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Hedging Covid-19 risk with ESG disclosure

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A B S T R A C T

Covid-19 has led to major changes worldwide and has had a significant impact on market risk. We characterize this uncertainty as innovations extracted from the Covid Risk Index on the *Wall Street Journal* through a textual analysis of high-dimensional data. We hedge the risk with mimicking portfolios constructed using the ESG (environmental, social, and governance) disclosure score as a measure of firm-level exposure to Covid-19 risk. The hedge portfolios perform well both in and out of sample. We also test the role of ESG in hedging and discover that during the Covid-19 pandemic firms with greater ESG disclosure generate higher returns as well as experience lower downside risk. The further analysis suggests that the portfolio returns can be explained by Covid risk shock and investment inflow, and the hedge effect mainly comes from the social part of ESG.

1. Introduction

The Covid-19 pandemic has both social and economic repercussions for the world, generating great turmoil in financial markets. The way to hedge Covid-19 risk is quite important to explore for investors around the world. Existing studies on this issue mainly emphasize the role of gold as a safe haven during the pandemic period (Akhtaruzzaman et al., 2021; Salisu et al., 2021; Sikiru & Salisu, 2021). However, gold is not actually a hedge asset in the strict sense because the returns of hedge assets need to be highly consistent with the trend of the risk we hedge on. In this way, we can almost avoid Covid-19 risk by longing the hedge asset and realize gains when facing an intensified risk.

Our paper focuses on attempts to hedge Covid-19 risk. As there is no direct target asset in the market that can hedge Covid-19 risk, we apply the mimicking portfolio approach advocated by Lamont (2001). This approach projects Covid-19 risk on a set of asset returns, and the synthetic portfolio is called a “mimicked hedge portfolio.”

In applying the mimicking portfolio approach, the first challenge we face is how to measure Covid-19 risk—that is, quantitatively characterizing the volatility that every market participant encounters. We begin with the observation that media coverage of the pandemic tends to increase dramatically when cases are increasing and conditions are declining. As investors commonly keep up with the latest trends through news reports, the extent to which they are exposed to daily coronavirus-related articles generally leads them to revise their concerns about the risk. Thus, we represent Covid-19 risk as news coverage of relevant reports.

Another challenge is to find the individual characteristics that can reflect a firm’s exposure to Covid-19 risk. We use ESG

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(environmental, social, and governance) disclosure as the firm-level characteristic to build up our hedge portfolio. Many recent studies have proved there exist close relationships between ESG disclosure and stock performance during the pandemic period (Broadstock et al., 2021; Ferriani and Natoli, 2021; Folger-Laronde, Pashang, Feor, & ElAlfy, 2022). On the one hand, well-run companies often act for reasons beyond simple value maximization, so they care more about ESG issues (Hartzmark & Sussman, 2019). These firms have more chances to survive a global market crash such as the Covid-19 pandemic. On the other hand, firms with higher ESG or corporate social responsibility (CSR) generally deserve more trust from investors and stakeholders and thus tend to be more resilient throughout a crisis (Lins et al., 2017). Investors are also more willing to allocate their assets in those firms. In the first quarter of 2020, there was an inflow of USD 45.6 billion to the global sustainable fund universe, compared to an outflow of USD 384.7 billion experienced by the overall fund universe (Morningstar, 2020).

Our data are primarily based on the US stock market. We consider March 2020 the start of the pandemic per the World Health Organization (WHO). For an adequate number of observations and comparability, we set January 2017 to be our starting point of the sample and December 2021 as the end point. We define the period between January 2017 and February 2020 as the pre-pandemic period and the subsequent period as the pandemic. For the measure of Covid-19 risk, we use the *Wall Street Journal* (WSJ) as the sole source of news reports. The daily WSJ articles are publicly accessible from an online archive. Based on that, we construct a time series—denoted as Covid-19 risk index—to capture news about the coronavirus through textual analysis of news reports. The Covid-19 risk index is calculated as the correlation, or the cosine similarity between news content and a Covid-related vocabulary. For the measure of a firm's exposure to Covid-19 risk, we use the ESG disclosure score from Bloomberg as a proxy for a firm' ESG disclosure. The sub-scores of environmental (E), social responsibility (S), and corporate governance (G) also come from Bloomberg.

In the empirical analysis, we examine the role of ESG disclosure as firms' exposure to Covid-19 risk first. The results suggest that firms with higher ESG disclosure score experience better performance with significantly higher returns and lower downside risk. Even when the full sample period is considered, the impact of Covid-19 risk, measured by either the news index or the dummy variable, on stock performance is significantly greater for firms with higher ESG disclosure. These results support our adoption of ESG disclosure as the characteristic or the exposure for the target risk in forming the mimicked hedge portfolio.

After verifying the role of firm-level ESG disclosure in hedging Covid-19 risk, we examine the effectiveness of mimicked hedge portfolio. We find that the correlation between its returns and the Covid-19 risk index is significantly positive both in and out of sample, indicating that investors can avoid Covid-19 risk if they allocate assets according to our hedge portfolio. In the robustness test, our methodology uses two alternative measures of Covid-19 risk or compare the hedge effect of mimicked portfolio with the great-minus-poor (GMP) portfolio—a portfolio constructed by simply longing stocks with ESG disclosure scores in the top third and shorting stocks with scores in the bottom third. Delightedly, we pass all these tests as the results show that the mimicked hedge portfolio is still effective.

We further decompose the returns of our hedge portfolios. The Fama-French three-factor loadings cannot fully explain the variation in portfolio returns as the alpha is still significant. However, the alpha reduces to insignificance once variables of Covid risk shock and investment inflow are included. In addition, we decompose ESG disclosure into E, S, and G disclosure, respectively, and redo the mimicking portfolio approach. The in-sample and out-of-sample fit results indicate that the hedge effect of constructed portfolios mainly comes from the social part of ESG. This finding is consistent with the study by Lins et al. (2017) that social responsibility helps firms earn trust or social capital during market downturns.

Our research contributes to literatures on hedging Covid-19 risk. Prior studies tried to find assets with low variability during financial crises or uncertainties (Arif et al., 2022; Chemkha et al., 2021; Sikiru & Salisu, 2021). The properties of safe haven seem to help investors "hedge" Covid-19 risk. However, low variability does not mean we can realize gains when holding these assets during the pandemic period—that is, the realization in these assets may not cover the loss incurred by exposures to Covid-19 risk. In this paper, we apply the mimicking portfolio approach and construct a portfolio whose return is solely exposed to Covid-19 risk. This hedge portfolio has one unit beta to Covid-19 risk shocks, which ensures that investors can offset their losses when Covid-19 risk increases.

Our research also complements literatures that concentrate on the extent to which firm-level ESG impacts stock performance during the Covid-19 pandemic. Many prior studies have proven that high-ESG stocks or funds outperform those with low ESG, and the role of ESG performance is more prominent during the Covid-19 pandemic–related financial market crash (Broadstock et al., 2021; Ferriani & Natoli, 2021; Rubbaniy et al., 2021). Our study stands in line with the argument affirming the role of ESG, because the results indicate that the formed hedge portfolio assigning greater weight to high-ESG stocks is significantly effective under several tests.

Our research is an extension of the recent study by Engle et al. (2020), who develop a procedure to dynamically hedge climate change risk with the mimicking portfolio approach. We apply this approach in hedging Covid-19 risk and demonstrate that the hedge portfolio constructed by this approach also performs well. Additionally, our research is related to Baker et al. (2016), who propose to measure economic policy uncertainty based on news coverage. We apply these methodologies in generating the Covid-19 risk index.

The remainder of this paper proceeds as follows. Section 2 is the literature review. Section 3 provides the methodology of how we construct the hedge portfolio and how ESG disclosure functions in it. Section 4 describes the data, variables, and summary statistics of all variables. Section 5 presents the empirical results including baseline results, robustness tests, and further analysis. Section 6 concludes the paper.

2. Literature review

With the advent of Covid-19, scholars set out to hedge the related risk. Previous studies tried to find tradable assets that proved to demonstrate low volatility during financial turmoil, including gold/precious metals (Akhtaruzzaman et al., 2021; Salisu et al., 2021; Sikiru & Salisu, 2021), Bitcoin/cryptocurrencies (Chemkha et al., 2021; Conlon et al., 2020), and climate/green bonds (Arif et al., 2022; Dutta et al., 2021). These assets appear less vulnerable to economic downturns and are thus most favorable to long-term investors. However, such a property is actually closer to the definition of safe haven rather than hedge. Baur and Lucey (2010) define a safe-haven (hedge) asset as an asset that is uncorrelated (negatively correlated) with other assets in times of market stress or turmoil.

The mimicking portfolio approach advocated by Lamont (2001) attempts to form a portfolio with its return highly correlated with the hedge target. If the hedge target is a certain risk, investors will obtain gains in this portfolio to offset the losses caused by the increase in the risk. Basu and Miffre (2013) claim that mimicking portfolios that capture the hedging pressure risk premium of commodity futures present a Sharpe ratio that exceeds the benchmarks. Engle et al. (2020) apply this approach in hedging climate change risk and construct the hedge portfolio, of which the yield trend is found to nearly overlap the risk index.

Regarding the role of ESG in determining stock performance during the pandemic, many research studies have affirmed it. Broadstock et al. (2021) use evidence from China CSI300 to prove that high-ESG portfolios generally outperform low-ESG portfolios in mitigating risk during the crisis, which is attenuated in normal times and therefore confirms the incremental importance of ESG during a crisis. Ferriani and Natoli (2021) show that low ESG risks positively affect inflows into equity funds during Covid-19, highlighting investors' preference for ESG funds in times of uncertainty. Rubbaniy et al. (2021) explore the positive co-movement of the global Covid-19 fear index (GFI) with ESG stock indices, which confirms hedging and safe-haven properties of ESG stocks using the health fear proxy of Covid-19.

3. Methodology

This section discusses the methodology to construct hedge portfolios against the Covid-19 pandemic. We adopt the mimicking portfolio approach to construct it. Meanwhile, the close relationship between ESG disclosure and stock performance during the pandemic period allows us to incorporate ESG disclosure as firms' Covid-risk exposure.

3.1. Construction of the hedge portfolios

Our hedge target is a time series of Covid-19 pandemic risk, which is denoted as CP_t. The construction of hedge portfolios follows the methodology adopted by Engle et al. (2020). They propose a procedure to dynamically hedge climate change risk using a mimicking portfolio approach. In implementing the hedging strategy, they also model a time series that captures long-run climate risk.

We apply the mimicking portfolio approach by directly projecting the hedge target onto a set of asset returns. The set itself, however, is huge. Because of the limited number of observations, the problem of data mining might be severe, which generally leads to a hedge portfolio that performs very well in sample but is not stable out of sample. Engle et al. (2020) address these concerns by parsimoniously parameterizing the weights of the portfolio using a characteristics-based approach. Specifically, the Covid-19 pandemic risk CP_t is projected onto characteristics-sorted portfolios as in Equation (1):

$$CP_t = \xi + w' Z'_{t-1} r_t + e_t \tag{1}$$

where r_t $(n \times 1)$ is a return vector including a pool of n individual stocks; Z'_{t-1} $(k \times n)$ is a matrix of k firm-level characteristics appropriately cross-sectionally normalized; and w' $(1 \times k)$ is an adjusting vector that adjusts the portfolio return into the same scale of hedge target. The interaction $w' Z'_{t-1} r_t$ therefore represents the returns of the portfolio onto which the hedge target is projected. Theoretically, the mimicked portfolio will capture any movement in the hedge target.

The exposure of different firms to the pandemic risk is measured by Z_t. The evaluation of firm-level characteristics relates to the stock performance of the resulting hedge portfolio (with in-sample estimated weights of $\hat{w}' Z'_{t-1}$), which is determined based on how well it hedges the pandemic risk out of sample (e.g., CP_t; CP_{t+1}, …). This process determines whether the characteristics chosen can differentiate firms with respect to certain risks.

3.2. Role of ESG disclosure in the hedge portfolios

As discussed in the literature review, quite a few studies have found a relationship between Covid-19 pandemic and ESG disclosure—firms with higher ESG disclosure tend to be more resilient during the pandemic period. It suggests that ESG disclosure can reflect firms' exposure to Covid-19 risk. Therefore, we introduce a characteristic in Equation (2) as a measure of firm-level ESG disclosure. The ESG disclosure level of firm i at time t, or ESG_{it}, helps to filter stocks through the pandemic period. We use two approaches to transform the raw scores into the characteristics vector $Z_t^{ESG} = (z_{1t}^{ESG}, z_{2t}^{ESG}, \ldots, z_{nt}^{ESG})$ (a) by demeaning the absolute value of each firm's $Score_{it}$ cross-sectionally to generate $Z_t^{ESG\_A}$ and (b) by ranking firms' ESG disclosure score cross-sectionally and standardizing the resulting ranks to range between -0.5 and $+0.5$ to generate $Z_t^{ESG\_R}$. We compare the results using either approach for completeness of our analysis.

In addition to portfolios sorted by firm-level ESG disclosure, Equation (2) also includes three factors that are dominant in the literature for explaining the cross-section of returns and are presumably correlated with the risk factor: size, value, and the market. Specifically, we use the cross-sectionally standardized market value of each firm to create Z_t^{size} (so that large cap firms have a positive weight while small cap firms have negative weight) and the cross-sectionally standardized book-to-market value to create Z_t^{value} and set Z_t^{market} as equaling the share of total market value. For example, if we apply the first approach of cross-sectionally demeaning absolute values to derive the characteristics vector, or $Z_t^{ESG\_A}$, then the final regression becomes:

$$CP_t = \xi + w_{ESG} Z_{t-1}^{ESG\_A'} r_t + w_{size} Z_{t-1}^{size'} r_t + w_{value} Z_{t-1}^{value'} r_t + w_{market} Z_{t-1}^{market'} r_t + e_t \quad (2)$$

where $w_{ESG}, w_{size}, w_{value},$ and w_{market} are scalars that adjust the weights of stocks in the mimicked (also hedge) portfolios for Covid-19 risk shock. For comparability, we also evaluate the stock performance of hedge portfolios constructed using the returns on two ESG-related exchange-traded funds (ETFs), instead of the returns on portfolios of stocks sorted by their ESG disclosure scores.

According to the mimicking portfolio approach, each firm i's weight at time t, w_{it}, in the hedge portfolio is determined by Equation (3):

$$w_{it} = \widehat{w}_{ESG} z_{it}^{ESG\_A} + \widehat{w}_{size} z_{it}^{size} + \widehat{w}_{value} z_{it}^{value} + \widehat{w}_{market} z_{it}^{market} \quad (3)$$

where $\widehat{w}_{ESG}, \widehat{w}_{size}, \widehat{w}_{value},$ and $\widehat{w}_{market}$ are the estimated parameters. It is seen that w_{it} increases with $z_{it}^{ESG\_A}$, suggesting that the hedge portfolio weights more on stocks with greater value in ESG score. If ESG is assumed to bring firms better performance under Covid-19, this portfolio will help investors gain profit when there is rising risk in Covid-19.

4. Data and variables

The variables in this paper include three aspects: (a) Covid-19 risk, which is our hedge target, (b) ESG disclosure, introduced to reflect a firm's risk exposure to the Covid-19 pandemic, and (c) other variables, including measures of stock performance and control variables. The following discusses in detail of all these variables and their data source. At the end, we provide an overview of our sample and its descriptive statistics.

4.1. Measure of Covid-19 risk

We employ the news-based approach to construct the Covid Risk Index. This approach follows Engle et al. (2020), who propose the Climate Change News Index calculated as the correlation between news content and a fixed vocabulary on climate change. This approach provides a rigorous methodology for defining topic-related risk.

Media coverage of the pandemic surges when conditions deteriorate and exacerbate uncertainty in the financial market. As investors rely heavily on various kinds of media to update their information about the market, the extent to which they are exposed to relevant daily reports demonstrates their level of concern about Covid-19.

The WSJ offers unparalleled analysis and unique reporting that informs decisions and includes coverage of US and world news, politics, arts, culture, health, and more. Another consideration that supports our choice is that the full text of the WSJ daily articles is accessible from the online archive at relatively low cost. We collect those raw news reports from the WSJ's official website and obtain approximately 70,000 articles annually from 2017 to 2021.

Our starting point is to build a Covid-19 vocabulary for reference by obtaining a corpus of authoritative texts on the subject of the coronavirus. These include 20 white papers from both government officials and nongovernmental organizations, such as the Centers for Disease Control and Prevention (CDC), the State Council Information Office of the People's Republic of China, the United Nations (UN), and the WHO. We add 20 coronavirus glossaries from sources such as the CDC, the Pan American Health Organization (PAHO), and *Merriam-Webster* online guide. The Appendix provides the full list.

We preprocess each text, combine the 40 documents, and summarize the frequency of each term in the aggregate corpus, which ultimately leads to the creation of a Covid-19 Vocabulary list.[1] Fig. 1 illustrates a word cloud summary of Covid-19 Vocabulary in which the size of a term is proportional to its frequency.

Similarly, we combine articles with the same date and treat each daily issue of the WSJ as a single document for which the number of terms is counted and further transformed into term frequency–inverse document frequency (*tf-idf*) scores, which is a statistical measure used to evaluate the importance of a word to a document in a collection, or corpus. The term frequency (*tf*) score tallies the number of times a word appears in a document, and the inverse document frequency (*idf*) score measures the importance of a term by weighting common terms downward. The overall *tf-idf* score is generated by multiplying the two scores so that the importance of a word increases in proportion to the number of times that it appears in the document but is offset by the frequency of the word in the corpus.[2]

We apply the same procedure to our Covid-19 Vocabulary, with the *idf* calculated from the WSJ corpus, which ensures that the document-frequency weights of vocabulary terms match the weights of WSJ terms. For Covid-19 Vocabulary and every daily issue of the WSJ, we take the final step of calculating the index as the cosine similarity between their *tf-idf* scores. Cosine similarity is a common practice in textual analysis that helps determine the similarity of two data objects, irrespective of their size. Therefore, the index measures the extent to which daily reports are dedicated to the topic of the pandemic, as it rises on days when keywords (words of high frequency) in the Covid-19 Vocabulary list are used in WSJ articles. We multiply the index by 10,000 and average the daily values at

[1] For each text, we screen out common stop words, make the letters lower case, and split the content into unigrams and bigrams. The term for the pandemic appears in several different forms such as "covid", "covid19", "covid-19", "coronavirus" and "coronavirus-19". We convert them into "covid" for uniformity.

[2] For example, common terms that appear in many documents earn low scores (high *tf* but low *idf*), while those that appear infrequently overall but frequently in a limited number of documents score high (high *tf* and high *idf*).

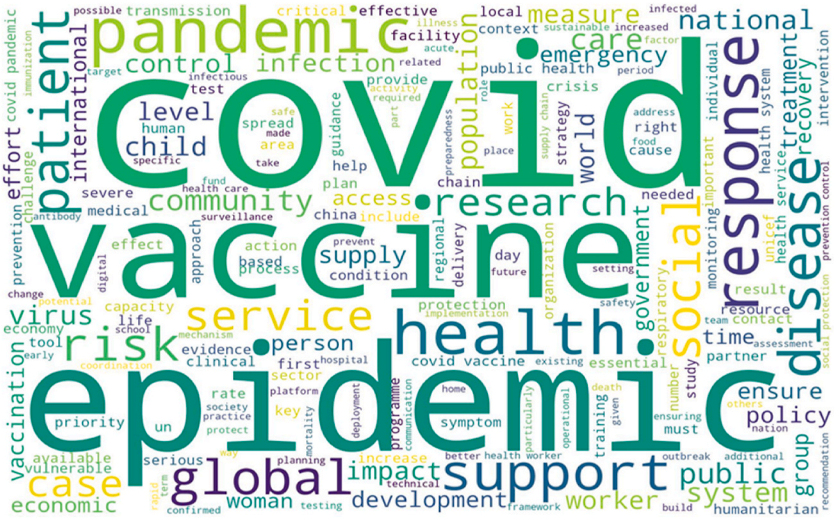


Fig. 1. Covid-19 Vocabulary
Note: This figure plots a word cloud of Covid-19 Vocabulary from a corpus of forty authoritative coronavirus texts. The size of terms is proportional to their frequency in the corpus.

the monthly level to facilitate further analysis. The resulted index is called the Covid Risk Index. Media coverage of the pandemic surges when conditions deteriorate and exacerbates uncertainty in the financial market. As investors rely heavily on various kinds of media to update their information about the market, the extent to which they are exposed to relevant daily reports demonstrates their level of concern about Covid-19.

Fig. 2 plots the resulting time series. The index is flat and changes little before 2020. However, we observe a steady increase in the first two months of 2020 (when Covid-19 initially broke out worldwide) and a surge in March, which coincides with the official announcement of a global pandemic by the WHO. The index largely falls after its peak but remains high compared to its pre-pandemic levels, with a much more volatile pattern.

Following Engle et al. (2020), we regress the monthly index using an AR(1) model. The resulting residual series extracts innovations from the cumulative risks and is also the hedge target of our portfolios. We denote it as the measure of CP_t in Equation (2), Covid-19 pandemic risk.

4.2. Measure of ESG disclosure

We use the Bloomberg ESG disclosure score, which is widely used in academia and industry as a measure of firm-level ESG disclosure. The score rates companies annually based on their disclosure of quantitative and policy-related data over ESG issues, with hundreds of metrics tracked during the process, from emissions to shareholder rights. Each data point is weighted in terms of importance, with data such as greenhouse gas emissions carrying greater weight than disclosures of other information. The more information that is disclosed, the higher the score, ranging from 0.1 to 100. For details, see, for example, Li et al. (2018) and Grewal et al. (2021).

We define the ESG disclosure score of a firm i in month t as ESG_{it}. We assign the same score to all months in the relevant year because these variables are reported only annually. We limit our scope of equities to US common shares (codes 10 and 11) traded on AMEX, NASDAQ, and NYSE, with Bloomberg ESG data and obtain a final sample of 2,936 stocks.

4.3. Other variables

We focus on two aspects as defining a superior stock performance: excess returns and reduced downside risk. Specifically, two measures of returns are considered: the pandemic-period return as well as the abnormal pandemic-period return. The former is the individual firm's buy-and-hold return throughout Covid-19 (from March 2020 to December 2021) whereas the latter is the market-model-adjusted raw return.[3] Downside risk during the pandemic is also measured in two complementary ways. The first measure is the firm's value at risk (VaR) (Duffie & Pan, 1997) whereas the second measure captures the distribution of returns that fall below the zero threshold, calculated as the lower partial moment (LPM) of the second order (Fishburn, 1977). We take the absolute values of VaR ranked in the bottom 5th percentile, so a smaller number indicates less downside risk. We relate these measures, both returns and

[3] The abnormal return, or the market-model-adjusted raw return, is the raw return minus the expected return based on the market model estimated over the 38-month period from January 2017 to February 2020. The CRSP value-weighted index is used as the market proxy.

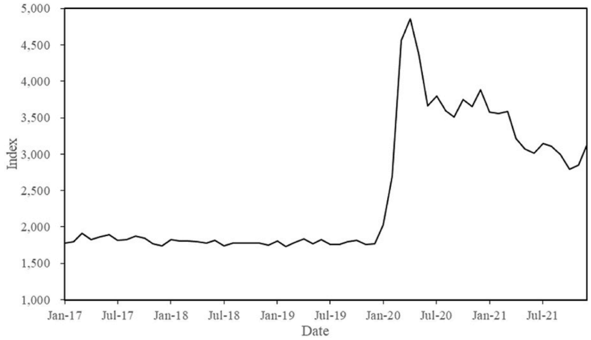


Fig. 2. The Covid-19 Risk Index
Note: This figure plots the monthly series of the Covid-19 Risk Index from January 2017 to December 2021. The index is calculated by the average of document similarity between WSJ daily report and Covid-19 vocabulary over a month, and multiplied by 10,000. See also the natural disease risk index in Hua et al. (2023).

downside risk, as a function of the 2019 ESG disclosure score, the latest pre-pandemic updates that proxy for firm-level ESG disclosure.

We control for a firm's financial health and other firm characteristics that have been found to affect stock performance. This allows us to address the concern that the superior stock performance of high-ESG-disclosure firms during Covid-19 may be due to omitted variables correlated with firm-level ESG disclosure, rather than the ESG disclosure itself. Following Lins et al. (2017), we include cash holdings (cash and marketable securities divided by assets), short-term debt (current liabilities divided by assets), long-term debt (long-term debt divided by assets), and profitability (operating income in fiscal year 2019 divided by assets) as proxies for a firm's financial health. We also control for the firm characteristics, including the book-to-market value (book value of equity divided by market cap of equity), momentum (the firm's cumulative raw returns one year ahead of the pandemic), a negative book-to-market dummy (equals 1 if the firm's book-to-market value is negative and 0 otherwise), and idiosyncratic risk (the residual variance from the market model estimated over the 38-month period ending in February 2020, using monthly data).

4.4. Summary statistics

Our sample contains a panel of 176,160 firm-year observations during the period from January 2017 to December 2021. The data on sample companies are from financial reports of 2,936 US common shares (codes 10 and 11) traded on AMEX, NASDAQ, and NYSE, which are obtained from the Bloomberg database. We define January 2017 to February 2020 as the pre-pandemic period, and March 2020 to December 2021 as the post-pandemic period.

The definitions and descriptions of the variables employed in our analysis are shown in Table 1. Table 2 displays the descriptive statistics (Panel A) and correlation matrix (Panel B) of firm-level variables. From the standard deviation and percentiles, it is seen that there are significant differences between firms, indicating that it is necessary to control firm characteristics and other unobservable fixed effect in regressions. From the correlation matrix, we find that *ESG* is positively correlated with *RaRtn* (0.123) and *AbRtn* (0.042), tentatively verifying our assumption that ESG can improve stock performance. In addition, the VIF value of our multicollinearity test is 2.93, which is much less than 10. This indicates that there is no multicollinearity in our model.

5. Empirical results

5.1. Test of ESG disclosure as a firm's exposure to Covid-19 risk

In the construction of hedge portfolios, we assume ESG disclosure can reflect firms' exposure to Covid-19 pandemic risk. It is necessary to test whether this assumption holds. To this end, we design two regressions: the first regression investigates the effect of ESG disclosure on firms' stock performance during the pandemic period; the second regression examines whether ESG disclosure can moderate the effect of Covid-19 risk on firms' stock performance.

First, we conduct empirical tests on the relationship between firm-level ESG disclosure and pandemic-period stock performance, which includes two measures of return (*RawRtn* and *AbRtn*) and two measures of downside risk (*LPM* and *VaR*). We cross-sectionally regress averaged return measures or downside risk measures on the ESG disclosure score for the year 2019, along with a series of control variables taking the averaged value during the pre-pandemic period. The regression formula is Equation (4):

$$Perfm_{i,post} = \beta \bullet ESG_{i,pre} + \gamma \bullet Control_{i,pre} + \varepsilon_i \tag{4}$$

where the subscript i denotes different firms; $Perfm_{i,post}$ is the cumulative value of four performance measures during the Covid-19 pandemic period (March 2020 - December 2021) for a given firm; $ESG_{i,pre}$ is the ESG disclosure score of firm i for the pre-pandemic year 2019; and *Control* is a set of control variables including *CashHold*, *ShortDebt*, *LongDebt*, *ROA*, *B/M*, *Momntm*, *NegB/M*, and *IdioRisk*. All control variables also take the value at the end of year 2019.

Table 1
Variable definition and description.

Variable	Definition and description
a. Covid-19 variables	
CovidIndex	Covid-19 risk index, calculated by the average of the document similarity between a daily news report from WSJ and Covid-19 vocabulary over a month.
CovidDummy	A dummy variable which takes 1 during the Covid-19 pandemic period (2020.3–2021.12), and 0 otherwise.
b. ESG variables	
ESG	Bloomberg score based on the extent of a firm's environmental, social and governance (ESG) disclosure. The score ranges from 0.1 for firms that disclose minimum amount of ESG data to 100 for those that disclose evert data point.
Environ	Bloomberg score based on the extent of a firm's environmental disclosure as part of ESG data. The score ranges from 0.1 to 100.
Social	Bloomberg score based on the extent of a firm's social disclosure as part of ESG data. The score ranges from 0.1 to 100.
Govnce	Bloomberg score based on the extent of a firm's governance disclosure as part of ESG data. The score ranges from 0.1 to 100.
c. Stock performance variables	
RawRtn	The monthly stock return of a firm.
AbRtn	The monthly abnormal stock return of a firm calculated by the CAPM model.
LPM	The lower partial moment of the second order, calculated by the standard deviation of returns that fall below the 0% threshold.
VaR	Value at risk, equaling a firm's stock return ranked in the bottom 5% percentile of its distribution.
d. Control variables	
CashHold	Firm's cash holding, equaling cash and marketable securities divided by assets.
ShortDebt	Short-term debt ratio, equaling current liabilities scaled by total assets.
LongDebt	Long-term debt ratio, equaling long-term fixed liabilities scaled by total assets.
ROA	Return on assets, defined as operating revenue scaled by total assets.
B/M	Book-to-market ratio, book value of equity scaled by market cap of equity.
Momntm	Firm's cumulative monthly raw returns over the past 12 months.
NegB/M	Dummy for whether the value of book-to-market is negative, and it equals 1 if the firm's book-to-market value is negative and 0 otherwise.
IdioRisk	The idiosyncratic risk of firm's stock return, calculated by the residual variance from the market model estimated over the past three years.

Table 2
Descriptive statistics of variables.

Panel A: Summary statistics

	Mean	Std Dev	25th perc.	Median	75th perc.
ESG	21.889	11.823	14.876	16.942	22.967
Environ	14.578	17.195	2.326	5.039	23.256
Social	18.836	12.236	8.772	17.544	22.807
Govnce	53.204	6.919	50.785	51.786	55.357
RawRtn	0.223	0.724	−0.083	0.233	0.571
AbRtn	−0.081	0.904	−0.453	−0.127	0.226
LPM	0.031	0.013	0.022	0.028	0.037
VaR	0.055	0.02	0.039	0.051	0.067
CashHold	0.198	0.252	0.026	0.084	0.258
ShortDebt	0.191	0.535	0.070	0.147	0.248
LongDebt	0.229	0.238	0.038	0.174	0.352
ROA	−0.047	0.436	−0.025	0.027	0.079
B/M	0.550	1.089	0.179	0.416	0.758
Momntm	−0.165	0.521	−0.338	−0.104	0.092
NegB/M	0.056	0.23	0.000	0.000	0.000
IdioRisk	0.016	0.047	0.003	0.007	0.018

Panel B: Correlation matrix

	ESG	Environ	Social	Govnce	RawRtn	AbRtn	LPM	VaR
ESG	1.000							
Environ	−0.042	1.000						
Social	0.031	0.006	1.000					
Govnce	0.046	0.062	0.478	1.000				
RawRtn	0.123	0.002	−0.083	−0.067	1.000			
AbRtn	0.042	−0.040	−0.079	−0.076	0.745	1.000		
LPM	−0.242	−0.110	−0.028	−0.075	−0.180	0.020	1.000	
VaR	0.318	0.095	−0.008	0.020	0.114	−0.151	−0.763	1.000

Note: This table shows descriptive statistics for the main variables in our analysis. The sample consists of 2,936 firms with nonmissing ESG disclosure score data. Accounting data are measured at the end of December 2019, or as close as possible to it for firms that do not have a December fiscal year-end. Panel A summarizes the data in detail; Panel B presents a correlation matrix between the variables.

Panel A of Table 3 displays the results for returns as the explained variables. Columns 1 and 2 show that firms with higher ESG disclosure perform significantly better during Covid-19. A one-standard-deviation increase in ESG disclosure score can result in a 5.91-percentage-point increase in raw returns and a 2.72-percentage-point increase in abnormal returns.[4] Columns 3 and 4 of Table 5 show that the effect of ESG disclosure is still significantly positive after control variables are included. A one-standard-deviation increase in the score is now associated with a 3.72-percentage-point increase in raw returns and a 2.48-percentage-point increase in abnormal returns (the standard deviation of coefficient is 12.406). This is consistent with our previous finding that higher ESG disclosure results in excess returns during the pandemic period.

Panel B of Table 3 follows the same procedure as Panel A but now examines the impact of downside risk, measured as either *VaR* or *LPM*. Columns 1 and 2 show that firms with higher ESG disclosure scores experience significantly lower downside risk during the pandemic. Again, this effect weakens but remains significant after we include control variables in Columns 3 and 4. Additionally, firms in better financial health, as well as firms with a lower book-to-market value, are associated with lower downside risk. The overall findings show that firms with greater ESG disclosure suffer less in the pandemic with higher returns and lower downside risk and that this effect is not due to differences in financial health.

We have shown that high-ESG disclosure firms have higher returns and lower downside risk during the pandemic period. Now we examine whether the impact is unique during Covid-19 or is common even before the outbreak of the pandemic. If ESG disclosure can reflect firms' exposure to Covid-19 risk, the impact of the Covid-19 risk index on a firm's stock performance will be moderated by ESG disclosure. The corresponding regressions are shown as:

$$Perfm_{it} = \beta_1 \bullet ESG_{it} \times \ln\left(CovidIndex_t\right) + \beta_2 \bullet \ln\left(CovidIndex_t\right) + \gamma \bullet Control_{it} + \alpha_i + \alpha_y + \varepsilon_{i,t} \tag{5}$$

where the dependent variable is a panel of monthly returns or downside risk, measured in two ways as before, for all the firms over the full sample period during January 2017 to December 2021. ESG_{it} is the firm's ESG disclosure score for firm i at year-month time t. $CovidIndex_t$ is the constructed Covid-19 risk index based on news coverage in our paper. Therefore, the coefficient β_1 of their interaction $ESG_{it} \times \ln\left(CovidIndex_t\right)$ means the moderating effect of ESG disclosure, linking Covid-19 risk and firms' stock performance. *Control* is a set of control variables including *CashHold*, *ShortDebt*, *LongDebt*, *ROA*, *B/M*, *Momntm*, *NegB/M*, and *IdioRisk*. α_i and α_y are the firm and year fixed effect, respectively. The standard error is clustered at the firm level to mitigate autocorrelation of the dependent variables.

The results for stock returns or downside risks as explained variables are presented in Panel A of Table 4. Columns 1 and 2 are the estimation results of the impact of the interaction term on two measures of returns (*RawRtn* and *AbRtn*). The corresponding coefficients are 0.134 and 0.163, both of which are significant at the 1% confidence level. Columns 3 and 4 present the results with the two measures of downside risk as the explained variables (*LPM* and *VaR*). The coefficients of *ESG* × *ln(CovidIndex)* are significantly negative at the 1% confidence level (−0.299 and −0.135). These results suggest that Covid-19 risk has greater impact on stock returns and downside risks for samples with higher ESG disclosure intensity, and high-ESG-disclosed firms tend to experience better performance with higher returns and lower downside risks when facing the pandemic. The findings support our adoption of ESG disclosure as firms' exposure to Covid-19 risk. In particular, the degree of exposure falls as the ESG disclosure score increases.

To further prove our assumption, we substitute *CovidIndex* with *CovidDummy* and run Equation (5) again. *CovidDummy* is a dummy variable set at 1 during the pandemic period (March 2020 - December 2021) and at 0 before Covid-19 (January 2017 - Februray 2020). The coefficient on the interaction between the ESG disclosure score and the Covid-19 pandemic dummy, *ESG* × *CovidDummy*, captures the differential impact of ESG disclosure on stock performance during the pandemic period, compared with that before the pandemic period. The results in Panel B of Table 4 show that firms with high ESG disclosure generate significantly higher returns during Covid-19. The coefficients of *ESG* × *CovidDummy* in Columns 1–4 are all significant at the 1% confidence level, supporting the hypothesis that exposure to Covid-19 risk differs among firms with diverse ESG disclosure.

5.2. Performance of hedge portfolios

Our empirical study follows two procedures: an in-sample fit and an out-of-sample test. We start by running Equation (2) over the full sample period and compare the two transforming approaches, along with the result after we replace characteristics-sorted portfolios with ESG-related ETFs. Table 5 presents the results.

Columns 1 and 2 show that portfolios based on the ESG disclosure score are positively related to Covid-19 risk shock (Z_t^{ESG-A} and Z_t^{ESG-R}), indicating that our hedge portfolios (which long firms with higher scores and short firms with lower scores) generate larger excess returns in times of surging coronavirus risk or more risk shocks. In terms of the transforming methodology, the absolute-value approach appears to be better than the ranking approach in that it achieves a higher level of significance and a much higher R-squared (0.665 for Z_t^{ESG-A} and 0.310 for Z_t^{ESG-R}). Column 3 includes the returns on two ESG-related ETFs instead of the returns on a characteristics-sorted portfolio: the iShares ESG MSCI EAFE (ticker: ESGD) and the iShares ESG Aware MSCI USA ETF (ticker: ESGU). The in-sample fit for both portfolios based on the ESG disclosure score is somewhat higher than that of the portfolio based on ESGD and ESGU, which suggests that the characteristics-weighted portfolios might have some advantages over portfolios constructed using ESG-related ETFs in hedging Covid-19 risk.

We continue our empirical study with the second procedure, an out-of-sample test. The test examines the hedge portfolio's ability

[4] The coefficient of *ESG* has the standard deviation of value 11.82, so 5.91 = 11.82 × 0.005 and 2.72 = 11.82 × 0.002.

Table 3
The effect of ESG disclosure on post-pandemic stock performance.

Panel A: Taking post-pandemic returns of stocks as explained variables				
	RawRtn (1)	AbRtn (2)	RawRtn (3)	AbRtn (4)
ESG	0.005***	0.002**	0.003***	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
CashHold			0.132*	0.356***
			(0.069)	(0.079)
ShortDebt			−0.393***	−0.775***
			(0.095)	(0.101)
LongDebt			−0.117*	0.134*
			(0.066)	(0.078)
ROA			0.495***	0.163**
			(0.064)	(0.076)
B/M			0.103***	0.304***
			(0.023)	(0.029)
Momntm			0.030	−0.591***
			(0.029)	(0.036)
NegB/M			0.093	0.316***
			(0.060)	(0.074)
IdioRisk			−0.083	0.317***
			(0.792)	(0.097)
Constant	−0.192**	−0.238**	−0.279***	−0.225***
	(0.083)	(0.113)	(0.086)	(0.053)
Firm FE	Yes	Yes	Yes	Yes
R-squared	0.117	0.096	0.156	0.255
Observations	2,936	2,936	2,936	2,936

Panel B: Taking post-pandemic downside risks as explained variables				
	VaR (1)	LPM (2)	VaR (3)	LPM (4)
ESG	−0.055***	−0.026***	−0.028***	−0.022***
	(0.003)	(0.002)	(0.002)	(0.002)
CashHold			−0.002	−0.002**
			(0.001)	(0.001)
ShortDebt			−0.002	−0.001
			(0.002)	(0.002)
LongDebt			−0.003**	0.006***
			(0.001)	(0.001)
ROA			−0.015***	−0.010***
			(0.001)	(0.001)
B/M			0.007***	0.003***
			(0.001)	(0.001)
Momntm			−0.006***	−0.001**
			(0.001)	(0.001)
NegB/M			0.008***	0.004***
			(0.001)	(0.001)
IdioRisk			0.322***	0.132***
			(0.017)	(0.013)
Constant	0.063***	0.035***	0.054***	0.030***
	(0.003)	(0.002)	(0.003)	(0.002)
Firm FE	Yes	Yes	Yes	Yes
R-squared	0.312	0.216	0.569	0.357
Observations	2,936	2,936	2,936	2,936

Note: This table shows the results of cross-section regressions of the pandemic-period performance on firm-level transparency. The dependent variables in Panel A are pandemic-period returns. Columns 1 and 3 use raw pandemic-period returns whereas Columns 2 and 4 use abnormal pandemic-period returns. The dependent variables in Panel B are pandemic-period downside risk. Columns 1 and 3 use the absolute values of value at risk (VaR) whereas Columns 2 and 4 use the lower partial moment (LPM) of the second order. A series of control variables are included and compared. All regressions include industry dummies defined at the GICS 11-sector level and control for the firm's factor loadings based on the Fama-French three-factor model. The sample consists of 2,936 firms. Standard errors are in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

to hedge the innovations of Covid-19 risk in months that are not included in the estimation of the portfolio weights. Specifically, for a certain time t, we estimate the hedge portfolio weight using data before t and explore the correlation between returns on the estimated portfolio and realization of the shock, both in period t. For example, if we pick January 2021 as the time, we can use data between January 2017 and December 2020 to generate the estimated portfolio weights (if we apply the first absolute-value approach): $\widehat{w}_{ESG}Z_{Dec20}^{ESG\_A'} + \widehat{w}_{size}Z_{Dec20}^{size'} + \widehat{w}_{value}Z_{Dec20}^{value'} + \widehat{w}_{market}Z_{Dec20}^{market'}$. We can then compare the returns of this portfolio in January 2021 to $Shock_{Jan21}$.

For every month t, we apply the same procedure. Because running the regression requires a certain number of observations, we set t to start in July 2019, which gives us a minimum of 30 observations. Fig. 3 presents scatterplots of the realization of Covid risk shock,

Table 4
The moderating effect of ESG disclosure on the impact of Covid-19 risk.

Panel A: The Covid-19 risk is measured by the news index				
	RawRtn (1)	AbRtn (2)	VaR (3)	LPM (4)
$ESG \times \ln(CovidIndex)$	0.134***	0.163***	−0.299***	−0.135***
	(0.043)	(0.043)	(0.025)	(0.011)
$\ln(CovidIndex)$	−0.057**	−0.036	0.272***	0.119***
	(0.024)	(0.025)	(0.021)	(0.009)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.175	0.176	0.282	0.230
Observations	176,160	176,160	176,160	176,160
Panel B: The covid-19 risk is measured by a pandemic-period dummy				
	RawRtn (1)	AbRtn (2)	VaR (3)	LPM (4)
$ESG \times CovidDummy$	0.128***	0.162***	−0.322***	−0.119***
	(0.039)	(0.048)	(0.098)	(0.013)
$CovidDummy$	−0.063***	−0.045***	0.240***	0.175***
	(0.037)	(0.029)	(0.018)	(0.015)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.141	0.153	0.291	0.211
Observations	176,160	176,160	176,160	176,160

Note: This table shows results of panel regressions that compare the effects of firms-level transparency before and during the pandemic period. The dependent variable captures return in Columns 1 and 2 and downside risk in Columns 3 and 4. The ESG disclosure score is scaled to facilitate our analysis. Standard errors are clustered at the firm level in parentheses. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Table 5
In-sample fit results for the hedge portfolios.

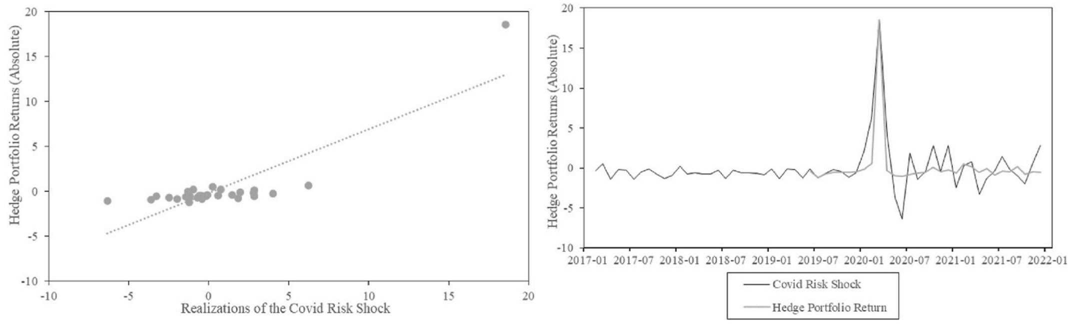
	(1)	(2)	(3)
$Z_{t-1}^{ESG\_A'} r_t$	0.359***		
	(0.046)		
$Z_{t-1}^{ESG\_R'} r_t$		8.092*	
		(4.651)	
r_t^{ESGD}			−1985.014
			(1675.750)
r_t^{ESGU}			2155.693
			(1942.998)
$Z_{t-1}^{size'} r_t$	0.336	1.818	−0.549
	(1.657)	(3.045)	(2.722)
$Z_{t-1}^{value'} r_t$	1.080	−2.606*	−1.199
	(0.885)	(1.368)	(1.116)
$Z_{t-1}^{market'} r_t$	−318.580	−1781.224**	−20948.370**
	(576.471)	(835.825)	(7799.957)
Constant	−9.200	−53.867	−6.867
	(32.697)	(46.443)	(47.370)
R-squared	0.665	0.310	0.389
N	59	59	59

Note: This table shows the results of Equation (2). Columns 1 and 2 show the results of the ESG Disclosure Score-based portfolios using two different transforming approaches; Column 3 shows results of the ETF-based portfolios. The dependent variable captures innovations for the Covid Risk Index. The unit of observation is a month, and the sample period is January 2017 to December 2021. Standard errors are in parentheses. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

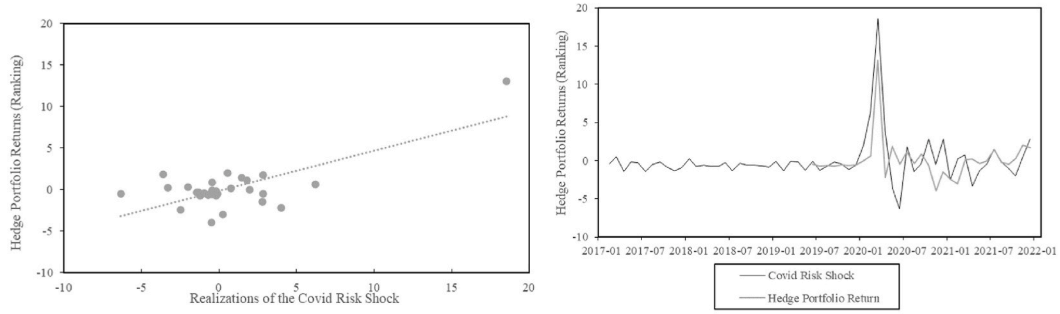
along with out-of-sample returns of the hedge portfolios, with portfolio weights estimated using in-sample data. The top part uses the absolute-value approach for regression, while the bottom part applies the ranking approach. We identify a clear, positive out-of-sample correlation with $Shock_t$ for the hedge portfolios, thereby validating the hedging ability of our portfolios as well as our choice of characteristic, or the ESG disclosure score, on which we base the hedge portfolios.

5.3. Robustness tests

We further prove the fitness of our constructed hedge portfolio with robustness tests. One test uses different measures of Covid-19 risk. Another test uses GMP as a comparison with our constructed hedge portfolios to further support the superiority of the latter.



(a) Absolute value approach



(b) Ranking approach

Fig. 3. Out-of-sample tests for the hedge portfolios
Note: This figure evaluates the out-of-sample performance of the hedge portfolios constructed with in-sample estimates. The top panel uses the absolute value approach for regression, and the bottom panel applies the ranking approach. Both highlight a positive correlation between realizations of Covid risk shock and returns on the hedge portfolios, with 0.85 in 3a and 0.74 in 3b.

5.3.1. *Alternative measures of Covid-19 risk*

We introduce two alternative measures for Covid-19 risk. The first alternative measure draws on the study of Baker et al. (2016) and is calculated by the share of negative news reports discussing Covid-19. This measure uses news reports with negative sentiment to capture risk and relies on a broader news outlet.[5] To begin with, we carefully examine the vocabulary list and select words that occur frequently in the list and are the most representative as keywords for Covid-19. The final keywords selected are "covid", "epidemic", "pandemic", "vaccine", "virus", "infection" and "omicron".[6] Next, we tally the number of negative news reports that contain at least one of these keywords over a month. The resulting numbers are then scaled by the number of news reports on that day, and multiplied by 10,000 to facilitate analysis.

The second alternative measure takes the residual of *CovidIndex* orthogonalized by CBOE Volatility Index (VIX). The news-based measures are highly likely to be influenced by investor sentiments. If investors have intensified fear, they might exaggerate the risk of the Covid pandemic and derive more news about it. To this end, we use VIX to proxy investor fear as prior studies suggest and then regress *CovidIndex* on VIX with the method of orthogonal regression.[7] The resulting residual is the new measure of Covid-19 risk.

Using the mimicking portfolio approach, we construct the hedge portfolios based on these two alternative measures. Table 6 shows the in-sample fit of Equation (2) with these two alternative Covid-19 measures as the explained variable (hedge target). We find that

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[5] As risk is sometimes defined as the possibility of bad events happening, the positive side of news cannot be regarded as risk. We use TextBlob, a well-known Python package for sentiment analysis, to identify news reports with negative scores. The collection of news reports relies on the digital archives of not only WSJ but nine other newspapers with high circulation: *USA Today*, *New York Times*, *Washington Post*, *New York Post*, *Los Angeles Times*, *Chicago Tribune*, *Star Tribune*, *Tampa Bay Times*, and *Newsday*.

[6] We omit words that frequently appear in the list but are not specific to the coronavirus, such as "response" and "social". Despite their relatively low frequency, the words "virus", "infection" and "omicron" are included because we believe they are closely related to the context.

[7] The orthogonal regression minimizes the sum of squared perpendicular distances from the data points to the regression line, which differs from the least squares regression.

Table 6
In-sample fit results for the hedge portfolios with alterative Covid-19 risk measures.

Panel A: Covid-19 risk is measured by the share of negative news reports			
	(1)	(2)	(3)
$Z_{t-1}^{ESG\_A'} r_t$	0.759***		
	(0.087)		
$Z_{t-1}^{ESG\_R'} r_t$		12.457	
		(13.538)	
r_t^{ESGD}			148.758
			(3220.988)
r_t^{ESGU}			56816.860***
			(15267.370)
$Z_{t-1}^{size'} r_t$	−0.269	4.267	−3.429
	(3.109)	(6.136)	(5.232)
$Z_{t-1}^{value'} r_t$	0.942	−6.344**	−3.707*
	(1.660)	(2.757)	(2.145)
$Z_{t-1}^{market'} r_t$	495.272	−2425.217	−57257.390***
	(1081.328)	(1684.384)	(14992.430)
Constant	−56.947	−149.063	−18.364
	(61.332)	(93.594)	(91.051)
R-squared	0.701	0.305	0.441
N	59	59	59

Panel B: Covid-19 risk is measured by the residual of VIX-orthogonalized *CovidIndex*			
	(1)	(2)	(3)
$Z_{t-1}^{ESG\_A'} r_t$	0.391***		
	(0.104)		
$Z_{t-1}^{ESG\_R'} r_t$		9.376*	
		(5.771)	
r_t^{ESGD}			−1460.387
			(1549.007)
r_t^{ESGU}			4897.512
			(7342.241)
$Z_{t-1}^{size'} r_t$	2.875	2.174	3.688
	(1.864)	(2.616)	(2.516)
$Z_{t-1}^{value'} r_t$	2.152**	−0.391	0.764
	(0.995)	(1.175)	(1.031)
$Z_{t-1}^{market'} r_t$	−626.258	−1603.58**	−4934.100**
	(648.466)	(718.101)	(7210.018)
Constant	12.833	−13.870	−1.624
	(36.781)	(39.902)	(43.787)
R-squared	0.375	0.249	0.231
N	59	59	59

Note: This table shows the results of Equation (2) using alternative Covid-19 risk measures. Panel A is based on the measure taking the share of negative news reports, whereas Panel B is the residual of *CovidIndex* orthogonalized by VIX. Columns 1 and 2 show the results of the ESG Disclosure Score-based portfolios using two different transforming approaches; Column 3 shows results of the ETF-based portfolios. The dependent variable captures innovations on the measures. The unit of observation is a month, and the sample period is January 2017 to December 2021. Standard errors are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

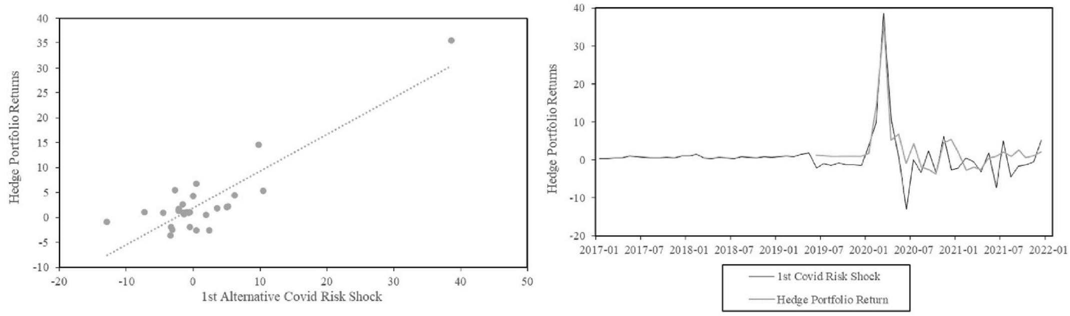
portfolios based on ESG disclosure score still have a positive and significant relationship with Covid-19 risk. Fig. 4 plots the out-of-sample fit of the hedge portfolio. It is found that the returns of hedge portfolios are still highly correlated with Covid-19 risk, suggesting that the constructed portfolios help investors hedge Covid-19 risk well.

Additionally, we find the coefficient of $Z_{t-1}^{ESG\_A'} r_t$ in Panel B of Table 6 is quite close to that in Table 5, with 0.391 compared to 0.359. The calculated correlation in Fig. 4b (0.72) is also close to Fig. 3b (0.74). We attempt to orthogonalize our Covid risk measure to VIX but find the coefficient is not significant at the 5% confidence level. Therefore, taking the residual is actually equivalent to taking the measure itself. The reason may be that Covid-related news will incur investor fear and market turmoil, but investor fear may not exactly result in Covid-related news as investor fear or the market volatility (VIX) is affected by many other risks or uncertainties such as military war, economic policy, and political campaign (Baker et al., 2016).

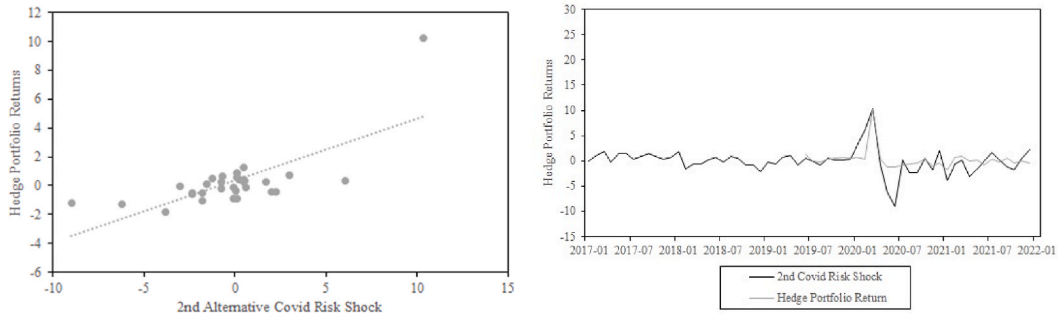
5.3.2. Comparison to the GMP portfolios

As shown above, the ESG disclosure score is a persuasive characteristic for filtering stocks during the pandemic. We can sort firms based on their scores or different levels of transparency. The hedge portfolios constructed by the mimicking portfolio approach seem to give positive weight to stocks with high ESG disclosure score and negative weight to stocks with a low score. What if we simply long those high-ESG-disclosed stocks and short those low-ESG-disclosed stocks? Does this naive portfolio achieve the same hedge effect as the mimicked portfolio?

We use portfolios constructed by the simple GMP approach as a comparison and investigate whether this portfolio is still highly



(a) Covid-19 risk is measured by the share of negative news reports



(b) Covid-19 risk is measured by the residual of VIX-orthogonalized *CovidIndex*

Fig. 4. Out-of-sample tests for the hedge portfolios with alternative Covid-19 risk measures
Note: This figure evaluates the out-of-sample performance of the hedge portfolios constructed with in-sample estimates, using two alternative Covid-19 risk measures as hedge target. The top panel measures Covid-19 risk by the share of negative news reports whereas the bottom panel by the residual of VIX-orthogonalized *CovidIndex*. The both highlight a positive correlation between realizations of Covid risk shock and returns on the hedge portfolios s, with 0.88 in 3a and 0.72 in 3b. The transformation of ESG raw scores into the characteristics vector is based on the ranking approach.

correlated with Covid-19 risk. The resulting portfolio, denoted as GMP, represents the spread of value-weighted returns between stocks with scores in the top third and those with scores in the bottom third. The ranking is calculated based on Bloomberg's latest reported data so that the portfolio is updated annually. To some extent, the GMP is identical to our previous hedge portfolios in that both have long firms with high scores and short firms with low scores. Table 7 shows the out-of-sample fit of the GMP portfolio. Its correlation to the Covid-19 risk index is much smaller than the mimicked portfolio, with the correlation of 0.42 compared to 0.74 (ranking approach) in Fig. 5.

5.4. Further analysis

5.4.1. Return decomposition of the hedge portfolios

We next examine the primary source of the mimicked portfolio. Panel A of Table 7 presents an overview of portfolio performance as well as the results of a related preliminary decomposition. As reported in Column 1, the mimicked portfolio achieves an average of 220 bps per month (with a *t*-statistic of 3.29). Columns 2 and 3 show the results of regressing mimicked portfolio returns on Fama and French's (1993) three factors. The performance can be explained only in part by exposure to these factors in that the constant, or the alpha, of mimicked portfolio remains statistically significant despite a decrease in value. The negative correlation of mimicked portfolio returns with the small-minus-big (SMB) factor indicates its tilt toward larger stocks.

The failed attempts at a preliminary decomposition for mimicked portfolio returns lead us to the hypothesis that its superior performance might have something to do with the pandemic and its related risks. Two facts support our assumption. The first is the sudden performance growth of mimicked portfolio since the outbreak of Covid-19, compared to its pre-pandemic levels. The second is that we relied solely on the ESG disclosure score to construct the portfolio, which proves convincing in hedging Covid-19 risk. Based on the foregoing, we introduce coronavirus-related factors into the decomposition of mimicked portfolio returns. In addition, the

Table 7
Return decomposition of the hedge portfolio.

Panel A: Preliminary decomposition			
	(1)	(2)	(3)
Constant	0.022***	0.010**	0.008**
	(0.007)	(0.004)	(0.004)
Mkt-Rf		0.874***	0.950***
		(0.093)	(0.094)
SMB			−0.400**
			(0.164)
HML			−0.047
			(0.118)
R-squared	0.000	0.606	0.647
N	60	60	60

Panel B: Formal decomposition				
	(1)	(2)	(3)	(4)
$Index_{t-1}$	0.228***	0.256**		
	(0.072)	(0.012)		
$Shock_t$			−0.159	−0.241
			(0.230)	(0.227)
$Shock_{t-1}$			0.750***	0.691***
			(0.230)	(0.227)
$Flows_{t-1}$		−61.395		250.122*
		(200.011)		(125.096)
Constant	−0.033*	−0.036*	0.022***	0.004
	(0.019)	(0.021)	(0.006)	(0.011)
Three-factor loadings	Yes	Yes	Yes	Yes
R-squared	0.151	0.152	0.164	0.222
N	59	59	58	58

Note: This table shows the results of a return decomposition of hedge portfolio. Panel A is the preliminary decomposition, and Panel B is the formal decomposition. In Panel A, Column 1 summarizes the portfolio returns; Columns 2 and 3 show results of portfolio returns with exposure to Fama-French's three factors. Mkt-Rf is the excess market return. Small-minus-big (SMB) and high-minus-low (HML) are the size and value factors. In Panel B, Columns 1 and 3 show the results after including realization of the Covid Risk Index and the Covid risk shock, respectively; Columns 2 and 4 further include ESG fund flows that proxy for investors' ESG preferences. The dependent variable captures the portfolio returns. The unit of observation is a month, and the sample period is January 2017 to December 2021. Standard errors are in parentheses. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

performance of the portfolio might also be influenced by the popularity of ESG products among investors.[8] We use the quarterly flows into US sustainable funds, derived from the Morningstar's *2021 Sustainable* Funds *U.S. Landscape Report*, to proxy for investors' ESG preferences.[9] We assign the same common average flows to all the months in the quarter and scale the flows by the total market cap of US common shares. We denote the resulting variable *Flow*. The results are shown in Panel B of Table 7.

From Panel B of Table 7, Columns 1 and 2 (with $Flow_{t-1}$) show the results of regressing mimicked portfolio returns on the lagged Covid Risk Index. They have a clear, positive relationship (0.228 and 0.256, respectively), which indicates that higher cumulative coronavirus risk, as measured by the Covid Risk Index, tends to forecast greater returns. The constant (or alpha) of the mimicked portfolio is significantly negative under both circumstances. Column 3 displays the result of regressing mimicked portfolio returns on innovation from risk, or the Covid risk shock. The relationship between the mimicked portfolio returns and current risk shocks is insignificant. However, the correlation on lagged shocks, 0.750, is statistically significant and nearly five times larger in magnitude. Column 4 includes $Flow_{t-1}$ in the regression and has a similar result. The positive and significant coefficient of the added variable suggests that greater passion among investors for ESG products likely results in higher yields for ESG data–based portfolios. The alpha of the portfolio turns insignificant and decreases sharply in Column 4 compared to Column 3.

We can eliminate the effects of the independent variables in these estimates by assuming zero risk or shocks and ESG fund flows, which also equals the sum of the regression constant and the residual series. This procedure generates a sequence of mimicked portfolio returns net of exposures to the pandemic factors (both risks and shocks). Fig. 6 plots the four resulting series together with the realization of mimicked portfolio returns, or the factual performance. In all cases, the counterfactual lines are well below the factual line. We observe that the strong performance of the mimicked portfolio is reversed after the effects of the Covid Risk Index are excluded. The situation deteriorates after we remove the flows, amounting to cumulative returns of −234%. By comparison, the

[8] We assume that increased Covid-19 concerns are likely to boost demand by investors for ESG products and affect stocks that are sorted accordingly.

[9] Morningstar reports that for a fund to be included in its sustainable fund universe, it must hold itself out to be a sustainable investment, which means that ESG concerns must be central to its investment process.

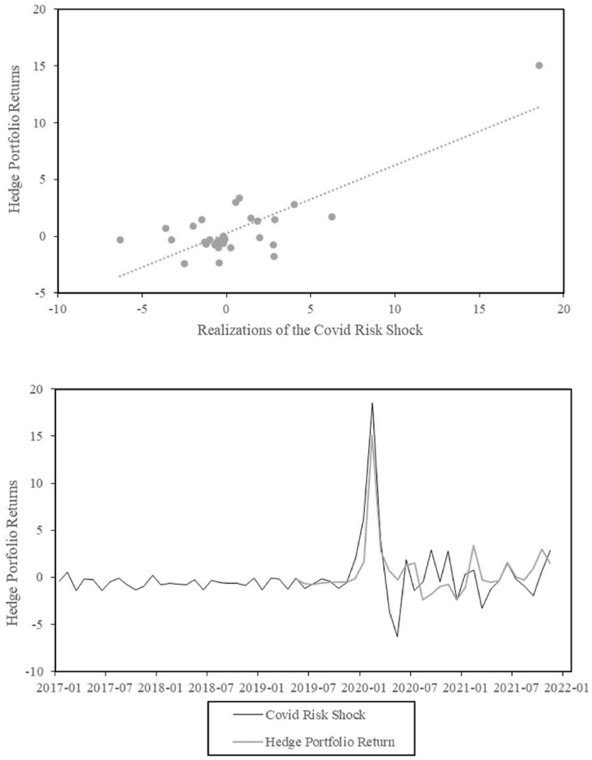


Fig. 5. Out-of-sample tests for the GMP portfolios
Note: This figure evaluates the out-of-sample performance of the GMP portfolios, of which the correlation to Covid-19 risk index is much smaller than that of the mimicked portfolios. The correlation is calculated as 0.42.

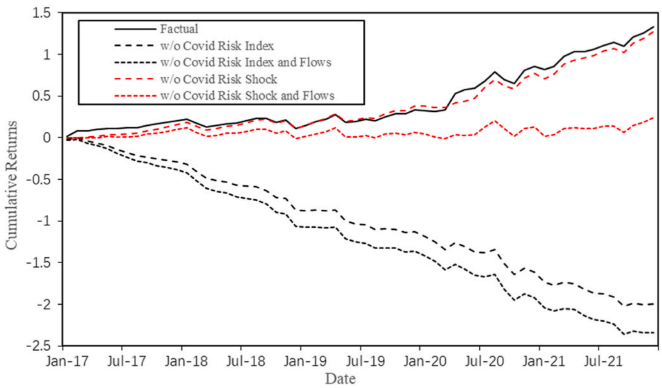


Fig. 6. Factual and counterfactual returns of the hedge portfolios
Note: This figure plots the cumulative returns of the factual hedge portfolio as well as four counterfactual hedge portfolio net of exposures to Covid risks or shocks and ESG preferences from January 2017 to December 2021. The dashed red line, dotted red line, dashed black line, and dotted black line omit the effects of independent variables estimated in Columns 1 to 4, respectively.

mimicked portfolio remains relatively unchanged in the absence of the Covid risk shock but sharply declines when the effects of ESG preferences are also ignored. The results coincide with our previous assumption that mimicked portfolios' outperformance might originate in pandemic factors, without which the characteristics-sorted portfolio would have failed. In other words, the positive impact of the ESG disclosure score on returns is limited to the pandemic period.

In the Appendix, we include a series of tests that examine the robustness of our results by replacing the dependent variable with the hedge portfolio's alpha on Fama-French's three factors (Table A1) or its returns of positive and negative positions, respectively (Table A2). Performance of the hedge portfolios and its subcomponents are illustrated in Figure A1. Finally, we show results for individual stocks using panel regressions. The overall results do not change qualitatively.

5.4.2. ESG decomposition of hedging effects

A key element in the good performance of our hedge portfolio is to use ESG disclosure as a characteristic variable that reflects the exposure of different companies to Covid-19 risk. The negative relationship between ESG disclosure and pandemic risk exposure means that firms with higher ESG level have stronger ability to resist the risk, so they performance better during the Covid-19 period. However, ESG is a comprehensive system including three components: environment, social responsibility, and corporate governance. It is an interesting topic to think about which component supports the firm to obtain a strong risk resilience, which helps us understand what leads to the better performance of the constructed hedge portfolio.

We perform our methodology again with three sub-scores (E, S and G) of ESG disclosure, and these sub-scores are also provided by Bloomberg. The relevant variables for ESG disclosure index are denoted as *Environ*, *Social*, and *Govnce*, respectively, and their descriptive statistics are presented in Table 2. It demonstrates that *Environ* has more diversity among firms with lower mean and higher standard deviation. From the correlation matrix, only *Environ* has a positive correlation with *RawRtn*, but the value (0.002) is very close to zero. In the row of *LPM*, the values are all negative for *Environ*, *Social*, and *Govnce*. Therefore, it is hard to draw any useful information from the correlation matrix, which leads us to the following analysis.

Table 8 presents the in-sample fit results for the mimicked hedge portfolios with E, S, and G disclosure score as characteristics, respectively. Only the S-based hedge portfolio has a positive and significant relationship with innovations to the Covid-19 risk index, suggesting that the hedge effect comes to the social part of ESG. To compare the out-of-sample fit of them, Fig. 7 demonstrates the correlation plots and trend comparisons between Covid risk shock and the hedge portfolio return based on E, S, and G disclosure score. Their calculated correlations are 0.68, 0.85, and 0.61 for the E-, S- and G-based hedge portfolio, respectively, suggesting that the S-based portfolio has the best hedge effect out of the three. Even if we remove the outlier in the upper-right corner of the correlation plots, the S-based hedge portfolio still has the greatest correlation value of 0.47.

To summarize, the results of in-sample and out-of-sample fit provide more evidence for the argument that the social part of ESG plays the dominant role in our hedge effect against Covid-19 risk. Investors have more trust in firms that devote more effort to social welfare. The reason may be investors believe these firms to be more proactive in responding to and resolving operational crises and defending the interests of investors during the pandemic, instead of letting the company fall into debt crisis or even bankruptcy liquidation. This finding is consistent with the study by Lins et al. (2017).

6. Conclusions

This paper proposes a procedure to dynamically hedge Covid-19 risk using the mimicking portfolio approach. In implementing the procedure, we quantitatively measure Covid-19 risk as the hedge target through textual analysis of media reports. We use the ESG disclosure score as a proxy for firm-level exposure to Covid-19 risk in the hedge portfolio, based on its positive impact on returns and downside risk during the pandemic period. Particularly, firms with higher ESG disclosure scores exhibit significantly higher returns and lower downside risk. Sub-scores of Environmental, Social, and Governance disclosure are examined for comparison.

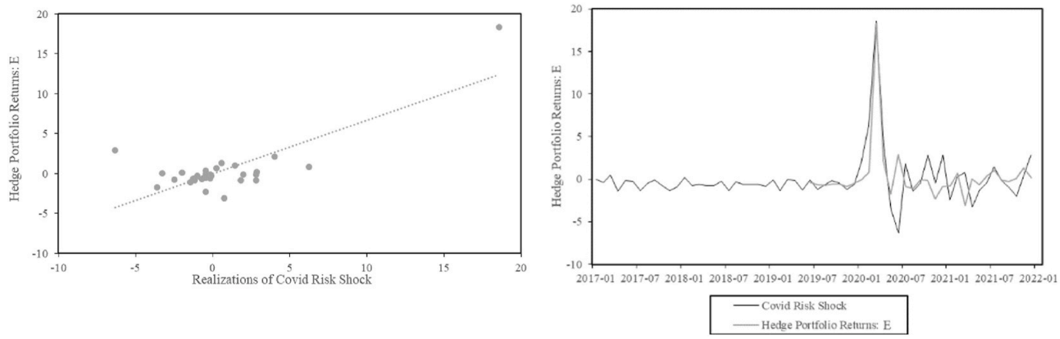
We verify the hedging effect of the mimicking portfolio with a significantly positive correlation between its returns and the Covid-19 risk index both in and out of sample. The correlation is much greater than the portfolio constructed by a simple characteristic-sorted long-short portfolio. This indicates that investors are able to avoid Covid-19 risk if they allocate assets according to the hedge portfolio weights. These findings are robust when we adopt alternative measures of Covid-19 risk as the hedge target.

We further analyze the primary source of our mimicking portfolio. After return decomposition, the outperformance of the hedge

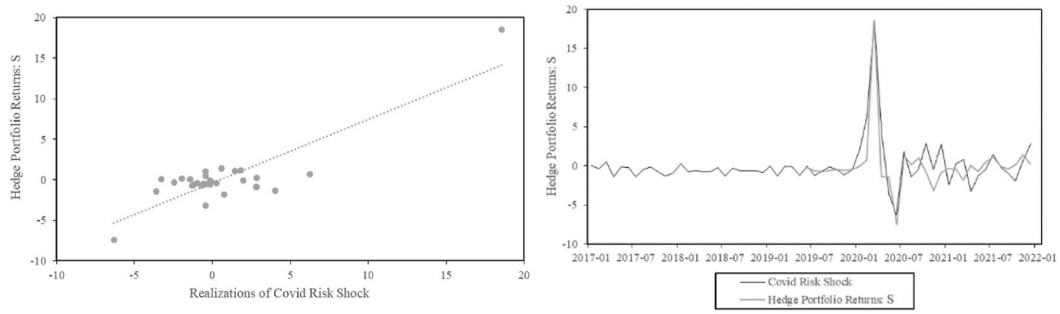
Table 8
In-sample fit results for the hedge portfolios with E, S and G disclosure score as characteristics respectively.

	Environment (E) (1)	Social responsibility (S) (2)	Governance (G) (3)
$Z_{t-1}^{E\prime} r_t$	0.259		
	(0.207)		
$Z_{t-1}^{S\prime} r_t$		0.574**	
		(0.268)	
$Z_{t-1}^{G\prime} r_t$			0.871
			(0.620)
$Z_{t-1}^{size\prime} r_t$	4.769**	4.916**	4.326*
	(2.298)	(2.224)	(2.331)
$Z_{t-1}^{value\prime} r_t$	−1.740	−1.552	−1.689
	(1.158)	(1.130)	(1.211)
$Z_{t-1}^{market\prime} r_t$	−1311.686	−1508.957*	−1496.336*
	(809.996)	(777.254)	(813.214)
Constant	−50.421	−47.334	−50.107
	(46.281)	(45.084)	(46.954)
R-squared	0.312	0.347	0.292
N	59	59	59

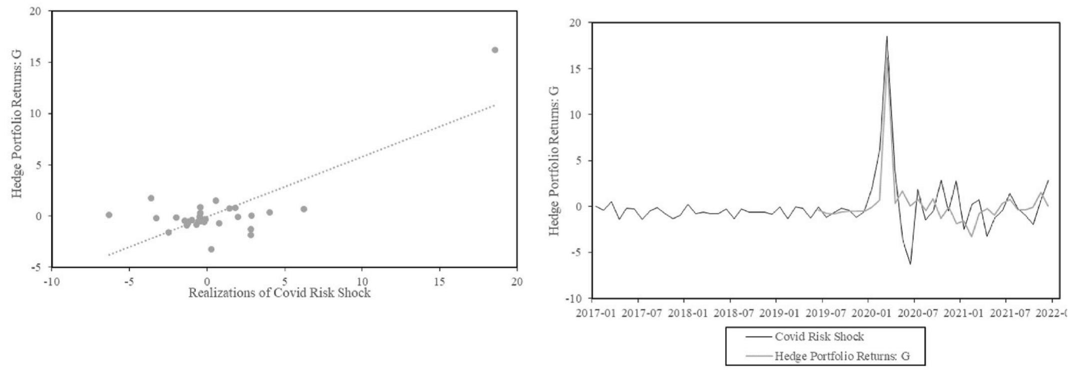
Note: This table shows the results of Equation (2) using detailed compositions of the ESG Disclosure Score. Columns 1, 2 and 3 show the results of Environment, Social responsibility and Governance Disclosure Score-based portfolios, respectively. The dependent variable captures innovations for the Covid Risk Index. The unit of observation is a month, and the sample period is January 2017 to December 2021. Standard errors are in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.



(a) E-based hedge portfolio



(b) S-based hedge portfolio



(c) G-based hedge portfolio

Fig. 7. Out-of-sample tests for the hedge portfolios with E, S and G disclosure score as characteristics respectively
Note: This figure evaluates the out-of-sample performance of the hedge portfolios constructed with compositions of Environmental, Social and Governance Disclosure Score, respectively. All the three hedge portfolios highlight a positive correlation between realizations of Covid risk shock and returns. The transformation of ESG raw scores into the characteristics vector is based on the ranking approach. The calculated correlations are 0.68, 0.85 and 0.61 for E-, S- and G-based hedge portfolio, respectively.

portfolio proves to be limited to the pandemic period. Once Covid-19 risk factors are excluded, the mimicking portfolio experiences a flat or even reversed performance. This suggests that the hedging effect of our constructed portfolio is unique to Covid-19 risk. We also find that the hedging effect is driven more by Social than Environmental and Governance.

Acknowledgements

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Appendix

A.1 Sources used in compiling our Covid-19 Vocabulary List

To create the Covid-19 Vocabulary list, we collected twenty white papers from government officials and nongovernmental organizations, such as the Centers for Disease Control and Prevention (CDC), the State Council Information Office of the People's Republic of China, the United Nations (UN), and the World Health Organization (WHO). Then, we added coronavirus glossaries from twenty sources, such as the CDC, the Pan American Health Organization (PAHO), and Merriam-Webster's online guide to coronavirus-related words. These white papers and glossaries are detailed below.

A.1.1 White papers on Covid-19

The twenty white papers related to coronavirus that we used are (with the institution and year of publication in parentheses): *United Nations Comprehensive Response to COVID-19: Saving Lives, Protecting Societies, Recovering Better* (UN, 2020a), *UN Research Roadmap for the COVID-19 Recovery* (UN, 2020b), *Policy Brief-COVID-19 and Universal Health Coverage* (UN, 2020c), *A UN framework for the immediate socio-economic response to COVID-19* (UN, 2020d), *WHO strategic action and resource requirements to end the acute phase of the COVID-19 pandemic 2021* (WHO, 2021a), *Technical specifications of personal protective equipment for COVID-19* (WHO, 2021i), *COVID-19 Strategic Preparedness and Response Plan* (WHO, 2021b), *Looking back at a year that changed the world: WHO's response to COVID-19* (WHO, 2021c), *Modelling the health impacts of disruptions to essential health services during COVID-19* (WHO, 2021d), *WHO SPRP 2021 Mid-term Report: WHO Strategic Action Against COVID-19* (WHO, 2021e), *Guidance on developing a national deployment and vaccination plan for COVID-19 vaccines* (WHO, 2021f), *Living guidance for clinical management of COVID-19* (WHO, 2021g), *Therapeutics and COVID-19* (WHO, 2021h), *Fighting Covid-19: China in Action* ((State Council Information Office of the People's Republic of China, 2020)), *UNICEF Annual Report 2020: responding to Covid19* ((UNICEF, 2020)), *Current Perspectives on Coronavirus* (Gupta et al., 2020), *Vaccinations During the COVID-19 Pandemic* (CVSHealth, 2020, *Navigating the Uncertainty: Economic Impact of COVID-19* (AIR, 2020), *Effects of a COVID-Induced Economic Recession* (MMHPI, 2020), and *Stopping COVID-19: short term actions for long term impacts* (MITRE, 2020).

A.1.2 Covid-19 glossaries

We added twenty coronavirus glossaries from Centers for Disease Control and Prevention (CDC), Pan American Health Organization (PAHO), Texas Medical Center (TMC), National Institutes of Health (NIH), Merriam-Webster, Johns Hopkins Bloomberg School of Public Health, Johns Hopkins Medicine, Yale Medicine, University of Rochester, KFF, UVA Health, NPS MedicineWise, EverydayHealth, Henry Ford, Mariposa County, Lungevity, English Club, UK Parliament, North Dakota Health and OSF HealthCare.

Table A1
Alpha decomposition of the hedge portfolios

	(1)	(2)	(3)	(4)
$Index_{t-1}$	0.115***	0.021*		
	(0.043)	(0.010)		
$Shock_t$			0.454***	0.403***
			(0.120)	(0.117)
$Shock_{t-1}$			0.283**	0.625**
			(0.120)	(0.117)
$Flows_{t-1}$		104.821		152.976**
		(118.407)		(64.281)
Constant	−0.019*	−0.011	0.008**	−0.003
	(0.013)	(0.012)	(0.003)	(0.006)
R-squared	0.110	0.156	0.359	0.421
N	59	59	58	58

Note: This table shows the results of an alpha decomposition of hedge portfolio calculated as a sum of the constants and residuals after regressing portfolio returns on the Fama-French's three factors. Columns 1 and 3 show the results after including the realization of the Covid Risk Index and the Covid risk shock, respectively; Columns 2 and 4 further include the ESG fund flows, which proxy for investors' ESG preferences. The unit of observation is a month, and the sample period is January 2017 to December 2021. Standard errors are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

Table A2
Position decomposition of the hedge portfolio

	(1)	(2)	(3)	(4)
$Index_{t-1}$	0.392**	0.136*		
	(0.172)	(0.079)		
$Shock_t$			−0.772**	−0.531***
			(0.334)	(0.149)
$Shock_{t-1}$			0.925***	0.234
			(0.334)	(0.149)
$Flows_{t-1}$	−143.508	−82.113	400.369**	150.247*
	(293.272)	(135.859)	(183.917)	(82.126)
Constant	−0.058*	−0.022	−0.001	−0.006
	(0.030)	(0.014)	(0.016)	(0.007)
R-squared	0.148	0.123	0.217	0.212
N	59	59	58	58

Note: This table shows the results of a formal decomposition of the two hedge portfolio components, positive and negative positions, respectively. Columns 1 and 3 show the results of the decomposition of positive positions; Columns 2 and 4 show the results of the decomposition of negative positions. Both decompositions include realization of the Covid Risk Index or the Covid risk shock. The unit of observation is a month, and the sample period is January 2017 to December 2021. Standard errors are in parentheses. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

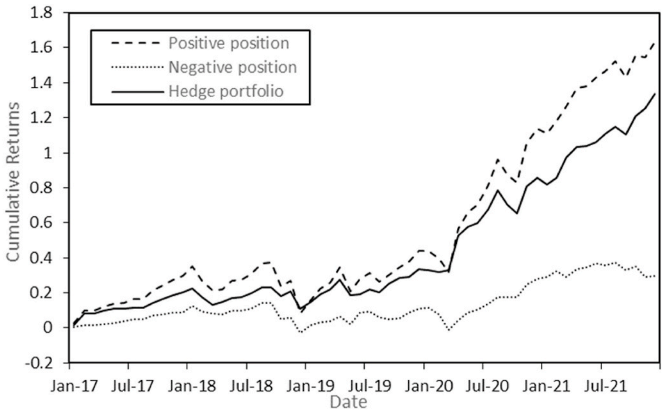

Fig. A1. Performance of the hedge portfolios and its subcomponents
Note: This figure plots the cumulative monthly returns of hedge portfolio and its subcomponents from January 2017 to December 2021. The dashed line represents the portion with great transparency and the dotted line represents the portion with poor transparency. The return spread, or hedge portfolio, is represented by the solid line.

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