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WHEN THE PANIC BROKE OUT: COVID-19 AND INVESTMENT FUNDS' PORTFOLIO REBALANCING AROUND THE WORLD

by Massimiliano Affinito* and Raffaele Santioni*

Abstract

To contribute to the understanding of investment funds' (IFs) behaviour, the paper exploits the exogenous shock of the Covid-19 pandemic and analyses more than 12 million security sales and purchases during the first four months of 2020 by over 20,000 IFs from more than 40 national jurisdictions and investing in more than 100 economies and 20 industries. Our estimates reveal that, when the emergency strikes, IFs do not sell indiscriminately but divest from assets considered the most vulnerable at the moment, that is, those issued by more Covid-affected countries and industries. Our results also show several dimensions of heterogeneity according to the pandemic outbreak phase, asset type, IF category and performance, extent of unitholders' outflows, and nationality of IFs. Our results, on the one hand, provide new evidence on the intrinsic fragility of IFs, but, on the other, they also show that IF industry includes heterogeneous institutions that behave very differently. Finally, our results document that monetary policy measures have a reassuring effect also for IFs, which corroborates recent evidence on a non-bank financial institution channel of unconventional monetary policies.

JEL Classification: G01, G12, G15, G32.
Keywords: coronavirus, investment funds, Morningstar holdings, pandemic, portfolio rebalancing, resilience.
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Contents

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1. Introduction[1]

Investment funds (IFs) have grown substantially since the global financial crisis, partly as a result of the increased regulation of banks. IFs hold a large fraction of world savings, purchase and sell securities all over the globe, and play a crucial role in the financing of governments and firms. The IF industry receives a great deal of attention from practitioners, academics, and institutions. Studying IFs' behaviour can help illuminate investor strategies, market functioning, and price developments. Moreover, since the financial crisis, the debate about IFs has also addressed their intrinsic fragility and the possible implications of their conduct for financial stability (e.g., Chen et al., 2010; Financial Stability Board, 2017; Goldstein et al., 2017).[2]

The Covid-19 crisis provides a valuable opportunity to gain insights into drivers of IF behaviour and strategies. Their responses and resilience may be tested by exploiting the impact of a major (and truly exogenous) worldwide shock.[3] In early 2020, the outbreak of the pandemic and the subsequent containment measures imposed in many countries caused a sudden and sharp deterioration in the economic outlook and heightened the risk aversion among investors, giving rise to a major re-pricing in global financial markets (Figure 1). In this paper, we exploit this shock to perform a comprehensive empirical analysis of the world IF industry. We have the advantage of using a unique, granular dataset, which contains more than 12 million observations on security sales and

[1]We would like to thank Giorgio Albareto, Rui Albuquerque, Emilia Bonaccorsi di Patti, Alessio De Vincenzo, Philip E. Strahan, Luca Zucchelli, and two anonymous referees, for useful comments and suggestions. We are also grateful to Morningstar for access to the Historical holdings dataset. We particularly would like to thank Emanuela Bassi (Sales Director) and Guillermo Gutierrez Santos at Morningstar Inc. for their invaluable advice. The views expressed in this article are those of the authors and do not necessarily represent those of Banca d'Italia.

[2]IFs often invest in illiquid assets and guarantee their investors high levels of liquidity, although (different from banks) IF investors are not guaranteed to receive a fixed amount when they withdraw their funds.

[3]The economic turmoil triggered by Covid-19 differs from past crises with respect to the cause, scope, and severity. Bernanke (2020) stresses that, while financial imbalances and risks grew over many years leading up to the 2008 global financial crisis, the Covid-19 crisis erupted abruptly.

purchases during the first four months of 2020 by over 20,000 IFs located in over 40 national jurisdictions and investing in more than 100 economies and 20 sectors. We believe ours is the first paper to assess IFs' portfolio reactions to Covid-19 worldwide as a function of the spreading news on the pandemic and to comprehensively depict their decisions when the shock arrived and the panic broke out.

We first show that the pandemic triggered portfolio recomposition by IFs all over the world. IFs do not sell indiscriminately but divest from financial assets considered at the moment most troubled, that is, those issued in countries and by industries more affected by Covid-19. We document that the bulk of the adjustment in IFs' portfolios occurs abruptly and severely during the "fever" of the Covid-19 crisis (that is, in March 2020), while signs of resurgence begin to appear already in April, following the exceptional policy measures taken worldwide by public authorities.

We then examine the portfolio rebalancing in more detail, exploring several dimensions of IF heterogeneity. First, we find that the rebalancing effect is homogeneous for domestic and foreign assets (revealing that IFs sell even their own country's securities if this allows them to move toward less-Covid affected portfolios). Second, we find that IFs with more outflows exacerbate the sales of securities issued in more Covid-affected countries (indicating that IFs and their unitholders may tend not to offset each other and thus may make fire sales more likely). Third, we find that the rebalancing is heterogeneous by type of financial asset and IF category (reflecting the greater impact of the pandemic on illiquid assets and the varying risk appetites embedded in investment policies of different IF categories). Fourth, we find that IFs with an average higher performance do not deleverage along with other IFs (suggesting that IF industry includes heterogeneous institutions, which pursue different portfolio strategies that partially balance each other). Fifth, we find that the rebound in April 2020 mainly concerns IF purchases of corporate bonds, which are, to a large extent, the financial asset targeted by central banks' programmes in the period (corroborating the existence and effectiveness of a channel of unconventional monetary policies acting through non-bank financial institutions).

Our empirical approach relies on two regression models, which analyse whether, in response to the Covid-19 shock, IFs reallocate their holdings across *countries* and *industries*. The viral outbreak and subsequent policy measures varied substantially across countries and industries, both in the intensity and timing. First, until late February, 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. Second, the effects of the Covid-19 and of the related containment measures were heterogeneous even within countries and 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.[4]

Our dataset is obtained by combining varied sources. Security-by-security information on portfolios of over 20,000 open-ended IFs worldwide is obtained by matching the Morningstar historical holdings data with the Centralised Securities Database of the European System of Central Banks. The exposures to the disease across countries are

[4] 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.

computed 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. The exposures to the disease across industries are computed through the indexes recently introduced in labour economics, 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 fund-by-fund and asset-by-asset granularity of our data allows us to include an extensive set of fixed effects in the estimations, in the spirit of Khwaja and Mian (2008), Paravisini (2008), Amiti and Weinstein (2018) and Degryse et al. (2019). 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 of IFs that may otherwise blur the results.

Our paper relates to some of the major strands of the literature on IF behaviour. Section 2 reviews this literature and summarizes our contribution. Our results on the massive sales of Covid-affected assets contribute to the literature stressing that, in time of crisis, IFs sell the most troubled assets, that is, those more likely to suffer fire sales. Our results on higher sales of Covid-affected assets by IFs with more redemptions offer new evidence on the relationship between the sales of institutional investors and those of their unitholders. Our results on the contrasting reactions of IFs with different investment policies and performance abilities show that IF industry is not monolithic and financial stability implications may change across IF categories. Our results on the impact of policy measures suggest that central bank liquidity injections are an effective financial stability tool that can help reduce the fragility of non-bank financial institutions too. In addition, our paper complements the fast growing literature on stock markets' reactions to the outset of the Covid-19: this literature typically finds that pandemic-resilient issuers suffer less during the outbreak, we show that IFs prioritize the pandemic resilience of the issuers.

The rest of the paper is structured as follows. Section 2 reviews the main literature relating to the paper and clarifies our contribution. Section 3 describes the data. Section 4 discusses the empirical methodology. Section 5 reports the baseline results. Section 6 summarizes our extensions. Section 7 describes robustness checks. Section 8 concludes.

2. Related Literature: review and contribution

Our paper comprehensively analyses IFs' behaviour at the outbreak of the panic surrounding Covid-19 and relates to several strands of the literature.

First, it contributes to the literature that analyses the behavior of IFs to understand their investment strategies and the ultimate impact on price developments. Three particular themes traditionally examined by this literature are herding, positive-feedback or trend chasing, and short horizons. Herding refers to the tendency of buying (or selling) simultaneously the same stocks as other institutional investors. Positive-feedback trading or trend chasing refers to the habit of buying past winners and selling past losers. Short horizons refers to the lack of foresight that is traditionally attributed to IFs. These three aspects are elements of the overall argument that IFs can destabilize stock prices, because they tend to jump on the bandwagon and buy overpriced stocks or sell underpriced ones, pushing prices away from fundamentals, especially during crises.[5]

[5]The literature argues that institutional investors "herd" because they prefer trading with the crowd,

These issues relates also to the literature on fire sales, which shows that, especially during financial crises, institutional investors contribute to depressing the prices of the securities they hold (e.g., Manconi et al., 2012; Ben-David et al., 2012; Cella et al., 2013), leading to fire sales (Gabaix et al. (2006); Stein (2009)). In this respect, Coval and Stafford (2007) show that common ownership by institutional investors increases the downward pressure on stock prices during asset fire sales. Greenwood and Thesmar (2011) show that firms whose equities are widely held by institutional investors are more susceptible to nonfundamental shifts in demand. Koijen et al. (2020) show how changes in portfolio holdings influence market valuations.

Our paper contributes to these streams of the literature by confirming, on the one hand, that IFs massively sell assets considered the most troubled in the early pandemic period, that is, those issued by Covid–affected countries and industries (even irrespective of other intrinsic characteristics), thus contributing to increase the likelihood of fire sales. But, on the other hand, our results (both those of sales of more affected assets in March and rise of purchases in April) are also consistent with an opposing view of institutional investors as rational investors who pursue not a positive-feedback strategy but a negative-feedback strategy, that is, they sell stocks that have risen too far and buy those that have fallen too far (e.g., Lynch and Musto, 2003; Manconi et al., 2012; Spiegel and Zhang,

rather than facing the reputational risk of making mistakes alone, or simply because they receive correlated private information, perhaps from analyzing the same indicators (Lakonishok et al., 1992; Grinblatt et al., 1995; Daniel et al., 1997; Sias and Starks, 1997; Nofsinger and Sias, 1999; Graham, 1999). Regarding positive-feedback, the strategy of buying winners and selling losers relates to the belief that trends are likely to continue or to the idea that adding winners to the portfolio and eliminating losers has the advantage of "window dressing" (De Long et al., 1990; Lakonishok, 1991). Regarding short horizons, IFs are expected to trade over short spans because their optimal response is to attempt to beat the market by selling immediately. Thus their trading tends to drive prices below fundamental values (Bernardo and Welch, 2004; Morris and Shin, 2004). Several influential theoretical papers show that short-horizon investors specialize in strategies that focus on predicting the short-run trades of other market participants, rather than long-run movements in asset values driven by fundamentals (De Long et al., 1990; Froot et al., 1992; Dow and Gorton, 1994; Stein, 2005; Allen et al., 2006). In contrast, long-horizon investors tend to hold their shares and "wait out the storm". They typically include insurance companies, pension funds, and trusts (e.g., Bessembinder and Maxwell, 2008).

2013; Schmidt et al., 2016; Pastor et al., 2021; Jin et al., 2021). Most importantly, we find heterogeneous results according to the pandemic outbreak phase, asset type, IF category, performance ability, and nationality. All in all, our results offer a more nuanced view of IFs: we find they are neither smart negative-feedback investors nor destabilizers who herd and chase trends. Instead, they turn out to include heterogeneous institutions, which use a variety of portfolio strategies that at least partially offset each other (Lakonishok et al., 1992; Kacperczyk and Schnabl, 2013; Zeng, 2017; Zhu, 2021; Pastor et al., 2021; Jin et al., 2021).

Second, the paper contributes to the literature on the relationship between sales of institutional investors and the behaviour of their unitholders. In addition to being investors (who invest in financial assets on the asset side of their balance sheets), IFs are also funded agents (who receive financing on the liability side of their balance sheet). Of course, IF asset-side decisions may well relate to liability-side developments. The literature (e.g., Coval and Stafford, 2007; Baker et al., 2003; Duchin et al., 2010; Hau and Lai, 2013; Cella et al., 2013) points out that IF managers tend to expand their holdings with capital inflows and liquidate positions to pay for redemptions; such flow-induced trading can significantly impact both individual stock returns (contributing to driving prices temporarily away from information-efficient benchmarks) and the real investment decisions of firms (which may be shaped by non-informative, liquidity-motivated trading). We find that IFs with more redemptions intensify their sales of Covid-affected assets, and therefore our results corroborate the view that IFs may increase market volatility during times of turmoil because they face the risk of having to respond to massive (often retail) redemptions (e.g., Simutin, 2014; Barrot et al., 2016; Chernenko and Sunderam, 2020; Li et al., 2020).[6]

[6]Even if this is not the case in all systems, in many countries (such as the United States), the bulk of IF shares/units is held by retail investors and, in particular, households; the pressure caused by capital flows

Third, our paper contributes to the literature on market timing and the stock-picking of institutional investors, which has practical implications for investors and theoretical implications for market efficiency. Most studies find little evidence that IFs possess market timing ability (that is, the ability to increase the exposure to the market index prior to market advances and to decrease exposure prior to market declines; e.g., Henriksson, 1984; Graham and Harvey, 1996; Becker et al., 1999; Jiang, 2003). In contrast, the findings on the stock-picking talents (that is, the ability to select outperforming assets) are mixed. A number of traditional studies conclude that mutual funds' performance on average falls short of a set of passive benchmarks (e.g., Jensen, 1968; Elton, 1993; Gruber, 1996; Carhart, 1997), while many other papers find that some mutual funds can choose stocks that outperform benchmarks, even after accounting for expenses and fees (e.g., Grinblatt and Titman, 1989; Grinblatt and Titman, 1993; Grinblatt et al., 1995; Kacperczyk and Seru, 2007; Jiang et al., 2007; Kacperczyk et al., 2008; Fama and French, 2010). Our evidence confirms, on the one hand, that on average IFs do not beat market benchmarks, and indeed we find that they perform even worse during the early phase of the pandemic. However, on the other hand, some IFs do stand out from the others, both in the pre-pandemic year and in the outbreak phase.

Fourth, our work relates to the literature on the stock market's response to the onset of the Covid-19 pandemic, which shows equity prices reactions to news about the virus and an increase in market volatility.[7] Our analysis differs and complements this literature, which typically takes the point of view of security issuers and investigates the

tends to be stronger when it originates from retail investors (Lou, 2012). Moreover, the literature shows that mutual fund shareholders, even when they are not retail investors, behave in ways generally considered unsophisticated (e.g., Solomon et al., 2014; Kaniel and Parham, 2017).

[7]In particular, Acharya and Steffen (2020) provide evidence that firms with access to liquidity perform better during the first quarter of 2020. Ramelli and Wagner (2020) show that non-financial firms with high exposure to China and greater dependence on international trade as well as with lower cash holdings and higher leverage are more affected than other firms. Hassan et al. (2020) find that stock returns relate significantly and negatively to disease exposures. Alfaro et al. (2020) show that stock prices drop in response to high unexpected infections. Albuquerque et al. (2020) show that stocks with high environmental and social

characteristics of funded agents that are more likely to amplify or mitigate the pandemic effect. We instead take the point of view of investors that finance those agents. This literature typically finds that pandemic-resilient firms suffer less, we show that investors consider the pandemic resilience of issuers (countries and industries) in allocating their funds.[8]

Finally, our paper contributes to the debate on policy implications of IF fragility. In particular, our paper relates to a few recent studies addressing the issue of IF fragility in the Covid- crisis (Falato et al., 2020; Haddad et al., 2020; Ebsim et al., 2020; Pastor et al., 2021) and shows that IF portfolio allocation can increase the volatility of financial markets following a shock. However, our results suggest that policy measures taken by monetary authorities after the outbreak of the panic provided a liquidity backstop that reassured non-bank financial institutions (Falato et al., 2020, Gilchrist et al., 2020, and Boyarchenko et al., 2020; O'Hara and Zhou, 2021).

3. Data

We build a novel dataset, which combines several sources. After combining all the sources and eliminating observations with partial information, we end up with a unique dataset containing more than 12 million observations on security-by-security sales and purchases during the first four months of 2020 by more than 20,000 IFs from more than 40 national jurisdictions and investing in more than 100 economies and 20 industries.

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ratings have significantly higher returns and lower volatility. Pagano et al. (2020) document that stocks of more pandemic-resilient firms outperform those with lower resilience during the outbreak. Ding et al. (2020) show that firms with stronger balance sheets and less exposure to Covid-19 perform better during the first quarter of 2020.

[8]Glossner et al. (2020) is the only other paper that analyses changes in holdings of institutional investors. However, they only consider the percentage shares of stocks held by institutional investors for a sample of US firms and study whether the changes of those percentages relate to specific firm characteristics during the outbreak of the pandemic. In contrasts, we examine the entire ISIN-by-ISIN portfolio of a massive set of IFs worldwide, and we explicitly investigate whether the pandemic outbreak itself steers the selection of financial assets.

Our final dataset is well representative of the global IF industry, as it corresponds to about 40% of the worldwide IFs' total net assets, according to official statistics (EFAMA, 2020).[9] The dataset's representativeness is very high for all countries with a major IF industry.[10]

Our dataset draws from four sources. The main one is Morningstar's database of historical holdings, which contains portfolio holdings at IF and security-by-security level for the entire universe of "actively managed" open-ended IFs in the global market.[11] We retrieve monthly ISIN-by-ISIN portfolio information from December 2019 to April 2020 for all IFs that provide all ISIN-by-ISIN data in each month of our analysis. We also draw from the Morningstar database the investment objective and legal domicile of each IF.[12]

The second data source is the Centralised Securities Database (CSDB) of the European System of Central Banks (ESCB), a security-by-security database developed by the ECB and jointly operated by the National Central Banks (NCBs) of the ESCB. The CSDB contains reference, price, rating, and statistical classification data for more than 5 million active debt securities, equity shares, and investment fund units issued worldwide.[13] We use the CSDB as a register to decrypt and classify IFs' ISIN-by-ISIN hold-

[9]According to (EFAMA, 2020), the entire universe of long-term funds (those classified as equity, bond, and mixed) amounted at the end of the first quarter of 2020 to about € 36,000 billion.

[10]The final representativeness is around 40% of total net assets of the country for IFs coming from 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.

[11]"Actively manged funds" follow an active market strategy as opposed to "passive funds", such as exchange traded funds or index funds, which mechanically follow the index they track. Due to their large differences from the other IFs, passive funds as well as money market funds are not included in our analysis.

[12]Therefore we exclude necessarily (only) those 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 IFs.

[13]The CSDB contains information on all individual securities, provided that they are either issued by EU residents or denominated in euros or held or transacted by EU residents. It therefore contains almost all securities in the world. 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.*

ings under three dimensions of the issuer: country, sector of economic activity, and category of financial instrument.

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.[14]

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 *affectedshare*, 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.[15] 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

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

[15]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.

industries for which the measures on the vulnerability to the Covid-19 crisis are unavailable, we carry out several robustness checks (described in Section 7).[16]

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 IF in each month from January to April 2020. We therefore can distinguish exactly the portfolio changes due to the market price revaluation effect from those due to the actual financial transactions.[17]

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). In the pandemic period, IFs experience large decreases both in the market values of their security holdings and in the actual net purchases. Also the dispersion of all variables across IFs increases during the Covid-19 shock. 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. All measures show a wide heterogeneity (across countries and industries) after the Covid-19 outbreak. 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).

[16]As mentioned, we use the CSDB as a register to decrypt and classify IFs' ISIN-by-ISIN holdings. However, the CSDB provides NACE codes, while the KP metric is based on three-digit NAICS classifi-cation. 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.

[17]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 are provided in Table A1.

4. Empirical strategy

To evaluate whether, to what extent, and how IFs react to the Covid-19 outbreak and rebalance their portfolios, we estimate two regression models. The first model analyses the Covid-19 impact in driving the selection of financial assets by country (controlling for industry specific characteristics). The second model investigates the Covid-19 impact in influencing the selection of 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 IF f in each month t, scaled by the net asset value of the same IF 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 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 IF (each i may belong to only one country c.)

Exploiting the granularity of our dataset, we conduct our estimates by including interactions between different sets of fixed effects: $\delta_{f,t}$ are interactions between time and IF fixed effects, while $\phi_{1\,s,t}$ are interactions between time and industry fixed effects. The inclusion of the around 90,000 fund-time fixed effects ($\delta_{f,t}$) and the 80 industry-time fixed effects ($\phi_{1\,s,t}$) conditions out all time-varying factors across funds and industries and is therefore the most effective control for accounting for other (different from the Covid-19) risks and demand conditions that might influence IF decisions and to allow for possible unobservable characteristics of securities and IFs that could otherwise blur the results. In particular, the time-varying IF 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 IFs may systematically invest in securities involving different levels of risk. Moreover, $\delta_{f,t}$ also controls for the country of origin of each IF and therefore conditions out all time-varying and time-invariant cross-country traits, such as differences in economic, financial, institutional, legal, and regulatory systems. 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). Finally, since we allow these effects to vary over time, they account for the rapid deterioration in the global financial markets during our sample period. Equation 1 is estimated with robust standard errors by IF-level clustering, as portfolio choices may vary across IFs.

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 IF (and thus each i belongs to only one industry s).[18] 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 IFs invest, such as differences in growth, economic

[18] 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.

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 IF).

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 Covid-19 impact across countries; while 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 Covid-19 impact across industries. In some specifications, to further explore whether and how IFs respond to the pandemic, we interact our Covid-19 measures with different IF individual characteristics (still controlling for economy-time, industry-time and fund fixed effects).

5. Baseline results

Table 3 reports results of Equation 1. In Specifications (1)-(3), the key regressor $Country\ Covid19_{c,t}$ is the ratio of the number of cases to population, while in Specifications (4)-(6), it is the ratio of the number of deaths to population. For each measure, the first two specifications progressively include the different sets of time-varying fixed effects, while 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).

The results show that the coefficient of the variable of interest $Country\ Covid19_{c,t}$ is always significantly negative, which means that the pandemic outbreak leads IFs to sell mainly financial assets issued by more affected countries and thus to rebalance their portfolios in favour of assets issued from less affected ones. The economic impact is also relevant: for example, moving from the 25th to the 75th percentile of the Covid cases of specification (2), 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.

Table 4 reports results of Equation 2. The table reports two specifications progressively adding the sets of time-varying fixed effects. Again, the coefficient of the variable of interest $Industry\ Covid19_{s,t}$, which is now the index of the pandemic impact across industries, is statistically negative, meaning that, after the shock, IF portfolios move toward financial assets issued by less affected industries. The magnitude is again economically relevant: moving from the 25^{th} to the 75^{th} percentile of the KP metric distribution, the asset experiences an extra 40 percent drop, compared to the average net purchases.

For a more exact identification of the moment in which IFs' sales react to the Covid-19 shock, we repeat estimations of Equations 1 and 2, allowing the effects to vary over time through interaction-terms between our Covid indexes and time dummies.[19] At the country level (Table 5) during the "incubation" and the "outbreak" periods (i.e., January and February, respectively, using the terminology of Ramelli and Wagner, 2020), the Covid-19 impact variables are not statistically significant, suggesting that IFs were not yet rebalancing their portfolios in response to pandemic risk. By contrast, during the "fever" of the virus (i.e., in March), the Covid-19 impact becomes statistically significant both at the country (Table 5) and industry level (Table 6). 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 5) and a sharp reduction of the Covid-19 impact at the industry level (Table 6). Although the exposures remain lower than in the pre-pandemic period, the result of April, after the very first trigger of the pandemic in March, 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

[19] 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 of zero values).

the next section, analysing which kinds of assets were more hit by sales of March and which benefited more from the rebound of April.

To illuminate the portfolio rebalancing, a related question is whether the Covid impact is larger for more exposed portfolios; that is, whether the net sales of more Covid-affected securities are amplified by IFs with greater initial percentage shares of (ex post) Covid affected securities and by IFs with more (ex post) Covid-oriented portfolios. To test this hypothesis, we run 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 IF 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 are in IF portfolios, the more they are sold when the pandemic breaks 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 IF 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.[20] If this interaction term were negative, it would indicate that, the more the IF portfolios were Covid-oriented, the more the IFs 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 7 and 8), which confirms even more that the sales were not indiscriminate but were concentrated among Covid-affected assets and helped rebalance IF portfolios.

[20] 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.

6. Extensions

To further explore the issue of IF portfolio rebalancing and behaviour during the shock, we extend the baseline models to investigate whether IF reactions are heterogeneous across types of assets and categories or characteristics of IFs. Specifically, we estimate a slight different version of Equations 1 and 2, basically adding interactions between new regressors (which capture specific aspects of holdings or IFs) 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, while in the baseline estimations our empirical approach allows us to control 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, here the scope is different. Here, we aim to verify whether and how the differences matter, that is, whether and how the portfolio rebalancing changes across assets or IFs. Moreover, as we detail in the following analysis, the use of interactions allows us to carry out these analyses without reverting to the sets of fixed effects of our baseline approach.

Domestic versus foreign rebalancing

The sales of Covid-affected securities might be amplified when the country of residence of financial asset issuers differs from the country of domicile of IFs, for example, because IFs could have less confidence in foreign investments during a crisis. To test this possibility, we repeat estimations of Equations 1 and 2, augmenting the model with two dummies, identifying domestic and foreign securities, and interacting these dummies with our variables of interest in each month (both $Country\ Covid19_{c,t}$ and $Industry\ Covid19_{s,t}$). The exercises 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). Table 9, in column (1), reports results of the exercise for Equation 1.[21] The coefficients of the interaction terms between our Covid-impact measures and the two (domestic and non-domestic) dummies are always negative in March, and the magnitude is very close. This means that the pandemic shock prompts IFs to sell Covid-affected securities, regardless of where they are issued (i.e., both by domestic and foreign agents), and therefore on average IFs sell even their own country's securities if this rebalances their portfolios toward less-Covid affected holdings. On the other hand, interestingly, the regression shows that the positive result of April is totally driven by non-domestic purchases, which are therefore the first ones to recover after the initial shock. This result clashes with a stream of the literature that points out that foreign investors may have a destabilizing effect, because they overreact or are prone to financial panic (Dornbusch and Park, 1995; Radelet and Sachs, 1998; Choe et al., 1999), but it comports with Glossner et al. (2020), who find the stock price drop is more pronounced for firms held by local (U.S.) investors.

Rebalancing according to the funds flowing out of IFs

As mentioned, the literature on IFs stresses that funds encountering more redemption requests might be forced more than peers to sell. Accordingly, at the outbreak of the Covid crisis, IFs behaviour might reflect at least partially the point of view of their unitholders, who may panic and may want to quickly unload Covid-affected securities. In the baseline estimations, our empirical approach allows us to control for the specific differences in IFs policies and developments and thus also for specific differences in reimbursements. Instead, here we estimate a different version of Equations 1 and 2, verifying exactly whether IFs with larger redemptions by their unitholders sell more Covid-affected securities.

[21] As for Equation 2, the exercise provides very similar outcomes, and, for brevity's sake, it is not reported.

To verify this hypothesis, it is sufficient to add in both Equations 1 and 2 the covariate $outflows_{f,t}$, which measures, for each IF, the amount of withdrawals in the period. These estimations are necessarily run replacing the time-varying IF fixed effects $\delta_{f,t}$ with two additive components (IF and time fixed effects), which control for time-invariant characteristics at the fund level and time-variant general developments. The results (reported in Table 10) show that the coefficient of $Country\ Covid19_{c,t}$ remains negative as in the baseline estimations, and the coefficient of $outflows_{f,t}$ is negative as well, confirming that IFs characterized by more withdrawals sell more when the pandemic breaks out. Notably, the interaction term between $Country\ Covid19_{c,t}$ and $outflows_{f,t}$ is also significantly negative, meaning that IFs with more outflows exacerbate the sales of securities issued in more Covid-affected countries. In other words, IFs seem to second their financiers by rebalancing more when their unitholders are more concerned. On the other hand, in the estimation of Equation 2, the coefficients of the variables $Industry\ Covid19_{s,t}$ and $outflows_{f,t}$ are negative, while the coefficient of the interaction term is statistically and economically insignificant, suggesting that unitholders' inputs affect the selection of countries more than of industries.[22]

Rebalancing across IF categories: the role of IF investment policy

To verify whether and how different IF categories behave differently, we split IFs in our sample, according to the prevailing assets in which they invest, which reflects the differing risk appetites embedded in their investment policies. We detect three groups of IFs (equity, fixed income, and mixed funds), which are identified through three dummies. Then we interact the dummies with our variables of interest in each month. From a methodological point of view, as mentioned, here the scope is not to estimate an "all things being equal" result but to explore whether and in which direction IF categories

[22]The results on $outflows_{f,t}$ by industry are unreported but available from the authors.

matter. The results are reported in column (1) of Table 11 at the country level and in column (2) of Table 12 at the industry level. They show that IF categories indeed do matter, as groups characterized by different investments and risk appetites react heterogeneously to the crisis: mixed and fixed income IFs rebalance mainly by country, while equity IFs rebalance mainly across industries. This is consistent with the underlying policies: the former ones are more interested in government bonds and thus rebalance by country, while equity IFs are more concerned with firms and thus rebalance mainly across industries.

Rebalancing across IF categories: the role of IF performance ability

To explore whether IF performance ability matters in the pandemic crisis, we proceed in two ways. First, we compute at monthly frequency, from January 2019 to April 2020, a measure of IF benchmark-adjusted returns, which are the excess returns with respect to a market benchmark. Specifically, we compute, for each IF, 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 our dataset from Morningstar, IFs are classified into more than 300 asset categories, and for each of category, a market benchmark is provided, so we can use 300 different benchmarks. Figure 2 reports the results (aggregated for all IFs in our dataset) and shows, consistent with the prevailing literature, that on average IFs do not exceed their benchmark market index. In fact, during 2019, the mean benchmark-adjusted returns, sized in Figure 2 by the red spots, tend to be on the zero line. IF returns are even lower in March 2020 (the red spot is well below the zero line), suggesting that IF performance ability decreases in the panic.

Second, we exploit the granularity of these benchmark-adjusted returns and identify three IF categories related to performance capabilities. We first identify the quartiles of the measure, computed for all IFs in our dataset over the months of 2019, and then we include IFs in three groups characterized on average, respectively, by low, medium, and high returns.[23] Then, as in the other exercises, we interact the three IF categories, sized by three dummies, with our variables of interest in each month. The results are reported in Table 13. Notably, IFs with higher pre-pandemic returns are the only group not selling in March (the coefficient is negative but statistically insignificant only for this group) and purchasing in April. In other words, IFs that are characterized on average by a stronger performance ability do not herd even during the crisis.

Rebalancing according to the country of origin of IFs

Reaction to the Covid crisis may also differ across countries of origin of IFs. IFs from the same country share common regulatory requirements as well as similar policy and cultural sensitivities, which in turn may affect their portfolio choices, especially during crises. To examine this possibility, we use the same approach of interacting the dummies capturing the country of origin of each IF with our Covid-19 measures by month.[24] To ease the interpretation of results, we group the countries of origin of IFs in four groups: North American, Euro Area, emerging markets, and the rest of world.[25] Results by country (column (2) of Table 11) show that in March only North American IFs present a positive coefficient, which indicates that only IFs from the United States

[23]IFs are classified with "low", "medium" and "high" returns, respectively, if during the entire 2019 they are in the bottom quartile, in the second or third quartile, or in the top quartile.

[24]The baseline results (obtained "all things being equal") take into account the effect of the origin country, which here is the focus of the exercise.

[25]North American countries include the United States and Canada. Euro Area countries include Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain. Emerging markets include the BRICS (Brazil, Russia, India, China, and South Africa) and MINT (Mexico, Indonesia, Nigeria, and Turkey) countries. The rest of the world includes the remaining countries. There are different taxonomies of emerging markets; our list covers the main countries in the IF industry. In percentage terms, the IFs from North America represent about 60 percent of the world industry, both according to EFAMA and in our dataset. The Euro Area IFs account for around 22 percent, according to EFAMA, and 20 percent in our dataset. Emerging markets' IFs account for 5 percent, according to EFAMA, and 10 percent in our dataset. Results do not change if the Hong Kong IFs are considered with those of China.

and Canada do not rebalance security holdings towards less Covid-impacted countries. By contrast, emerging markets' IFs are the most concerned about Covid, as they present in March the highest negative coefficient and in April continue selling Covid-affected securities.[26] The result suggests that, in emerging markets, still quite untouched by the virus in March (apart from China, which, however, owns a low share of the worldwide IF industry), the response of IFs may have been more "emotional" toward events in distant countries.

Security type rebalancing: the role of assets' liquidity

The impact of the Covid outbreak could also be heterogeneous across security types, for example, because investors may be concerned about a potential greater effect of the pandemic on certain types of assets. In particular, financial assets are characterized by very different levels of liquidity: equities and government bonds are typically very liquid, while corporate bonds are illiquid (as equities and government bonds are traded many times throughout the day, while corporate bonds may not be traded for weeks and cannot be easily and cheaply liquidated). To explore whether security types and their liquidity matter, we distinguish between the three kinds of financial assets (equities and government and corporate bonds) and 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.

More interestingly, the second exercise verifies whether and which security type is sold more. We re-estimate Equations 1 and 2 (again in a single empirical model instead than in a sample splitting), augmenting the model with the three dummies (i.e., one

[26] Results by industry provide similar outcomes and are not reported; they are, however, available from the authors.

for each type of financial asset) interacted with our variables of interest in each month (again, both $Country\ Covid19_{c,t}$ and $Industry\ Covid19_{s,t}$). Our results show that IFs sell only equities to decrease their exposures toward Covid-affected countries (column 2 of Table 9), while they sell all kinds of assets to rebalance their portfolios across industries (column 1 of Table 12). Mainly, the results show that the rebound effect of April only concerns corporate bonds. The higher sales of equities as well as the minor sales of corporate bonds on March may be explained by their different marketability.[27] However, in particular, the positive coefficient of corporate bonds in April appears associated with the policy measures taken by the authorities in the period. Corporate bonds are in fact the financial asset on which central banks concentrated their intervention during the pandemic crisis.[28] The result tallies with the findings of Falato et al. (2020), who stress that, during the Covid crisis, the effect of monetary policy on non-bank financial institutions worked mainly through the corporate bond market. Our results complement theirs: they highlight the role of corporate bonds, looking only at the US market, while our evidence refers to world data; they show mainly an effect through reverse outflows, while we show one through purchases. Moreover, we carry out another (unreported) test combining security type dummies and country-of-origin dummies of IFs and find that the rebound of April involved corporate bonds held by IFs coming from the United States as well as from the Euro Area and several other countries.

[27] Haddad et al. (2020) and Ebsim et al. (2020) provide interesting evidence on major liquidity problems in the corporate-bond market during the pandemic. The literature reviewed in Section 2, which points to IF fragility, refers mainly to corporate bond funds, which allow investors to redeem their money on a daily basis, as well as the other IFs, despite the illiquidity of their holdings.

[28] In the United States, starting in mid-March, the Federal Reserve purchased a substantial amount of securities, but at the end of March and into April, the Fed announced, for the first time in the US history, its purchase of corporate bonds. 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 trillion, which expanded eligibility to non-financial commercial paper under the corporate sector purchase programme.

7. Robustness checks

Market price revaluations

We run also estimations with the same structure as Equations 1 and 2, where, however, the dependent variable is no longer 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 IF portfolios and global market developments. The results (reported at country level in Table 14 and at industry level in Table 15) are as expected: the market price effect on the value of securities at ISIN level in IF 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 IFs' sales are amplified when the issuer of financial assets belongs simultaneously to a more Covid-affected country and industry. To verify this expectation, we interact 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 are sold more.[29]

[29]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 7 are available from the authors upon request.

Financial asset characteristics: rating scores, pressure, equities' liquidity, and firm balance sheet data

Financial asset characteristics may affect IF net-purchase decisions and could have some impact on our results, for example, because they are less rated. Our dataset includes a massive quantity of assets issued all over the world. To verify whether other intrinsic characteristics of financial assets (other than those linked to the Covid impact) affect our results and the sales of IFs at the outbreak of the pandemic, we add and interact with our Covid exposure measures two variables: the rating scores and the "pressure" of each asset. The rating scores are taken from the CSDB and refer to a large subsample of our data (around 40 percent of all financial instruments in the sample).[30] 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 estimations confirm our baseline results: our variables of interest, both at country and industry level, remain significantly negative.

Furthermore, we run two additional tests on equities, which are the financial asset on which more data are available. First, we run a new test on the role of liquidity. Our results already show that, at the pandemic's outbreak, equities are more sold than other types of financial assets. Here, we compute the degree of liquidity of each equity through the "illiquidity" measure introduced by Amihud (2002).[31] The exercise shows that, while baseline results are confirmed, the intrinsic liquidity of each stock does not play a significant additional role. Second, we run a new test on equities is-

[30] 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).

[31] The illiquidity measure is the daily ratio of absolute stock return to its dollar volume (or counter-valued in other currencies), averaged over some period. This can be interpreted as the daily price response associated with one dollar of trading volume, thus serving as a rough measure of price impact. This measure is obtained by retrieving daily stock return and counter-valued volume from Refinitiv (Datastream).

sued by non-financial firms. Given the adverse impact of the pandemic on non-financial firms, heterogeneity in firms' access to cash and credit may influence firm performance and hence net purchases from IFs.[32] To evaluate whether and how firm characteristics influence net-purchases and our results, we match (though the ISIN code) equities in IF portfolios to individual firm balance sheet data.[33] Results are reported in Table 16 both by country and industry. This confirms once again our baseline results and shows interestingly that firms with more cash and less leverage experience less severe sales than otherwise identical firms.

Placebo tests

To obtain placebo tests of our results, we repeat 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 IFs and the fake Covid-19 measures.

Alternative proxies and other control variables

Several checks are devoted to the use of alternative proxies and the inclusion of other control variables. First, all results remain unchanged when the dependent variable $Net\ purchases_{i,f,t}$ is scaled by the net asset value (NAV) at 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 IFs (i.e., those with a NAV of less than 20

[32]E.g., Harford, 1999; Bates et al., 2009; Kahle and Stulz, 2013; Pinkowitz et al., 2015; Giroud and Mueller, 2017; Ding et al., 2020.

[33]We retrieve firm financial data in December 2019 (the last year data before the pandemic crisis) from Morningstar Direct. We obtain data on over 20,000 firms across 99 countries and four basic financial characteristics: *Total assets*, which equals the natural logarithm of the book value of total assets; *Leverage*, which equals the ratio of book value of debt divided by the book value of total assets; *Cash*, which equals the total amount of cash and short-term investments divided by total assets; and *Return on Assets*, which is the ratio of net income to total assets.

million euros, which correspond to the 5th 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, still regarding the estimation of Equation 1, results remain unchanged when we include as an additional regressor an index of government responses to the crisis.[34] The inclusion of this index would affect our results if 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, for example, because major public interventions are correlated to major Covid effects. Instead, while the index of government responses is hardly significant, its inclusion as an additional regressor does not change the effect of our variable of interest.

Fifth, regarding the estimation of Equation 2, as mentioned, the variable of interest $Industry\ Covid19_{s,t}$ is not available for all industries; in particular, it has not been computed 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 carry 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 are alternatively either the average value across the industries of the country or the value of the industry of administrative services. Re-

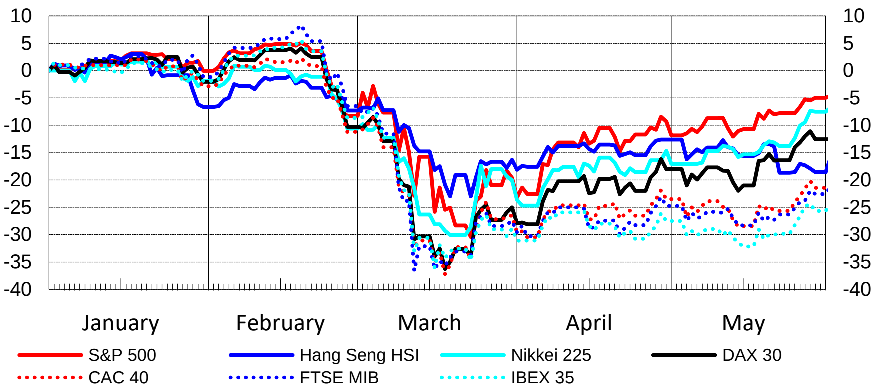
[34] We use the index provided by the University of Oxford through the Oxford Covid-19 Government Response Tracker (OxCGRT). The OxCGRT defines a set of indexes to measure governments' responses to the pandemic across countries (190 countries) and over time (over the period of the disease's spread (Hale et al., 2020)). Data are available through the GitHub repository. In particular, we rely on the "Overall Government response index", which captures several dimensions, such as (i) closures and containment measures (e.g., school closing, workplace closing, or cancellation of public events), (ii) economic measures (e.g., income support or debt/contract relief), and (iii) health measures (e.g., testing or contact tracing).

sults of *Industry* $Covid19_{s,t}$ remain always negative (as in the baseline estimations), and the coefficient of the dummy public sector is negative as well.

8. Conclusions

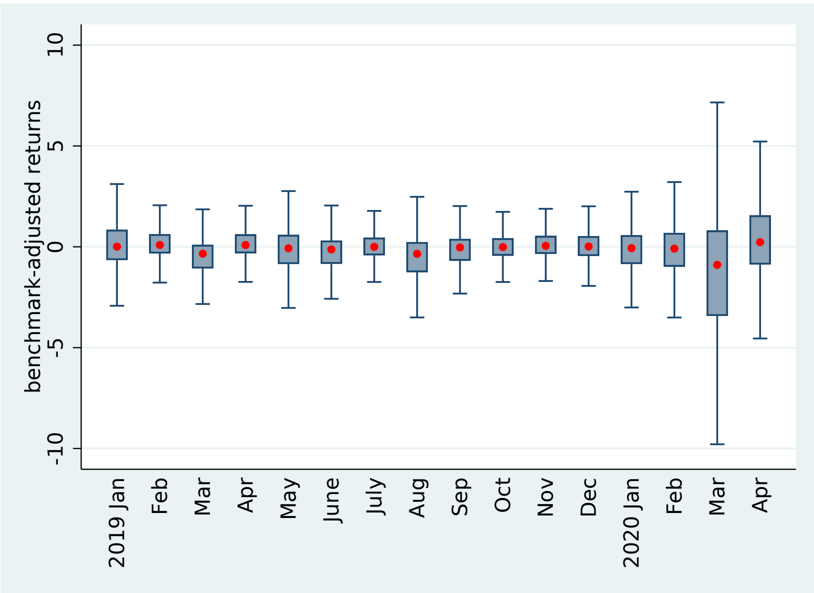
The paper takes advantage of a massive, granular database to analyse the impact of the Covid-19 outbreak on IFs' portfolio strategies and contributes to the literature on funds' behaviour in several ways. First, it complements the literature on the stock market response to Covid-19, taking the point of view of investors, instead than that of firms, and it shows that Covid-19 triggered a worldwide rebalancing of portfolios, which is not indiscriminate and horizontal but focuses on pandemic-vulnerable assets across countries and industries. Second, the paper contributes to the literature on IFs' conduct and the impact on prices, showing that IFs sell assets perceived as more troubled and this exacerbates the risk of fire sales. Third, the paper enhances the literature on flow-induced trading, showing that the risk of fire sales is intensified as IFs and their holders are seized by the same frenzy to sell. Fourth, the paper echoes the traditional literature on the heterogeneity across institutions, showing that IF categories matter as funds tend to behave differently according to their investment policies, return ability, and geographical distance from the crisis. Fifth, the paper enriches the literature on market timing and stock-picking, showing that, while the bulk of IFs sell more the most Covid-affected assets, outperforming funds stand apart and do not follow the herd. Finally, the paper contributes to the debate on the role of IFs after the global financial crisis, demonstrating, on the one hand, that their portfolio choices can increase the volatility of financial markets, but, on the other, that they slow their sales coincident with the monetary policy interventions. This suggests that monetary authorities may also operate through non-bank financial institutions.

Figure 1: **Stock market returns during Covid-19 pandemic**



The figure plots the cumulative stock market returns since the spread of Covid-19 for each of the selected economies. (Source: Morningstar Direct).

Figure 2: **Benchmark-adjusted returns**



The figure plots the benchmark-adjusted returns at monthly frequency for all investment funds in our sample. (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 reports summary statistics for the industries with the highest number of holdings (more than two-thirds of our sample). We report the industries' 3-digit NAICS code, their description and the number of holdings in the respective industries. In addition, the table presents KP's $affectedshare$, as defined by Koren and Pető (2020), and the average net purchases and revaluations, both scaled by the end of previous period NAV. Data on social distancing exposure by sector are retrieved from Koren's website; NAICS code for each single financial asset, identified through its ISIN code, are retrieved from 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 between cumulative Covid-19 confirmed cases and population in a specific country-time. Covid-19 deaths is the ratio between cumulative Covid-19 deaths and population in a specific country-time. All models control for fund fixed effects. ***, **, 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 KP's affected share (Koren and Pető, 2020) at industry level and sets of fixed effects. Affected share explicitly accounts for teleworkability and also for physical proximity to others, i.e. exactly what social distancing rules aim to avoid. It measures the percentage of workers in occupations that are communication-intensive and/or require physical presence in close proximity to others, in a specific sector. All models control for fund fixed effects. ***, **, 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 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 between cumulative Covid-19 confirmed cases and population in a specific country-time. Covid-19 deaths is the ratio between cumulative Covid-19 deaths and population in a specific country-time. All models control for fund fixed effects. ***, **, 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 6: **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. Affected share explicitly accounts for teleworkability and also for physical proximity to others, i.e. exactly what social distancing rules aim to avoid. It measures the percentage of workers in occupations that are communication-intensive and/or require physical presence in close proximity to others, in a specific sector. All models control for fund fixed effects. ***, **, 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 7: **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 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 between cumulative Covid-19 confirmed cases and population in a specific country-time. Covid-19 deaths is the ratio between cumulative Covid-19 deaths and population in a specific country-time. All models control for fund fixed effects. ***, **, 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			-0.0110***	
			(0.0030)	
Covid-19 deaths*				
portfolio Covid-oriented				-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 8: **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. Affected share explicitly accounts for teleworkability and also for physical proximity to others, i.e. exactly what social distancing rules aim to avoid. It measures the percentage of workers in occupations that are communication-intensive and/or require physical presence in close proximity to others, in a specific sector. All models control for fund fixed effects. ***, **, 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 9: **Net-purchases of financial assets and the Covid-19 impact across countries, by residency and financial asset type**

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 between cumulative Covid-19 confirmed cases and population in a specific country-time. Covid-19 deaths is the ratio between cumulative Covid-19 deaths and population in a specific country-time. All models control for fund fixed effects. ***, **, 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	Residency		Instrument type		
	Non-domestic	Domestic	Equity	Gov.Bonds	Corp.Bonds
Covid-19 cases*Jan.	-0.3157	190.5417*	-1.6809	7.9896	16.8253***
	(2.5505)	(109.3910)	(2.7618)	(7.0397)	(5.3333)
Covid-19 cases*Feb.	-0.0812	-1.8544	-0.2179*	1.3892	0.3579
	(0.1294)	(2.5961)	(0.1322)	(1.0079)	(0.4656)
Covid-19 cases*Mar.	-0.0393***	-0.0306***	-0.0810***	0.0049	0.0087*
	(0.0052)	(0.0092)	(0.0087)	(0.0228)	(0.0048)
Covid-19 cases*Apr.	0.0097***	-0.0010	0.0000	0.0087	0.0190***
	(0.0022)	(0.0029)	(0.0028)	(0.0085)	(0.0031)
Fund*Time FE	Yes		Yes		
Industry*Time FE	Yes		Yes		
Fund Clustered Std. Errors	Yes		Yes		
Observations	11,709,741		11,709,741		
R^2	0.094		0.094		

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 between cumulative Covid-19 confirmed cases and population in a specific country-time. Covid-19 deaths is the ratio between cumulative Covid-19 deaths and population in a specific country-time. All models control for fund fixed effects. ***, **, 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		Jan.	Feb.	Mar.	Apr.
Covid-19 cases	-0.0149***	-0.0724	0.1813	-0.0687***	0.0060
	(0.0035)	(2.3650)	(0.2339)	(0.0065)	(0.0037)
Outflows	-0.0041***	-0.0042***	-0.0047***	-0.0035***	-0.0051***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0005)
Covid-19 cases*Outflows	-0.0042***	1.0107	0.0461	-0.0078***	-0.0000
	(0.0016)	(0.9273)	(0.0988)	(0.0013)	(0.0022)
Fund FE	Yes	Yes			
Time FE	Yes	Yes			
Industry*Time FE	Yes	Yes			
Fund Clustered Std. Errors	Yes	Yes			
Observations	9,664,932	9,664,932			
R^2	0.045	0.045			

Table 11: **Net-purchases of financial assets and the Covid-19 impact across countries, by IF category and country of origin**

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 between cumulative Covid-19 confirmed cases and population in a specific country-time. Covid-19 deaths is the ratio between cumulative Covid-19 deaths and population in a specific country-time. All models control for fund fixed effects. ***, **, 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	Type of fund			Country of origin/area			
	Equity	Fixed-Income	Mixed	US & CAN	EME's	EA	RoW
Covid-19 cases*Jan.	-1.8351	3.6434*	79.2831	1.0797	1.1646	1.8597	-5.3876
	(3.2518)	(2.1839)	(75.8366)	(1.1206)	(30.1787)	(2.2131)	(9.2404)
Covid-19 cases*Feb.	-0.0905	0.0136	4.1433	-0.0967	-5.3203	-0.0685	-0.0937
	(0.1376)	(0.3167)	(17.2876)	(0.1159)	(8.7930)	(0.2817)	(0.2712)
Covid-19 cases*Mar.	-0.0038	-0.0452***	-0.3852**	0.0105**	-0.2118***	-0.0507***	-0.0303***
	(0.0089)	(0.0057)	(0.1600)	(0.0047)	(0.0815)	(0.0068)	(0.0109)
Covid-19 cases*Apr.	0.0019	0.0071***	-0.0876	0.0045*	-0.1286***	0.0132***	0.0029
	(0.0030)	(0.0027)	(0.0859)	(0.0027)	(0.0413)	(0.0032)	(0.0041)
Fund*Time FE	Yes			Yes			
Industry*Time FE	Yes			Yes			
Fund Clustered Std. Errors	Yes			Yes			
Observations	11,444,131			11,709,741			
R^2	0.096			0.094			

Table 12: **Net-purchases of financial assets and the Covid-19 impact across industries, by financial asset type and IF category**

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. Affected share explicitly accounts for teleworkability and also for physical proximity to others, i.e. exactly what social distancing rules aim to avoid. It measures the percentage of workers in occupations that are communication-intensive and/or require physical presence in close proximity to others, in a specific sector. All models control for fund fixed effects. ***, **, 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	Instrument type			Type of fund		
	Equity	Gov.Bonds	Corp.Bonds	Equity	Fixed-Income	Mixed
Affected share*Mar.	-0.0001***	-0.0002**	-0.0002***	-0.0001***	-0.0001***	-0.0002
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Affected share*Apr.	-0.0000***	-0.0004***	0.0000	-0.0000	-0.0001***	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Fund*Time FE	Yes			Yes		
Country*Time FE	Yes			Yes		
Fund Clustered Std. Errors	Yes			Yes		
Observations	7,066,585			6,935,616		
R^2	0.119			0.119		

Table 13: **Net-purchases of financial assets and the Covid-19 impact across countries, the role IFs' 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 between cumulative Covid-19 confirmed cases and population in a specific country-time. Covid-19 deaths is the ratio between cumulative Covid-19 deaths and population in a specific country-time. All models control for fund fixed effects. ***, **, 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) Quartiles of adjusted returns		
	Q1	Q2–Q3	Q4
Covid-19 cases*Jan.	9.7304***	0.2146	-2.0285
	(2.4108)	(1.0745)	(5.0504)
Covid-19 cases*Feb.	0.0704	-0.0343	0.0999
	(0.2363)	(0.1569)	(0.4749)
Covid-19 cases*Mar.	-0.0616***	-0.0404***	-0.0100
	(0.0140)	(0.0062)	(0.0088)
Covid-19 cases*Apr.	0.0080	-0.0000	0.0146***
	(0.0063)	(0.0023)	(0.0037)
Fund*Time FE	Yes		
Industry*Time FE	Yes		
Fund Clustered Std. Errors	Yes		
Observations	9,921,165		
R^2	0.084		

Table 14: **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 between cumulative Covid-19 confirmed cases and population in a specific country-time. Covid-19 deaths is the ratio between cumulative Covid-19 deaths and population in a specific country-time. All models control for fund fixed effects. ***, **, 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 15: **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. Affected share explicitly accounts for teleworkability and also for physical proximity to others, i.e. exactly what social distancing rules aim to avoid. It measures the percentage of workers in occupations that are communication-intensive and/or require physical presence in close proximity to others, in a specific sector. All models control for fund fixed effects. ***, **, 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

Table 16: **Net-purchases of financial assets and the Covid-19 impact across countries and industries, the role of firm characteristics**

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 of KP's affected share (Koren and Pető, 2020) at industry level and sets of fixed effects. Covid-19 cases is the ratio between cumulative Covid-19 confirmed cases and population in a specific country-time. Covid-19 deaths is the ratio between cumulative Covid-19 deaths and population in a specific country-time. Affected share explicitly accounts for teleworkability and also for physical proximity to others, i.e. exactly what social distancing rules aim to avoid. It measures the percentage of workers in occupations that are communication-intensive and/or require physical presence in close proximity to others, in a specific sector. All models control for fund fixed effects. ***, **, 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.	-0.7981	
	(3.0240)	
Covid-19 cases*Feb.	-0.2789**	
	(0.1399)	
Covid-19 cases*Mar.	-0.0199***	
	(0.0074)	
Covid-19 cases*Apr.	0.0021	
	(0.0028)	
Affected share*Mar.		-0.0001***
		(0.0000)
Affected share*Apr.		0.0000
		(0.0000)
Cash	0.0001***	0.0000***
	(0.0000)	(0.0000)
Return on assets	0.0000	-0.0000
	(0.0000)	(0.0000)
Leverage	-0.1630***	-0.2276***
	(0.0627)	(0.0633)
Total assets	-0.0002	-0.0002
	(0.0002)	(0.0002)
Fund*Time FE	Yes	Yes
Industry*Time FE	Yes	No
Country*Time FE	No	Yes
Fund Clustered Std. Errors	Yes	Yes
Observations	5,032,629	4,984,723
R^2	0.13	0.127

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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 and/or requiring close physical proximity to others. This measure is based on the North American Industry Classification System (NAICS) (Source: Koren and Pető (2020))
Confirmed cases	Ratio between number of cumulative Covid-19 confirmed cases and total population in country c in month t. (Source: Systems Science and Engineering, John Hopkins University)
Deaths cases	Ratio between number of cumulative Covid-19 deaths and 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)
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)
Total exposure (lag)	Total exposure of fund f into ISIN i in previous month. (Source: Morningstar)

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