Mutual funds' portfolio rebalancing with heterogeneous choices: a worldwide analysis exploiting the impact of the Covid-19 shock

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Abstract

This paper performs a comprehensive analysis of mutual funds' (MF) portfolio decisions taking advantage of, first, the Covid-19 outbreak as a true exogenous shock, and, second, an extensive, granular and worldwide database of 12 million observations on fund-by-fund and security-by-security purchases and sales of 20,000 MFs from 40 countries. These advantages allow us to apply for the first time an identification strategy that controls for all other unobservable characteristics that could influence MFs' behaviour. Our results show that in the crisis MFs divested from assets considered most at risk at the time, i.e., those issued by more Covid-affected countries and industries, and increased divestment when they experienced more outflows from their unitholders. These results confirm concerns raised in the debate on funds' intrinsic fragility. However, we also reveal several dimensions of heterogeneity in the MF industry (according to the type of assets held, investment policies, performance abilities), as well as the existence of an unconventional monetary policy channel acting precisely through MFs, which may have relevant implications for financial stability.

Keywords: Coronavirus, Covid-19, investment funds, Morningstar holdings, pandemic, portfolio rebalancing, resilience.

JEL Classifications: G01, G12, G15, G32.

1. Introduction

Mutual funds (MFs) have grown substantially since the global financial crisis, partly as a result of the increased regulation of banks. They hold a large fraction of world savings, purchase and sell securities all over the globe, play a crucial role in the financing of governments and firms, and their behavior drives market functioning and price developments. The need to gain insights into MF conduct and strategies has proportionally increased (e.g., Chen et al., 2010; Financial Stability Board, 2017; Goldstein et al., 2017).

In this paper, we perform a comprehensive empirical analysis of MFs' portfolio decisions. We have two advantages compared to the previous literature. First, we can exploit the impact of a major - and truly exogenous - worldwide shock: the Covid outbreak. In early 2020, the outbreak of the pandemic and the subsequent containment measures caused a sudden and sharp deterioration in the economic outlook, heightened the risk aversion among investors and gave rise to a large re-pricing in global financial markets (Figure 1). Bernanke (2020) stresses that the economic turmoil triggered by Covid-19 differs from past crises with respect to the cause, scope, and severity, because, while financial imbalances and risks had been growing for many years leading up to the 2008 global financial crisis, the Covid-19 crisis erupted abruptly. Second, we have the advantage of using a unique, extensive, granular, and worldwide dataset, which contains more than 12 million observations on fund-by-fund and security-by-security sales and purchases of more than 200,000 financial assets during the first four months of 2020 by over 20,000 MFs (about 40% of the global industry in terms of total net assets), located in more than 40 national jurisdictions and with investments in more than 100 countries and 20 industries. This richness makes it possible to apply to the global MF industry, for the first time to our knowledge, a robust identification strategy, which, in the spirit of Khwaja and Mian (2008), Paravisini (2008), Amiti and Weinstein (2018) and Degryse et al. (2019), uses a broad set of fixed effects to control for all contributing factors and unobservable characteristics that might influence MF decisions.

Our results, first, show that the pandemic triggered portfolio recomposition by MFs all over the world. In particular, consistent with the debate on their vulnerability, we show that MFs divested from financial assets considered at the moment most troubled, that is, those issued in countries and by industries more affected by Covid-19, irrespective of other inherent characteristics of the assets, which confirms the view that MFs, especially during crises, can push asset prices away from fundamentals. Furthermore, we document that MFs with more outflows from unitholders exacerbated the sales of more Covid-affected assets, which indicates that fund managers' portfolio adjustments worked in the same direction as investor outflows rather than mitigating the outflow effect. These results corroborate the concern that the open-end nature of these investment vehicles leads to run-like risk making fire sales and price volatility more likely.

However, we then examine the portfolio rebalancing in detail and uncover several dimensions of MF heterogeneity. We document that MFs did not overreact to financial investments abroad, and thus foreign MFs do not appear to raise this additional concern as is the case for other types of financiers. Then, we provide evidence that the MF industry includes very heterogeneous institutions, which employ a variety of portfolio strategies and reactions according to their investment policies, performance abilities, and types of assets held, which from a financial stability perspective suggests that policies and regulations for the different categories of MF should be adjusted to account for the different risk appetites resulting from their different behaviours. In particular, we show that the better managed funds, that is, the funds that were able to outperform their benchmark market index in the year before the pandemic, were the only MFs that did not respond to the shock selling indistinctly all Covid affected securities or following the fears of their unitholders. Finally, we document that, when the shock arrived and the panic broke out, the bulk of the adjustment in MFs' portfolios occurred during the "fever" of the Covid-19 crisis (that is, in March 2020), while we find signs of a resurgence as early as in April. Specifically, we find that the rebound in April mainly concerned MF purchases of corporate bonds, which were, to a large extent, the financial asset targeted by central banks' programmes in the period. The result corroborates therefore the existence of a channel of unconventional monetary policy operating through non-bank financial institutions, which can enrich the policy toolkit of monetary authorities and suggests a new instrument to ensure the financial stability of the MFs themselves.

As mentioned, our identification strategy exploits the pandemic emergency outbreak as a real exogenous shock. More specifically, we exploit the circumstance that the emergency outbreak and subsequent policy measures varied widely across *countries* and *industries*, in both intensity and timing. In fact, until late February 2020, the news of a health emergency only involved China, Korea, and a handful of other Asian countries. In the second half of February, the contagion reached Europe, but some European countries, such as Italy and Spain, experienced the spread of virus and lockdowns several weeks earlier than other countries, such as France, Germany, and the United Kingdom. Spread to the United States occurred even later. Moreover, the effects of the Covid-19 and of the related containment measures were heterogeneous even within countries, across industries. For example, in high-tech industries, firms adapted quite well to social distancing requirements by resorting extensively to teleworking. But in other industries, such as food catering, travel, and tourism, this was infeasible, and the effect of the Covid-19 on businesses, sales and profits was much more pervasive.[1] We can leverage these heterogeneous impacts across space, sector, and time to analyse MF responses and portfolio decisions. We compute the expo-

[1] Also the re-pricing was rather heterogeneous at both country and industry level. During the first quarter of 2020, for instance, the S&P 500 fell by 34 percent, from its high to its low; the exchanges in Spain, Italy, Germany and France experienced high-low declines of 45 percent, 42 percent, 40 percent, and 39 percent respectively, while Japan and Hong Kong saw declines of 31 percent and 25 percent. The heterogeneity was even more visible across industries, even within the same country, with firms in high-tech industries, such as Apple, Microsoft and Google, outperforming the market, while those in food catering, travel and tourism, such as Marriott, United Airlines, and Royal Caribbean, massively underperforming.

sures to the disease *across countries* through two alternative indexes: the ratios of total number of Covid-19 confirmed cases or confirmed deaths to total population. As is well known, these two ratios are imperfect measures of the real spread of the contagion and the extent of the health emergency. However, they are perfectly suitable to our purposes because they reflect the perception of international investors and the knowledge that they had on the impact of Covid-19 across countries and over time. Instead, we compute the exposures to the disease *across industries* through the indexes recently introduced in labour economics and intended to capture the extent to which firms' operations in each sector are compatible with social distancing and lockdowns (Dingel and Neiman, 2020; Hensvik et al., 2020; Koren and Pető, 2020). These measures quantify, in each sector, the degree to which jobs can be done from home and do not rely on human interaction in physical proximity.

The second advantage of our identification strategy relies on our massive data. Our dataset is obtained by combining varied sources. Security-by-security information on portfolios of over 20,000 open-ended MFs worldwide is obtained by matching the (fund-by-fund and ISIN-by-ISIN) Morningstar historical holdings data with the Centralised Securities Database of the European System of Central Banks, which contains information on virtually all securities traded in the world. Moreover, in order to verify whether other intrinsic characteristics of financial assets (other than those linked to the Covid impact) affect our results, we match the security-by-security data with information on the characteristics of each financial asset (rating scores, pressure, return) and each firm that issued the assets all over the world (size, profitability, leverage). However, as mentioned, the real advantage of our empirical strategy relies on the fund-by-fund and asset-by-asset granularity of our dataset, which allows us to include an extensive set of fixed effects in the estimations. These sets of fixed effects account for all factors affecting the portfolio decisions, before and during the Covid-19 shock, which are different from the pandemic impact, and therefore they are the most effective means to allow for possible unobservable characteristics of securities and MFs that may otherwise blur the results.

Our paper contributes to some of the major strands of the literature on MFs. First, our results on the massive sales of Covid-affected assets, those perceived as more in distress in the period, provide granular, worldwide and robust evidence to the literature on MFs' intrinsic fragility, which stresses that, especially in times of crisis, MFs sell the most troubled assets and contribute to the risk of fire sale events by pushing prices away from fundamentals (e.g., Grinblatt et al., 1995; Nofsinger and Sias, 1999; Coval and Stafford, 2007; Stein, 2009; Manconi et al., 2012; Ben-David et al., 2012; Cella et al., 2013). Second, our results on higher sales of more Covid-affected securities by MFs with more outflows contribute to the debate in the literature on the relationship between the sales of institutional investors and those of their unitholders. In particular, our results support the view that during times of turmoil MFs are likely to increase market volatility and depress the prices of the securities they hold because they have to respond to massive (often retail) redemptions (e.g., Coval and Stafford, 2007; Baker et al., 2003; Duchin et al., 2010; Hau and Lai, 2013; Cella et al., 2013; Solomon et al., 2014; Kaniel and Parham, 2017). Third, however, our results on large sales of Covid-affected securities wherever issued, even domestically, reject for foreign MFs the "flight to home" hypothesis (documented instead for foreign banks after the global financial crisis; Giannetti and Laeven, 2012; De Haas and Van Horen, 2013), and also reject concerns that foreign MFs may have a more destabilizing effect because they overreact to financial panics (Dornbusch and Park, 1995; Radelet and Sachs, 1998; Choe et al., 1999). Fourth, and remarkably, our results on the several dimensions of MF heterogeneity by type of assets held, investment policy, and performance ability provide a more nuanced view of MFs, which result to include heterogeneous institutions and therefore are neither all smart investors who only sell overpriced stocks nor all destabilizer investors who herd and chase trends (Lakonishok et al., 1992;

Kacperczyk and Schnabl, 2013; Zeng, 2017; Zhu, 2021; Jin et al., 2021). In particular, our results on the ability of some MFs to stand out in terms of performance and portfolio selection show that some well-managed funds preferred not to trade with the crowd nor followed the fears of their unitholders, and outperformed their benchmarks (e.g., Kacperczyk et al., 2008; Fama and French, 2010; Pastor and Vorsatz, 2020). Finally, our results on a non-bank financial institution channel of unconventional monetary policies contribute to a recent stream of the literature suggesting a new instrument to face MF fragility itself (Falato et al., 2020; Gilchrist et al., 2020; Boyarchenko et al., 2020; O'Hara and Zhou, 2021).

The rest of the paper is structured as follows. Section 2 and Section 3 describe, respectively, the data and the empirical methodology. Section 4 reports the baseline results. Section 5 discusses MF heterogeneity across fund and asset types. Section 6 describes robustness checks. Section 7 concludes.

2. Data

We built a novel and unique dataset, which combines four sources, and contains more than 12 million observations on fund-by-fund and security-by-security sales and purchases during the first four months of 2020 by more than 20,000 MFs from more than 40 national jurisdictions and investing in more than 100 countries and 20 industries. Our dataset corresponds to about 40% of the worldwide MFs' total net assets, according to official statistics (EFAMA, 2020), and therefore it is well representative of the global MF industry. The dataset is very representative also at country level, for all countries with a major MF industry.[2]

[2] The representativeness is around 40% for the United States, the United Kingdom, Luxembourg, Brazil, and Switzerland; it is about 30% for Germany, Italy, and Spain. It is even higher than 60% for India and Sweden, while it is a bit lower, around 20%, for France and Ireland. In percentage terms, the MFs from North America represent about 60 percent of the world industry, both according to EFAMA and in our dataset. The Euro Area MFs account for around 22 percent, according to EFAMA, and 20 percent in our dataset. Emerging markets' MFs account for 5 percent, according to EFAMA, and 10 percent in our dataset.

Our main data source is Morningstar's database of historical holdings. We retrieve monthly MF-by-MF and ISIN-by-ISIN portfolio information from December 2019 to April 2020, in addition to the investment objective and legal domicile of each MF. Information we use refers to the entire global market universe of "actively managed" open-ended MFs, that is, we consider all those funds that follow an active market strategy as opposed to "passive funds", such as exchange traded funds or index funds, which are instead excluded because they mechanically follow the index they track. Similarly, money market funds are also excluded.[3]

The second data source is the Centralised Securities Database (CSDB) of the European System of Central Banks (ESCB), which contains information on almost all securities traded in the world. The CSDB is a security-by-security database developed by the ECB and jointly operated by the National Central Banks (NCBs) of the ESCB. To be included in the CSDB, it is sufficient that the security is either issued by EU residents or denominated in euros or *held* or *transacted* by EU residents: this involves almost all securities traded in the world. We use the CSDB as a register to decrypt and classify MFs' ISIN-by-ISIN holdings under three dimensions of the issuer: country, sector of economic activity, and category of financial instrument.[4]

Third, to measure each country's vulnerability to the Covid-19, we compute two ratios: the number of confirmed cases and the number of deaths over total population, as monthly sums of the daily data for each country, collected by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.[5]

[3] Moreover, we exclude those (few) funds that do not provide a (complete) disclosure of their holdings in each month of our sample period. Morningstar's database is survivorship bias-free; that is, it includes data on both active and no longer active funds. We use information only on active MFs.

[4] The CSDB contains reference, price, rating, and statistical classification data for more than 5 million active debt securities, equity shares, and mutual fund units issued worldwide. It is accessible to the entire ESCB and is updated daily with inputs from NCBs and several commercial data providers. For more details, see *The centralised securities database in brief*.

[5] The Covid-19 Global Database of the CSSE at Johns Hopkins University, which is managed by Dong et al. (2020) and organized as an interactive web-based dashboard, tracks in real time the number of confirmed Covid-19 cases and

Fourth, to measure the vulnerability to the Covid-19 of each industry, we rely on the indexes recently introduced in labour economics by Koren and Pető (2020), Dingel and Neiman (2020) and Hensvik et al. (2020), which are intended to capture the extent to which firms' operations are compatible with the social distancing necessitated by the Covid-19. Our first choice among these measures is the pandemic-resilience index proposed by Koren and Pető (2020), the KP's *affected share*, which is an industry-level measure of the percentage of employees affected by the Covid-19 pandemic, due to their occupations being communication-intensive or requiring close physical proximity to others, or both. We choose this as our main proxy of the Covid impact at the industry level, because, besides teleworkability, it explicitly accounts for physical proximity to others.[6] These measures are estimated for US industries and are applied to the corresponding industries of other countries. The idea is that the Covid-19 impact should be very similar for industry types across the world, after controlling for country-specific characteristics, and would be so perceived by international investors. As for the few industries for which the measures on the vulnerability to the Covid-19 crisis are unavailable, we carry out several robustness checks (described in Section 6).[7]

Thanks to the granularity of our dataset at the fund and ISIN level on quantities and prices, we compute for each financial asset (identified through its ISIN code) the monthly net purchases (i.e., gross purchases minus gross sales) carried out by each MF in each month from January to April 2020. We therefore can distinguish exactly the portfolio changes due to the market price

the number of deaths around the world. It is updated daily and is available through GitHub repository.

[6] Hensvik et al. (2020) rely on the American Time Use Survey (2011-2018) to estimate the fraction of employees who work at home and at the workplace as well as the hours worked at home and at the workplace at the industry level. Alternatively, Dingel and Neiman (2020) use data from O*Net surveys to assess the teleworkability of occupations and provide industry-level estimates for the percentage of jobs that can be done at home as well as for the percentage of wages associated with teleworkable occupations.

[7] As mentioned, we use the CSDB as a register to decrypt and classify MFs' ISIN-by-ISIN holdings. However, the CSDB provides NACE codes, while the KP metric is based on three-digit NAICS classification. To match the KP metric to our ISIN-by-ISIN dataset, we retrieve from Refinitiv (Datastream) the NAICS codes of all holdings included in our sample. A minor share of financial assets (less than 5 percent of the total) remains unclassified.

revaluation effect from those due to the actual financial transactions.[8]

Table 1 reports summary statistics of our sample with data broken into two spans: a pre Covid-19 period (i.e., January and February 2020) and a Covid-19 shock period (i.e., March and April). Table 2 reports summary statistics of the KP metric for those industries with the highest number of holdings in our sample (covering more than two-thirds of the sample). The measures of Covid-19 impact on countries (number of cases and deaths over population) are zero until the end of February for the most of countries; those on Covid-19 impact on industries (KP's affected shares) are set to zero until the end of February.

3. Empirical strategy

We estimate two regression models. The first model analyzes the MF selection of financial assets exploiting the heterogeneous impact of Covid-19 outbreak *across countries* (controlling for industry specific characteristics). The second model investigates the selection exploiting the heterogeneous impact of Covid-19 outbreak *across industries* (controlling for country specific characteristics).

In formal terms, the first regression model has the following structure.

$$Net\ purchases_{i,f,t} = \beta_1 * Country\ Covid19_{c,t} + \delta_{f,t} + \phi_{1\,s,t} + \epsilon_{i,f,t} \tag{1}$$

where the dependent variable $Net\ purchases_{i,f,t}$ measures the monthly net purchases of each financial asset i (identified through its ISIN code) run by each MF f in each month t, scaled by the net asset value of the same MF at the end of the previous month. In Equation 1, the covariate of interest is $Country\ Covid19_{c,t}$, which is the index of the Covid-19 impact in each country measured

[8]The *market price effect* (revaluation) is measured for each security as the change in market price between month t and $t-1$ on the overlapping quantity, i.e., $(p_t - p_{t-1}) * min(q_t, q_{t-1})$. Then *net purchase* (actual financial transaction) at ISIN level is obtained as the difference between the total portfolio change of each asset and its market price revaluation. Details on our measures and variable definitions are provided in Table A1 of the Appendix.

by the ratio of total number of cases (or alternatively total number of deaths) to total population in country c in the month t. The subscript c indicates therefore the country of destination of the financial investment i of each MF (each i may belong to only one country c.)

We conduct this estimate by including interactions between two sets of fixed effects: $\delta_{f,t}$ are interactions between time and MF fixed effects; $\phi_{1s,t}$ are interactions between time and industry fixed effects. The around 90,000 fund-time fixed effects $\delta_{f,t}$ and the 80 industry-time fixed effects $\phi_{1s,t}$ remove all time-invariant and time-varying, observable and unobservable factors across funds and industries that could mist up the results and are therefore the most effective control for accounting for other (different from the Covid-19) risks and demand conditions that might influence MF decisions. In particular, the time-varying MF fixed effects $\delta_{f,t}$ control for everything specific to a given investor and affecting the overall size of its portfolio. This is important, given that different MFs may systematically invest in securities involving different levels of risk. Moreover, $\delta_{f,t}$ also controls for the country of origin of each MF and therefore conditions out all time-varying and time-invariant traits linked to economic, institutional, and legal characteristics of countries of each MF. Likewise, industry-time fixed effects $\phi_{1s,t}$ remove all sources of bias related to economic and financial conditions at the industry level, developments in credit risk or financing needs associated with a given industry, and differences in the intensity of required in-person contact with customers, suppliers, and coworkers (which might influence industry level reactions to the pandemic and are therefore the focus of the second model). Furthermore, since we allow these effects to vary over time, they account for the rapid deterioration in the global financial markets during our sample period.

The second regression model has the following symmetric structure.

$$Net\ purchases_{i,f,t} = \beta_2 * Industry\ Covid19_{s,t} + \delta_{f,t} + \phi_{2c,t} + \epsilon_{i,f,t} \tag{2}$$

where the dependent variable $Net\ Purchases_{i,f,t}$ is defined as in Equation 1 as are the interacted fixed effects $\delta_{f,t}$. What changes is the covariate of interest $Industry\ Covid19_{s,t}$, which is now the index of the Covid-19 impact in each industry. The subscript s refers to the industry of destination of the financial investments of each MF (and thus each i belongs to only one industry s).[9] Like Equation 1, which includes industry-time fixed effects, Equation 2 includes the interactions ($\phi_{2c,t}$) between time t and country of destination c fixed effects, which control for all time-varying and time-invariant characteristics of the countries where MFs invest, such as differences in growth, economic conditions, legal and political systems, reactions to the crisis, institutions and cultural norms, and demographic and other cross-economy characteristics (while, as in Equation 1, the interacted fixed effects $\delta_{f,t}$ control also for the country of *origin* of each MF).

In a nutshell, in Equation 1, $\phi_{1s,t}$ removes all sources of bias at industry level and allows estimations to focus on countries and, in particular, on our measure of the heterogeneous Covid-19 impact across countries. In Equation 2, $\phi_{2c,t}$ removes all potential sources of bias at country level and allows estimations to focus on our measure of the heterogeneous Covid-19 impact across industries.

Three other features of our empirical strategy are worth mentioning. First, our estimates are performed with robust standard errors by clustering at the MF-level. Second, as detailed below, although our dataset includes a huge quantity of assets, issued globally, our estimations include a number of control variables, in order to further check the stability of our results, defined at both the financial asset level (such as rating scores, pressure scores, return) and the level of firms that issued the assets held by MFs (such as size, leverage, profitability). Finally, as detailed below, we examine not only the reaction and behaviour of MFs as a whole, but also whether and how the different types and categories of MFs responded to the pandemic shock. To this end, we enrich both Equations

[9] As mentioned, the KP metric used to estimate Equation 2 is based on three-digit NAICS classification, whereas industry fixed effects of Equation 1 are based on one-digit NACE industry classification. One-digit NACE industry classification includes 21 sections, of which there 20 in our dataset. Three-digit NAICS classification is much more detailed and includes 84 groups.

1 and 2 by allowing our Covid-19 measures to interact with various individual characteristics of MFs, while still controlling for economy-time, industry-time, and fund fixed effects.

4. Baseline results

Table 3 reports results of Equation 1; Table 4 those of Equation 2. The tables report different specifications progressively adding the sets of time-varying fixed effects. In Table 3, Specifications 1-3 use as the key regressor $Country\ Covid19_{c,t}$ the ratio of the number of cases to population, while Specifications 4-6 use the ratio of the number of deaths to population; moreover, the third specification includes additional country characteristics to control for other specific destination-country features (since economy-time fixed effects are the main fixed effects in Equation 2). In Table 4 the key regressor $Industry\ Covid19_{s,t}$ is the index of the pandemic impact across industries.

The results show that in both cases the coefficients of the variables of interest $Country\ Covid19_{c,t}$ and $Industry\ Covid19_{s,t}$ are always significantly negative, which means that the pandemic outbreak led MFs to sell mainly financial assets issued by more affected countries and by more affected industries, and thus to rebalance their portfolios in favour of less affected assets. The economic impact is also relevant: for example, moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of the Covid cases of Specification 2 of Table 3, the dependent variable $Net\ Purchases_{i,f,t}$ decreases by 0.001%, which is a quite sizeable magnitude, since represents about 18 percent of the average net purchases in the period. Likewise, moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of the KP metric distribution in Table 4, the asset experiences an extra 40 percent drop, compared to the average net purchases.

More exposed portfolios

To illuminate the portfolio rebalancing we then verify whether the Covid impact was larger for more exposed portfolios, that is, whether the net sales of more Covid-affected securities were amplified by MFs with greater initial percentage shares of Covid affected securities and by MFs with more Covid-oriented portfolios. We run therefore two additional tests. First, we include in both Equations 1 and 2 the interaction-term between our Covid-impact measures and the variable $share_{i,f,t-1}$, which computes, for each MF f, the weight of each financial asset i on the total portfolio in the previous month $t-1$. If this interaction term were negative, it would indicate that, the more relevant the Covid-affected securities were in MF portfolios, the more they were sold when the pandemic broke out. Second, we introduce in both Equations 1 and 2 the interaction-term between our Covid measures and the variable $Covid\_oriented\_portfolio_{f,t-1}$, which measures to what extent the portfolio held by each MF f in the previous moth $t-1$ was Covid-oriented, that is, to what extent it was affected by the Covid-19 impact, as observed in the month t.[10] If this interaction term were negative, it would indicate that, the more the MF portfolios were Covid-oriented, the more the MFs sold Covid-affected securities. The results of both exercises show that, both across countries and industries, the coefficients of the interacted-terms are always significantly negative (Tables 5 and 6), which confirms even more that the sales were not horizontal, but were concentrated among Covid-affected assets, and helped MFs to rebalance portfolios toward assets considered at the moment less risky.

The moment of the adjustment

Figure 2 provides a visual quantification of the impact of the Covid shock on portfolio decisions in the months of the pandemic outbreak. The figure alone clearly suggests that the different conduct of MFs towards less and more Covid-affected countries was concentrated in March.[11] However, for a more exact identification of the moment in which MFs reacted to the Covid-19 shock, we repeat estimations of Equations 1 and 2, allowing the effects to vary over time through

[10] In other words, the variable $Covid\_oriented\_portfolio_{f,t-1}$ is obtained as a weighted portfolio, where the share of each financial asset i in the month $t-1$ is weighted by our Covid-19 ratios in the month t.

[11] In Figure 2 less Covid-affected countries (more Covid-affected) are defined as those below (above) the 75th percentile of our measure of Covid-19 exposure across countries.

interaction-terms between our Covid indexes and time dummies.[12] The Covid-19 variable interacted with the dummies for January and February is not statistically significant (Table 7) confirming that MFs were not yet rebalancing their portfolios in response to pandemic risk. By contrast, in March the Covid-19 impact coefficient becomes statistically significant both at the country (Table 7) and industry level (Table 8). Also the coefficient and the marginal effect are larger in March than in the overall regression. Instead, in April, we find relevant seeds of resurgence at the country level (Table 7) and a sharp reduction of the Covid-19 impact at the industry level (Table 8). The result of April may be a sign that the exceptional policy measures taken in those days helped avoid further propagation of financial stress. We turn to this issue in the next section, analyzing which kinds of assets were more hit by sales of March and which benefited more from the rebound of April.

Issuing firm and market characteristics of financial assets

In order to further evaluate whether other intrinsic characteristics (other than those linked to the Covid impact) of financial assets influence net-purchases of MFs at the onset of the pandemic, we run new versions of both Equations 1 and 2 by adding to the sets of fixed effects various regressors defined at the financial asset level.

First, with respect to the full set of financial assets in MFs' portfolios (which consists of more than 200,000 securities where MFs made net-purchases globally in the first quarter of 2020), we include in Equations 1 and 2 and interact with our Covid exposure measures two key additional control variables that capture crucial specific characteristics of the assets: the rating scores and the "pressure" of each asset. The rating scores are taken from the CSDB and refer to a large (across

[12] There are four month dummies at the country level (form January to April 2020) and two month dummies at the industry level (where January and February are excluded because assume always zero values). These exercises, such as all the following ones, are run in a single empirical model rather than in split samples so as to gain efficiency and allow direct comparison among the coefficients (e.g., Morck et al., 1988).

types) subsample of our data (around 50 percent of all financial instruments in the sample).[13] The variable "pressure" is defined as the difference between "forced buys" and "forced sales" scaled by the total number of mutual fund owners (Coval and Stafford, 2007). These two estimates confirm all our results: the variables of interest remain significantly negative at both country and industry level, implying that, even when controlling for specific characteristics of financial assets, MFs sold the most Covid-affected assets.

Second, with respect to the subsample of equities, we can include in the estimates a complete set of asset-specific regressors, which control for all issuing firm and market trend characteristics. It is worth highlighting that equities not only make up nearly half of our dataset (about 5 million observations) and are not only the financial asset for which more data are available, but also are the most purchased and sold financial asset in MF portfolios over the period. Specifically, we include four firm level characteristics (*Total assets*; *Financial Leverage*; *Liquidity*; and *Return on Assets*), which capture crucial factors of the issuers such as the size, the level of indebtedness, liquidity and profitability.[14] Our data cover over 20,000 firms across 99 countries. Moreover, we add two market trend covariates (*Stock return* and *Stock Return volatility*), which can seize the attractiveness of each equity in the world.

Results are reported in Table 9, both by country and industry. The exercise confirms that both firm and market characteristics matter in MF portfolio choices. Financial assets issued by more liquid firms and those with higher stock returns and less volatility experience less severe sales than otherwise identical assets. However, even controlling for firm and market characteristics, the

[13] Among the rating scores available for the same ISIN, due to the presence of different agencies (i.e., Fitch, Moody's and S&P), we apply the first-best rating, following the Eurosystem's general eligibility criteria for collateral (Bindseil et al., 2017).

[14] See, for example, Bates et al., 2009; Kahle and Stulz, 2013; Ding et al., 2020. Firm characteristics are obtained matching (trhough the ISIN code) equities in MF portfolios to individual firm balance sheet data. We retrieve firm accounting data in December 2019 (the last available year before the pandemic crisis) from Morningstar Direct. *Firm Total assets* equals the natural logarithm of the book value of total assets and it is usually used as a proxy of firm size. For more details on variable definitions, see Table A1 of the Appendix.

exercise confirms once again all the previous results: the sales were significantly related to the Covid impact across countries and industries.

5. MF heterogeneity across fund and asset types

So far, we have documented that the pandemic triggered globally a portfolio reallocation of MFs toward less Covid-affected assets, corroborating concerns that MFs are likely to facilitate sell-off events. In this Section we extend the baseline models to examine whether and how MF portfolio decisions were heterogeneous across MF categories and asset types. Specifically, we enrich Equations 1 and 2 adding interactions between new regressors (which capture specific aspects of MFs or of their holdings) and our two variables of interest $Country\ Covid19_{c,t}$ and $Industry\ Covid19_{s,t}$. From a methodological point of view, it is worth highlighting that in the baseline estimations our empirical approach controls for these differences, thanks to the set of time-varying fixed effects, and therefore our baseline results are obtained under an "all things being equal" equilibrium, which allows us to document (taking into account individual differences) the behaviour of MFs as a whole. Here, the scope is different. Here we aim to verify whether and how those differences matter, that is, whether and how the portfolio rebalancing was different across MFs or assets, and therefore whether and how MFs behave differently. Moreover, as we detail in the following analysis, the use of interactions allows us to carry out these extensions without reverting to the sets of fixed effects of our baseline approach.

Rebalancing according to the funds flowing out of MFs

As pointed out from the Introduction, the debate on MFs stresses that mutual funds may be fragile institutions especially because when they encounter more redemption requests are more likely to sell than to mitigate the outflow effect, creating in this way a run-like risk. Figure 3 provides a visual quantification of the impact on MF decisions caused by the funds flowing out of MFs during the pandemic shock. The figure clearly shows that MFs with limited outflows sold much less than those with strong outflows.[15] In the baseline estimations, our empirical approach controls for MF specific differences and thus also for specific differences in reimbursements. Now instead we are interested in verifying exactly whether MFs with larger redemptions by their unitholders sold more Covid-affected securities. To this purpose, we estimate a different version of Equations 1 and 2 by adding the covariate $outflows_{f,t}$, which measures, for each MF, the amount of withdrawals in the period.

Given the presence of the variable $outflows_{f,t}$, these estimates are necessarily run by replacing the time-varying MF fixed effects $\delta_{f,t}$ with two additive components (MF and time fixed effects), which control for time-invariant fund-level characteristics and time-variant general developments. On the other hand, we add a relevant regressor defined at the fund-level, *Fund Liquidity*, which measures the degree of liquidity of each MF in the previous month.[16] The results are reported in Table 10, for both the entire set of financial assets in our dataset (Specifications 1 and 2), and the subset of equities (Specifications 3 and 4, which include the additional asset-specific regressors as before). Specifications 1 and 3 are run for the entire period, while Specifications 2 and 4 are run at the monthly level.

The results confirm that the coefficient of $Country\ Covid19_{c,t}$ is always negative, both in the aggregate specifications and in the monthly specifications in March, both in the regressions on the full set of financial assets and in the regressions on the subsample of equities. As expected, the coefficient of $outflows_{f,t}$ is also negative, revealing that MFs characterized by more withdrawals sold more. However, these estimations reveal more. The interaction term between $Country\ Covid19_{c,t}$

[15] MFs with limited outflows correspond to MFs up to the third quartile of the distribution of the variable $outflows_{f,t}$, which measures the amount of MFs' withdrawals in the period; MFs with strong outflows correspond to those in the fourth quartile. As in Figure 2, less Covid-affected countries (more Covid-affected) are defined as those below (above) the 75th percentile of our measure of Covid-19 exposure across countries.

[16] It includes deposit that can be withdrawn at any time scaled by total net assets.

and $outflows_{f,t}$ is also significantly negative (again, in both aggregate specifications and in March), meaning that MFs with more outflows not only sold more, but exacerbated exactly the sales of securities issued in more Covid-affected countries. These results provide new and robust evidence to the debate on the fragility of MFs and show that, far from allaying investors' fears, the decisions of MFs reflect and stress the point of view of their unitholders.[17]

Rebalancing across MF categories: the role of domestic and foreign MFs

To verify whether MF types differ in reactions and portfolio decisions, we begin by distinguishing domestic and foreign MFs. The literature on the "flight home" effect documented a withdrawal of credit by foreign banks after the global financial crisis and argued that it was a consequence of discrimination towards foreign borrowers (Giannetti and Laeven, 2012) or lack of information by foreign lenders (De Haas and Van Horen, 2013). Our analysis allows us to verify whether the same phenomenon may be induced also by MFs as a different set of financiers and therefore whether their domestic or foreign nationality influenced the reaction to the Covid outbreak. In this respect, we repeat estimations of Equations 1 and 2 augmenting the model with two dummies that identify domestic and non-domestic MFs, that is, capture if the country of residence of the issuer of each financial asset coincides or differs from the country of domicile of each MF. Then we interact these two dummies with our variables of interest in each month (both $Country\ Covid19_{c,t}$ and $Industry\ Covid19_{s,t}$). Table 11 reports results of the exercise for Equation 1. The coefficients of the interaction terms between our Covid-impact measures and the two (domestic and foreign) dummies are always negative in March, and the magnitude is very close. This means that the pandemic shock prompted MFs to sell Covid-affected securities regardless of

[17] The effect is confirmed in the estimation of Equation 2 (unreported but available from the authors). It is also to notice that, with respect to equities, the coefficients of the variable $outflows_{f,t}$ and of the interaction-term between $Country\ Covid19_{c,t}$ and $outflows_{f,t}$ are negative also in April, implying that equities were sold also in this month. We return to this point later.

where they were issued. Therefore, MFs sold even their own country's securities if this contributed to rebalance their portfolios toward less risky holdings.[18] The result also clashes with the literature that points out that foreign investors may have a larger destabilizing effect because they overreact or are more prone to financial panic than domestic investors (Dornbusch and Park, 1995; Radelet and Sachs, 1998; Choe et al., 1999).

Rebalancing across MF categories: the role of MF investment policy

To verify whether and how MFs behave differently on the basis of their investment policies, we split MFs in our sample according to the prevailing assets in which they invest, which reflects the differing risk appetites embedded in their policies. We detect three groups of MFs - equity, fixed income, and mixed funds - and identify them through three dummies. Then we interact the three dummies with our variables of interest in each month.[19] Table 12 reports results for both equations: across countries (Specification 1) and industries (Specification 2). Results show that MF categories indeed do matter. Mixed and fixed income MFs rebalanced mainly by country, while equity MFs rebalanced mainly by industry. The evidence is consistent with the underlying policies of MFs: the former are more interested in government bonds and thus rebalanced by country, while equity MFs are more corporate-focused and thus rebalanced mainly across industries. More in general, these results are relevant as they document that MFs characterized by different investment policies effectively reacted differently (even) in a crisis phase and therefore suggest that they could be subject to differentiated prudential requirements.

[18] As for Equation 2, the exercise provides very similar outcomes, and, for brevity's sake, it is not reported. The same exercise performed for the subset of equities, including therefore the asset-specific regressors, provides a very similar outcome; indeed, the coefficient of domestic assets results larger than the corresponding coefficient of foreign assets, suggesting that, as for equities, domestic assets were even more sold than foreign ones.

[19] In this and in the following exercises, results refer to the complete set of financial assets in our dataset. Specifications referring only to equities would be meaningless.

Rebalancing across MF categories: the role of MF performance ability

To explore whether MFs behave differently according also to their performance ability, we proceed in two ways. First, we compute at monthly frequency, from January 2019 to April 2020, a measure of MF benchmark-adjusted returns, which are the excess returns with respect to a market benchmark. We compute, for each MF, the benchmark-adjusted return as the difference between its monthly net returns and the specific benchmark return provided in the Morningstar dataset for its category. In the dataset from Morningstar, MFs are classified into more than 300 asset categories, and a market benchmark is provided for each category, so we can use 300 different benchmarks. Figure 4 reports the results (aggregated for all MFs in our dataset) and shows, consistent with the prevailing literature, that on average MFs do not exceed their benchmark market index. In fact, during 2019, the mean benchmark-adjusted returns (sized in Figure 4 by the red spots) tend to be on the zero line. Figure 4 also shows that MF returns were even lower in March 2020 (the red spot is well below the zero line), suggesting that MF performance abilities on average decreased in response to the unexpected negative shock.

Then, we exploit the granularity of these benchmark-adjusted returns and identify three categories of MF performance capabilities, corresponding to MFs with low, medium and high returns.[20] We interact the three MF groups, seized by three dummies, with our variables of interest in each month. The results are reported in Specification 1 of Table 13. Remarkably, MFs with higher pre-pandemic returns (those of the top quartile, reported in the column Q4) were the only group that did not sell in March (the coefficient is negative, but statistically insignificant only for this group) and bought in April. Therefore, MFs that were characterized on average by a stronger performance ability did not herd even during the pandemic crisis.

[20]MFs are classified with "low", "medium" and "high" returns, respectively, if during the entire 2019 they are in the bottom quartile (the group Q1), in the second or third quartile (Q2-Q3), or in the top quartile (Q4) of the measure computed for all MFs in our dataset over the months of 2019.

This result confirms and reinforces our findings from the previous subsections, that is, MFs are not all the same. Specifically, this result shows that not all MFs traded with the crowd, and therefore not all of them contributed to destabilizing stock prices and driving them away from fundamentals during the onset of the crisis. Further confirmation is provided by the exercise reported in Specification 2 of Table 13, where we repeat the same estimation as in Specification 1 adding the covariate $outflows_{f,t}$, which measures the amount of withdrawals in the period for each MF (as in Table 10).[21] Unlike in Table 10, now that we take into account MF performances, the coefficient of $outflows_{f,t}$ is significantly negative only for MFs in group Q1, that is, only for MFs with low returns. Therefore, the result shows that only MFs with poorer performance abilities worsened the sales in line with their unitholders' feelings and withdrawals, while MFs with outperforming capabilities, and presumably better management skills and forces, were able to weather the storm better, which is also relevant from a financial stability perspective.

Security type rebalancing and the monetary policy measures

To explore whether security types MFs hold matter as well, we distinguish between three relevant kinds of financial assets: equities, government bonds, and corporate bonds.[22] We carry out two exercises. First, we regress Equations 1 and 2 adding only the interactions between the three security-type dummies identifying the three assets and the time dummies. This exercise (unreported) confirms that, even taking into account security type, the sales are larger for more Covid-affected assets.

[21] It is to notice that in the estimations of Specification 2 the covariate $outflows_{f,t}$ is added without giving up the interacted fixed effects, since the regressor $outflows_{f,t}$ is not estimated alone but interacts with the three dummies related to the three groups of MF performance capabilities.

[22] It is worth stressing that a crucial factor of difference is the degree of liquidity of the three asset types. Equities and government bonds are typically very liquid (as they are traded many times throughout the day), while corporate bonds are typically illiquid (as they may not be traded for weeks and cannot be easily and cheaply liquidated). As mentioned, the literature that points to MF fragility refers mainly to funds that allow investors to redeem their money on a daily basis despite the illiquidity of their holdings.

More interestingly, the second exercise verifies whether and which security type is sold more. We re-estimate Equations 1 and 2 augmenting the model with the three dummies interacted with our variables of interest in each month (again, both $Country\ Covid19_{c,t}$ and $Industry\ Covid19_{s,t}$). Results (reported in Table 14) show that MFs sold only equities to decrease their exposures toward Covid-affected countries, while they sold all kinds of assets to rebalance their portfolios across industries. Mainly, the results show that the rebound effect of April only concerned corporate bonds. This result appears associated with the policy measures taken by the authorities in the period. Corporate bonds were in fact the financial asset on which central banks (notably, for the first time) concentrated their intervention during the pandemic crisis, in particular in the United State and in the Euro Area.[23] We carried out another (unreported) test combining security type dummies and country-of-origin dummies of MFs and found that the rebound of April involved corporate bonds held by MFs mainly coming exactly from the United States and the Euro Area. Our results corroborate recent evidence on a channel of unconventional monetary policy acting exactly though non-bank financial institutions (Falato et al., 2020; Gilchrist et al., 2020; Pastor and Vorsatz, 2020; O'Hara and Zhou, 2021), which reveals a new policy option to address MF fragility itself. In summary, then, on the one hand, our results document that MFs are indeed fragile institutions that can exacerbate or even destabilize market conditions in times of crisis. On the other hand, however, our results show that MFs comprise different institutions with varying reactions and

[23]In the United States, the Federal Reserve began purchasing securities in mid-March; however, it was not until March 23 that the Fed, together with the Department of the Treasury, announced the purchase of corporate bonds for the first time in US history, creating a facility to directly purchase investment-grade corporate bonds of U.S. companies in the secondary markets (the Secondary Market Corporate Credit Facility - SMCCF). In the Euro Area, the ECB increased the existing Asset Purchase Programme and complemented it with the launch of a temporary Pandemic Emergency Purchase Programme with an overall capacity of €750 billion, which expanded eligibility to non-financial commercial paper under the corporate sector purchase programme. The FED's announcement was made March 23. The ECB decision is dated March 24. Purchases began only a few days later, and mainly the scale and scope of the programmes were increased in April. This timing well explains why the programmes have an impact in our monthly estimates in April. Regarding liquidity problems in the corporate-bond market during the pandemic, see Haddad et al. (2020) and Ebsim et al. (2020).

portfolio strategies, which can thus be addressed by different prudential requirements, and can also be managed by monetary policy measures.

6. Additional robustness checks

Market price revaluations

We ran also estimations with the same structure as Equations 1 and 2, where, however, the dependent variable was not the $Net\ purchases_{i,f,t}$ of each financial asset, but the market price revaluations experienced by each financial asset at the outbreak of Covid-19. The exercise is relevant as, while providing a check of robustness of our data and results, it verifies the correspondence of market price effects between MF portfolios and global market developments. The results (reported at country level in Table 15 and at industry level in Table 16) are as expected: the market price effect on the value of securities at ISIN level in MF portfolios is negative in the time window of the Covid-19 outbreak, both for the securities issued in more Covid-affected countries and for those of more Covid-affected industries.

Rebalancing countries along with industries

The expected implication of our baseline results is that MFs' sales were amplified when the issuer of financial assets belongs simultaneously to a more Covid-affected country and industry. To verify this expectation, we interacted in a single equation our two Covid measures ($Country\ Covid19_{c,t}$ and $Industry\ Covid19_{s,t}$). The coefficient of the interaction-term turns out to be negative, confirming that Covid-affected industries in Covid-affected countries were sold more.[24]

[24]The regression is necessarily performed either including the interaction-term (between $Country\ Covid19_{c,t}$ and $Industry\ Covid19_{s,t}$) and all time-varying fixed effects but excluding the separate components of the interaction-term (that is, the two separate variables $Country\ Covid19_{c,t}$ and $Industry\ Covid19_{s,t}$) or including the interaction-term and the two components but excluding time-varying fixed effects (and adding time, country, and industry as non-interacted fixed effects). All unreported results of Section 6 are available from the authors upon request.

The role of government responses

Results remain unchanged when we include as additional regressors in Equation 1 variables that capture government responses to the crisis. To this purpose, we used the indices provided by the University of Oxford that measure governments' responses to the pandemic in 190 countries during the period of the disease's spread (Hale et al., 2020).[25] The inclusion of these indices could affect our results if, for example, the variable $Country\ Covid19_{c,t}$ were also capturing (in addition to the Covid health emergency impact across countries) the effect of measures taken by governments, because major public interventions are correlated to major Covid effects. Their inclusion could also affect our results on the April rebound effect if it were due to government policies rather than to the unconventional policy measures. Instead, while the indices of government responses are hardly significant, their inclusion as additional regressors does not change the effect of our variables of interest.

Placebo tests

To obtain placebo tests of our results, we repeated the same regressions of Equations 1 and 2 over different spans, by artificially linking our Covid-19 measures to the months of January and February 2020, before the outbreak of the pandemic, instead of March and April. The results confirm there is no statistically significant relationship between changes in the portfolio allocation of MFs and the fake Covid-19 measures.

Alternative proxies and other control variables

Several checks were devoted to the use of alternative proxies. First, all results remain unchanged when the dependent variable $Net\ purchases_{i,f,t}$ is scaled by the net asset value (NAV) at

[25]The University of Oxford provides a set of indices through the Oxford Covid-19 Government Response Tracker (OxCGRT). Data are available through the GitHub repository. The indices capture dimensions such as closures and containment actions (e.g., school or workplace closures, or cancellation of public events); economic measures (e.g., income support or debt/contract relief); and health measures (e.g., testing or contact tracing).

the beginning of the sample period, instead than at the end of the previous month. Second, all results remain unchanged when we exclude the smallest MFs (i.e., those with a NAV of less than 20 million euros, which correspond to the 5^{th} percentile of the NAV distribution). Third, regarding the estimation of Equation 1, results are stable when we compute the two $Country\ Covid19_{c,t}$ measures as monthly *averages* of the daily data, instead than as monthly *sums* of the daily data for each country.

Fourth, regarding the estimation of Equation 2, as mentioned, the variable $Industry\ Covid19_{s,t}$ was not computed by Koren and Pető (2020) for the public sector, because the Covid vulnerability of the public sector is deemed to relate to country characteristics more than to specific industry features. However, to check the robustness of results when the public sector is included in the estimations, we carried out two exercises ascribing conventional values to the variable for the public sector and controlling these conventional values through a specific dummy equal to one for the public sector. The conventional values were alternatively either the average value across the industries of the country or the value of the industry of administrative services. Results of $Industry\ Covid19_{s,t}$ remained always negative (as in the baseline estimations), and the coefficient of the dummy public sector was negative as well.

7. Conclusions

This work exploits the heterogeneous impact of the Covid-19 outbreak across countries and industries to conduct a comprehensive analysis of MFs' portfolio decisions, benefiting from two advantages over the previous literature: the opportunity to make use of an undoubtedly exogenous shock and the possibility to utilize a massive and granular database that allows us to apply a robust identification strategy and a worldwide perspective. Our results contribute to the broad debate on MFs in several ways. First, we show that Covid-19 triggered a global rebalancing of MF portfolios, which focused on financial assets that were considered more at risk in the period, that is, those issued in countries and industries more affected by the pandemic, regardless of other intrinsic characteristics, which corroborates the concern that MFs, especially during crises, can push asset prices away from fundamentals. Second, we show that MFs with more unitholder outflows disproportionately increased sales of holdings exposed to the Covid shock, which supports concerns that MFs are fragile institutions that, rather than mitigating investor reactions, amplify run-like risks and sell-off events. Third, however, we provide evidence that globally investing MFs did not overreact when invested abroad, and thus foreign MFs are not a source of additional concern. Fourth, and most importantly, we document that MFs include very heterogeneous institutions that behaved differently in the crisis depending on their investment policies, return abilities and asset holdings. In particular, we show that at the emergency outbreak high-performing funds did not follow the herd or the fears of their unitholders, which suggests that some well-managed MFs are able to stand out even during panic phases. Fifth, we show that monetary policy interventions induced a rebound effect in MF purchases, which suggests that monetary authorities can act through non-bank financial institutions and help stabilize the effects of their fragility.

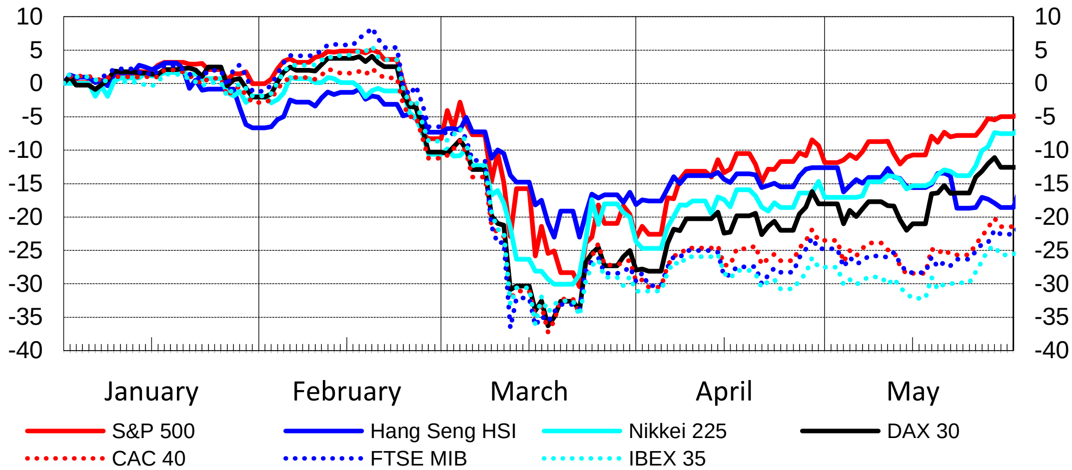

Figure 1: Stock market returns at the Covid-19 pandemic outbreak. The figure shows the cumulative stock market returns of some countries. (Source: Morningstar Direct).

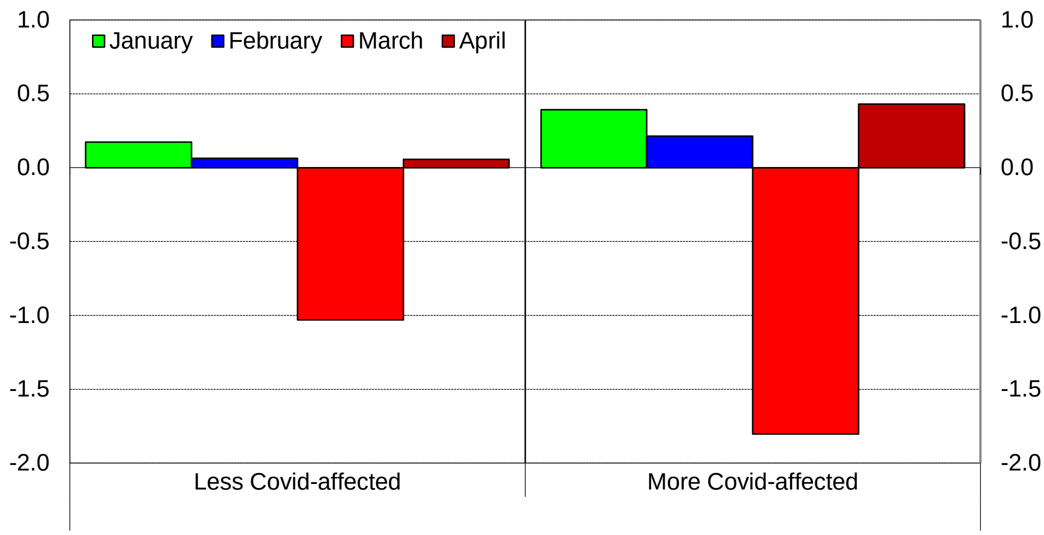

Figure 2: Net purchases of financial assets and Covid exposure. For all mutual funds in our sample, the figure shows monthly net purchases of securities issued in both less and more Covid-affected countries. (Source: Morningstar Direct).

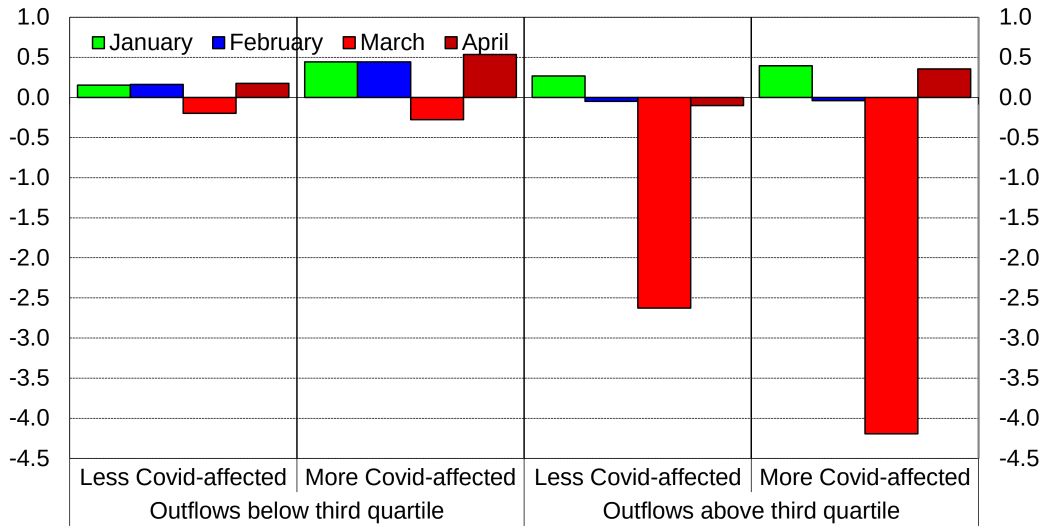

Figure 3: Net purchases of financial assets, Covid exposure and mutual fund outflows. For all mutual funds in our sample, the figure shows monthly net purchases of securities issued in both less and more Covid-affected countries, distinguishing between mutual funds with low and high outflows. (Source: Morningstar Direct).

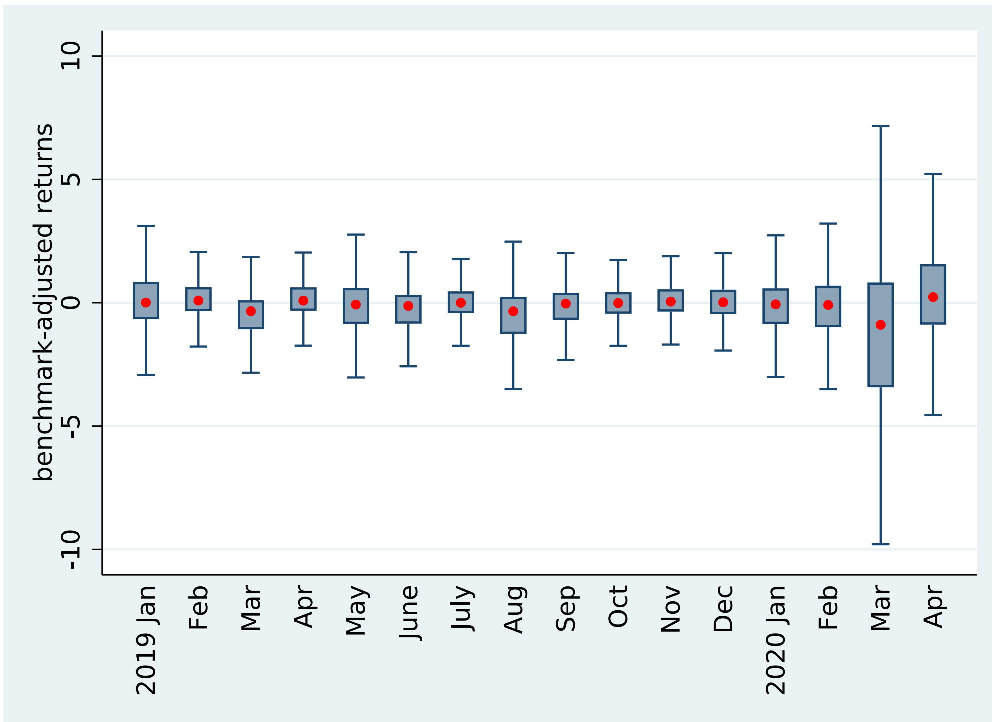

Figure 4: Benchmark-adjusted returns. For all mutual funds in our sample, the figure shows the benchmark-adjusted returns at monthly frequency from January 2019 to April 2020. Benchmark-adjusted returns are computed for each mutual fund as the difference between its monthly net returns and the specific benchmark return provided in the Morningstar dataset for its category, among 300 asset categories. Red dots indicate the average of benchmark-adjusted returns for all mutual funds in the sample; istograms indicate the interquartile distribution; lines indicate the full distribution. (Source: Morningstar Direct).

Table 1: **Summary statistics**

The table reports summary statistics (percentage shares) of the key variables used in the analyses. See Table A1 in the Appendix for variable definitions.

VARIABLES	mean	sd	p5	p25	p50	p75	p95	count
Pre Covid-19								
net purchases/NAV	0.0022	0.2086	-0.0949	0.0000	0.0000	0.0000	0.118	6,359,181
revaluations/market value	-2.0361	7.4683	-15.1475	-5.7212	0.0000	1.7878	7.4251	5,556,971
revaluations/NAV	-0.0107	0.069	-0.0961	-0.0031	0.0000	0.0006	0.027	6,359,181
confirmed cases/population	0.0001	0.0006	0.0000	0.0000	0.0000	0.0000	0.0002	6,879,766
deaths/population	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	6,879,766
affected share	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	3,958,012
Post Covid-19								
net purchases/NAV	-0.0057	0.245	-0.2276	0.0000	0.0000	0.0000	0.179	5,876,498
revaluations/market value	-2.4218	15.399	-32.8691	-9.4977	0.0000	5.2297	22.0331	5,564,463
revaluations/NAV	-0.0124	0.1062	-0.1788	-0.0067	0.0000	0.0028	0.1036	5,876,498
confirmed cases/population	0.1155	0.1053	0.0014	0.0333	0.06	0.223	0.2675	6,833,431
deaths/population	0.0084	0.0105	0.0000	0.001	0.0022	0.0177	0.0314	6,833,431
affected share	33.9217	17.3186	13.0000	21.0000	29.0000	46.0000	71.0000	3,958,012

Table 2: **Summary statistics at industry level**
The table presents summary statistics for the industries with the highest number of securities (more than two-thirds of our sample) in our data. The table reports the three-digit NAICS codes of the industries, their description, and the number of securities in each industry. In addition, the table shows KP's $affectedshares$, as defined by Koren and Pető (2020), and the average net purchases and revaluations, both scaled by the NAV at the end of the previous period. (Source: Koren's website and Refinitiv-Datastream).

NAICS	description	holdings	KP	net purch.	reval.
325	Chemicals	324,218	21	0.0031	0.0066
334	Computer and electronic products	274,786	13	0.001	0.0018
541	Professional and technical services	225,990	23	0.0029	-0.0048
221	Utilities	220,796	46	0.0012	-0.0173
531	Real estate	209,992	52	-0.0071	-0.0218
523	Securities, commodity contracts, investments, and funds and trusts	198,942	29	-0.0011	-0.0102
524	Insurance carriers and related activities	173,864	28	-0.0031	-0.0207
336	Transportation equipment	149,128	19	0.0007	-0.0221
517	Telecommunications	145,802	51	0.0001	-0.0092
333	Machinery	128,768	20	0.0032	-0.0105
511	Publishing industries, except Internet	106,590	16	0.0062	0.0087
236	Construction of buildings	98,760	24	-0.0074	-0.0148
311	Food manufacturing	93,318	23	0.0025	-0.0021
211	Oil and gas extraction	74,436	30	-0.0111	-0.0155
312	Miscellaneous nondurable goods manufacturing	72,796	37	0.0013	-0.0104
324	Petroleum and coal products	71,044	31	-0.0109	-0.0342
212	Mining, except oil and gas	68,010	71	0.003	-0.0034
339	Miscellaneous durable goods manufacturing	64,394	16	0.0001	0.0009
561	Administrative and support services	57,284	35	-0.0042	-0.0175
519	Other information services	52,830	24	0.0063	0.0039
331	Primary metals	49,822	34	-0.0047	-0.0146
515	Broadcasting, except Internet	49,350	35	-0.0022	-0.007
488	Support activities for transportation	48,440	45	-0.01	-0.0208
424	Wholesale trade: Nondurable goods	47,758	29	-0.001	-0.0084
445	Food and beverage stores	44,918	63	0.0085	0.0022

Table 3: **Net purchases of financial assets and the Covid-19 impact across countries**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of Covid-19 impact measures at country level and sets of fixed effects. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. Covid-19 deaths is the ratio of cumulative Covid-19 deaths to population in a given country-period. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Covid-19 cases	-0.0056***	-0.0058***	-0.0107***			
	(0.0019)	(0.0019)	(0.0023)			
Covid-19 deaths				-0.0756***	-0.0719***	-0.0562***
				(0.0163)	(0.0165)	(0.0179)
Public debt/GDP			-0.0000			0.0000
			(0.0000)			(0.0000)
GDP growth rate			0.0004**			0.0002*
			(0.0001)			(0.0001)
Fund × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	No	Yes	Yes	No	Yes	Yes
Fund Clustered Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,153,206	11,709,741	9,698,918	12,153,206	11,709,741	9,698,918
R^2	0.093	0.094	0.098	0.093	0.094	0.098

Table 4: **Net purchases of financial assets and the Covid-19 impact across industries**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of the KP's affected share (Koren and Pető, 2020) at industry level and sets of fixed effects. The KP's $affected\ share$ is an industry-level measure of the percentage of employees affected by the Covid-19 pandemic, due to their occupations being communication-intensive or requiring close physical proximity to others, or both. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

VARIABLES	(1)	(2)
Affected share	-0.0001***	-0.0001***
	(0.0000)	(0.0000)
Fund × Time FE	Yes	Yes
Country × Time FE	No	Yes
Fund Clustered Std. Errors	Yes	Yes
Observations	7,066,595	7,066,585
R^2	0.119	0.119

Table 5: **Net-purchases of financial assets and the Covid-19 impact across countries, by Covid exposure of initial portfolios**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at the fund-month level, as a function of the Covid-19 impact across countries and sets of fixed effects. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. Covid-19 deaths is the ratio of cumulative Covid-19 deaths to population in a given country-period. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

VARIABLES	(1)	(2)	(3)	(4)
Covid-19 cases × share (lag)	-0.1085***			
	(0.0091)			
Covid-19 deaths × share (lag)		-1.1483***		
		(0.0685)		
Covid-19 cases × portfolio Covid-oriented (lag)			-0.0110***	
			(0.0030)	
Covid-19 deaths × portfolio Covid-oriented (lag)				-0.0454***
				(0.0315)
Fund × Time FE	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes
Fund Clustered Std. Errors	Yes	Yes	Yes	Yes
Observations	8,392,534	8,392,534	11,278,036	8,708,169
R^2	0.108	0.105	0.0878	0.0903

Table 6: **Net-purchases of financial assets and the Covid-19 impact across industries, by Covid exposure of initial portfolios**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of KP's affected share (Koren and Pető, 2020) at industry level and sets of fixed effects. The KP's $affected\ share$ is an industry-level measure of the percentage of employees affected by the Covid-19 pandemic, due to their occupations being communication-intensive or requiring close physical proximity to others, or both. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

VARIABLES	(1)	(2)
Affected share × share (lag)	-0.0009***	
	(0.0001)	
Affected share × portfolio Covid-oriented		-0.0001***
		(0.0000)
Fund × Time FE	Yes	Yes
Country × Time FE	Yes	Yes
Fund Clustered Std. Errors	Yes	Yes
Observations	5,088,476	6,818,852
R^2	0.141	0.112

Table 7: **Net-purchases of financial assets and the Covid-19 impact across countries, by outbreak phase**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of Covid-19 impact measures at country level and sets of fixed effects. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. Covid-19 deaths is the ratio of cumulative Covid-19 deaths to population in a given country-period. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

VARIABLES	(1)	(2)
Covid-19 cases × Jan.	-0.4413	-0.2543
	(2.5543)	(2.5489)
Covid-19 cases × Feb.	-0.2014	-0.0902
	(0.1299)	(0.1294)
Covid-19 cases × Mar.	-0.0399***	-0.0372***
	(0.0049)	(0.0049)
Covid-19 cases × Apr.	0.0082***	0.0070***
	(0.0020)	(0.0020)
Fund × Time FE	Yes	Yes
Industry × Time FE	No	Yes
Fund Clustered Std. Errors	Yes	Yes
Observations	12,153,206	11,709,741
R^2	0.093	0.094

Table 8: **Net-purchases of financial assets and the Covid-19 impact across industries, by outbreak phase**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of KP's affected share (Koren and Pető, 2020) at industry level and sets of fixed effects. The KP's $affected\ share$ is an industry-level measure of the percentage of employees affected by the Covid-19 pandemic, due to their occupations being communication-intensive or requiring close physical proximity to others, or both. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

VARIABLES	(1)	(2)
Affected share × Mar.	-0.0001***	-0.0001***
	(0.0000)	(0.0000)
Affected share × Apr.	-0.0000***	-0.0000***
	(0.0000)	(0.0000)
Fund × Time FE	Yes	Yes
Country × Time FE	No	Yes
Fund Clustered Std. Errors	Yes	Yes
Observations	7,066,595	7,066,585
R^2	0.119	0.119

Table 9: **Net-purchases of equities and the Covid-19 impact across countries and industries, the role of issuing firm and market trend characteristics**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each equity at fund-month level, as a function of Covid-19 impact measures at country level, and of KP's affected share (Koren and Pető, 2020) at industry level, sets of fixed effects and issuing firm and market trend characteristics. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. The KP's *affected share* is an industry-level measure of the percentage of employees affected by the Covid-19 pandemic, due to their occupations being communication-intensive or requiring close physical proximity to others, or both. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Covid-19 cases × Jan.	-0.7221	-0.8448	7.9669		
	(3.0230)	(3.0717)	(45.2477)		
Covid-19 cases × Feb.	-0.2810**	-0.5182***	-1.0604***		
	(0.1397)	(0.1444)	(0.2061)		
Covid-19 cases × Mar.	-0.0193***	-0.0133*	-0.0364***		
	(0.0073)	(0.0074)	(0.0071)		
Covid-19 cases × Apr.	0.0021	-0.0021	-0.0076**		
	(0.0028)	(0.0029)	(0.0034)		
Affected share × Mar.				-0.0001***	-0.0000***
				(0.0000)	(0.0000)
Affected share × Apr.				0.0000	0.0000
				(0.0000)	(0.0000)
Firm Liquidity	0.0001***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm ROA	0.0000	-0.0000**	-0.0000**	-0.0000	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm Financial leverage	-0.0000***	0.0000	-0.0000	-0.0000***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm Total asset	-0.0002	-0.0003*	-0.0004*	-0.0002	-0.0003**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Stock return		0.0451***	0.0381***		0.0469***
		(0.0023)	(0.0023)		(0.0023)
Stock return volatility		-0.0582***	-0.0993***		-0.1228***
		(0.0128)	(0.0146)		(0.0141)
Public debt/GDP			-0.0000		
			(0.0000)		
GDP growth rate			0.0018***		
			(0.0002)		
Fund × Time FE	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	No	No
Country × Time FE	No	No	No	Yes	Yes
Fund Clustered Std. Errors	Yes	Yes	Yes	Yes	Yes
Observations	5,105,736	4,942,813	4,016,512	5,057,933	4,895,967
R^2	0.128	0.130	0.133	0.127	0.129

Table 10: **Net-purchases of financial assets and the Covid-19 impact across countries, the role of funds' outflows**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of Covid-19 impact measures at country level and sets of fixed effects. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. Covid-19 deaths is the ratio of cumulative Covid-19 deaths to population in a given country-period. Specifications (1) and (2) refer to the entire set of financial assets in our dataset; Specifications (3) and (4) to the subset of equities. Specifications (1) and (3) are aggregate specifications; Specifications (2) and (4) include interactions of regressors with month dummies. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

	(1)	(2)				(3)	(4)			
VARIABLES		Jan.	Feb.	Mar.	Apr.		Jan.	Feb.	Mar.	Apr.
Covid-19 cases	-0.0159***	-0.2026	-0.2486*	-0.0710***	0.0036	-0.0070**	1.4389	-0.5881***	-0.0166**	-0.0052*
	(0.0023)	(2.0145)	(0.1505)	(0.0058)	(0.0023)	(0.0031)	(2.4455)	(0.1721)	(0.0075)	(0.0031)
Outflows	-0.0029***	-0.0025***	-0.0035***	-0.0027***	-0.0027***	-0.0036***	-0.0032***	-0.0042***	-0.0035***	-0.0024***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0004)
Covid-19 cases × Outflows	-0.0017**	0.1106	0.1284	-0.0124***	0.0001	-0.0009	0.7502	0.1942**	-0.0155***	-0.0036***
	(0.0006)	(0.9152)	(0.0831)	(0.0019)	(0.0010)	(0.0010)	(1.1698)	(0.0921)	(0.0025)	(0.0013)
Fund Liquidity	0.0037***	0.0037***				0.0035***		0.0035***		
	(0.0002)	(0.0002)				(0.0004)		(0.0004)		
Firm Liquidity						0.0000***		0.0000***		
						(0.0000)		(0.0000)		
Firm ROA						-0.0001***		-0.0001***		
						(0.0000)		(0.0000)		
Firm Financial leverage						0.0000		0.0000		
						(0.0000)		(0.0000)		
Firm Total assets						-0.0007***		-0.0007***		
						(0.0001)		(0.0001)		
Stock return						0.0424***		0.0425***		
						(0.0023)		(0.0024)		
Return Volatility						-0.0671***		-0.0648***		
						(0.0133)		(0.0135)		
Fund FE	Yes		Yes			Yes		Yes		
Time FE	Yes		Yes			Yes		Yes		
Industry × Time FE	Yes		Yes			Yes		Yes		
Fund Clustered Std. Errors	Yes		Yes			Yes		Yes		
Observations	9,326,179		9,326,179			4,057,296		4,057,296		
R^2	0.024		0.024			0.027		0.027		

Table 11: **Net-purchases of financial assets and the Covid-19 impact across countries, distinguishing domestic and non-domestic MFs**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of Covid-19 impact measures at country level and sets of fixed effects. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. Covid-19 deaths is the ratio of cumulative Covid-19 deaths to population in a given country-period. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

	(1)	
	Residency	
VARIABLES	Non-domestic	Domestic
Covid-19 cases × Jan.	-0.3157	190.5417*
	(2.5505)	(109.3910)
Covid-19 cases × Feb.	-0.0812	-1.8544
	(0.1294)	(2.5961)
Covid-19 cases × Mar.	-0.0393***	-0.0306***
	(0.0052)	(0.0092)
Covid-19 cases × Apr.	0.0097***	-0.0010
	(0.0022)	(0.0029)
Fund × Time FE	Yes	
Industry × Time FE	Yes	
Fund Clustered Std. Errors	Yes	
Observations	11,709,741	
R^2	0.094	

Table 12: **Net-purchases of financial assets and the Covid-19 impact across countries or industries: the role of MF investment policy**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of Covid-19 impact measures at country level, KP's affected share (Koren and Pető, 2020) at industry level and sets of fixed effects. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. Covid-19 deaths is the ratio of cumulative Covid-19 deaths to population in a given country-period. The KP's *affected share* is an industry-level measure of the percentage of employees affected by the Covid-19 pandemic, due to their occupations being communication-intensive or requiring close physical proximity to others, or both. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

	(1)			(2)		
VARIABLES	MF investment category			MF investment category		
	Equity	Fixed-Income	Mixed	Equity	Fixed-Income	Mixed
Covid-19 cases × Jan.	-1.8351	3.6434*	79.2831			
	(3.2518)	(2.1839)	(75.8366)			
Covid-19 cases × Feb.	-0.0905	0.0136	4.1433			
	(0.1376)	(0.3167)	(17.2876)			
Covid-19 cases × Mar.	-0.0038	-0.0452***	-0.3852**			
	(0.0089)	(0.0057)	(0.1600)			
Covid-19 cases × Apr.	0.0019	0.0071***	-0.0876			
	(0.0030)	(0.0027)	(0.0859)			
Affected share × Mar.				-0.0001***	-0.0001***	-0.0002
				(0.0000)	(0.0000)	(0.0002)
Affected share × Apr.				-0.0000	-0.0001***	-0.0001
				(0.0000)	(0.0000)	(0.0002)
Fund × Time FE	Yes			Yes		
Industry × Time FE	Yes			No		
Country × Time FE	No			Yes		
Fund Clustered Std. Errors	Yes			Yes		
Observations	11,444,131			6,935,616		
R^2	0.096			0.119		

Table 13: **Net-purchases of financial assets and the Covid-19 impact across countries, the role MFs' performance ability**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of Covid-19 impact measures at country level and sets of fixed effects. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. Covid-19 deaths is the ratio of cumulative Covid-19 deaths to population in a given country-period. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

	(1)			(2)		
VARIABLES	Quartiles of adjusted returns			Quartiles of adjusted returns		
	Q1	Q2–Q3	Q4	Q1	Q2–Q3	Q4
Covid-19 cases × Jan.	9.7304***	0.2146	-2.0285	9.2889***	0.5427	-1.7177
	(2.4108)	(1.0745)	(5.0504)	(2.3817)	(1.0609)	(5.1186)
Covid-19 cases × Feb.	0.0704	-0.0343	0.0999	0.0673	-0.0506	0.0919
	(0.2363)	(0.1569)	(0.4749)	(0.2342)	(0.1588)	(0.4766)
Covid-19 cases × Mar.	-0.0616***	-0.0404***	-0.0100	-0.0605***	-0.0397***	-0.0094
	(0.0140)	(0.0062)	(0.0088)	(0.014)	(0.0062)	(0.0088)
Covid-19 cases × Apr.	0.0080	-0.0000	0.0146***	0.0086	-0.0002	0.0145***
	(0.0063)	(0.0023)	(0.0037)	(0.0063)	(0.0023)	(0.0037)
Outflows × Jan.				-0.00016***	-0.00017	0.0000
				(0.0000)	(0.0001)	(0.0000)
Fund × Time FE		Yes			Yes	
Industry × Time FE		Yes			Yes	
Fund Clustered Std. Errors		Yes			Yes	
Observations		9,921,165			9,843,687	
R^2		0.084			0.0785	

Table 14: **Net-purchases of financial assets and the Covid-19 impact across countries or industries: financial asset type rebalancing**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is net-purchases of each financial asset at fund-month level, as a function of Covid-19 impact measures at country level, KP's affected share (Koren and Pető, 2020) at industry level and sets of fixed effects. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. Covid-19 deaths is the ratio of cumulative Covid-19 deaths to population in a given country-period. The KP's *affected share* is an industry-level measure of the percentage of employees affected by the Covid-19 pandemic, due to their occupations being communication-intensive or requiring close physical proximity to others, or both. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

	(1)			(2)		
VARIABLES	Financial asset type			Financial asset type		
	Equity	Gov.Bonds.	Corp.Bonds	Equity	Gov.Bonds.	Corp.Bonds
Covid-19 cases × Jan.	-1.6809	7.9896	16.8253***			
	(2.7618)	(7.0397)	(5.3333)			
Covid-19 cases × Feb.	-0.2179*	1.3892	0.3579			
	(0.1322)	(1.0079)	(0.4656)			
Covid-19 cases × Mar.	-0.0810***	0.0049	0.0087*			
	(0.0087)	(0.0228)	(0.0048)			
Covid-19 cases × Apr.	0.0000	0.0087	0.0190***			
	(0.0028)	(0.0085)	(0.0031)			
Affected share × Mar.				-0.0001***	-0.0002**	-0.0002***
				(0.0000)	(0.0001)	(0.0000)
Affected share × Apr.				-0.0000***	-0.0004***	0.0000
				(0.0000)	(0.0001)	(0.0000)
Fund × Time FE	Yes			Yes		
Industry × Time FE	Yes			No		
Country × Time FE	No			Yes		
Fund Clustered Std. Errors	Yes			Yes		
Observations	11,709,741			7,066,585		
R^2	0.094			0.119		

Table 15: **Price revaluation of financial assets and the Covid-19 impact across countries, by outbreak phase**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is price revaluation of each financial asset at fund-month level, as a function of Covid-19 impact measures at country level and sets of fixed effects. Covid-19 cases is the ratio of cumulative confirmed Covid-19 cases to population in a given country-period. Covid-19 deaths is the ratio of cumulative Covid-19 deaths to population in a given country-period. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

VARIABLES	(1)	(2)	(3)	(4)
Covid-19 cases × Jan.	-9.2348***	-8.7181***		
	(0.8073)	(0.7970)		
Covid-19 cases × Feb.	1.5822***	1.6355***		
	(0.0932)	(0.0938)		
Covid-19 cases × Mar.	-0.0434***	-0.0326***		
	(0.0021)	(0.0020)		
Covid-19 cases × Apr.	0.0347***	0.0340***		
	(0.0010)	(0.0010)		
Covid-19 deaths × Jan.			-403.7270***	-378.5886***
			(37.0502)	(36.5327)
Covid-19 deaths × Feb.			90.0971***	93.2126***
			(5.7364)	(5.8223)
Covid-19 deaths × Mar.			-0.4133***	-0.3199***
			(0.0242)	(0.0239)
Covid-19 deaths × Apr.			-0.0026	-0.0134**
			(0.0052)	(0.0053)
Fund × Time FE	Yes	Yes	Yes	Yes
Industry × Time FE	No	Yes	No	Yes
Fund Clustered Std. Errors	Yes	Yes	Yes	Yes
Observations	12,153,206	11,709,741	12,153,206	11,709,741
R^2	0.476	0.477	0.476	0.477

Table 16: **Price revaluation of financial assets and the Covid-19 impact across industries, by outbreak phase**

The table reports OLS regression coefficients and associated robust standard errors in parentheses. The dependent variable is price revaluation of each financial asset at fund-month level, as a function of KP's affected share (Koren and Pető, 2020) at industry level and sets of fixed effects. The KP's *affected share* is an industry-level measure of the percentage of employees affected by the Covid-19 pandemic, due to their occupations being communication-intensive or requiring close physical proximity to others, or both. ***, **, and * indicate that the coefficient estimate is significantly different from zero at 1%, 5%, and 10%, respectively. See Table A1 in the Appendix for variable definitions.

VARIABLES	(1)	(2)
Affected share × Mar.	-0.0001***	-0.0001***
	(0.0000)	(0.0000)
Affected share × Apr.	-0.0002***	-0.0002***
	(0.0000)	(0.0000)
Fund × Time FE	Yes	Yes
Country × Time FE	No	Yes
Fund Clustered Std. Errors	Yes	Yes
Observations	7,066,595	7,066,585
R^2	0.463	0.469

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Appendix A.

Table A1: Variable definitions

Affected share	Industry-level measure of the percentage of employees affected by the Covid-19 pandemic, due to their occupations being communication-intensive or requiring close physical proximity to others, or both. The measure is based on the North American Industry Classification System (NAICS) (Source: Koren and Pető (2020))
Confirmed cases	Ratio of the number of cumulative confirmed Covid-19 cases to total population in country c in month t. (Source: Systems Science and Engineering, John Hopkins University)
Deaths cases	Ratio of the number of cumulative Covid-19 deaths to total population in country c in month t. (Source: Systems Science and Engineering, John Hopkins University)
Domicile	The country in which the fund is legally incorporated. (Source: Morningstar)
Fund Size	Total net asset value in EUR millions of the fund. (Source: Morningstar)
GDP growth rate	Annual growth rate of gross domestic product (GDP). (Source: OECD)
Firm Liquidity	Cash (i.e., currency and coins, negotiable checks, and balances in bank accounts) divided by total assets as of December 2019.
Firm Financial leverage	The book value of debt divided by the book value of total assets as of December 2019. (Source: Morningstar Direct)
Firm Return on Assets	The net income as a percentage of total assets at the end of December 2019. (Source: Morningstar Direct)
Firm Size	The natural logarithm of total assets as of the month of December 2019. (Source: Morningstar Direct)
Fund Liquidity	Cash (i.e., currency and coins, negotiable checks, and balances in bank accounts) divided by total net assets in previous month.
Net purchase	The actual transaction on each security in two subsequent months obtained as the difference between market value development and price revaluation. (Source: Morningstar)
Outflows	Morningstar calculates asset outflows and inflows for individual funds on a monthly basis, using an industry-standard approach: net flows is the change in assets not explained by the performance of the fund. Outflows is measured reversing the sign of net flows. (Source: Morningstar)
Price revaluation	Measured for each security as change in market price between two subsequent months on the overlapping quantity, i.e. $(p_t - p_{t-1}) * min(q_t, q_{t-1}$. (Source: Morningstar)
Public debt-to-GDP ratio	It measures the gross debt of the general government as a percentage of GDP. It is a key indicator for the sustainability of government finance. Debt is calculated as the sum of the following liability categories (as applicable): currency and deposits; debt securities, loans; insurance, pensions and standardised guarantee schemes, and other accounts payable. (Source: OECD)
Stock Return	The firm's stock return, computed in month $t-1$. (Source: Morningstar Direct)
Stock Return Volatility	The standard deviation of daily stock returns during month $t-1$. (Source: Morningstar Direct)
Total exposure (lag)	Total exposure of fund f into ISIN i in previous month. (Source: Morningstar)