Climate Change Vulnerability and Currency Returns

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Abstract

Using measures of physical risk from climate change, we develop a methodology to allocate currency pairs according to a country's vulnerability to climate change and construct portfolios with decreasing vulnerability to physical risk. We show that non-G10 currencies are more vulnerable to physical risk, have become less vulnerable over time, and that the vulnerability measure is correlated with higher losses from natural disasters. Portfolios exposed to currencies with decreasing vulnerability have exhibited positive abnormal returns, with the abnormal return coming from currencies that have relatively high levels of vulnerability. These results exist in non-G10 currencies, while no relation to returns exist within G10 currencies.

Keywords: *climate change, physical risk, climate vulnerability, foreign exchange, currency returns, emerging market*

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1. Introduction

Climate change causes changes in the physical environment, such as increased frequency and intensity of hurricanes or heatwaves, sea level rise and variability in rainfall and temperature patterns (IPCC 2020). In turn, these physical impacts could affect investments, accumulation of human capital and economic growth (Gallup, Sachs, and Mellinger 1999; Dell, Jones, and Olken 2012; Cuaresma 2010).

Climate change has already had substantial physical impacts across countries. For example, climate related physical impacts caused €436 billion of economic losses in Europe between 1980 and 2016, with losses doubling between 2010 and 2016 compared to the 1980s (European Environment Agency 2018). These physical impacts are expected to accelerate in the next years and decades as many of the effects from increased concentration of greenhouse gas emissions in the atmosphere are effectively ‘locked in’, meaning even if we were to stop emitting carbon today the physical impacts will unfold over decades (Woetzel et al. 2020). Moreover, those effects are highly localized with the probability and magnitude of the physical impacts varying based on the geographic location (Ciscar et al. 2011).

Past studies have analyzed how those physical impacts might be related to financial market outcomes with evidence of a link to asset values (Bansal, Kiku, and Ochoa 2016; Bernstein, Gustafson, and Lewis 2019) and sovereign borrowing costs (Painter 2019; Kling, Lo, Murinde, and Volz 2018; Cevik and Jalles 2020), as negative climate shocks affect economic development, impair human capital development, and exacerbate a country’s trade imbalances (Loayza et al 2012; Cuaresma 2010; Gassebner, Keck, and Teh 2010). In this paper we create a framework for the analysis of country physical risk in currency markets. As Engel (2016) suggests, the foreign exchange rate is one of the few, if not the only, aggregate asset for an economy, whose price is readily measurable. This characteristic in turn allows us to understand how changes in asset prices might be related to a country's change in vulnerability to climate change.

To do so we use data from the Notre Dame Global Adaptation Initiative (ND-GAIN Index) that measures a country's vulnerability to climate change. Vulnerability is defined as the propensity or predisposition of human societies to be negatively impacted by climate hazards. The data allow us to measure both the level but also changes in a country's vulnerability over time. Moreover, the data allow us to differentiate between a country's exposure, sensitivity, and adaptive capacity to the physical impacts of climate change. These three dimensions determine a country's vulnerability.

We start by analyzing the vulnerability measure for 29 currencies between 1995 and 2018. Because G10 currencies (all developed markets) and non-G10 currencies (predominantly emerging markets) exhibit systematically different characteristics, we first analyze whether emerging markets exhibit different vulnerability. We find that emerging markets are significantly more vulnerable to physical risks from climate change and that this increased vulnerability is due to lower adaptive capacity instead of exposure or sensitivity. Moreover, we find that their vulnerability gap to developed markets has decreased over time as their adaptive capacity has improved. This finding motivates us to present results using a sample of all currencies with available data but also separately for G10 and non-G10 currencies.

To validate but also provide an economic mapping for the vulnerability metric we connect it to historical economic losses and human lives affected from natural disasters. We find that countries with higher vulnerability have higher economic losses and percentages of the population affected. For example, historically an increase in the vulnerability measure from that of Canada to that of India is associated with additional economic losses of about 7 basis points of GDP annually.

Given that the physical impacts of climate change will intensify in the future and they have likely been measured inadequately in the past, this likely underestimates the future economic losses associated with vulnerability.

Next, we construct a model that connects the vulnerability measure to a set of economic fundamentals, including economic development and activities (GDP per capita, industrial production, and retail sales), condition of the labor market (unemployment rate), trade flows (current account), financial health of a country (debt to GDP), and inflation that have been shown to be linked to currency market dynamics. The model explains about 80 percent of the variation in the vulnerability measure, but considerably less of the change in vulnerability. Because of this large correlation between vulnerability levels and economic fundamentals, but also because the focus moving forward would be on how countries can decrease their vulnerability to climate change and become more resilient, we focus our attention on changes in vulnerability as a measure that investors could use to construct portfolios with declining exposure to climate change vulnerability. However, we examine levels of vulnerability when we implement a double-sort portfolio formation based on both levels and changes in vulnerability.

Our next step is to investigate the relationship between climate vulnerability and currency return at the portfolio level from 2002 to 2019. Investors increasingly use climate data to construct portfolios that limit their vulnerability to climate change from transition and physical risks (Andersson, Bolton, and Samama 2011; Cheema-Fox et al. 2021; Bolton and Kacperczyk 2021). In the context of physical risk, we use the momentum in vulnerability to create long-short currency investment strategies. We control for several currency factors across developed and emerging markets (market, carry, momentum and value).

This strategy produces noticeably positive and significant alphas in the period of our analysis. This result exists for non-G10 currencies and for crosses between G10 and non-G10 currencies. The estimate is insignificant for G10 currencies. This finding is consistent with evidence that emerging markets are more vulnerable to physical risk from climate change (Lange, Wodon, and Carey 2018; Tesselaar, Wouter, Botzen, and Aerts 2020).

To further understand the sources of the abnormal return we conduct a series of tests. First, we find that increasing the spread in vulnerability momentum between the currency pairs in the long and the short portfolio increases the estimated abnormal return, consistent with more meaningful differences in vulnerability change being associated with larger abnormal returns. Second, to understand if this abnormal return is subsumed by economic fundamentals, we construct macro factors based on a set of country-level characteristics that could link to both climate vulnerability and currency returns. We demonstrate in a multi-factor setting that our vulnerability momentum portfolio still generates a positive and significant alpha after controlling these macro factors as well as the currency risk factors. Third, we decompose the source of the return and show that positive interest rate differentials with no associated spot price deprecation accounts for most of the excess return, and that the vulnerability momentum strategy is distinct from a carry trade strategy. Lastly, when we implement double sorted portfolios based on both the level and change in vulnerability, we find that using the level and change in vulnerability, the high vulnerability and declining vulnerability portfolio is the source of the positive abnormal return.

Our paper contributes to the literature in the following ways. First, recent work investigates how climate related disclosures and metrics are associated with market prices and returns. While most of the work has focused on the use of corporate carbon emission metrics in the context of transition risk (Cheema-Fox et al. 2021; Bolton and Kacperczyk 2021), we focus on country vulnerability metrics in the context of physical risk. Second, our paper speaks to a literature that analyzes how past trends in fundamentals forecast currency returns (Dahlquist and Hasseltoft 2020). What distinguishes our paper is that we find past trends in the physical risk of climate change predict currency returns and this effect is still significant after controlling for the macro variables, as in Dahlquist and Hasseltoft (2020). Third, our findings contribute to ample research on the relation between natural disaster and economic fundamentals (Melecky and Raddatz 2011; Koetsier 2017; Burke, Hsiang and Miguel 2015; Day et al. 2019; Gassebner, Keck, and Teh 2010; Loayza et al. 2012; Dell, Jones, and Olken 2012; Fomby, Ikeda, and Loayza 2013; Felbermayr, Gröschl, and Felbermayr 2013; Beirne, Renzhi, and Volz 2020) and the relation between natural disaster/rare events and currency returns (Burnside, Eichenbaum, Kleshchelski, and Rebelo 2011; Jurek 2014; Farhi and Gabaix 2016). What differentiates our work is that instead of using the realization of natural disasters, which can only be observed ex-post by an investor, we use a climate vulnerability measure which can be evaluated ex-ante.

The remainder of the paper is organized as follows. The next section provides the motivation and literature review. Section 3 presents a description of the physical risk measure and its relation to economic fundamentals and natural disasters. Section 4 presents the sample, portfolio construction and currency return analysis results. Section 5 concludes.

2. Motivation and Literature Review

A growing literature analyzes the relationship between physical impacts from climate change and a country's economy. There are multiple mechanisms that could affect an economy thereby affecting the price of a currency. For example, losses and the costs of reconstruction from natural disasters could increase the need for public spending. This, in addition to the presence of lost tax revenues from disruptions in economic activity, could worsen the debt profile of a country (Melecky and Raddatz 2011; Koetsier 2017). Moreover, higher current and future expected public spending towards adaptation needs for more vulnerable countries could further put pressure on public finances. Past research has documented higher sovereign borrowing costs for more vulnerable countries and those that have suffered natural disasters (Cevik and Jalles 2020; Böhm 2020; Beirne, Renzhi, and Volz 2020; Kling et al. 2018). For example, the costs of adaptation are estimated between $140-300 billion per year by 2030 and between $280-500 billion per year by 2050 (Puig et al. 2016).

Furthermore, as climate events are more likely to affect more vulnerable countries, they could divert investment from long-term goals, such as improvements in education and building the country's human capital, towards short term necessities (Cuaresma 2010; McDermott 2012). This, in addition to reduced labor productivity due to changes in weather patterns (Burke, Hsiang and Miguel 2015), could reduce efficiency of the export sector while damage to productive capacity from a climate event could create demand for imports, thereby negatively impacting the trade balance (Gassebner, Keck, and Teh 2010). The impact on exports and trade balance could also manifest via damages to physical infrastructure and reduced agricultural output (Loayza et al. 2012; Dell, Jones, and Olken 2012; Fomby, Ikeda, and Loayza 2013; Felbermayr, Gröschl, and Felbermayr 2013; Beirne, Renzhi, and Volz 2020). Moreover, supply chains from vulnerable countries are also more likely to suffer disruption, as supply chains currently serviced by an impacted country may be re-evaluated with an eye to reducing dependency on a country prone to event risk (Pankratz and Schiller 2019; Beirne, Renzhi, and Volz 2020).

Finally, since a looser monetary policy is a probable response to a disaster (Klomp 2019), disasters could result in lower interest rates. In turn, local currency money market instruments could become less attractive from a yield-seeking perspective and in line with the "forward premium puzzle" (Fama 1984; Engel 1996) the local currency could depreciate (Eichenbaum and Evans 1995; Froot and Thaler 1990). Dampened foreign demand could then result in a reduction to carry-aligned institutional portfolio flows (Breedon, Rime, and Vitale 2015).

We note that many of the above effects are likely to be more significant for emerging market economies and thereby for the non-G10 currencies. This is partly because emerging market economies are more likely to be vulnerable, because of higher sensitivity and lower adaptive capacity to climate change, an issue we formally test in the paper. Moreover, natural capital has been found to be of particular importance for wealth creation in emerging markets that tend to rely more on agriculture and tourism, which in turn can be significantly impacted by natural disasters (Lange, Wodon, and Carey 2018). In addition, emerging markets are more likely to be affected by natural disasters because of lower insurance penetration. Insurance has been shown to increase economic resilience and accelerate recovery after disasters (Tesselaar, Wouter, Botzen, and Aerts 2020).

In summary, the negative realized or expected events from vulnerability to climate change are likely to impact the exchange rate by affecting the relative attractiveness of the financial and nonfinancial assets of a country.

3. Physical Risk Data

To measure a country's physical risk, we use the climate vulnerability data from the Notre Dame Global Adaptation Initiative (ND-GAIN).[1] The ND-GAIN Vulnerability data measures a

[1] ND-GAIN also provides scores for Readiness and a composite Adaptation Index incorporating both Vulnerability and Readiness. Readiness captures a country's ability to leverage investment to adaptation actions from three components: economic, governance and social. Since Readiness is a broader measure that extends beyond the impact

country's propensity or predisposition to be negatively impacted by climate-related disruptions and disasters. To assess a country's vulnerability to climate change, it considers six life-supporting sectors including food, water, health, ecosystem services, human habitat, and infrastructure. Within each sector, six indicators are evaluated from three components: the exposure of the sector to climate-related or climate-exacerbated hazards, the sensitivity of that sector to the impacts of the hazard, and the adaptive capacity of the sector to cope or adapt to these impacts, as shown in Table A1 in appendix.

The advantage of this vulnerability measure is that it not only considers the physical factors of a country (*Exposure*), such as geographic locations and physical climate impact that contribute to vulnerability externally, but also takes into account a country's degree of dependency on sectors that are climate sensitive (*Sensitivity*), as well as the ability of the economy to mitigate potential damages during and after those negative climate shocks (*Adaptive Capacity*).[2] Moreover, it is a measure that is readily available, consistently calculated across countries, and for a long period of time, allowing for use in archival research.

3.1.Analysis of Physical Risk

We first look at the level and trend of climate physical risk with annual ND-GAIN vulnerability data from 1995 to 2018. The vulnerability measure and its components Exposure, Sensitivity and Adaptive Capacity, have values ranging from zero to one, with one being most risky.[3] Figure 1

from climate-related hazards, the study of Readiness and Adaptation Index, although of potential interest, is beyond the scope of the paper.

[2] For example, for the infrastructure sector's exposure component, projected change of hydropower generation capacity and projection of sea level rise impacts are estimated for a country; for sensitivity, dependency on imported energy and population living under five-meter sea level are evaluated; for adaptive capacity, electricity access and disaster preparedness are assessed.

[3] For each variable in ND-GAIN data, raw data are scaled into scores ranging from 0 to 1 to facilitate the comparison among countries. Scaling is based on reference points using a formula for the vulnerability indicator: the vulnerability

below shows vulnerability levels for G10 economies in Panel A, and for non-G10 economies in Panel B. Table 1 summarizes the means and standard deviations for Vulnerability as well as the three components for 29 currencies from 1995 to 2018.[4] Since our goal is to link the climate vulnerability to currency returns, the rows are labelled with currency acronyms and the vulnerability for Eurozone is aggregated using member GDP weights.[5]

We observe emerging economies, in non-G10 currencies, are in general more vulnerable to physical risk than developed economies in G10 currencies. Within G10, Japan has the highest vulnerability, due to high exposure and sensitivity to physical risk. New Zealand and Switzerland have both seen meaningful decreases in vulnerability. For emerging markets, the vulnerability level is on average 17% higher than those in the G10 market, but the downward trend is more noticeable. For example, Turkey, Chile, and Peru show more than 8% reduction in vulnerability in 2018 comparing to their levels in 1995. On average, vulnerability has decreased 5.64% for non-G10 and 1.17% for G10 from 1995 to 2018. As can be seen in Table 1, both sensitivity and adaptive capacity vary over time while exposure is a time invariant measure.

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score is then calculated by first taking the arithmetic mean of 6 constituent indicators for each sector, and then equally weighting across 6 sectors.

$$score = \left| \frac{raw\ data - reference\ point}{basline\ maximum - baseline\ minimum} \right|$$

[4] Exposure level for each economy is not time-variant and is at a fixed value according to the ND-GAIN data.

[5] Before year 2000, the Eurozone vulnerability is proxied using the vulnerability level for Germany.

Figure 1: Vulnerability Measure

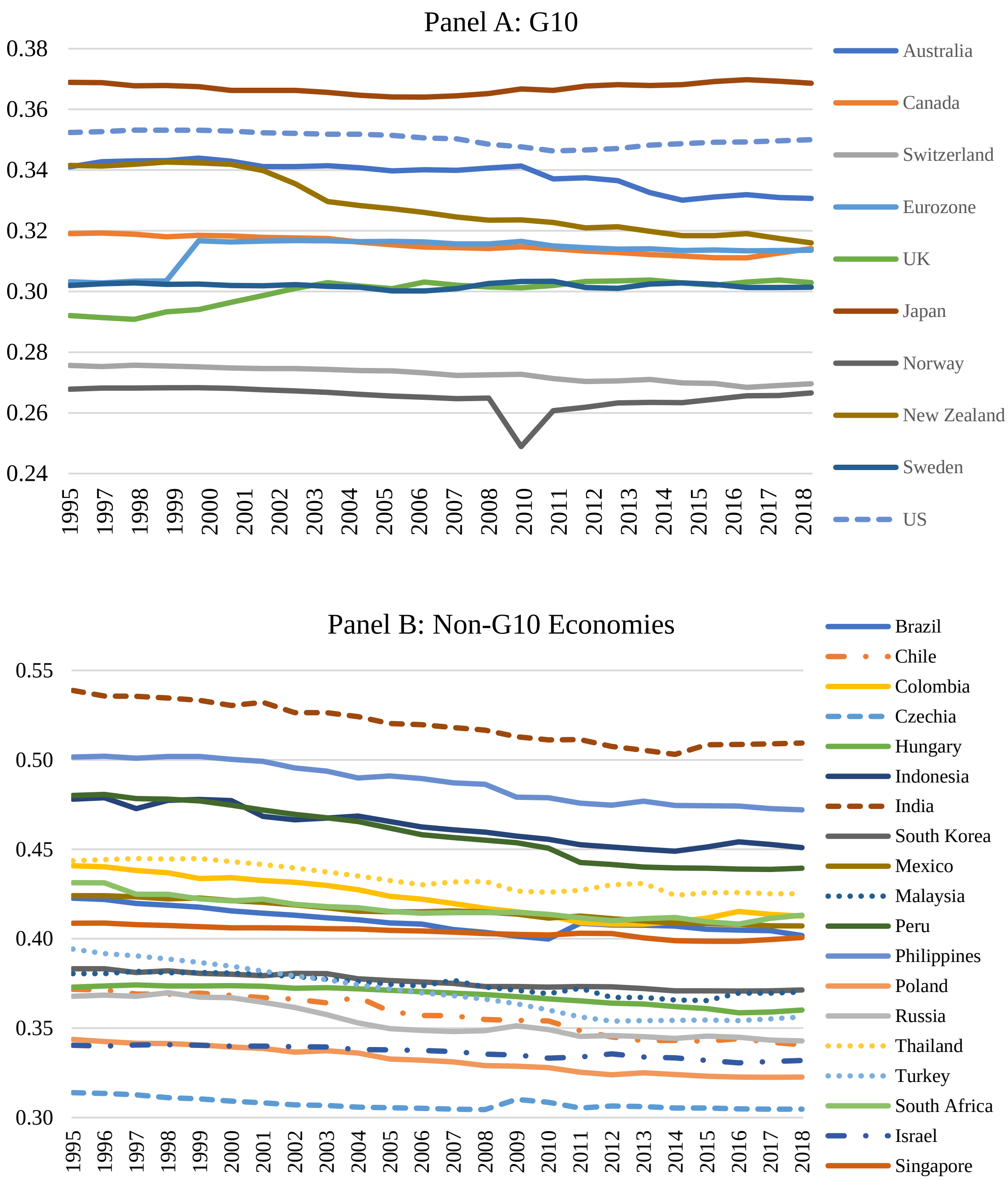

Figure 1 presents the vulnerability to physical risk for developed and emerging economies in our sample from 1995 to 2018. Before year 2000, the Eurozone vulnerability is proxied using the vulnerability level for Germany. Source data: ND-GAIN

Table 1: Summary Statistics of Physical Risk Measures

	Vulnerability		Exposure		Sensitivity		Adaptive Capacity	
Currency	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
AUD	0.3367	0.0044	0.4797	0.0000	0.1961	0.0060	0.3280	0.0082
BRL	0.4064	0.0036	0.5013	0.0000	0.2787	0.0070	0.4521	0.0090
CAD	0.3140	0.0020	0.4335	0.0000	0.2098	0.0014	0.2904	0.0050
CHF	0.2716	0.0020	0.3085	0.0000	0.2631	0.0016	0.2430	0.0043
CLP	0.3520	0.0090	0.3842	0.0000	0.2501	0.0022	0.4215	0.0258
COP	0.4169	0.0076	0.5013	0.0000	0.2015	0.0110	0.5479	0.0142
CZK	0.3059	0.0015	0.2733	0.0000	0.2872	0.0056	0.3411	0.0069
EUR	0.3150	0.0013	0.3839	0.0009	0.3163	0.0025	0.2466	0.0053
GBP	0.3025	0.0010	0.3900	0.0000	0.2688	0.0045	0.2486	0.0034
HUF	0.3661	0.0049	0.3488	0.0000	0.3699	0.0028	0.3909	0.0158
IDR	0.4574	0.0067	0.5179	0.0000	0.2883	0.0130	0.5918	0.0125
ILS	0.3350	0.0028	0.2838	0.0000	0.4411	0.0036	0.2838	0.0069
INR	0.5140	0.0074	0.5715	0.0000	0.3658	0.0081	0.6097	0.0180
JPY	0.3668	0.0019	0.5195	0.0000	0.3726	0.0063	0.2110	0.0016
KRW	0.3740	0.0032	0.4941	0.0000	0.3066	0.0016	0.3198	0.0100
MXN	0.4124	0.0037	0.4874	0.0000	0.2526	0.0021	0.4972	0.0122
MYR	0.3716	0.0042	0.4430	0.0000	0.2621	0.0036	0.4014	0.0140
NOK	0.2638	0.0042	0.3893	0.0000	0.1789	0.0053	0.2160	0.0107
NZD	0.3231	0.0051	0.4516	0.0000	0.2654	0.0031	0.2502	0.0156
PEN	0.4505	0.0112	0.4565	0.0000	0.2769	0.0098	0.6182	0.0242
PHP	0.4815	0.0081	0.4923	0.0000	0.3527	0.0058	0.5995	0.0194
PLN	0.3283	0.0052	0.3341	0.0000	0.2677	0.0038	0.3831	0.0188
RUB	0.3486	0.0050	0.4396	0.0000	0.2293	0.0113	0.3864	0.0083
SEK	0.3018	0.0010	0.4101	0.0000	0.2317	0.0033	0.2635	0.0039
SGD	0.4023	0.0025	0.5383	0.0000	0.3460	0.0070	0.3444	0.0010
THB	0.4297	0.0046	0.4576	0.0000	0.3743	0.0046	0.4606	0.0128
TRY	0.3629	0.0090	0.4153	0.0000	0.2732	0.0019	0.4101	0.0290
USD	0.3494	0.0018	0.4810	0.0000	0.2922	0.0020	0.2753	0.0037
ZAR	0.4135	0.0030	0.4306	0.0000	0.2929	0.0029	0.5747	0.0121

Table 1 presents the summary statistics of the vulnerability measure as well as its three components, exposure, sensitivity and adaptive capacity for 29 countries/regions in our sample from 1995 to 2018. Before year 2000, we use data for Germany as proxy for Eurozone. Exposure level for each economy is constant and thus has zero standard deviation. Source data: ND-GAIN.

Regression analysis in Table 2 suggests that indeed emerging markets exhibit different vulnerability from developed markets, which is attributable to their differing abilities to adapt to climate shocks. The emerging markets indicator variable is positive and significant in the regression for vulnerability as well as in the regression for adaptive capacity and is weakly significant for sensitivity. This suggests that emerging markets are significantly more vulnerable to physical risk due to lower adaptive capacity rather than higher sensitivity and exposure. This observation is consistent with our expectations that emerging economies have fewer resources, and those at hand are less readily deployable to cope with and recover from negative shocks of climate change than developed economies. Another finding from Table 2 is that the vulnerability gap between developed and emerging economies has decreased over time as suggested by the negative and significant estimate on the interaction term of the EM variable with time; and the decreasing vulnerability of EM could be explained by their improving adaptive capacity and decreasing sensitivity to these negative shocks.

Table 2: Physical Risk Across Emerging and Developed Markets

	Dependent Variables						
	Vulnerability		Exposure	Sensitivity		Adaptive Capacity	
Intercept	0.331	0.327	0.4239	0.290	0.287	0.276	0.266
	32.27	31.71	20.63	14.16	13.97	22.92	21.83
EM	0.076	0.084	0.020	0.007	0.013	0.209	0.229
	4.64	4.97	0.76	0.32	0.56	8.06	8.51
EM * Time trend		-0.001			-0.001		-0.002
		-4.69			-1.89		-5.00
Adjusted R-squared	37.7%	37.7%	-1.31%	-2.8%	-2.9%	62.9%	63.0%
N	527	527	527	527	527	527	527

Table 2 presents the results of regressing vulnerability and its components on EM dummy variable and an interaction of EM dummy and time trend using data from 2002 to 2018. Regressions are estimated using panel data with year fixed effects. T-statistics are based on clustered standard errors clustered by country/region. Source data: ND-GAIN.

3.2. Climate Vulnerability and Natural Disasters

To assess the validity of the vulnerability measure, we utilize the International Disaster Database (EM-DAT), which provides data on the occurrence and impact of natural and technical disasters at the country and event level globally. An event is recorded in EM-DAT if it meets at least one of the following criteria: at least ten victims recorded; at least one hundred affected people recorded; international relief aid sought; or a state of emergency declared. We collect data specifically on climate-related events that are classified as climatological (e.g. droughts), hydrological (e.g. floods) or meteorological (e.g. extreme temperature) given our focus on climate. Particularly, we are interested in how vulnerability is associated with the magnitude of economic losses and number of lives affected due to natural disasters.[6] In Table 3, we present results for panel regressions of economic losses (as percentage of GDP) and the percentage of population affected on the level of vulnerability.[7] Coefficients are estimated with year fixed effects. T-statistics are based on two-way clustered standard errors, clustered by country/region and year.[8]

We find countries that are more vulnerable to climate changes experience higher economic losses and percentages of population affected due to natural disasters, as shown in the positive and significant estimates for the vulnerability measure. This suggests that historically an increase in the vulnerability measure from that of Canada to that of India is associated with an additional economic loss of about seven basis points of GDP annually or $2.03 billion losses for India in 2018. In terms of human lives affected, a two-standard deviation change in vulnerability is linked to 2.6% more of the population affected. In the example of India, it translates to roughly 35 million more lives impacted negatively.

While we can document a significant relation between the vulnerability measure and real outcomes from natural disasters, the magnitude of the relation is not as large as one might expect. A potential explanation is that vulnerable countries with significant economic and population

[6] The International Disaster Database (https://www.emdat.be/) is created by Center for Research on the Epidemiology of Disasters (CRED) with initial support of the World Health Organization (WHO) and the Belgian government. For our analysis, we focus on the economic losses and number of lives affected from natural disasters and leave out the impact due to technical disasters.

[7] Percentage of population affected is calculated as a ratio of EM-DAT Affected indicator to the total country/region population. Affected indicator measures number of people requiring immediate assistance during an emergency situation due to natural disasters

[8] In the regressions of Table 3, economic losses and % of population affected are winsorized at 99%. Regression results are similar when adding log(GDP) as a control variable.

effects from natural disasters might not have the resources to properly document the effects leading to those effects to be underestimated and downward biases estimated coefficients in Table 3.

Table 3: Vulnerability and Economic Losses and Lives Affected from Natural Disasters

	Dependent Variables	
	Economic Losses (as % of GDP)	% of Population Affected
Intercept	-0.0012	-0.0676
(T-stat)	-1.27	-3.12
Vulnerability	0.0060	0.2081
	2.80	3.68
Adjusted R-squared	4.53%	9.54%
N	476	459

Table 3 presents the results of regressing economic losses and human lives affected on vulnerability from 2002 to 2018. Regressions are estimated using panel data with year fixed effects. T-statistics are based on two-way clustered standard errors, clustered by country/region and year. Economic losses and percentage of population affected are winsorized at 99%. We only use data on climate related events that are classified as climatological (droughts, glacial, and glacial lake outburst), hydrological (flood, landslide, and wave action) or meteorological (extreme temperature, fog and storm). Source data: ND-GAIN, EM-DAT.

3.3. Climate Vulnerability and Economic Fundamentals

In this section, we investigate the relationship between climate vulnerability and economic fundamentals of a country. Particularly, we want to understand which economic fundamental variables that have been shown to correlate with currency returns are also correlated to our vulnerability measure. Failing to understand those relations could give rise to correlated omitted variable bias.

Motivated by previous research that finds predictability of macroeconomic variables in currency returns (Engel and West 2005; Sarno and Schmeling 2014; Della Corte, Riddiough, and Sarno 2016; Nucera, 2017; Dahlquist and Hasseltoft 2020), as well as abundant work on the relationship between natural disasters and macro variables as documented in the literature review section, we estimate a panel model of climate vulnerability on a range of frequently considered fundamentals at country level, relating to overall economic development and activities (GDP per capita, industrial production, and retail sales), condition of the labor market (unemployment rate), trade flows (current account), financial health of a country (debt to GDP), as well as the direct role played by inflation in currency valuation.

The contemporaneous panel regressions are estimated based on the data of the 29 countries/regions in our sample from 2002 to 2018 using year fixed effects, and standard errors clustered both by year and country. We collect the GDP, population, unemployment, inflation and current account data from World Bank, and industrial production and retail sales from OECD. Deb-to-GDP data are obtained from BIS and World Bank. Since the industrial production and retail sales data from OECD only cover about 20 economies (G10 and ten non-G10, with missing values for some countries in the early 2000), we have a smaller set of observations in the specifications where we include all seven variables.

Results are shown in Table 4. In Panel A, level of vulnerability is the dependent variable and the independent variables are all based on levels of the respective fundamental variables as well.[9] We find that these five to seven economic variables explain roughly 77 to 80% of the variation in the level of physical risk, which means most information contained in the level of vulnerability is subsumed by the macro features. We observe the vulnerability metric is negatively correlated with log GDP per capita and unemployment rate, and positively correlated with debt-to-GDP in the five-factor model. In Table 4 Panel B, we estimate a model with both dependent and independent variables based on the 5-year momentum calculated as the log difference of these variables from the levels. We convert all variables from stocks to flows to preserve symmetry with the measurement of the dependent variable, but we also include levels of log GDP per capita. This variable is associated with innovations in vulnerability, but less so compared to levels of

[9] We use cumulated flow measures where necessary. For example, price level is based at 100 for 1994 for all countries in our sample, and we accumulate the inflation rates to generate the price levels for subsequent years.

vulnerability. The adjusted R-squared is less than 30%, suggesting most information from the innovation in vulnerability is not reflected in the changes in these macro fundamentals. After controlling for log GDP per capita, we do not observe any statistically significant relationships between the momentum in vulnerability and the trends in macro variables.

Consistent with Figure 1, our estimates from Table 4 suggest that a portfolio construction on the level of vulnerability would effectively allocate non-G10 currencies in the short portfolio and G10 currencies in the long portfolio, making any inferences difficult given the intertwined relation with economic fundamentals and in particular GDP-per-capita. Therefore, we focus on the momentum of climate vulnerability instead of the level of vulnerability, and the construction of climate resilient portfolios based on the momentum metric of physical risk. We do examine the relevancy of the level of vulnerability in Section 4.3.2 where we test the portfolio performance double-sorted on both the level and the trend.

Table 4: Panel Regressions of Climate Vulnerability on Economic Fundamentals

Panel A: Based on Levels

	Dependent Variable: Vulnerability	
	Model 1	Model 2
Log GDP per capita	-0.973	-0.835
(t-stat)	-11.50	-4.70
Price level	-0.036	-0.033
	-0.45	-0.27
Cumulative current account	0.009	-0.378
	0.07	-4.69
Debt-to-GDP	0.203	0.190
	2.45	2.52
Unemployment	-0.185	-0.385
	-2.59	-3.99
Industrial production		0.029
		0.30
Retail sales		0.026
		0.20

Panel B: Based on 5-year Momentum

	Dependent Variable: Δ Vulnerability	
	Model 3	Model 4
Δ GDP per capita	-0.160	-0.120
(t-stat)	-1.51	-0.94
Inflation	-0.134	0.023
	-1.19	0.20
Current account	-0.004	-0.145
	-0.04	-1.46
Δ Debt-to-GDP	0.007	-0.088
	0.08	-0.54
Δ Unemployment	0.060	-0.001
	0.81	-0.01
Δ Industrial production		-0.158
		-1.11
Δ Retail sales		-0.057
		-0.31

Adjusted R-squared	80.2%	76.9%
N	493	282
Year fixed effects	Yes	Yes

Log GDP per capita	0.330	0.402
	2.52	1.87
Adjusted R-squared	29.8%	24.6%
N	493	260
Year fixed effects	Yes	Yes

Table 4 presents the results of panel regressions of climate vulnerability on macroeconomic from 2002 to 2018. T-statistics are calculated based on two-way clustered standard errors, clustered by country/region and year. All regressions are estimated with an intercept, which are omitted in the table. All variables are z-scored. In Panel A, the dependent variable is the vulnerability level and the independents variables are based on level as well. All independent variables are winsorized at 95% except log GDP per capita. In Table 4 Panel B, both dependent and independents variables are based on 5-year change or the 5-year momentum calculated as the log difference from the levels. Regressions are controlling for log GDP per capita. All independent variables are winsorized at 5% and 95% except log difference in GDP per capita. Source data: ND-GAIN, World Bank, OECD, BIS.

4. Currency Data

Following prior studies (e.g. Engel 2016, Asness, Moskowitz, and Pedersen 2013), we obtain foreign exchange quotes for spot and forward exchange rates from WM Reuters via DataStream.[10] In addition to spot rates, we utilize forward points inferred from WM/Reuters 1-year forwards. In our multi-factor regression analysis, we control for standard risk factors such as carry, momentum, and value factors as they pertain to foreign exchange (for similar applications to risk attribution see Pojarliev and Levich 2012). These indices are taken from Bloomberg with the tickers in Appendix Table A2. We utilize the DXY index (taken from DataStream) return less the 1-month US T Bill rate as a G10 market factor.

4.1. Sample

We first selected the 31 most traded currencies covered by ND-GAIN data from both G10 and non-G10 markets.[11] We then excluded Chinese Yuan and Danish Krone from this analysis since these two currencies have pegged exchange rates historically, resulting in a universe encompassing

[10] Where available, we use quoted pair values as provided; where lacking (for example in crosses such as CZK/PLN), we infer cross-rates by passing through the appropriate pairs of available crosses (e.g. USD/CZK and USD/PLN to infer CZK/PLN). For these constructed crosses our convention is to sort alphabetically and take the first currency as the base currency, the second as the quote currency.

[11] These 31 currencies were most traded from 1995 to 2018 based on State Street's propriety trading data.

29 currencies in total: the G10 plus 19 currencies, 16 of which are classified as emerging markets and three are high GDP-per-capita countries (Israel, South Korea, and Singapore).[12] To make our climate-resilient strategies readily implementable in the foreign exchange market, we build our portfolios based on currency pairs. Given that currency pair trading depends on the base currency, and market participants can easily arbitrage by executing a series of transitions using a third currency if any mispricing arises, we extend our sample from the most traded pairs based on the 29 currencies to 406 currency pairs, including all possible combinations of any two currencies from the 29 currencies. We also break down our sample into G10, non-G10 and G10/non-G10 samples considering these groups of currencies could behave systematically differently. The G10 sample consists of pairs such that both quote and base currencies are from G10; the non-G10 sample has both quote and base currencies from non-G10; and the G10/non-G10 sample contains the G10 and non-G10 crosses only.

Because our portfolios are formed based on past five-year's climate vulnerability changes, the first set of results are from 2001. However, for several emerging market currencies in our sample, the one-year forward prices are not reliable in 2001. Therefore, our FX climate portfolios range from 2002 to 2019, and are constructed based on vulnerability data going back to 1996.

4.2. Portfolio Tests: Motivation and Mechanics

Our portfolios are constructed based on the past 5-year changes in vulnerability as shown below.[13]

$$x_{i,t} = (Vul_{i,t-1}^{quote\ curr} - Vul_{i,t-6}^{quote\ curr}) - (Vul_{i,t-1}^{base\ curr} - Vul_{i,t-6}^{base\ curr})\ ,$$

[12] G10: AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, USD. Non-G10: BRL, CLP, COP, CZK, HUF, IDR, ILS, INR, KRW, MXN, MYR, PEN, PHP, PLN, RUB, SGD, THB, TRY, ZAR. Before 1999 we use DEM quotes for the EUR. We exclude pegged currencies such as HKD, DKK, and CNY from our analysis.

[13] We also tested portfolios formed based on *percentage* change in past 5-year vulnerability and the results are similar to those based on the change in past 5-year vulnerability.

where $x_{i,t}$ is the signal for currency pair *i* at year *t*; $Vul_{i,t-1}^{quote\ curr}$ indicates the vulnerability of the quote currency country at year *t*-1; and $Vul_{i,t-1}^{based\ curr}$ indicates the vulnerability of the base country at year *t*-1. To form the physical risk resilient portfolio, we long the base and short the quote currency when the climate vulnerability has improved for the base country relatively to that for the quote currency country in the past five years, or when $x_{i,t}$ is positive; while we short the base and long the quote currency when the base country has deteriorated relative to the based country in the past 5 years, or when $x_{i,t}$ is negative. All currency pairs are equally weighted in the long-short portfolios.[14]

We also conduct tests restricting to pairs with the widest spreads in the changes of our risk measures between the currencies in each cross. This allows us to determine whether any observed effects are stronger when differences in risk are more pronounced. We expect that as the spread of physical risk momentum between the quote and base currency increases, the spread in returns should also widen. Wider spreads in risk should result in greater differences in return if the features we examine are related to returns. Thus, we build our base-case strategy on 50% of the spread, meaning we only trade the currency pairs whose absolute value of spread of vulnerability momentum are in the top 50% of absolute differences. This allows us to leave out pairs where the difference in vulnerability is trivial. We then test the portfolios constructed based on various sizes of spread and report the corresponding performance.

While our primary focus has been on the composite measure of vulnerability, we have also disentangled this into the distinct sensitivity and adaptability components and tested sorts on each

[14] For example, consider JPY/TRY. Turkey has seen improving physical risk in the past two decades while Japan has increasing vulnerability due to its exposure and increasing sensitivity to physical risk. Thus in this portfolio construction, we long Turkish lira and short Japanese Yen most times.

of these.[15] In addition to evaluating the full space of currency pairs, we consider in isolation subgroups of crosses as a robustness check: G10 crosses only, non-G10 crosses only, G10/non-G10 crosses. The existing literature suggests that physical climate risk might be a more important consideration for non-G10 currencies. Moreover, this separation allows us to understand how our results might be driven by systematic differences across G10 and non-G10.

All portfolios are formed on an annual basis on the last business day of the year from 2001 to 2018, with mid prices of spot and 1-year forward contracts. For the currency pairs that are not directly tradable, prices are inferred from triangle trade with either US dollar or Euro. The portfolio returns are calculated as follows:

$$Portfolio\ Return_t = \frac{1}{n_t}\sum_{i\in n_t}\left(\frac{S_{i,t}}{F_{i,t-1}} - 1\right) \times sign(x_{i,t}),$$

where i indicates currency pair, $i \in n_t$ if $|x_{i,t}|$ is equal or greater than the median of $|x_{1,t}|, |x_{2,t}|, \dots |x_{N,t}|$, and N = 406 in the base-case strategy; $S_{i,t}$ is the spot price at t and $F_{i,t-1}$ is the 1-year forward price at t-1.

4.3. Portfolio Tests: Results and Interpretation

What should we expect from these physical risk momentum portfolios, and why? Present-value models suggest that the exchange rate can be expressed as a function of current and expected economic fundamentals (Meese and Rogoff 1983). Recent evidence suggests that trends in economic fundamentals do predict currency returns with a strategy that goes long (short) currencies in countries with relatively strong (weak) economic momentum exhibiting an annualized Sharpe ratio of 0.70 over the 1976–2017 period (Dahlquist and Hasseltoft 2020).

[15] Note that we do not sort on changes in exposure, since exposures are static over our entire sample according to ND-GAIN data.

Similar to economic fundamentals, we hypothesize that trends in climate change fundamentals could predict currency returns as the physical risk of climate change has the potential to impact economic activities, as discussed earlier. Here, we buy the currency with the relative decline in vulnerability and sell the currency that has seen relative increases for each pair.

To understand whether this portfolio formation methodology is tilting towards particular currencies, we track and summarize the net positions in each currency (summing across the various pairs involving each currency) and report in Figure 2 below. The portfolio formed on the trend of vulnerability is relatively balanced between average long and short positions across currencies, except for USD and JPY which are always the funding currencies. We performed robustness checks by excluding USD and JPY crosses from our sample, and we find similar results.[16] Also, we do observe on average the portfolio tilts towards long non-G10s and short G10s. This is one of the reasons why we also report results for G10 or non-G10 only portfolios. Finally, we observe this portfolio has a relatively low annual turnover rate about 36.6% due to the slow-moving nature of the signal.[17]

[16] The portfolio with 27 currencies and excluding USD and JPY generates an excess return of 2.36%, standard deviation of 4.11%, and an alpha of 1.82% (statistically significant at 1% level) annually from 2002 to 2019.

[17] The portfolio turnover is relatively low as compare to Menkhoff et al. (2012), who report their lowest frequency momentum strategies with turnover of over 70% p.a..

Figure 2: Currency Weights and Positions

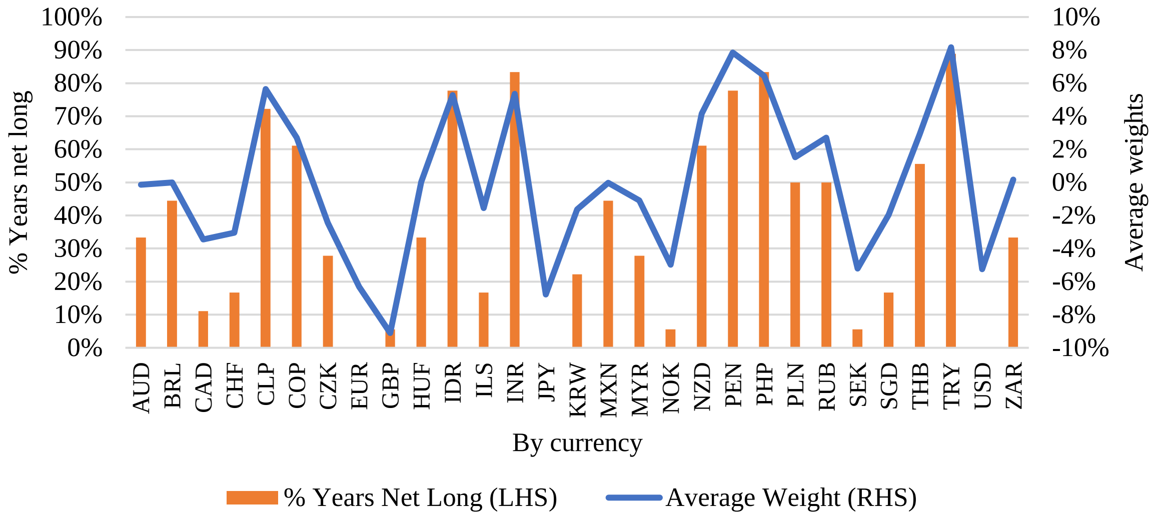

Figure 2 presents the average weights and percentage of years net long for each currency in the climate-resilient portfolios based on 5-year change in vulnerability from 2002 to 2019. This portfolio longs currencies with decreasing vulnerability and shorts currencies with increasing vulnerability. We only trade the currency pairs whose absolute value of spread of vulnerability momentum are in the top 50% of absolute differences in the sample. This portfolio is formed annually on the last business day of the year and returns are calculated using spot and 1-year forward contracts. Source data: ND-GAIN, DataStream.

Figure 3 and Table 5 below present portfolio level results for all measures. We find the portfolio sorted on the momentum of physical risk (buying relative decliners in risk and selling relative risers in risk) has resulted in a positive excess return of 255 bps annually for the sample with 29 currencies including both G10 and non-G10 (under "All" column in Table 5). The multi-factor regression (as shown in Appendix Table A2) suggests that this physical risk portfolio has positive exposures to a set of FX risk factors including G10 market, G10 value, EM market, EM momentum, and the global carry factors. But these risk factors only account for a moderate proportion (about 33%) of the returns. Investing in such a portfolio could generate a positive and significant alpha of about 170 bps per annum.

Turning to the subsets of our samples in Table 5, the return spreads are more pronounced across non-G10 pairs and G10/non-G10 crosses as compared to G10 pairs, which aligns with the greater relative risk differentials across non-G10 and between G10 and non-G10 currencies. The most distinct risk-adjusted returns manifests in the non-G10 portfolio with an alpha of 351 bps annually. In raw and risk-adjusted returns alike, the presence of non-G10 currencies widens return spreads across all metrics, resulting in positive significant alphas for this vulnerability momentum strategy. In terms of factor exposures, these portfolios consistently have positive loadings on the global carry and G10 market factors. We then stratify our portfolios in Table 5 Panel B to isolate the more extreme pairwise differentials. We see relatively monotonic increase in portfolio return and risk as the spread in momentum of physical risk widens, while Sharpe ratio maxes out between 40% to 60% of spread due to risk increasing faster than return in the more extreme cases.

Among the subcomponents, portfolios based on momentum of sensitivity exhibit a similar profile to the corresponding vulnerability result with somewhat stronger performance. While the portfolios based on change of adaptive capacity have positive performance as well, their risk-adjusted returns are not statistically significant.

Figure 3: Cumulative Excess Returns for Portfolios formed on Momentum of Physical Risk Metrics

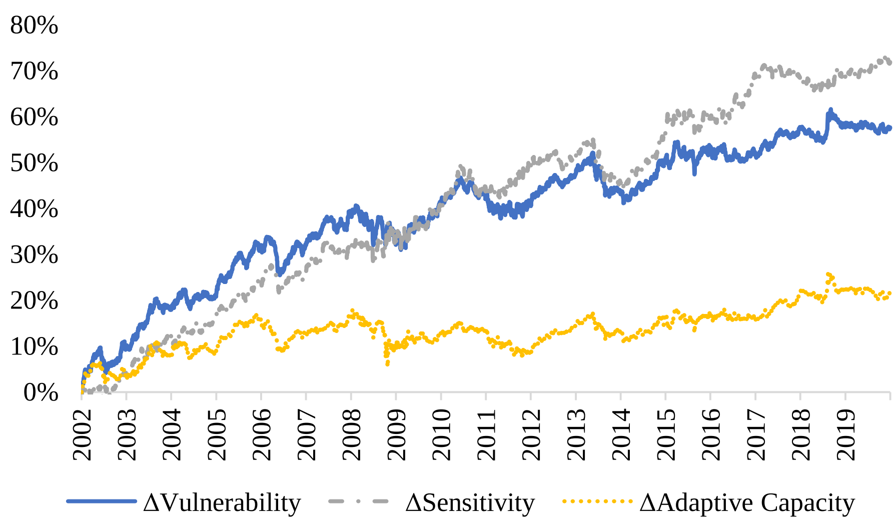

Figure 3 presents the cumulative excess returns for the long-short portfolios based on various physical risk metrics from 2002 to 2019. These portfolios are constructed based on past 5-year change in vulnerability, sensitivity, and adaptive capacity, respectively.

In all portfolios, currencies with decreasing risk are funded by currencies with increasing risk and currency pairs are equally weighted. We form these portfolios annually on the last business day of the year using spot and 1-year forward contracts. We only trade the currency pairs whose absolute value of spread of physical risk metric are in the top 50% of absolute differences in the samples. Source data: ND-GAIN, DataStream.

Table 5: Forming Portfolios on Momentum of Physical Risk Metric

Panel A: Summary Statistics

	All	G10	Non-G10	G10/ non-G10
ΔVulnerability				
Annual return	2.55%	1.34%	2.96%	2.61%
Annual risk	3.82%	4.81%	4.45%	4.85%
Sharpe ratio	0.67	0.28	0.67	0.54
Max drawdown	7.3%	9.7%	7.5%	10.0%
Hit rate	53.7%	53.0%	52.1%	53.2%
Alpha	1.70%	0.39%	3.51%	1.33%
Alpha t-stat	2.48	0.43	3.44	1.83
ΔSensitivity				
Annual return	3.05%	2.14%	2.49%	3.49%
Annual risk	3.70%	5.53%	4.57%	4.44%
Sharpe ratio	0.82	0.39	0.54	0.79
Max drawdown	7.0%	17.2%	10.0%	8.9%
Hit rate	52.1%	53.5%	50.2%	52.3%
Alpha	2.56%	1.25%	3.04%	2.55%
Alpha t-stat	3.72	1.26	3.24	3.59
ΔAdaptive Capacity				
Annual return	1.09%	1.09%	0.90%	1.48%
Annual risk	3.70%	4.49%	4.25%	4.40%
Sharpe ratio	0.29	0.24	0.21	0.34
Max drawdown	10.6%	9.8%	12.6%	9.8%
Hit rate	51.8%	51.5%	50.5%	53.0%
Alpha	0.29%	0.41%	1.21%	0.26%
Alpha t-stat	0.41	0.42	1.21	0.38
Avg no. of pairs in traded	190	23	78	90

Panel B: Results from Multivariate models for different levels of physical risk change spread

	Spread in Physical Risk Metric				
ΔVulnerability	>=0%	>=20%	>=40%	>=60%	>=80%
Annual return	1.31%	1.61%	2.21%	2.58%	2.50%
Annual risk	2.46%	2.97%	3.53%	4.14%	4.86%
Sharpe ratio	0.53	0.54	0.63	0.62	0.52
Alpha	0.66%	0.83%	1.35%	1.70%	1.47%
Alpha t-stat	1.58	1.66	2.19	2.28	1.67
ΔSensitivity					

Annual return	1.72%	2.17%	2.71%	2.99%	3.23%
Annual risk	2.33%	2.81%	3.34%	4.14%	5.21%
Sharpe ratio	0.74	0.77	0.81	0.72	0.62
Alpha	1.30%	1.69%	2.24%	2.63%	3.21%
Alpha t-stat	3.17	3.38	3.65	3.36	3.09
ΔAdaptive Capacity					
Annual return	0.70%	0.84%	0.95%	1.16%	1.53%
Annual risk	2.52%	3.06%	3.57%	3.98%	5.21%
Sharpe ratio	0.28	0.27	0.27	0.29	0.29
Alpha	0.17%	0.18%	0.21%	0.28%	0.31%
Alpha t-stat	0.38	0.33	0.32	0.37	0.29
Avg no. of pairs traded	378	302	227	152	78

Table 5 presents the portfolio performance based on 5-year change in vulnerability from 2002 to 2019 for our sample (column named “All”) as well as the subsamples G10, non-G10 and G10/non-G10. Panel A provides the summary statistics as well as the alphas and t-stats from the multi-factor regressions of portfolio returns on FX risk factors including G10 market, G10 carry, G10 value, G10 momentum, EM market, EM carry, EM momentum and global carry. In these portfolios, currencies that are less vulnerable are funded by more vulnerable currencies; and currency pairs are equally weighted in the portfolio. Portfolios are formed annually on the last business day of the year using spot and 1-year forward contracts. In the base case strategies in Panel A, we only trade the currency pairs whose levels of physical risk spread are in the top 50% in respective samples. Panel B provides the long-short portfolio performance statistics based on different levels of physical risk change spread. Source data: ND-GAIN, DataStream, Bloomberg.

The above portfolio tests have all been conducted by trading forward contracts, meaning that part of the return earned is due to interest rate differentials and part due to spot rate changes. While we have controlled for interest rate effects broadly by including carry factor return controls (including G10 carry, EM carry and global carry factors) in our risk-adjustments, it is still illuminating to perform an explicit decomposition of returns into spot (appreciation/depreciation) and interest rate differential components, following Menkoff et al. (2012).

We find a positive return contribution of 3.22% from forward points and a negative contribution of -0.67% from spot changes using the sample with all currencies, even though the depreciation in spot price is not statistically significant. Focusing on the non-G10 sample, we find a positive return contribution of 2.44% and 0.52% from forward points and spot changes respectively. Because in this case, we buy currencies with declining relative vulnerability and sell currencies with increasing relative vulnerability, this means that currencies experiencing a decrease in vulnerability have benefited from positive interest rate differentials which has not been counteracted by declines in spot rates. This is consistent with the positive loading on the global carry factor in the multifactor model. In other words, investors are rewarded with a high interest rate even though they invest in currencies with declining vulnerability, which represents a sign that future potential negative effects from climate change might be mitigated.

Since most of the positive excess returns of the vulnerability momentum strategy come from the interest rate differentials, and not from spot price changes, this observation might lead to a question of whether the vulnerability momentum strategy is a form of a carry strategy. While there might be some overlap between the two strategies, they are different. First, the cross-sectional correlation between the 5-year trend in vulnerability and one-year implied interest rate differentials (which are sorted on in a carry trade) is moderate, about 33.3% on average from 2001 to 2018. This suggests that our vulnerability momentum signal, although correlated with the carry signal, contain largely different information. Consistently, in the multi-factor regression of the vulnerability momentum portfolio on carry factors, we find positive loadings on the EM carry and global carry factors; however the carry factors along with other FX risk factors only explain 33.4% of the excess returns of the portfolio.

Moreover, for the carry trade, currencies which the strategy is long (i.e. currencies with high interest rates) on average depreciate relative to currencies with low interest rates, especially in EM currencies (Lustig, Roussanov, and Verdelhan 2011; Hassan and Mano 2017; Bansal and Dahlquist 2000; Frankel and Poonawala 2010; Gilmore and Hayashi 2011). Hassan and Mano (2017) document a global carry trade that portfolio loses 2.15% of annualized returns due to this depreciation. Consistent with these studies, using our sample of all currencies from 2002 to 2019, we find the carry trade is associated with a negative and sizable spot return of about -3.84% annually, much larger in magnitude than that of the vulnerability momentum portfolio, which sees a corresponding spot return not statistically significant from zero. This indicates that relative to carry trade, the currencies in the long side of the vulnerability momentum strategy, or the currencies with decreasing vulnerability, do not experience much depreciation.

4.3.1. Vulnerability Momentum Portfolio and Macro Factors

In Section 3.3. we have seen that the trend in climate vulnerability is not correlated with the trends in economic fundamentals even though most variations in the level of vulnerability could be explained by these fundamentals. In this section, we examine these relationships with cross-sectional data at the portfolio level. Specifically, we build portfolios based on the same set of fundamentals including 5-year growth in GDP per capita, inflation, current account balance, and change in debt-to-GDP, and unemployment, in the same fashion as for the vulnerability momentum portfolio. Past research has shown that trends in those economic fundamentals can be predictive of currency returns (Dahlquist and Hasseltoft 2020). We then examine the relationships between our climate vulnerability portfolio and these macro factor portfolios. Industrial production and retail sales are excluded from this exercise due to smaller sample coverage and the insignificant relationship with climate vulnerability as found earlier.

Table 6 Panel A provides the summary statistics of the five macro portfolios' performance. We see that portfolios based on inflation and debt-to-GDP generate positive excess returns from 2002 to 2019 while those formed on GDP per capita, current account, and unemployment are associated with negative returns.[18] The multi-factor regression in Panel B Model 1 reveals that our vulnerability momentum portfolio is positively correlated with the portfolios based on GDP per

[18] For GDP per capita, inflation, and current account balance, we construct the portfolios by going long on the currencies with relative positive 5-year change and short on currencies with relative negative 5-year change in these macro variables respectively; for Debt-to-GDP and unemployment, we construct the portfolios by going long on the currencies will relative negative 5-year change and short on currencies with relative positive 5-year change in these macro variables respectively.

capita, inflation, and current account balance. However, the five macro factors only subsume 79 bps or 31% of the vulnerability portfolio returns, which means 176 bps or 69% of the performance is attributable to the incremental information in physical risk of climate change. In Model 3, we test the portfolio performance while controlling for both the traditional FX risk factors as well as the macro factors, and we observe the vulnerability momentum portfolio still generates positive and significant alphas, similar in magnitude and significance to the alpha in Model 1 (only controlling for macro factors), and the alpha in Model 2 (only controlling for FX risk factors), which suggests there is considerable overlap between the macro factors and FX risk factors. Therefore, we conclude that the momentum of vulnerability contains pertinent information about currency returns which are not accounted in these macroeconomic fundamentals.

Table 6: Climate Portfolio and Macro Factors

Panel A: Summary Statistics

	ΔGDP per capita	Inflation	Current account	Δ Debt-to-GDP	Δ Unemployment
Excess Returns	-1.07%	2.69%	-0.94%	1.25%	-0.75%
Risk	4.57%	5.12%	3.69%	3.28%	3.70%
Sharpe Ratio	-0.23	0.52	-0.25	0.38	-0.20
Max drawdown	20.6%	13.0%	18.3%	12.5%	15.3%
Hit Rate	49.5%	54.3%	47.4%	52.0%	48.4%

Panel B: Multi-factor Regressions

Dependent Variable: Portfolio returns based on 5-year change in vulnerability

Factor returns	Model 1	Model 2	Model 3
Alpha	1.76%	1.70%	1.56%
	2.20	2.48	2.37
Δ GDP per capita	0.093		0.080
	3.18		3.84
Inflation	0.403		0.287
	5.75		4.07
Current account	0.187		0.064

	2.53		0.86
Δ Debt-to-GDP	0.014		0.024
	0.29		0.47
Δ Unemployment	0.059		0.040
	1.03		0.99
G10 Market		0.324	0.246
		27.31	10.16
G10 Carry		-0.001	0.028
		-0.10	2.69
G10 Momentum		-0.016	-0.011
		-1.70	-1.26
G10 Value		0.078	0.090
		8.20	6.54
EM Market		0.106	0.084
		7.81	5.88
EM Carry		0.014	0.001
		0.70	0.04
EM Momentum		0.026	0.030
		3.19	4.02
Global Carry		0.045	-0.072
		3.66	-3.01
Adjusted R-squared	26.1%	44.5%	49.2%
N	4696	4696	4696

Table 6 Panel A presents the summary performance for portfolios based on macro variables including 5-year growth in GDP per capita, inflation, current account balance, and change in debt-to-GDP and unemployment. For GDP per capita, inflation, and current account balance, we construct the portfolios by going long on the currencies with relative positive 5-year change and short on currencies with relative negative 5-year change in these macro variables respectively ; for Debt-to-GDP and unemployment, we construct the portfolios by going long on the currencies will relative negative 5-year change and short on currencies with relative positive 5-year change in these respective macro variables respectively. The rest of the portfolio construction is the same as for the vulnerability momentum portfolio. Industrial production and retail sales are excluded from this exercise due to smaller sample coverage and also insignificant relationship with climate vulnerability as found earlier. Panel B presents the multi-factor regressions of the vulnerability momentum portfolio on the macro factor returns and/or the FX risk factors. Source data: ND-GAIN, DataStream, Bloomberg, World Bank, and BIS.

4.3.2. Portfolio Tests: Double Sorts

So far we have examined vulnerability momentum without considering whether differences exist between changes from high or low initial levels of physical risk. To determine whether the vulnerability setting has any impact on how changes in vulnerability relate to returns, we conduct a double-sort analysis. We separate groups of pairs based on relative levels of vulnerability and relative changes in vulnerability into four quadrants: high levels of vulnerability with increasing vulnerability, high levels of vulnerability with decreasing vulnerability, low levels of vulnerability with increasing vulnerability, and low levels of vulnerability with increasing vulnerability.

Table 7 and Figure 4 summarize these results. The standout among these is the performance of the portfolio with high but decreasing level of relative vulnerability. This high risk but improving quadrant pairs earn statistically significant risk adjusted returns of 1.98% per annum, indicating that turning points for relative risk among the greatest cross-currency differences in these risk levels have resulted in the most salient returns among our quadrant portfolios. However, these results indicate that the level of vulnerability provides important context – improving from a risky base is rewarded more than improving from a less risky base. Moreover, levels of vulnerability are dominated by changes in vulnerability as can be seen by the negative returns on high but increasing vulnerability portfolio and by the positive returns on low but decreasing vulnerability.

Table 7: Double Sort on Level and Change of Vulnerability

	High and Increasing Vulnerability	High and Decreasing Vulnerability	Low and Increasing Vulnerability	Low and Decreasing Vulnerability
Excess annual return	-1.39%	2.73%	-1.11%	0.97%
Annual risk	4.30%	3.82%	4.87%	4.21%
Sharpe ratio	-0.32	0.72	-0.23	0.23
Max drawdown	34.1%	6.8%	21.0%	13.4%
Hit rate	47.6%	52.4%	47.2%	50.8%
Avg no. of pairs traded	67	121	124	67
Alpha	-0.14%	1.98%	-0.30%	0.83%
Alpha t-stat	-0.16	2.70	-0.50	1.20

Table 7 presents the double-sorted portfolio performance from 2002 to 2019. We sort the 406 currency pairs (including both G10 and non-G10) into four quadrants based on their relative level of vulnerability and change in vulnerability from the past five years. The multi-factor regressions of portfolio returns are controlling for FX risk factors including G10 market, G10 carry, G10 value, G10 momentum, EM market, EM carry, EM momentum and global carry. Currency pairs are equally weighted in the portfolios. Portfolios are formed annually on the last business day of the year using spot and 1-year forward contracts. Source data: ND-GAIN, DataStream, Bloomberg.

Figure 4: Double-Sorted Portfolio Performance

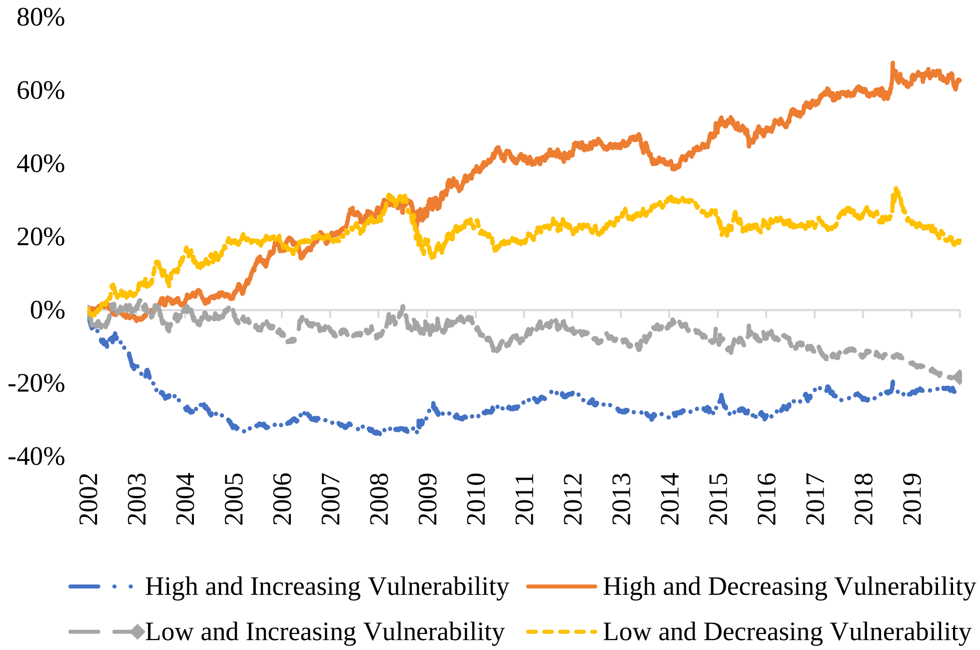

Figure 4 presents the double-sorted portfolio performance from 2002 to 2019. We sort the 406 currency pairs (including both G10 and non-G10) into four quadrants based on their relative level of vulnerability and change in vulnerability from the past five years. The multi-factor regressions of portfolio returns are controlling for FX risk factors including G10 market, G10 carry, G10 value, G10 momentum, EM market, EM carry, EM momentum and global carry. Currency pairs are equally weighted in the portfolios. Portfolios are formed annually on the last business day of the year using spot and 1-year forward contracts. Source data: ND-GAIN, DataStream, Bloomberg.

The fact that we do not observe positive (negative) returns for portfolios with high (low) levels of vulnerability level suggests that physical risk from vulnerability has not been a risk factor that has been priced in currency markets historically. As physical impacts from climate change manifest with increased intensity and frequency this could change in the future but in our data, we do not observe such an effect. Instead, we find positive (negative) returns for currencies with relative declines (increases) in vulnerability. Significant and positive returns are attributed to the portfolio with high but declining levels of vulnerability, with the source of the return being high positive interest rate differential with no offsetting spot price declines, as would be predicted by theory. One explanation for this could be these countries are more resilient than expected by market participants to environmental impacts, thereby leading to less depreciation in spot prices. In that sense, markets do not properly "price" climate vulnerability, such that investors could harvest the interest rate differentials without bearing much risk in currency depreciation under the vulnerability momentum strategy.

5. Conclusion

In this paper, we have examined the variation in physical risk from climate change across countries using the measure of climate vulnerability and considered how vulnerability could link to currency returns in a portfolio setting. We find that emerging economies have higher climate vulnerability than developed economies due to lower adaptive capacity instead of exposure or sensitivity; however, this vulnerability gap between EM and DM has been shrinking over time. By linking to natural disaster loss data, we confirm that more vulnerable countries experience greater economic losses and more human lives affected by natural disasters. Also, we find that while the level of climate vulnerability can be largely explained by the economic fundamentals, only a small proportion in the change in vulnerability can be analogously explained, suggesting that most information in vulnerability momentum is not reflected in these country-level characteristics.

Most importantly, we find past trend in climate vulnerability predicts currency returns. We demonstrate how investors can construct portfolios with decreasing vulnerability based on past 5-year momentum in vulnerability with 29 currencies including both G10 and non-G10 currencies. This portfolio generates positive and significant alphas from 2002 to 2019, even after controlling for a set of fundamental macroeconomic factors and common currency risk factors. We find this phenomenon is more pronounced among non-G10 pairs, and G10/non-G10 pairs while not significant in G10 currencies. Lastly, double-sorting on both level and momentum in vulnerability reveals that the level of vulnerability provides important context to vulnerability momentum – improving from a risky base is rewarded more than improving from a less risky base. We hope our paper provides early evidence in a portfolio setting of how investors could use liquid currency instruments and information in climate vulnerability to manage future negative climate shocks.

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Appendix

Table A1: ND-GAIN Vulnerability Indicators

Sector	Exposure component	Sensitivity component	Adaptive Capacity component
Food	Projected change of cereal yields	Food import dependency	Agriculture capacity (Fertilizer, Irrigation, Pesticide, Tractor use)
	Projected population change	Rural Population	Child malnutrition
Water	Projected change of annual runoff	Fresh water withdrawal rate	Access to reliable drinking water
	Projected change of annual groundwater recharge	Water dependency ratio	Dam capacity
Health	Projected change of deaths from climate change induced diseases	Slum population	Medical staffs (physicians, nurses, and midwives)
	Projected change of length of transmission season of vector-borne diseases	Dependency on external resource for health services	Access to improved sanitation facilities
Ecosystem Services	Projected change of biome distribution	Projected change of biome distribution	Protected biomes
	Projected change of marine biodiversity	Ecological footprint	Engagement in International environnemental conventions
Human Habitat	Projected change of warm period	Urban concentration	Quality of trade and transport-related infrastructure
	Projected change of flood hazard	Age dependency ratio	Paved roads
Infrastructure	Projected change of hydropower generation capacity	Dependency on imported energy	Electricity access
	Projection of Sea Level Rise impacts	Population living under 5m above sea level	Disaster preparedness

Source: ND-GAIN.

Table A2: FX Risk Factor Indices

Factor	Bloomberg Ticker	Source
G10 Carry	DBFXCRDU Index	Deutsche Bank
G10 Momentum	DBFXMOMU Index	Deutsche Bank
G10 Value	DBFXVALU Index	Deutsche Bank
Global Carry	DBFXCRGU Index	Deutsche Bank
EM Carry	SEBSFXCE Index	Skandinaviska Enskilda Banken
EM Momentum	NMEMMOMU Index	Nomura
EM Market (note, subtract UST 1m rate)	FXCTEM8 Index	Bloomberg

Source: Bloomberg

Table A3: Multivariate Models based on Change in Physical Risk Metric

	Δ Vulnerability				Δ Sensitivity				Δ Adaptive Capacity			
	All	G10	Non-G10	G10/non-G10	All	G10	Non-G10	G10/non-G10	All	G10	Non-G10	G10/non-G10
Alpha	1.70%	0.39%	3.51%	1.33%	2.56%	1.25%	3.04%	2.55%	0.29%	0.41%	1.21%	0.26%
(t-stats)	2.48	0.43	3.44	1.83	3.72	1.26	3.24	3.59	0.41	0.42	1.21	0.38
G10 Market	0.324	0.052		0.450	0.253	0.063		0.382	0.231	0.023		0.340
	27.31	3.32		31.02	16.63	3.01		24.56	17.05	1.53		20.77
G10 Carry	-0.001	0.287		-0.048	-0.046	0.348		-0.081	0.030	0.168		-0.011
	-0.10	29.06		-4.50	-4.99	14.24		-8.86	2.70	7.98		-1.05
G10 Momentum	-0.016	0.025		-0.030	0.043	0.009		0.023	-0.053	0.034		-0.051
	-1.70	2.13		-2.82	5.99	0.42		2.91	-4.91	1.70		-4.51
G10 Value	0.078	0.034		0.079	0.048	-0.036		0.039	0.054	0.064		0.069
	8.20	1.76		7.85	4.25	-1.00		3.47	5.72	3.21		6.08
EM Market	0.106		-0.168	0.200	0.005		-0.218	0.092	0.120		-0.004	0.186
	7.81		-10.49	14.49	0.36		-14.61	6.38	7.69		-0.14	12.98
EM Carry	0.014		0.087	-0.015	0.071		0.151	0.019	-0.054		-0.035	-0.047
	0.70		2.59	-0.77	4.51		6.73	1.06	-2.41		-0.93	-2.44

EM Momentum	0.026		0.008	0.020	0.016		0.008	0.022	0.019		-0.008	0.013
	3.19		0.61	2.25	2.05		0.59	2.75	2.12		-0.53	1.58
Global Carry	0.045			0.132	0.069			0.159	0.065			0.129
	3.66			11.88	3.81			11.02	4.62			11.16
Adj. R^2	44.5%	34.0%	11.3%	57.4%	39.2%	37.4%	18.5%	53.5%	34.8%	14.5%	0.2%	51.2%
N	4696	4696	4696	4696	4696	4696	4696	4696	4696	4696	4696	4696

Table A3 presents the multi-factor regression results for portfolio returns based on past 5-year change in vulnerability, sensitivity and adaptive capacity respectively from 2002 to 2019 for our sample (column named "All") as well as the subsamples G10, non-G10 and G10/non-G10. These regressions are controlling for common FX risk factors including G10 market, G10 carry, G10 value, G10 momentum, EM market, EM carry, EM momentum and global carry. All portfolios are constructed long-short neutral – currencies that are less vulnerable are funded by more vulnerable currencies; and currency pairs are equally weighted in the portfolio. Portfolios are formed annually on the last business day of the year using spot and 1-year forward contracts. These portfolios only trade the currency pairs whose absolute value of spread of vulnerability are in the top 50% of absolute differences. Source data: ND-GAIN, DataStream, Bloomberg.