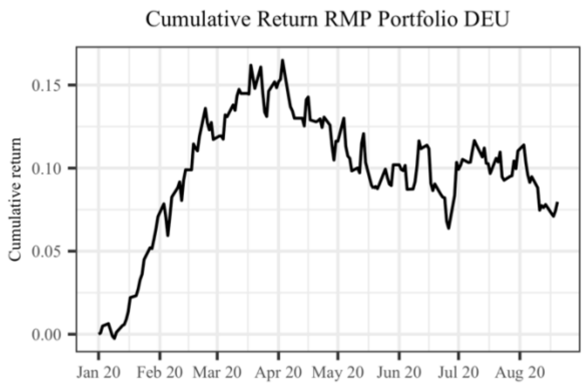


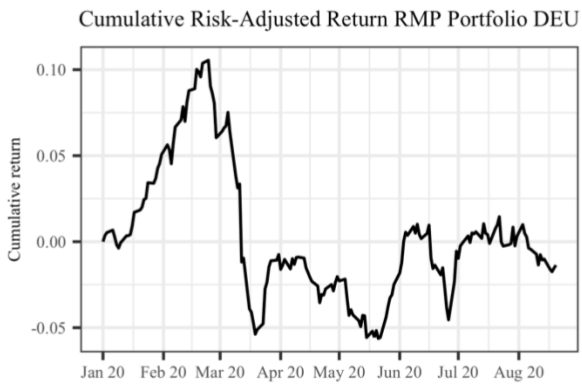


6.5 Country-level returns: Germany

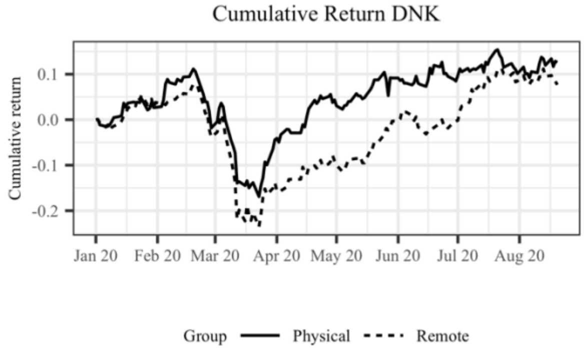


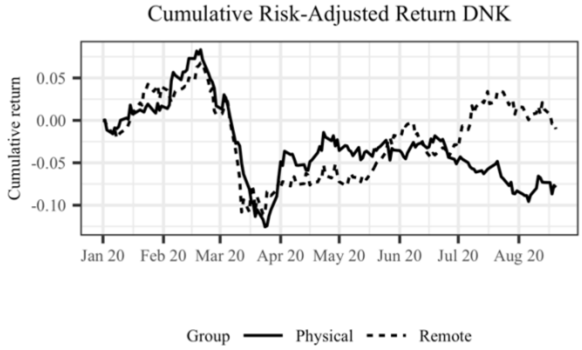


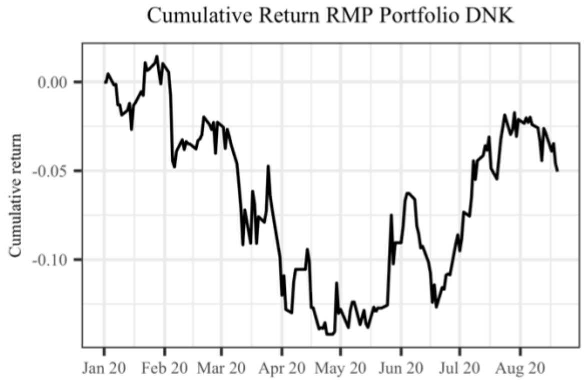


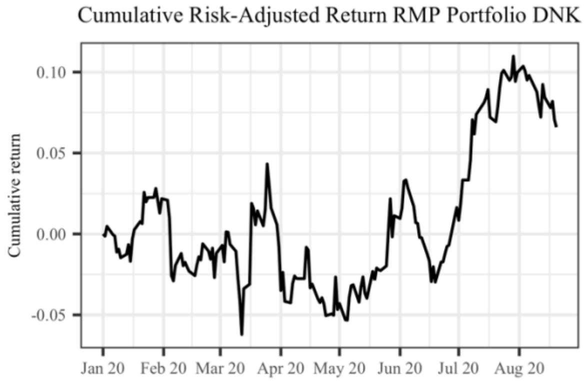


6.6 Country-level returns: Denmark

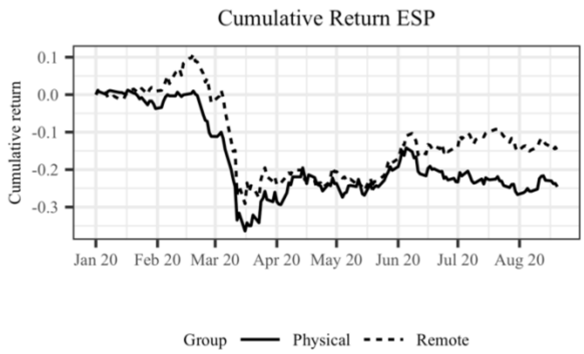


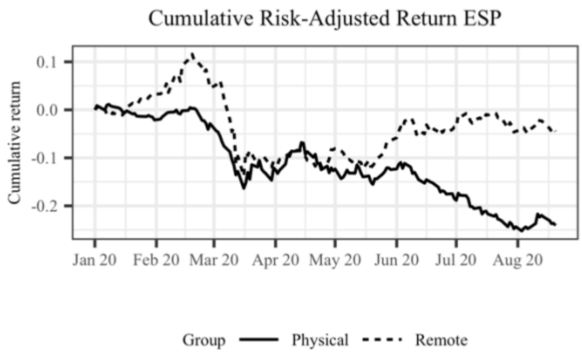


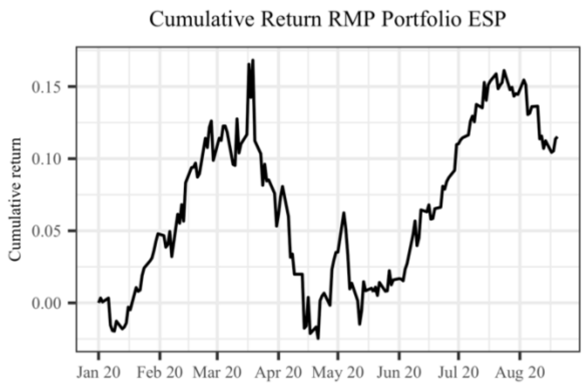




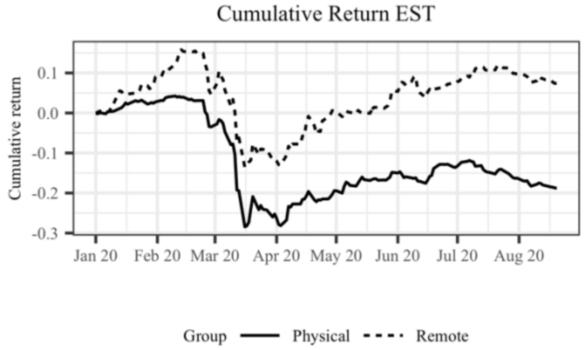
6.7 Country-level returns: Spain

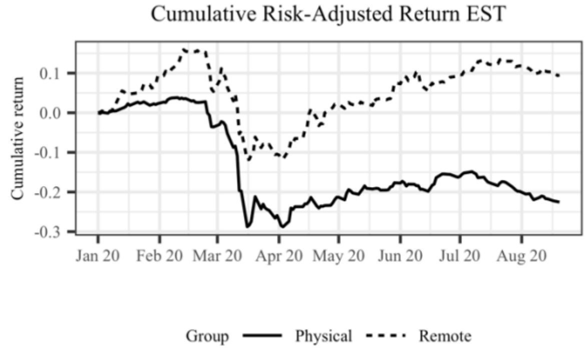


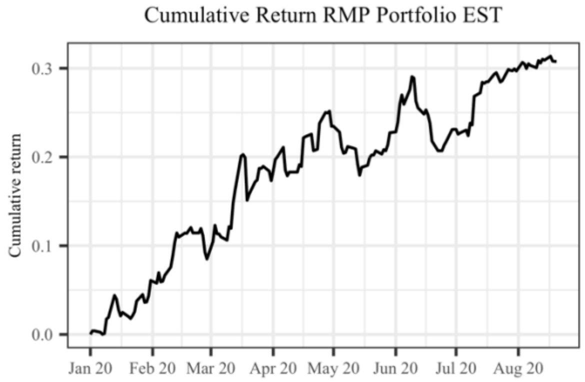


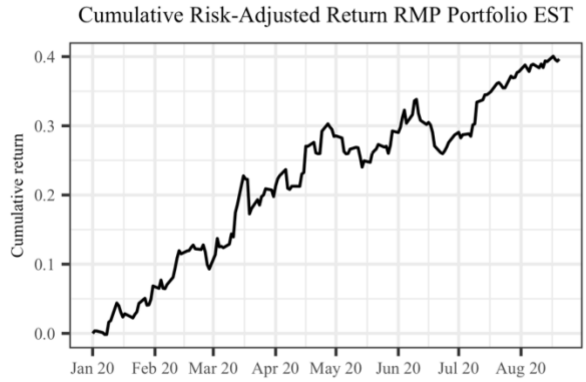


6.8 Country-level returns: Estonia

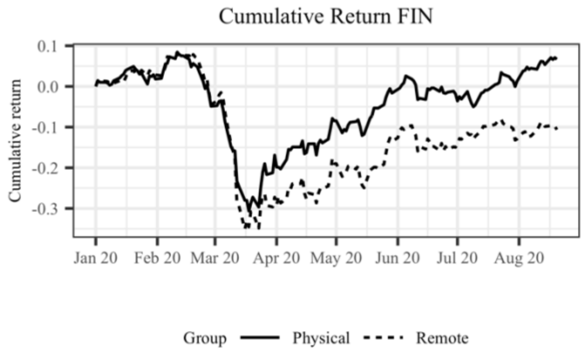


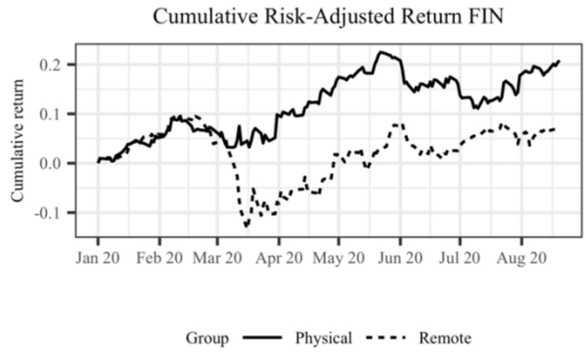


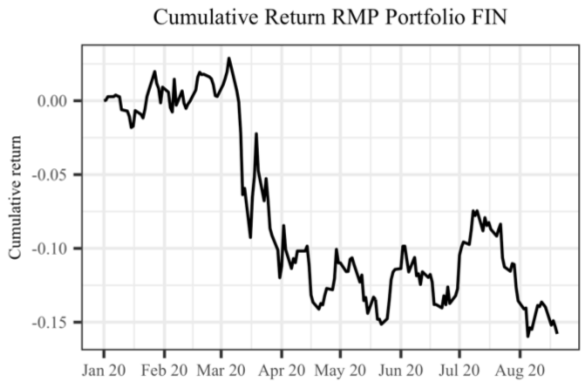


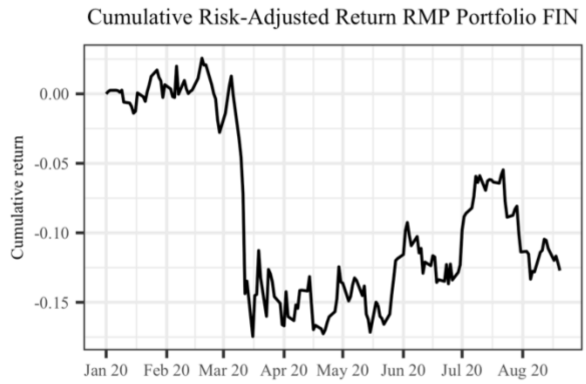


6.9 Country-level returns: Finland









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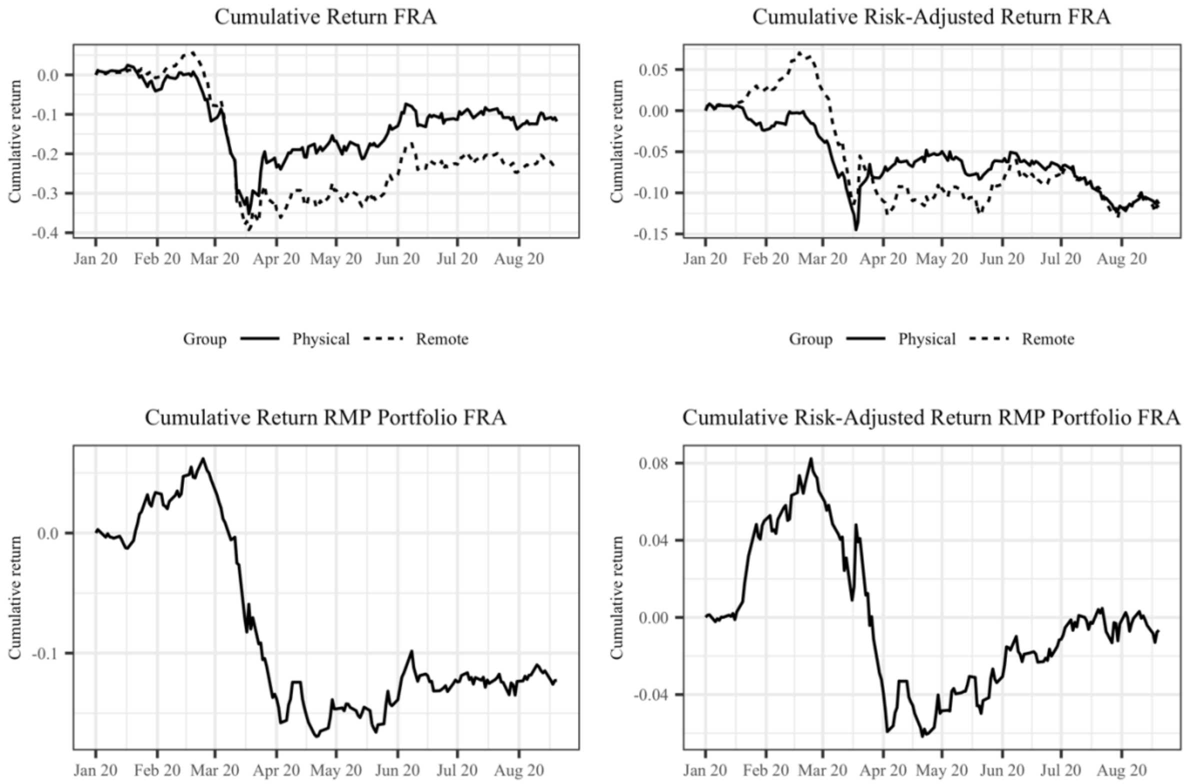
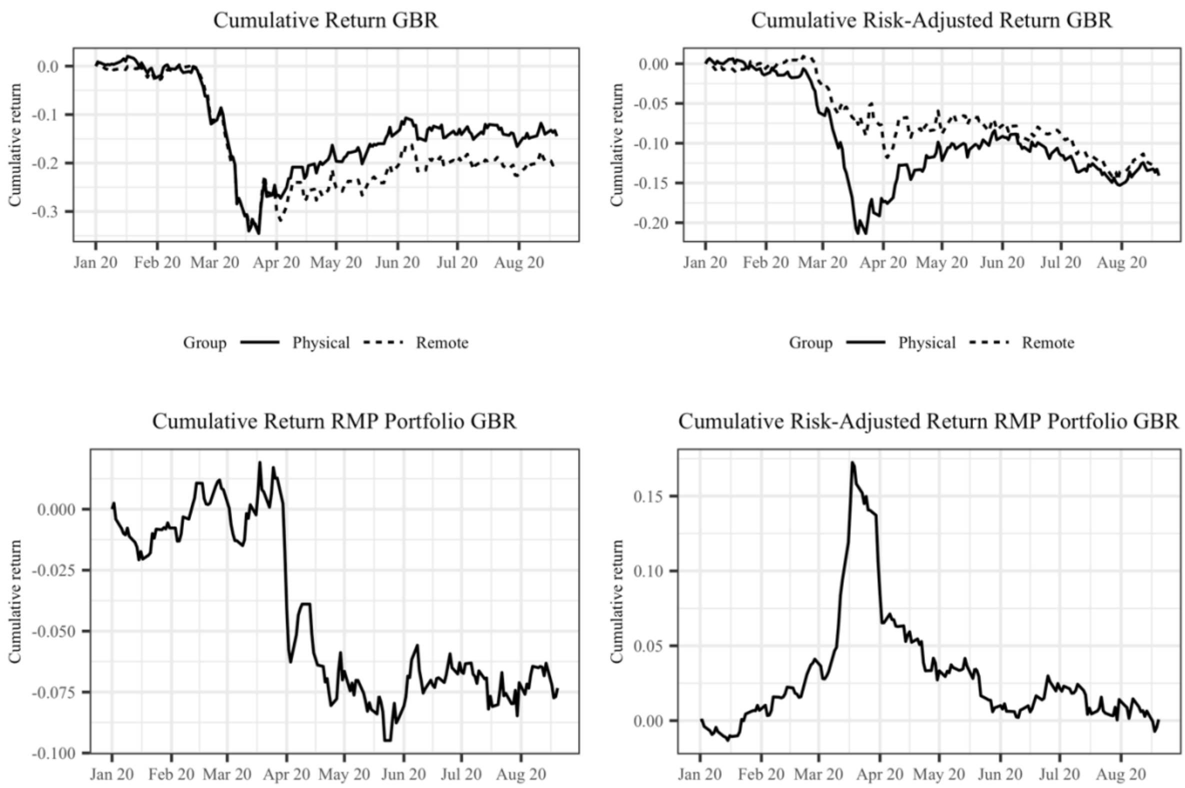
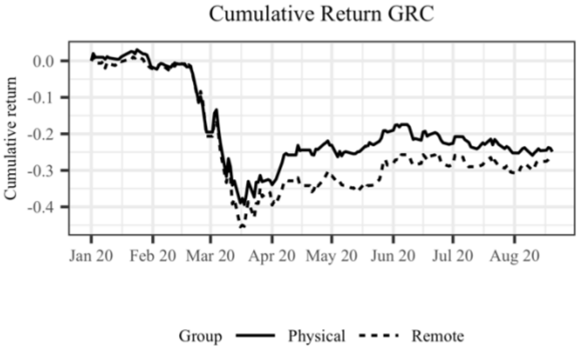
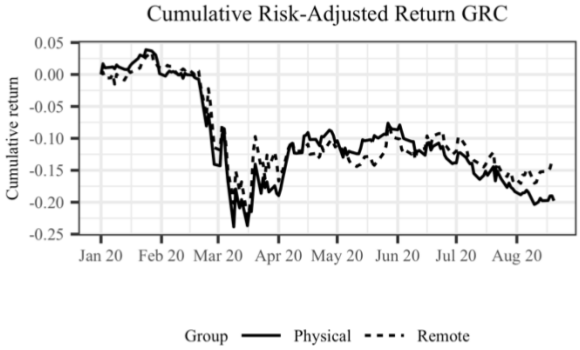


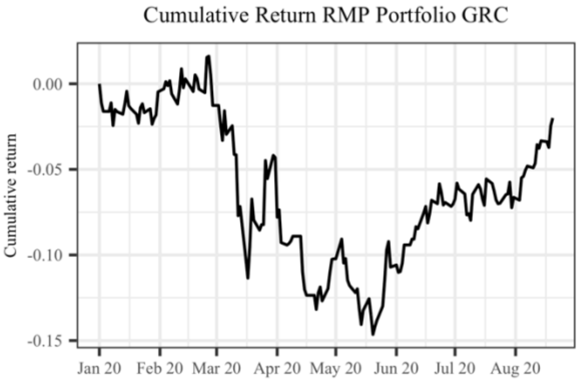
6.11 Country-level returns: United Kingdom

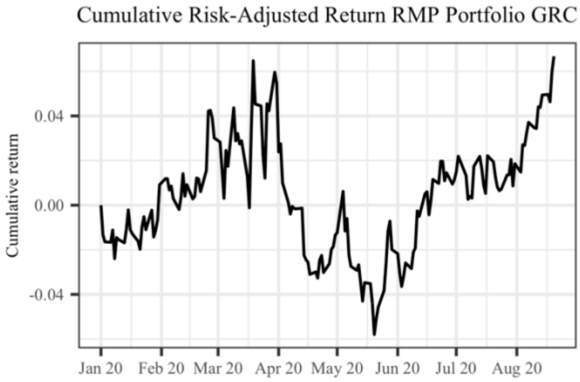


6.12 Country-level returns: Greece

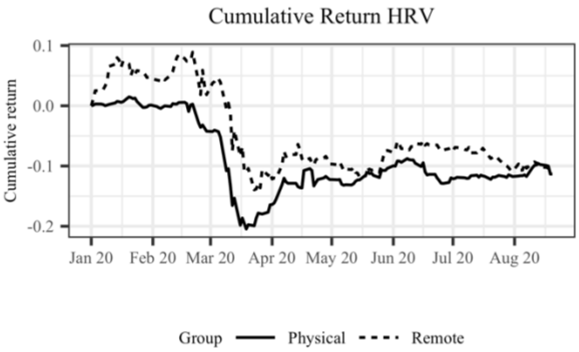


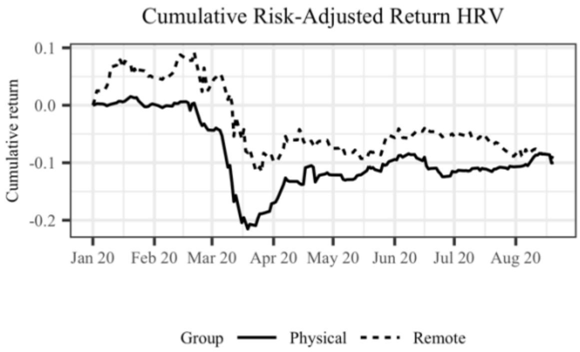


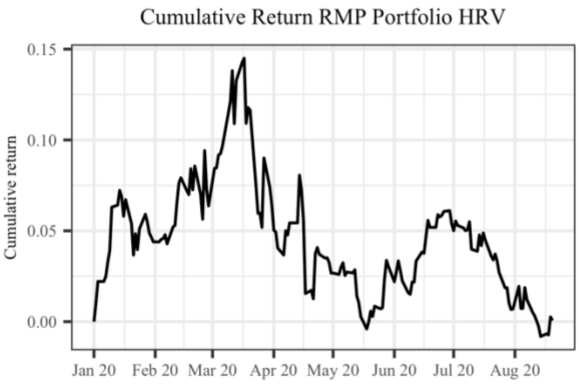


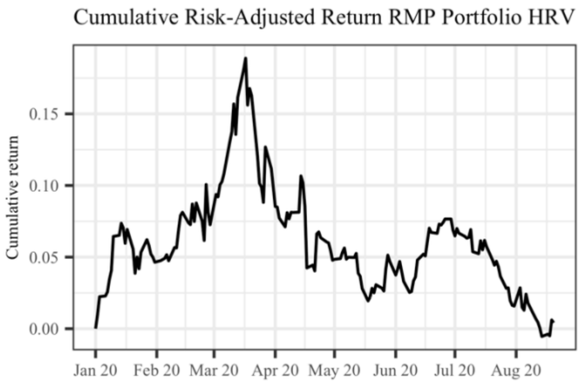


6.13 Country-level returns: Croatia









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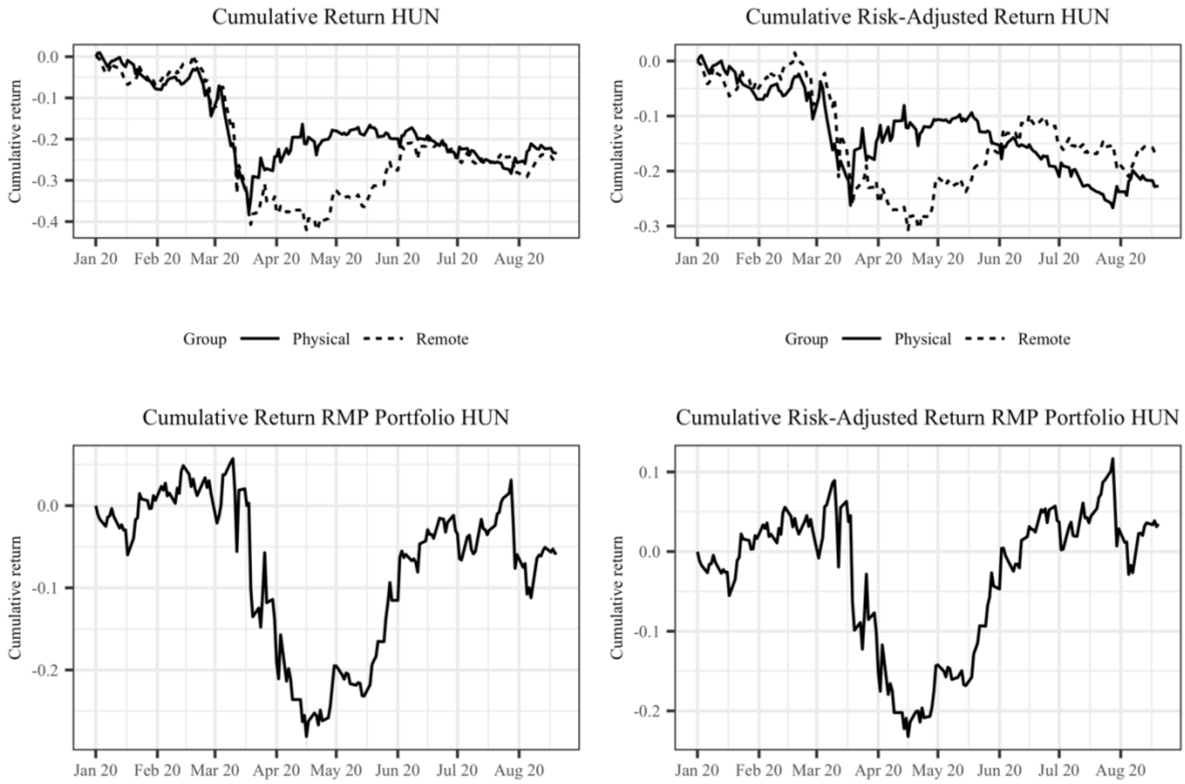
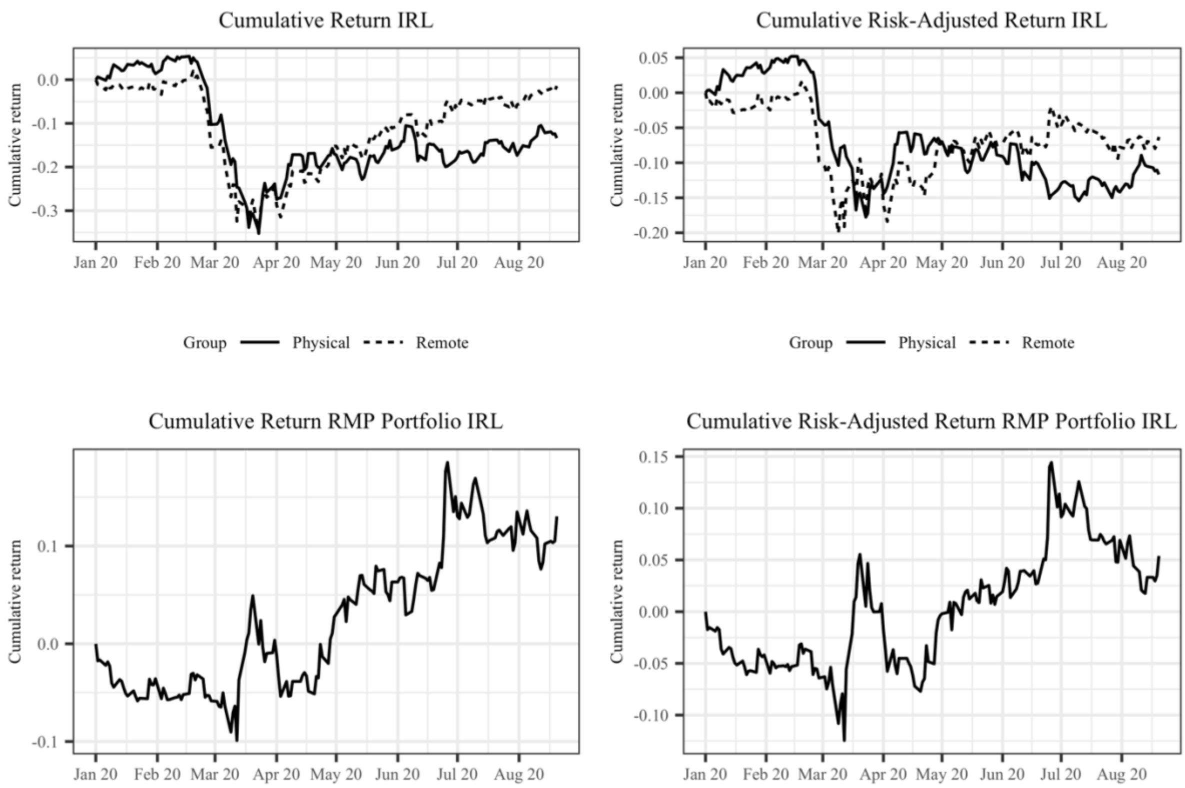


6.15 Country-level returns: Ireland



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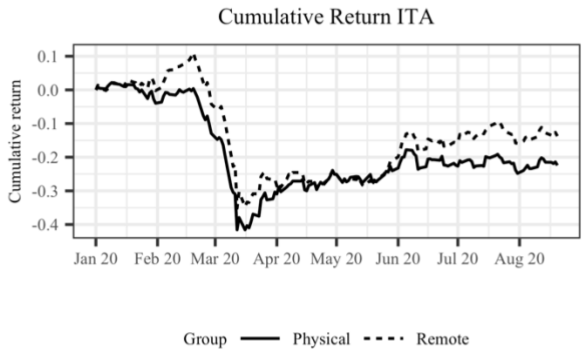
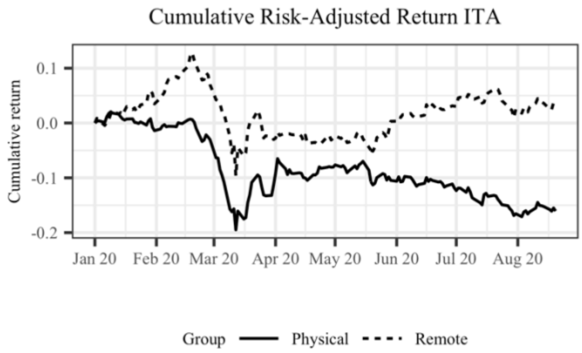
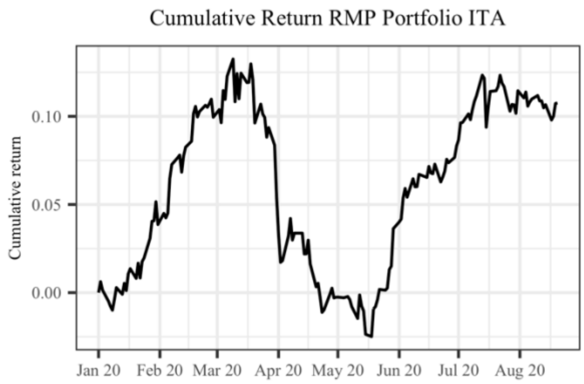
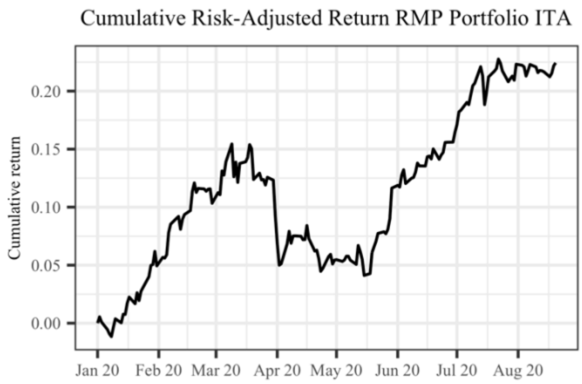
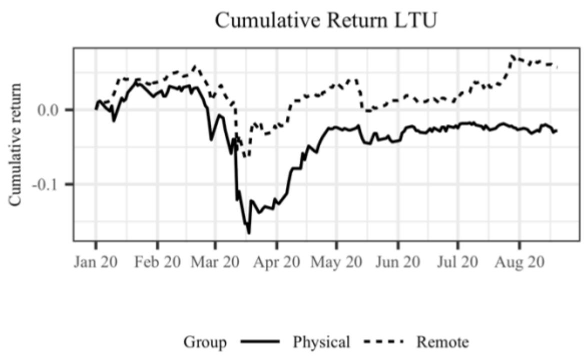


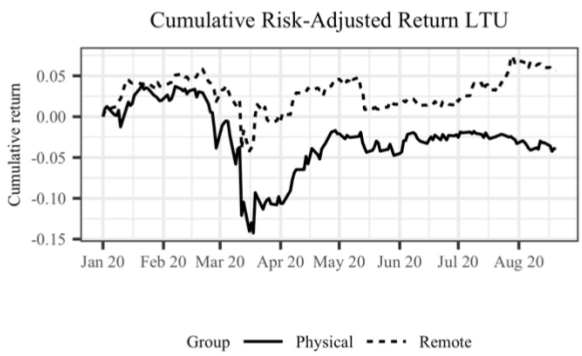


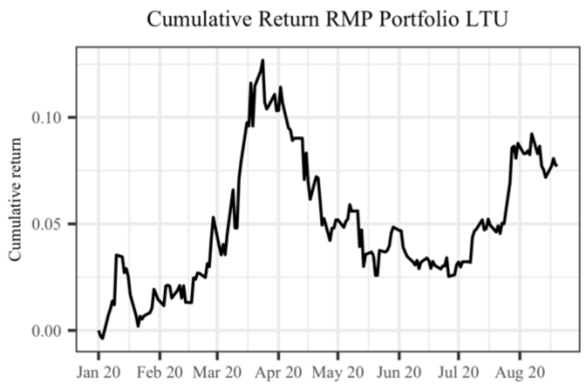




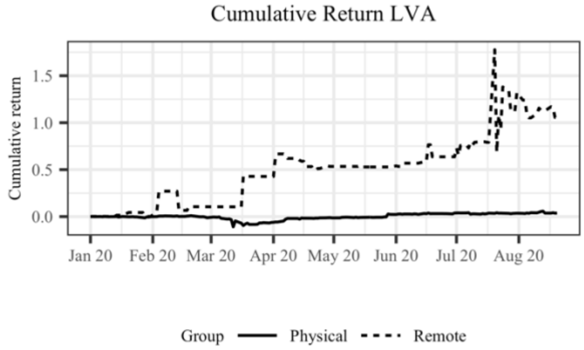
6.17 Country-level returns: Lithuania

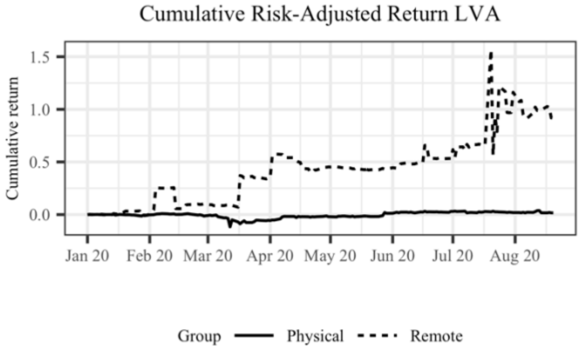


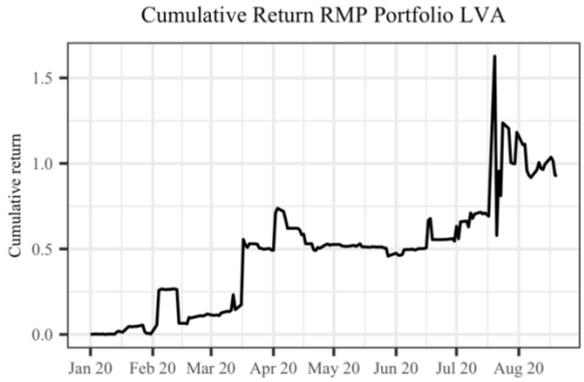


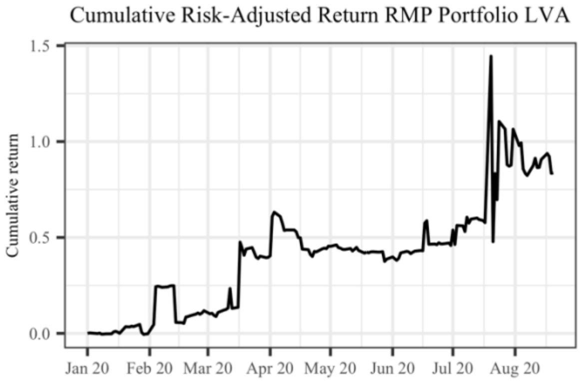


6.18 Country-level returns: Latvia

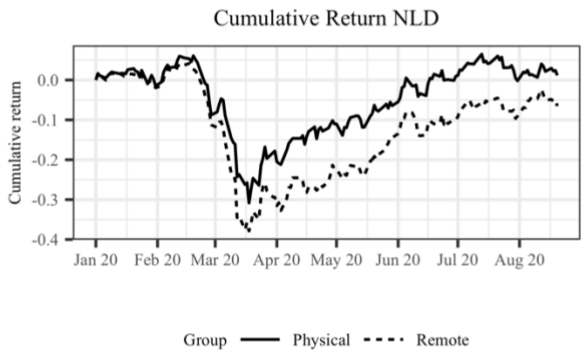


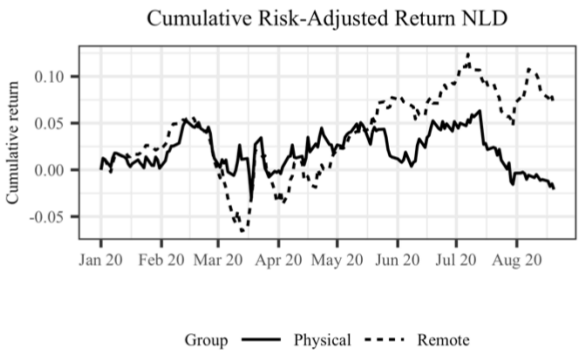


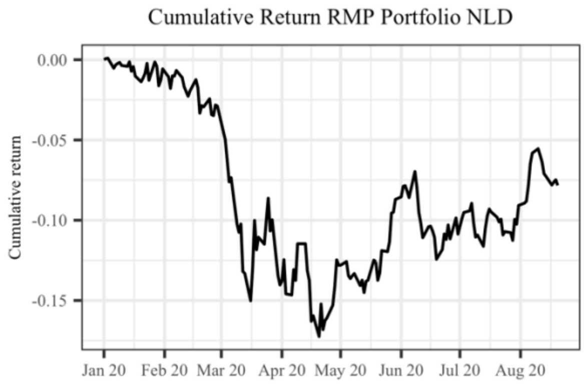


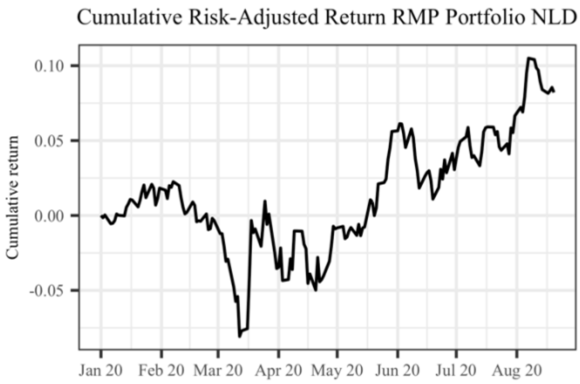


6.19 Country-level returns: Netherlands









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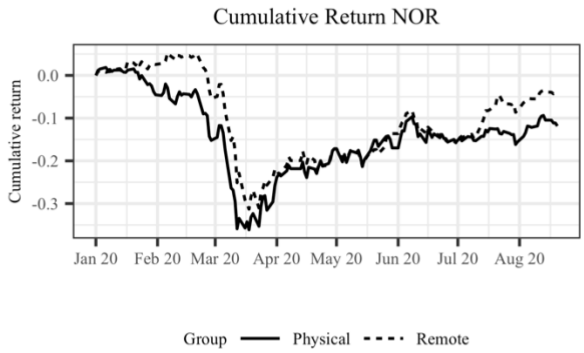

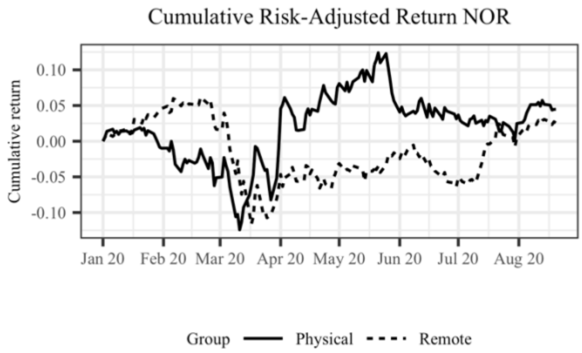

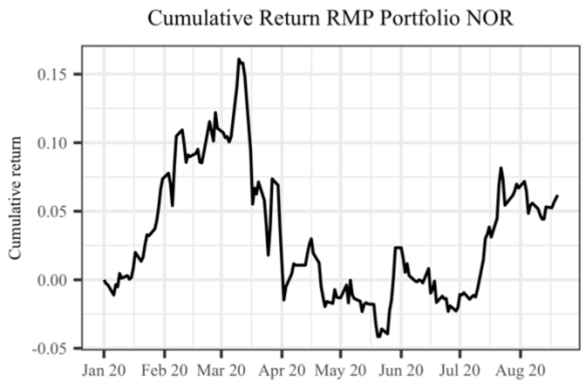

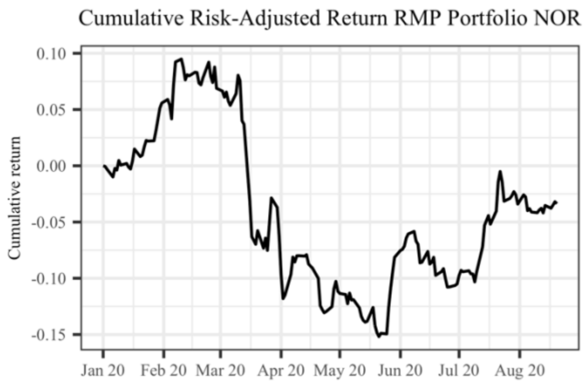

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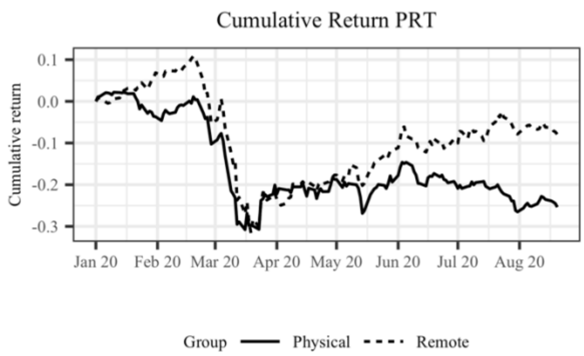

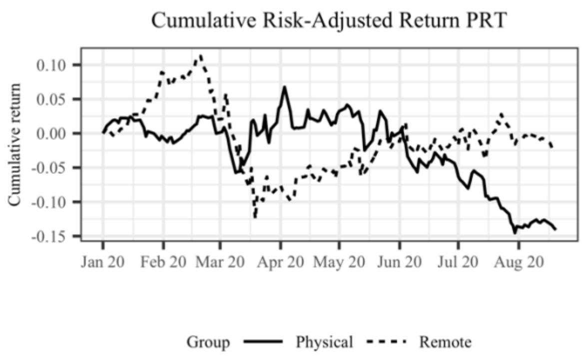

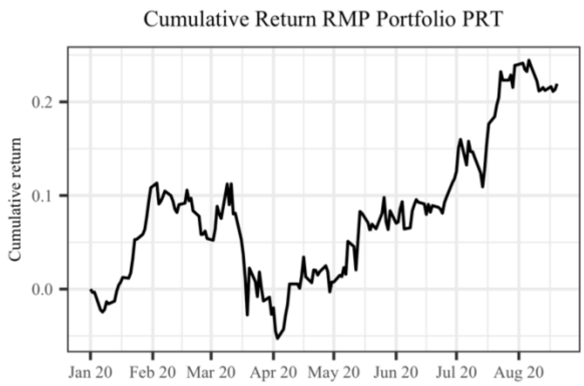

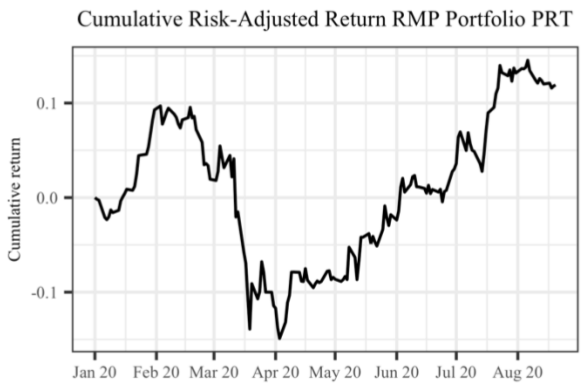

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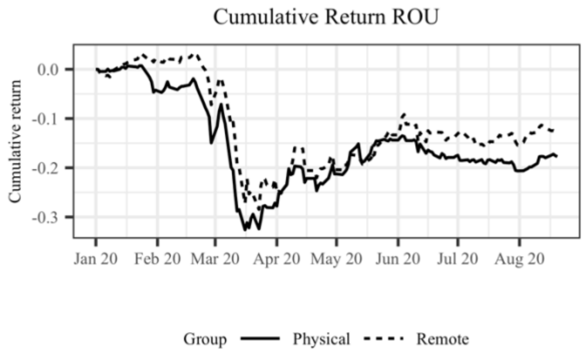
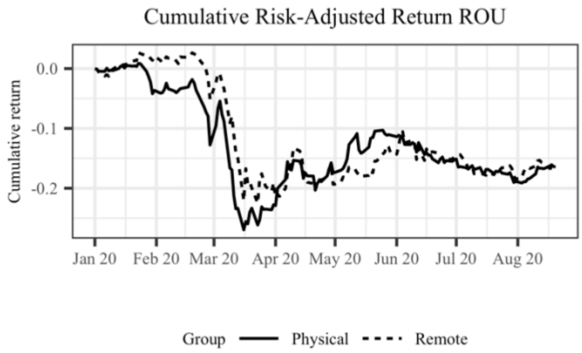
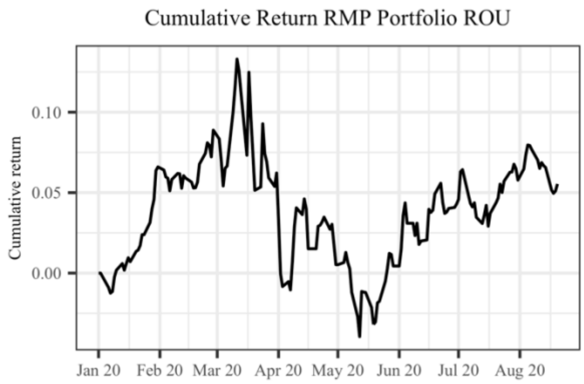
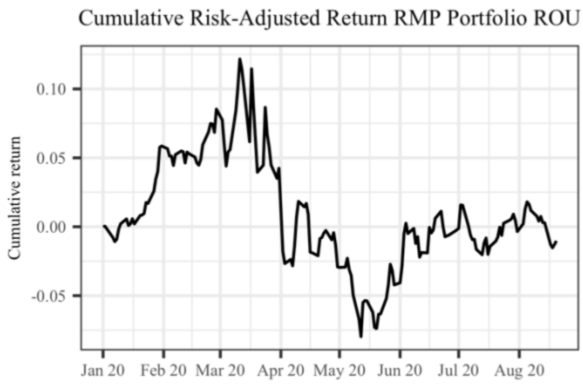
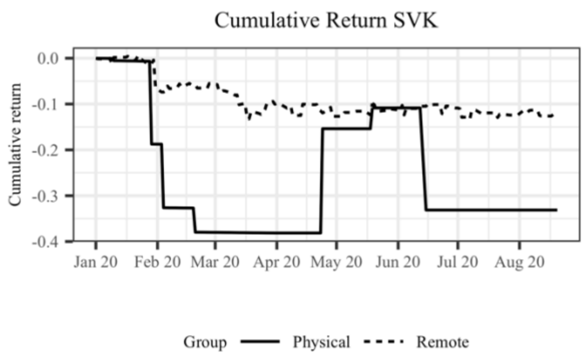


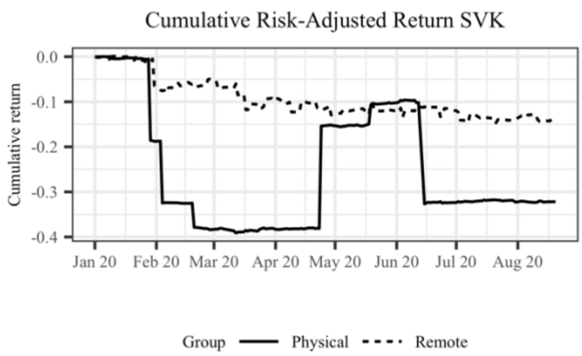


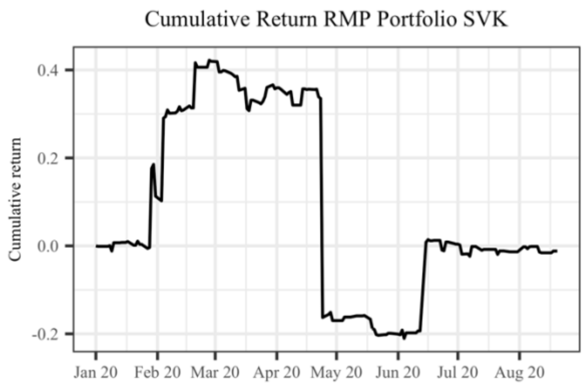


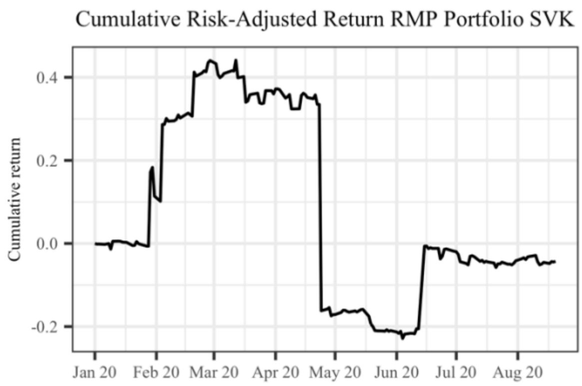


6.23 Country-level returns: Slovakia

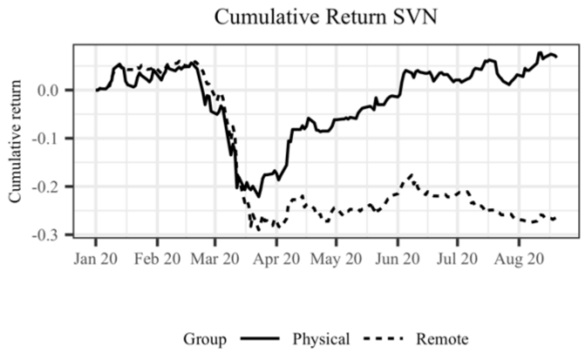


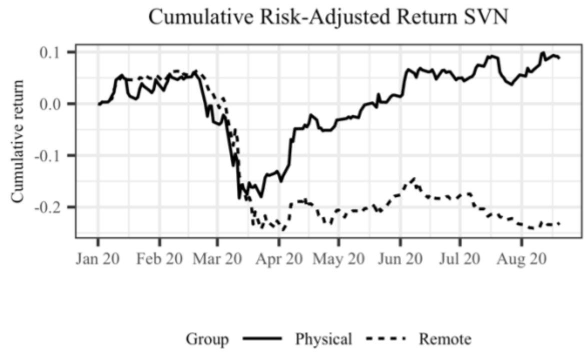


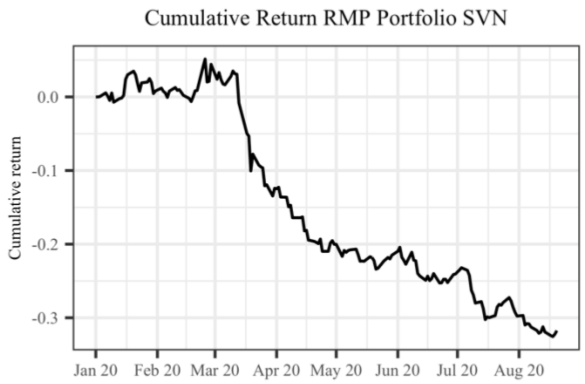


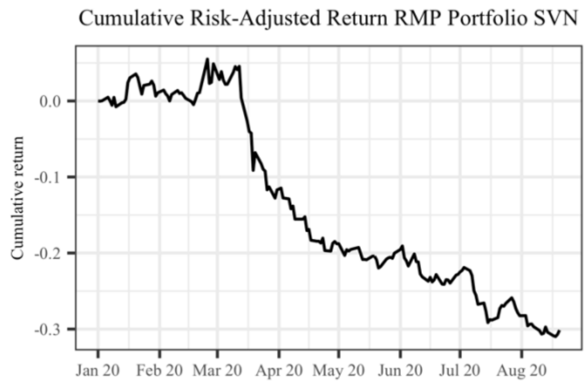


6.24 Country-level returns: Slovenia

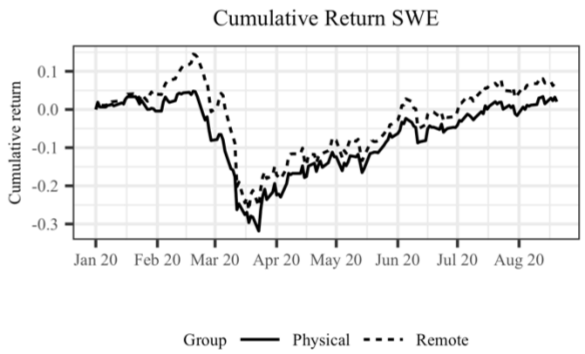


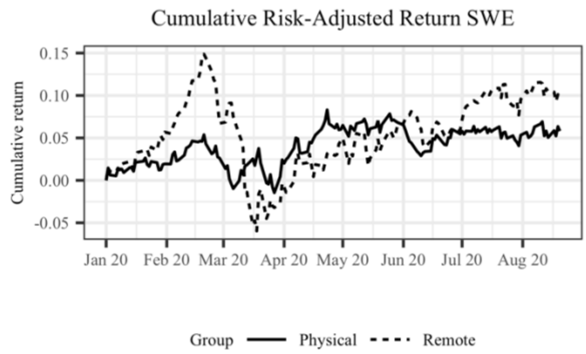


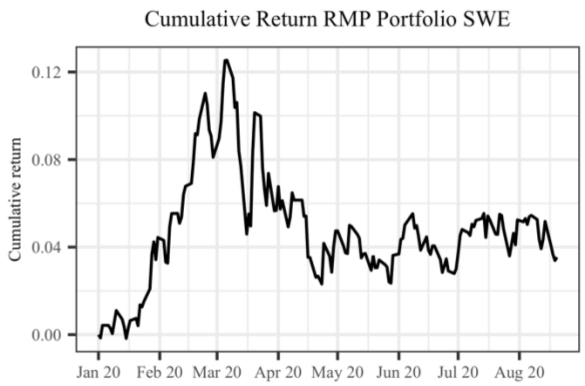


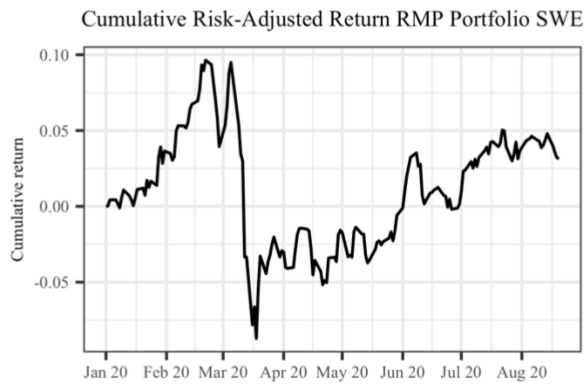


6.25 Country-level returns: Sweden

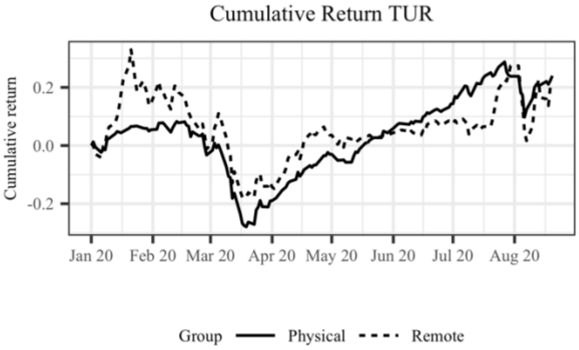


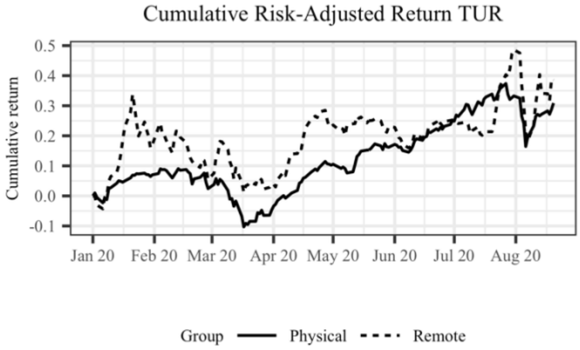


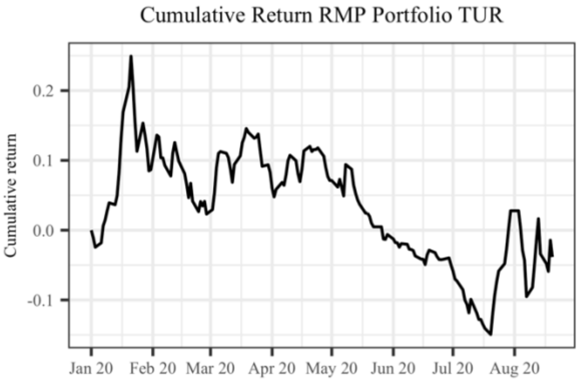


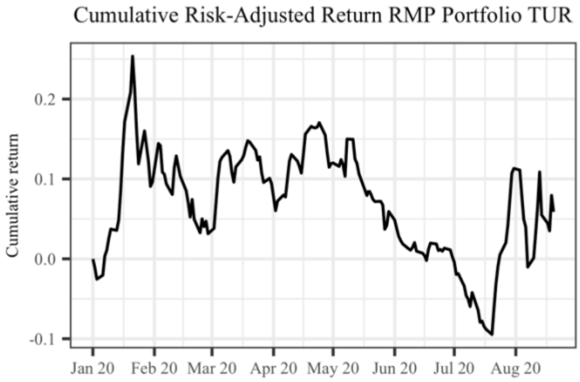


6.26 Country-level returns: Turkey









Appendix 7: Reduced Sample RMP Returns for Pre- and Post-Lockdown Windows

Appendix 7- Table I: Reduced Sample
Cross-country RMP Returns for Pre-and Post-lockdown Window in Europe

			Ending 09. March		Ending 24. April	
	Ø Number of stocks		Cum. returns		Cum. returns	
Country	Remote	Physical	Unadjusted	Risk adj.	Unadjusted	Risk adj.
Austria	26	44	**14.0%**	**12.2%**	**-16.0%**	**-17.3%**
Belgium	63	70	**17.3%**	**15.4%**	**-6.4%**	**-2.6%**
Switzerland	100	134	**-3.4%**	**3.1%**	**-11.4%**	**-1.5%**
Germany	345	384	**10.2%**	**1.3%**	**-0.6%**	**-6.3%**
Denmark	68	77	**-5.6%**	**-3.6%**	**-10.0%**	**-4.0%**
Spain	105	98	**8.6%**	**4.8%**	**-8.1%**	**-6.4%**
Finland	69	90	**1.3%**	**-3.4%**	**-13.3%**	**-13.2%**
France	251	411	**-1.3%**	**1.8%**	**-16.0%**	**-9.9%**
United Kingdom	782	639	**-0.5%**	**4.6%**	**-6.7%**	**-1.3%**
Greece	54	114	**-1.1%**	**5.4%**	**-10.5%**	**-7.1%**
Croatia	19	60	**6.3%**	**7.7%**	**-7.0%**	**-5.9%**
Hungary	20	10	**6.9%**	**9.4%**	**-29.9%**	**-27.1%**
Ireland	14	28	**-3.4%**	**-5.0%**	**8.5%**	**6.7%**
Italy	150	177	**12.3%**	**13.2%**	**-12.6%**	**-9.3%**
Netherlands	56	82	**-9.5%**	**-6.3%**	**-6.5%**	**0.8%**
Norway	87	105	**11.3%**	**4.7%**	**-13.8%**	**-18.2%**
Portugal	22	23	**7.8%**	**1.9%**	**-8.4%**	**-12.8%**
Romania	21	55	**8.2%**	**7.4%**	**-5.9%**	**-8.0%**
Sweden	253	489	**10.2%**	**3.6%**	**-6.8%**	**-8.3%**
Turkey	135	246	**-8.0%**	**-6.5%**	**0.7%**	**3.1%**
# Positive			12	15	2	3
# Negative			8	5	18	17
Median			6.6%	4.1%	-8.3%	-6.7%
Difference					-14.9pp	-10.8pp
Shapiro-Wilk W (p-value)					0.97 (0.80)	0.96 (0.73)
Wilcoxon signed rank test						
V					196	190
p-value					0.0002***	0.0007***

*This table depicts the cumulative returns of the RMP portfolio for two consecutive 46-day windows with a smaller sample based on the criterion of at least 10 stocks per "remote" or "physical" group. Hence, the sample is reduced by countries: Czech Republic, Estonia, Latvia, Lithuania, Slovakia and Slovenia. The first window "ending 9.March" spans the period from 23rd January, the day of the lockdown announcement in the Chinese province of Wuhan, until the 9th of March, the day of the first European lockdown announcement in Italy. The second window "ending 24. April" spans the period from March 10th until April 24th. The columns Ø Remote and Ø Physical denote the average number across the two periods of stocks in the "Remote" and "Physical" group subset respectively. Columns "Unadjusted" denote the unadjusted cumulative excess return. Columns "Risk adj." denote the returns after adjusting for the Fama and French (1992) three factor model risk factors. The rows # Positive and # Negative denote the number of sample countries with positive and negative cumulative returns respectively. The row "Difference" denotes the percent point difference in the equally weighted median returns for both "Unadjusted" and "Risk Adjusted" returns. W denotes the Shapiro Wilk (1965) test statistic for normality with the Null Hypothesis "The data is normally distributed". V denotes the test statistic for the Wilcoxon (1945) signed rank test. The null hypothesis amounts to "the medians of both samples are equal". *** denotes statistical significance at the 1%-level.*

Appendix 8: 2019 Control Windows for RMP Returns

Appendix 8 - Table I:
Cross-country RMP Returns for Control Windows in 2019

			Ending 09. March		Ending 24. April	
	Ø Number of stocks		Cum returns		Cum returns	
Country	Remote	Physical	Unadjusted	Risk adj.	Unadjusted	Risk adj.
Austria	25	44	-2.3%	-1.6%	2.3%	3.4%
Belgium	64	72	-5.3%	-2.5%	0.1%	1.9%
Switzerland	105	134	-4.2%	-0.9%	2.0%	3.7%
Czechia	4	1	-3.3%	-2.5%	-1.5%	-2.2%
Germany	345	387	0.5%	1.0%	0.8%	1.5%
Denmark	68	80	1.3%	4.5%	3.0%	4.8%
Spain	111	100	-5.1%	-3.4%	1.6%	2.8%
Estonia	4	11	3.6%	3.1%	5.0%	4.9%
Finland	72	92	-2.9%	-1.4%	-4.9%	-3.5%
France	262	417	-5.7%	-3.0%	1.9%	3.4%
United Kingdom	818	673	-3.0%	-1.2%	0.9%	1.8%
Greece	57	121	5.4%	4.8%	5.2%	3.7%
Croatia	19	65	6.1%	6.4%	-6.6%	-6.5%
Hungary	21	11	4.1%	3.4%	1.8%	1.5%
Ireland	17	28	-1.7%	-1.3%	10.0%	9.7%
Italy	156	177	3.1%	5.3%	-0.3%	0.9%
Lithuania	8	21	-2.0%	-1.3%	1.6%	2.0%
Latvia	2	18	26.1%	23.6%	-2.1%	-4.3%
Netherlands	57	83	-6.9%	-2.9%	-0.7%	1.2%
Norway	93	103	2.1%	2.9%	-2.2%	-1.3%
Portugal	23	25	-1.3%	-0.4%	2.4%	3.1%
Romania	21	55	1.3%	1.1%	-2.1%	-2.0%
Slovakia	7	2	-0.1%	-0.6%	-3.6%	-3.7%
Slovenia	10	12	3.2%	1.2%	-2.7%	-3.9%
Sweden	259	494	-6.7%	-5.7%	-8.4%	-7.4%
Turkey	133	248	-3.1%	-2.4%	1.2%	2.3%
# Positive			11	11	15	17
# Negative			15	15	11	9
Median			-1.5%	-0.7%	0.8%	1.6%
Difference					2.4pp	2.4pp
Shapiro-Wilk W (p-value)					0.83 (0.0005)	0.81 (0.0003)
Wilcoxon signed rank test						
V					136	149
p-value					0.3276	0.5153

Table I depicts the cumulative returns of the RMP portfolio for all 26 sample countries for two consecutive 46-day windows in the control period in 2019, the year prior to COVID-19. The columns Ø remote and Ø physical denote the average number across the two periods of stocks in the "Remote" and "Physical" group subset respectively. Columns "Unadjusted" denote the unadjusted cumulative excess return. Columns "Risk adj." denote the returns after adjusting for the Fama and French (1992) three factor model risk factors. The rows # Positive and # Negative denote the number of sample countries with positive and negative cumulative returns respectively. The row "Difference" denotes the percent point difference in the equally weighted median returns for both "Unadjusted" and "Risk adj." returns. W denotes the Shapiro Wilk (1965) test statistic for normality with the Null Hypothesis "The data is normally distributed". V denotes the test statistic for the Wilcoxon (1945) signed rank test. The null hypothesis amounts to "the medians of both samples are equal".

Appendix 9: Country Stock Market Indices

Appendix 9 - Table I:
Overview of National Stock Indices Applied in the Analyses

Country	Index
United Kingdom	FTSE 100 Index
Turkey	ISE 100 Index-Turkey
Switzerland	Swiss Market Index
France	CAC 40 Index
Germany	Deutscher Aktienindex (DAX) Index
Greece	Athens Stock Exchange General Index
Austria	ATX Index
Belgium	Belgium 20 Index
Ireland	Irish SE Index (ISEQ)
Netherlands	Amsterdam AEX - Index
Croatia	Zagreb Crobex Index
Slovakia	Slovakian SAX Index
Portugal	PSI 20 Index
Denmark	KAX CSE All Share Index
Estonia	Tallinn Stock Exchange Index
Hungary	Budapest Stock Exchange Index
Sweden	OMX Stockholm 30 Index
Spain	IBEX 35 Index
Norway	OSE All Share Index
Czechia	Prague Stock Exchange PX 50 Index
Italy	FTSE MIB INDEX
Finland	OMX Helsinki 25 Index
Lithuania	OMX Vilnius
Latvia	OMX Riga
Romania	BET
Slovenia	SBI Top

Table I depicts the national stock indices applied in the sections 5.3 and 6. Data were obtained from the Compustat database.

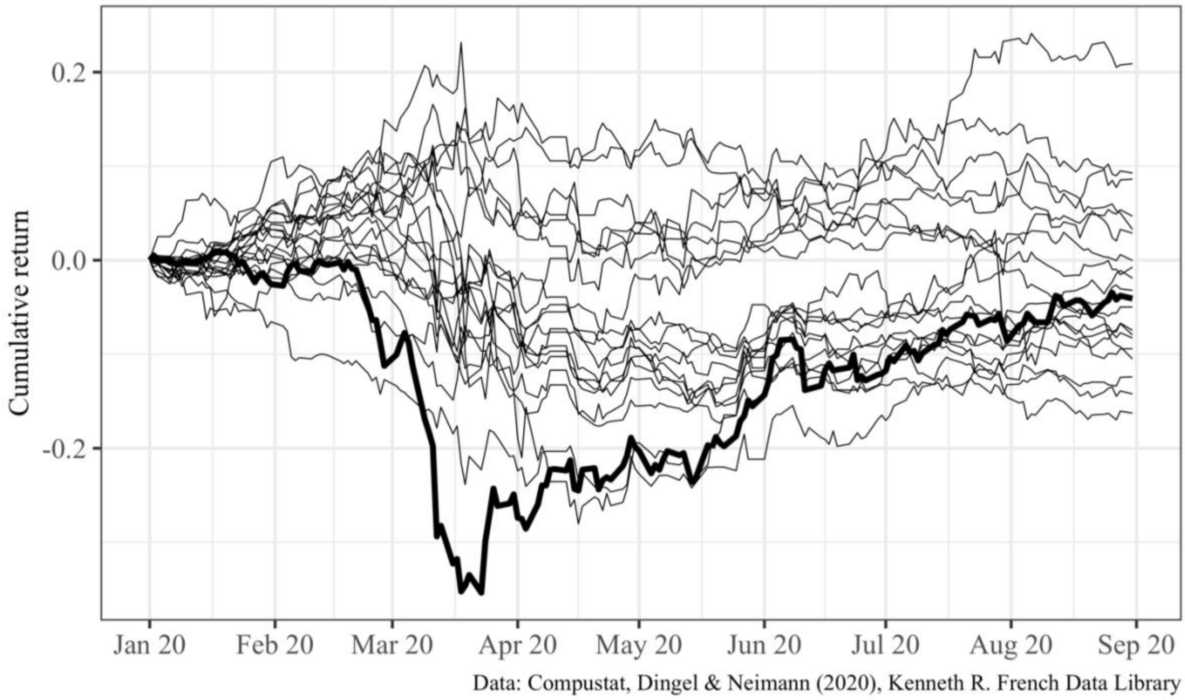
Appendix 10: Results under Assumptions of the Robustness Tests

10.1 “Pennsylvania Robustness Test”

Appendix 10.1 – Table I: Pennsylvania List Robustness Test
Cross-country RMP Returns for Pre and Post-lockdown Window in Europe

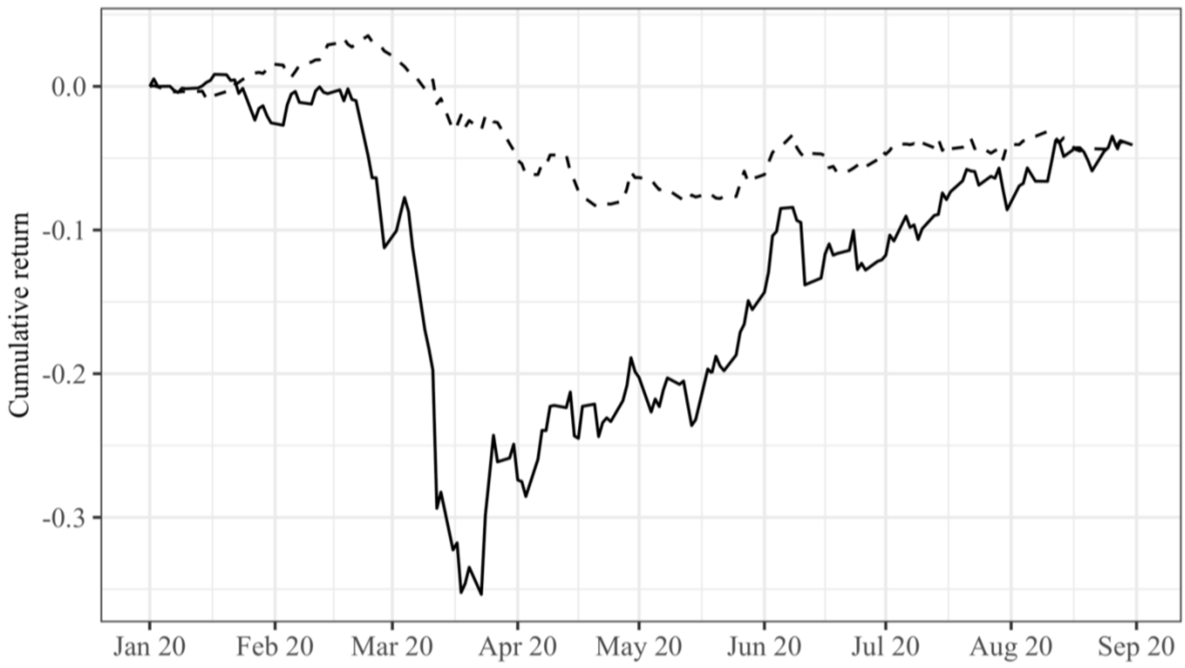
			Ending 09. March		Ending 24. April	
	Ø Number of stocks		Cum. returns		Cum. returns	
Country	Remote	Physical	Unadjusted	Risk adj.	Unadjusted	Risk adj.
Austria	31	38	**2.6%**	**-1.8%**	**-11.3%**	**-13.6%**
Belgium	67	66	**17.4%**	**15.8%**	**-5.8%**	**-1.8%**
Switzerland	104	129	**-3.9%**	**2.8%**	**-11.0%**	**-1.2%**
Czechia	4	1	**0.4%**	**4.6%**	**-10.5%**	**-7.2%**
Germany	370	358	**8.1%**	**-0.2%**	**1.4%**	**-3.9%**
Denmark	79	66	**-12.0%**	**-2.5%**	**-10.2%**	**2.6%**
Spain	108	94	**7.5%**	**2.9%**	**-7.6%**	**-6.5%**
Estonia	7	9	**0.1%**	**-0.5%**	**-2.1%**	**-1.5%**
Finland	76	83	**1.2%**	**-3.5%**	**-13.3%**	**-13.2%**
France	284	377	**-1.8%**	**0.9%**	**-16.1%**	**-10.4%**
United Kingdom	916	505	**-3.4%**	**3.5%**	**-5.4%**	**2.0%**
Greece	65	103	**-1.8%**	**4.2%**	**-10.1%**	**-6.7%**
Croatia	28	49	**4.9%**	**5.9%**	**-6.1%**	**-5.9%**
Hungary	21	9	**6.9%**	**9.4%**	**-29.9%**	**-27.1%**
Ireland	20	22	**-4.9%**	**-1.4%**	**3.3%**	**6.9%**
Italy	166	161	**2.2%**	**3.5%**	**-12.5%**	**-7.8%**
Lithuania	11	17	**4.2%**	**5.8%**	**-0.2%**	**0.5%**
Latvia	5	14	**5.2%**	**5.8%**	**0.5%**	**2.9%**
Netherlands	62	74	**-9.8%**	**-6.3%**	**-5.9%**	**2.0%**
Norway	126	66	**4.7%**	**0.0%**	**-13.4%**	**-17.0%**
Portugal	23	22	**7.0%**	**1.5%**	**-8.2%**	**-12.3%**
Romania	27	49	**11.4%**	**8.9%**	**-6.6%**	**-8.6%**
Slovakia	6	2	**37.7%**	**40.8%**	**-39.9%**	**-40.7%**
Slovenia	11	10	**-0.6%**	**0.2%**	**-21.7%**	**-21.3%**
Sweden	281	459	**8.1%**	**2.4%**	**-5.8%**	**-6.7%**
Turkey	149	231	**-10.5%**	**-10.1%**	**1.8%**	**3.2%**
# Positive			17	18	4	7
# Negative			9	8	22	19
Median			2.4%	2.6%	-7.9%	-6.6%
Difference					-10.3pp	-9.2pp
Shapiro-Wilk W (p-value)					0.79 (0.0001)	0.75 (0.00003)
Wilcoxon signed rank test						
V					324	309
p-value					0.00004***	0.0003***

*Table I depicts the cumulative returns of the RMP portfolio for all 26 sample countries for two consecutive 46-day windows under the assumptions of the robustness test according to the Pennsylvania List. The first window "Ending 9.March" spans the period from 23rd January, the day of the lockdown announcement in the Chinese province of Wuhan, until the 9th of March, the day of the first European lockdown announcement in Italy. The second window "Ending 24. April" spans the period from March 10th until April 24th. The columns Remote and Physical denote the average number across the two periods of stocks in the "Remote" and "Physical" group respectively. Columns "Unadjusted" denote the unadjusted cumulative excess return. Columns "Risk adj." denote the returns after adjusting for the Fama and French (1992) three factor model risk factors. The rows # Positive and # Negative denote the number of sample countries with positive and negative cumulative returns respectively. The row "Difference" denotes the percent point difference in the equally weighted median returns for both "Unadjusted" and "Risk adj." returns. W denotes the Shapiro Wilk (1965) test statistic for normality with the Null Hypothesis "The data is normally distributed". V denotes the test statistic for the Wilcoxon (1945) signed rank test. The null hypothesis amounts to "the medians of both samples are equal". *** denotes statistical significance at the 1%-level.*



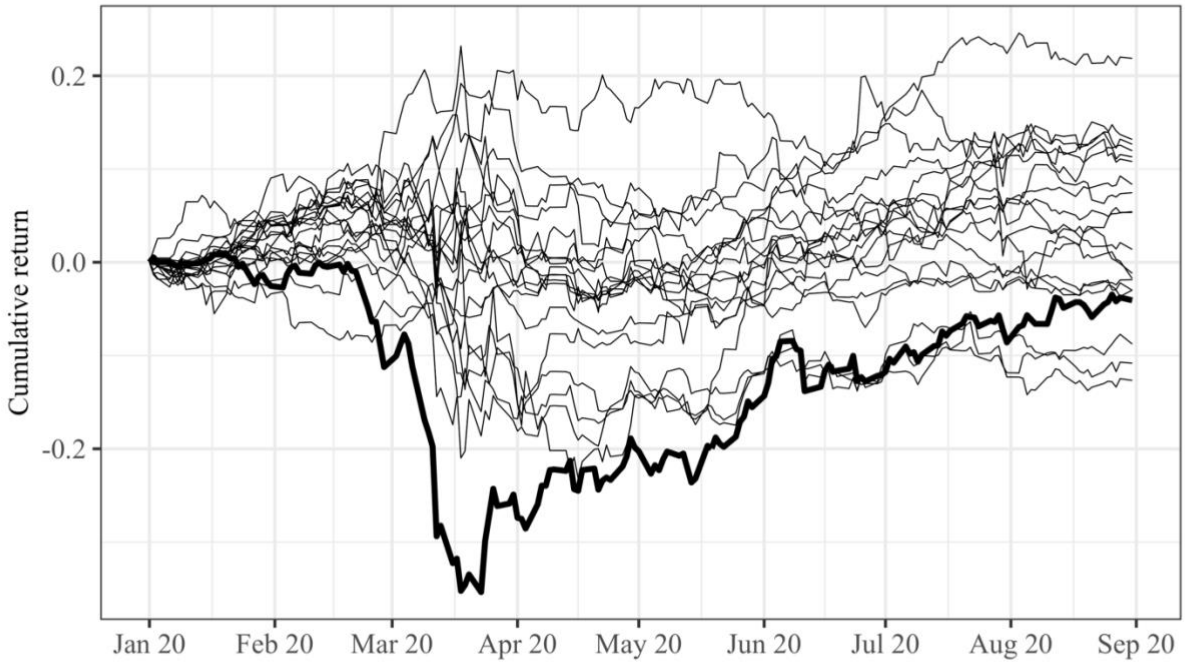
Appendix 10.1 – Figure 1: "**Pennsylvania Robustness Test": Cumulative Return of the RMP Portfolio for Sample of European Countries Against Market Return**

Figure 1 plots the cumulative return of the RMP portfolio for a sample of 20 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded. Critical industries have been reclassified as "remote" based on the Pennsylvania List of Critical Industries.



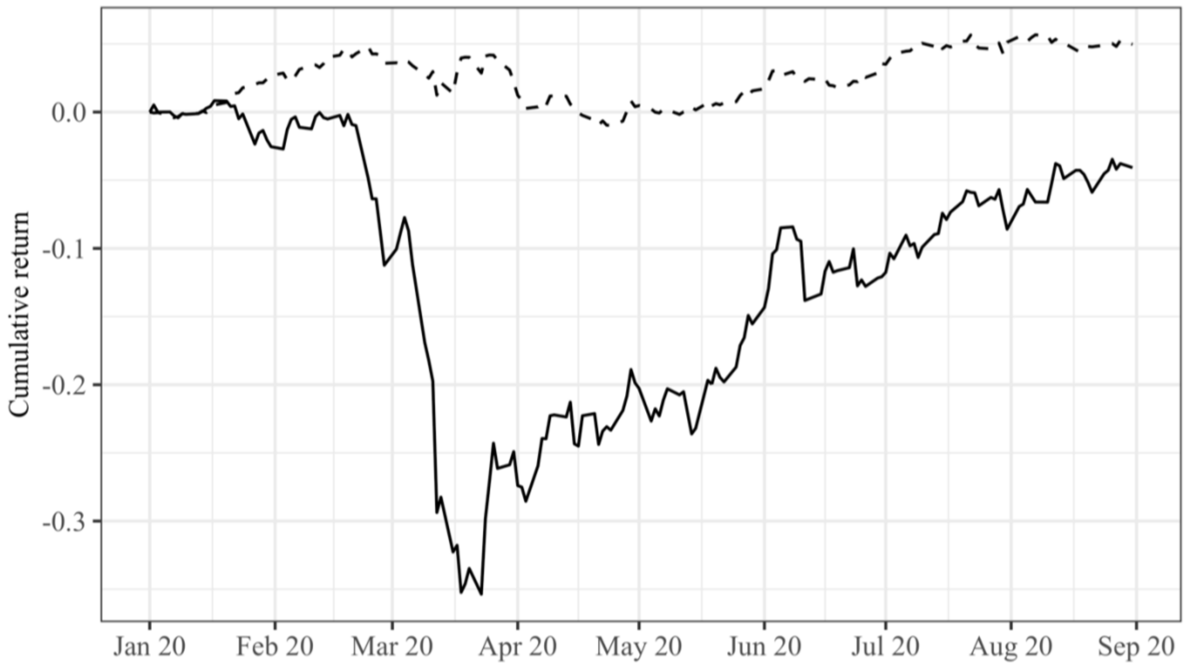
Appendix 10.1 – Figure 2: "**Pennsylvania Robustness Test": Cumulative Return of the "European" RMP Portfolio Against Market Return**

Figure 2 plots the cumulative return of the "European" RMP portfolio aggregated over 20 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded. Critical industries have been reclassified as "remote" based on the Pennsylvania List of Critical Industries.



Appendix 10.1 - Figure 3: "**Pennsylvania Robustness Test": Cumulative Risk Adjusted Return of the RMP Portfolio for Sample of European Countries Against Market Return**

Figure 3 plots the cumulative risk-adjusted return of the RMP portfolio for a sample of 20 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded. Critical industries have been reclassified as "remote" based on the Pennsylvania List of Critical Industries.



Appendix 10.1 - Figure 4: "**Pennsylvania Robustness Test": Cumulative Risk Adjusted Return of the "European" RMP Portfolio Against Market Return**

Figure 4 plots the cumulative risk-adjusted return of the "European" RMP portfolio aggregated over 20 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded. Critical industries have been reclassified as "remote" based on the Pennsylvania List of Critical Industries.

Appendix 10.1 – Table II:
Pennsylvania Robustness Test: Random Effects Model of the Remote Minus Physical (RMP) Returns on COVID-19 Pandemic and Country-level Characteristics.

	Dependent variable:			
	RMP risk adjusted return			
	(1)	(2)	(3)	(4)
Closed Dummy	0.070***	0.113***	0.049	0.176***
Change in New Deaths	0.0003	0.0003	0.001***	0.001***
Average Institutional Quality			-0.004***	-0.004***
Digital Skills			-0.00002	0.001***
Broadband			0.0002**	0.0003***
Market Capitalisation Weight		0.634***	2.015***	1.591***
Labour Regulation				0.038***
Closed Dummy x Change in New Deaths	-0.001**	-0.001**	-0.001***	-0.001***
Closed Dummy x Average Institutional Quality			-0.003	-0.002**
Closed Dummy x Digital Skills			0.004**	0.003***
Closed Dummy x Broadband			0.001**	0.001***
Closed Dummy x Market Capitalisation Weight		-1.009***	-2.342***	-1.965***
Closed Dummy x Labour Regulation				-0.066***
Constant	-0.013	-0.028*	0.254***	0.187***

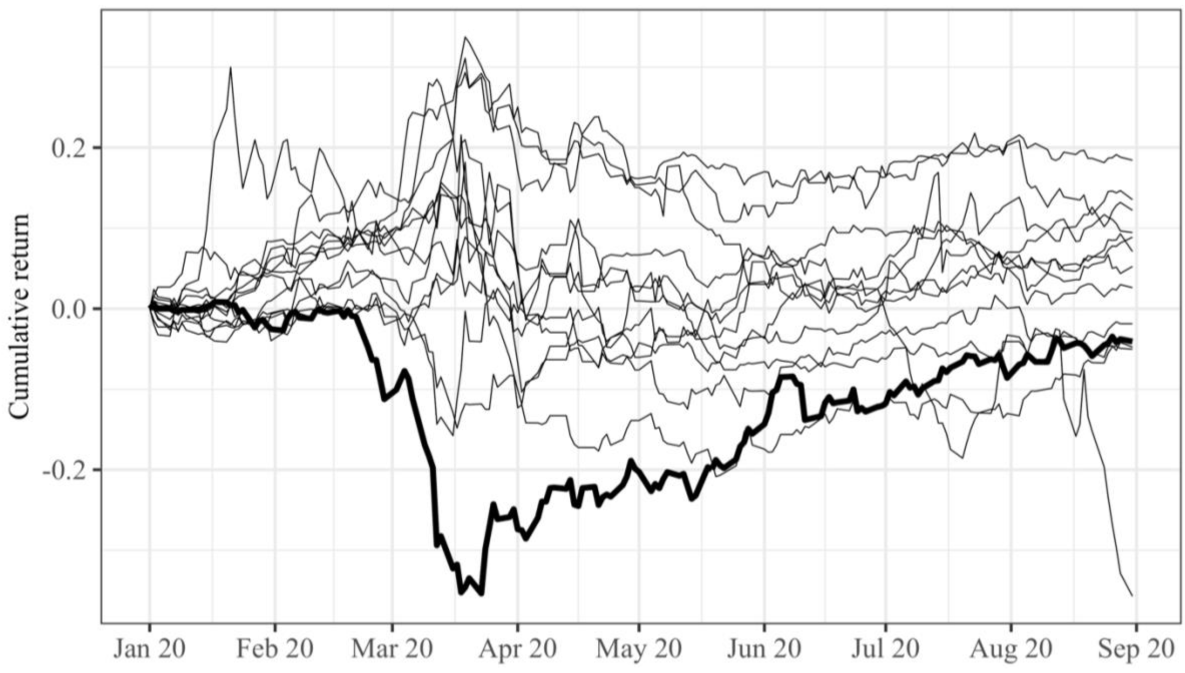
*Table II shows the results from a random effects model of the COVID-19 pandemic and country-specific characteristic variables for the period from 1st January to 31st August 2020 under the assumptions of the "Pennsylvania List Robustness Test". We regress the daily RMP risk adjusted returns for each country on the COVID-19 pandemic and country-specific characteristics. To account for differences between countries we use a random effects estimator. The portfolios are constructed for each country individually and weighted based on the market capitalisation of the stocks. Each portfolio is held for all existing trading days during the two years and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. Remote and physical stocks are defined as having an above or below median Dingel-Neiman (2020) value taking into account critical industries. The pandemic characteristics included are the daily change in new COVID-19 deaths as well as the workplace closure which is an ordinal variable ranging from 0 to 3. The country-specific characteristics are the size of the stock market on 1st January 2020, the average institutional quality , the broadband speed , the digital skills of employees and labour protection laws . Due to a lack of sufficient stock market and country-specific data, we restrict our sample to 15 countries for which we observe at least 10 companies in each portfolio trading continuously and have complete data for the regressors. In the first model specification we only include the COVID-19 pandemic characteristics. The second model further controls for the size of the capital market while the third model also incorporates other country-specific characteristics. The last specification tests our hypothesis of labour regulation effects on the RMP return. The table reports coefficient estimates that have heteroskedasticity robust standard errors. *,** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.*

10.2 “Top and Bottom” Robustness Test

Appendix 10.2 – Table I: "Top and Bottom" Robustness Test
Cross-country RMP Returns for Pre- and Post-lockdown Window in Europe

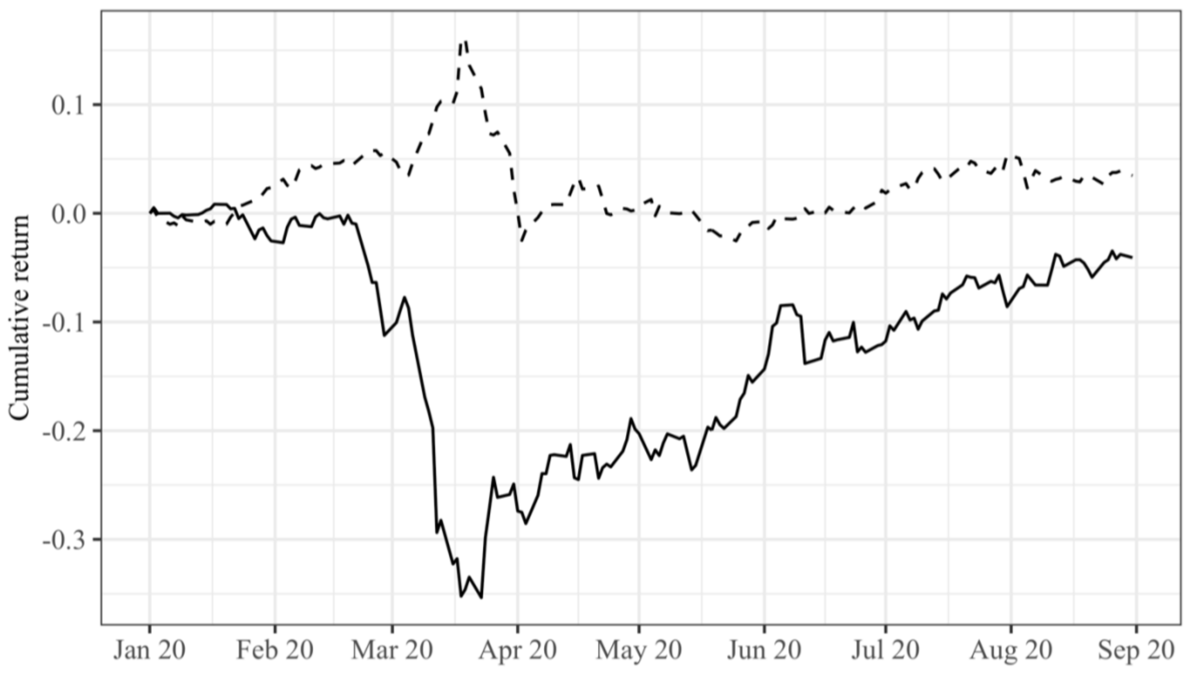
	Ø Number of stocks		Ending 09. March Cum returns		Ending 24. April Cum returns	
Country	Remote	Physical	Unadjusted	Risk adj.	Unadjusted	Risk adj.
Austria	17	7	**19.2%**	**26.9%**	**-18.8%**	**-14.9%**
Belgium	48	5	**10.1%**	**6.4%**	**-2.3%**	**-3.4%**
Switzerland	75	5	**-11.1%**	**-7.3%**	**-22.2%**	**-10.2%**
Germany	264	29	**9.6%**	**10.0%**	**4.6%**	**1.4%**
Denmark	59	8	**17.4%**	**13.0%**	**8.1%**	**3.8%**
Spain	70	34	**3.1%**	**10.2%**	**-7.4%**	**0.9%**
Finland	64	12	**-2.2%**	**0.6%**	**0.8%**	**4.1%**
France	215	61	**9.4%**	**10.6%**	**-13.7%**	**-15.2%**
United Kingdom	691	205	**4.5%**	**5.3%**	**-8.1%**	**-8.5%**
Greece	44	33	**-1.9%**	**4.7%**	**-14.2%**	**-10.5%**
Croatia	14	21	**6.0%**	**6.8%**	**-4.2%**	**-4.1%**
Ireland	13	8	**-3.6%**	**-13.0%**	**20.9%**	**6.5%**
Italy	123	39	**4.9%**	**15.9%**	**-8.3%**	**5.7%**
Netherlands	52	9	**-2.1%**	**-9.5%**	**8.8%**	**-1.3%**
Norway	76	35	**22.8%**	**11.5%**	**-16.8%**	**-25.4%**
Portugal	14	8	**4.8%**	**1.0%**	**-10.8%**	**-10.8%**
Romania	13	11	**2.5%**	**3.6%**	**-0.4%**	**-3.6%**
Sweden	200	64	**14.4%**	**9.8%**	**0.8%**	**0.1%**
Turkey	104	56	**-0.1%**	**5.7%**	**-1.9%**	**3.8%**
# Positive			13	16	6	8
# Negative			6	3	13	11
Median			4.8%	6.4%	-4.2%	-3.4%
Difference					-9.0pp	-9.8pp
Shapiro-Wilk W (p-value)					0.92 (0.11)	0.92 (0.10)
Wilcoxon signed rank test						
V					162	166
p-value					0.005***	0.003***

*Table I depicts the cumulative returns of the RMP portfolio for two consecutive 46-day windows under the assumptions of the robustness test according to the top and bottom 30% DN scores. Countries with less than 20 stocks were excluded from the sample for the purposes of this test. The first window "Ending 9.March" spans the period from 23rd January, the day of the lockdown announcement in the Chinese province of Wuhan, until the 9th of March, the day of the first European lockdown announcement in Italy. The second window "Ending 24. April" spans the period from March 10th until April 24th. The columns Remote and Physical denote the average number across the two periods of stocks in the "Remote" and "Physical" group subset respectively. Columns "Unadjusted" denote the unadjusted cumulative excess return. Columns "Risk adj." denote the returns after adjusting for the Fama and French (1992) three factor model risk factors. The rows # Positive and # Negative denote the number of sample countries with positive and negative cumulative returns respectively. The row "Difference" denotes the percent point difference in the equally weighted median returns for both "Unadjusted" and "Risk adj." returns. W denotes the Shapiro Wilk (1965) test statistic for normality with the Null Hypothesis "The data is normally distributed". V denotes the test statistic for the Wilcoxon (1945) signed rank test. The null hypothesis amounts to "the medians of both samples are equal". *** denotes statistical significance at the 1%-level.*



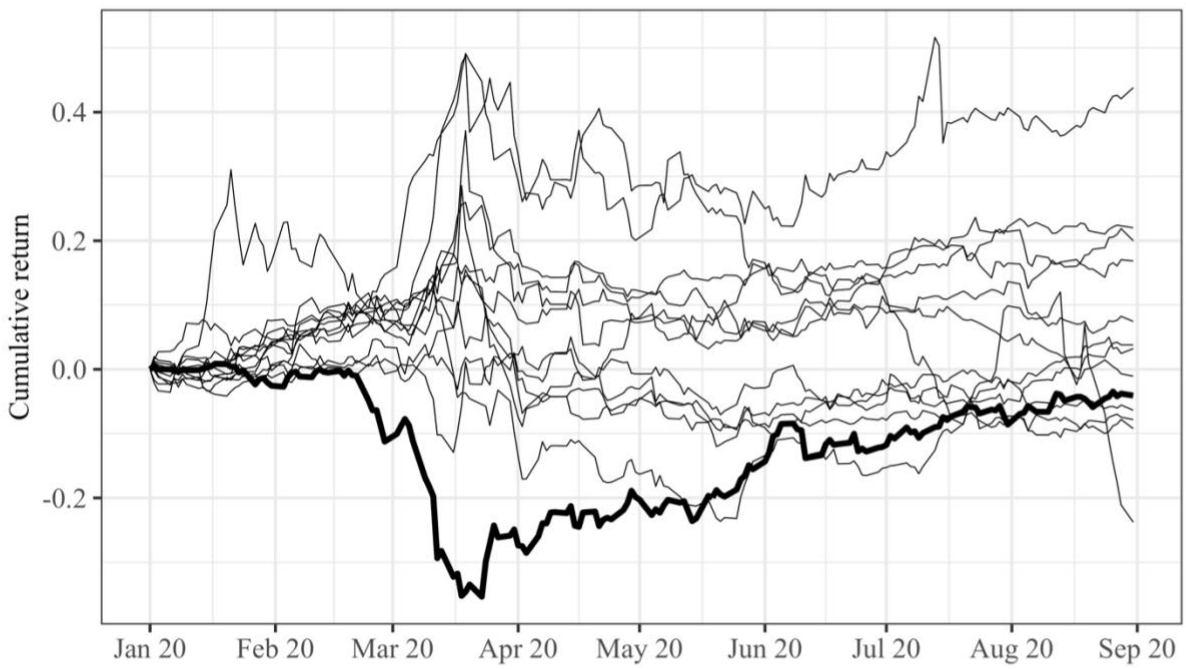
Appendix 10.2 - Figure 1: "**Top and Bottom" Robustness Test: Cumulative Return of the RMP Portfolio for Sample of European Countries Against Market Return**

Figure 1 plots the cumulative return of the RMP portfolio for a sample of 12 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded. Only industries in the top and bottom 30%-percentile of DN estimates have been considered for the portfolio formation.



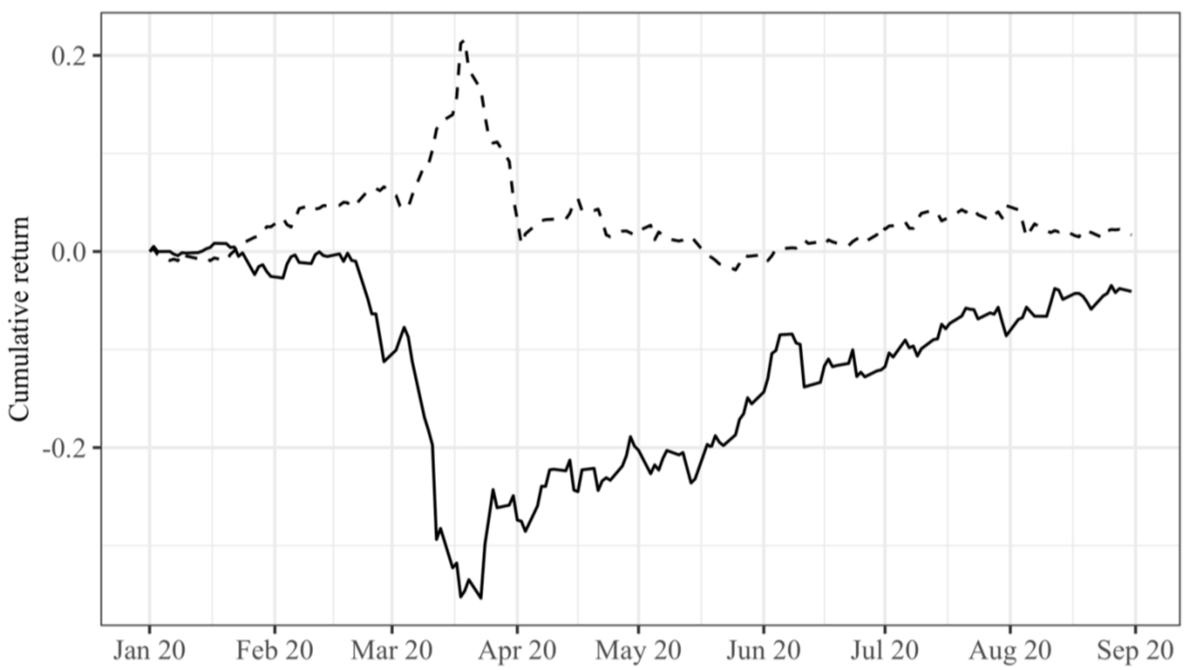
Appendix 10.2 - Figure 2: "**Top and Bottom" Robustness Test: Cumulative Return of the "European" RMP Portfolio Against Market Return**

Figure 2 plots the cumulative return of the "European" RMP portfolio aggregated over 12 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded. Only industries in the top and bottom 30%-percentile of DN estimates have been considered for the portfolio formation.



Appendix 10.2 - Figure 3: "**Top and Bottom" Robustness Test: Cumulative Risk Adjusted Return of the RMP Portfolio for Sample of European Countries Against Market Return**

Figure 3 plots the cumulative risk-adjusted return of the RMP portfolio for a sample of 12 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded. Only industries in the top and bottom 30%-percentile of DN estimates have been considered for the portfolio formation.



Appendix 10.2 - Figure 4: "**Top and Bottom" Robustness Test: Cumulative Risk Adjusted Return of the "European" RMP Portfolio Against Market Return**

Figure 4 plots the cumulative risk-adjusted return of the "European" RMP portfolio aggregated over 12 European countries between the 1st of January and 31st of August 2020. Countries with less than 10 stocks per group were excluded. Only industries in the top and bottom 30%-percentile of DN estimates have been considered for the portfolio formation.

Appendix 10.2. Table II:
"Top and Bottom" Robustness Test: Random Effects Model of the Remote Minus Physical (RMP) Returns on COVID-19 Pandemic and Country-level Characteristics.

	Dependent variable:			
	RMP risk adjusted Return			
	(1)	(2)	(3)	(4)
Closed Dummy	0.042	0.017	0.683***	-0.341**
Change in New Deaths	0.0004*	0.0004*	0.0005	0.0004
Average Institutional Quality			0.011***	0.013***
Digital Skills			-0.013***	-0.019***
Broadband			0.0002	-0.001***
Market Capitalisation Weight		-3.609**	-0.673	7.214***
Labour Regulation				-0.348***
Closed Dummy x Change in New Deaths	0.0003	0.0003	0.0004	0.0004
Closed Dummy x Average Institutional Quality			-0.017***	-0.018***
Closed Dummy x Digital Skills			0.015***	0.021***
Closed Dummy x Broadband			-0.001*	0.0003
Closed Dummy x Market Capitalisation Weight		3.009*	0.056	-7.923***
Closed Dummy x Labour Regulation				0.314***
Constant	0.008	0.081**	-0.072	1.034***

Table II shows the results from a random effects model of the COVID-19 pandemic and country-specific characteristic variables for the period from 1st January to 31st August 2020. We regress the daily RMP risk adjusted returns for each country on the COVID-19 pandemic and country-specific characteristics. To account for differences between countries we use a random effects estimator. The portfolios are constructed for each country individually and weighted based on the market capitalisation of the stocks. Each portfolio is held for all existing trading days during the two years and rebalanced every month based on the closing market capitalisation on the last trading day of the previous month. Remote and physical stocks are defined as having Dingel-Neiman (2020) value in the top and bottom 30% for their respective industry. The pandemic characteristics included are the daily change in new COVID-19 deaths as well as the workplace closure which is an ordinal variable ranging from 0 to 3. The country-specific characteristics are the size of the stock market on 1st January 2020, the average institutional quality, the broadband speed , the digital skills of employees and labour protection laws . Due to a lack of sufficient stock market and country-specific data, we restrict our sample to 15 countries for which we observe at least 10 companies in each group trading continuously and have complete data for the regressors. In the first model specification we only include the COVID-19 pandemic characteristics. The second model further controls for the size of the capital market while the third model also incorporates other country-specific characteristics. The last specification tests our hypothesis of labour regulation effects on the RMP return. The table reports coefficient estimates that have heteroskedasticity robust standard errors.

, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.*

Appendix 11: Limitations - Data and Methodology

Data span. One limitation concerns the relatively short data span of our analysis. We apply the setting of the global pandemic as a "labouratory setting" and although we find support for the role of WfH-ability during the pandemic the scope of our paper does not allow us to draw conclusions on whether WfH-ability has actually been a risk driver before the pandemic. Research of Pagano et al. (2020) suggests that this was the case by looking at a US sample of approximately 6 years before the outbreak of COVID-19. Further studies could fruitfully explore differentials driven by the ability to WfH in a cross-country setting throughout a longer sample. The presented measures proxying the ability to WfH (Hensvik et al. (2020), Koren and Petö (2020), Dingel and Neimann (2020))[28] could prove problematic in this matter: First, they prevalently rely on employment and job-characteristic data of *one* year employing these measures would require to boldly assume that technological characteristics of industries have remained constant throughout the longer sample. This issue could be overcome by future research by re-estimating occupational WfH-ability repeatedly for a longer time span. This matter might be particularly interesting for researchers aiming at providing measures for the ability to WfH.

The WfH measure. A further limitation of our paper lies in applying the DN measure across countries. The methodology of task-based WfH-measures to date neglects heterogeneity regarding WfH-ability within occupations, for which WfH ability is assumed to be constant (Adams-Prassl et al. 2020). Therefore, by design, we can not capture within-industry differences of WfH-ability and essentially do not account for the fact that some firms within one industry might be better at shifting from workplace presence to WfH through operational practises such as well-functioning WfH-arrangements and an IT infrastructure enabling effective WfH. Finally, in aggregating the DN-measure from the employment level to the NACE section-level, we might give up granularity in assessing industry-level WfH ability. Here, we are constrained by the data as the applied dataset from the ILO comprised the occupational employment for NACE section-level industries only. We acknowledge that there might well be pronounced variation of WfH-ability across deeper levels of industrial classification standards. As the discussion above suggests, the outcome of aggregating occupational WfH-estimates to the industry-level should be viewed as a proxy for industry-level WfH-ability. The clearest picture could be achieved by obtaining WfH-estimates on the

[28] Notably, measures such as the measure proposed by Alipour et al. (2020) could be seen as actual WfH-measures as they are based on employee surveys which ask explicitly about the individual's ability to perform the respective job at home. Such a measure – on a cross-country basis – matched with individual firms could alleviate the limitations arising from WfH proxies.

individual firm level. Therefore, we conclude that within future research, investigating firm-level WfH-ability, for example through a survey approach might prove important. Clearly, this would prove challenging in a cross-country setting, especially if the aim is to obtain longitudinal WfH-measures as suggested in the paragraph above.

Resilience drivers other than the ability to WfH. Throughout our work, we viewed the ability to WfH as a key factor determining firm resilience towards the impact of Covid-19. This is in line with a fast-growing literature on the economics of COVID-19 (See for example Brodeur et al. (2020), Papanikolaou et al. (2020)). Nevertheless, research has found different channels of disaster resilience towards Covid-19. Therefore, we see the need for future research to extend the notion of disaster resilience, including more factors that drive firms' resilience, both during COVID-19 specifically but also during health crisis at large. This could also lead to a clearer view on the degree to which different factors impact disaster resilience. In short, we suggest a replication of our research results, replacing the RMP portfolio with a portfolio that could be named "Resilient minus Non-resilient" which should account for resilience-drivers beyond the ability to WfH.

Extension to more risk factors. Within our work, we aimed at accounting for risk factors proposed by the FF3 model. Even after adjusting returns for these risk factors we found the RMP return differential to be persistent. Nevertheless, we suggest testing this finding after accounting for a broader range of risk factors proposed in the literature in future research.