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IDENTIFYING SHOCKS TO SYSTEMATIC RISK IN TIMES OF CRISIS

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ABSTRACT

We characterize how risk evolves during a crisis. Using high-frequency data, we find that the first two principal components (PCs) of the covariance matrix of global asset returns experience large, sudden, and temporary spikes coinciding with well-known crises – Covid-19 pandemic, Global Financial Crisis, and Brexit. Despite the origin of these crises being very different, the risk dynamics share remarkably common features: PC1 shocks come solely from asset volatility, while PC2 shocks come from changing loadings/composition, effectively making it a "crisis" factor. Using the exogenous nature of Covid-19, we provide novel identification of risk dynamics by linking these changes to news about the virus and epidemiological model forecast errors over time and across countries. We conclude with investment implications, where shocks to systematic risk sharply reduce diversification benefits and ex ante attempts to hedge it are futile, which may be a defining characteristic of a crisis – that it is unavoidable.

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1 Introduction

The last two decades experienced a number of global economic shocks – the global financial crisis (GFC), Eurozone crises (Euro debt crisis and Brexit), and the Covid-19 pandemic. These crises have led to wide-scale economic costs, such as large drops in GDP growth, and impacted global financial assets. Little is known, however, about the changing covariance of asset returns during these times. Anecdotally, claims of increased systematic risk and rising correlations are a popular narrative, but little evidence exists on these issues. We shed light on this topic by detailing how the covariance structure shifts during crises and how that shift impacts traditional asset portfolios.

We use unique high-frequency data to precisely estimate the fast-changing correlation matrix of 24 asset returns (12 country equity indices, eight government fixed-income futures, and six exchange rates). Focusing on the first two principal components (PC1 and PC2) of global asset returns, we first describe the changing covariance structure of global asset returns over the whole sample period. We then focus on changes during the Covid-19 global pandemic. Covid being an exogenous event allows us to more clearly identify and measure how covariances evolve, where we can tie covariance dynamics to specific variation in Covid news over time and across countries, providing novel identification of risk dynamics. We then apply the insights from Covid to other large changes in the factor structure that coincide with other well-known crises (GFC, Brexit). Despite the origin of these crises being fundamentally different from Covid and each other, the risk patterns that emerge are remarkably similar. Finally, we investigate the implications of our findings for investment portfolios by assessing the ability to diversify or hedge changing risk during these times.

Over the full sample period, the loadings of the PCs tend to cluster within the three asset classes – global equities, government bonds, and dollar-based currencies. PC1, which loads positively on equities and negatively on fixed income, explains 25% to 60% of the correlation matrix of asset returns. PC2 adds an additional 10% to 15% of explanatory power on average. However, in contrast to PC1, PC2 has a large positive loading on fixed income on average, and (interestingly) a positive loading on gold futures. While both PCs have relatively stable equity and fixed income loadings through time, their loadings vary with the currency dollar basket. Furthermore, and the focus of this paper, the PC return structure is subject to occasional, sudden, and large spikes, where the nature of those spikes is different for PC1 and PC2.

The greatest spikes take place between February 27th and April 7th, 2020, coinciding with the onset of the Covid-19 global pandemic. The pandemic is uniquely an exogenous event, which allows us to identify the direct relation between changes in the factor structure and

Covid-19 news, which is unlikely to be confounded by other shocks. This feature is distinctly different from other crises, such as the GFC, which was driven by the financial sector itself. With Covid, the economy and financial markets are responding to the news of the pandemic. For other crises, it may be the economy and financial markets causing the crisis or being jointly determined by an omitted factor. Moreover, Covid news and shocks can be measured and therefore linked to changing covariances. We extract news about the pandemic from unstructured text from various media sources using natural language processing (NLP).

A key result we find is that changes in the PC1 factor return distribution are driven solely by chaning asset return volatility, with the composition and loadings of PC1 remaining stable. This is not the case for PC2, whose changes are primarily driven by changes in factor loadings and composition. In essence, PC2 becomes a "crisis factor." Exploiting cross-sectional variation in Covid-19-specific news across countries, we provide further identification for this crisis factor by documenting a strong relationship between each country's Covid-19 news and asset exposure within each country to PC2. Working off this close connection between a country's factor return and Covid-19 news shocks, we relate factor returns to forecast errors from epidemiological models of Covid-19 death predictions (from arguably one of the best-known global research institutes at Imperial College). Here, we also find a strong contemporaneous relation between country factor returns and death forecast errors, further linking the factor structure to Covid-19 exposure.[1]

The Covid-19 shock is not the only period containing abrupt changes in the factor structure of global asset returns. In particular, the global financial crisis (GFC) and the U.K.'s exit from the European Union (Brexit) show similar patterns. We find that despite these crises originating from very different sources, they share remarkably similar features in terms of factor structure. In particular, the factor structures are more similar during crisis periods than outside of those periods, which suggests something unique about the onset of a crisis.

Finally, we explore the implications of our findings for investment portfolios. The return volatility of asset portfolios increases dramatically during crisis periods, and we document that these increases are systematic in nature, driven primarily by the volatility of the PC factors and changing factor exposures. As a consequence, we find a large reduction in diversification benefits across assets and countries during crises. Moreover, this shock to risk is not easy to hedge. Hedge ratios change so rapidly that ex ante hedging attempts lead to meager results, with significant "residual" variance remaining. The rise in risk and inability to avoid it suggests that the extraordinary level of risk during crises is extremely difficult to

[1]Interestingly, we also document the ability (albeit small) of the country factor returns to forecast fatality rates above and beyond the epidemiological model forecasts. This striking result is consistent with the informational efficiency of financial markets and is further testament to the link between risk structure and Covid-19.

manage and mitigate – which is perhaps a defining characteristic of a crisis.

The rest of the paper is organized as follows. Section 2 presents the methodology for describing the factor structure of returns and investigates how this structure changes over time. Section 3 provides a detailed analysis of the Covid-19 crisis period and relates the changing factor structure to news about the disease and to death forecasts. Section 4 provides analysis of other large factor structure changes during other crisis periods. Finally, Section 5 shows how traditional asset portfolios are affected by these structural risk changes, providing economic magnitudes of the impact of changing risk structure from crises and whether these changes can be managed or mitigated. Section 6 concludes.

2 The Global Factor Structure of Asset Returns

Factor models to decompose the risk of traded assets into common sources can change because either the factors' variance-covariance matrix, the asset's factor loading, or the idiosyncratic variance change. However, another, and less discussed, possibility is that the factor itself may change through time with different weights on the base assets. The simplest example of this case is changing value-weights of the market portfolio. Few empirical investigations of how aggregate factors change through time exist, however, largely because we do not know what these aggregate traded factors are. A popular approach applies statistical tools, such as principal components analysis (PCA), to extract asset weights that explain the most return covariation.

A difficulty in understanding factor dynamics, however, is that, when using this methodology, the number of assets is large relative to the time-series, hence the properties of the PCA are poor. This problem is further magnified by the small sample size when inferring multiple PCAs over time to try and capture changing dynamics. Recent work by Ait-Sahalia and Xiu (2017; 2019) provides an asymptotic justification for a PCA approach using high-frequency data of continuous-time asset price processes.

There is growing recognition that a low dimensional factor model explains aggregate assets.[2] A number of theories have been offered to jointly explain the dynamics of bonds, stocks, and exchange rates (see, for example, Hau and Rey (2006), Bansal and Shaliastovich (2013), Farhi and Gabaix (2016), Lustig et al. (2019) and Koijen and Yogo (2020)). In this paper, we use high frequency data across global assets to measure how asset return variances and covariances change through time.

[2] For example, within classes, see Fama and French (2012) for stock returns, Dahlquist and Hasseltoft (2013) and Jotikasthira et al. (2015) for bond returns, Lustig et al. (2011) and Lustig and Verdelhan (2019) for currency returns, and, across asset classes, see Asness et al. (2013).

2.1 Data

We use minute-by-minute prices of twelve equity futures on country indices (Australia, Brazil, Germany, Canada, Spain, France, India, Italy, Japan, Switzerland, UK and US), eight fixed income futures on 10-year government bonds (Australia, Germany, Canada, France, Italy, Japan, UK and US), and six spot exchange rates (Australia, Euro, Canada, Japan, Switzerland, UK in terms of $US). These 26 assets cover the vast majority (over 70%) of the market values of global equity, fixed income and exchange rate markets, with the notable exception of China. For additional analysis, we also collect high frequency data on three liquid economic commodities relevant to the global economy: agriculture (corn), energy (crude oil) and industry (copper).

An important element of high frequency estimation is the continuous availability of data throughout the day. Unlike Aït-Sahalia and Xiu (2017), who have access only to the 6 ½ US equity trading hours, global futures contracts and spot exchange rates have many more trading hours. Table 1 documents the coverage of the 26 assets across the 24-hour period over the Covid-19 sample.[3] We calculate the percentage of 5-minute returns that are available during each hour. Table 1 shows that the majority of assets have nearly 24-hour coverage.[4]

2.2 Methodology

We perform a PCA using the correlation matrix of the 26 global asset returns. Because equities are much more volatile than either fixed income or currencies, we analyze the correlation matrix as opposed to the covariance matrix. However, our analysis also focuses on measuring changing variances and covariances.[5]

Because news about the Covid-19 pandemic is so fast moving, the PCA is applied to biweekly high frequency data.[6] The analysis is conducted every two weeks, starting in

[3]While we show the Covid-19 sample (*i.e.*, January 1, 2020 to June 30, 2020) given its emphasis in this paper, note that we use data in the paper going back to 2007. This earlier sample for the most part has similar coverage to the Covid-19 sample.

[4]Fixed income futures markets have the least amount of coverage with Italy and France at 11 hours and the U.K. at 10 hours; nevertheless, other fixed income markets have better coverage (*i.e.*, Australia (22 hours), Canada (15 hours), Germany (20 hours), Japan (19 hours) and U.S. (23 hours)).

[5]One drawback, however, is that the PCs (generated from the correlation matrix) applied to variance-covariance space are no longer uncorrelated. We adjust for this issue when estimating asset return betas.

[6]Our data analysis shows that the five-minute high frequency intervals, biweekly horizon and cross-section of assets have sufficient data to back out reasonable estimates of the correlation matrix. Shorter horizons or longer intervals add additional sampling error. In estimating their weekly covariance matrix, Aït-Sahalia and Xiu (2017) estimate the integrated (*i.e.*, average) eigenvalues of the "spot" variance-covariance matrix (using one-minute intervals over 2 ½ hours), while we choose to measure the eigenvalues of the integrated variance-covariance matrix (*i.e.*, 2 weeks in this case). The underlying asymptotic theory implies that in estimating over any fixed period (e.g., 2 weeks), there are an infinite number of subperiods in continuous-time, allowing the researcher to estimate the "spot" covariance matrix and capture the instantaneous dynamics, and then

January 1, 2007 through June 30, 2020. In terms of estimating the biweekly correlation matrix, the goal is to use as much of the 24 hours of high frequency data available to obtain a more efficient estimate of asset return correlations than using daily data (e.g., see Barndorff-Nielsen and Shephard (2004) and Andersen, Bollerslev, Christoffersen and Diebold (2006; 2013)). As Table 1 shows, there are many coincident hours for a number of assets, especially exchange rates and equity futures in the larger markets.

We use the following procedure for any two assets, A and B. First, we select the one minute intervals where prices are available for both A and B. If no transactions occur for either A or B within the one minute interval, we move to two minutes; and if no transactions occur for either A or B within two minutes, we move to three minutes, and so on. Second, following standard conventions, we re-index the returns of A and B to five minute intervals in order to minimize the impact of market microstructure. Finally, we estimate the covariance between the return on asset A and B by summing up their five-minute cross-terms with a lead-lag adjustment for microstructure non-syncronicity and bid-ask bias. Similarly, we estimate each asset return's variance by summing over their five-minute squared returns plus a microstructure adjustment for first-order serial autocorrelation. We also impose a liquidity requirement in which we only sample from the hours when more than 50% of the data is available. This requirement necessarily means we ignore periods of market closures, so that if either asset A or B is closed over a given period, we do not count their comovement from close-to-open. However, for each asset's own variance, we incorporate both trading and nontrading returns.

Specifically, for day T, we use five-minute bars (re-sampled from one-minute bars to avoid microstructure noise) from the previous day $T-14$ (16:00:01 EST) to previous day $T-1$ (16:00:00 EST). Let r_t denote the log return from t minus 5 minutes to t. We compute the high frequency realized variance as of day T as follows:

$$\sigma^2_{T,adjusted} = \left(\sum_{t=T-14d}^{T-1d} r_t^2 + 2 r_t r_{t-1} \right). \tag{1}$$

The first term is the integrated variance over the lookback period; the second term adjusts for the one-period (5 minute) autocorrelation, so $\sigma_{T,adjusted}$ is an unbiased estimator of the previous biweekly realized volatility. When five-minute data is not available (for example, overnight hours), we use the gap returns. For example, if there is no trading between 3:00am and 3:20am, we use the twenty-minute return for r_t.

integrate over these to capture the 2-week covariance matrix. The practical issue is that in finite time each subperiod has a large amount of estimation error due to its short interval and multiple assets.

We compute the high frequency covariance as of day T as follows:

$$cov_{T,adj} = \left(\sum_{t=T-14d}^{T-1d} r_{A,t}r_{B,t} + r_{A,t-1}r_{B,t} + r_{A,t}r_{B,t-1}\right). \tag{2}$$

The first term is the integrated covariance over the lookback period. The second and third terms adjust for 1-period (5 minute) lead-lag autocovariances. The five-minute returns are only sampled over the periods where both securities have five-minute returns available. For example, say security A trades from 9am to 6pm while security B trades from 1pm to 9pm; the covariance will be computed using the data from 1pm to 6pm. The percent of bars available are shown in Table 1. In estimating the correlation between returns A and B, the covariance is divided by their integrated standard deviations over the coincident period (e.g., from 1:00 to 6:00 pm in the above example). However, when working with the full variance-covariance matrix of returns, the correlation matrix is scaled up by each assets' 24-hour biweekly return variance, *i.e.*, including both trading and nontrading hours.

In the next section, we perform a PCA on the biweekly high frequency correlation matrix of the returns on the 26 global assets, constructed from the pairwise correlation estimates described above. The implicit assumption is that the correlations over the coincident periods are representative of those over 24-hour periods. For some assets, such as exchange rates and equity markets in the U.S. and Europe, the coincident periods cover much of the 24 hours. To better understand the impact of this assumption across all the assets, Table 2 documents the mean and standard deviation of biweekly correlations of global assets within and across equities, fixed income and exchange rates using high frequency and daily data over the full period 2007-2020, the Covid-19 period (January 29 – May 5 2020) and the prior quarter (October – December 2019).

First, both within and across asset classes, the standard deviation of the correlation estimates is much smaller using high frequency than daily data for both the normal and Covid-19 periods. The high frequency estimates appear more precise and efficient. Over the Covid-19 period, the standard deviation of the biweekly correlation using daily versus high frequency data is 0.162 versus 0.105 among equities, 0.286 versus 0.184 among fixed income instruments, and 0.349 versus 0.192 among currencies. Similar results hold for cross-correlations across asset classes.

Second, the mean correlation estimates are similar across and within asset classes using either high frequency or daily data, providing support for the coincident period assumption for assets in the high frequency setting. For example, within each asset class using daily versus high frequency, the average correlation is 0.786 versus 0.724 for equities, 0.471 versus 0.466 for bonds and 0.410 versus 0.371 for currencies.

Finally, the average correlation estimates suggest some important changes in the variance-covariance matrix over the last quarter of 2019 to the Covid-19 period. Correlations among equity and exchange rate markets increase, respectively, from 0.550 to 0.724 and 0.284 to 0.371 and decrease for fixed income markets from 0.621 to 0.466. With respect to the cross-correlations across asset classes, the correlation between equity and fixed income becomes more negative (from -0.194 to -0.299), while the correlation between equity and exchange rates increases from -0.040 to 0.064.

2.3 The Factor Structure of Asset Returns

We estimate the high-frequency correlation matrix of 30 asset returns (*i.e.*, the 26 aggregate assets, 3 commodities, and gold) and corresponding standard deviations using two-week periods. For each of these biweekly periods, we extract the first two principal components from the correlation matrix of the 26 aggregate asset returns. In this subsection, we characterize key features of the first (PC1) and second (PC2) principal components.

Figure 1 plots factor loadings for each of the three asset classes (equal-weighted equity, bonds, and exchange rates) for PC1 and PC2 respectively, defined as $w_{i1,t}$ and $w_{i2,t}$ for each asset in their respective asset class for 2007 to 2019 and for 2020 separately, to focus on the Covid period.

For PC1, equity and fixed income have opposite-signed loadings of similar magnitude. Since PCs are sign-invariant, we fix the (cross-sectional) average equity loading to be positive so that PC1 is long equities and short bonds on average and produces a positive expected return. This fix also makes the sign of the factor loadings comparable across equities, fixed income, and exchange rates through time. In a similar manner, we also assume the cross-sectional average fixed income loading to be positive for PC2.[7] Thus, PC1 of global asset returns is long the equity market and short the bond market. Another consistent finding is that the yen/dollar is not clustered with the other exchange rates and almost always has a more negative loading – an interesting finding consistent with the notion of the yen having special "risk-off" properties.

PC1's loadings are remarkably persistent given each period represents a new draw of asset return data. This finding points strongly towards a fundamental factor structure of asset returns unlikely due to measurement error. While the loadings on exchange rates are also persistent through time, their PC1 loadings swing throughout the period. Specifically, the exchange rate loadings move from negative to positive during the GFC and thereafter

[7] For PC2, there is one instance where we allow the average fixed income loading to be negative because PC2 clearly flips sign, as evidenced by the fact that requiring average equity loadings to be positive results in large average absolute differences in factor loadings from the adjunct periods.

for a number of years, trending back negative until recently turning positive again during the Covid-19 period. The equal-weighted exchange rate has a specific interpretation as the basket of foreign currencies against the dollar (*i.e.*, dollar-basket). We investigate below what could be driving the variation in exchange rate loadings on PC1 through time.

For PC2, variation in loadings is larger than for PC1. Equity has a near-zero PC2 loading on average, while fixed income has a large positive loading. The second PC is long the bond market and neutral to equity markets. Both the equity and fixed income weights have more significant dynamics than that of PC1. For exchange rates, however, the loadings are even more volatile. The dollar basket of currencies has a large positive loading at the start of the GFC and trends consistently downward to become negative by mid-2016. Importantly, the dynamics are not sudden but gradual over the whole time period.

For all three asset classes, there are large temporary changes in their loadings on both PCs. Some of these spikes appear to be related to three specific events over the past 14 years – the GFC, Brexit, and the Covid-19 pandemic.[8] Figure 1 highlights these episodes with vertical dashed lines, choosing as identification points the biweek including September 15, 2008 (Lehman Brothers bankruptcy), June 23, 2016 (Brexit vote), and March 11, 2020 (WHO declaring a global pandemic). There are some interesting observations. While there are clearly movements in PC1 loadings during these periods, there are much larger changes in PC2's loadings. The onset of all three crises has consistently greater structural impact on the second PC factor. Compared to PC1, PC2's loadings on the fixed income asset class are subject to large temporary spikes that switch sign. This result may be consistent with government bonds necessarily changing during a crisis as the government's main financial tool to combat a crisis. Additionally, the factor weights of the currency dollar-basket for both PCs spike up around crisis periods, often moving from negative to positive sharply. A positive loading implies that an asset positively correlated with the PCs is effectively short the dollar-basket, consistent with the dollar being a hedge in these periods.

Figure 2 plots average PC1 and PC2 loadings of the dollar basket through time against the interest rate differences between the U.S. and the average of the six other countries.[9] Interest rate differences negatively correlate with the PC1 loadings of the dollar basket (the correlation is -0.32 and is statistically significant at the 5% level.[10]) The dollar basket is

[8] There are several large spikes outside of these three periods. For example, one of the larger spikes occurs for fixed income PC1 loadings over several quarters starting in May 2013. This period includes the "taper tantrum" in which the Fed announced it would be ending its quantitative easing program. Of some note, Figure 1 also includes the Euro debt crisis which arose from the GFC but contained two periods of severe disruption, the spring of 2011 and summer of 2012.

[9] We use each countries' 3-month interbank lending rate from the FRED dataset available from the St. Louis Fed.

[10] This result is robust to other specifications, such as regressing the average PC loadings of the US dollar

essentially a strategy that longs the six exchange rates and shorts the dollar. When the U.S. interest rate is relatively low, the dollar basket strategy is positively exposed to the carry strategy and vice versa. The negative relation between the interest rate differences and the PC1 loadings of the dollar basket indicate that fluctuations of the average loadings of the exchange rates reflect the carry strategy. In addition, the negative loading on the yen/dollar reflects the fact that the dollar is almost always a carry currency relative to the yen over our sample period. The results suggest that the carry in currencies is directly tied to the covariance structure of currency returns, consistent with risk-based explanations for the carry premium.

To investigate PC1's FX loadings further, we reorganize the loadings of the dollar basket of currencies into loadings of a carry basket strategy which goes long the exchange rates of the three countries with relatively high interest rates and shorts the exchange rates of the three countries with relatively low interest rates. Figure 2 plots the average loadings of the carry portfolio for PC1 and PC2. The loadings are considerably more stable over time compared to those of the dollar basket. For PC1, the loadings of the carry strategy are positive throughout the sample, and there is no discernible trend. The PC1 loadings on carry are 0.42 correlated with the interest rate spread underlying the long-short carry strategy.

Our finding that the dollar-basket plays a key role in the changing correlation structure of global assets, and that this role depends on the dollar's carry status, is a novel result. This result is broadly consistent with Lustig, Roussanov, and Verdelhan (2014), who document a positive premium for what they call "the dollar carry trade" – long (short) the dollar basket when the dollar is a carry (funding) currency – above and beyond the normal carry strategy. Our finding suggests that the dollar carry trade is related to the covariance structure of global asset returns.

Figures 1 and 2 show that PC1 loads positively on equity and dollar carry exposure. Figure 2 panel (b) shows that the dollar basket of currencies' varying exposure to PC2 is correlated with the dollar's relative interest rate to other countries (-0.57 correlation, significant at the 5% level, which is related to the dollar's weight in a carry strategy). Whether the U.S. has relatively high or low interest rates is therefore important for PC2's loadings on the dollar basket.

Unlike PC1, when we reorganize the PC2 dollar-basket loadings into those of a carry strategy, Figure 2 panel (d), shows that the carry loadings do not exhibit a trend. Indeed, the correlation between the PC2 loadings on carry and the interest rate spread of the strategy

basket on a dummy variable for whether U.S rates are above or below the average short-term rate of the six countries.

is just 0.17 and statistically insignificant. At first glance, PC2's loadings on FX appear to be related to the dollar carry but not carry itself. However, Lustig et al. (2014) show that the dollar carry trade has independent pricing information to the broader carry trade, and Boudoukh et al. (2020) provide additional evidence that this pricing information is not related to dollar exposure per se.

To explore the differences between PC1 and PC2 more closely, we consider their relationship to gold. Gold is often considered to be a safe asset and arguably contrasts with PC1's "risk-on" properties. Using the high frequency biweekly correlation matrix between Gold futures returns and the 26 global asset returns, we run a theoretical multivariate regression of gold returns on the returns of PC1 and PC2. Figure 3 graphs the R^2s and multivariate PC betas over the sample period. While there is substantial variation in R^2s over the sample period, there is a clear pattern in the PC betas. Specifically, PC2's beta is consistently positive (with a few exceptions) and PC1's beta is either zero or negative for significant parts of the sample. The different exposures of PC1 and PC2 to gold is in the same direction as their relationship to carry.

Finally, the large spikes in factor loadings exhibited during crises are also consistent with PC2's average loadings of the carry portfolio documented in Figure 2. The carry loadings spike downward, suggesting funding currencies may also provide a hedge in crisis periods. The relative interest rate levels of the U.S. during these periods further suggests that the nature of the dollar plays an additional role during crises beyond its carry status.

2.4 Changes in Factor Loadings Through Time

To investigate how the large changes in factor loadings during crises shift risk across assets, Figure 4 graphs the absolute value of differences in PC1 and PC2 through time. Each day, we take the absolute value of that quarter's PC weights minus the previous quarter's weights times that day's asset return, *i.e.*,

$$|PC1_{qt-(q-1)t,k}| \equiv |\sum_i \left(w_{i1qt} - w_{i1(q-1)t}\right) R_{iqt+k}| \tag{3}$$

and

$$|PC2_{qt-(q-1)t,k}| \equiv |\sum_i \left(w_{i2qt} - w_{i2(q-1)t}\right) R_{iqt+k}| \tag{4}$$

where R_{iqt+k} is the return on the k-th day of the i-th asset in quarter q_t, and w_{i1qt} (w_{i2qt}) is the current quarter loading of PC1 (PC2) on asset i. The returns of both $PC1_t$ and $PC2_t$ are standardized to have zero mean and unit variance using the full sample moments.

Two observations stand out from Figure 4. First, for both PC1 and PC2, the largest changes occur during the GFC and the Covid-19 pandemic as marked by dashed lines. The Covid-19 period represents the largest change in both PC1 and PC2 over the entire sample period, and the absolute difference is a magnitude higher than in other periods. Three of the four largest changes for PC1 and the two largest changes for PC2 are during the Covid-19 period. Other large changes to PC1 and PC2 occur during the GFC and Brexit. For PC1, five of the top ten changes occur during the GFC. For PC2, among the ten largest shocks, four occur during the GFC and three during Brexit. However, the Covid pandemic was particularly acute. In terms of the magnitude of the Covid-19 period, the changes in PC1 and PC2 relative to the GFC and Brexit are, respectively, 2.5 times and 1.8 times larger. Compared to the average change outside of crises, these changes are almost twelve and nine times larger. Second, the absolute value of the PC differences is much higher for PC2 than PC1, approximately four times higher. Since PC1 and PC2 returns are standardized, this suggests that the change in the factor structure is much greater for PC2 during these times.

Note that if the weights do not change from quarter to quarter, *i.e.*, $w_{i1qt} \approx w_{i1(q-1)t}$ then $|PCJ_{qt-(q-1)t,k}| \approx 0$. However, even if $w_{i1qt} \neq w_{i1(q-1)t}$, then $|PCJ_{qt-(q-1)t,k}| \gg 0$ only if asset returns R_{iqt+k} are highly variable. In other words, both conditions must be true. While the PC weights are constructed from the correlation matrix of global asset returns, the variance of PC1 and PC2 also depend on the variance levels of asset returns. To better understand the driver of the changing PC factor return structure, Figures 4 and 5 graph respectively the average absolute differences of loadings over time and the high frequency realized biweekly volatility of PC1 and PC2 from January 1, 2007 through June 30, 2020. While both PC1 and PC2 loadings change the most, and return volatilities reach their highest levels during crisis periods, there is an important and notable difference between PC1 and PC2. Figure 4 shows that the scale of the changes in PC2 loadings are three times those of PC1, while Figure 5 shows the opposite for return volatility – PC1's return volatility is four times that of PC2's.

2.5 Correlation of Factors with Economic Variables

Crisis periods represent large shocks to the global economic system. In order to link these global economic shocks more closely to the factor structure, we document the high frequency correlation between three commodity returns representing different parts of the economy – copper (industrial), oil (energy), and corn (agriculture). In particular, we use our high-frequency variance-covariance matrix to generate R^2s of each commodity return on the two PC returns constructed from the 26x26 correlation matrix of aggregate asset returns.

These results are graphed in Figure 6. First, the figure shows that there are periods when the R^2s are quite high for two of the commodities – copper and oil – in excess of 25% and reaching 50%. The two PCs of equities, bonds, and currencies explain a significant amount of variation in key economic commodities. Second, the R^2s vary through time, where the factor structure is increasingly correlated with both oil and copper for long periods after the financial crisis, but then flattens. The fact that these patterns are similar for copper and oil during the GFC does not appear to be random or coincidental. Third, marking the three crises by dashed lines in Figure 6, there are clear spikes in R^2s for the three economic commodities during crises. This evidence suggests that large movements in the factor structure during these periods are related to underlying economic variation. For example, while corn returns have low R^2s throughout most of the period (*i.e.*, less than 10%), its R^2 spikes close to 25% around the GFC and the Covid-19 pandemic. For all three commodities, the R^2s go through a very sudden, large move during the Covid-19 period. In the next section, we investigate the Covid-19 period in detail.

3 Global Factor Return Structure and Covid-19

On December 31, 2019, the World Health Organization (WHO)'s China office was informed of a new form of pneumonia circulating in Wuhan City, Hubei Province. Within a week, the cause of the pneumonia was identified as a novel coronavirus, named Covid-19, related to previous coronaviruses such as SARS and MERS. Much more transmittable than either SARS or MERS, Covid-19 would soon spread throughout Wuhan City and begin popping up in various countries, eventually leading to a global pandemic and millions of deaths. Economies for many months were shut down with wide-scale unemployment and large drops in GDP. Arguably, the Covid-19 pandemic has been the largest global catastrophe since World War II.[11]

The importance of the Covid-19 pandemic period for global asset return variation is evident from our results so far. Here, we focus on two deeper inquiries. First, we document several characteristics of the factor structure during this period, including a biweekly analysis of how the factor structure changed, formal tests of these changes, and a breakdown of these changes. Second, we investigate the relationship between the factor returns and Covid-19 news during this period.

This second analysis is especially important because, unlike other crises, the Covid-19 pandemic represents an exogenous shock to the global and economic financial system. If

[11]The impact of Covid-19 has spurred a recent literature in finance, including Alfaro et al. (2020); Baker et al. (2020); Falato et al. (2020); Giglio et al. (2020); Gormsen and Koijen (2020); Haddad et al. (2021); Hassan et al. (2020); He et al. (2022); Pastor and Vorsatz (2020); Ramelli and Wagner (2020); Wu (2020).

we can identify Covid-19 shocks/news, then the analysis is potentially revealing because it allows us to uncover a fundamental causal relationship between crisis shocks and the factor structure of returns. Specifically, we explore two relationships between the factor structure of global asset returns and Covid-19 news shocks. First, we use country-specific Covid-19 news from Ravenpack, which tracks and aggregates local media sources and news stories. We treat the index of news from each country as a country's exposure to Covid-19 and treat changes in the news index as innovations to this exposure. We relate (i) the PC returns to these innovations, (ii) each country's specific factor return component to each country's Covid-19 news innovation, and (iii) each country's asset beta with respect to the PCs to that country's Covid-19 news index. Second, we relate each country's specific factor return component to short-term forecast errors of each country's Covid-19 deaths made by arguably one of the world's leading epidemiological research teams on Covid-19.

3.1 Factor Loadings

Figure 7 plots the factor loadings for each asset i for PC1 and PC2, respectively, defined as $w_{i1,t}$ and $w_{i2,t}$, over 14 periods – the average of the biweeks in the final quarter of 2019 and the 13 biweeks throughout the Covid-19 period. Equities, fixed income, and exchange rates are graphed in blue, red, and green, respectively.

For the "normal" period leading up to Covid-19 and the first three biweeks of Covid-19 (through February 11th, 2020), the factor loadings of PC1 and PC2 are relatively stable. Equity, fixed income, and exchange rate loadings are clustered by asset class. The PC1 loadings are positive for equity and slightly positive (with the exception of the Yen/$) for exchange rates and strongly negative for fixed income. The PC2 loadings are both positive for equities and fixed income, but strongly negative for exchange rates. Biweek 4 is similar except Italy drops out of the cluster. Biweek 4 runs from February 12th through 25th, including the first lockdown outside of China, in the Lombardy region of Italy.

The factor structure begins to change during the 5th biweek (February 26th through March 10th). This period includes the emergence of community spread in Europe and the United States. The majority of loadings on exchange rates turn negative for PC1 in this biweek but change back in the following biweeks. The loadings on FX turn positive for PC2. The largest changes, however, occur during the 6th and 7th biweeks for PC2. As Figure 7 shows, equities in biweek 7 have mostly neutral loadings for PC2, and exchange rates all switch to a strongly positive loading compared to the negative loadings from earlier weeks – PC2 loads positively on the dollar basket. If an asset is correlated to PC2, and PC2 has changed to reflect exposure to Covid-19, then this asset is short the dollar. Even though the U.S. was hard hit, the dollar remains a hedge against Covid-19. These two biweeks – March 11th through April 7th – represent the height of the pandemic crisis, including the WHO declaring a pandemic on March 11th and the U.S. declaring a national emergency on March 13th, a ban on European travel, and essentially stay-at-home orders across the country, leading to the wide scale closings of non-essential businesses, schools, and travel.

For biweeks 8-10, the loadings of PC2 transition back to the earlier period. The positive FX loadings become neutral and the equity loadings begin to drift back up. By biweek 11, the transition is complete and the loadings closely resemble those of the normal period. Towards the end of biweek 7, and throughout this subsequent period, the Federal Reserve enacted an extraordinary set of policies, Congress passed the unprecedented $2.2 trillion economic stimulus bill (the CARES Act), the U.S. announced Operation Warp Speed (an accelerated program to develop, trial, and produce vaccines) and preliminary trials of experimental vaccines by Pfizer and Moderna started. Most European countries took similar actions.

3.2 Factor Structure

Table 3 summarizes the information for PC1 and PC2 during the Covid-19 period and just prior to it. Table 3 Panel A provides the mean, volatility, and autocorrelation of the two PCs. During the Covid-19 pandemic period, PC1 has an annualized mean return of -54.1% with volatility of 142.4%. As noted, PC1 is a leveraged position long equities and short fixed income, the yen and, to a lesser extent, the dollar. In contrast, PC2 has a mean of 1.7% and volatility of 41.4%. As described previously, PC2 has offsetting long positions in equity and fixed income with holdings in $-based exchange rates flipping signs throughout the period.

As a measure of how PC1 and PC2 change during the Covid-19 period, Table 3 Panel B documents two relevant summary statistics: (i) the high frequency standard deviations of PC1 and PC2 for each biweek during the period, and (ii) the correlation between PC1 using the PC loadings of each biweek compared to PC1 using the PC loadings from the biweeks of the "normal" quarter from October 2019 to December 2019, for each of the 13 Covid-19 biweeks. The same analysis is performed on PC2. This analysis examines the importance of changing factor structure due to changing loadings, while holding volatility constant, in order to isolate the role of changing correlations. With respect to (i), note that the high frequency realized biweekly volatility of PC1 and PC2 is given by $\sqrt{var\left(PC1_{t+1}\right)} = \sqrt{w_{t+1}^{\prime 1} \sum_{t+1} w_{t+1}^{1}}$ and $\sqrt{var\left(PC2_{t+1}\right)} = \sqrt{w_{t+1}^{\prime 2} \sum_{t+1} w_{t+1}^{2}}$.

Panel B shows that the volatility of PC1 is 37%, 397%, and 838% higher in biweeks 4, 5, and 6 relative to the average volatility over biweeks 1–3. After the large volatility of PC1 in biweek 6, the volatility falls every biweek thereafter, going from 374% in biweek 7 to 89%

in biweek 13. At the end of the sample, the resulting volatility is still elevated relative to biweeks 1–3. As mentioned above, biweek 12 is somewhat special and the volatility jumps back up, only to drop back again in biweek 13.

Similarly, the volatility of PC2 is 396% and 350% higher in biweeks 5 and 6 relative to the average volatility over biweeks 1–4. Volatility drops back after biweeks 5 and 6 but again to elevated levels. Specifically, relative to biweeks 1–4, the volatility in biweeks 7–13 are higher by 73% to 157% or approximately twice that of the normal period. The volatility of PC2 is approximately 1/2 to 1/5 of PC1's volatility.

Even though the PC1 weights change significantly, as shown in Figure 7, the loadings on equity remain stable throughout the period. Given equity's much higher volatility during this period, the correlation between PC1 using the Covid-19 weights and PC1 using the normal period weights, is 0.99. Thus, changes are dominated by Covid-19 return volatility and not correlation changes. In contrast, the PC2 weight changes lead to much different correlations, especially during the peak of the Covid-19 crisis. In particular, biweek 6, where the correlation between PC2 using normal period weights versus using biweek 6 weights is 0.72, and for biweek 7 the correlation between PC2 using contemporaneous weights and PC2 using normal weights, is only 0.13.[12]

Table 3 Panel C provides formal tests of large absolute differences in the PC structure during Covid-19 relative to other periods. The first test compares $|PCJ_{qt-(q-1)t,k}|$ during Covid-19 versus all other periods for both PC1 and PC2. The differences for PC1 and PC2 are 0.113 and 0.545, respectively, with corresponding t-statistics of 15.32 and 11.32. While these calculations measure the differences in the PCs, they include the variability of returns. The second test simply calculates the average difference in weights from quarter to quarter, $|\sum_i \left(w_{iJqt} - w_{iJ(q-1)t}\right)|$, for both PC1 and PC2 in Covid-19 versus the rest of the sample. The difference is significantly positive with PC1 and PC2 respectively being 0.018 (with t-statistic 3.45) and 0.033 (with t-statistic 2.29). Since the absolute value of the weights averages a little less than 0.2, the estimated differences of 0.018 and 0.033 represent 9.0% and 16.5% changes, respectively.

Figure 6 documents the implied R^2 (*i.e.*, based on the high-frequency return variance-covariance matrix) of three commodity returns on the two PC factors over the sample period. Table 3 Panel D reports these R^2s during the Covid-19 period. Consistent with the discussion in Section 2.5, the R^2s reach their high in biweek 5 (44.37%, 24.04%, and 50.36% for copper, corn and oil, respectively). Compared to biweek 1, this R^2 is particularly high (22.39%,

[12]The correlations of PC2 using contemporaneous versus normal weights differ from one throughout other times of the Covid-19 period, but less so. For example, biweeks 3 to 5 produce high frequency correlations of 0.90, 0.90, and 0.95 for the PC2s.

3.39%, and 20.03% for copper, corn, and oil, respectively). Thus, the largest change in global PC factors coincides with the highest correlation between the PC factors and the three economic commodities, which occurs at the peak of the Covid-19 crisis and suggests a fundamental economic shock occurred during the crisis.

3.3 Changing Factor Structure

Figure 5 shows that the volatility of PC1 and PC2 reach their highest level during the Covid-19 period, but how much of this is due to changing PC weights versus changing asset return variances?

To address this question, we decompose the changes of the realized biweekly variances into two components:

$$\begin{aligned} var\left(PCi_{t+1}\right) - var\left(PCi_t\right) &= w'^{i}_{t+1}\Sigma_{t+1}w^{i}_{t+1} - w'^{i}_{t}\Sigma_t w^{i}_{t} \\ &= \left(w'^{i}_{t+1}\Sigma_{t+1}w^{i}_{t+1} - w'^{i}_{t}\Sigma_t w^{i}_{t}\right) + \left(w'^{i}_{t}\Sigma_{t+1}w^{i}_{t} - w'^{i}_{t}\Sigma_{t+1}w^{i}_{t}\right) \\ &= \underbrace{w'^{i}_{t}\left(\Sigma_{t+1} - \Sigma_t\right)w^{i}_{t}}_{Due\ to\ Changing\ VarCov} + \underbrace{\left(w'^{i}_{t+1}\Sigma_{t+1}w^{i}_{t+1} - w'^{i}_{t}\Sigma_{t+1}w^{i}_{t}\right)}_{Due\ to\ Changing\ PC\ weights}. \end{aligned} \tag{5}$$

For each biweek of the Covid-19 period, Table 4 reports these two components (biweekly variances are scaled by 10,000 to be in percentage terms).

Decomposing the change in variance of PC1 over the Covid-19 period, almost all of it comes from a change in the underlying asset returns' variance-covariance matrix, Σ_t, as opposed to a change in the loadings of PC1. The notable exceptions are some of the peak Covid-19 period transitions, where the biweek of February 12 has 21.4% coming from changing PC loadings and the biweek of March 11 has 37.8% due to changing PC weights.

In contrast, most of the change in the variance of PC2 is due to changing weights that play a much larger role in its variation. For example, 42.2% of the large increase in variance from biweek 4 to biweek 5 comes from changing weights, and although the variance of PC2 drops only 17% in biweek 6, -1995% of the drop is due to changing Σ_t, offset by a 2095% jump due to changing weights w_t. Throughout most of the Covid-19 period, Δw_t is just as important as $\Delta\Sigma_t$ with many offsetting changes.

3.4 Factor Returns and Covid-19

We show a significant change in the factor structure of global asset returns during the Covid-19 period. A reasonable inference is that these changes are likely due to Covid-19 specific news during this period and their effect on the macroeconomy.

One of the unique features of the Covid-19 crisis is that we can identify its causes, which come from the onset and spread of the disease that is exogenous and otherwise unrelated to economic conditions. Consequently, we can use news about the disease to measure exogenous shocks to the crisis and its potential impact on risk. By linking direct measures of news to the covariance structure of asset returns, we can identify how risk evolves during the crisis.

3.4.1 News Data

Ravenpack is a commercial vendor who employs natural language processing (NLP) algorithms to measure specific events and sentiment generated from unstructured text contained in a variety of media sources and company reports. Their analysis is both at the firm level as well as at the aggregate level. Starting in January 2020, in response to the coronavirus outbreak, Ravenpack produced a set of related Covid-19 news indices for every country, as well as a worldwide index. Specifically, they report on a daily basis (i) *Coronavirus Panic Index*, (ii) *Coronavirus Media Hype Index*, and (iii) *Coronavirus Media Coverage Index* for each country.[13] We use changes in these indices to represent unexpected news. We also construct a composite index of these three Covid-19 news indices for each country. Each index is standardized to have a zero mean and unit variance, and then the composite index is the average of the three standardized indices. Because news has a seasonal component (e.g., weekday versus weekend, Monday versus Friday), we deseasonalize each index.[14] Figure 8 graphs the deseasonalized composite index for each of the countries in our sample from January 1, 2020 to June 30, 2020.

Figure 8 offers several observations. First, time-series variation of the indices is intuitive. In January, 2020 there is little news about Covid-19. The first country's index to react is Japan, as the lone Asian country represented in our sample of ten countries. Towards the end of January, almost all the indices spike up as China locked down and many countries imposed travel bans. For much of February, the index level plateaus, until a large spike in Italy, followed by all other countries, in late February. As previously mentioned, people became aware that the coronavirus was spreading in northern Italy by the late third week of February. The indices reached their peak throughout March into early April as it became

[13]These measures are meant to capture the amount of news related to Covid-19 (such as references to panic/hysteria, percent of news coverage, etc.). As described by Ravenpack, the Coronavirus Panic Index "measures the level of news chatter that makes reference to panic or hysteria and coronavirus"; the Coronavirus Media Hype Index "measures the percentage of news talking about the novel coronavirus"; and the Coronavirus Media Coverage Index "calculates the percentage of all news sources covering the topic of novel coronavirus."The three indices are all highly correlated.

[14]For the six months of data, we calculate the average ratio of each day's index level relative to a -3 day/+3 day window. The average for each day of the week is then calculated over the entire sample and then used to adjust the index level through time.

clear the virus had spread widely, and economies began to lockdown globally. Thereafter, there is a slow downward trend as news about Covid-19 levels off. Second, there is clear cross-sectional variation across countries. At different times, Japan has both the highest and lowest level of the composite index; Italy is an outlier during the peak Covid-19 period; and some countries are consistently at opposite ends of the spectrum, such as Switzerland and Spain. Finally, while there is a trend of the index for all countries through time, there is clear time variation across the country indices. We will show in the next subsection that this variation contains economic content about asset covariance structure and systematic risk.

3.4.2 Global Results

Table 5, Panel A documents results for regressions of weekly changes in each of the Ravenpack Coronavirus worldwide indices on contemporaneous PC1 and PC2 returns. For the regressions on the first principal component, the t-statistics are −3.26, −5.53, −4.10, and −4.55 (with R^2s 34.0%, 37.8%, 28.4%, and 33.6%), respectively for the *Panic*, *Media Hype*, *Media Coverage* and the composite index. For regressions on the second principal component, the t-statistics are −3.17, −4.71, −4.23, and −4.38 (with R^2s 24.4%, 42.2%, 36.8%, and 38.3%), respectively. Both PC1 and PC2 are highly negatively correlated with changes in Covid-19 news. Because the sign of the loadings on PC1 and PC2 are restricted to have positive average equity loadings (for consistency through time), this negative relationship is intuitive – an increase in the Coronavirus news indices is associated with negative equity returns.

As noted in Section 2, PC1 and PC2 are correlated because the PC factor structure is generated from the correlation matrix as opposed to the variance-covariance matrix. A natural question is which of the factor returns is more related to Covid-19? The last four columns of Table 5 report results from a multivariate regression of changes in the worldwide Coronavirus news index on both PC1 and PC2 simultaneously. While coefficient estimates on PC1 and PC2 are both still negative, there is a substantive drop in PC1's coefficient estimates with only two of the coefficients being even marginally significantly different from zero. In contrast, the coefficients on PC2 remain highly significant and negative. From this perspective, PC2 seems to be more related to Covid-19 news shocks.

As shown in Section 2, PC2's changing variance during the Covid-19 period is largely driven by changing PC weights. A question, therefore, is whether PC2 returns are related to Covid-19 news through these changing PC weights. We calculate the difference between PC returns using the PC weights estimated over the Covid-19 period versus those estimates over the "normal" period (*i.e.*, prior quarter). We then apply these weights to the same realized returns of the underlying assets (daily) over the Covid-19 period. In this way, we can see if the risk weights from the estimated PCs shift significantly from the period before to the Covid period, holding constant the returns of the underlying assets themselves during the Covid period.

Table 5, Panel B reports regression results for the return difference between the PCs calculated using the Covid-estimated weights (PC) and the PCs calculated using risk weights estimated in the prior/normal period (PC^N). With respect to PC1, there is little evidence that the change in PC weights are correlated with Covid-19 news shocks. None of the coefficients for any of the news indices are significant. In contrast, the return spread between PC2 using Covid-19 versus "normal" PC2 weights is significantly negatively correlated with Covid-19 news shocks for three of the four news indices.

3.4.3 Country-Level Results

On average, we find a significant relationship between worldwide Covid-19 news shocks and the PC returns, especially for PC2. However, as Figure 8 shows, there is substantial cross-sectional variation in country-level Covid-19 news shocks. We exploit that country-level variation here as a further test of how Covid-19 news is related to asset return covariance structure and to gain further insight into how evolution of news about the pandemic impacts risk. More generally, the exogenous nature of the Covid news shocks and our ability to measure them provides a rare opportunity to track the evolution of a financial crisis and identify its dynamics – being able to do this both over time and across countries – to yield further insights about changing risks during a crisis.

Table 6 documents results from a panel regression of each country's Covid-19 news innovation on that country's systematic factor return component, defined as the component of an asset's return coming from the two PCs. Specifically, for asset j in country i, from time t to $t+1$, we estimate its systematic component of returns, $F_{ij;t,t+1}$ as:

$$R_{ij;t,t+1} = \alpha_{ij} + \underbrace{\beta_{ij1;t-1,t+1} PC1_{t,t+1} + \beta_{ij2;t-1,t+1} PC2_{t,t+1}}_{F_{ij;t,t+1},\ systematic\ factor\ return\ component} + \epsilon_{ij;t,t+1}. \tag{6}$$

Returns for asset class j in country i are measured weekly.[15] We run three panel regressions: one for each of equity, fixed income, and currencies.

For equities, the systematic return component has a signficant negative coefficient with respect to all four of the Ravenpack country-specific news indices. In contrast, the fixed in-

[15]Ideally, the betas, $\beta_{ij1;t-1,t+1}$ and $\beta_{ij2;t-1,t+1}$, should also be estimated weekly but, due to the high frequency variance-covariance matrix being biweekly, the betas used in constructing the factor returns are measured over two weeks on an overlapping basis. Importantly, these betas are implied by the high frequency variance-covariance matrix.

come systematic component has a positive, but insignificant coefficient on Covid-19 country-specific news. The systematic component of currency returns, however, is consistently negative, though not always reliably different from zero. As shown in Figure 7, the loadings on fixed income are mostly negative. The impact of Covid-19 news has two effects on fixed income securities. On the one hand, bad news implies a worsening fiscal and credit problem for a country, leading to a fall in bond prices. On the other hand, a weaker economy pushes down interest rates, and along with a flight to "safety," increases bond prices. The net effect is a small positive effect, suggesting the interest rate and flight to quality effects dominate during the crisis. For exchange rates, Figure 7 shows that FX loadings flip sign during the Covid-19 period, but the net effect on exchange-rates is negative, consistent with the dollar rallying relative to other currencies during the crisis.

Unlike asset returns which primarily relate to unexpected Covid-19 shocks, as represented by news innovations, the realized betas, $\beta_{ij1;t-1,t+1}$ and $\beta_{ij2;t-1,t+1}$, have an expected component ($E_{t-1}\left[\beta_{ij1;t-1,t+1}\right]$ and $E_{t-1}\left[\beta_{ij2;t-1,t+1}\right]$), and an unexpected component. To differentiate between these two pieces, we run three panel regressions of biweekly betas of each asset in each country on the level of the Ravenpack Coronavirus indices averaged over the corresponding biweek. Panel A of Table 7 runs this regression contemporaneously, while Panel B runs the same regression but lags the news index by one biweek to capture the expected beta component.

For the contemporaneous regressions for PC1, the relationship for equity and fixed income is positive and highly significant. Countries with higher equity and fixed income PC1 betas are those countries more exposed to Covid-19 (as measured by higher Coronavirus news index levels). Specifically, the coefficients for equity and fixed income are respectively 0.085 and 0.066 (with t-statistics of 3.28 and 4.20). Since we standardize the index to be mean zero, unit variance, the estimates suggest that a one-standard deviation increase in the level of the news index produces 0.085 and 0.066 higher beta to PC1 for equities and bonds, respectively. Figure 7 shows that the loadings of PC1 are more related to equity and fixed income than exchange rates. Therefore, perhaps not surprisingly, the PC1 betas for currencies are not significantly related to the Covid-19 news index.

For PC2, which Figure 1 shows is more driven by exchange rates, the results are reversed. For FX, the PC2 betas are significantly related to the Covid-19 news index – countries more exposed to Covid-19 have currency returns (relative to the US dollar) that are more exposed to the PC2 factor. Specifically, the coefficient estimate is 0.120 with a t-statistic of 1.80. In contrast, the factor exposures of equity and fixed income returns in these countries are not significantly related to the PC2 factor. As a whole, these results support the thesis that a country's asset return exposure to PC1 and PC2 seems to be fundamentally related to that country's Covid-19 exposure (as measured by the country's Coronavirus news index).

Panel B also produces similar results using lagged levels of the news index in order to capture the expected component of factor exposure. The coefficient estimates of equity and fixed income PC1 betas on the lagged Covid-19 index are almost identical to those using the contemporaneous Covid-19 index. Similar results are also obtained for the coefficient estimate of FX PC2 betas when using the lagged news index. These findings suggest that cross-sectional variation across asset classes with respect to PC1 and PC2 betas are forecastable based on cross-sectional variation in Covid-19 news index levels across countries. Countries more highly exposed to Covid-19, or more precisely countries whose news is more dominated by Covid-19, have higher future factor exposures or larger systematic risk during the Covid-19 period. These results indicate that assets and markets more exposed to Covid-19 news subsequently become more exposed to systematic risk. Tracking news about Covid-19, and its relation to asset markets, is a reliable indicator of changing systematic risk exposure across assets, countries, and time.

3.4.4 Epidemiological Model Forecast Errors

While tracking news about Covid-19 is one way to measure exposure to Covid-19 across asset markets, another direct measure is to appeal to epidemiological models of the spread of the disease.

In the wake of the Covid-19 pandemic, leading epidemiological groups within research institutions began to produce forecast models of infection rates and deaths both within and across countries. Of particular focus was analyzing the impact of mitigation efforts such as sheltering-in-place, partial shutdowns, social distancing, and mask wearing. Two of the better-known research groups, the MRC Centre of Global Infectious Disease Analysis and Abdul Latif Jameel Institute for Disease and Emergency Analytics at the Imperial College of London and the Institute for Health Metrics and Evaluation at the University of Washington provided models and forecasts of global Covid-19 deaths as early as mid-March.[16]

As one of their forecasting analyses, the Imperial College of London group produced one-week ahead forecasts of cumulated deaths for up to 69 countries as reported by the European Centre for Disease Prevention and Control (ECDC).[17] These one-week ahead forecasts start

[16]These research institutions took different approaches to modelling Covid-19. The Imperial College of London group's models are more in the vein of Susceptible Exposed Infectious Recovered (SEIR) epidemiological models while the University of Washington group provides empirical curve fitting models based on Covid-19 cases, hospitalizations and deaths. For an excellent discussion of SEIR models in the recent economic literature, see, for example, Atkeson (2020) and Stock (2020), and Eichenbaum et al. (2021) and Jones et al. (2021) for theoretical economic models using SEIR models.

[17]The ECDC is considered one of the main reporters of Covid-19 data along with Johns Hopkins University, the World Health Organization (WHO) and the U.S. Center for Disease Control (CDC). All of the data

on March 15, 2020 for Italy and the U.S. with the other eight countries in our sample having forecasts initiated over the next few weeks. The forecast model is an ensemble average of four related models.[18]

For four of the representative countries (across three continents), Figure 9 documents the total number of deaths each day (in solid blue) and the one-to-seven day ahead forecasts of deaths each week (given by red dots), from the start of the forecast period to June 31, 2020. The difference between the blue and red points therefore represent forecast errors. While some of the variation in ECDC deaths are related to random variation in reported deaths, there is nevertheless some clear patterns. Japan aside, the forecasts of the other representative countries' death rates increase sharply, then decline thereafter. When deaths start to increase at a high rate, almost all the forecasts, irrespective of the country, overestimate deaths in the following weeks. Moreover, these forecast errors occur at different times for different countries. For example, the errors take place in late March to early April for Italy but early April to mid-April for Germany. Finally, the forecasts for the U.S. tend to be overly pessimistic over most of the period. While the U.S.'s Covid-19 cases continued to climb over much of the period, fatality rates *ex-post* declined, possibly due to increasing testing of people who were less sick, different infection rates across demographics (*i.e.*, younger people getting sick), and better hospital care for those who are ill.

Table 8 provides evidence that a country's systematic factor return component for an asset class possesses information about current and future short-term forecast errors of total deaths. The death forecast models described above rely on assumptions about the coronavirus transmissibility, accuracy of reported cases, fatality rates, infections and demographics in the country, future ability to service hospitalized patients along with emerging therapeutics. It is an interesting question whether financial markets, captured by the returns of our systematic factors $F_{ij;t,t+1}$ have something to add to these forecasts and, at the very least,

produced by these agencies are highly correlated but can differ at any given point in time. The Imperial College research group calibrates their models to the ECDC.

[18]For a detailed description of the model, see "Short-term Forecasts of Covid-19 Deaths in Multiple Countries" developed by the Imperial College Covid-19 Response Team, https://mrc-ide.github.io/Covid19-short-term-forecasts/. The first two models are based on estimating transmissibility of the coronavirus and use this rate to forecast the incidence of death. Both models use back data to estimate the model's parameters and simulations to provide mean and median one week forecasts. The third model uses reported cases, probability of death given infection, and distribution of times from infection to death, to forecast the number of deaths over the next week. As with the first two models, this model is couched in an assumed distributional framework, resulting in mean and median forecasts from simulations of the model. The fourth model is an empirical Bayesian model that works backwards from deaths to estimate transmission rates and infections under different mitigation approaches such as social distancing, public event bans, school closures, quarantining, lockdowns, *etc.* An important aspect of these models is the adjustment for demographical differences in age distributions across countries and different fatality rates within these age distributions. We thank Sangeeta Bhatia of Imperial College for providing us with the relevant forecast data.

are contemporaneously related to forecast errors of total deaths.

To investigate this question, we run a panel regression of the log growth rate in weekly cumulative Covid-19 deaths for each country against the Imperial College of London's ensemble forecast model along with the country's lagged systematic factor return for equity, fixed income, and exchange rates. Specifically,

$$\ln\left(\frac{D_{it+1}}{D_{it}}\right) = \mu + \gamma_1 \ln\left(\frac{FD_{it}^{t+1}}{D_{it}}\right) + \gamma_2 F_{ij;t-k,t-k+1} + \eta_{it,t+1} \tag{7}$$

where D_{it} is the cumulative Covid-19 deaths at time t for country i, FD_{it}^{t+1} is the forecast at time t for the cumulative Covid-19 death total at time $t+1$, $F_{ij;t-k,t-k+1}$ is the aforementioned country's systematic factor return component for asset class j from time $t-k$ to $t-k+1$, where time t is measured in weeks.

Table 8, panel A reports the results. First, and perhaps not surprisingly because much of the relevant information for next week's Covid-19 death totals is known, (*i.e.*, reported cases from weeks back and fatality rates), the coefficients on $\ln\left(\frac{FD_{it}^{t+1}}{D_{it}}\right)$ are close to the theoretical value of 1 with high R^2s. For the countries in our sample, the coefficient estimates are, respectively 0.86, 0.92, and 0.89 with R^2s of 83%, 85% and 86%. Second, and most interesting, when the model forecast and the country factor return are included in a multivariate regression simultaneously, the coefficient on the one-week lagged equity-specific factor return is negative and statistically significant. The coefficient is −2.21 with a t-statistic of −2.33, increasing the R^2. This result indicates that a negative factor return component on a country's equity index helps forecast next week's Covid-19 death rate above and beyond leading epidemiological forecasts. The fact that this coefficient is negative is consistent with a country's factor return component being associated with bad Covid-19 news, which in turn portends higher than expected Covid-19 death totals. Note that factor returns weeks ago may contain information about Covid-19 infection rates weeks earlier which are determining factors for next week's Covid-19 death rates. Consistent with this idea, the coefficients on the two- and three-week lagged equity factor return are still negative albeit smaller and of weaker significance. Third, the results associated with fixed income and exchange rate factor component returns are mixed, consistent with earlier results on the weaker relationship between Covid-19 shocks and fixed income and exchange rate factor returns.

Table 8, Panel B provides results for a different analysis than those generated by regression equation (7). Suppose the Imperial College model provides the "best" forecast of week ahead Covid-19 deaths, implying that the forecast error, $\ln\left(\frac{D_{it+1}}{D_{it}}\right) - \ln\left(\frac{FD_{it}^{t+1}}{D_{it}}\right)$, represents an unexpected shock. What impact do these shocks have on the factor return components of the country's equity, fixed income, and exchange rate returns? Given the results associated with Ravenpack's news index innovations, we might expect positive (negative) forecast errors to represent bad (good) news for the country's economy and to financial markets. To test this idea, we regress the death forecast error on the contemporaneous return in a panel regression. With respect to equity markets, the coefficient estimate is strongly significant with an intuitive negative sign (−14.52 with a t-statistic of −3.29 and an R^2 of 9.5%). As discussed, the *ex-ante* sign of fixed income and exchange rates is ambiguous, and their respective coefficients are −31.28 (t-statistic −1.41) and 36.09 (with t-statistic 1.96), consistent with a weak relationship.

Alfaro et al. (2020) develop their own curve-fitting model for Covid-19 infections for the U.S. and then relate forecast errors of their model to future short-term U.S. equity returns, where unexpected model shocks for Covid-19 cases appear able to predict future returns. Panel B reports results for a similar exercise for Imperial College's forecast errors for Covid-19 deaths across our sample of countries. In contrast to Alfaro et al. (2020), we find no statistically significant evidence that forecast errors can predict country factor component returns of either equity, fixed income, or exchange rates. The coefficients are respectively 13.10, −69.92, and 48.35 (with t-statistics of 1.20, −1.41, and 1.19).

4 Global Changing Risk in Other Crises

Sections 2.3-2.5 document how the factor structure shifts through time, especially during times of crisis. The largest changes in the factor structure appear to be related to three events: the global pandemic, the global financial crisis and, to a lesser extent, Brexit. The change in the PC structure is sudden around the onset of each crisis, but seems to be only temporary, and the first two PCs change in different ways. The first PC is mostly driven by changes in the underlying asset return volatility, while the second PC is driven by changes in factor loadings due to shifts in the correlation of asset returns. Section 3 provides a detailed analysis of the Covid-19 global pandemic, where Covid-19 shocks, being exogenous, allow us to identify how the timing and characteristics of the changes in the first two PCs relate to crisis shocks.

In this section, we extend the analysis to other crisis periods, looking for similar patterns we found in the Covid-19 crisis, in an attempt to generalize the changing nature of systematic risk and risk exposure during a crisis. We compare how the factor structure of asset returns changes during other crisis periods compared to Covid-19, finding some common features.

4.1 The GFC and Brexit

Figure 4 shows that the global financial crisis (GFC) from 2007 to 2009, especially around the bankruptcy of Lehman Brothers in the Fall of 2008, exhibits substantial changes in the PC1 and PC2 factor structure. Figure 5 and Table 3 show that the volatility of the PC returns is also second highest to the Covid-19 period.

In addition, the period around June 23, 2016 when the U.K. voted to leave the EU (*i.e.*, Brexit) also shows similar patterns. Table 3 documents that the third largest change in PC2, and the sixth and fifth highest PC1 and PC2 volatilities all occur during the biweek (biweek 13) of the Brexit vote.

Table 9, Panel A reports a similar analysis to Table 3 – comparing both $|PCJ_{qt-q(t-1)t,k}|$ and $|\sum_i (w_{iJqt} - w_{iJ(q-1)t})|$ for PC1 and PC2 during crisis versus non-crisis periods – for the GFC and Brexit crisis periods. The differences for PC1 and PC2, respectively, are 0.087 (t-stat of 12.91) and 0.666 (t-stat of 17.00) for the GFC period and 0.007 (t-stat of 1.08) and 0.604 (t-stat of 15.23) for the Brexit period, which are similar to those we obtained for the Covid-19 period (*i.e.*, 0.113 and 0.545). Because the differences in PCs also include the variability of returns, we also report the average difference in weights for both PC1 and PC2 for the GFC and Brexit periods. The results are also quite similar to those obtained over the Covid-19 period: 0.017 (t-stat of 1.85) and 0.054 (t-stat of 3.72) for the GFC and 0.016 (t-stat of 2.29) and 0.150 (t-stat of 2.18) for Brexit (Covid-19's results were 0.018 and 0.033).

To delve deeper into these crisis periods, we replicate the analysis of Figure 7 for the GFC and Brexit periods. Specifically, we follow 13 biweek periods during 2008 (biweek 14, July 1-14 through biweek 26, December 15-28) and in 2016 (biweek 9, April 22-May 5 through biweek 21, October 7-20).[19] Figure 10 plots the factor loadings for each asset i for PC1 and PC2 for the GFC and Brexit periods. Equities, fixed income, and exchange rates are graphed respectively in blue, red, and green.

There are many similarities between the pre-GFC and pre-Brexit periods with the pre-Covid-19 period. The asset class loadings are still clustered together, with PC1 having a positive loading on equity, negative loadings on fixed income, and neutral-to-negative loadings on exchange rates. However, the loadings on PC2 differ across asset classes, with equity and fixed income having neutral-to-positive loadings for pre-Covid-19 and pre-Brexit

[19] Biweek 19 includes the Lehman Brothers declared bankruptcy on September 15, the bailout of AIG, a run on money markets on September 16th, and preliminary legislation to address these issues on September 20th. Many other biweeks also include relevant news. For example, a large retail bank, IndyMac, failed on July 11th (biweek 14); the government sponsored enterprises (GSEs), Fannie Mae and Freddie Mac, were placed into receivership on September 7 (biweek 18); the proposed government bailout was rejected by Congress on the 29th and a later version was passed on October 3rd (biweek 20); and, with the collapse in global equity markets on October 6th, unprecedented action and programs by central banks to restore liquidity in markets over the next few weeks (biweek 21 and 22).

periods, but not in the pre-GFC period. Exchange rates have positive loadings for pre-GFC and pre-Brexit, but not for the pre-Covid-19 period.

When the crises emerge (around biweek 18 for the GFC and biweek 13 for Brexit), the exchange rate loadings on PC1 mostly turn positive, which is consistent with the results for Covid-19. Across all three crisis periods, the factor loading on Yen/$ is negative. A positive (negative) loading means PC1 is long (short) the foreign currency against the dollar. The Yen currency is well-known as a funding currency and a safe haven (sometimes called "risk-off") asset. This result suggests the Yen/$ plays a unique role with respect to the correlation of global asset returns during a crisis. As documented for the Covid-19 period, and confirmed by the Covid-19 news analysis, most of the action is seen in PC2. While the factor structure is different pre-crisis, there is some convergence to similar loadings during the crisis week and immediate weeks thereafter: equities have mostly neutral loadings with positive loadings for fixed income and exchange rates for the GFC, Brexit, and Covid-19. It is interesting that even with different factor structures pre-crisis, there is sudden convergence towards a similar factor structure at the height of a crisis, no matter its origin. Consistent with our discussion in Section 2.3, note that US short-term rates are below the average rates of other countries pre-GFC and pre-Brexit, but above these rates pre-Covid-19.[20]

Along with the three crises analyzed here, many economists also point to the Eurozone debt crisis that emerged in the Spring of 2011, and then re-emerged during the Summer of 2012, as another crisis. Unlike the other crises, however, there was no trigger event but rather a gradual recognition that Greece was effectively bankrupt and there were growing credit default swap spreads of countries in the southern periphery – Italy, Portugal and Spain. It is interesting to analyze the factor structure during the Euro crisis. However, despite the large movement in government bond spreads of some of the European countries in our sample, there is little evidence of any meaningful change in the factor structure.[21]

[20] While the sample size is small, the point estimates are telling. Both the equity and exchange rate loadings are much more similar across the three crisis periods than they are pre-crisis. For the Covid-19, GFC, and Brexit periods, equity PC1 and PC2 are, respectively, (0.268, 0.263 and 0.271) and (0.053, 0.023, and 0.009) compared to pre-crisis (0.236, 0.275 and 0.262) and (0.160, 0.087, 0.123), while exchange rate PC1 and PC2 are respectively (0.004, 0.051 and 0.033) and (0.288, 0.201, and 0.328) compared to pre-crisis (-0.024, -0.004, and -0.155) and (-0.184, 0.315, 0.351). The evidence is more mixed with respect to fixed income loadings: for PC1, the Covid-19, GFC, and Brexit crises have more differential loadings (-0.111, -0.218 and 0.051) versus pre-crisis (-0.205, -0.215 and -0.004), whereas, for PC2, they are somewhat similar (0.091, 0.169 and 0.201) versus (0.218, 0.196, and 0.315).

[21] In the appendix, Figure A.7 (the counterpart of Figures 7 and 10 for the three crisis periods) graphs the four most relevant biweeks during 2011 (from biweek 7, March 27-April 9, to biweek 10, May 8-May 22) and four biweeks during 2012 (from biweek 14, July 1-July14, to biweek 17, August 12-August 25). Each of the coincident biweeks has almost identical characteristics with no obvious change. The appendix also reproduces Table 9, where formal tests of absolute differences in PC1 and PC2, as well as absolute differences in loadings of PC1 and PC2, show significant differences (albeit small) for both the Eurozone Spring 2011 and Eurozone Summer 2012 crises. However, the differences are *negative*, unlike the other crises, indicating

This lack of abrupt change may be due to the gradual release of information about this particular crisis versus the others. The other crises all share the same common characteristic of a sudden piece of news or series of news that is large and unanticipated. The European debt crisis was a slower process, where much learning could have taken place with gradual events over multiple quarters: Greece's default, to widening spreads and capital outflows in Italy and Spain, to unprecedented action by the ECB. One piece of evidence in favor of this conjecture is the transitory nature of the factor structure changes around the trigger events for the other crises. These other crises are characterized by a large unanticipated shock, that seems to have a major impact on the risk structure of global assets, but only a temporary one. Such a shock is largely absent for the Eurozone crisis periods.

5 An Application to Investment Portfolios

Finally, we investigate the implications of our findings for popular investment portfolios, with a particular focus on their volatility and systematic risk exposure.

We explore the implications of the changing factor structure during crisis periods on four portfolios: equal-weighted $-denominated equity, equal-weighted $-denominated fixed income, and equal-weighted $-basket of currencies), and an active risk portfolio (risk-parity portfolio of equity, fixed income, and currencies with equal volatility in each asset, as measured over the previous quarter).[22]

We answer two questions in particular. The first is how does the volatility of these portfolio returns change during crisis periods and what percent of the variance is due to the two PCs? We document that systematic risk increases across all assets which severely limits the ability to diversify risk across assets. As an illustration, we compare the variance of the return on the passive equal-weighted portfolio to the average variance of each underlying asset return within that portfolio. The second question is, given systematic risk has increased, can this risk be hedged on an *ex-ante* basis during the crisis periods? We find the answer is no due to the rapid and temporary nature of crisis risk.

that changes during the Eurozone crisis periods are smaller than in normal times. Table A.9B further shows that the average loadings of equity, fixed income and exchange rates for PC1 and PC2 during these two Eurozone crisis periods are effectively the same as the period before these crises emerge.

[22]The equity and fixed income $-denominated portfolios effectively hedge out exchange rate risk. Any correlation with the FX portion of the PCs arises from the correlation between exchange rates and equities/fixed income (as opposed to exchange rates directly).

5.1 The Changing Systematic Risk of Portfolios

Table 10 reports summary statistics for the return on the four portfolios (equity, fixed income, currency and risk-parity) over the three crisis periods. Their annualized daily return volatilities are respectively 43.4%, 10.4%, 8.2% and 9.3% (Covid-19); 48.1%, 12.7%, 13.9% and 10.4% (GFC), and 19.3%, 7.2%, 7.4% and 4.0% (Brexit). The annualized daily return volatilities over the entire sample period are 21.3%, 7.3%, 7.2%, and 8.7%, respectively. Even though the risk parity portfolio, which is arguably built around diversification, tends to be more negatively skewed and kurtotic, both its volatility and maximum drawdown during the crisis periods are low relative to the equity, fixed income and currency portfolios.

We further decompose the variance of these portfolios into their systematic versus idiosyncratic components. The variance of each portfolio p can be written as:

$$\begin{aligned} Var\left(R_{pt}\right) &= w_p' \sum_t w_p \\ &= w_p' \left(\sum_t^{sys} + \sum_t^{idio}\right) w_p \\ &= w_p' \sum_t^{sys} w_p + w_p' \sum_t^{idio} w_p \end{aligned} \tag{8}$$

where w_p is the vector of weights for each of the 26 assets of portfolio p, $\sum_t^{sys}$ is the 26×26 variance-covariance matrix of $\beta_{ij1;t,t+1} PC1_{t,t+1} + \beta_{ij2;t,t+1} PC2_{t,t+1}$ for country i and asset class j, and $\sum_t^{idio}$ is the 26×26 variance-covariance matrix of the idiosyncratic returns for country i and asset j.

Table 11 breaks down the systematic risk for the four aggregate portfolios for each biweek during the Covid-19, GFC, and Brexit periods in Panels A, B, and C, respectively. We report the high frequency volatility of the return on the three passive portfolios (equity, fixed income, and exchange rates) and the risk-parity portfolio for the "normal" period and the 13 biweeks, as well as the two factor PC betas, the R^2 of the 2-factor model, and the ratio of the portfolio return variance to the average variance of each underlying asset return within the portfolio.[23]

[23]As discussed earlier, because the PCs are derived from the correlation matrix and not the variance-covariance matrix, the PC returns will be correlated. All the high frequency betas are calculated using the high frequency variance-covariance matrix of the asset returns. Specifically, we run the implied regression using the high frequency variance-covariance matrix:

$$R_{pt} = \alpha_P + p_{1pt} PC1_t + \beta_{2pt} PC2_t + \epsilon_{pt}$$

where

$$\beta_{1pt} = \frac{\sigma_{R_{pt}} corr\left(R_{pt}, PC1_t\right)}{\sigma_{PC1_t}\left(1 - corr(PC1_t, PC2_t)^2\right)} - \frac{\sigma_{R_{pt}} corr\left(R_{pt}, PC2_t\right) corr(PC1_t, PC2_t)}{\sigma_{PC1_t}\left(1 - corr(PC1_t, PC2_t)^2\right)},$$

$$\beta_{2pt} = \frac{\sigma_{R_{pt}} corr\left(R_{pt}, PC2_t\right)}{\sigma_{PC2_t}\left(1 - corr(PC1_t, PC2_t)^2\right)} - \frac{\sigma_{R_{pt}} corr\left(R_{pt}, PC1_t\right) corr(PC1_t, PC2_t)}{\sigma_{PC2_t}\left(1 - corr(PC1_t, PC2_t)^2\right)}.$$

5.1.1 Covid Pandemic

Consider first the Covid-19 pandemic period. All of the portfolios have relatively stable volatilities through the first three biweeks. The volatility of the equity portfolio is 16.32% in the fourth biweek and then shoots up 3.3 times and another 1.8 times in the fifth and sixth biweeks. The volatility then falls by about half in the seventh biweek, and drifts down half again over the next 6 biweeks, but still remains more than 2.3 times the level of the "normal" period. The fixed income and currency portfolios mimic the return volatility behavior of the equity portfolio, though less dramatically. In particular, the volatilities have a huge jump in biweeks 5 and 6, drop in biweek 7, spike again in biweek 12, and level off at a higher level than the "normal" period. The risk parity portfolio shows a similar pattern. The return volatilities start increasing around biweek 4 and remain high through biweek 7 with biweek 6 being the peak. Interestingly, by the 13th biweek, the volatility of the risk parity portfolio drops to much lower levels than the three underlying asset portfolios.

Table 11 Panel A also reports the PC1 and PC2 betas for the three passive and risk-parity portfolios for each biweek during the Covid-19 period. While all the PC1 betas are positive for the equity portfolio throughout the period, the three lowest betas occur in biweeks 5, 6, and 12, accompanied by substantial Covid-19 news. PC2 betas are even more dramatic. The betas are generally small or negative except during biweeks 5-7 and 12, where they are large and positive. For the fixed income portfolio, PC2 betas are also mostly positive from biweek 5 onwards. Arguably, the most dramatic change occurs for the FX portfolio. For biweeks 5-7, the PC1 and PC2 betas flip sign and then reverse thereafter in biweek 8 (with a blip in biweek 12 from Covid news).

With respect to the factor PCs' contribution to portfolio return variance, all three passive portfolios see an increase from biweek 1 to biweek 5. For equities, the systematic component of variance rises from 77.9% to 99.1%. For fixed income, the systematic component rises from 34.2% to 73.4%, and for currencies it increases from 8.0% to 47.7%. For the risk-parity portfolio, the PC's variance contribution rises from 70.2% to 95.2%. These levels remain elevated for the equity and exchange rate portfolios for the remaining biweeks, but revert for fixed income after biweek 7. Although not shown in the table, it is the second factor, PC2, that greatly increases the contribution of the systematic portion of return variance. For fixed income, PC2 increases the systematic portion of variance from 50.2% to 72.9% and for exchange rates from 22.5% to 47.9%. PC1 explains most of the variation of equity returns (93.8%). The evidence indicates that during the Covid-19 pandemic, systematic risk is a significantly larger portion of the variance of asset class portfolios.

We compare the variance of the return on a passive equal-weighted portfolio of equity, fixed income, and exchange rates versus the risk-parity portfolio by taking the average variance of each underlying asset return within the portfolio. If the number of assets within the portfolio is large, all (most) of the idiosyncratic variance of the individual assets should be diversified away. The ratio of the portfolio variance to the average variance of the underlying assets would therefore roughly equal the ratio of systematic risk to total risk (systematic risk plus average idiosyncratic risk) of the assets.

The higher the ratio the more that systematic risk dominates the individual asset risk and the less benefit from diversification. We report this ratio, $\frac{Var(P)}{Var(i)}$, in the last column for each portfolio in Table 11. The most striking results are for the FX portfolio. Through the early part of Covid-19, including biweek 5, the ratio ranges from 27.6% to 39.6%. From biweek 6 onward, the ratio increases to between 50.2% and 58.5%. Diversification benefits across the six exchange rates are significantly reduced as the Covid-19 period progresses. The equity portfolio exhibits similar behavior, albeit with a smaller change. For equities, the ratio ranges from 69.9% to 77.8% over biweeks 1-3 compared to 78.2% to 82.9% over biweeks 11-13. Table 2 shows that for both equities and exchange rates, the intra-correlation within these asset classes increased during the Covid-19 period, consistent with reduced diversification benefits. However, for fixed income the correlation is lower during Covid-19. Consistent with these facts, Table 11 Panel A documents that the $\frac{Var(P)}{Var(i)}$ ratio drops from 50.1 − 59.0% during the first four biweeks to 37.4 − 48.8% in biweeks 5 and 6. During the peak Covid-19 weeks, the lower systematic risk suggests higher benefits to diversification for fixed income, consistent with the earlier correlation results from Table 2. Fixed income assets incorporate a “flight to safety” feature during this period and may also face some credit risk, both of which decrease the correlation among global fixed income instruments.

Table 11 Panels B and C repeat the above analysis for the GFC and Brexit periods. Similar to the Covid-19 pandemic period, the volatility of the return on the three passive portfolios sharply increases around Lehman’s bankruptcy (biweek 19 of the GFC) and the vote for the UK to leave the EU (biweek 13 of Brexit). The volatility remains elevated for the GFC, but not Brexit. Interestingly, like the Covid-19 period, the return volatility for the GFC crisis at the end of the 13 biweek period is 1.97 times the average in the first three biweeks of the pre-crisis period.

5.1.2 GFC and Brexit

Table 11 Panels B and C report the PC1 and PC2 betas for the three passive portfolios and risk-parity portfolio for each biweek during the GFC and Brexit periods. Unlike the Covid-19 and Brexit periods, the more dramatic changes for the GFC period are with respect to PC1 betas as opposed to PC2 betas. The PC1 betas of the equity portfolio take a big jump as markets quickly deteriorate in biweek 18 (when the GSEs head into receivership) and remain high throughout. The PC1 betas of the fixed income portfolio are negative through biweek 17 and zero in biweek 18, with near-zero betas thereafter. Similarly, the PC1 betas of the FX portfolio are also negative through biweek 17, and then turn positive in biweek 18 and stay positive through the Winter of 2008.

However, in terms of comparing *how* the PC1 betas change, the peak periods for all three crises show similar patterns. For example, the fixed income PC1 betas are negative in all three pre-crisis periods, then move closer to zero at the peak of each crisis, and turn positive thereafter. For FX, despite the PC1 betas being different in the pre-periods before each crisis (being negative during the pre-GFC and pre-Brexit periods, but positive during the Covid-19 pandemic) these betas become quite similar at the crisis peaks (converging to zero, and these turn positive thereafter for each crisis). In terms of PC2 betas, the equity, fixed income, and FX betas all turn strictly positive during the crisis periods, even though they have different and disimilar signs pre-crisis (being negative during Covid-19 and positive during the GFC. Thus, it is the crisis periods where risk behaves similarly, even though the pre-crisis periods show variation in risk exposure. This evidence suggests there is something special about a crisis that generates common risk. The three crises we examine all have different pre-crisis risk characteristics and despite also having different origins – one a banking crisis, another a vote on economic integration and trade, and one a health pandemic – the characteristics of global assets share striking similarities during these crises. This novel result helps define and identify a crisis and its economic impact.

Panels B and C report the $\boldsymbol{R}^2$s of each asset portfolio on the two PC factors to describe the systematic variation of the passive portfolios during the GFC and Brexit periods. In contrast to the Covid-19 period, the $\boldsymbol{R}^2$s are equally high for both the equity and FX portfolios throughout the 13 biweeks of the GFC. The GFC crisis covers the period prior to Lehman's bankruptcy, where the $\boldsymbol{R}^2$s become higher for the fixed income portfolio as the crisis emerges. There is less of a pattern for the Brexit crisis, with systematic risk being lower around the trigger event date and in the subsequent biweeks. For example, for the fixed income portfolio, the $\boldsymbol{R}^2$s are 0.951, 0.866, and 0.935 in biweeks 10, 11, and 12 prior to the Brexit vote, but only 0.405 during biweek 13 of the vote. Similarly, low $\boldsymbol{R}^2$s occur for the FX portfolio during biweeks 11 and 15 surrounding the actual vote.

As a final comparison between the three crises, we investigate the diversification benefits of the three passive portfolios during the GFC and Brexit. Consistent with the results from the Covid crisis, the benefits of diversification are reduced for equities, where the ratio of systematic risk to total risk increases from low 60% in biweeks 15-17 to more than 80% in the peak GFC biweeks 18-21, and staying high thereafter. For Brexit, the ratios are similar during the peak Brexit biweeks 13-14. Also, similar to the Covid crisis period, diversification benefits increase for fixed-income during the GFC and Brexit, with the ratio declining from about 60% in biweeks 15-17 to as low as 31.5% in biweeks 18-21 (with ratios hovering in the low 40%+ thereafter) for the GFC, and for Brexit declining from mid 50% in biweeks 10-12 to as low as 14% during the peak Brexit biweeks 13-14. The major difference between these crisis periods, however, occurs with respect to currencies. In contrast to Covid-19, there are substantive benefits to holding a cross-section of exchange rates, with the ratio declining from 64.0% in biweeks 15-17 to as low as 26.6% in biweeks 18-21 for the GFC, and declining from 54.1% in biweeks 10-12 to 22.3% in biweeks 13-14 during Brexit.

5.2 Can Systematic Risk Be Hedged During a Crisis?

What are the implications of the above results for the risk mitigation properties of these portfolios? Given the large increase in systematic risk during crisis periods, can we hedge out this risk using out-of-sample estimates of the two PC factors?

We look at whether investors can hedge the systematic risk of these portfolios during the Covid-19, GFC, and Brexit periods. We compare the variance of the idiosyncratic error from an implied regression of the portfolio return on the systematic factors using the *ex-post* PC betas to a regression using investor's most recent estimate of the PC betas (the current biweek PC betas). Assuming the most recent beta is the investor's "best" estimate, the ratio of idiosyncratic variances provides a measure of the hedging ability during a crisis.

Using high frequency data, we back out the idiosyncratic variance from an *ex-post* multivariate regression of each of the portfolio returns, $R_{p;t,t+1}$, on the two PC factors, $PC1_{t,t+1}$ and $PC2_{t,t+1}$,

$$\underbrace{var\left(\epsilon_{p;t,t+1}\right)}_{\text{ex-post hedged}} \equiv var\left(R_{p;t,t+1}\right) - var\left(\beta^{ex-post}_{p1;t,t+1} PC1_{t,t+1} + \beta^{ex-post}_{p2;t,t+1} PC2_{t,t+1}\right). \tag{9}$$

We then compare the ex-post idiosyncratic error variance to similarly calculated errors from a PC factor hedging exercise in which the idiosyncratic variance is calculated from an *ex-ante* multivariate regression of the same portfolio returns on the same two PC factors, but using the *ex-ante* betas from the previous biweeks,

$$\underbrace{var\left(\epsilon^{H}_{p;t,t+1}\right)}_{\text{ex-ante hedged}} \equiv var\left(R_{p;t,t+1}\right) - var\left(\beta^{ex-ante}_{p1;t-1,t} PC1_{t,t+1} + \beta^{ex-ante}_{p2;t-1,t} PC2_{t,t+1}\right). \tag{10}$$

When the ratio, $\frac{var\left(\epsilon_{p;t,t+1}\right)}{var\left(\epsilon^{H}_{p;t,+1}\right)}$, is close to 1, this implies it is possible to hedge out the systematic risk from these portfolios. The ratio provides an approximate guide to hedging possibilities during crisis periods in attempt to capture the fast-changing covariance structure of a crisis.

Figure 11 graphs the ratio, $\frac{var\left(\epsilon_{p;t,t+1}\right)}{var\left(\epsilon^{H}_{p;t,+1}\right)}$, for the three passive portfolios. We present the results for 13 biweeks of each crisis period. Week 0 is the defacto crisis event, such as the biweek of September 15, 2008 for the GFC, June 23rd of 2016 for Brexit, and March 11th of 2020 for Covid-19.

Consider first the equal-weighted equity portfolio during the Covid-19 pandemic. Even though most of the risk of this portfolio is systematic, it cannot be hedged during the crisis. For example, while the hedge ratio is high and close to one in event weeks -2 and -3 (biweeks 2 and 3), this ratio drops close to zero from event biweek -1 through biweek 2 (i.e., biweeks 4-7, the peak of the crisis). The ratio goes back up in the next three biweeks, but drops again in the last two biweeks (biweek 12 and 13) due to the large changes in biweek 12. In other words, when it is needed most – during the severe Covid-19 biweeks – the changes in the factor structure and factor exposures reduce the ability to hedge, and attempting to hedge these risks ex ante proves fruitless.

The fixed income and exchange rate portfolios suffer similarly. As with the equity portfolios, these portfolios are easy to hedge in the first few biweeks with PC1 and PC2 being relatively stable, and hence the ex-ante hedged residual variance is similar to the ex-post hedged residual variance. However, the ratio of ex-ante hedged to ex-post hedged residual variance drops precipitously during the peak crisis biweeks 4-7. And, while the ratios increase again in later biweeks, the ratios also fall again sharply in biweek 12. The fact that all three asset portfolios suffer from the same inability to hedge the portfolio's systematic risk at the same time highlights a major challenge – that the factor structure changes so dramatically and rapidly during crisis periods that it makes it nearly impossible to hedge the changing risk.

Both the GFC and Brexit crises also produce poor ex-ante hedging results. When the crisis triggers and worsens, the *ex-post* to *ex-ante* hedging ratio drops sharply. While perhaps not as dramatic as the Covid-19 period, the pre-crisis event periods for both GFC and Brexit generally produce higher ratios of *ex-post* to *ex-ante* variance for the passive portfolios. Once the crisis hits, these ratios drop considerably. The similarity between the Brexit, GFC, and Covid-19 periods on the difficulty of hedging highlights the rapid change in factor structure and exposures during crisis periods. This feature of all three crisis periods may be a defining characteristic of a crisis – the inability to ex ante hedge systematic shocks to risk and avoid financial consequences.

6 Conclusion

Using high-frequency data, we characterize the changing factor structure of global assets over the period 2007 to 2020. While these loadings are relatively stable and persistent through time – with the first PC loading positively on equities and negatively on fixed income, and the second PC loading positively on fixed income – they are subject to occasional, sudden, and large changes. The largest changes are associated with three crises – the Global Financial Crisis, Brexit, and the Covid-19 pandemic. Despite these crises ech having vastly different origins and despite the composition of PCs being quite different before each crisis, the composition and loadings of the PCs converge to similar values during all crisis periods, suggesting something unique or special about crises.

Exploiting the exogenous nature of Covid-19, we use Covid news to help identify the evolution of a crisis. We show that news about the virus is directly linked to the risk structure of global asset returns, affecting PC1 and PC2 differently. Changes in PC1 are driven by increasing asset return volatility, while changes in PC2 are driven by changing loadings due to Covid-19 news. Moreover, these changes are also tied to the changing prices of economic commodities (copper, corn and oil) in an intuitive way, giving support to the mechanism by which risk is changing. The results suggest something fundamental about crisis shocks that permeates the second moments of global asset returns.

We find similar patterns for two other crises – GFC and Brexit – where the factor structure shifts dramatically, raising volatilities and correlations that diminish diversification benefits substantially. Moreover, this shock is nearly impossible to hedge *ex-ante*, indicating that crisis shocks became the major source of common risk for assets globally.

Our findings may have implications for future crises and how risk exposure shifts dramatically, where crises provide an identifiable shock to systematic risk that is unavoidable. This feature is perhaps the defining characteristic of a crisis.

References

Aït-Sahalia Y, Xiu D. 2016. Increased correlation among asset classes: Are volatility or jumps to blame, or both? *Journal of Econometrics* **194**: 205–219.

Aït-Sahalia Y, Xiu D. 2017. Using principal component analysis to estimate a high dimensional factor model with high-frequency data. *Journal of Econometrics* **201**: 384–399.

Aït-Sahalia Y, Xiu D. 2019. Principal component analysis of high-frequency data. *Journal of the American Statistical Association* **114**: 287–303.

Alfaro L, Chari A, Greenland AN, Schott PK. 2020. Aggregate and firm-level stock returns during pandemics, in real time. Technical report, National Bureau of Economic Research.

Andersen TG, Bollerslev T, Christoffersen PF, Diebold FX. 2006. Volatility and correlation forecasting. *Handbook of Economic Forecasting* **1**: 777–878.

Andersen TG, Bollerslev T, Christoffersen PF, Diebold FX. 2013. Financial risk measurement for financial risk management. In *Handbook of the Economics of Finance*, volume 2. Elsevier, 1127–1220.

Asness CS, Moskowitz TJ, Pedersen LH. 2013. Value and momentum everywhere. *The Journal of Finance* **68**: 929–985.

Atkeson A. 2020. What will be the economic impact of covid-19 in the us? rough estimates of disease scenarios. Technical report, National Bureau of Economic Research.

Baker SR, Bloom N, Davis SJ, Kost K, Sammon M, Viratyosin T. 2020. The unprecedented stock market reaction to covid-19. *The Review of Asset Pricing Studies* .

Bansal R, Shaliastovich I. 2013. A long-run risks explanation of predictability puzzles in bond and currency markets. *The Review of Financial Studies* **26**: 1–33.

Barndorff-Nielsen OE, Shephard N. 2004. Econometric analysis of realized covariation: High frequency based covariance, regression, and correlation in financial economics. *Econometrica* **72**: 885–925.

Barro RJ, Ursúa JF, Weng J. 2020. The coronavirus and the great influenza pandemic: Lessons from the âspanish fluâ for the coronavirusâs potential effects on mortality and economic activity. Technical report, National Bureau of Economic Research.

Boudoukh J, Richardson MP, Thapar AK, Wang F. 2020. Is there a dollar risk factor? *Working Paper* .

Bretscher L, Hsu A, Simasek P, Tamoni A. 2020. Covid-19 and the cross-section of equity returns: Impact and transmission. *The Review of Asset Pricing Studies* **10**: 705–741.

Cheng IH. 2020. Volatility markets underreacted to the early stages of the covid-19 pandemic. *The Review of Asset Pricing Studies* **10**: 635–668.

Dahlquist M, Hasseltoft H. 2013. International bond risk premia. *Journal of International Economics* **90**: 17–32.

Eichenbaum MS, Rebelo S, Trabandt M. 2021. The macroeconomics of epidemics. *The Review of Financial Studies* **34**: 5149–5187.

Falato A, Goldstein I, Hortaçsu A. 2020. Financial fragility in the covid-19 crisis: The case of investment funds in corporate bond markets. Technical report, National Bureau of Economic Research.

Fama EF, French KR. 2012. Size, value, and momentum in international stock returns. *Journal of Financial Economics* **105**: 457–472.

Farhi E, Gabaix X. 2016. Rare disasters and exchange rates. *The Quarterly Journal of Economics* **131**: 1–52.

Giglio S, Maggiori M, Stroebel J, Utkus S. 2020. Inside the mind of a stock market crash. Technical report, National Bureau of Economic Research.

Giglio S, Xiu D. 2019. Asset pricing with omitted factors. *Chicago Booth Research Paper* .

Gormsen NJ, Koijen RS. 2020. Coronavirus: Impact on stock prices and growth expectations. *The Review of Asset Pricing Studies* **10**: 574–597.

Gormsen NJ, Lazarus E. 2021. Duration-driven returns. *Available at SSRN 3359027* .

Haddad V, Moreira A, Muir T. 2021. When selling becomes viral: Disruptions in debt markets in the covid-19 crisis and the fedâs response. *Review of Financial Studies* **34**: 5309–5351.

Hassan TA, Hollander S, van Lent L, Tahoun A. 2020. Firm-level exposure to epidemic diseases: Covid-19, sars, and h1n1. Technical report, National Bureau of Economic Research.

Hau H, Rey H. 2006. Exchange rates, equity prices, and capital flows. *The Review of Financial Studies* **19**: 273–317.

He Z, Nagel S, Song Z. 2022. Treasury inconvenience yields during the covid-19 crisis. *Journal of Financial Economics* **143**: 57–79.

Jackwerth J. 2020. What do index options teach us about covid-19? *The Review of Asset Pricing Studies* **10**: 618–634.

Jones CJ, Philippon T, Venkateswaran V. 2021. Optimal mitigation policies in a pandemic: Social distancing and working from home. *The Review of Financial Studies* **34**: 5188–5223.

Jotikasthira C, Le A, Lundblad C. 2015. Why do term structures in different currencies co-move? *Journal of Financial Economics* **115**: 58–83.

Koijen RS, Yogo M. 2020. Exchange rates and asset prices in a global demand system. Technical report, National Bureau of Economic Research.

Liu Y, Moskowitz TJ. 2020. Economic correlations. *Yale University Working Paper* .

Loughran T, McDonald B. 2016. Textual analysis in accounting and finance: A survey. *Journal of Accounting Research* **54**: 1187–1230.

Lustig H, Roussanov N, Verdelhan A. 2011. Common risk factors in currency markets. *The Review of Financial Studies* **24**: 3731–3777.

Lustig H, Roussanov N, Verdelhan A. 2014. Countercyclical currency risk premia. *Journal of Financial Economics* **111**: 527–553.

Lustig H, Stathopoulos A, Verdelhan A. 2019. The term structure of currency carry trade risk premia. *American Economic Review* **109**: 4142–77.

Lustig H, Verdelhan A. 2019. Does incomplete spanning in international financial markets help to explain exchange rates? *American Economic Review* **109**: 2208–44.

Pastor L, Vorsatz MB. 2020. Mutual fund performance and flows during the covid-19 crisis. *The Review of Asset Pricing Studies* **10**: 791–833.

Pelger M. 2020. Understanding systematic risk: a high-frequency approach. *The Journal of Finance* **75**: 2179–2220.

Ramelli S, Wagner AF. 2020. Feverish stock price reactions to covid-19 .

Stock JH. 2020. Data gaps and the policy response to the novel coronavirus. Technical report, National Bureau of Economic Research.

Wu X. 2020. Regulations as automatic stabilizers during covid-19. *Working Paper* .

Table 1: Asset Coverage for High Frequency Correlation Calculations

The table documents the coverage of the 26 global equity, fixed income, and exchange rate assets, as well as four commodities, across the 24-hour period around the onset of the Covid-19 pandemic from January to June 2020. The first row of the table starts from 12am EST to 12:59am to the last row from 11:00pm to 11:59pm EST. We calculate the percentage of 5-minute returns that are available during the hour. (See Section 2.2 for a description of the exact methodology used.) Along with documenting the actual % covered, the table provides a color scale to visually reflect the coverage, i.e., from full coverage in dark green to lesser and lesser shades of green as coverage declines, with no coverage (0%) in no color.

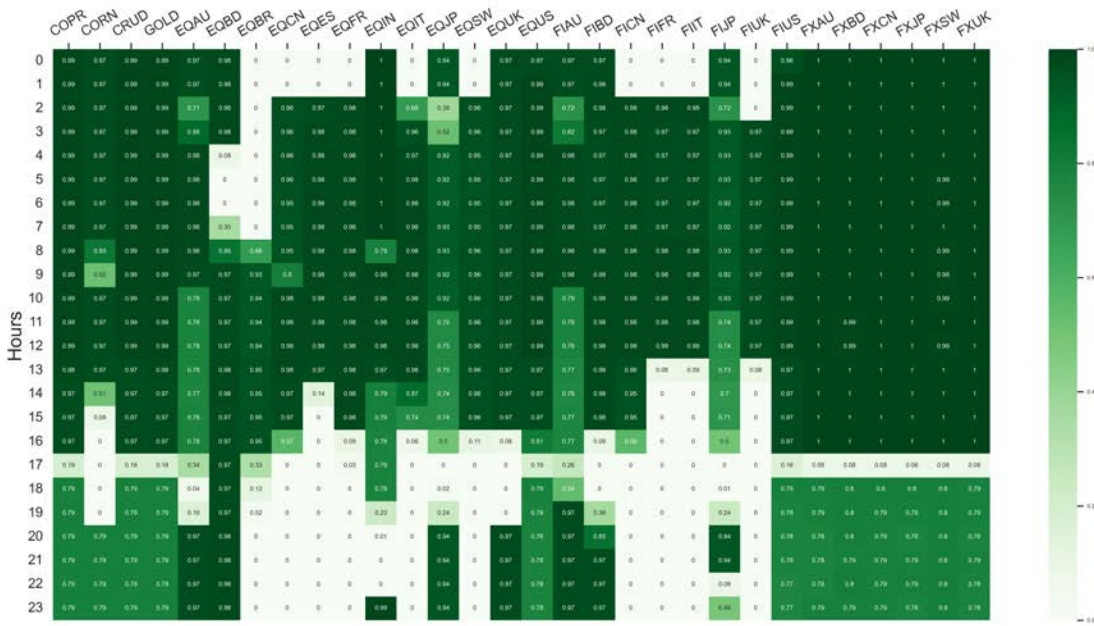


Table 2: High Frequency vs. Daily Correlation Estimates

The table documents the mean and standard deviation of biweekly correlations of global assets within and across equities, fixed income, and exchange rates using high frequency and daily data over the period 2007 to 2020, the quarter containing the onset of Covid-19 (January 29 - May 5, 2020) and prior quarter before the Covid-19 pandemic (October - December 2019).

Daily Correlation Between Group 1 and 2				HF Correlation Between Group 1 and 2			
Group 1	Group 2	Mean ρ	SD ρ	Group 1	Group 2	Mean ρ	SD ρ
Full Sample Period (2007 to 2020)							
EQ	EQ	0.550	0.280	EQ	EQ	0.568	0.145
EQ	FI	-0.198	0.368	EQ	FI	-0.216	0.190
EQ	FX	0.078	0.394	EQ	FX	0.061	0.224
FI	EQ	-0.198	0.368	FI	EQ	-0.216	0.190
FI	FI	0.461	0.307	FI	FI	0.500	0.172
FI	FX	0.020	0.388	FI	FX	0.031	0.197
FX	EQ	0.078	0.394	FX	EQ	0.061	0.224
FX	FI	0.020	0.388	FX	FI	0.031	0.197
FX	FX	0.406	0.339	FX	FX	0.385	0.194
Normal Period Before Covid (October to December 2019)							
EQ	EQ	0.506	0.273	EQ	EQ	0.550	0.109
EQ	FI	-0.150	0.408	EQ	FI	-0.194	0.186
EQ	FX	-0.101	0.346	EQ	FX	-0.040	0.130
FI	EQ	-0.150	0.408	FI	EQ	-0.194	0.186
FI	FI	0.629	0.240	FI	FI	0.621	0.103
FI	FX	0.083	0.392	FI	FX	0.056	0.137
FX	EQ	-0.101	0.346	FX	EQ	-0.040	0.130
FX	FI	0.083	0.392	FX	FI	0.056	0.137
FX	FX	0.317	0.345	FX	FX	0.284	0.141
Covid Period (January 29 to May 5, 2020)							
EQ	EQ	0.786	0.162	EQ	EQ	0.724	0.105
EQ	FI	-0.338	0.308	EQ	FI	-0.299	0.197
EQ	FX	-0.004	0.395	EQ	FX	0.064	0.206
FI	EQ	-0.338	0.308	FI	EQ	-0.299	0.197
FI	FI	0.471	0.286	FI	FI	0.466	0.184
FI	FX	0.140	0.380	FI	FX	0.004	0.197
FX	EQ	-0.004	0.395	FX	EQ	0.064	0.206
FX	FI	0.140	0.380	FX	FI	0.004	0.197
FX	FX	0.410	0.349	FX	FX	0.371	0.192

Table 3: Summary Statistics of PC Factors

The table provides summary statistics of PC1 and PC2 of the 26 global asset returns during the Covid-19 period. Panel A shows the mean, standard deviation, and autocorrelations of PC1 and PC2. Panel B shows the biweek-by-biweek annualized high frequency volatility of PC1 and PC2, as well as the correlation between the PCs using actual loadings and the PCs using the prior normal period loadings. Panel C provides formal tests of how the Covid-19 factor structure changes relative to the rest of the ample. The first test compares $|PCJ_{qt-(q-1)t,k}|$ during Covid-19 versus all other periods for both PC1 and PC2. The second test calculates the average difference in weights from quarter to quarter, $|\sum_i (w_{iJqt} - w_{iJ(q-1)t})|$, for both PC1 and PC2 in Covid-19 versus the rest of the sample. Summary statistics are annualized. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels. Panel D reports implied R^2 (i.e., based on the high-frequency return variance-covariance matrix) of three commodity returns on the two PC factors biweek-by-biweek during the Covid-19 period.

Panel A: Summary Statistics of Covid-19 Period

Factor	Mean	SD	Autocorrelation
PC1	-0.541	1.424	-0.265
PC2	0.017	0.414	-0.044

Panel B: PC SD and Corr Diff Biweek by Biweek

Biweek # Start Date	$\sigma(PC1)$	$\rho(PC1)$ $covid, norm$	$\sigma(PC2)$	$\rho(PC2)$ $covid, norm$
1: 1/1	0.329	0.999	0.171	0.993
2: 1/15	0.315	0.999	0.146	0.976
3: 1/29	0.377	1.000	0.133	0.900
4: 2/12	0.466	0.999	0.162	0.899
5: 2/26	1.691	0.999	0.759	0.959
6: 3/11	3.194	0.997	0.689	0.722
7: 3/25	1.614	0.998	0.280	0.130
8: 4/8	0.941	0.997	0.393	0.991
9: 4/22	0.796	0.995	0.275	0.971
10: 5/6	0.705	0.997	0.265	0.945
11: 5/20	0.599	0.996	0.280	0.991
12: 6/3	0.891	0.997	0.307	0.934
13: 6/17	0.643	0.996	0.319	0.995

Panel C: Covid vs. Normal Period				
Absolute Differences in PC				
		PC1		PC2
Covid		0.113***		0.545***
		(15.32)		(11.32)
R^2		0.0636		0.0357
Absolute Differences in Loadings				
	PC1	PC2	PC1	PC2
Covid	0.018***	0.033**	0.017***	0.034**
	(3.45)	(2.29)	(3.49)	(2.29)
Index FE	N	N	Y	Y
R^2	0.0086	0.0051	0.1848	0.0759

Panel D: R^2s of Commodities on PC1, PC2	Copper	Corn	Oil
1: 1/1	22.39%	3.39%	20.03%
2: 1/15	35.78%	8.30%	25.18%
3: 1/29	31.39%	4.21%	22.37%
4: 2/12	40.54%	3.75%	41.55%
5: 2/26	44.37%	24.04%	50.36%
6: 3/11	35.92%	9.25%	35.34%
7: 3/25	40.78%	9.46%	8.04%
8: 4/8	27.15%	4.72%	7.18%
9: 4/22	30.84%	6.08%	9.12%
10: 5/6	35.08%	5.20%	10.50%
11: 5/20	35.79%	4.62%	16.11%
12: 6/3	44.41%	5.42%	28.35%
13: 6/17	41.70%	1.69%	32.07%

Table 4: Changing PC Variances

The table reports results for decomposing changing PC variances into changing PC weights versus the changing variance-covariance matrix of global asset returns. The sample covers the biweekly periods from January to June 2020. Changes of PC variances can be decomposed as:

$$Var\left(PCi_{t+1}\right) - Var\left(PCi_{t}\right) = \underbrace{\left(w_t'^i \Sigma_{t+1} w_t^i - w_t'^i \Sigma_t w_t^i\right)}_{A:\ Due\ to\ changing\ var\text{-}cov} + \underbrace{\left(w_{t+1}'^i \Sigma_{t+1} w_{t+1}^i - w_t'^i \Sigma_{t+1} w_t^i\right)}_{B:\ Due\ to\ changing\ PC\ weights},$$

where w are the PC weights and $\sum$ is the variance-covariance matrix of global asset returns. Variance estimates are multiplied by 10,000 to put in percent.

Biweek #: Start Date	$\Delta Var\left(PC1_{t+1}\right)$	$\Delta Var\left(PC1_{t+1}\right)$ %A: $\Delta\Sigma_{t+1}$	$\Delta Var\left(PC1_{t+1}\right)$ %B: Δw_{t+1}	$\Delta Var\left(PC2_{t+1}\right)$	$\Delta Var\left(PC2_{t+1}\right)$ %A: $\Delta\Sigma_{t+1}$	$\Delta Var\left(PC2_{t+1}\right)$ %B: Δw_{t+1}
1: 1/1	0.829	81.40%	18.60%	0.082	135.30%	-35.30%
2: 1/15	-0.344	94.07%	5.93%	-0.309	61.80%	38.20%
3: 1/29	1.689	102.35%	-2.35%	-0.145	-92.24%	192.24%
4: 2/12	3.003	78.61%	21.39%	0.333	150.66%	-50.66%
5: 2/26	104.869	95.27%	4.73%	21.833	57.77%	42.23%
6: 3/11	291.388	62.20%	37.80%	-4.005	-1994.55%	2094.55%
7: 3/25	-301.502	99.00%	1.00%	-15.748	85.87%	14.13%
8: 4/8	-68.275	95.62%	4.38%	3.015	-66.62%	166.62%
9: 4/22	-9.973	104.87%	-4.87%	-3.134	48.30%	51.70%
10: 5/6	-5.391	89.28%	10.72%	-0.218	408.42%	-308.42%
11: 5/20	-5.524	90.52%	9.48%	0.330	-265.80%	365.80%
12: 6/3	17.258	100.99%	-0.99%	0.635	469.56%	-369.56%
13: 6/17	-15.057	99.36%	0.64%	0.288	-607.05%	707.05%

Table 5: Factor Returns and Covid-19 News Shocks

Panel A documents results for regressions of weekly changes in each of the three Ravenpack Coronavirus worldwide indices (*Panic*, *Media Hype*, and *Media Coverage*) and the composite index on contemporaneous PC1 and PC2 returns. Employing natural language processing (NLP) algorithms to measure specific events and sentiment generated from unstructured text contained in a variety of media sources and company reports, Ravenpack constructs on a daily basis (i) *Coronavirus Panic Index*, (ii) *Coronavirus Media Hype Index*, and (iii) *Coronavirus Media Coverage Index* for each country. All of these measures are meant to capture the amount of news related to Covid-19 (such as references to panic/hysteria, percent of news coverage, *etc.*). Panel B repeats the same regressions, but uses the difference between PC returns calculated using the PC weights estimated over the Covid-19 period versus those estimates over the "normal" period (*i.e.*, prior quarter). We then apply these weights to the same realized returns of the underlying assets (daily) over the Covid-19 period. Results are reported based on 7-day cumulative overlapping observations. The standard errors are Newey-West adjusted with 5 lags. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels.

Panel A:	ΔPanic	ΔHype	ΔCoverage	ΔComposite	ΔPanic	ΔHype	ΔCoverage	ΔComposite	ΔPanic	ΔHype	ΔCoverage	ΔComposite
$PC1$	-0.836***	-0.649***	-0.204***	-1.890***					-0.435*	-0.251*	-0.031	-0.662
	(-3.255)	(-5.529)	(-4.097)	(-4.545)					(-1.748)	(-1.801)	(-0.756)	(-1.642)
$PC2$					-2.478***	-2.015***	-0.683***	-5.935***	-1.406	-1.398***	-0.607***	-4.304**
					(-3.169)	(-4.713)	(-4.225)	(-4.384)	(-1.569)	(-2.727)	(-3.118)	(-2.615)
R^2	0.2399	0.3783	0.2836	0.3355	0.2440	0.4218	0.3678	0.3832	0.2633	0.4386	0.3697	0.3954
Panel B:	ΔPanic	ΔHype	ΔCoverage	ΔComposite	ΔPanic	ΔHype	ΔCoverage	ΔComposite				
$PC1 - PC1^N$	0.340	-0.045	0.008	0.205								
	(0.729)	(-0.159)	(0.069)	(0.213)								
$PC2 - PC2^N$					-0.056	-0.055**	-0.025**	-0.172**				
					(-1.220)	(-2.354)	(-2.651)	(-2.074)				
R^2	0.0466	0.0021	0.0005	0.0046	0.0315	0.0798	0.1253	0.0829				

Table 6: Country Factor Returns and Covid-19 News Shock

Table 6 documents results from a panel regression of each country's Ravenpack Covid-19 news innovation on that country's systematic factor return component for asset class j (EQ, FI or FX) from time t to $t+1$, *i.e.*, $F_{ij;t,t+1}$, where $F_{ij;t,t+1}$ is constructed from the return regression $R_{ij;t,t+1} = \alpha_{ij} + \underbrace{\beta_{ij1;t-1,t+1} PC1_{t,t+1} + \beta_{ij2;t-1,t+1} PC2_{t,t+1}}_{F_{ij;t,t+1},\ \mathit{systematic\ factor\ return\ component}} + \epsilon_{ij;t,t+1}$, with the corresponding returns for country i and asset class j measured weekly, and the betas, $\beta_{ij1;t-1,t+1}$ and $\beta_{ij2;t-1,t+1}$, used in constructing the factor return $F_{ij;t,t+1}$ are measured over two weeks on an overlapping basis. We run three panel regressions, one for each of the asset classes. Index fixed effects are included. Standard errors are Newey-West adjusted with 5 lags. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. var.	ΔPanic	ΔHype	ΔCoverage	ΔComposite	ΔPanic	ΔHype	ΔCoverage	ΔComposite	ΔPanic	ΔHype	ΔCoverage	ΔComposite
Asset class	EQ	EQ	EQ	EQ	FI	FI	FI	FI	FX	FX	FX	FX
factor	-3.572**	-2.664**	-1.481	-2.572**	35.353*	28.913	19.922	28.062	-4.513	-7.677**	-4.922*	-5.704*
	(-2.198)	(-2.362)	(-1.609)	(-2.347)	(1.772)	(1.245)	(1.324)	(1.460)	(-0.977)	(-2.298)	(-1.989)	(-1.787)
constant	0.183	0.296*	0.236*	0.238*	0.169	0.256*	0.211*	0.212*	0.157	0.280*	0.224*	0.220*
	(1.470)	(1.898)	(1.985)	(1.834)	(1.399)	(1.882)	(1.966)	(1.783)	(1.262)	(1.955)	(2.039)	(1.835)
Observations	288	288	288	288	192	192	192	192	144	144	144	144
R^2	0.0422	0.0205	0.0109	0.0248	0.0754	0.0567	0.0421	0.0653	0.0172	0.0189	0.0124	0.0131

Table 7: Country PC Betas and Covid-19 News Shocks

Panel A reports results from three panel regressions of biweekly country-specific PC1 and PC2 betas for each of the three asset classes (EQ, FI and FX) on the level of the Ravenpack Coronavirus indices averaged over the corresponding biweek. Panel B reports results from the same regressions but where we lag the index by one biweek to capture the expected beta component. Ravenpack measures are the average of the corresponding biweek. Ravenpack variables are standardized to have mean zero and unit standard deviation. Time fixed effects are included. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels.

Panel A: Contemporaneous News Index								
Equity	Beta1	Beta1	Beta1	Beta1	Beta2	Beta2	Beta2	Beta2
Panic	0.054***				-0.071**			
	(3.539)				(-1.979)			
Hype		0.073***				-0.059		
		(2.909)				(-1.009)		
Coverage			0.066				-0.015	
			(1.422)				(-0.140)	
Composite				0.085***				-0.090
				(3.279)				(-1.484)
R^2	0.1312	0.1059	0.0627	0.1204	0.0982	0.0783	0.0713	0.0865
Fixed Income	Beta1	Beta1	Beta1	Beta1	Beta2	Beta2	Beta2	Beta2
Panic	0.036***				-0.019			
	(3.945)				(-1.175)			
Hype		0.058***				-0.011		
		(3.565)				(-0.355)		
Coverage			0.091***				-0.069	
			(3.233)				(-1.371)	
Composite				0.066***				-0.031
				(4.199)				(-1.071)
R^2	0.5597	0.5466	0.5356	0.5688	0.4700	0.4620	0.4732	0.4686
Foreign Exchange	Beta1	Beta1	Beta1	Beta1	Beta2	Beta2	Beta2	Beta2
Panic	-0.006				0.060**			
	(-0.269)				(1.978)			
Hype		0.056				0.077		
		(1.201)				(1.128)		
Coverage			0.030				0.118	
			(0.432)				(1.146)	
Composite				0.014				0.120*
				(0.307)				(1.803)
R^2	0.4354	0.4482	0.4365	0.4356	0.8202	0.8145	0.8146	0.8204

Panel B: Lagged News Index								
Equity	Beta1	Beta1	Beta1	Beta1	Beta2	Beta2	Beta2	Beta2
lagPanic	0.043***				-0.077**			
	(2.634)				(-2.007)			
lagHype		0.048*				-0.079		
		(1.744)				(-1.250)		
lagCoverage			-0.041				0.095	
			(-0.835)				(0.846)	
lagComposite				0.054*				-0.091
				(1.900)				(-1.385)
R^2	0.0956	0.0670	0.0488	0.0713	0.0991	0.0808	0.0743	0.0835
Fixed Income	Beta1	Beta1	Beta1	Beta1	Beta2	Beta2	Beta2	Beta2
lagPanic	0.020*				-0.000			
	(1.957)				(-0.012)			
lagHype		0.025				0.023		
		(1.376)				(0.737)		
lagCoverage			0.014				0.011	
			(0.455)				(0.203)	
lagComposite				0.030*				0.008
				(1.683)				(0.274)
R^2	0.4574	0.4439	0.4316	0.4505	0.4677	0.4715	0.4680	0.4682
Foreign Exchange	Beta1	Beta1	Beta1	Beta1	Beta2	Beta2	Beta2	Beta2
lagPanic	0.012				0.026			
	(0.518)				(0.718)			
lagHype		0.108**				-0.056		
		(2.420)				(-0.797)		
lagCoverage			0.100				-0.060	
			(1.438)				(-0.562)	
lagComposite				0.066				0.006
				(1.441)				(0.079)
R^2	0.4661	0.5159	0.4832	0.4833	0.8201	0.8205	0.8195	0.8184

Table 8: Epidemiological Forecast Errors and Country Factor Returns

The table documents the relationship between epidemiological Covid-19 forecasts and factor returns. Panel A reports results from a panel regression of the log growth rate in weekly cumulative Covid-19 deaths for each country against the Imperial College of London's ensemble forecast model along with the country's lagged systematic factor return for equity, fixed income and exchange rates. Specifically, $\ln\left(\frac{D_{it+1}}{D_{it}}\right) = \mu + \gamma_1 \ln\left(\frac{FD_{it}^{t+1}}{D_{it}}\right) + \gamma_2 F_{ij;t-k,t-k+1} + \eta_{it,t+1}$, where D_{it} is the cumulative Covid-19 deaths at time t for country i, FD_{it}^{t+1} is the forecast of deaths at time t for the cumulative Covid-19 death total at time $t+1$, $F_{ij;t-k,t-k+1}$ is the aforementioned country's systematic factor return component for asset class j from time $t-k$ to $t-k+1$, and time t is measured in weeks constructed from $R_{ij;t,t+1} = \alpha_{ij} + \underbrace{\beta_{ij1;t-1,t+1} PC1_{t,t+1} + \beta_{ij2;t-1,t+1} PC2_{t,t+1}}_{F_{ij;t,t+1},\ systematic\ factor\ return\ component} + \epsilon_{ij;t,t+1}$. Panel B provides results for both contemporaneous and predictive regressions of returns (EQ, FI and FX) on epidemiological forecast errors of death predictions $\ln\left(\frac{D_{it+1}}{D_{it}}\right) - \ln\left(\frac{FD_{it}^{t+1}}{D_{it}}\right)$. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels.

Panel A: Deaths on Forecast and Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Asset class	EQ	EQ	EQ	EQ	FI	FI	FI	FI	FX	FX	FX	FX
FD	0.859***	0.849***	0.818***	0.860***	0.921***	0.920***	0.914***	0.929***	0.886***	0.885***	0.830***	0.920***
	(12.154)	(11.405)	(11.504)	(12.495)	(15.160)	(16.293)	(14.070)	(16.835)	(11.611)	(12.226)	(16.998)	(16.727)
factor		-2.207**				-0.498				0.119		
		(-2.331)				(-0.109)				(0.019)		
lag2factor			-1.881				-5.913				-12.023***	
			(-1.747)				(-0.682)				(-3.360)	
lag3factor				-0.251				6.724*				6.869**
				(-0.219)				(1.796)				(2.225)
Index FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	115	115	115	115	95	95	95	95	61	61	61	61
R^2	0.8301	0.8395	0.8389	0.8302	0.8528	0.8528	0.8557	0.8573	0.8550	0.8556	0.8780	0.8651

Panel B: Predicting Forecast Errors

	(1)	(2)	(3)	(4)	(5)	(6)
	Cont	Lead	Cont	Lead	Cont	Lead
Asset class	EQ	EQ	FI	FI	FX	FX
factor	-14.517***	13.096	-31.280	-62.925	36.093*	48.350
	(-3.288)	(1.203)	(-1.409)	(-1.408)	(1.963)	(1.189)
Observations	127	118	102	95	66	61
R^2	0.0947	0.0977	0.0557	0.1002	0.0664	0.0986

Table 9: Differences in PC Structure during Crisis Periods

Table 9 summary results for differences in the PC structure for crisis periods (GFC, Brexit and Covid-19) versus normal periods over the sample period 2007-2020. Panel A compares $|PCJ_{qt-(q-1)t,k}|$ and the average difference in weights from quarter to quarter, $|\sum_i (w_{iJqt} - w_{iJ(q-1)t})|$, for both PC1 and PC2 during the GFC and Brexit periods versus other periods. Panel B compares the average loadings for PC1 and PC2 across the three main asset classes (EQ, FI and FX) during the peak of Covid-19, GFC and Brexit crises versus the period immediately before these crises emerge. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels.

Panel A: Crisis vs. Normal Periods

	Absolute Differences in PC	
	PC1	PC2
GFC	0.087***	0.666***
	(12.91)	(17.00)
R^2	0.0460	0.0772
Brexit	0.007	0.604***
	(1.08)	(15.23)
R^2	0.0003	0.0629

	Absolute Differences in Loadings			
	PC1	PC2	PC1	PC2
GFC	0.017*	0.054***	0.018*	0.053***
	(1.85)	(3.72)	(2.05)	(3.60)
Index FE	N	N	Y	Y
R^2	0.0062	0.0157	0.1838	0.0896
Brexit	0.016**	0.150***	0.015**	0.151***
	(2.287)	(7.771)	(2.178)	(7.689)
Index FE	N	N	Y	Y
R^2	0.0068	0.1578	0.1831	0.2334

Panel B: Loadings Pre- vs. During Crises

		Covid	GFC	Brexit
Pre-Crisis	β^{EQ}_{PC1}	0.236	0.275	0.262
Crisis	β^{EQ}_{PC1}	0.268	0.263	0.271
Pre-Crisis	β^{EQ}_{PC2}	0.160	0.087	0.123
Crisis	β^{EQ}_{PC2}	0.053	0.023	0.009
Pre-Crisis	β^{FI}_{PC1}	-0.205	-0.215	-0.004
Crisis	β^{FI}_{PC1}	-0.111	-0.218	0.051
Pre-Crisis	β^{FI}_{PC2}	0.218	0.196	0.315
Crisis	β^{FI}_{PC2}	0.091	0.169	0.201
Pre-Crisis	β^{FX}_{PC1}	-0.024	-0.004	-0.155
Crisis	β^{FX}_{PC1}	0.004	0.051	0.033
Pre-Crisis	β^{FX}_{PC2}	-0.184	0.315	0.351
Crisis	β^{FX}_{PC2}	0.288	0.201	0.328

Table 10: Portfolio Summary Statistics

The table reports summary statistics (mean, standard deviation, skewness, kurtosis, and maximum drawdown) for the return on the four aggregate portfolios (equity, fixed income, currency and risk-parity) over the three crisis periods measured over six-months. The three asset portfolios are equal-weighted across countries and dollar denominated. The risk-parity portfolio of equity, fixed income and currencies is weighted to have equal volatility in each asset, as measured over the previous quarter. Returns are annualized.

Covid-19	Mean	SD	Skewness	Kurtosis	Max Drawdown
EW $-EQ	-0.089	0.434	-0.986	8.740	-35.815%
EW $-FI	0.059	0.104	-1.170	9.063	-11.070%
EW FX	-0.027	0.082	-0.507	5.692	-8.729%
RP	-0.039	0.093	-2.152	13.697	-10.754%

GFC	Mean	SD	Skewness	Kurtosis	Max Drawdown
EW $-EQ	-0.660	0.481	0.218	4.498	-46.173%
EW $-FI	0.023	0.127	0.598	6.640	-13.579%
EW FX	-0.225	0.139	0.790	4.614	-19.690%
RP	-0.074	0.104	0.331	5.144	-11.439%

Brexit	Mean	SD	Skewness	Kurtosis	Max Drawdown
EW $-EQ	0.122	0.193	-2.521	18.767	-10.087%
EW $-FI	0.049	0.072	0.463	5.163	-3.117%
EW FX	-0.010	0.074	-0.301	5.991	-4.302%
RP	0.058	0.040	-1.040	6.365	-1.803%

Table 11: Systematic Portion of Portfolio Return Variance

The table reports the systematic portion of various portfolios' return variance. Panels A, B, and C report results for the Covid-19 period, the Great Financial Crisis period, and the Brexit period, with the defining event occurring in biweek 5, 19 and 13 for these three crises, respectively. \$-EQ, \$-FI, FX, and RP represent a dollar-denominated equal-weighted equity portfolio, a dollar-denominated equal-weighted fixed income portfolio, a foreign exchange equal-weighted portfolio, and a risk parity portfolio that assumes equal risk to to each asset (unconditional volatility), respectively. The dollar-denominated portfolios include the corresponding assets with exchange rate information. In terms of the statistics, σ is the annualized volatility of the portfolio, β_{PC1} is the beta with respect to PC1, β_{PC2} is the beta with respect to PC2, R^2 is the implied R^2 based on the two PCs, and $\frac{Var(p)}{Var(i)}$ is the ratio of the variance of the portfolio returns and the average of the individual asset returns in the portfolio.

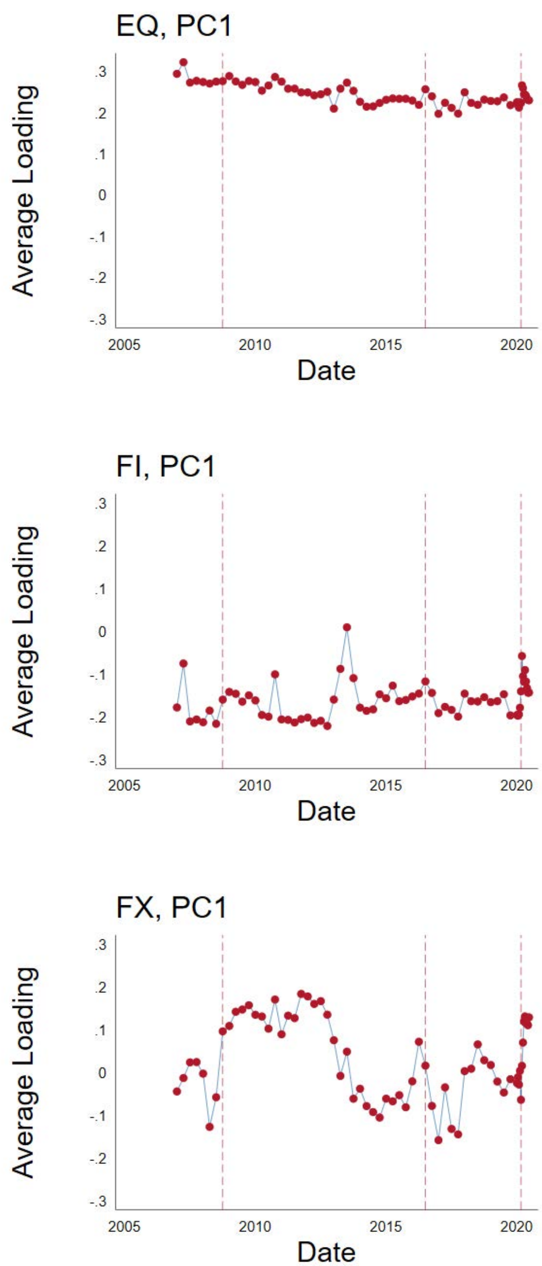
Panel A: Portfolios (Covid-19)

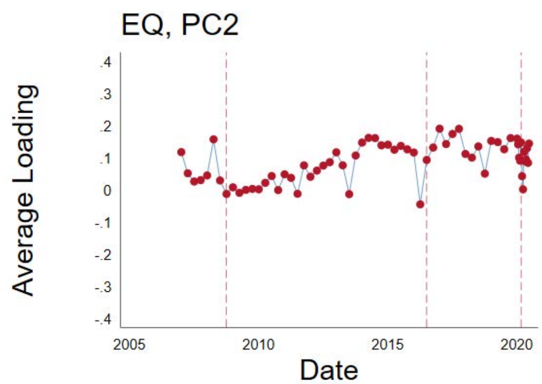
	\$-EQ					\$-FI					FX					RP				
Biweek	σ	β_{PC1}	β_{PC2}	R^2	$\frac{Var(p)}{Var(i)}$	σ	β_{PC1}	β_{PC2}	R^2	$\frac{Var(p)}{Var(i)}$	σ	β_{PC1}	β_{PC2}	R^2	$\frac{Var(p)}{Var(i)}$	σ	β_{PC1}	β_{PC2}	R^2	$\frac{Var(p)}{Var(i)}$
1	10.78%	0.256	0.090	0.779	0.699	6.22%	-0.150	0.160	0.342	0.501	3.82%	0.013	-0.078	0.080	0.276	2.44%	-0.004	0.124	0.702	0.080
2	10.06%	0.299	0.014	0.906	0.736	4.41%	-0.106	0.052	0.427	0.518	2.97%	0.052	-0.173	0.387	0.326	2.15%	0.018	0.086	0.631	0.069
3	11.76%	0.305	-0.028	0.916	0.778	4.88%	-0.082	-0.023	0.453	0.590	3.16%	0.043	-0.220	0.484	0.313	2.39%	0.035	0.042	0.527	0.065
4	16.32%	0.374	-0.131	0.950	0.804	4.95%	-0.027	-0.105	0.315	0.540	3.71%	0.073	-0.283	0.678	0.393	3.22%	0.053	0.018	0.705	0.089
5	53.18%	0.143	0.389	0.991	0.859	12.10%	-0.146	0.224	0.734	0.488	7.71%	-0.087	0.155	0.477	0.275	10.73%	0.009	0.118	0.952	0.096
6	97.76%	0.272	0.190	0.979	0.793	22.39%	-0.059	0.416	0.814	0.374	18.01%	-0.038	0.307	0.707	0.503	21.26%	0.036	0.163	0.971	0.110
7	53.30%	0.314	0.300	0.990	0.791	11.98%	-0.006	0.423	0.951	0.479	12.51%	0.009	0.419	0.937	0.532	9.24%	0.046	0.141	0.958	0.078
8	33.47%	0.363	-0.029	0.974	0.863	7.44%	-0.030	0.131	0.130	0.435	7.85%	0.108	-0.170	0.322	0.584	5.41%	0.005	0.114	0.834	0.075
9	27.94%	0.343	0.008	0.968	0.772	7.15%	-0.037	0.229	0.279	0.432	7.01%	0.068	-0.065	0.303	0.559	4.73%	0.004	0.148	0.866	0.072
10	25.30%	0.334	0.062	0.977	0.830	6.44%	-0.086	0.343	0.486	0.470	6.80%	0.025	0.086	0.333	0.550	4.10%	-0.011	0.175	0.922	0.068
11	22.63%	0.417	-0.105	0.973	0.782	5.98%	0.048	-0.037	0.109	0.488	6.58%	0.175	-0.275	0.479	0.557	3.36%	0.018	0.062	0.686	0.058
12	33.09%	0.260	0.338	0.988	0.816	7.90%	-0.129	0.501	0.732	0.489	8.24%	-0.023	0.249	0.504	0.535	4.49%	-0.024	0.206	0.979	0.055
13	24.44%	0.416	-0.086	0.981	0.829	5.54%	0.066	-0.068	0.181	0.490	6.65%	0.196	-0.287	0.613	0.566	3.21%	0.011	0.068	0.768	0.052

	$-EQ					$-FI					FX					RP				
Biweek	σ	β_{PC1}	β_{PC2}	R^2	$\frac{Var(p)}{Var(i)}$	σ	β_{PC1}	β_{PC2}	R^2	$\frac{Var(p)}{Var(i)}$	σ	β_{PC1}	β_{PC2}	R^2	$\frac{Var(p)}{Var(i)}$	σ	β_{PC1}	β_{PC2}	R^2	$\frac{Var(p)}{Var(i)}$
Panel B: Portfolios (GFC)																				
15	19.72%	0.146	0.479	0.989	0.674	9.38%	-0.187	0.254	0.780	0.669	7.79%	-0.176	0.315	0.958	0.640	4.42%	-0.005	0.161	0.793	0.075
16	16.86%	0.148	0.491	0.992	0.591	9.23%	-0.184	0.293	0.756	0.630	7.79%	-0.155	0.327	0.963	0.612	4.35%	-0.008	0.167	0.808	0.095
17	16.54%	0.239	0.482	0.974	0.632	9.23%	-0.109	0.277	0.670	0.569	9.07%	-0.097	0.356	0.945	0.606	4.31%	0.027	0.142	0.700	0.100
18	26.40%	0.403	0.298	0.979	0.805	11.45%	-0.001	0.333	0.785	0.561	11.29%	0.039	0.356	0.957	0.486	5.62%	0.061	0.110	0.764	0.101
19	43.26%	0.341	0.386	0.986	0.817	16.38%	-0.066	0.326	0.773	0.521	14.79%	-0.029	0.361	0.948	0.462	8.03%	0.040	0.118	0.720	0.073
20	49.31%	0.416	0.321	0.993	0.770	15.59%	0.009	0.377	0.768	0.484	13.68%	0.045	0.359	0.944	0.440	9.85%	0.072	0.129	0.844	0.099
21	99.57%	0.367	0.286	0.998	0.824	21.79%	-0.045	0.468	0.753	0.315	18.61%	-0.008	0.297	0.654	0.266	20.62%	0.053	0.164	0.979	0.134
22	84.62%	0.452	0.161	0.991	0.783	22.90%	0.091	0.347	0.836	0.424	19.41%	0.083	0.253	0.777	0.288	15.40%	0.081	0.078	0.916	0.098
23	63.46%	0.409	0.313	0.996	0.859	20.04%	0.023	0.627	0.959	0.486	17.97%	0.032	0.488	0.852	0.377	11.71%	0.060	0.161	0.963	0.114
24	61.08%	0.379	0.200	0.987	0.816	16.07%	-0.058	0.443	0.514	0.441	14.79%	0.028	0.139	0.402	0.373	10.53%	0.005	0.237	0.964	0.093
25	55.51%	0.467	0.200	0.991	0.834	14.16%	0.107	0.265	0.542	0.438	13.52%	0.136	0.320	0.906	0.396	9.19%	0.070	0.045	0.717	0.079
26	34.99%	0.412	0.380	0.968	0.841	16.86%	0.094	0.469	0.906	0.492	16.54%	0.084	0.460	0.879	0.499	8.47%	0.085	0.176	0.965	0.152
Panel C: Portfolios (Brexit)																				
10	16.90%	0.295	0.332	0.984	0.708	7.36%	-0.102	0.444	0.951	0.584	7.16%	-0.135	0.476	0.749	0.541	3.56%	0.000	0.161	0.950	0.085
11	11.91%	0.218	0.391	0.942	0.620	6.10%	-0.187	0.501	0.866	0.525	5.89%	-0.128	0.395	0.355	0.454	2.73%	-0.019	0.189	0.978	0.082
12	16.22%	0.281	0.380	0.982	0.709	8.26%	-0.102	0.411	0.935	0.563	7.95%	-0.081	0.442	0.939	0.495	3.20%	0.019	0.115	0.859	0.072
13	56.34%	0.416	0.113	0.990	0.697	7.57%	0.040	0.187	0.405	0.140	10.98%	0.144	-0.255	0.845	0.223	7.45%	0.029	0.061	0.916	0.060
14	16.98%	0.341	0.323	0.979	0.659	7.66%	-0.055	0.386	0.864	0.452	7.48%	-0.033	0.420	0.936	0.398	2.84%	0.021	0.098	0.691	0.053
15	12.91%	0.334	0.023	0.830	0.615	6.73%	-0.077	0.118	0.080	0.439	6.52%	-0.002	0.010	0.000	0.371	2.65%	-0.019	0.155	0.779	0.067
16	10.92%	0.260	0.169	0.715	0.583	7.23%	-0.146	0.419	0.634	0.552	6.68%	-0.074	0.027	0.082	0.467	3.01%	-0.019	0.183	0.812	0.088
17	11.14%	0.257	0.344	0.964	0.666	7.51%	-0.131	0.468	0.982	0.672	6.68%	-0.185	0.409	0.800	0.606	2.94%	-0.011	0.151	0.947	0.114
18	12.01%	0.441	0.073	0.948	0.664	8.35%	0.286	0.397	0.964	0.740	7.16%	0.300	0.304	0.774	0.641	3.61%	0.149	0.073	0.969	0.153
19	14.75%	0.408	0.115	0.954	0.750	7.89%	0.200	0.474	0.956	0.621	6.52%	0.181	0.332	0.552	0.512	4.56%	0.135	0.137	0.992	0.185
20	13.62%	0.328	0.083	0.893	0.668	5.87%	-0.081	0.316	0.323	0.488	5.57%	0.029	0.007	0.036	0.422	3.51%	0.023	0.172	0.904	0.119
21	13.47%	0.277	0.350	0.922	0.584	8.34%	-0.122	0.554	0.836	0.314	8.27%	-0.075	0.378	0.289	0.277	3.64%	0.004	0.196	0.961	0.123

Figure 1: Average PC Loadings Over Time

This graph shows the average PC1 and PC2 loadings of an equal-weighted index of 12 global equity futures (EQ), 8 global fixed income futures (FI), and 6 exchange rates against the dollar (FX) over the sample period 2007-2020. The PCs are estimated with the correlation matrix of the 26 global asset returns using high frequency data. In terms of the average loadings, the averages are reported over quarters pre 2020 and over biweeks for the 2020 Covid-19 crisis period. The dashed lines represent three crisis events, the 5th biweek of 2020 (Covid-19), the 13th biweek of 2016 (Brexit), and the 19th week of 2008 (GFC).

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Average Loading
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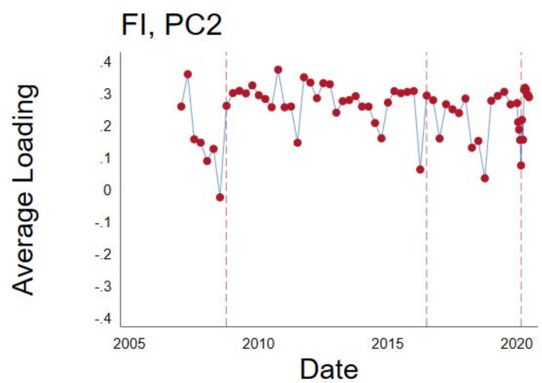
.3
.2
.1
0
-.1
-.2
-.3
-.4
2005
2010
2015
2020
Date


FI, PC2
Average Loading
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.3
.2
.1
0
-.1
-.2
-.3
-.4
2005
2010
2015
2020
Date

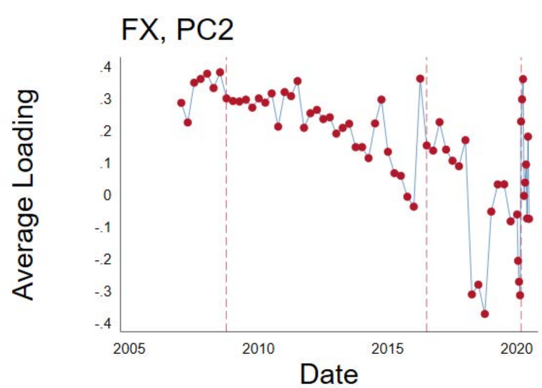
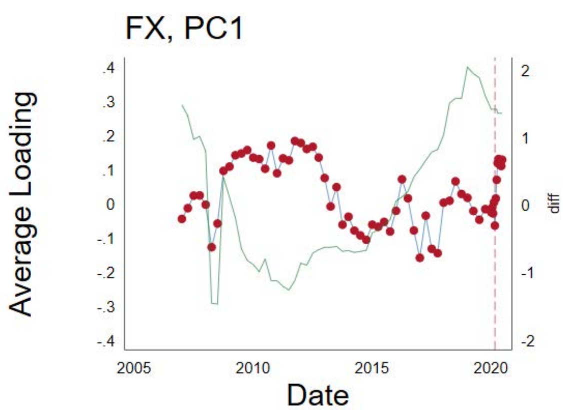

FX, PC2
Average Loading
.4
.3
.2
.1
0
-.1
-.2
-.3
-.4
2005
2010
2015
2020
Date

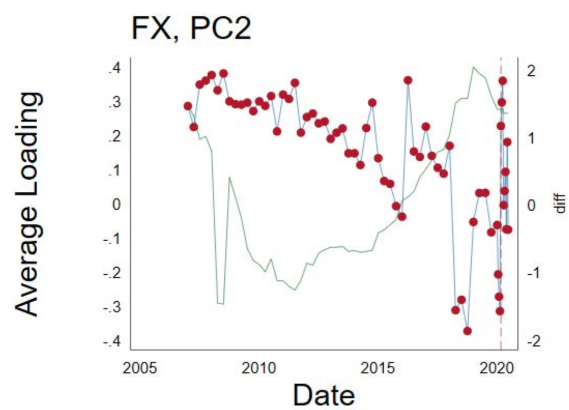
Figure 2: Average PC Loadings of Carry Strategy

This graph plots PC loadings over time related to the FX carry strategy. Panels A and B shows the average PC1 and PC2 loadings of an equal-weighted index of 6 exchange rates against the dollar (FX) over the sample period 2007-2020, graphed alongside the spread between US short-term rates and an average of these rates for the six countries. Panels C and D plot the average PC1 and PC2 loadings of FX, restructured as a carry strategy. The carry strategy longs the exchange rates of the three countries with relatively high interest rates and shorts the other three countries with relatively low interest rates. In terms of the average loadings, the averages are reported over quarters pre 2020 and over biweeks for the 2020 Covid-19 crisis period. The dashed lines represent three crisis events, the 5th biweek of 2020 (Covid-19), the 13th biweek of 2016 (Brexit), and the 19th week of 2008 (GFC).

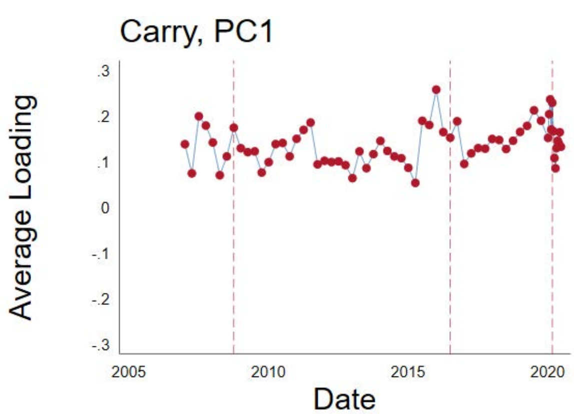
(a)



(b)



(c)



(d)

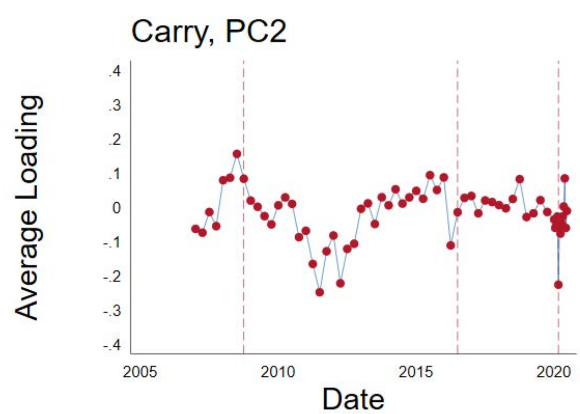
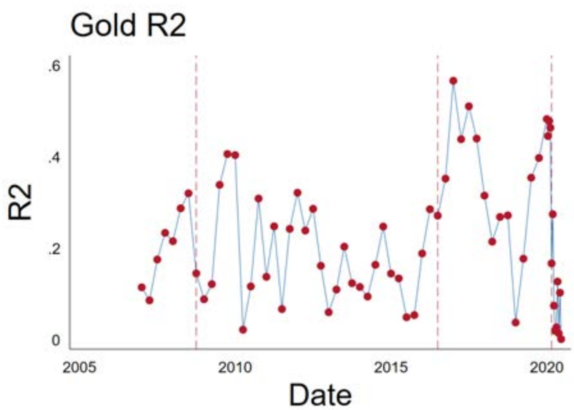


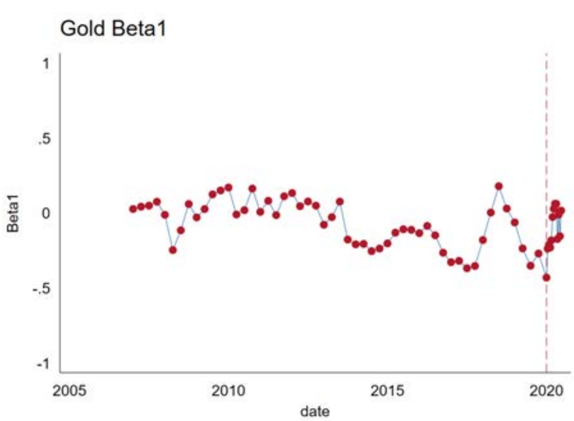
Figure 3: The Relationship Between the PCs and Gold

This figure plots the relationship between gold futures returns and the two PC returns, where the PCs are constructed from the correlation matrix of 26 global asset returns using high frequency data over over the period 2007-2020. The dashed lines represent three crisis events, the 5th biweek of 2020 (Covid-19), the 13th biweek of 2016 (Brexit), and the 19th week of 2008 (GFC). The results are reported over quarters pre 2020 and over biweeks for the 2020 Covid-19 crisis period. Panel A shows the implied R^2s of a multivariate regression of gold returns on the returns of PC1 and PC2. Panels B and C provide the implied betas of PC1 and PC2 associated with this regression.

(a)



(b)



(c)

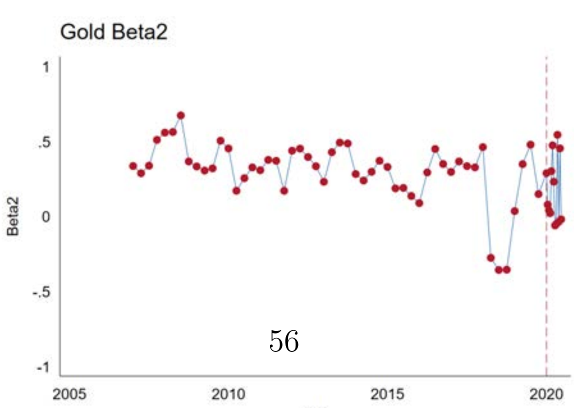
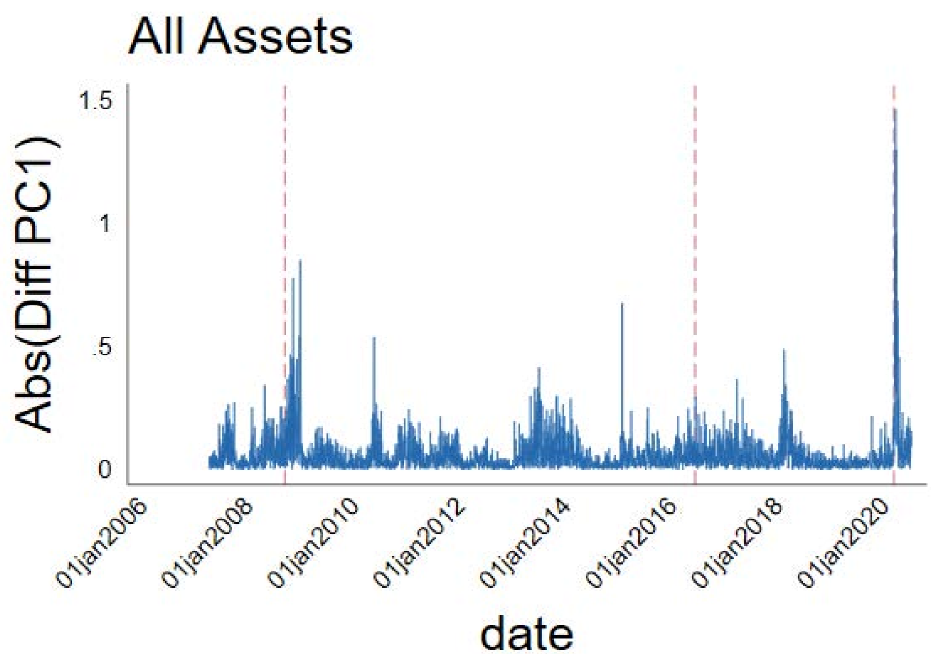


Figure 4: Changes in Factor Structure Over Time

The figure graphs the absolute value of differences in PC1 and PC2 through time. Each day, we take the absolute value of that quarter's PC weights minus last quarter's weights times that day's asset return, *i.e.*, $|PC1_{qt-(q-1)t,k}| \equiv |\sum_i (w_{i1qt} - w_{i1(q-1)t}) R_{iqt+k}|$ and $|PC2_{qt-(q-1)t,k}| \equiv |\sum_i (w_{i2qt} - w_{i2(q-1)t}) R_{iqt+k}|$ where R_{iqt+k} is the return on the k-th day of the i-th asset in quarter q_t, and w_{i2qt}, for example, is the current quarter loaindg of PC2 on asset i. The returns of both $PC1_t$ and $PC2_t$ are standardized to have zero mean and variance 1 using the full time-series of $PC1_t$ and $PC2_t$ over the 2007-2020 period.

(a)



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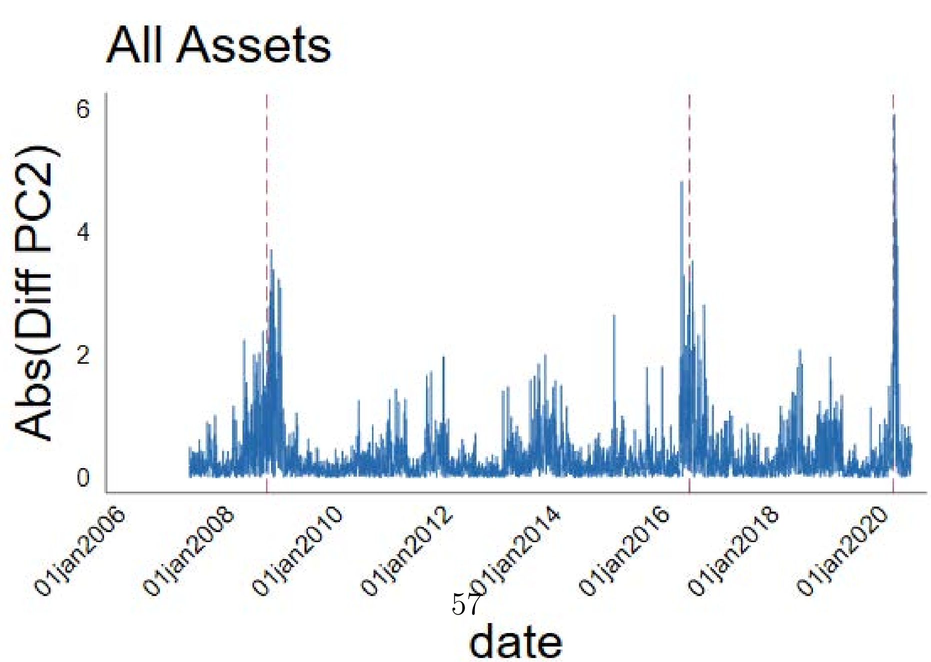
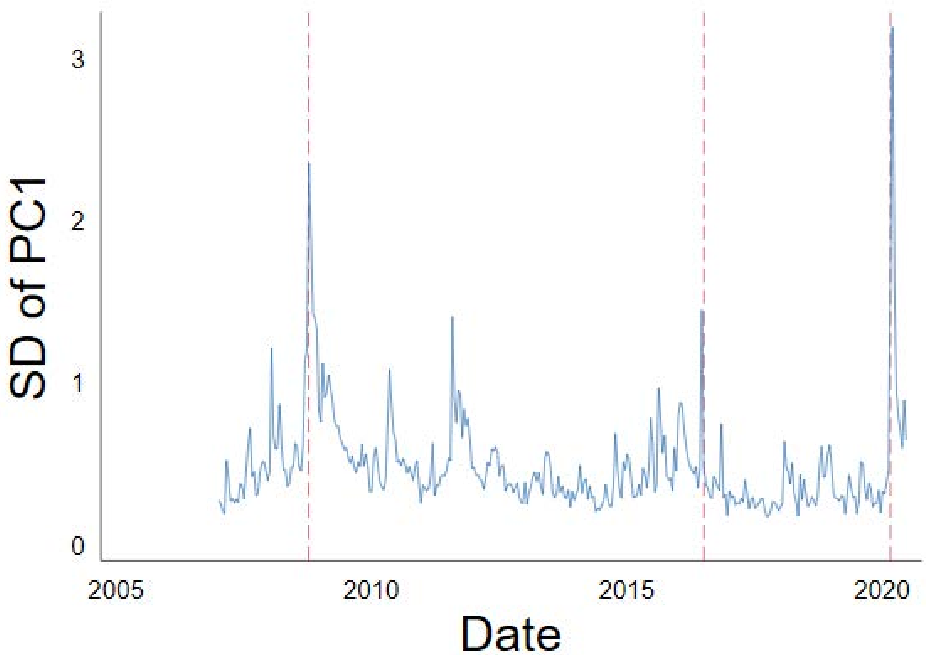


Figure 5: PC1 and PC2 Volatility

The figure graphs the high frequency realized biweekly volatility of PC1 and PC2, where the PCs are constructed from the correlation matrix of 26 global asset returns using high frequency data over biweekly periods in the period 2007-2020. The dashed lines represent three crisis events, the 5th biweek of 2020 (Covid-19), the 13th biweek of 2016 (Brexit), and the 19th week of 2008 (GFC).

(a)



(b)

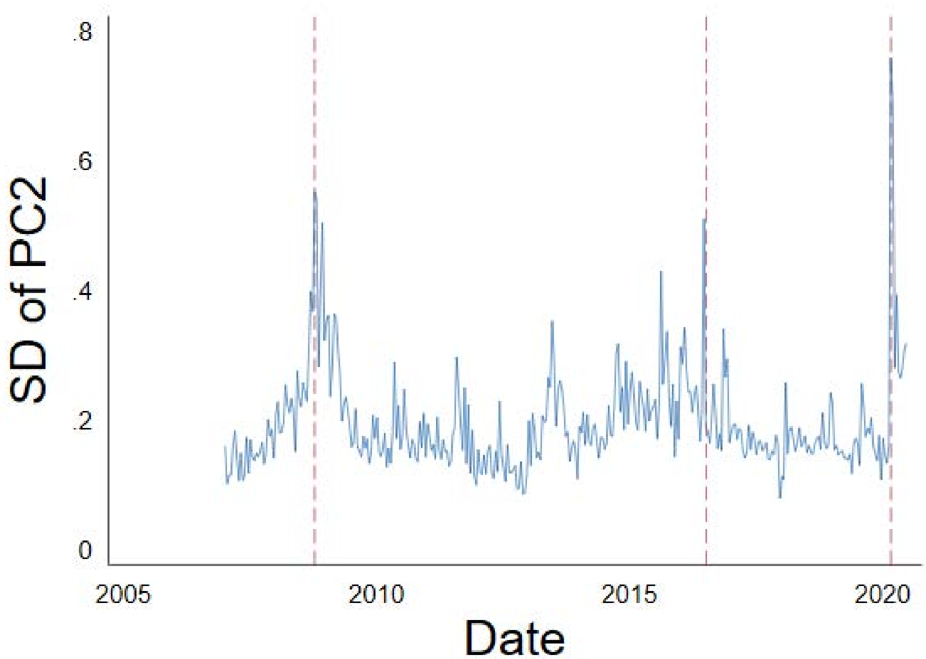


Figure 6: R^2s of Commodity Returns on PC Factors

This figure plots the implied R^2s of a multivariate regression of commodity returns (copper, corn and oil) on the returns of PC1 and PC2, where the PCs are constructed from the correlation matrix of 26 global asset returns using high frequency data over the period 2007-2020. The results are reported over quarters pre 2020 and over biweeks for the 2020 Covid-19 crisis period. The dashed lines represent three crisis events, the 5th biweek of 2020 (Covid-19), the 13th biweek of 2016 (Brexit), and the 19th week of 2008 (GFC).

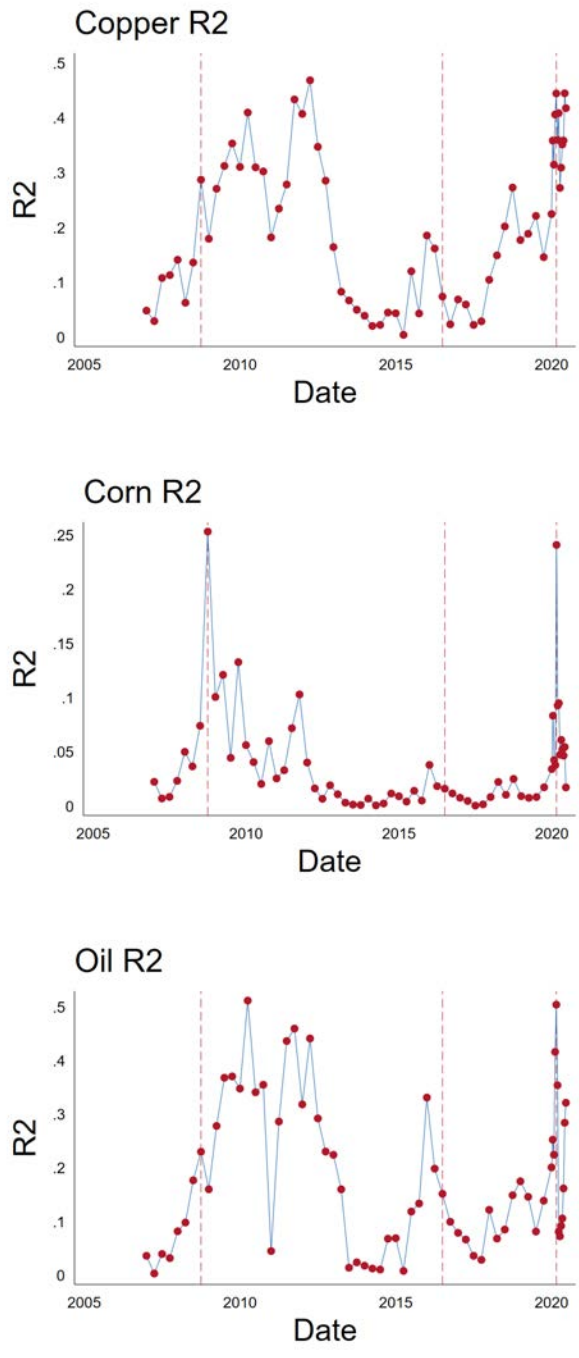


Figure 7: Factor Loadings of Asset Classes During the Covid-19 Period

This figure shows biweekly PC1 and PC2 loadings of EQ, FI, and FX future indexes during the onset of the Covid-19 period as measured over January to June, 2020. The indices include 12 equity futures (Australia, Brazil, Germany, Canada, Spain, France, India, Italy, Japan, Switzerland, UK and US) in blue, 8 fixed income futures on 10-year government bonds (Australia, Germany, Canada, France, Italy, Japan, UK and US) in red, and six spot exchange rates (Australia, Euro, Canada, Japan, Switzerland, UK in terms of $US) in green. The PCs are constructed from the correlation matrix of the 26 global asset returns using high frequency data over the relevant biweekly periods.

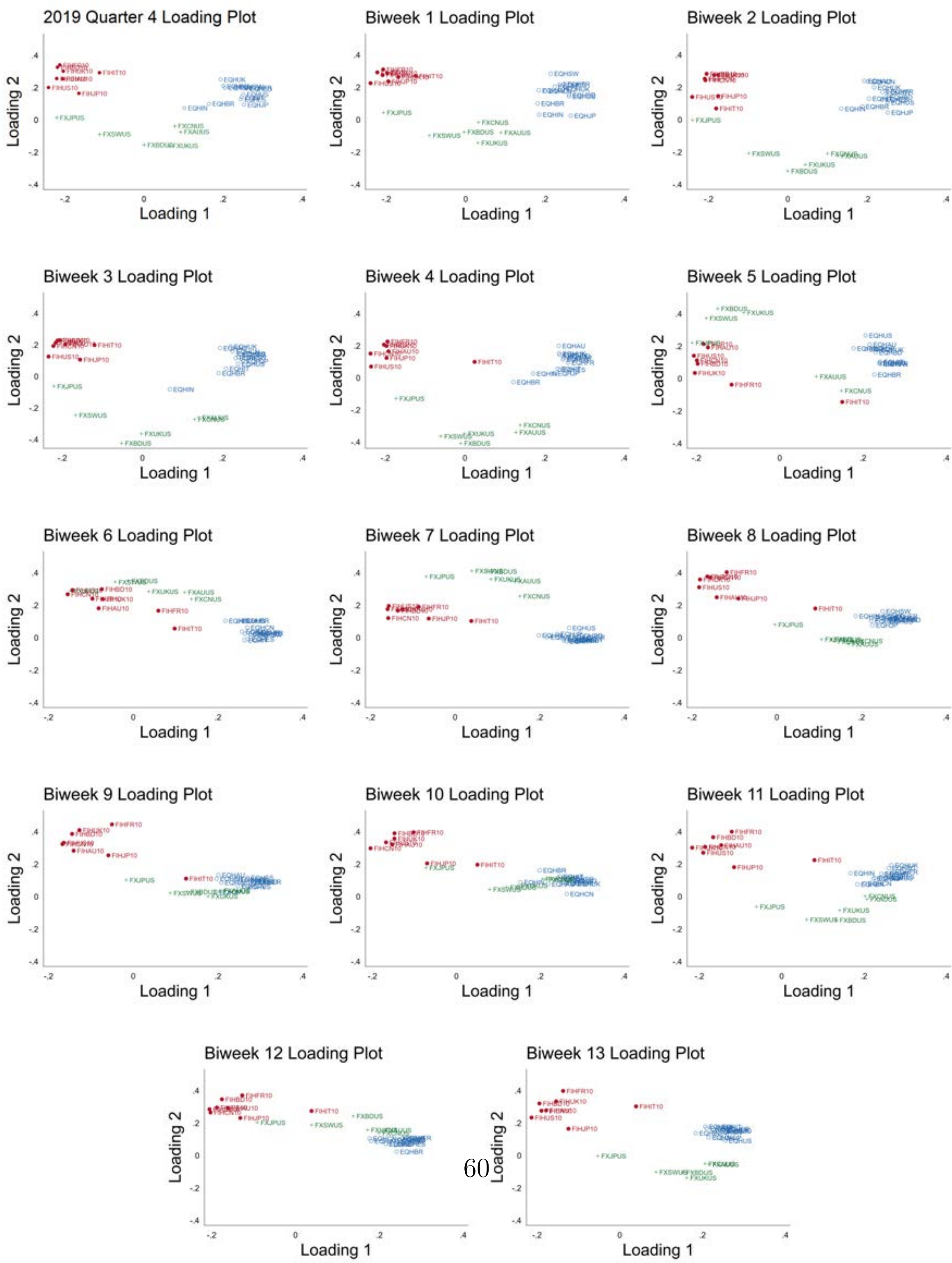


Figure 8: Covid-19 Composite News Indices Across Countries

This figure shows a composite Covid-19 measure for 10 countries during the January-June 2020 Covid-19 period. The composite index is an average of three standardized Coronavirus indices provided by Ravenpack (*Panic*, *Media Hype*, and *Media Coverage*), who employ a natural language processing (NLP) algorithm to measure specific events and sentiment related to Covid-19 generated from unstructured text contained in a variety of media sources and company reports.

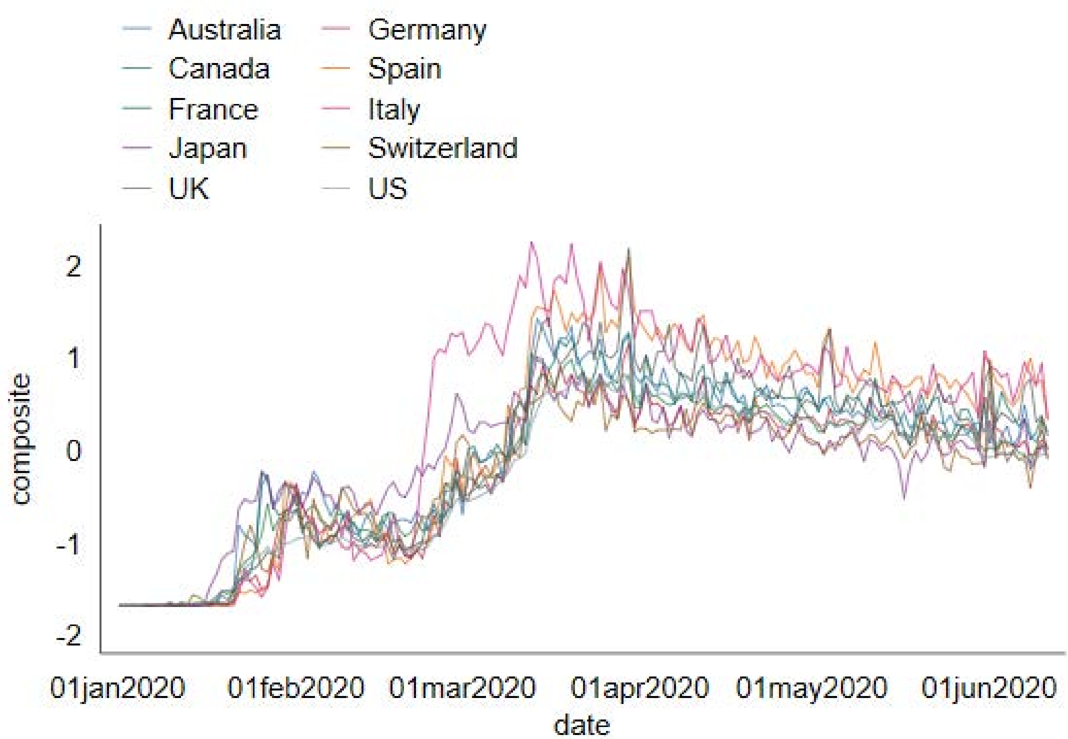


Figure 9: Epidemiological Model Forecast Errors

This figure shows the actual Covid-19 deaths and epidemiological model forecasted deaths in four representative countries in 3 continents, *i.e.*, United States (North America), Japan (Asia), and Germany and Italy (Europe))during the Covid-19 period. The forecasts are provided by the MRC Centre of Global Infectious Disease Analysis and Abdul Latif Jameel Institute for Disease and Emergency Analytics at the Imperial College of London. Specifically, the figure documents the total number of deaths each day (in solid blue) and the one to seven day-ahead forecasts of deaths each week (given by red dots) from the start of the forecast period to June 31, 2020. The difference between the blue and red points therefore represent forecast errors.

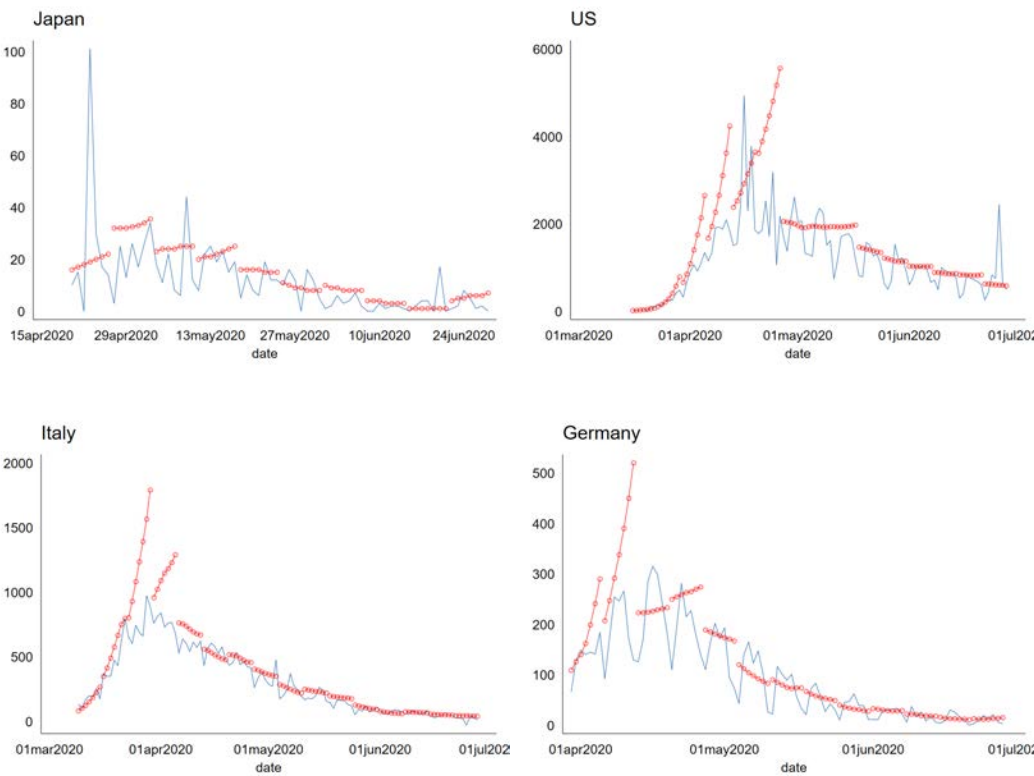
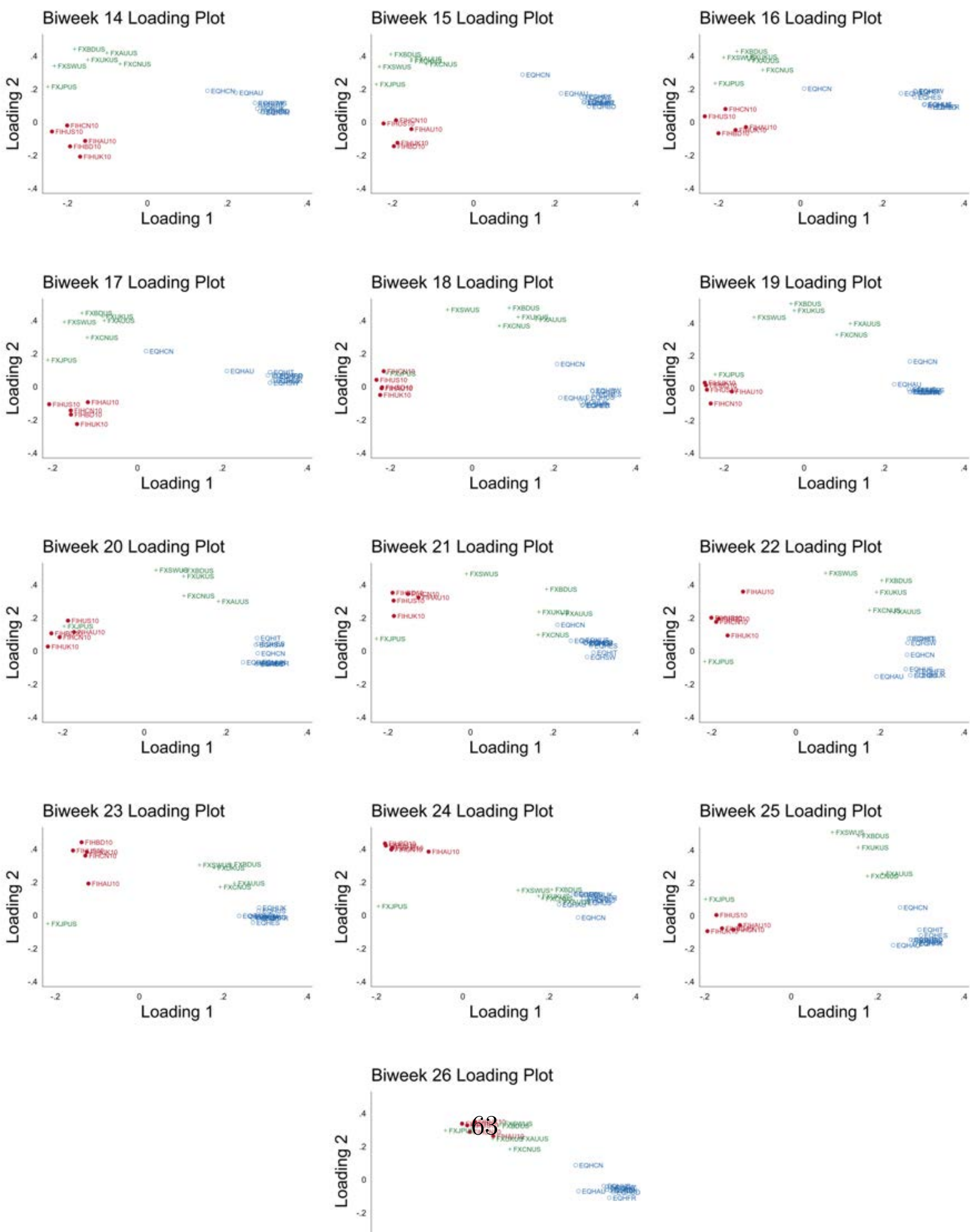
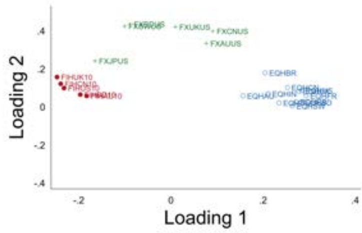


Figure 10: GFC & Brexit Loadings

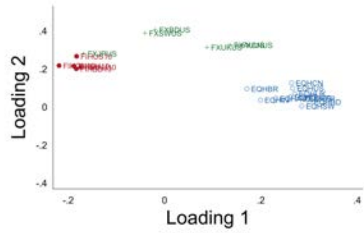
This figure shows biweekly PC1 and PC2 loadings of EQ, FI, and FX future indexes around the peak of the Global Financial Crisis (GFC) (biweek 14 through biweek 26 of 2008, with biweek 19 being the Lehman bankruptcy) and the Brexit vote (biweek 9 through biweek 21 of 2016, with biweek 13 being the vote). The indices include 12 equity futures (Australia, Brazil, Germany, Canada, Spain, France, India, Italy, Japan, Switzerland, UK and US) in blue, 8 fixed income futures on 10-year government bonds (Australia, Germany, Canada, France, Italy, Japan, UK and US) in red, and six spot exchange rates (Australia, Euro, Canada, Japan, Switzerland, UK in terms of $US) in green. The PCs are constructed from the correlation matrix of the 26 global asset returns using high frequency data over the relevant biweekly periods.



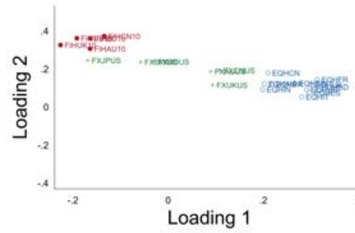
Biweek 9 Loading Plot



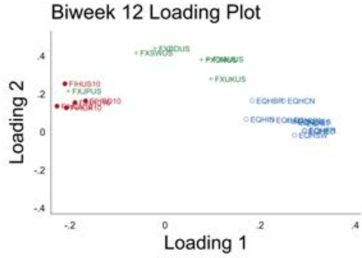
Biweek 10 Loading Plot



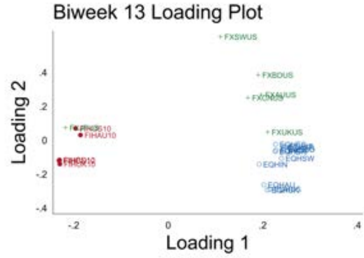
Biweek 11 Loading Plot



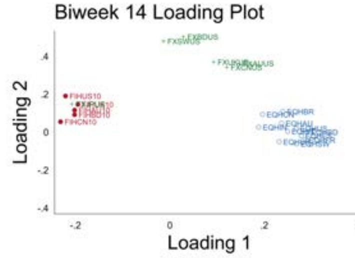
Biweek 12 Loading Plot



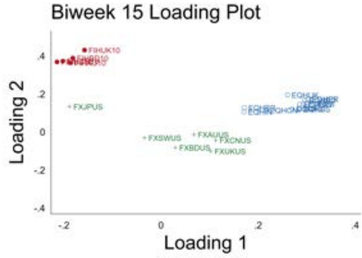
Biweek 13 Loading Plot



Biweek 14 Loading Plot



Biweek 15 Loading Plot



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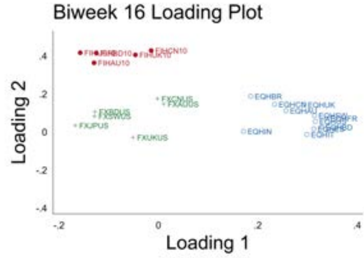
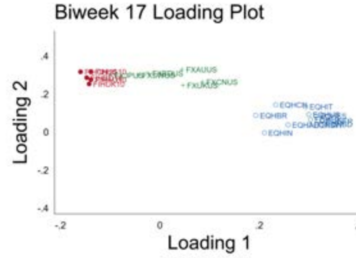
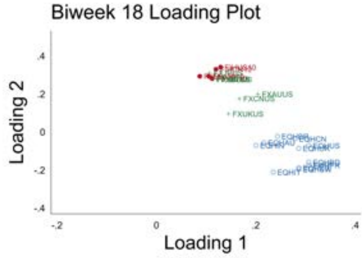


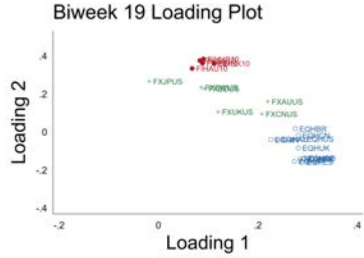
Biweek 17 Loading Plot



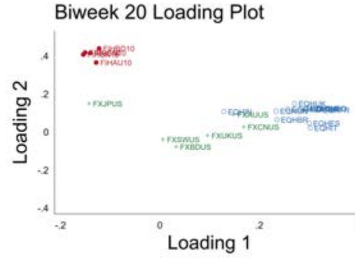
Biweek 18 Loading Plot



Biweek 19 Loading Plot



Biweek 20 Loading Plot



Biweek 21 Loading Plot

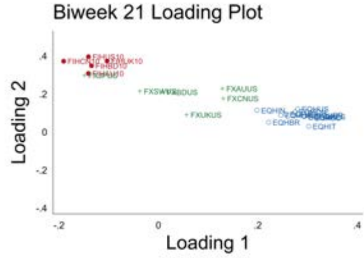
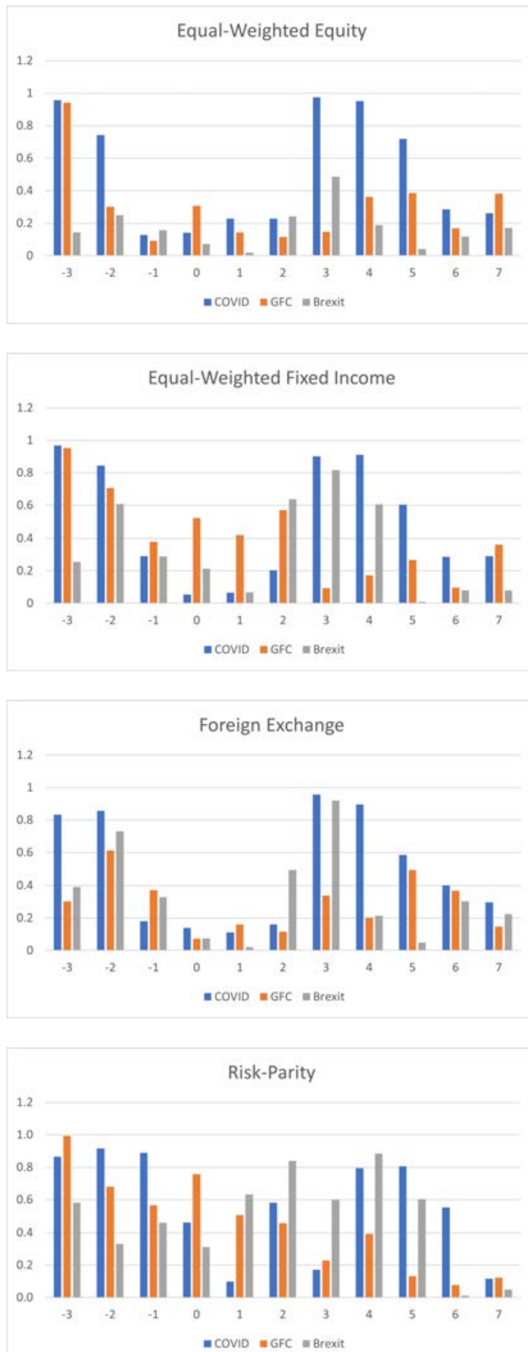


Figure 11: Hedging Systematic Risk During Crises

This table reports the results for hedging systematic risk of four aggregate portfolios during the GFC (in orange) , Brexit (in grey) and Covid- 19 (in blue) periods. Three portfolios (equity, fixed income, currency) are equal-weighted across countries and dollar denominated, while the fourth is a risk-parity portfolio of equity, fixed income and currencies, weighted to have equal volatility in each asset. For each portfolio, the figure graphs the ratio between the realized idiosyncratic component's variance and the idiosyncratic component's variance using lagged PC1 and PC2 betas. Event date 0 is biweek 19 of 2008, biweek 13 of 2016 and biweek 5 of 2020 for the GFC, Brexit and Covid-19 respectively.



Appendix

Table A.3C & Table A.9B: The Euro Crisis

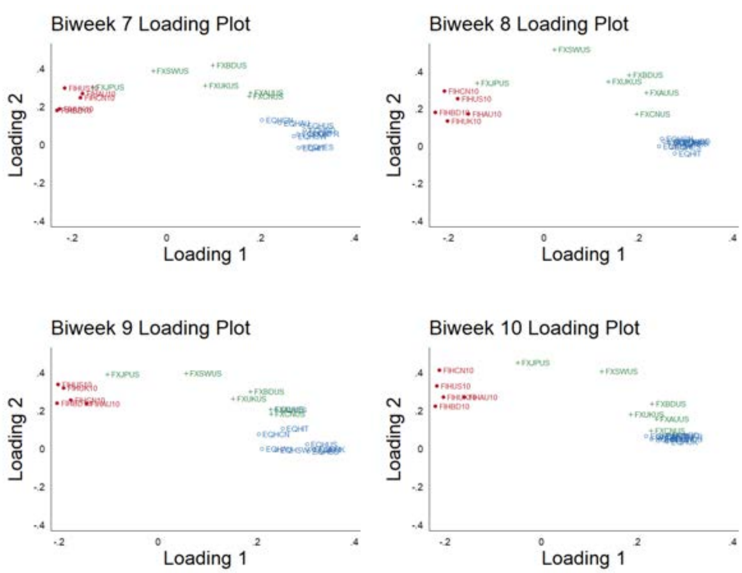
This table provides an analysis of how the Euro Crisis factor structure changes relative to the rest of the 2007-2020 sample period. Panel A.3C compares $|PCJ_{qt-(q-1)t,k}|$ during the Euro crisis period versus all other periods for both PC1 and PC2, and also calculates the average difference in weights from quarter to quarter, $|\sum_i \left(w_{iJqt} - w_{iJ(q-1)t}\right)|$, for both PC1 and PC2 during the Euro crisis versus the rest of the sample. The Euro crisis is defined by biweeks 7–10 of 2011 and biweeks 14–17 of 2012. Panel A.9B compares the average loadings for PC1 and PC2 across the three main asset classes (EQ, FI and FX) during the peak of the Euro crises versus the period immediately before these crises emerge.

Panel C: Test of Diff EuroCrisis vs Normal Period					
Absolute Differences in PC					
		PC1	PC2	PC1	PC2
Euro1		-0.03*	-0.23**		
		(-1.81)	(-2.31)		
Euro2				-0.03*	-0.23**
				(-2.02)	(-2.32)
Observations		3,457	3,457	3,457	3,457
R^2		0.001	0.002	0.001	0.002
Absolute Differences in Loadings					
		PC1	PC2	PC1	PC2
Euro1		-0.01*	-0.04**		
		(-1.20)	(-2.51)		
Euro2				-0.03***	-0.030*
				(-3.04)	(-1.75)
Observations		1,234	1,234	1,234	1,234
R^2		0.001	0.005	0.007	0.003
Panel D: Avg Loadings Across Asset Classes & Crises					
EQ, PC1	Euro1	Euro2	EQ, PC2	Euro1	Euro2
-4 to -2	0.277	0.238	-4 to -2	0.030	0.057
0 to 2	0.269	0.242	0 to 2	0.038	0.058
FI, PC1	Euro1	Euro2	FI, PC2	Euro1	Euro2
-4 to -2	-0.195	-0.216	-4 to -2	0.242	0.239
0 to 2	-0.196	-0.208	0 to 2	0.241	0.309
FX, PC1	Euro1	Euro2	FX, PC2	Euro1	Euro2
-4 to -2	0.095	0.166	-4 to -2	0.322	0.230
0 to 2	0.096	0.175	0 to 2	0.319	0.237

Figure A.7: PC Loadings of Asset Classes During the Euro Crisis Period

This figure shows biweekly PC1 and PC2 loadings of EQ, FI, and FX future indexes during the onset of the Covid-19 period as measured over by biweeks 7–10 of 2011 and biweeks 14–17 of 2012. The indices include 12 equity futures (Australia, Brazil, Germany, Canada, Spain, France, India, Italy, Japan, Switzerland, UK and US) in blue, 8 fixed income futures on 10-year government bonds (Australia, Germany, Canada, France, Italy, Japan, UK and US) in red, and six spot exchange rates (Australia, Euro, Canada, Japan, Switzerland, UK in terms of $US) in green. The PCs are constructed from the correlation matrix of the 26 global asset returns using high frequency data over the relevant biweekly periods.

Biweeks 7–10 of 2011:



Biweeks 14–17 of 2012: