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Climate Change and Real Estate Prices

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Abstract

Direct real estate returns are correlated with shifts in weather patterns, which are proxied by changes in four moments of distribution for differences in average and maximum daily temperatures, deviations from optimal temperatures and climate risk index reported by Germanwatch. Changes in the volatility of daily temperatures are inversely correlated with direct real estate returns. The volatility effect appeared to be marginal in 1996-2007, but it became more pronounced in 2010-2017. Other moments of the distribution, including changes in means, skewness and kurtosis, fail to obtain predictive power. Results are robust to tests in a smaller sample of capital cities and the exclusion of observations with the most significant volatility increases.

Keywords: climate change, direct real estate, residential real estate, moments of distribution, volatility, temperature

1. Introduction

Increase in global average temperatures has been documented since the mid-twentieth century, and weather scientists agree that global surface temperatures will increase by 1.5-2.0 degrees Celsius between by the end of the 21st century relative to 1986-2005, triggering heatwaves and changes in precipitations (IPCC, 2014).

Climate change affects economic outcomes directly and indirectly. First, it can impact the aggregate level of output, including labour productivity. Second, it can lower forward-looking asset prices by applying higher discount rates due to uncertainty and risk and/or by changing expected cash flows. The latter strand of literature includes explanations based both on market efficiency (Giglio, Maggiori, Stroebel, & Weber, 2015) and ehavioural arguments (Hirshleifer & Shumway, 2003).

Not surprisingly, forecasts of climate change on economic activity differ. Initially, weather impact research focused on the most vulnerable industries – health, insurance, tourism (Butsic, Hanak, & Valletta, 2011; Dlugolecki, 2008) and construction (see Ballesteros-Perez, Smith, Lloyd-Papworth, & Cooke, 2018, for excellent literature overview on the impact of climate change on construction). With a growing realization of climate change onset, the effort shifted from measuring weather impact to analysis of most vulnerable industries and areas of the globe (Patt et al., 2010; E. Somanathan, R. Somanathan, Sudarshan, & Tewari, 2015; Zander, Botzen, Oppermann, Kjellstrom, & Garnett, 2015). Finally, several studies attempted to performa broader assessment of climate risk impact on the aggregate economy (Deryugina & Hsiang, 2014).

Roback's (1982) study was the first to study impact of climate on house prices. More recently, a growing body of research attempted to establish a link between real estate economics and climate change (Bunten & Kahn, 2014; Giglio et al., 2015). In its methodological approach, this study follows previous work that utilized a regression framework to assess the effects of climate change on asset prices (Kahn, 2009; Hanak & Valetta, 2011; Albouy et al., 2016). Our paper contributes to a growing body of research on climate adaptation policies (Lesnikowski et al., 2019; Mechler et al., 2019).

In the real estate space, our paper is directly related to studies on market efficiency and risk premiums (Linneman, 1986; Case & Shiller, 1989; Ho, Addae-Dapaah, & Glascock, 2015). Several authors, including Case and Shiller (2003), Krainer and Wei (2004) and Campbell, Davis, Gallin, and Martin (2009), related house price inflation to lower expected risk premiums, suggesting one possible link between real estate returns and proxies for climate changes.

This paper attempts to estimate the potential impact of change in weather conditions on real estate prices using a sample of international data. We do not find a link between temperature increases and house inflation, but volatility changes in average daily temperatures are inversely related to price dynamics. These results suggest that the real estate market could be pricing in changes in long-term weather trends.

The rest of the article is structured as follows. The next section introduces my empirical methodology, which is followed by a description of the data, discussion of results, robustness checks, and concluding remarks. The appendix describes sources of data for weather and several control variables used in this study.

2. Methodology

2.1 Motivation

Ex-ante, it is not apparent that climate change will negatively affect asset prices, including direct real estate. Bunten and Kahn (2014) cite price increases in Miami, a coastal area at high risk of sea-level rise, suggesting that homeowners are not compensated for risk with a price discount.   to other market segments, direct real estate is a prime candidate to test the impact of weather changes. First, it is a physical asset directly exposed to elements. Second, whereas corporations can diversify their asset base via cross-border investments and acquisitions, residential real estate is trapped by geography.

I put to the test several variables to examine their potential impact on housing prices. First, I 1st, 2nd and 4th moments of the distribution on daily temperature changes over 1996-2017 period compared to a control sample of 1950-1990. Real estate price changes could react to both temperature changes and shift in the properties of the distribution – higher volatility and fatter tails. Further, climate change is primarily related to temperature increases, so we examine the change in statistical properties of both average and maximum daily temperatures. In existing literature, Li, Cheng, and Shoaib (2018) document impact of temperature on real estate prices in the Hong Kong market, and Li (2009) finds inverse relationship between volume of monthly residential properties transactions and various weather metrics in Hong Kong.

The motivation to examine higher moments of distribution is related to Nordhaus (2001), Weitzman (2011) and Barro (2006). Barro employs rare-disasters framework to explain high equity premiums, low real interest rates and volatile stock returns and suggests an extension of the asset menu to include real estate and related housing price to disaster probabilities. This is the proposition tested in this study using higher moments of distribution and climate risk index reported by Germanwatch (see discussion below).

Second, we investigate whether asset prices are related to temperature deviation from optimal levels. Two benchmarks were tested – a daily average of 65 degrees Fahrenheit (18.3 degrees Celsius), a preferential daily average of the U.S. households (Albouy et al., 2016) and 57.7 degrees Fahrenheit (14.3 degrees Celsius), the daily average temperature in San Francisco in 1950-1990. This avenue of investigation was motivated by Bunten and Kahn (2014), who postulated that real estate price differential between San Francisco and Detroit could narrow if the climate in New England improves.

Finally, we examine whether housing prices are related to the risk of extreme events using climate risk index (CRI) developed by Germanwatch e.V., which uses data from the Munich Re reinsurance company. The index takes on low values when the climate is consistently fraught with risks or if a country is temporarily affected by adverse weather events.

Methodologically it is difficult to untangle climate trends defined as longer-term shifts in the climate over several decades from climate shocks - extreme weather events like natural disasters, floods, and droughts which are exacerbated by climate trends. However, the use of different proxies can help capture some of the effects of climate changes on asset prices.

2.2 Time Effects

We divide our sample into three subperiods using two classification criteria. One is related to the incidence of climate change, and the other reflects the onset of the financial crisis. To measure how climate risk assessment has changed over the period included in this study, we examined how the number of publications on related topics has changed in media outlets. We conducted a search on “climate change” string in the Factiva database and determined that coverage increased dramatically in 2007 (see figure 1).

This finding, together with the timing of the most recent financial crisis, prompted sample separation into three subperiods, including 1996-2007, 2008-2009 and 2010-2017. We examine the impact of weather metrics on property prices in each of these subsamples.

2.3 Literature Review and Model Specifications

Literature that examines the influence of macroeconomic variables on house prices could be grouped into three broad categories: econometric models, affordability indicators and asset pricing approach (Girouard, Kennedy, van den Noord, & Andre, 2006; Kishor & Marfatia, 2017). This study falls into the first of the three groups – it employs econometric models to establish fiscal policies impact on housing prices.

To the best of our knowledge, this the first study that relates climate change to a panel dataset of international residential real estate. One of the advantages of this paper is that it puts to test a variable that is clearly exogenous in the context of employed econometric models.

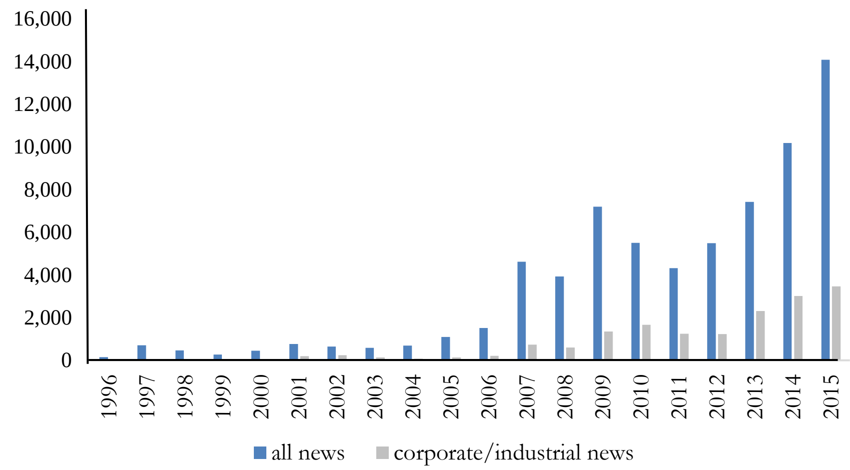

Figure 1. Number of hits on "climate change" in Factiva in "All News" and "Corporate/Industrial News" category

We use two model specifications to differentiate between long-term and transitory effects - short-run price reaction can differ from the long-run response (Adams & Füss, 2010; Kishor & Marfatia, 2017). First, we run an OLS regression with mean changes in inflation-adjusted real estate returns as a dependent variable, weather change proxies and a group of control variables:

$$\bar{r} = \alpha_i + \beta_{WEATHER} ? \Delta_{WEATHER} + \beta_t ? X_{it} + e_{it}, \quad (1)$$

where a mean inflation-adjusted return on real estate $\Delta_{WEATHER}$ measures climate change impact and X_{it} is a vector of country characteristics. Second, I re-visit the results using a panel data set, annual frequency data and Newey-West corrected errors. We put weather change variable to test in six models. All OLS models with means – see tables 4, 6 and 8 – use the same specifications as reported in panel A in table 4, but due to space considerations, we report only betas on climate change proxies and goodness-of-fit statistics. In a similar vein, all annual regressions reported in tables 5 and 7 replicate models from panel A of table 5. In each table, weather change betas are reported for three subperiods.

Explanatory variables aim to capture demand- and supply-side factors. The determinants from the demand side include real interest rate, population and immigration increases, domestic currency depreciation, changes in household credit and real GDP per capita growth, while supply (cost) side is captured by a change in building permits and construction costs (see Appendix A for sources of data).

3. Data

Daily weather data were retrieved from the National Centers for Environmental Information of National Oceanic and Atmospheric Administration (see Appendix A for exact locations). Weather stations were chosen based on proximity to capital (major) cities; when data were incomplete, the second- and third-best options were chosen. When fewer than 360 observations were available for each year, that data was omitted from calculations. This filter reduced weather sample size by 8 percent in 1950-2017. Table 1 reports averages for three moments of distribution based on daily average and maximum temperatures, and changes in subsequent periods.

Regression models test weather change variables in OLS models with means and Newey-West models using data with annual frequencies. To make results directly comparable, we restricted our sample to include countries for which data was available for all years in 2010-2017 period. This left 50 countries in the sample.

Table 1. Moments of distribution for weather variables in national markets

	Mean	Volatility	Kurtosis	Mean of maximum	Volatility of maximum	Kurtosis of maximum
1951 - 1990	13.1	6.64	-0.63	17.3	7.49	-0.59
1996 - 2007	0.78	-0.04	0.03	0.82	-0.07	0.00
2008 - 2009	1.08	-0.19	-0.04	1.28	-0.22	0.00
2010 - 2017	1.10	0.09	-0.02	1.23	-0.02	0.02

Note. the table reports first, second and fourth moment of distribution for average and maximum daily temperatures for control period from 1951 to 1990 and changes in subsequent periods.

Data on GDP growth, population changes, net migration and foreign exchange rates were sourced from the World Bank and the International Monetary Fund for Taiwan. The World Bank reports net migration in five-year intervals, so each figure was spread over a five-year period and scaled by starting population level to measure annual change. Total credit to households was obtained from the Bank for International Settlements credit to the non-financial sector (CRE) dataset (Note 1). Appendix A reports sources for interest rates, building permits and construction cost series from the DataStream database system. Use of a 10-year Treasury bond yield as a measure of nominal long-term discount rate is consistent with Lai and Van Order (2017) and Campbell et al. (2009).

4. Empirical Analysis

4.1 Weather Proxies and Correlations Analysis

Table 2 reports pairwise correlations between inflation-adjusted returns and various climate change proxies. Increase in volatility is inversely related to housing inflation in 2010-2017 and, less significantly, in 1996-2007. Maximum temperatures convey less information than average daily temperatures. Finally, neither climate risk index nor changes in temperature deviations from optimal values were significant in 2010-2017. It appears that households valued temperature changes toward optimum in 1996-2007, but not in later periods. In the remainder of this article, our analysis will focus on changes in the second moment of distribution for daily average temperatures.

Table 2. Pairwise correlations

	Variable means over each period			Annual frequencies		
	2010-2017	2008-2009	1996-2007	2010-2017	2008-2009	1996-2007
Mean	-0.20	-0.05	0.24	-0.02	0.10	0.08
Volatility	-0.49***	0.15	-0.28*	-0.19***	-0.00	-0.07
Excess kurtosis	-0.12	-0.08	0.39**	-0.04	-0.06	0.02
Mean of maximum	-0.33	0.07	0.37**	-0.04	0.20	0.14*
Volatility of maximum	-0.37*	0.16	-0.31	-0.13*	-0.09	-0.10
Excess kurtosis of max.	-0.04	0.11	0.23	-0.01	0.08	0.05
Climate risk index	0.07	-0.19	0.24	0.03	-0.08	0.12**
Deviation from 65 Fahr.	-0.02	0.25*	-0.45***	-0.04	0.16	-0.21***
Deviation from California	0.20	0.25*	-0.38**	0.04	0.13	-0.16***

Note. the table reports pairwise correlations of inflation-adjusted real estate returns and various weather change proxies - three moments of distribution for average and maximum daily temperatures, climate risk index and two measures of average temperature deviation from optimal temperatures defined as 65 Fahrenheit and San Francisco averages in 1950-1990. *,** and *** indicate a p-value of 10%, 5%, and 1%, respectively.

Table 3 reports 2010-2017 inflation-adjusted returns in 50 national markets included in this study, 28 capital cities and three moments of distribution that characterize weather changes relative to the 1950-1990 control period – change in mean annual temperature, the volatility of temperature and kurtosis, which measures fat tails of the distribution.

Table 3. Changes in moments of distribution in 2010-2017 relative to 1950-1990 control period

N	Country	Return in national market	Return in capital cities	Change in mean	Change in volatility	Change in kurtosis
1.	Spain	-3.4%	n.a.	1.59	0.78	-0.09
2.	Russia	-6.7%	-6.5%	1.58	0.75	-0.22
3.	Mexico	0.6%	3.6%	3.01	0.56	-0.39
4.	Croatia	-1.0%	-1.9%	2.00	0.54	0.04
5.	Serbia	-4.7%	-0.6%	1.49	0.44	0.16
6.	Greece	-6.2%	-7.0%	0.91	0.43	0.02
7.	Chile	2.4%	3.5%	0.84	0.42	0.00
8.	Hungary	1.1%	5.8%	1.41	0.42	0.06
9.	Czech	1.6%	n.a.	1.28	0.37	-0.01
10.	Romania	-2.3%	-4.9%	1.45	0.36	0.14
11.	Korea	0.1%	n.a.	0.79	0.34	-0.05
12.	Morocco	-1.2%	0.3%	0.89	0.33	-0.26
13.	Japan	1.5%	2.4%	0.89	0.27	-0.06
14.	Latvia	2.1%	n.a.	1.07	0.26	0.36
15.	Italy	-3.4%	n.a.	1.02	0.25	0.04
16.	Estonia	5.1%	n.a.	1.01	0.25	0.33
17.	Australia	4.0%	5.6%	0.65	0.23	-0.12
18.	Malta	-1.4%	n.a.	0.92	0.23	0.01
19.	Slovakia	0.2%	n.a.	1.11	0.18	0.03
20.	Israel	6.8%	n.a.	1.56	0.15	0.02
21.	Slovenia	-1.4%	-0.2%	1.45	0.14	0.00
22.	Austria	4.2%	4.3%	1.28	0.14	0.07
23.	Lithuania	1.4%	2.1%	0.99	0.13	0.22
24.	Kazakhstan	0.5%	n.a.	1.67	0.13	-0.17
25.	Luxembourg	3.7%	n.a.	1.53	0.12	0.02
26.	Malaysia	6.2%	7.2%	0.85	0.08	-0.37
27.	Cyprus	-0.3%	n.a.	1.47	0.06	0.09
28.	Taiwan	4.9%	n.a.	0.53	0.05	0.01
29.	Indonesia	-0.1%	-1.2%	1.05	0.04	-0.08
30.	Brazil	4.4%	1.0%	0.69	0.03	-0.24
31.	Portugal	0.1%	n.a.	0.35	0.02	-0.06
32.	South Africa	0.0%	n.a.	0.17	0.02	0.06
33.	United States	1.7%	n.a.	1.26	0.01	-0.03
34.	Switzerland	3.5%	n.a.	0.75	0.00	0.03
35.	Germany	2.4%	6.9%	1.18	0.00	0.06
36.	Ireland	-0.3%	3.0%	0.11	-0.03	0.03
37.	Singapore	-0.1%	n.a.	0.73	-0.05	-0.36
38.	Canada	5.3%	7.1%	1.14	-0.06	-0.12
39.	Thailand	1.7%	1.7%	0.67	-0.08	0.35
40.	France	0.3%	4.0%	1.04	-0.09	0.04
41.	New Zealand	5.6%	6.0%	0.39	-0.09	0.09
42.	United Kingdom	2.1%	5.2%	1.05	-0.09	0.04
43.	Netherlands	-1.2%	n.a.	1.34	-0.09	0.02
44.	Belgium	0.7%	n.a.	0.87	-0.20	0.08
45.	Colombia	4.8%	5.2%	0.96	-0.22	-0.87
46.	Sweden	5.6%	n.a.	1.32	-0.26	-0.06
47.	Iceland	5.1%	5.4%	0.96	-0.30	-0.29
48.	Finland	0.2%	0.5%	1.60	-0.33	0.06
49.	Norway	3.9%	5.3%	0.99	-0.50	-0.03
50.	Denmark	1.4%	n.a.	0.80	-0.73	0.18

Note. the table reports selected data for 2010-2017, including mean inflation-adjusted returns in the national market and capital cities, and changes in mean, volatility and kurtosis of average daily temperatures. Years with fewer than 360 observations are omitted. Countries are ranked by changes in volatility in descending order.

Results suggest several possible lines of investigation. First, changes in the volatility of daily temperatures could be correlated with levels of ; countries at the top of the list are less developed than the G7 group. Second, it appears that an increase in average temperature may be positively correlated with volatility increases. Pairwise correlation between the first and second moment of distribution reported in table 3 is 0.39, and the statistic is significant at one percent level. However, the result does not hold for data with annual frequencies and is not observed in previous periods.

4.2 Multivariate Tests

We proceed to test changes in volatility in regression with means. In panel A in table 4 volatility variable attains significance at conventional levels in all models; in a univariate model, it explains 24 percent of the variance in real estate returns. The result does not appear to be spurious – betas are negative in the 1996-2007 period, although they attain significance in only two models out of six in panel C of table 4. In 1996-2007, volatility increase explained 8 percent of the variance the dependent variable.

Table 4. Regressions with means for national markets

Panel A. OLS Regression models results for domestic markets, 2010-2017						
	(1)	(2)	(3)	(4)	(5)	(6)
Change in volatility	-0.05***	-0.04***	-0.05***	-0.05***	-0.04***	-0.05***
	0.01	0.01	0.01	0.01	0.01	0.02
Real interest rate		-0.37***				
		0.17				
FX depreciation		-0.39***				
		0.15				
Immigration			2.21*			
			1.18			
Population increase, net				1.23**		
				0.49		
Increase in household credits						0.13
						0.15
Increase in building permits					0.07**	
					0.03	
Construction costs						-0.02
						0.02
Growth, GDP per capita			0.57**	0.47**		
			0.24	0.23		
N. of observations	50	48	49	50	45	32
R-square	0.24	0.38	0.35	0.38	0.34	0.29
Adjusted R-square	0.23	0.34	0.30	0.34	0.30	0.21
Panel B. Betas and goodness-of-fit measures, 2008-2009						
Change in volatility	0.02	0.02	0.01	0.01	0.02	0.01
	0.02	0.02	0.02	0.02	0.02	0.02
R-square	0.02	0.24	0.19	0.12	0.03	0.02
Panel C. Betas and goodness-of-fit measures, 1996-2007						
Change in volatility	-0.09*	-0.11**	-0.06	-0.06	-0.07	-0.04
	0.05	0.05	0.04	0.04	0.05	0.03
R-square	0.08	0.25	0.47	0.46	0.06	0.57

Note. This table reports OLS regression model results with variable means for each variable. The dependent variable is inflation-adjusted return in national real estate markets. Panel A reports results for the 2010-2017 period; intercept is suppressed. Panels B and C report betas on change in volatility and measures of goodness-of-fit for 2008-2009 and 1996-2007, respectively. *,** and *** indicate a p-value of 10%, 5%, and 1%, respectively.

Control variables suggest that results are plausible. Interest rates and domestic currency depreciation are negatively correlated with housing price inflation, whereas GDP growth, population increases and migration fuel price appreciation. Finally, the positive coefficient on building permits increase is in line with previously reported results – Hwang and Quigley (2006) report a positive coefficient on housing supply, whereas Case and Shiller (2003) argue that housing starts may measure supply restrictions. Overall, results in annual regressions suggest that volatility increases lowered real estate price increases in 2010-2018. Next, we examine whether results can be replicated using data with annual frequencies and in a sample of twenty-eight capital cities using regressions with means (tables 5 and 6). To make results directly replicable, capital cities subsample includes only observations for which national-level data are available.

Table 5. Regressions with annual data frequency for national markets

Panel A. Selected output for models with annual rates, 2010-2017						
	(1)	(2)	(3)	(4)	(5)	(6)
Change in volatility	-0.015***	-0.013***	-0.012***	-0.012***	-0.013***	-0.012**
	0.005	0.005	0.005	0.004	0.005	0.006
N. of observations	329	313	323	328	288	401
R-square	0.03	0.08	0.14	0.15	0.03	401
Adjusted R-square	0.03	0.07	0.13	0.14	0.03	0.057
Panel B. Betas and goodness-of-fit measures, 2008-2009						
Change in volatility	-0.00	0.02	0.01	0.01	0.00	-0.00
	0.02	0.02	0.02	0.02	0.02	0.01
R-square	0.00	0.04	0.27	0.20	0.00	0.02
Panel C. Betas and goodness-of-fit measures, 1996-2007						
Change in volatility	0.00	0.00	0.00	-0.00	-0.01	0.00
	0.02	0.01	0.01	0.01	0.02	0.01
R-square	0.00	0.15	0.13	0.08	0.05	0.17

Note. The table reports selected output for models with inflation-adjusted return in national markets, annual data frequencies and Newey-West standard errors. Panels A-C report results for the 2010-2017, 2008-2009 and 1996-2007, respectively. *,**,*** indicate p-values of 10%, 5%, and 1%, respectively.

Regressions with annual data frequencies in table 5 employ Newey-West standard errors, and control variables in both tables are suppressed – beta signs on them are consistent with output reported in table 4 for national real estate markets. In both tables – table 5 with annual frequency data and table 6 with means for capital cities - betas on volatility changes take on a negative sign and are statistically significant.

Table 6. Regressions with means for capital cities

Panel A. Selected output for regression models, 2010-2017						
	(1)	(2)	(3)	(4)	(5)	(6)
Change in volatility	-0.07***	-0.05***	-0.04**	-0.06**	-0.05**	-0.07**
	0.02	0.02	0.02	0.02	0.02	0.03
N. of observations	28	28	28	28	23	18
R-square	0.29	0.51	0.54	0.43	0.38	0.34
Adjusted R-square	0.26	0.45	0.48	0.36	0.32	0.20
Panel B. Betas and goodness-of-fit measures, 2008-2009						
Change in volatility	0.04	0.02	0.04	0.04	0.06	0.04
	0.04	0.04	0.04	0.04	0.04	0.06
R-square	0.04	0.14	0.32	0.21	0.13	0.11
Panel C. Betas and goodness-of-fit measures, 1996-2007						
Change in volatility	-0.09**	-0.09*	-0.06	-0.07	-0.10*	-0.04
	0.04	0.05	0.05	0.05	0.05	0.03
R-square	0.21	0.26	0.30	0.31	0.29	0.74

Note. The table reports OLS regression model results with variable means for each variable. The dependent variable is inflation-adjusted return in national real estate markets. Panels A-C report results for the 2010-2017, 2008-2009 and 1996-2007, respectively. *,** and *** indicate a p-value of 10%, 5%, and 1%, respectively.

5. Robustness checks

In table 7, we confirm that earlier results are not driven by outliers. We exclude Spain and Russia – two markets with the most significant increases in the volatility of temperature in 2010-2017 – from the original sample of 50 national markets. Change in volatility variable attains significance at conventional levels in all but one model (#6), in which only 30 out of 48 observations are used due to lack of data on the increase in household credits and construction costs, none of which attains significance.

Further robustness checks augmented models with fixed-year effects, starting level of wealth (lagged GDP per capita log), and sample expansion to incorporate countries for which data on returns are available for 2011-2017 rather than 2010-2017. This increases the sample size to 54 observations, adding two large markets – China and India – to the list. None of these changes affected the conclusions (results are available upon request).

Table 7. Robustness check - regressions with means for national markets

Panel A. Regression model results in models with annual frequencies, 2010-2017						
	(1)	(2)	(3)	(4)	(5)	(6)
Change in volatility	-0.04***	-0.03**	-0.03**	-0.03**	-0.02*	-0.02
	0.01	0.01	0.01	0.01	0.01	0.02
R-square	0.14	0.30	0.27	0.30	0.26	0.22
Panel B. Betas and goodness-of-fit measures, 2008-2009						
Change in volatility	0.03	0.05**	0.01	0.01	0.03	0.02
	0.02	0.02	0.02	0.02	0.02	0.02
R-square	0.04	0.30	0.19	0.12	0.06	0.03
Panel C. Betas and goodness-of-fit measures, 1996-2007						
Change in volatility	-0.08	-0.10*	-0.07	-0.07	-0.05	-0.07**
	0.05	0.05	0.04	0.04	0.05	0.03
R-square	0.06	0.24	0.43	0.43	0.03	0.36

Note. The table reports OLS regression model results with variable means for each variable in 48 national markets. Data sample excludes markets with the largest increase in volatility - Spain and Russia. Panels A-C report results for the 2010-2017, 2008-2009 and 1996-2007, respectively. *,** and *** indicate a p-value of 10%, 5%, and 1%, respectively.

6. Concluding Remarks

Our results provide direct statistical evidence that weather changes affect asset prices. We test changes in weather conditions using higher moments of the distribution, deviations from optimal temperatures and climate risk index reported by Germanwatch to measure the impact of extreme weather events. In 2010-2017, residential real estate prices were inversely related to changes in temperature volatility, but not other tested metrics.

Interestingly, volatility changes are positively correlated with temperature increases in this period. Therefore, volatility may capture the impact of changes in other weather-related characteristics. This is one potential area of future research.

Given the size of the real estate market and its allocation in the households' aggregate balance sheet (Note 2), The results of this paper can be of interest to both retail investors and investment advisors. Also, they are relevant for policymakers due to the climate's impact on social dynamics and climate adaptation policies. Hsiang, Burke, and Miguel (2013) summarize sixty studies from different fields and document that one standard deviation change in climate variables is associated with a probability change of intergroup conflict and interpersonal violence by fourteen percent and four percent, respectively. Increase in intergroup tensions provides another channel through which weather changes could affect real estate prices.

One of the shortcomings of this study is that it uses a straightforward metric to gauge the influence of weather changes, whereas the effects are likely non-linear (Albuoy et al., 2016; Zivin & Neidell, 2012). Further, climate change impact may not be measured directly and immediately – among other consequences; higher temperatures lead to species extinction and ecosystem dysfunction. It is, therefore, possible that in other periods weather changes may be captured through different moments of the distribution. This study represents the first step to fill this knowledge void.

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Notes

Note 1. https://home.kpmg.com/xx/en/home/services/tax/tax-tools-and-resources/tax-rates-online/individual-income-tax-rates-table.html (accessed November 1, 2019).

Note 2. see U.S. data provided by the Federal Reserve at https://fred.stlouisfed.org/series/OEHRENWBSHNO and www.federalreserve.gov/releases/z1/dataviz/z1/balance_sheet/chart/, accessed on Dec 30, 2018.

Appendix A. Sources of data for daily temperatures, interest rates and building permits

The appendix reports weather station names from National Centers for Environmental Information of National Oceanic and Atmospheric Administration, Datastream series names for interest rates and building permits. Interest rates are measured – in descending order – using yields on 10-year government bonds, instruments with shorter maturities or bank regulators' re-financing rate.

	GIS TEMP station	Building permits series	Construction costs	Interest rate series
Australia	East Sale Airport	AUYODI15G	AUWOPVCOF	TRAU10Y
Austria	Wien	OEESK1HFE	OEYOP003F	TROE10T
Belgium	Uccle	BGESK1HFG	BGESPPUZR	TRBG10T
Brazil	Sao Paolo Aeroport	n.a.	BRCPCIM.F	BRSELIC prior to 2006; TRBR10T starting 2006
Canada	L'Assomption, QC	CNYODI15Q	CNYOP003F	TRCN10T
Chile	Arturo Menino Benitzz International	CLYOD008Q	n.a.	TRCL10T
Colombia	Bogota Eldorado	CBYODI15G	CBHOUSE%R	CBBCBPR before 2002; TRCO10T starting 2002
Croatia	Zagreb Gric	CTESUM8SF	CTAPWC4.	CTPRATE. before 2008; TRHR10T starting 2008

Cyprus	General Bernardo O Higgins	CPESUM8SH	CPCONSTRF	CPY61...
Czech Republic	Praha Libus	CZYODI15H	CZESXY7DR	CZBCBPR prior to 2000; TRCZ10T starting 2000
Denmark	Koebenhavn Landbohojskolen 1	DKYODI15Q	DKESXY7DR	TRDK10T
Estonia	Tallinn	EOYODI15P	DKESXY7DR	EOIBK1Y in 1999-2011; EOQIR076R otherwise
Finland	Helsinki Kaisaniemi AWS	FNYODI15H	FNYOP005F	TRFN10T
France	Paris Le Bourget	FRYODI15G	FRESXY7DR	TRFR10T
Germany	Berlin Tegel	BDYODI15G	BDYOP003F	TRBD10T
Greece	Larissa	GRYODI15H	GRCCIRESF	TRGR10T
Hungary	Debrecen	HNYODI15G	HNESXY7DR	HNBBASE prior to 1999; TRHN10T starting 1999
Iceland	Reykjavik	ICHOUSCN	ICYOP003F	ICBCBPR prior to 2003; TRIS10T starting 2003
Indonesia	Zamboanga	n.a.	n.a.	IDYIR076R in 1998-2002; TRID10T starting 2003
Ireland	Dublin Phoenix Park	IRYODI15Q	IRESTICKR	TRIE10T
Israel	Elat	ISYODI15H	ISBLDPRCF	ISMIR080R
Italy	Roma Ciampino	ITESUM8SF	ITYOP003F	TRIT10T
Japan	Tokyo	JPYWSI41Q	JPCSBNDLF	TRJP10T
Kazakhstan	Almaty	KZCONRESA	KZCSTPRCF	KZGBOND.
Korea, South	Seoul City	KOYOD008Q	KOPPSMCTFA	KOQIR063R prior to 2000; KOOIR080R starting 2000
Latvia	Daugavpils	LVYODI15H	LVESXY7DR	LVYIR076R in 1998-1999; LVGBD5Y starting 2000
Lithuania	Vilnius	LNQODI15H	LNESXY7DR	LNRPAON prior to 2003; LNGBOND starting 2003
Luxembourg	Luxembourg Airport	LXYODI15G	LXESXY7DR	LXBENCH
Malaysia	Kuala Lumpur International	n.a.	n.a.	MYGBOND.
Malta	Luqa	MAESUM8SF	MAESXY7DR	MAY61... prior to 2007; MAGBD10 starting 2007
Mexico	Cuernavaca	MXGD8FCRA	MXPPDCONFAC	MXYIR066R prior to 2002; MXYIR080R starting 2002
Morocco	Tangier City	n.a.	n.a.	MCGBOND.; when not available, MCPRATE.
Netherlands	Den Helder 1	NLESK1HFE	NLESXY7DR	NLGBOND.
New Zealand	Invercargill Airpor	NZYODI15G	NZPIBUCOF	NZYIR080R
Norway	Oslo Blindern	NWYODI15G	NWESTICKR	NWGBOND.
Portugal	Lisboa Geofisica	PTYODI15H	PTYOP005F	TRPT10T
Romania	Bucuresti Baneasa	RMESUM8SH	RMES3W6JQ	TRRO10T
Russia	Moscow	RSCONBRN	RSCRPTOT	TRRS6MT prior to 1999; RSQIR080R starting 1999
Serbia	Belgrade Observatory	n.a.	n.a.	SBBCBPR
Singapore	Singapore Changi International	SPPRSUPIP	n.a.	TRSG10T
Slovakia	Hurbanovo	SXOAJ32XA	SXESXY7DR	SXOIR080R
Slovenia	Ljubljana Bezigrad	SJYODI15P	SJESXY7DR	SJESSFUB after 2002; SJTBL3M in 1998-2002
South Africa	Upington Agr.	SAYODI15O	SAAVMCONA	TRSA10T
Spain	Madrid Barajas	ESYODI15H	ESESXY7DR	TRES10T
Sweden	Stockholm	SDYODI15H	SDESXY7DR	TRSD10T
Switzerland	Zuerich Fluntern	SWAOD008Q	SWESXY7DR	TRSW10T
Taiwan	Ishigaki	TWBPNUHHP	TWCONCSTF	TRTW10T
Thailand	Chanthaburi	THCONRESP	THEAAVCOA	THGBOND.
United Kingdom	Heathrow	UKAOD008Q	UKESXY7DR	TRUK10T
United States	La Guardia Airport	USBCIPEHO	USPMTCFCE	TRUS10T