Climate Change and Long-Run Discount Rates: Evidence from Real Estate

Stefano Giglio[*] Matteo Maggiori[†] Krishna Rao[‡] Johannes Stroebel[§] Andreas Weber[¶]

Abstract

We show that housing markets provide information about the appropriate discount rates for valuing investments in climate change abatement. We document that real estate is exposed to both consumption and climate risk and that its term structure of discount rates is downward-sloping, reaching 2.6% for payoffs beyond 100 years. We use a tractable asset pricing model that incorporates features of climate change to show that the term structure of discount rates for climate-hedging investments is thus upward-sloping but bounded above by the risk-free rate. At horizons where risk-free rates are unavailable, the estimated housing discount rates provide an upper bound.

JEL Codes: G11, G12, R30.
Keywords: Climate Change, Discounting, Cost-Benefit Analysis, Real Estate

[*]Yale University, NBER, CEPR

[†]Harvard University, NBER, CEPR

[‡]Zillow

[§]Stern School of Business, New York University, NBER, CEPR

[¶]Stern School of Business, New York University.

This version: January 2021. We thank several referees, Arthur van Benthem, Robert Barro, John Campbell, Thom Covert, Simon Dietz, Robert Engle, Xavier Gabaix, María Pilar Martínez-García, Kenneth Gillingham, Christian Gollier, Michael Greenstone, Ben Groom, Bob Hall, Lars Hansen, Geoffrey Heal, Larry Karp, Derek Lemoine, Martin Lettau, Antony Millner, Stijn van Nieuwerburgh, William Nordhaus, Monika Piazzesi, Nick Stern, Thomas Sterner, Christian Traeger, Martin Weitzman, and numerous conference and seminar participants. We thankfully acknowledge generous research support from the Harvard Weatherhead Center for International Affairs, the Center for the Global Economy and Business, the Fama-Miller Center, the Initiative on Global Markets, the Norwegian Finance Initiative, and the Global Risk Institute. We thank Zillow, iProperty, and Rightmove for sharing part of their data, and Konhee Chang, Hongbum Lee, Sung Lee, Gil Nogueira, and Andreas Schaab for excellent research assistance. Send correspondence to Johannes Stroebel, KMC 9-98, 44 West 4th Street, New York, NY 10012. Telephone: 650-888-3441. Email: johannes.stroebel@nyu.edu.

Any consideration of the costs of meeting climate objectives requires confronting one of the thorniest issues in all climate-change economics: how should we compare present and future costs and benefits? [...] A full appreciation of the economics of climate change cannot proceed without dealing with discounting. **(Nordhaus, 2013)**

Much of the economics literature on the optimal policy response to climate change focuses on the trade-off between the immediate costs and the potentially uncertain long-run benefits of reducing carbon emissions. Discount rates play a central role in this debate, since even small changes in discount rates can dramatically alter the present value of investments that pay off over long horizons. For example, assume that an investment to reduce carbon emissions costs $3 billion, and is expected to avoid environmental damages worth $100 billion in 100 years. At a discount rate of 3%, the present value of those damages is $5.2 billion, and the project should be implemented. At a slightly higher discount rate, such as 5%, the present value of the investment drops to $760 million and the investment is no longer attractive. However, despite the importance of these discount rates for optimal policy design, economists and policy makers do not agree on what discount rates should be used to value investments in climate change mitigation.

In this paper, we make progress on this question by exploring the information that private market discount rates contain about how to appropriately value investments in climate change abatement. First, we provide new empirical evidence on the term structure of discount rates for an important asset class, real estate, up to the extremely long horizons that are relevant for analyzing climate change (hundreds of years). Second, we combine these new facts with insights from asset pricing theory to discipline the debate on the appropriate choice of discount rates for an investment in climate change abatement, which involves similar horizons as the housing asset but has a different risk profile.

Much of the prior debate on the appropriate discount rates for climate change investments has either relied on theoretical arguments, or has tried to infer discount rates from the realized returns of traded assets such as private capital, equity, bonds, and real estate. For example, in the context of the dynamic integrated climate-economy (DICE) model, Nordhaus (2013) chooses a discount rate of 4% to reflect his preferred estimate of the average rate of return to capital.[1] We show that this common practice of valuing investments in climate change abatement by discounting cash flows using the average rate of return to some traded asset often ignores important considerations regarding the *maturity* and *risk properties* of such investments.

In particular, asset pricing theory shows that the rate at which a particular expected

[1]See also Kaplow, Moyer and Weisbach (2010), Schneider, Traeger and Winkler (2012), and Weisbach and Sunstein (2009) for discussions of the normative and descriptive approaches to discounting.

cash flow should be discounted depends on the state of the world in which the cash flow is realized; cash flows that materialize in bad states are more desirable, and hence less risky for the investor. They should therefore be discounted at a lower rate. In addition, different assets pay off their cash flows at different maturities. Because risk in the economy is different for different horizons and preferences for risks can vary with the horizon as well, horizon-specific discount rates must be used when evaluating investments with different maturity profiles. The average rate of return to a particular asset, for example capital, only reflects the discount rate appropriate for that particular stream of cash flows. It is thus generally not informative for determining the appropriate discount rate for another asset, such as an investment in climate change abatement, which has benefits that tend to be delayed until much longer horizons and which have very different risk properties.

In theory, then, to understand the appropriate discount rate for investments in climate change abatement we would want to look at traded assets with similar *riskiness* and *horizon*. While this is difficult in practice, we show that researchers can still extract relevant information from the observed private market returns of assets such as real estate. This information can then be used together with asset pricing models to adjust for the maturity and riskiness of cash flows of investments in climate change abatement.

Our first empirical contribution is to provide estimates of the term structure of discount rates for an important asset class, real estate, over a horizon of hundreds of years. This represents the first data-driven characterization of a term structure of discount rates for any asset over the horizons relevant for investments in climate change abatement.[2] Using a variety of approaches, we estimate the average return to real estate to be around 6%. This contributes to a recent research effort to better document the return properties of residential real estate as an asset class (e.g., Favilukis, Ludvigson and Van Nieuwerburgh, 2017; Jorda et al., 2019; Chambers, Spaenjers and Steiner, 2019; Eichholtz et al., 2020). At the same time, recent estimates from Giglio, Maggiori and Stroebel (2015) show that the discount rate for real estate cash flows 100 or more years in the future is about 2.6%. This combination of high average (expected) returns and low long-run discount rates implies a downward-sloping term structure of discount rates for real estate. Intuitively, since real estate assets are claims to cash-flows (rents) at all horizons, their expected rate of return is an average of the discount rates on short-run and long-run cash-flows. If average returns are higher than long-run discount rates, then short-run discount rates must be higher than long-run discount rates (and higher than average returns).

[2]Binsbergen, Brandt and Koijen (2012) provide evidence of a downward sloping term structure of discount rates for equities over a 1-10 year horizon. Van Binsbergen and Koijen (2017) review related evidence across a number of asset classes.

These findings reinforce the problems of using the average rate of return to traded assets to discount investments in climate change abatement. Even if we assumed that climate-change-abatement investments and real estate had similar risk properties at all horizons, using an average rate of return would suggest that such investments should be discounted at 6%. Instead, the appropriate discount rate for the long-run benefits of these investments should be much lower, and their present value much higher.

Of course, this simple comparison ignores potential differences in risk properties of investments in climate change abatement and real estate. We thus also document the risk properties of real estate. We first show that real estate is indeed a risky asset: its returns are positively correlated with consumption growth, and therefore with the marginal utility of consumption, and it performs badly during consumption disasters, financial crises, and wars. This is consistent with the average return to real estate of about 6%, which is above the real risk-free rate, and thus includes a risk premium to compensate investors for bearing risk.

We then document that real estate is exposed specifically to climate change risk, and that this risk is reflected in house prices. This is an important step in helping us link the discount rates applicable to real estate and the discount rates for investments in climate change abatement. For this analysis, we work with a proprietary data set of housing transaction prices as well as for-sale and for-rent listings for properties located in the coastal states of Florida, New Jersey, North Carolina, and South Carolina. Properties in these states are exposed to climate change risk due to both rising sea levels and hurricanes. To obtain a measure of each property's physical exposure to climate risk, we geo-code the addresses of all properties to identify those properties that will be flooded with a 6-feet increase in the sea level, as measured by NOAA.

Since physical exposure to climate risk is correlated with unobserved property amenities, such as beach access, we cannot simply compare the prices across properties that are differentially exposed to such risk in order to estimate the price impact of climate risk. Instead, we test whether the prices of properties that are more exposed to climate change decline in relative terms when the perception of climate risk increases. We measure perception of climate risk in the housing market by performing a systematic textual analysis of the for-sale listings to measure the frequency with which climate-related text (e.g., mentions of hurricanes or flood zones) appears in the written description of the listed properties. The fraction of listings that include such texts is the basis for a "Climate Attention Index" that we construct at both the zip code-quarter and zip code-year level. Our interpretation of this index is that it reflects households' perceptions of the risk of future climate change on the cash flows from real estate in those locations.

We use data on the universe of property transactions from these states to conduct hedonic regressions that explore how the transaction prices of properties in the flood zone vary differentially when the "Climate Attention Index" changes, controlling for property characteristics and various fixed effects. Our analysis shows that when the fraction of property listings that mention climate change doubles, there is a 2% to 3% relative decrease in the prices of properties that are in the flood zone compared to otherwise comparable properties in the same zip code that are not in a flood zone. This result survives in a specification with property fixed effects, which only identifies the pricing of climate risks from multiple transactions of the same property in periods with differential perceptions of these risks. Furthermore, we show that annual rents of exposed and non-exposed properties do not vary differentially with movements in our "Climate Attention Index." This confirms that our estimates of differential price movements are not driven by differential changes in the flow utilities, but instead result from a differential change in the risks associated with future cash flows.

Based on these findings, we conclude that real estate prices directly reflect climate risk, making it a particularly interesting asset to study the valuation of investments to mitigate such risks. These findings are consistent with a quickly growing literature in finance that has documented the exposure of real estate to physical climate risk factors such as rising sea levels and wildfires (e.g., Hallstrom and Smith, 2005; McKenzie and Levendis, 2010; Atreya and Ferreira, 2015; Bakkensen and Barrage, 2017; Gibson, Mullins and Hill, 2017; Eichholtz, Steiner and Yönder, 2019; McCoy and Walsh, 2018; Ortega and Taspinar, 2018; Bernstein, Gustafson and Lewis, 2019; Garnache and Guilfoos, 2019; Baldauf, Garlappi and Yannelis, 2020).[3] Relative to much of this literature, our use of time-and-space-varying measures of climate risk attention and our focus on rents in addition to home sales allow us to address a number of alternative interpretations of the observed relative price differences between properties that are differentially exposed to climate risk.

In order to explore the implications of the downward-sloping term structure of risky real estate for valuing investments in climate change abatement, we build a tractable asset pricing model that incorporates crucial features of climate change and its related risks. Our aim is not to provide an entirely new asset pricing model, nor is it to fully incorporate the micro foundations of physical models of climate change. Rather, we aim to provide a transparent and portable framework to show how the insights of modern asset pricing theory can be used together with inputs from a physical model of climate change to

[3]Other research has explored the extent to which other asset classes, such as equities and fixed income assets, are exposed to climate risk (Engle et al., 2020; Huynh and Xia, 2020; Painter, 2020). See Giglio, Kelly and Stroebel (2020) for a review of this literature.

inform the appropriate discount rates for investments in climate change abatement.[4]

Our baseline model builds on the view that climate change is a form of disaster risk (see Weitzman, 2012; Barro, 2013, for prominent articulations of this view): it is a rare event with potentially devastating consequences for the economy. We embed this view in a general equilibrium model with a representative agent and complete markets based on the endowment economy studied by Lucas (1978). We further modify this classic setup to reflect two important important messages of the climate change literature.

First, we incorporate feedback loops between the state of the economy and the time-varying probability of a climate disaster. In particular, we allow the probability of a disaster to increase endogenously over time when the economy grows at a faster rate. Intuitively, this feature captures the notion that faster growth accumulates more environmental damages, such as greenhouse gas emissions and pollution, thereby increasing the probability of adverse climatic events, akin to tipping points (see Alley et al., 2003; Lemoine and Traeger, 2014). These damages in turn might feed on themselves, for example because rising temperatures lead to even more carbon emission for the same level of production. Our model captures these vicious cycles by allowing the probability of a further disaster to increase after a disaster occurs (see Cox et al., 2000).

Second, we allow for economic growth to pick up temporarily after a disaster. This feature captures the potential adaptation of the economy following a disaster, and reflects a variety of adaptation measures, including relocating production to less affected areas, investments to prevent further damages (e.g., sea walls), and investments such as air-conditioning that allow for productive work despite adverse climate conditions (see the discussions in Brohé and Greenstone, 2007; Desmet and Rossi-Hansberg, 2015; Burke and Emerick, 2016; Barreca et al., 2016). While we only capture these forces in reduced form, we show that they play a crucial role in capturing a more realistic evolution of the economy in response to climate change. In addition, this mean reversion of cash flows allows the model to match our data on the term structure of risky real estate. For assets exposed to the disaster risk, the partial mean reversion of the economy after a disaster implies that short-term cash flows are riskier than long-term cash flows, which only occur after the economy has partially recovered. This mechanism is central to generating downward-sloping term structures of discount rates: the riskier short-term cash flows are discounted at higher rates than the safer long-term cash flows.

Since climate change is a form of disaster risk, investments in the mitigation of this

[4]This modeling approach relates to exciting new work that mixes physical elements of climate change (tipping points, increasing ocean levels, etc.) with the likely response of economic activity (technological innovation, geographic relocation of production, etc.) as undertaken by Crost and Traeger (2014), Lemoine (2015), Lemoine and Traeger (2014), and others.

risk are hedges: similar to insurance policies, they pay off primarily in bad states of the world, and are thus particularly valuable. This has a number of implications for the discount rates used to value their cash flows. The first implication is that the *shape* of the term structure of discount rates for investments to abate climate change is the opposite of what we estimate for the term structure of housing, a risky asset. In fact, the term structure for abatement investments should be *upward-sloping*: hedging against effects of the disaster on short-term cash flows is more valuable than hedging the effects on long-term cash flows, since these long-term cash flows are affected less due to adaptation.

Importantly, however, this upward-sloping term structure does not imply that the *level* of discount rates for investments in climate change abatement is high at any horizon. In fact, it should be *below the risk-free rate at all horizons*, reflecting the investment's hedge characteristics. For shorter horizons, we can observe the real risk-free rate (given by real bond yields) directly in the data, providing us with a tight upper bound (1% – 2%) on the discount rate for short-term cash flows from investments in climate change abatement. For longer horizons, there are no reliable estimates of the level of the risk-free interest rate. However, our model suggests that the very long-run discount rate of 2.6% for risky real estate provides an upper bound on the risk-free rate, and therefore also on the discount rates for long-term cash flows from investments in climate change abatement. This simple upper bound is a powerful result that challenges a wide range of estimates previously used in the literature. For example, this bound is substantially below the 4% rate suggested by Nordhaus (2013). Quantitatively, it is more in line with long-run discount rates that are close to the risk-free rate, as suggested by Weitzman (2012), or the 1.4% suggested by Stern (2006). It is also close to the average recommended long-term social discount rate of 2.25% elicited by Drupp et al. (2015) in a survey of 197 experts.

Note that our finding that the appropriate term structure to discount cash flows from climate change abatement is *low but upward-sloping* contrasts with a number of papers that have argued for using declining discount rates for valuing investments in climate change abatement (Arrow et al., 2013; Cropper et al., 2014; Farmer et al., 2015; Traeger, 2014). These arguments have motivated policy changes in France and the U.K., which have adopted a downward-sloping term structure of discount rates for evaluating long-run investments, including those in climate change abatement. While these differences do not have a substantial effect on the actual discount rates used to value the long-run cash flows from such investments (they are relatively low, at approximately 2%, both under the term structures used in those countries and under our upward-sloping term structure), the two have substantially different implications for the economic mechanisms to create these low long-run discount rates.[5] In addition, they have substantially different implications for evaluating the payoffs from climate abatement investments that may accrue at shorter horizons. The calibration of our model suggests that climate disasters cause the most damage immediately after they hit, making it most valuable to hedge the immediate costs. As a result, the correct discount rates for investments that yield shorter-term protection against climate change disasters should be substantially below the risk-free rate of 1%-2%. In contrast, the downward-sloping term structures used in France and U.K. suggest discount rates of 4% and 3.5%, respectively, for the first 30 years of a project's cash flows.

Finally, in addition to exploring the discount rates appropriate for climate change mitigation within our disaster-risk view of climate change risk, we can use our model to understand discounting of climate investments in alternative models of climate change risk. In particular, our specification for the economy and climate change dynamics is general enough to also nest, under a different parametrization, an important alternative view of climate change: that of the DICE models of Nordhaus and Boyer (2000) and Nordhaus (2008), in which (i) climate change acts as a tax on output and climate damages are higher when the economy is doing well, and (ii) uncertainty about the path of the economy is the main driver of uncertainty about climate change. Under this parameterization, climate change mitigation investments pay off mostly in *good* states of the world (when the economy is expanding). The appropriate discount rates for these *risky* investments are thus *above* the risk-free rate. In this class of models, the climate "tax rate" can be increasing with the level of economic activity, so that the damages are disproportionally higher during booming economies. In our framework, such a feature implies discount rates for investments in climate change abatement that are *high and increasing with the horizon*. Intuitively, this occurs because a bad shock to the economy lowers both climate damages and the growth rate of damages over time. Our framework explains why the "disaster" view and the "tax" view of climate change have diametrically opposed predictions for the appropriate discount rates for investments in climate change abatement.

[5]The literature in climate change economics has sometimes motivated a downward slope in the discount rates for investments in climate change abatement with an extension of the Ramsey Rule to include uncertainty about consumption growth that increases with the horizon. This would have the effect of pushing down the long-run risk-free rate due to a precautionary savings motive that increases in the horizon (see Arrow et al., 2013). However, the predictions of this framework are inconsistent with the relatively flat term structure of real interest rates observed in the data. Moreover, the Ramsey framework does not consider the riskiness of cash flows, and therefore has no predictions on the term structure of risk premia. Consistent with this, the guidance on discount rates provided by governments recommending declining discount rates for cost-benefit analysis, usually does not indicate that the discount rate should vary with the risk properties of the investments.

1 Risk and Return Properties of Real Estate

As described in the introduction, private market discount rates have the potential to inform the valuation of investments in climate change abatement. In this section, we discuss a number of reasons why real estate discount rates are particularly valuable from this perspective. First, we show that real estate is both risky in general (i.e., it pays off more in good states of the world) and exposed to climate risk in particular. Second, we show that, for real estate, private markets reveal information about the term structure of discount rates up to horizons of hundreds of years. This feature of real estate is particularly beneficial to learn about the valuation of investments in climate change abatement, for which the potential benefits can stretch over very long time periods.

1.1 The Riskiness of Housing – Exposure to Climate Risk

We first provide direct evidence that climate risk is priced in real estate markets, with increased climate risk leading to relatively lower prices for more exposed properties. Our analysis has to overcome a number of empirical challenges. First, when comparing prices of properties that are differentially exposed to climate risk, it is difficult to control for all amenities that might be correlated with exposure to climate risk. For example, beach front properties are more exposed to climate risk than properties further inland—they are more likely to be flooded when sea levels rise—but they might still sell at a premium because of the value of the beach access. Controlling for such hard-to-measure amenities in hedonic regressions is challenging, which introduces concerns about omitted variable bias.

To overcome this challenge, we therefore investigate how the prices of properties that are differentially exposed to climate risk change in response to a change in that climate risk. As long as the amenity value of beach access does not change when climate risk changes, this analysis is informative about the pricing of climate risk in housing markets. However, such a "differences-in-differences" analysis presents a second challenge: true climate risk is a relatively slow-moving object that does not provide much of the time-series variation required to identify how it is priced. Our approach is to instead exploit the much more substantial time-series variation in the *attention* paid to climate risk in the housing market. Indeed, even though true climate risk might not change much from year to year, we show that the extent to which homebuyers focus on these risks changes much more frequently, and we would thus expect the pricing implications of climate risk to be particularly strong when households pay more attention to these risks.

1.1.1 Data Construction

Our empirical analysis builds on a number of data sets. Our baseline data contain the universe of for-sale and for-rent property listings from Zillow, a major online real estate data provider. We obtained listings from four coastal states with properties that are potentially exposed to climate risk through rising sea levels: Florida, New Jersey, North Carolina, and South Carolina. For each listing, we observe the textual description of the property provided by the real estate agents, in addition to the listing date and listing price. The for-rent listings cover the period between the first quarter of 2011 and the second quarter of 2017. The for-sales listings extend back to the first quarter of 2008.

Our second dataset contains the universe of public record assessor and transaction deeds data for the same states since the start of 2008. These data include detailed property characteristics, such as information on the property size and the number of bathrooms and bedrooms, as well as transaction prices and dates for all property sales.

To measure different properties' exposures to climate risk, we geo-code their addresses and map them to geographic shapefiles provided by the National Oceanic and Atmospheric Administration (NOAA) that indicate which regions will be flooded should sea levels rise by six feet or more. While flooding risk is only one of a number of climate risk factors, it is an important and easily measurable risk for properties in the coastal regions of the states analyzed in our study. Properties that are more exposed to climate risk on this measure tend to be closer to the waterfront, but there is substantial variation in exposure to climate risk across properties in the same narrow geography (see Figure 1, which shows the variation in our measure of climate risk exposure for downtown Miami).

We use our property listings data to build a novel measure of attention to climate risk. We construct this "Climate Attention Index" by calculating the proportion of for-sale listings with property descriptions that contain climate change-related words and phrases such as "hurricanes", "FEMA", "floodplain", and "flood risk". Most of the flagged listings include descriptions that highlight that a specific property is *less* exposed to climate risk (e.g., "Not in a flood zone, it's high and dry!"). We believe that this is sensible: if you are selling a property with particular exposure to climate risk, for example because it sits in a flood zone, you would not want to highlight this negative feature in a property listing. However, if you are selling a house that is *not* exposed to climate risk, this is something worth highlighting in a property listing, in particular in areas and at times when potential buyers pay more attention to these risks. Appendix A.2 provides more details on the construction of the Climate Attention Index, which we make publicly available to other researchers in the replication package associated with this paper.

There is substantial spatial and time-series variation in this measure of climate risk attention. The top panel of Figure 2 provides a heatmap of the Climate Attention Index for Florida, pooling across all listings in our sample at the zip code level (the Appendix includes corrsponding maps for the three other states). Properties near the coast are more susceptible to climate risk. Consistent with this, the Climate Attention Index is substantially higher for these properties in the cross section. The other panels of Figure 2 illustrate the time-series of the Climate Attention Index for each of the four states in our sample, both for the whole state (black solid line) and only for zip codes that include at least some properties in a flood zone (blue dashed line). Consistent with the heatmap, the attention paid to climate risk is substantially higher in zip codes that are located in parts of the country where properties will be flooded if sea levels rise substantially. There is also sizable time-series variation in the Climate Attention index within geographies. For example, in New Jersey, the Climate Attention Index nearly triples between 2011 and 2013, around the time of Hurricane Sandy, which rendered more than 20,000 homes in the state uninhabitable.

1.1.2 Empirical Analysis

We next estimate how climate risk is priced in real estate markets. Our baseline hedonic regression is given by equation 1:

$$log(Price)_{i,h,g,t} = \alpha + \beta log(Index_{g,t}) \times FloodZ_h + \gamma FloodZ_h + \delta X_h + \phi_g \times \psi_t + \epsilon_{i,h,g,t} \quad (1)$$

The unit of observation is a transaction i, of property h, in zip code g, at time t. The dependent variable is the log of the transaction price. We flexibly control for various property characteristics in X_h. We also include zip code-quarter fixed effects, $\phi_g \times \psi_t$, to capture differential house price movements across zip codes and time. We interact the log of the Climate Attention Index, $log(Index_{g,t})$, with the Flood Zone indicator, $FloodZ_h$.[6] This allows us to estimate the effects of changing climate attention for properties that are differentially exposed to physical climate risks. We also include the Flood Zone indicator directly, allowing us to control for the unconditional price effect of being located in a flood zone as well as of any unobserved property amenities that are correlated with this measure of exposure to climate risk.

Column 1 of Table 1, Panel A, shows estimates from this regression when we measure the Climate Attention Index at the zip code-year level. All else equal, properties that lie in the flood zone trade at a (statistically insignificant) premium to properties that are not

[6]To deal with the (small) number of zip code-years with no listing mentioning climate change, we add a small constant (0.01) to the Climate Attention Index before taking logs. Our results are robust to variation in the constant added, and to a linear (instead of log-linear) inclusion of the climate attention index.

in the flood zone, consistent with those properties also having more attractive amenities such as proximity to the beach. More importantly, we estimate a statistically significant negative β-coefficient. A doubling in the Climate Attention Index is associated with a relative 2.4% decline in the transaction prices of properties in the flood zone. The direct effect of increasing climate attention on all properties is absorbed by the zip code-quarter fixed effects.[7] Column 2 measures the Climate Attention Index at the zip code-quarter level, and presents similar estimates. In columns 3 and 4 of Table 1, Panel A, we include property fixed effects in the regressions from columns 1 and 2. In these specifications, the estimates of β are identified off properties that we observe transacting more than once. The estimates are nearly identical, suggesting that our baseline findings are not driven by unobserved property characteristics. In columns 5 and 6, we include the raw Climate Attention Index rather than the log of the Index. Interpreting the magnitudes suggests that a 1 percentage point increase in the number of listings that suggest particular attention to climate risk is associated with a 0.2% – 0.4% decrease in the transaction price.

One concern with the estimates presented above is that they might not just capture the pricing of future climate change risk, but that our estimates might also be picking up changes in the flow-utility of climate risk-exposed properties that could be correlated with climate risk attention. For example, it could be that climate risk attention rises after damaging storms that have a particularly strong direct effect on the utility of living in properties located in flood zones. To show that such a confounding story is not driving our results, Panel B of Table 1 runs regressions similar to equation 1, but now uses the log of the rental listing price as the dependent variable. In contrast to the transaction price regression, rental prices of properties exposed to climate risk increase during periods of increasing attention paid to climate risk, though the effect declines and is not statistically significant when we include property fixed effects. This is reassuring, because it suggests that our findings for transaction prices are not the result of a decline in the flow utility of these properties when climate risk increases. Instead, the decline in transaction prices most likely results from the increased present discounted cost of climate risk.[8]

Key Take-Aways. The evidence provided above shows that real estate has substantial exposure to climate risk, and thus fulfills an important criterion for us to use housing discount rates to learn about how to value investments in climate change abatement.

[7]While the coefficients on the control variables are not of primary interest in this study, Appendix A.2.2 shows that they are consistent with estimates from the literature (e.g., Kurlat and Stroebel, 2015; Stroebel, 2016): for example, larger and more recently upgraded homes trade at a premium.

[8]The positive effect on rents that we observe in some of these specifications could, for example, be the result of general equilibrium effects in the housing market. Increased attention to climate risk makes individuals who are interested in living near the coast less likely to want to buy a house. If instead these individuals choose to move into the rental market, this could be driving up rents.

1.2 The Riskiness of Housing – Exposure to Consumption Risk

We next show that in addition to being exposed to climate risk, real estate is exposed to consumption risk: its returns are higher in states of the world when the marginal utility of consumption is lower. To show this, we analyze the behavior of real house prices during financial crises and periods of rare consumption disasters; we also estimate the correlation between house prices and consumption as well as personal disposable income.

Panel A of Figure 3 shows the average reaction of real house prices during financial (banking) crises. The analysis is based on dates of financial crises in Schularick and Taylor (2012), Reinhart and Rogoff (2009), and Bordo et al. (2001) for 20 countries for the period 1870-2013, and on our own dataset of historical house price indices for these countries. Appendix A.3.1 provides details of the crisis dates and the house price series. The beginning of a crisis is normalized to be time zero. The house price level is normalized to be one at the onset of the crisis. House prices rise on average in the three years prior to a crisis, achieve their highest level just before the crisis, and fall by as much as 7% in the three years following the onset of the crisis. This fall in house prices during crisis periods, which are usually characterized by high marginal utilities of consumption, contributes to the riskiness of real estate as an asset.

Panel B of Figure 3 shows the average behavior of house prices during the rare consumption disasters as defined by Barro (2006). The consumption disaster dates for the 20 countries included in our historical house price index dataset are those defined by Barro and Ursua (2008). The dotted line tracks the level of consumption: following the start of a disaster, consumption falls for three years before reaching its trough (normalized to be time zero) and recovers in the subsequent three years. The solid line tracks the house price level: house prices fall together with consumption over the first three years of the disaster but fail to recover over the subsequent three years. The fall in house prices during these rare disasters also contributes to the riskiness of real estate as an asset class.

Panels C and D of Figure 3 show the time series of house prices and crisis years for the U.K. and Singapore—the countries with the best data on the term structure of housing discount rates (see below).[9] The pattern of house price movements during crises in these two countries is similar to the average pattern described above. House prices peak and then fall during major crises such as the 2007-08 global financial crisis. The 1984 banking crisis in the U.K. is the sole exception with increasing house prices.

Panel E of Figure 3 shows the performance of house prices durin World War I and

[9]All crisis dates are from Reinhart and Rogoff (2009) except the periods 1997-98 and 2007-08 for Singapore. The latter dates have been added by the authors and correspond to the Asian financial crisis of 1997-98 and the global financial crisis of 2007-08.

World War II (WWI and WWII). In both cases, time zero is defined to be the start date of the war period, 1913 and 1939 for WWI and WWII, respectively. The dotted line tracks house prices of five countries with data availability for the duration of WWI (1913-1918): Australia, France, Netherlands, Norway, and the United States. House prices fell throughout the war with a total decline in real terms of around 30%. Similarly, the solid line tracks house prices of six countries—now also including Switzerland—for the duration of WWII (1939-1945). House prices fell by 20% in real terms from 1939 to 1943 and then stabilized for the last two years of the war, 1944-45. Overall, we find wars to be periods of major declines in real house prices, which further contributes to the riskiness of real estate as an asset.[10]

We also investigate the average correlation between consumption and house prices over the entire sample rather than just during crisis periods. Table 2 reports the correlation of house price changes with consumption changes as well as consumption betas over the entire sample and for each country. The correlation is positive for all 20 countries, except for France (-0.05), and often above 0.5. Accordingly, consumption betas are also positive except for France (-0.10) and often above 1.0. The estimated positive correlation between house prices and consumption and the positive consumption betas reinforce the evidence that real estate is a risky asset: it has low payoffs in states of the world in which consumption falls and marginal utility is high. We also investigate the correlation between house price growth and alternative measures of economic activity by using data from Mack and Martínez-García (2011), and report the correlation between annual real house price growth and real personal disposable income growth in a panel of 23 developed and emerging countries (see Table 3). The average correlation is 0.33 and positive for all 23 countries, except for Croatia (-0.35), otherwise with a minimum of 0.04 for Norway and a maximum of 0.62 for Japan. The "personal disposable income beta" is positive for all countries except Croatia (-0.16) and often above 1.0 again. Overall, this evidence further corroborates the fact that real estate returns are risky.

[10]Despite extensive efforts to collect an exhaustive database, our results are still limited by the relatively small number of crises for which house price data are available, and by the relatively low quality of house price series before 1950. In addition, rental data is generally unavailable, preventing us from performing a comprehensive study of the riskiness of the underlying cash flows of housing. Nevertheless, our results suggest that real estate is an asset that has relatively lower payoffs during economic crises. Note that our results are likely to underestimate the riskiness of real estate and housing due to three effects. (1) House price indices are generally smoothed and therefore underestimate the true variation in house prices. (2) We only consider the behavior of house price changes (capital gains) and have not considered the behavior of rents (dividends). For the two countries for which long high-quality time series of rental indices are available (France for the period 1949-2010 and Australia for the period 1880-2013), we find rent growth to be positively correlated with consumption growth (0.36 and 0.15 respectively). (3) A sizable part of the housing stock is ofen destroyed during wars. The return to a representative investment in real estate would thus be lower than the fall in index prices as it would incorporate the physical loss of part of the asset.

1.3 The Term Structure of Real Estate Discount Rates

We next provide evidence on an important and previously unexplored dimension of real estate data: the term structure of housing discount rates. We first present our analysis of expected real estate returns, which we find to be relatively high, between 5.5% and 7.4%. We then combine these new data with the estimates of Giglio, Maggiori and Stroebel (2015) to provide evidence for the slope of the term structure of real estate discount rates. Our analysis suggests that this term structure is downward-sloping, and thus cautions against using real estate's *average* rate of return to infer discount rates for very *long-run* benefits associated with investments in climate change abatement. In subsequent sections, we will use insights from asset pricing theory to inform what can be learned from the downward-sloping term structure of risky real estate cash flows about the optimal discount rate for investments in climate change abatement.

1.3.1 Average Rate of Return to Housing and Rental Growth Rate

We employ two complementary approaches to estimate the average return to real estate. The first approach, which we call the *price-rent approach*, starts from a price-rent ratio estimated in a baseline year and constructs a time series of returns by combining a house price index and a rental price index: Without loss of generality, suppose we know the price-rent ratio at time $t = 0$. We can then derive the time series of the price-rent ratio as:

$$\frac{P_t}{D_{t+1}} = \frac{P_t}{P_{t-1}} \frac{D_t}{D_{t+1}} \frac{P_{t-1}}{D_t}; \qquad \frac{D_1}{P_0} \quad \text{given,} \tag{2}$$

where P is the price index and D the rental index. Note that, given a baseline price-rent ratio, only information about the growth rates in prices and rents is necessary for these calculations. Gross real housing returns are then:

$$R^G_{t,t+1} = \left(\frac{D_{t+1}}{P_t} + \frac{P_{t+1}}{P_t} \right) \frac{\pi_t}{\pi_{t+1}}, \tag{3}$$

where π is a price level index to adjusts for inflation. To compute expected net returns $E[R]$, we subtract maintenance costs and depreciation (δ) and any tax-related decreases in returns (τ):

$$E[R] = E[R^G] - \delta - \tau. \tag{4}$$

The second approach, which we label the *balance-sheet approach*, follows Favilukis, Ludvigson and Van Nieuwerburgh (2017) and Piketty and Zucman (2014): We obtain data on the value of the residential housing stock from countries' national accounts to estimate the value of the housing stock (i.e., its price), and data on the net capital income earned on the housing stock (i.e., the 'dividend' earned on the housing stock). Since we are only interested in the return to a representative property, we need to control for changes in the total housing stock to derive the net return to housing in each period as:

$$R_{t,t+1} = \frac{V_{t+1} + NI_{t+1}}{V_t} \frac{\pi_t}{\pi_{t+1}} \frac{S_t}{S_{t+1}}, \tag{5}$$

where V is the value of the housing stock, NI is net capital income on housing, π is a price level index that adjusts for inflation, and S is the stock of housing.

To adjust for the quality and quantity of the housing stock, we use several complementary approaches. In our first approach, we proxy for the change in the housing stock by population growth. In alternative specifications, we control for the change in the housing stock with the growth in residential housing units or the growth in residential floor space. In our most conservative approach, we rely on (constant-quality) quantity indices, which allows us to directly control for quality as well as "pure" quantity changes in the housing stock at the same time. For the U.S., we can also draw on holding gains from the national revaluation accounts, which directly hold the aggregate stock of housing constant. Finally, even though our main interest lies in net returns to housing, the national accounts also allow us to estimate maintenance costs and depreciation (δ) and tax-related decreases in returns (τ), and hence gross returns to housing $E[R^G]$, which we compare to our results from the price-rent approach.

Table 4 presents estimates of the return to housing for three countries. We explore data from the United Kingdom and Singapore, since we are able to measure very long-run discount rates for these countries (see below); we also provide estimates for the U.S. for comparison, since they have been the subject of an extensive literature (e.g., Flavin and Yamashita, 2002; Lustig and van Nieuwerburgh, 2005; Piazzesi, Schneider and Tuzel, 2007). Appendix A.4 provides details on our approach and the underlying data sources.

United States. For the U.S., our preferred estimates using the price-rent approach are based on a price-rent ratio from Trulia that includes a utilities correction (column 2); our prefered results using the balance-sheet approach use direct holding gains from the revaluation accounts (column 9). We also provide robustness checks that use alternative price and rental indices as well as alternative price-rent ratios for the price-rent approach, and various corrections for the growth in the housing stock for the balance-sheet approach. Both papproaches provide similar estimates for the average annual real gross return ($E[R^G]$): 9.7% based on the preferred estimated from the price-rent approach and 8.9% based on the preferred estimate from the balance-sheet approach. We estimate a maintenance and depreciation impact of 2.3% using the balance-sheet approach and calibrate the impact of maintenance and depreciation at 2.5% for the price-rent approach based on prior results from Harding, Rosenthal and Sirmans (2007). Our balance-sheet estimates imply a tax impact of 1.1% and we assume a property tax impact of 0.67% for a representative household for the price-rent approach. This results in average real net returns between 5.5% and 6.5% for the U.S. housing market. These estimates are similar to the estimates in Flavin and Yamashita (2002), who find a real return to real estate of 6.6%, and the estimates in Favilukis, Ludvigson and Van Nieuwerburgh (2017), who find a real return of 9-10% before netting out depreciation and property taxes.

United Kingdom. Columns 11 to 15 of Table 4 report the estimates for the real estate market in the U.K. The price-rent and the balance-sheet approaches provide similar estimates for the average annual real gross return ($E[R^G]$): 9.5% for the price-rent approach and 9.7% for the balance-sheet approach. We estimate a maintenance and depreciation cost of 2.4% using the balance-sheet approach and maintain a calibration of 2.5% for the price-rent approach. There are no property taxes to be considered in the U.K. Average real net returns in the U.K. real estate market are therefore between 7.0% and 7.4%.[11]

Singapore. Column 16 in Table 4 reports our price-rent approach estimate for the Singapore real estate market at 9.9%. We assume the cost of maintenance and depreciation to be 2.5%, in line with our estimates for the U.S., and the property tax impact to be 0.6%. Our estimate of the real net return in the Singapore real estate market is thus 6.8%. We do not calculate complementary balance-sheet approach estimates for Singapore for two reasons: Firstly, more than three quarters of residential dwellings are not in the private housing market but publicly governed and developed by the Housing and Development Board (HDB). Unfortunately, the national accounts data do not allow us to separate these out with sufficient accuracy. Secondly, the national accounts data do not allow us to determine the total consumption of real estate services excluding relevant costs, that is net rents, with sufficient accuracy.

Average Rate of Return: Summary. Overall, these estimates show that expected real returns for real estate are around 6% or higher for the countries we consider. These estimates are robust to the different methodologies we use. They are also in line with contemporaneous work from Jordà et al. (2017) that finds average returns to housing of around 7% before taxes across a number of countries. Our estimates are also consistent

[11] Numbers for the balance sheet approach may not add up due to rounding when moving from gross to net returns.

with the notion that average house price growth over extended periods of time is relatively low, as argued by Shiller (2006), with high rental yields being the key driver of real returns to real estate and housing. In fact, our estimated average capital gains are positive but relatively small for all three countries, despite focusing on samples and countries that are often regarded as having experienced major growth in house prices. Consistent with our results from Section 1.2, our estimates of average returns to real estate imply a positive real estate risk premium.

Growth Rate of Rental Income. Finally, we estimate the average real growth rate of rental income from the same data sources, which we denote by g. For all three countires, the estimated real growth rate of rents is low. For the U.S., we estimate $g = 0.7\%$, an estimate in line with that of Campbell et al. (2009), who obtain a median growth rate of 0.4% per year. We obtain a slightly higher estimate of $g = 1.4\%$ for the U.K. and a slightly lower estimate of $g = -0.4\%$ for Singapore (largely driven by a few deflationary periods). These results are consistent with Ambrose, Eichholtz and Lindenthal (2013), who find very low real rental growth in a long time series of rents for Amsterdam, and with Shiller (2006), who estimates long-run real house price growth rates to be very low, often below 1% (the equivalence of these two long-run growth rates is necessary for rental yields to be stationary).

1.3.2 Long-Run Housing Discount Rates

In recent work, Giglio, Maggiori and Stroebel (2015) use unique data from the U.K. and Singapore to estimate how much value households attach to future real estate cash flows accruing over a horizon of hundreds of years (see also Giglio, Maggiori and Stroebel, 2016). In these real estate markets, residential properties trade either as freeholds, which are permanent ownership contracts, or as leaseholds, which are pre-paid and tradable ownership contracts with finite maturity. The initial maturity of leasehold contracts generally varies between 99 years and 1,000 years. By comparing the relative prices of leasehold and freehold contracts for otherwise identical properties, the authors estimate the present value of owning a freehold after the expiration of the leasehold contract. They show how this present value is informative about the discount rate attached to real estate cash flows that occur in the very long run.

The red bars in Figure 8 report the estimates from Giglio, Maggiori and Stroebel (2015). They show the price discount of leaseholds with varying maturities compared to freeholds for otherwise identical properties. For the U.K. estimates, for example, the bucket with leaseholds of remaining maturity between 100 and 124 years shows that households are willing to pay 11% less for a leasehold with that maturity than for a freehold. Interpreted differently, 11% of the value of a freehold property is due to cash flows that accrue more than 100 years into the future. In general, leasehold discounts are strongly associated with maturity, with shorter leaseholds trading at bigger discounts: between 17.6% for leaseholds with remaining maturity of 80-99 years and 3.3% for remaining maturities of 150-300 years. Leaseholds with more than 700 years remaining maturity trade at the same price as freeholds. Pricing patterns are similar for properties in Singapore. The authors provide a detailed investigation of the institutional setup of leasehold and freehold contracts, and examine a number of possible explanations for the observed leasehold discounts. They conclude that leasehold price discounts are tightly connected to the contracts' maturity and that discount rates of around 2.6% for cash flows more than 100 years in the future are necessary to match the data from both countries.

1.3.3 Take-away: The Term Structure of Discount Rates in the Housing Market

In this section we showed (i) that real estate has a real expected rate of return of above 6% per year, and (ii) the relative pricing of freeholds and leaseholds implies discount rates of around 2.6% for rents 100 years or more in the future. Since the average return on real estate is simply a weighted average of the average returns of all of its cash flows (at all maturities), these two facts together are informative about the shape of the term structure of discount rates for the housing asset. It needs to be low at the long end, in order to match the 2.6% discount rate applied to the long-term housing claims. But it needs to be high enough at the short end to imply an *average* discount rate of 6%. In other words, the term structure of discount rates for the housing asset needs to be downward-sloping in order to explain the data. In the next section, we introduce an asset pricing model of real estate that is able to match these moments, and discuss its implications for valuing investments in climate change abatement.

2 Valuing Investments in Climate Change Abatement in a World with Declining Discount Rates for Risky Assets

The previous section provided empirical evidence that the term structure of discount rates for real estate, a risky asset, is downward-sloping, and that real estate is an asset class that is directly exposed to climate change risk. In this section, we introduce a general equilibrium model to study the link between climate change risk, the term structure of discount rates for real estate, and consumption. Our model has two objectives: First, it provides a quantitative framework, calibrated to asset markets and our new empirical evidence on the term structure of housing discount rates, from which one can extract appropriate discount rates for climate-change-abatement investments at any horizon. Second, it allows us to nest, in reduced form, a number of different approaches to modeling the economic impact of climate change, ranging from the "tax view" in the spirit of Nordhaus and Boyer (2000) and Nordhaus (2008), to the "disaster view" in the spirit of Weitzman (2012, 2014). This allows us to understand these views' different predictions for the discount rates of investments in climate change abatement.

2.1 A General Equilibrium Model with Climate Change Risks

Our model builds on a modified version of the Lucas (1978) representative-agent economy with power utility preferences. In order to provide a simple analytical framework for climate change, we introduce a production sector that, while exogenous, allows for important feedback effects between the growth rate of the economy and the probability of rare and adverse climate shocks that destroy parts of the output. The setup is rich enough to allow for key climate-related dynamics in the economy, including an endogenous relationship between consumption and climate risk, while also being stylized enough to be solved in closed form up to simple recursive expressions.

Model Setup. We assume that aggregate consumption follows:

$$\Delta c_{t+1} = \mu + x_t - J_{t+1}, \tag{6}$$

$$x_{t+1} = \mu_x + \rho x_t + \phi J_{t+1}, \tag{7}$$

where c_t is the log of aggregate consumption; since the economy is closed and does not feature investment, c_t also corresponds to aggregate output in equilibrium.[12] J_t is a jump process that takes value $\xi \in (0,1)$ with probability λ_t in each period, and value 0 otherwise. We interpret J as climate risk: a rare but possibly large negative shock to output. The climate disaster probability λ_t depends endogenously on the dynamics of the economy (see below).[13] The process x_t captures persistent changes in the growth rate of consumption and plays a key role in determining the term structure of discount rates.

[12]Note that we assume complete markets, so all risk is shared perfectly across households. The equilibrium effects of incorporating heterogeneity and incomplete risk-sharing in asset pricing models has been studied in a long literature (see, for example, Constantinides and Duffie, 1996). We leave to future research an exploration of the specific implications regarding climate change risks.

[13]Our model is designed to help researchers and policy makers understand how to value investments in climate change abatement. We thus remove any risk sources not related to climate risk. Other shocks could be added without changing the qualitative implications of the model.

As is standard in financial economics, we allow for a separate cash-flow process, d_t, for risky assets—which in our model corresponds to the rents of real estate—to capture the idea that asset markets only reflect a subset of total economic activity. The process for these rent cash-flows is similar to the one for aggregate consumption:

$$\Delta d_{t+1} = \mu_d + y_t - \eta J_{t+1}, \tag{8}$$

$$y_{t+1} = \mu_y + \omega y_t + \psi J_{t+1}. \tag{9}$$

The main difference between real estate rents and consumption is the larger exposure of rents to the underlying economic shocks, represented by climate risk J. This is captured by the multiplier $\eta > 1$. In our case, η reflects the empirical observation that housing has an above-average exposure to climate risk, primarily due to the immovability of land. Analogous to x_t, the process y_t captures persistent changes in the growth rate of rents. Having different processes for x_t and y_t allows for flexibility in the calibration of this model to different specific settings.

Our setup allows for partial mean reversion in the growth rate of consumption and rents after a disaster. Formally, after a disaster strikes, the growth rate of the economy increases ($\psi > 0, \phi > 0$) and this increase is persistent ($\rho > 0, \omega > 0$). As we show below, this partial mean reversion plays a crucial role in explaining the term structure of discount rates for risky assets (see also Gourio, 2008; Lettau and Wachter, 2011; Nakamura et al., 2013; Belo, Collin-Dufresne and Goldstein, 2015; Hasler and Marfe, 2016). In the context of climate risk modeling, the partial mean reversion captures the notion that economic activity picks up after a climate disaster as the economy adapts to new climatic circumstances. Numerous papers have highlighted the importance such adaptation processes, including Brohé and Greenstone (2007), Deschênes and Greenstone (2011), Desmet and Rossi-Hansberg (2015), Burke and Emerick (2016), and Barreca et al. (2016). Yet, since there have not been many global climate disasters (especially in modern data), such feature remains a possibility rather than an empirical regularity.

The last component of our model is an endogenous climate disaster probability, λ_t:

$$\lambda_{t+1} = \mu_\lambda + \alpha \lambda_t + \nu x_t + \chi J_{t+1}. \tag{10}$$

In designing this process, we aim to capture some of the main features of physical models of climate change, while at the same time maintaining a tractable solution to the asset pricing model. Two features of this process make it particularly useful for bringing climate risk into an asset pricing framework:

1. The disaster probability λ_t is an endogenous function of the growth rate of the economy. Since x_t—which captures the expected deviation of the growth rate of the economy from trend—enters additively and positively ($\nu > 0$) in equation 10, the probability of a disaster increases over time when the economy grows at a faster rate. Intuitively, this feature captures the notion that faster growth accumulates more environmental damages, such as greenhouse gas emissions and pollution, thereby increasing the probability of adverse climatic events, akin to tipping points (see Alley et al., 2003; Lenton et al., 2008; Overpeck and Cole, 2006; Lemoine and Traeger, 2014; Franklin and Pindyck, 2017).

2. The climate disaster probability λ_t increases following the occurrence of a disaster ($\chi > 0$), thus allowing climate shocks to induce a self-reinforcing cycle in which each shock increases the probability of the next shock (see, for example, Cox et al., 2000; Melillo et al., 2017). Note that, in contrast to the mean reversion in cash flows described above, this is a force that pushes towards making long-run cash flows more risky.

To illustrate the richness of these patterns, Figures 4 and 5 plot two sample paths of the economy. Figure 4 shows a path in which no disaster occurs, but the economy grows above trend for a sustained period of time, starting in year 10.[14] The top panel shows log deviations of the disaster probability λ_t from its steady-state value. We set the steady state value to 3% to reflect the Barro (2006) estimate of the average probability of a consumption disaster. The bottom panel shows the path of log rents, d_t, over time: rents (and the economy overall) increase at a decreasing rate, reaching a permanently higher level as a result of the growth spur. This sustained economic expansion induces a progressive increase in the probability of a climate disaster until the economy returns to its steady-state growth rate. The lags of the effect of greenhouse gas emissions and pollution on the disaster probability can be substantial: The disaster probability reaches its maximum approximately 7 years after the growth spur has started. Since the model is stationary, the disaster probability ultimately reverts to its mean, but the half-life of the shock is extremely long at 14 years.

Figure 5 instead shows a path in which the economy expands above trend, starting in year 10 (exactly as before), but with a climate disaster occurring after year 25. This disaster induces a large drop in consumption and rents. The dynamics of climate risks are particularly interesting. As before, the disaster probability increases as the economy

[14] As we discuss in Section 2.2, trend growth is calibrated at 2%. We assume that in period 10, growth of both consumption and rents increases to 5% and then slowly reverts to long-run trend growth. Since growth is a persistent process in the model, growth is above trend for approximately 20 years in this sample path.

accelerates. Once the disaster hits, the probability of a future disaster increases further. It takes almost 40 years (in a sample path chosen to have no further disasters) from the original growth spur shock for the probability of a disaster to revert back to its long-run mean. The bottom panel of Figure 5 also illustrates the mean reversion in the growth rate of the economy. After a disaster strikes, the growth rate of the economy increases ($\psi > 0$) and this increase is persistent ($\omega > 0$).

The Term Structure of Discount Rates for Risky Assets. Despite the richness of the underlying dynamics of the economy, we are able to solve quasi-analytically for the term structure of housing risk premia and the risk-free rate. We derive these objects assuming the existence of a representative agent who maximizes lifetime utility and faces a complete set of financial instruments. In our baseline model, the period utility function features constant relative risk aversion (γ) as in Lucas (1978):

$$U(C_t) = \delta^t \frac{C_t^{1-\gamma}}{1-\gamma}, \tag{11}$$

where δ is the rate of time preference. In Appendix A.6, we derive the prices of claims to consumption and rents at different horizons. Here, we focus on the crucial forces determining the term structure of housing discount rates. Formally, we are interested in the per-period discount rate of maturity n, denoted $\bar{r}_t^n$, that equates the price of a single cash flow $E_t\left[D_{t+n}\right]$ of maturity n, denoted $P_t^{(n)}$, with its present discounted value:[15]

$$P_t^{(n)} = \frac{E_t\left[D_{t+n}\right]}{(1+\bar{r}_t^n)^n}. \tag{12}$$

As we show in Appendix A.5, the term structure of discount rates $\bar{r}_t^n$ is closely linked to the term structure of one-period expected returns. Intuitively, the appropriate discount rate for cash flows of horizon n is simply the average across one-period expected returns $E_t[R_{t,t+1}^{(n)}]$ for claims to cash flows at each horizon up to n, where the holding-period returns over the next period are given by $R_{t,t+1}^{(n)} = P_{t+1}^{(n-1)}/P_t^{(n)}$. More formally:[16]

$$\bar{r}_t^n \simeq \frac{1}{n}\sum_{k=1}^{n} \ln(E_t[R_{t,t+1}^{(k)}]). \tag{13}$$

[15] We label objects that relate to single cash flows at a specific maturity n with superscript (n). The set of claims to a single cash flow at maturity n that we are interested in is a subset of a more general class of assets with maturity n that could pay cash flows such as rents at any point in time up to that maturity. We denote prices and returns of claims to more general classes of assets with maturity n with superscript n.

[16] See Appendix A.5.1 for a derivation. The result holds exactly when the term structure of discount rates is constant over time (though it can have any shape over maturities n). For example, a flat term structure of discount rates implies a flat term structure of expected one-period returns across maturities, and vice versa.

The expected one-period return for the n-maturity claim, $E_t[R^{(n)}_{t,t+1}]$, can in turn be thought of as the sum of the one-period risk-free rate, $R^f_{t,t+1}$, which is independent of the maturity of the claim, and a risk premium, $E_t[R^{(n)}_{t,t+1}] - R^f_{t,t+1}$, which varies with the horizon n. While Appendix A.6 provides the full solution of the model, and while the calibrated results presented below use this full solution, we next focus on a simple approximate solution that captures the main forces that shape the term structure of one-period excess returns in our model here:

$$\begin{aligned} E_t[R^{(n)}_{t,t+1}] - R^f_{t,t+1} &\simeq \gamma\, Cov_t[r^{(n)}_{t,t+1}, \Delta c_{t+1}] \\ &= \gamma\,[\eta - \psi e_{d,n-1} - \phi b_{d,n-1} - \chi f_{d,n-1}]\, \xi^2 \lambda_t (1-\lambda_t). \end{aligned} \tag{14}$$

The first equality above uses the fact that the log stochastic discount factor under power utility preferences is $m_{t,t+1} = \log\delta - \gamma\Delta c_{t+1}$, and the second equality represents the solution to the model, where b_d, e_d and f_d solve recursive equations derived analytically and reported in equations A.14c to A.14e in Appendix A.6.

Equation 14 highlights the components that drive the downward-sloping term structure of discount rates for risky assets (i.e., housing) in our framework. The *level* of the term structure is determined by the aggregate amount of risk in the economy, $\xi^2\lambda_t(1-\lambda_t)$, and by the agent's risk aversion, γ. Neither have a differential effect on the risk premia of cash flows with different maturities (there are no n-subscripts).

The *shape* of the term structure is determined by the terms inside the square bracket. The term b_d arises from the term structure of risk-free assets (term premia) and is essentially constant in realistic calibrations of the model that match the flat term structure of risk-free rates in the data. The term f_d is a quantitatively small adjustment for the risk that arises from changes in the disaster probability λ_t. The component that quantitatively dominates the shape of the term structure of housing risk premia is $\psi e_{d,n-1}$, which captures the term structure of exposures of claims of different maturity to the climate disaster (and the ensuing recovery). The model is parsimonious enough to admit an analytical solution for $e_{d,n}$ (see Appendix equation A.14e):

$$e_{d,n} = \frac{1-\omega^n}{1-\omega}. \tag{15}$$

Since this term enters negatively in equation 14, positive values for both ψ and ω imply a declining term structure of risk premia for rents. Recall that ψ determines the degree of mean reversion of the growth rate of the economy after a climate disaster, and ω captures the persistence of this growth rate increase. When $\psi > 0$, as in our baseline calibration below, rents (partially) mean-revert after a climate disaster. This mean reversion in cash flows implies that the occurrence of a disaster is worse for short-term claims than it is for long-term claims because immediate short-term cash flows drop by more than cash flows that are farther in the future.

Remark on Preferences. The previous discussion highlights that, in our setting, the observed downward-sloping term structure of risk premia for housing is generated by the dynamics of the cash flows (*risk quantities*) rather than by the term structure of *risk prices*, which are flat. One might wonder whether more sophisticated preferences, such as Epstein–Zin preferences that are popular in both the asset pricing and climate change literature, could also generate this downward slope. We discuss in Appendix A.5.3 that this is not the case. In fact, introducing Epstein–Zin preferences would push the slope of the term structure of discount rates for risky assets upwards. To match the data on a downward-sloping term structures of discount rates for risky real estate, we would thus require an even stronger mean reversion in cash flows.[17] More generally, we are not aware of a standard representation of preferences that would push towards a downward-sloping term structure of discount rates for risky assets such as real estate. As a result, capturing the observed downward-slope through the dynamics of risk quantities, as we do in our model, seems like the natural approach to us, in particular given that the required dynamics are highly consistent with empirical research on the adaptation to climate change.

2.2 Calibration

In this section, we turn to calibrating our model. The objective of our calibration is not to quantitatively match all conceivable moments of real and financial variables; since our model is only driven by a single climate disaster shock, J, we would certainly fail in such an exercise along many dimensions. Furthermore, history and scientific evidence only provide an incomplete and uncertain guidance on many key parameters related to climate events. What we strive for instead is a reasonable calibration that can match core moments of the data as they relate to the discounting of climate-change-abatement investments and, in particular, match our new empirical evidence on the risk and return properties of real estate, including the term structure of discount rates from Section 1.

[17]The long-run risk model of climate change by Bansal, Kiku and Ochoa (2013) and the model of Cai, Judd and Lontzek (2013) both use Epstein–Zin preferences.

2.2.1 Baseline Calibration

Whenever possible, we calibrate parameters following the existing asset pricing literature. The remaining parameters are calibrated to match some of our new moments estimated in Section 1. For example, we follow the asset pricing literature and set risk aversion $\gamma = 10$, the drop in consumption following a disaster $\xi = 21\%$, and the exposure of risky cash-flows to the climate shock $\eta = 3$ (see Bansal and Yaron, 2004; Barro, 2006; Barro and Jin, 2011). Average consumption growth in the absence of a disaster is set to $\mu = 2\%$. The remaining parameters of the consumption process are chosen to generate a recovery in consumption growth after disasters ($\phi > 0$), and persistent growth rates ($\rho > 0$). The magnitude of these parameters ($\phi = 0.025$, $\rho = 0.85$) targets a term structure of real interest rates that is slightly upward-sloping with a level of around 1%, matching our empirical estimates based on the U.K. gilts real yield curve between 1998 and 2016 reported in Figure 6. These data show that the U.K. real yield curve is approximately flat on average, with a real yield close to 1% for maturities between 1 and 25 years.[18]

In our calibration, rents are not only correlated with consumption, but also share many of its dynamics, including recovery after disasters ($\psi > 0$) and persistent rent growth ($\omega > 0$). The magnitudes of these parameters ($\psi = 0.24$, $\omega = 0.915$) are chosen to match the shape and the level of the observed term structure of discount rates in the housing market as described in Section 1. Finally, we set the steady-state conditional probability of disasters, $\overline{\lambda}$, to 3% per year, following the estimates in Barro (2006). The remaining parameters for the λ_t-process are chosen to obtain economically reasonable interactions between the real economy and the disaster probability, while at the same time matching the term structure of the risk-free rate. The risk-free rate is directly affected by the disaster probability dynamics through the precautionary savings channel; an increase in the disaster probability decreases the rate by increasing precautionary savings. In particular, the disaster probability is persistent ($\alpha = 0.75$), increases after a jump ($\chi = 0.05$), and increases when expected consumption growth x_t is above its trend ($\nu = 0.1$). Finally, we impose that rents and consumption have the same long-run growth rate and that x_t and y_t have mean zero.[19]

[18]Figure 6 plots the average shape of the real U.K. gilts curve for the period 1998-2016, as well as for two sub-periods: 1998-2007 and 2008-2016. The level of the yield curve shifted down during this latter period and the yield curve became hump-shaped. More recently, as more and more U.K. government bonds with longer maturities have been issued, reliable prices for such longer maturities have also become available. In 2016, the Bank of England therefore started to extend the real yield curve up to maturities of 40 years. For the short time period where data on such long maturities are available, the yield curve is essentially flat for these longer maturities as well.

[19]The resulting parameter restrictions are: $\mu_d = \mu + (\eta - 1)\bar{\lambda}\xi$, $\mu_x = -\bar{\lambda}\phi\xi$ and $\mu_y = -\bar{\lambda}\psi\xi$. See Appendix A.6 for details.

2.2.2 Calibration-Implied Housing Term Structure and Climate Risk Elasticities

Figure 7 plots the term structure of discount rates that the calibrated model implies for risk-free and risky assets. The model is able to match the approximately flat term-structure of risk-free rates observed in the data with an average level of around 1.0%. The model also produces a strongly declining term structure of discount rates for real estate, starting around 10% per year at short horizons and decreasing to around 3% per year at long horizons, matching the declining term structure of discount rates that we estimated for housing. To further assess how well we match our estimates of the real estate data, the two panels of Figure 8 report the leasehold price discounts estimated for housing in the U.K. and Singapore together with the ones implied by the calibrated model to highlight the close fit between the model and the data. The model also matches the average rate of return on housing (at around 5.5%) that we have independently estimated in the data.

Our model also helps rationalize the cross-sectional regularity that houses that are differentially exposed to climate risk have different price elasticities with respect to *news* about climate change. This is qualitatively consistent with the evidence reported in Section 1.1. That section focused on increase perception of climate risk, i.e., future climate affecting future rents but not current rents. Of course, current prices react immediately since they correspond to the present value of future rents. In our calibration, a house with a 1% higher exposure to climate change (i.e., higher η), responds to a one percentage point increase in the probability of a climate disaster (λ_t) with a price decline that is 0.4 percentage points larger relative to a house with lower exposure. Unfortunately, these magnitudes are not directly comparable to the estimates from Section 1.1, since such a comparison would require us to map changes in our climate attention index to (perceived) changes in λ_t.

2.3 Valuing Investments in Climate Change Abatement

We start this section by using our calibrated model to derive appropriate discount rates for various types of investments in climate change abatement. Since our model nests the key ideas of a variety of standard models in climate change economics, we then proceed to show how our results compare to and improve upon the implications of two key views in climate change economics – the "tax" view pioneered by Nordhaus and Boyer (2000) and Nordhaus (2008), and the "disaster view" pioneered by Weitzman (2012, 2014).

2.3.1 Valuing Investments in the Benchmark Model

To derive the appropriate discount rates for investments in climate change abatement, we need to model their cash flows and their relation with the climate shocks. We model climate change investments as assets that compensate the investor for future damages to production and rents due to climate change, akin to insurance policies on climate change. Climate change mitigation investments in our framework are not large enough to affect equilibrium consumption; they are infinitesimal investments that are therefore informative about marginal valuations. We denote the process of damages to rents due to climate change by Q_t and model its (log) dynamics as:

$$\Delta q_{t+1} = \mu_q - y_t + \eta J_{t+1}. \tag{16}$$

Intuitively, the occurrence of a climate disaster in our model induces an immediate destruction of rents $(\eta\xi)$, but these damages revert over time as the economy adapts (captured by y_t).[20] Investments in climate change abatement provide a payoff that at least partially offsets the damages. Specifically, we assume that an insurance contract insures a fixed proportion θ of the growth rate of damages: $\theta\Delta q_{t+1}$. Values of θ range from 1 (full insurance) to close to zero (no insurance). Of course, it is possible to specify alternative types of climate change mitigation investments, for example some that mitigate the long-run damages more strongly than in this specification. One advantage of our fully specified model is that it allows researchers to explore different types of climate interventions.

Figure 7 reports the appropriate discount rates for investments in climate change abatement of different maturity for three values of θ: 1, 0.5, and 0.1. Higher values of θ correspond to lower black lines.[21] The figure highlights a number of crucial results from our model:

1. **Appropriate discount rates for investments in climate change abatement are always below the risk-free rate.** This feature comes from these investments being a hedge: they pay off following a climate disaster, and therefore in states of the world with high marginal utility. For relatively short horizons, we have estimated a real risk-free rate of about 1%, providing us with a tight upper-bound on the appropriate discount rates.

[20] We set $\mu_q = \mu_d - 2\bar{\lambda}\eta\xi$ so that damages and rents have the same long-run growth rate.

[21] In some calibrations the appropriate discount rates are negative, especially at shorter maturities. This is not surprising given the insurance-contract nature of the investments; it simply means that investors are willing to pay a price today that is above the expected payoff of the project.

2. **At long horizons, the term structure of housing discount rates provides an upper bound on the appropriate discount rate.** While the risk-free rate provides a theoretically tight upper bound at all horizons, no reliable data exist on risk-free rates beyond horizons of about 30 years. This makes direct measurements of the risk-free-rate upper bound at horizons relevant for investments in climate change abatement infeasible. However, Section 1 described observed discount rates on risky housing for such long horizons, allowing us to bound the long-run discount rates for assets that are safer than real estate, including investments in climate change abatement, to be below 2.6%.

   Importantly, a discount rate below 2.6% (and even more so 1%) is lower than many estimates used in the existing literature and by policymakers for discounting investments in climate change abatement. For example, it is substantially below the 4% suggested by Nordhaus (2013). Quantitatively, it is more in line with long-run discount rates that are close to the risk-free rate, as suggested by Weitzman (2012), or the 1.4% suggested by Stern (2006), or results by Barro (2013). It is also close to the average recommended long-term social discount rate of 2.25% elicited by Drupp et al. (2015) in a survey of 197 experts, and falls within the range of 1% to 3% that more than 90% of these experts are comfortable with. Moreover, in light of the general disagreement in the literature regarding the appropriate discount rate, the interagency group tasked by the U.S. government to value reductions in CO_2 chose three certainty-equivalent constant discount rates: 2.5%, 3%, and 5% per year. Our estimates provide a tight bound that is only consistent with the lowest rate of 2.5% for investments providing a long-run hedge against climate disasters. Greenstone, Kopits and Wolverton (2013) report the cost of 1 metric-ton of CO_2 to be \$57 when using the suggested 2.5% discount rate, but only \$11 when using a 5% discount rate, illustrating the impact of this bound on climate-change-related welfare calculations.

3. **The term structure of discount rates for investments in climate change abatement is upward-sloping, making the housing discount rates a tighter bound for longer horizons.** Appropriate discount rates for investments in climate change abatement increase with the horizon, which disproportionally tightens our upper bound as the horizon increases. This feature is driven by the same mean reversion in cash flows that generates the downward slope in the term structure of risky assets (such as real estate): since cash flows that are farther in the future are reduced less by a climate disaster, the benefits of reducing its effects are smaller, too.

Note that the implied *low but upward-sloping* term structure of discount rates for investments in climate change abatement contrasts with a number of papers that have argued for using declining discount rates for valuing investments in climate change abatement (Arrow et al., 2013; Cropper et al., 2014; Farmer et al., 2015; Traeger, 2014). These arguments have motivated policy changes in France and the U.K., which have adopted a downward-sloping term structure of discount rates for evaluating long-run investments, including those in climate change abatement. While this disagreement about the term structures does not have a substantial effect on the actual level of discount rates to value the *long-run cash flows*—they are relatively low, at approximately 2%, under both the term structures used in those countries and under our estimated upward-sloping term structure—the two rely on different economic mechanisms. Importantly, they also make substantially different predictions for evaluating the payoffs from abatement investments that may accrue at shorter horizons. The calibration of our model suggests that climate disasters cause the most damage immediately after they hit, making it most valuable to hedge the immediate costs. As a result, the discount rates are substantially below the risk-free rate of 1%-2%. In contrast, the downward-sloping term structures used in France and the U.K. suggest discount rates of 4% and 3.5%, respectively, for the first 30 years of a project's cash flows.

2.3.2 Alternative Models: The "Tax" View vs. the "Disaster" View of Climate Change

Modeling climate change risk and its effects on the economy is a daunting task, both because the physical processes driving climate change are not fully understood and because of the sparsity of historical data to predict how climate change will affect the economy. It is unsurprising, therefore, that the literature has approached the modeling of climate change and its effects on the economy in many different ways.

One view, pioneered by Nordhaus and Boyer (2000) and Nordhaus (2008), thinks of climate change akin to a tax on output. When output is high, pollution and the costs of climate change are also high. In this view, the main source of uncertainty about the future of climate is the future path of the economy. If the economy does well, pollution and climate change damages will be high; if the economy deteriorates, pollution and damages will be low. Investments in climate change abatement are thus risky, as they pay off in states of the world in which the economy is already doing well.

The alternative view follows Weitzman (2012, 2014): climate change is a disaster-type risk that, if it materializes, causes output to drop (see also Barro, 2013; Lemoine, 2015; Wagner and Weitzman, 2015). In this "disaster" interpretation, climate change itself represents the main source of uncertainty, and is itself a source of aggregate risk for the economy. Alternatively, this "disaster" view of climate change can also represent the case in which uncertainty about the future path of the economy (and not uncertainty about the climate per se) is the dominant source of uncertainty, but nonlinearities in the feedback from the economy to climate change are so pronounced that sufficiently high economic expansion might ultimately lead to a disaster (if a tipping point is reached). In these cases, investments in climate change abatement are then hedges that reduce aggregate risk, because they pay off when consumption is low (after a climate disaster materializes).

Our own calibrated model is a special case of this "disaster" view of climate change. However, our framework is general enougth to nest both of these views and to shed light on the very different implications they have for the appropriate discount rates for investments in climate change abatement. To highlight this, equation 17 presents a generalized version of the dynamics of climate damages (equation 16 in our calibrated baseline specification):

$$\Delta q_{t+1} = \mu_q - \pi_q y_t + \eta_q J_{t+1}. \tag{17}$$

Different parameters of the model primitives under either the "tax view" or the "disaster view" map into different values of μ_q, π_q, and η_q in this general specification. For example, by setting $\pi_q = 1$ and $\eta_q = \eta$, we recover our benchmark specification in equation 16. To illustrate the discounting implications of the two different views, we compute the implied term structure of discount rates for a benchmark investment in climate change abatement that provides partial insurance. We assume the investment's payoff process to follow $\Delta q_{t+1}/10$, thus hedging 10% of the innovation in climate change damages.

The Basic "Disaster" View of Climate Change. Our framework can be made consistent with the core of Weitzman's original argument if we set the probability of a climate disaster to be constant ($\lambda_t = \bar{\lambda}$), remove the mean reversion in the economy ($x_t = y_t = 0$), and set $\pi_q = 0$ and $\eta_q = \eta$ in equation 17. The climate-change-damages process then follows:

$$\Delta q_{t+1} = \mu_q + \eta J_{t+1}. \tag{18}$$

Figure 9 reports the term structure of discount rates for the climate-change-abatement investment described above in this Weitzman-type model (lowest solid line). We can see that the original Weitzman logic implies discount rates that are low, indeed lower than the risk-free rate, but also invariant across horizons. This invariance across horizons clearly conflicts with our evidence on horizon-dependent term structures of discount rates for assets exposed to climate risk (such as housing).

Relative to this original Weitzman view, our model adds two features that allow us to capture richer dynamics in climate change damages and to match the empirically-observed horizon-dependent term structure of discount rates: mean reversion (adaptation) in the economy, and climate risk that depends endogenously on the growth rate of the economy as well as the occurrence of climate shocks. To illustrate, if we re-introduce mean reversion as in our benchmark calibration into this Weitzman economy, the climate-change-abatement investment starts to pay off whenever a climate disaster occurs (captured by the term ηJ_{t+1}), and continues to pay off at a declining rate in future periods (captured by the term $-\pi_q y_t$), reflecting higher economic growth due to adaptation. The lowest dashed line in Figure 9 indeed replicates our baseline results from Figure 7 and confirms that the discount rates for this investment are below the risk-free rate at all horizons, but increase with the horizon.

The Basic "Tax" View of Climate Change. We can also use our framework to explore the "tax" view of climate change elaborated on most prominently by Nordhaus. For exposition, we start by considering a simplified environment in which the tax rate that climate change imposes on the economy is constant, and the fundamental source of uncertainty stems from shocks to the economy. Such a setup corresponds to a linear damage function in the DICE model. The payoff to an investment in climate change abatement is then equivalent to the tax revenue from the climate tax, which can be captured by setting $Q_t = \tau D_t$, where τ is the climate tax rate. We keep all other processes in our economy unchanged, but remove the mean reversion ($x_t = y_t = 0$) to stay within the neoclassical-growth-model spirit of Nordhaus' DICE model.[22] Since the tax is constant, the payoff to climate-change-abatement investments behaves exactly like output. In particular, we can parameterize equation 17 by setting $\mu_q = \mu_d$, $\pi_q = 0$, and $\eta_q = -\eta$. The process for damages from climate change then becomes:

$$\Delta q_{t+1} = \Delta d_{t+1} = \mu_d - \eta J_{t+1}. \tag{19}$$

It follows immediately that investments in climate-change abatement in this setting are *risky*, since their payoff is positively correlated with consumption (see also Gollier, 2013). This is reflected by the negative loading on J_{t+1} in the above equation ($\eta_q = -\eta$). Note that this loading is positive in the corresponding equation for the "disaster" view (equa-

[22] In Weitzman's work, and in our benchmark model, the shocks J_{t+1} are a direct manifestation of climate change disasters and we parametrized them accordingly. In Nordhaus' work, climate change is a tax on the economy and the shocks J_{t+1} are to be interpreted as not directly related to climate change (e.g., they may capture shocks to productivity instead). We focus on showing how the views of Nordhaus and Weitzman can be mapped into our model and highlight their starkly different predictions for discount rates here. Since the difference in predictions is stark in a qualitative sense already (i.e., different signs of the covariance of climate risk with consumption), we thought it best not to recalibrate shocks when analyzing the implications of Nordhaus' view in our framework.

tion 18); these different loadings are at the core of the starkly different predictions that these two views offer for discounting investments in climate change abatement. Indeed, Figure 9 shows that in the "tax" view (in which shocks to the economy are the fundamental source of uncertainty and the relationship between production and climate change is not very nonlinear), discount rates are high, above the risk-free rate, and invariant across horizons (solid black line). The first implication, high discount rates, is a key characteristic of the "tax"-view of climate change. The second implication, a flat term-structure, derives from our assumption of a constant tax rate.

A richer model in the spirit of Nordhaus (2008) allows for the tax rate to increase with economic activity, such that damages are disproportionally higher when the output of the economy is higher. Yet, the nonlinearities are not sufficiently strong to actually imply *lower* consumption in paths of high economic growth compared with path of low economic growth (as in the tipping point literature captured by the "disaster" view). We capture the essence of this argument by assuming that tax proceeds follow $Q_t = \tau_{t-1} D_{g,t}$, where τ_{t-1} increases when output is high as specified below. We obtain that:

$$D_t = D_{g,t}(1 - \tau_{t-1}), \tag{20}$$

where $D_{g,t}$ are rents in the absence of climate damages, which we refer to as gross rents, and D_t are net rents. We assume that gross rents follow $\Delta d_{g,t+1} = \mu_d - \eta J_{t+1}$ as before. Net of the climate tax, rents then follow:

$$\Delta d_{t+1} = \Delta d_{g,t+1} + [\ln(1 - \tau_t) - \ln(1 - \tau_{t-1})] = \Delta d_{g,t+1} + y_t, \tag{21}$$

where $y_t = [\ln(1 - \tau_t) - \ln(1 - \tau_{t-1})]$ follows the same process as specified in equation 9.[23] As we can see, this richer Nordhaus view still implies an output process that can (approximately) be nested in equation 8 of our baseline model; the only difference lies in the interpretation of some of these processes. Note that this setup now also generates mean reversion in cash flows. However, while mean reversion in cash flows comes from adaptation to climate events in our baseline model, mean reversion is mechanically induced by the increasing schedule of the climate-change tax rate (τ) with respect to the level of economic activity in the present setup. As we will see, this leads to starkly different implications for discount rates.

Climate-change damages in this setup are given by: $\Delta q_{t+1} = \Delta d_{g,t+1} + [\ln \tau_t - \ln \tau_{t-1}]$. These damages are similar to those in the simpler Nordhaus setup in equation 19, but now

[23] That is, we are implicitly defining the tax rate to follows the process $[\ln(1 - \tau_{t+1}) - \ln(1 - \tau_t)] - [\ln(1 - \tau_t) - \ln(1 - \tau_{t-1})] = \mu_y + \omega\{[\ln(1 - \tau_{t1}) - \ln(1 - \tau_{t-1})] - [\ln(1 - \tau_{t-1}) - \ln(1 - \tau_{t-2})]\} + \psi J_{t+1}$.

include an extra term, $[\ln \tau_t - \ln \tau_{t-1}]$, that derives from time variation in the climate tax rate. To preserve the linearity and tractability of our model, we capture these damages in approximate form:[24]

$$\Delta q_{t+1} = \Delta d_{g,t+1} + [\ln \tau_t - \ln \tau_{t-1}] \approx \Delta d_{g,t+1} - k y_t = \mu_d - k y_t - \eta J_{t+1}. \tag{22}$$

The above process is now a special case of equation 17, in which $\mu_q = \mu_d$, $\pi_q = k$, and $\eta_q = -\eta$. As in the simpler constant-tax version of the Nordhaus view discussed above, investments in climate change abatement are risky (their payoffs are still positively correlated with output, $\eta_q = -\eta$). However, as shown in Figure 9, the increasing tax rate (captured by $-k y_t$) now induces discount rates for climate-change-abatement investments not only to be high (above the risk-free rate), but also to be increasing with the horizon (dashed black line). Intuitively, when the economy does badly, expected climate damages are persistently low, thus making long-term investments in climate-change abatement even riskier than short-term investments.

2.4 Key Take-Aways

The evidence in Section 1 uncovered a downward-sloping term structure of discount rates for real estate, an asset that has substantial exposure to both consumption risk and climate risk. The general equilibrium model developed in this section is able to match this downward-sloping term structure of discount rates by leveraging a simple mechanism: mean reversion in cash flows as the economy adapts after a climate disaster. The implication of this mean reversion is declining risk exposures of higher-maturity cash flows, since a climate disaster that strikes today has larger effects on immediate cash flows than on distant cash flows.

While much is still unknown about the dynamics of climate change and its impacts on the economy, the seminal work by Nordhaus, Weitzman, Gollier and others has substantially advanced our understanding of these issues. Our empirical and structural analysis contributes to this line of work, furthers our understanding of existing models, and provides new challenges for the next generation of climate change economics models.

Our modeling exercise has allowed us to establish a number of simple yet powerful results on appropriate discount rates for investments in climate change abatement that hedge disaster-type climate risks: (i) that these discount rates are *bounded above* by the

[24] We use the approximation $\ln \tau_t - \ln \tau_{t-1} \approx -k y_t$ and choose $k = \frac{1-\bar{\tau}}{\bar{\tau}}$. Recall that $y_t = \ln(1-\tau_t) - \ln(1-\tau_{t-1}) \approx \frac{\tau_{t-1}-\tau_t}{1-\tau_{t-1}}$, so that: $\ln \tau_t - \ln \tau_{t-1} \approx \frac{\tau_t - \tau_{t-1}}{\tau_{t-1}} = -y_t \frac{1-\tau_{t-1}}{\tau_{t-1}}$. Since we do not want the loading on y_t to be time varying, we set $k = \frac{1-\bar{\tau}}{\bar{\tau}}$, where $\bar{\tau}$ is the steady state tax rate.

risk-free rate, (ii) that for horizons at which we do not observe estimates of the risk-free rate, the estimated long-run discount rates for housing provide a relatively tight bound, and (iii) that the upward-sloping nature of discount rates for investments in climate change abatement means that this bound gets tighter as the horizon lengthens. In addition, our calibrated model—which generates a term structure of discount rates at all horizons—can be used to value actual climate change mitigation investments.

We also show how our model implications on discount rates for climate-change-abatement investments improve upon and differ from two key views of climate change economics: the "tax" view of Nordhaus and Boyer (2000) and Nordhaus (2008), and the "disaster view" of Weitzman (2012, 2014). In particular, while appropriate discount rates in our model are *low and bounded above* by the risk-free rate as in Weitzman-type settings, they are also *upward-sloping* and increasing towards the risk-free rate upper bound with horizon. This mirrors our empirical findings on the downward-sloping term structure of discount rates for risky real estate and reflects the investment's nature as a hedge. In Nordhaus-type settings by contrast, discount rates are *above* the risk-free rate, and on top of that also *increasing away* from the risk-free rate as the horizon increases when damages are a convex function of output.

3 Conclusion

In this paper, we showed how discount rates estimated from private markets, such as the housing market, can be informative about appropriate discount rates for investments in climate change abatement. While much is still unknown about the dynamics of climate change and its impacts on the economy, the seminal work by Nordhaus, Weitzman, Gollier and others has substantially advanced our understanding of these issues. Our empirical and structural analysis contributes to this line of work, furthers our understanding of existing models, and provides new challenges for the next generation of models hoping to capture the interaction of climate change, asset markets, and the economy.

References

Alley, Richard B, Jochem Marotzke, William D Nordhaus, Jonathan T Overpeck, Dorothy M Peteet, Roger A Pielke, Raymond T Pierrehumbert, Peter B Rhines, Thomas F Stocker, Lynne D Talley, et al. 2003. "Abrupt climate change." *Science*, 299(5615): 2005–2010.

Ambrose, Brent W., Piet Eichholtz, and Thies Lindenthal. 2013. "House Prices and Fundamentals: 355 Years of Evidence." *Journal of Money, Credit and Banking*, 45(2-3): 477–491.

Arrow, Kenneth, Maureen Cropper, Christian Gollier, Ben Groom, Geoffrey Heal, Richard Newell, William Nordhaus, Robert Pindyck, William Pizer, Paul Portney, et al. 2013. "How Should Benefits and Costs Be Discounted in an Intergenerational Context? The Views of an Expert Panel." *Resources for the Future Discussion Paper No. 12-53*.

Atreya, Ajita, and Susana Ferreira. 2015. "Seeing is believing? Evidence from property prices in inundated areas." *Risk Analysis*, 35(5): 828–848.

Bakkensen, Laura A, and Lint Barrage. 2017. "Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics: Going Under Water?" National Bureau of Economic Research.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis. 2020. "Does climate change affect real estate prices? Only if you believe in it." *The Review of Financial Studies*, 33(3): 1256–1295.

Bansal, Ravi, and Amir Yaron. 2004. "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles." *Journal of Finance*, 59(4): 1481–1509.

Bansal, Ravi, Dana Kiku, and Marcelo Ochoa. 2013. "Climate Change, Growth, and Risk."

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro. 2016. "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century." *Journal of Political Economy*, 124(1): 105–159.

Barro, Robert J. 2006. "Rare Disasters and Asset Markets in the Twentieth Century." *Quarterly Journal of Economics*, 121(3): 823–866.

Barro, Robert J. 2013. "Environmental Protection, Rare Disasters, and Discount Rates." National Bureau of Economic Research Working Paper 19258.

Barro, Robert J., and Jose F. Ursua. 2008. "Macroeconomic Crises since 1870." *Brookings Papers on Economic Activity*, 39(1): 255–350.

Barro, Robert J, and Tao Jin. 2011. "On the size distribution of macroeconomic disasters." *Econometrica*, 79(5): 1567–1589.

Belo, Frederico, Pierre Collin-Dufresne, and Robert S Goldstein. 2015. "Dividend dynamics and the term structure of dividend strips." *The Journal of Finance*, 70(3): 1115–1160.

Bernstein, Asaf, Matthew T Gustafson, and Ryan Lewis. 2019. "Disaster on the horizon: The price effect of sea level rise." *Journal of financial economics*, 134(2): 253–272.

Binsbergen, Jules van, Michael Brandt, and Ralph Koijen. 2012. "On the Timing and Pricing of Dividends." *American Economic Review*, 102(4): 1596–1618.

Bordo, Michael, Barry Eichengreen, Daniela Klingebiel, and Maria Soledad Martinez-Peria. 2001. "Is the Crisis Problem Growing More Severe?" *Economic Policy*, 16(32): 51–82.

Brohé, Arnaud, and Michael Greenstone. 2007. "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather." *The American Economic Review*, 97(1): 354–385.

Bureau of Economic Analysis. 2017. "Concepts and Methods of the U.S. National Income and Product Accounts."

Burke, Marshall, and Kyle Emerick. 2016. "Adaptation to climate change: Evidence from US agriculture." *American Economic Journal: Economic Policy*, 8(3): 106–40.

Cai, Yongyang, Kenneth L. Judd, and Thomas S. Lontzek. 2013. "The Social Cost of Stochastic and Irreversible Climate Change." *NBER Working Paper*, 18704.

Campbell, Sean D, Morris A Davis, Joshua Gallin, and Robert F Martin. 2009. "What Moves Housing Markets: A Variance Decomposition of the Rent–Price Ratio." *Journal of Urban Economics*, 66(2): 90–102.

Chambers, David, Christophe Spaenjers, and Eva Steiner. 2019. "The rate of return on real estate: Long-run micro-level evidence." *Available at SSRN 3407236*.

Constantinides, George M, and Darrell Duffie. 1996. "Asset pricing with heterogeneous consumers." *Journal of Political economy*, 104(2): 219–240.

Cox, Peter M, Richard A Betts, Chris D Jones, Steven A Spall, and Ian J Totterdell. 2000. "Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model." *Nature*, 408(6809): 184–187.

Cropper, Maureen L., Mark C. Freeman, Ben Groom, and William A. Pizer. 2014. "Declining Discount Rates." *American Economic Review*, 104(5): 538–43.

Crost, Benjamin, and Christian P. Traeger. 2014. "Optimal CO2 Mitigation Under Damage Risk Valuation." *Nature Climate Change*.

Deschênes, Olivier, and Michael Greenstone. 2011. "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US." *American Economic Journal: Applied Economics*, 3(4): 152–185.

Desmet, Klaus, and Esteban Rossi-Hansberg. 2015. "On the Spatial Economic Impact of Global Warming." *Journal of Urban Economics*, 88: 16 – 37.

Drupp, Moritz A., Mark Freeman, Ben Groom, and Frikk Nesje. 2015. "Discounting Disentangled: An Expert Survey on the Determinants of the Long-Term Social Discount Rate." *Centre for Climate Change Economics and Policy Working Paper No. 195*.

Eichholtz, Piet, Eva Steiner, and Erkan Yönder. 2019. "Where, When, and How Do Sophisticated Investors Respond to Flood Risk?" *Available at SSRN 3206257*.

Eichholtz, Piet, Matthijs Korevaar, Thies Lindenthal, and Ronan Tallec. 2020. "The total return and risk to residential real estate." *Available at SSRN 3549278*.

Engle, Robert F, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel. 2020. "Hedging climate change news." *The Review of Financial Studies*, 33(3): 1184–1216.

Farmer, J. Doyne, John Geanakoplos, Jaume Masoliver, Miquel Montero, and Josep Perelló. 2015. "Value of the Future: Discounting in Random Environments." *Physical Review E*, 91: 052816.

Favilukis, Jack, Sydney C Ludvigson, and Stijn Van Nieuwerburgh. 2017. "The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium." *Journal of Political Economy*, 125(1): 140–223.

Flavin, Marjorie, and Takashi Yamashita. 2002. "Owner-Occupied Housing and the Composition of the Household Portfolio." *American Economic Review*, 92(1): 345–362.

Franklin, Sergio L, and Robert S Pindyck. 2017. "Tropical Forests, Tipping Points, and the Social Cost of Deforestation." National Bureau of Economic Research.

Garnache, Cloé, and Todd Guilfoos. 2019. "A city on fire? effect of salience on risk perceptions." working paper.

Gibson, Matthew, Jamie T Mullins, and Alison Hill. 2017. "Climate change, flood risk, and property values: Evidence from New York City." Working Paper.

Giglio, Stefano, Bryan T Kelly, and Johannes Stroebel. 2020. "Climate Finance." *NBER Working Paper*, , (w28226).

Giglio, Stefano, Matteo Maggiori, and Johannes Stroebel. 2015. "Very Long-Run Discount Rates." *The Quarterly Journal of Economics*, 130(1): 1–53.

Giglio, Stefano, Matteo Maggiori, and Johannes Stroebel. 2016. "No-bubble condition: Model-free tests in housing markets." *Econometrica*, 84(3): 1047–1091.

Gollier, Christian. 2013. "Evaluation of Long-Dated Investments Under Uncertain Growth Trend, Volatility and Catastrophes." Toulouse School of Economics TSE Working Papers 12-361.

Gourio, François. 2008. "Disasters and recoveries." *The American Economic Review*, 98(2): 68–73.

Greenstone, Michael, Elizabeth Kopits, and Ann Wolverton. 2013. "Developing a Social

Cost of Carbon for US Regulatory Analysis: A Methodology and Interpretation." *Review of Environmental Economics and Policy*, 7(1): 23–46.

Hallstrom, Daniel G, and V Kerry Smith. 2005. "Market responses to hurricanes." *Journal of Environmental Economics and Management*, 50(3): 541–561.

Harding, John P, Stuart S Rosenthal, and CF Sirmans. 2007. "Depreciation of Housing Capital, Maintenance, and House Price Inflation: Estimates From a Repeat Sales Model." *Journal of Urban Economics*, 61(2): 193–217.

Hasler, Michael, and Roberto Marfe. 2016. "Disaster recovery and the term structure of dividend strips." *Journal of Financial Economics*, 122(1): 116–134.

Huynh, Thanh, and Ying Xia. 2020. "Climate Change News Risk and Corporate Bond Returns." *Journal of Financial and Quantitative Analysis, forthcoming*.

Jordà, Òscar, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan M. Taylor. 2017. "The Rate of Return on Everything, 1870-2015." *Working Paper*.

Jorda, Oscar, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan M Taylor. 2019. "The rate of return on everything, 1870–2015." *The Quarterly Journal of Economics*, 134(3): 1225–1298.

Kaplow, Louis, Elisabeth Moyer, and David A. Weisbach. 2010. "The Social Evaluation of Intergenerational Policies and Its Application to Integrated Assessment Models of Climate Change." *The B.E. Journal of Economic Analysis & Policy*, 10(2).

Kurlat, Pablo, and Johannes Stroebel. 2015. "Testing for information asymmetries in real estate markets." *The Review of Financial Studies*, 28(8): 2429–2461.

Lemoine, Derek. 2015. "The Climate Risk Premium." *Available at SSRN 2560031*.

Lemoine, Derek, and Christian P. Traeger. 2014. "Watch Your Step: Optimal Policy in a Tipping Climate." *American Economic Journal: Economic Policy*, 6(1): 137–166.

Lenton, Timothy M, Hermann Held, Elmar Kriegler, Jim W Hall, Wolfgang Lucht, Stefan Rahmstorf, and Hans Joachim Schellnhuber. 2008. "Tipping elements in the Earth's climate system." *Proceedings of the national Academy of Sciences*, 105(6): 1786–1793.

Lettau, Martin, and Jessica A. Wachter. 2011. "The Term Structures of Equity and Interest Rates." *Journal of Financial Economics*, 101(1): 90–113.

Lucas, Robert E, Jr. 1978. "Asset Prices in an Exchange Economy." *Econometrica*, 46(6): 1429–45.

Lustig, Hanno N., and Stijn van Nieuwerburgh. 2005. "Housing Collateral, Consumption Insurance, and Risk Premia: An Empirical Perspective." *Journal of Finance*, 60(3): 1167–1219.

Mack, Adrienne, and Enrique Martínez-García. 2011. "A Cross-Country Quarterly Database of Real House Prices: A Methodological Note." Federal Reserve Bank of Dallas Globalization and Monetary Policy Working Paper 99.

McCoy, Shawn J, and Randall P Walsh. 2018. "Wildfire risk, salience & housing demand." *Journal of Environmental Economics and Management*, 91: 203–228.

McKenzie, Russell, and John Levendis. 2010. "Flood hazards and urban housing markets: The effects of Katrina on New Orleans." *The Journal of Real Estate Finance and Economics*, 40(1): 62–76.

Melillo, Jerry M, Serita D Frey, Kristen M DeAngelis, William J Werner, Michael J Bernard, FP Bowles, Grace Pold, MA Knorr, and AS Grandy. 2017. "Long-term pattern and magnitude of soil carbon feedback to the climate system in a warming world." *Science*, 358(6359): 101–105.

Nakamura, Emi, Jón Steinsson, Robert Barro, and José Ursúa. 2013. "Crises and Recoveries in an Empirical Model of Consumption Disasters." *American Economic Journal: Macroeconomics*, 5(3): 35–74.

Nordhaus, William D. 2008. *A Question of Balance: Weighing the Options on Global Warming Policies.* Yale University Press.

Nordhaus, William D. 2013. *The Climate Casino: Risk, Uncertainty, and Economics for a Warming World.* Yale University Press.

Nordhaus, William D., and Joseph Boyer. 2000. *Warming the World: Economic Models of Global Warming.* MIT press.

Ortega, Francesc, and Suleyman Taspinar. 2018. "Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market." *Journal of Urban Economics*, 106: 81–100.

Overpeck, Jonathan T, and Julia E Cole. 2006. "Abrupt change in Earth's climate system." *Annu. Rev. Environ. Resour.*, 31: 1–31.

Painter, Marcus. 2020. "An inconvenient cost: The effects of climate change on municipal bonds." *Journal of Financial Economics*, 135(2): 468–482.

Piazzesi, Monika, Martin Schneider, and Selale Tuzel. 2007. "Housing, Consumption and Asset Pricing." *Journal of Financial Economics*, 83(3): 531–569.

Piketty, Thomas, and Gabriel Zucman. 2014. "Capital is Back: Wealth-Income Ratios in Rich Countries 1700-2010." *The Quarterly Journal of Economics*, 129(3): 1255–1310.

Reinhart, Carmen M., and Kenneth S. Rogoff. 2009. *This Time is Different: Eight Centuries of Financial Folly.* Princeton University Press.

Schneider, Maik T., Christian P. Traeger, and Ralph Winkler. 2012. "Trading Off Generations: Equity, Discounting, and Climate Change." *European Economic Review*, 56(8): 1621 – 1644.

Schularick, Moritz, and Alan M. Taylor. 2012. "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises." *American Economic Review*, 102(2): 1029–1061.

Shiller, Robert J. 2006. "Long-Term Perspectives on the Current Boom in Home Prices." *The Economists' Voice*, 3(4): 1–11.

Stern, Nicholas. 2006. *Stern Review on the Economics of Climate Change.* London, UK:Her Majesty's Treasury.

Stroebel, Johannes. 2016. "Asymmetric information about collateral values." *The Journal of Finance*, 71(3): 1071–1112.

Traeger, Christian P. 2014. "Why Uncertainty Matters: Discounting Under Intertemporal Risk Aversion and Ambiguity." *Economic Theory*, 56(3): 627–664.

Van Binsbergen, Jules H, and Ralph SJ Koijen. 2017. "The term structure of returns: Facts and theory." *Journal of Financial Economics*, 124(1): 1–21.

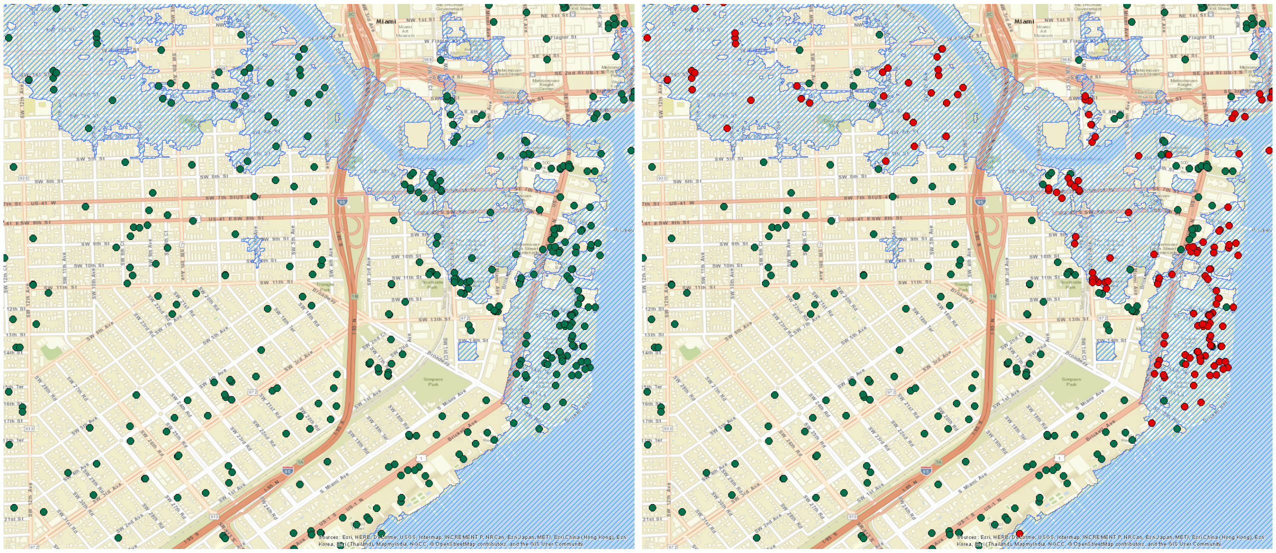
Wagner, Gernot, and Martin L. Weitzman. 2015. *Climate Shock: The Economic Consequences of a Hotter Planet.* Princeton, NJ:Princeton University Press.

Weisbach, David, and Cass R. Sunstein. 2009. "Climate Change and Discounting the Future: A Guide for the Perplexed." *Yale Law & Policy Review*, 27(2): 433 – 457.

Weitzman, Martin L. 2012. "Rare Disasters, Tail-Hedged Investments, and Risk-Adjusted Discount Rates." National Bureau of Economic Research Working Paper 18496.

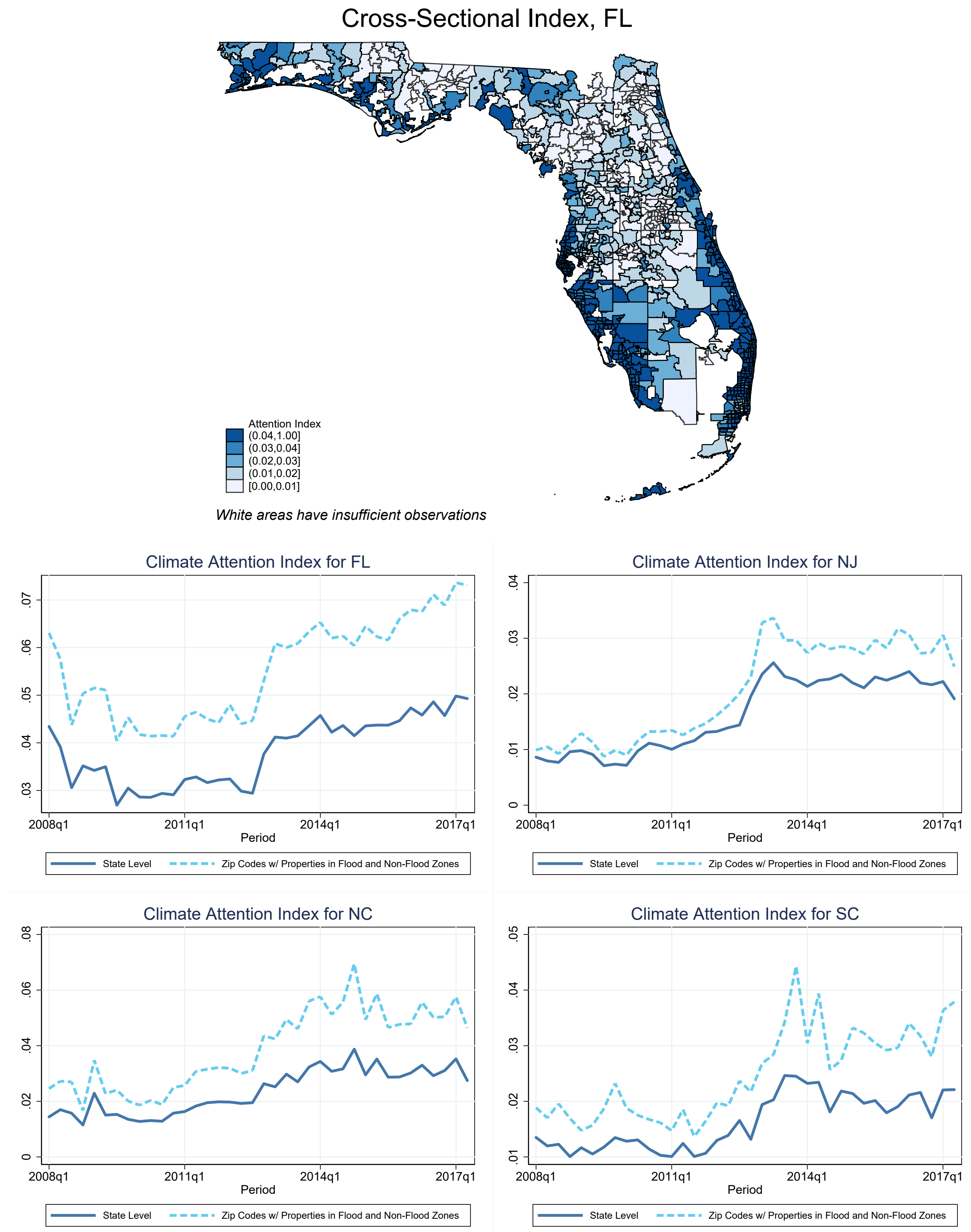
Weitzman, Martin L. 2014. "Fat tails and the social cost of carbon." *The American Economic Review*, 104(5): 544–546.

Figure 1: Illustration of Identifying Properties in the Flood Zone



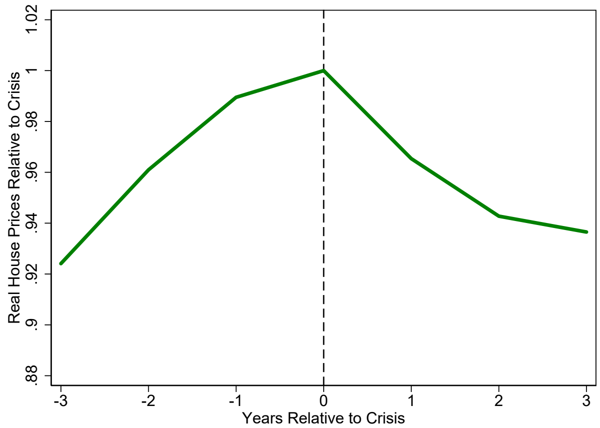
Note: Figure illustrates how we identify properties in the flood zone of downtown Miami, Florida. On the left, we plot each property as a green dot and overlay the NOAA's flood map. Then, on the right, we geocode to identify the properties that fall under the flood zone and color them as red dots. As seen above, as properties are closer to the coastal line, they are more likely to be in the flood zone.

Figure 2: Climate Attention Index in the Cross-Section and Time-Series

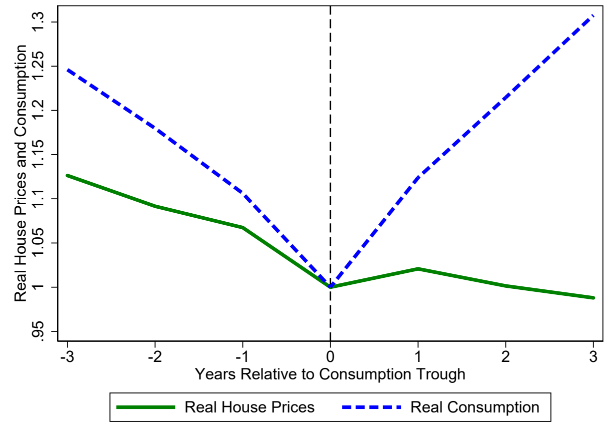


Note: The top panel shows a heatmap of our Climate Attention Index in Florida at the zip code level. The Climate Attention Index is defined as the fraction of for-sale listings whose description includes climate-related text for the period from 2008Q1 to 2017Q2. The other panels illustrate the quarterly time series of the Climate Attention Index aggregated at the state level as well as for zip codes that include at least some both properties in the Flood Zone.

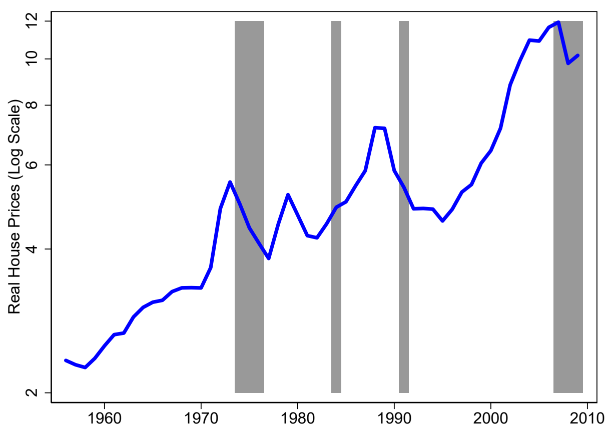
Figure 3: House Price Riskiness



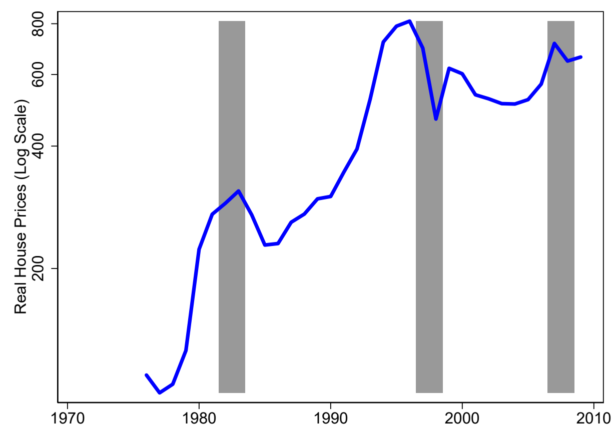
(A) Financial Crises



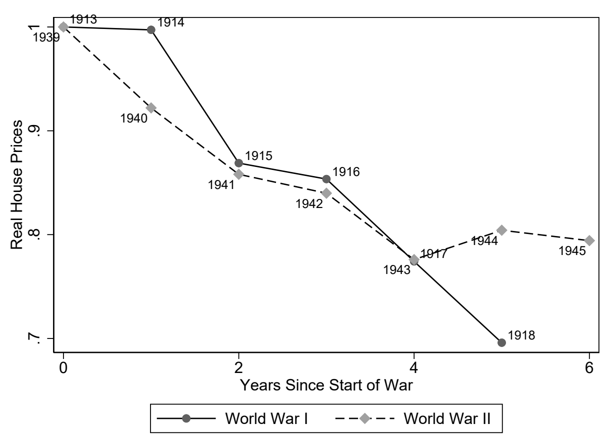
(B) Consumption Disasters



(C) House Prices: U.K.



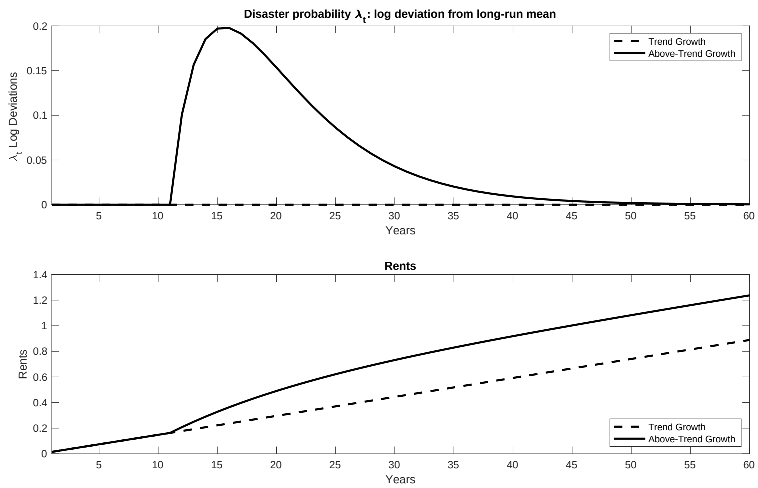
(D) House Prices: Singapore



(E) House Prices During World Wars

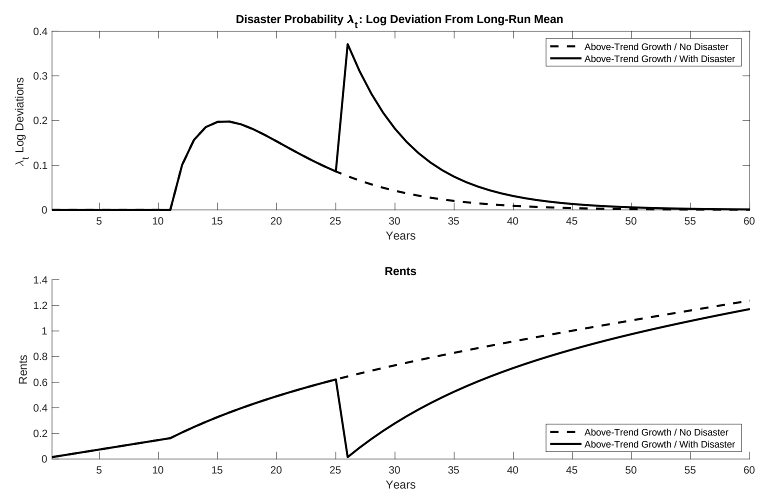
Note: Panel A shows average real house price movements relative to financial crises. Panel B shows average real house price movements and average real consumption relative to the trough of consumption disasters. Panels C and D show the evolution of real house prices in the U.K. and Singapore, respectively. Shaded regions are financial crises. Panel E shows the evolution of real house prices for countries with available house-price time series during World War I and World War II. See Appendix A.3.1 for a description of the data series.

Figure 4: Sample Paths: Trend Growth and Above-Trend Growth



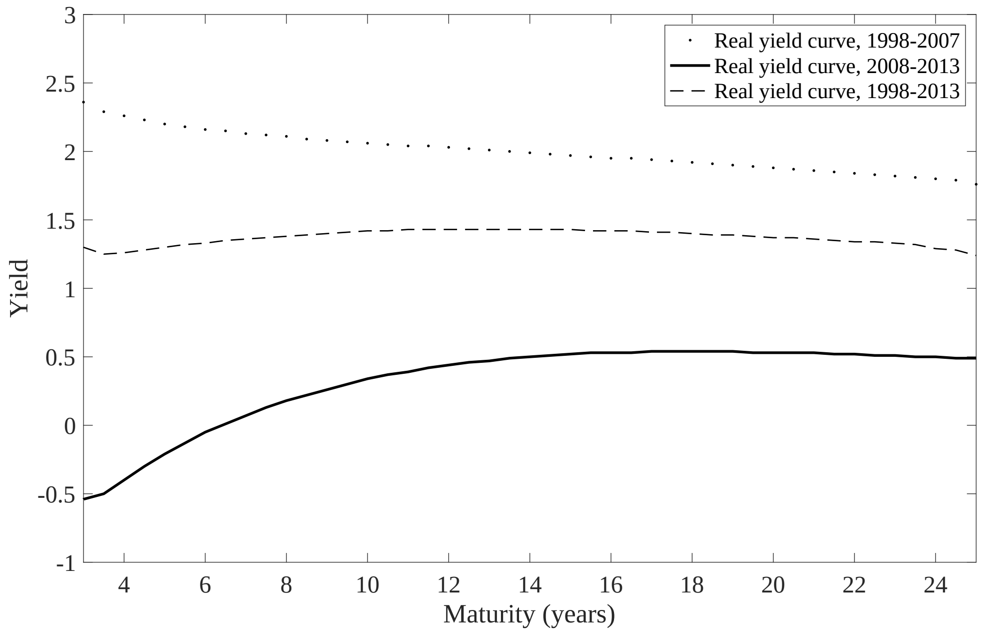
Note: The figure shows two sample paths of the economy under our baseline calibration. The top panel reports the log deviation of the climate disaster probability λ_t from its mean. The bottom panel reports the path of log rents d_t. The dotted line represents the baseline path in which the economy grows at its deterministic trend. The solid line represents a temporary deviation from trend in which growth accelerates.

Figure 5: Sample Paths: Above-Trend Growth, With and Without a Disaster



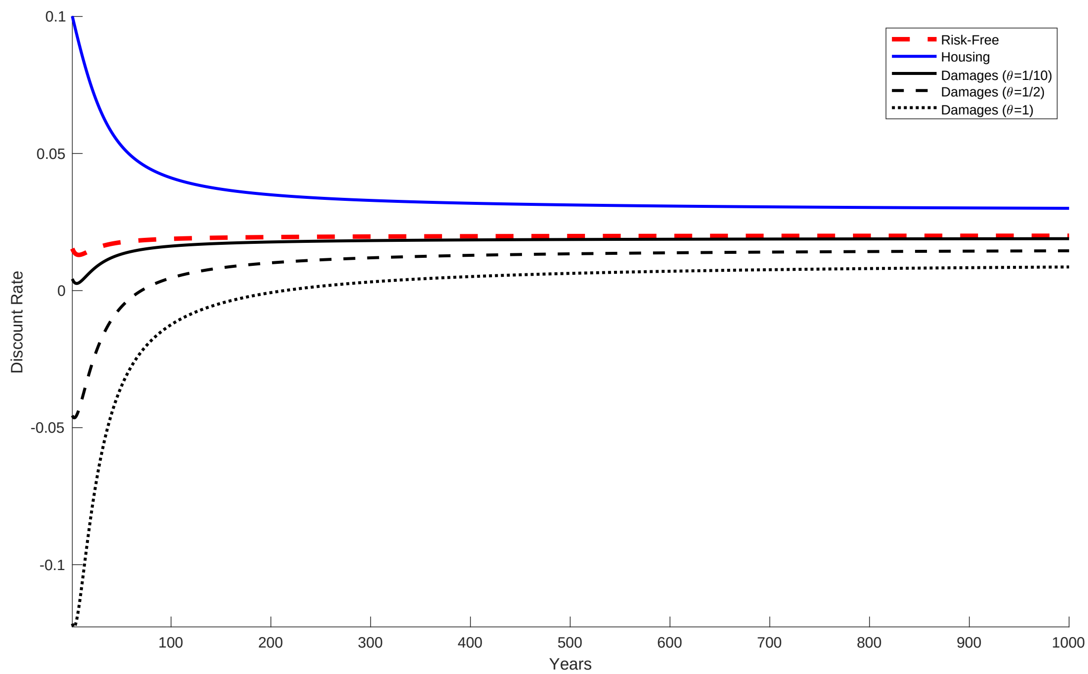
Note: The figure shows two sample paths of the economy under our baseline calibration. The top panel reports the log deviation of the climate disaster probability λ_t from its mean. The bottom panel reports the path of log rents d_t. The dotted line represents a path in which the economy grows at its deterministic trend, then experiences an increase in growth (the same as the solid line in Figure 4). The solid line represents an alternative path in which the increased probability of disasters due to the temporary acceleration in the economy leads to the occurrence of a disaster after year 25.

Figure 6: U.K. Gilts Real Yield Curve



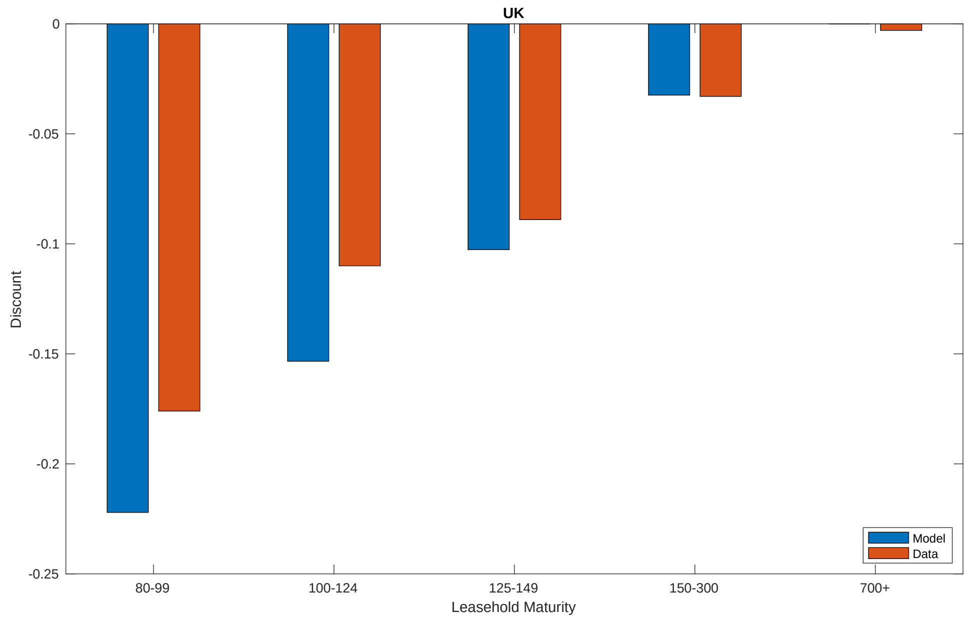
Note: The figure plots the real yield curve for U.K. gilts as computed by the Bank of England for the period 1998-2016, as well as for two sub-periods: 1998-2007 and 2008-2016. It is available at `http://www.bankofengland.co.uk/statistics/Pages/yieldcurve/archive.aspx`, last accessed July 2017. Until 2015, the U.K. government debt also included some perpetual bonds: the War Loans and the Annuities. These bonds comprised a negligible part of the outstanding U.K. government debt (£2.6bn out of £1.5trn of debt outstanding), and were classified as small and illiquid issuances by the U.K. Debt and Management Office. In 2015, following the passage of the Finance Act, all outstanding perpetuities were called in by the British government. They are excluded from our analysis, not only because they are nominal and we only use data on U.K. real gilts, but also because their negligible size, scarce liquidity, and callability make it hard to interpret their prices in terms of discount rates.

Figure 7: Discount Rates for Risk-Free Bonds, Housing, Damages

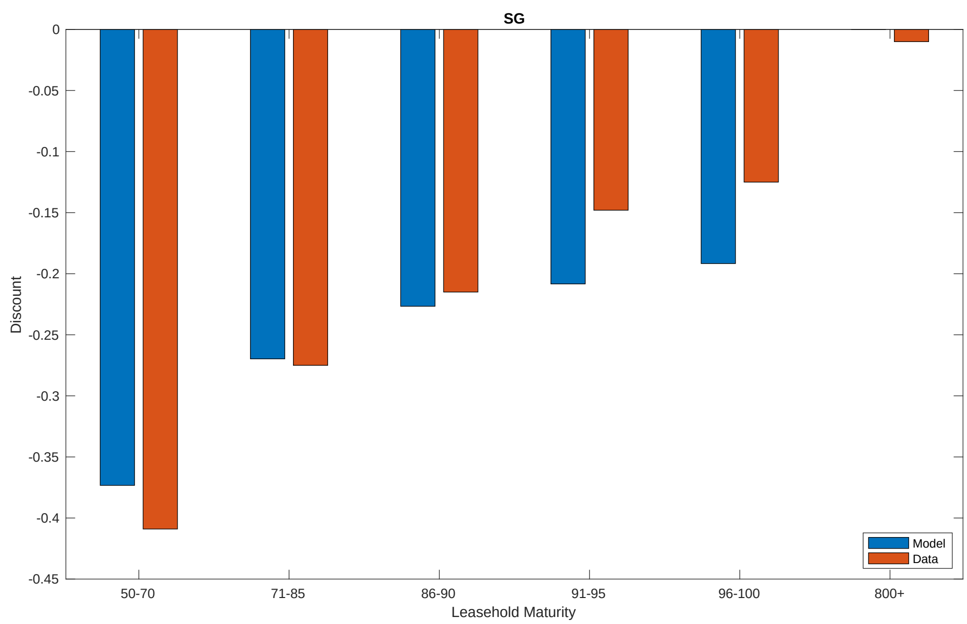


Note: The figure shows the per-period discount rate corresponding to different assets for maturities 1 to 1000 years, in our baseline model calibration. The top line represents the term structure of discount rates for the risky housing asset. The dashed line below it represents the real risk-free asset, that is, the real yield curve. The three black lines in the bottom represent different calibrations of the damage process with $\theta \in \{1, 0.5, 0.1\}$.

Figure 8: Leasehold Discounts



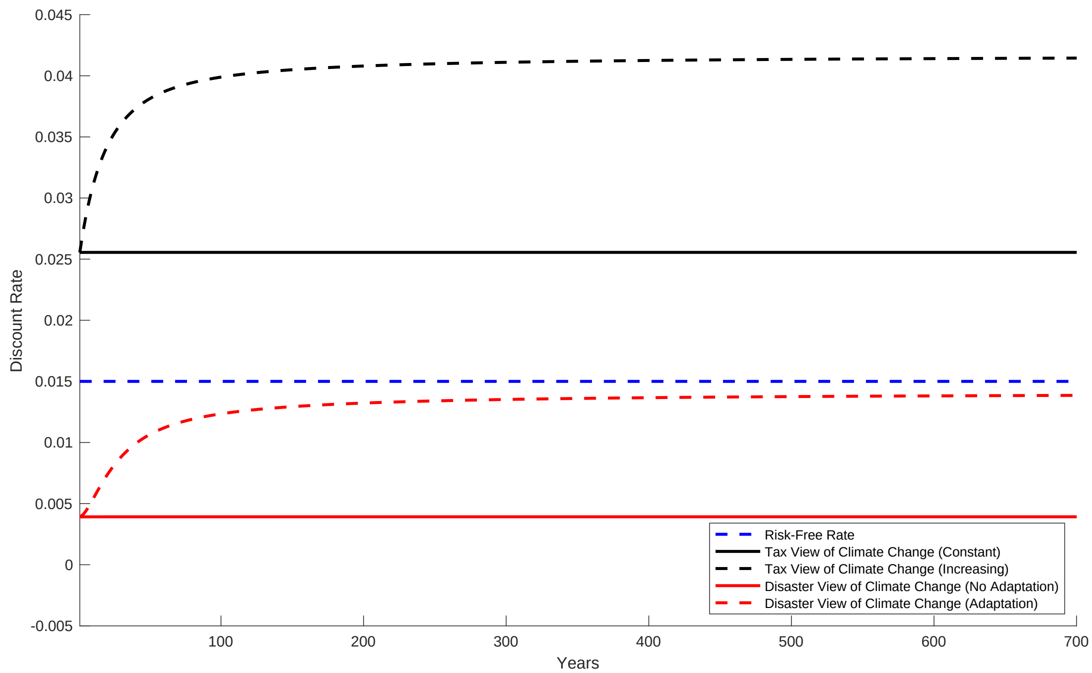
(A) Leasehold Discounts in the U.K.



(B) Leasehold Discounts in Singapore

Note: The figure shows the discount rates for housing assets predicted by the model (left bars) and in the data (right bars), for the U.K. (left panel) and Singapore (right panel). The discounts are estimated from a hedonic regression and reported in log points.

Figure 9: Leading Models of Climate Change: Predictions for Discount Rates



Note: The figure shows the per-period discount rate appropriate for climate-change-abatement investments under different models of climate change damages. In all these models, climate damages follow the process $\Delta q = \mu_q - \pi_q y_t + \eta_q J_{t+1}$; the discount rates in the figure correspond to those applied to an investment whose payoff is $\Delta q/10$. The "constant tax view" of climate change views damages as a constant fraction of output, so that $\mu_q = \mu_d$, $\eta_q = -\eta$, and $\pi_q = 0$. The "increasing tax view" views damages as a fraction of output that increases in good times, so that $\mu_q = \mu_d$, $\eta_q = -\eta$, and $\pi_q = k$. The "disaster view" with no mean-reversion views climate change damages as inducing a drop in output, so that $\mu_q = 0$, $\eta_q = \eta$, and $\pi_q = 0$. Finally, the "disaster view" with mean reversion corresponds to our baseline case, with $\mu_q = 0$, $\eta_q = \eta$, and $\pi_q = 1$.

Table 1: Transaction Prices vs. Rent Prices: Hedonic Analysis

	Panel A. Transaction Prices Dependent Variable: log(Transaction Prices)					
	(1)	(2)	(3)	(4)	(5)	(6)
Flood Zone	0.004 (0.015)	0.014 (0.013)			0.085*** (0.006)	
log(Index by Zip-Year) × Flood Zone	-0.024*** (0.005)		-0.029** (0.010)			
log(Index by Zip-Quarter) × Flood Zone		-0.020*** (0.004)		-0.021** (0.007)		
Index by Zip-Quarter × Flood Zone					-0.210** (0.071)	-0.367*** (0.091)
Property Controls	✓	✓	.	.	✓	.
Zip × Quarter FE	✓	✓	✓	✓	✓	✓
Property FE	.	.	✓	✓	.	✓
R-squared	0.585	0.585	0.721	0.721	0.585	0.721
N	7,287,000	7,233,113	3,485,238	3,443,265	7,233,113	3,443,265

	Panel B. Rent Prices Dependent Variable: log(Rent Prices)					
	(1)	(2)	(3)	(4)	(5)	(6)
Flood Zone	0.041*** (0.012)	0.033** (0.011)			-0.034*** (0.006)	
log(Index by Zip-Year) × Flood Zone	0.018*** (0.004)		0.005 (0.005)			
log(Index by Zip-Quarter) × Flood Zone		0.015*** (0.004)		0.003 (0.003)		
Index by Zip-Quarter × Flood Zone					0.415*** (0.072)	0.016 (0.042)
Property Controls	✓	✓	.	.	✓	.
Zip × Quarter FE	✓	✓	✓	✓	✓	✓
Property FE	.	.	✓	✓	.	✓
R-squared	0.728	0.728	0.942	0.942	0.728	0.942
N	2,142,433	2,142,240	1,191,657	1,191,642	2,142,240	1,191,642

Note: Table shows results from regression 1. The dependent variable is the log of the transaction price in Panel A and the log of the rental listing price in Panel B. In column 1, 2, and 5, we control for various property characteristics such as the property size, property age, and the number of bedrooms. In column 3, 4, and 6, we include property fixed effects. The Flood Zone indicator and the property controls are naturally dropped in these regressions due to perfect multicollinearity. Index by Zip-Year and Index by Zip-Quarter represent the fraction of listings whose description includes climate-related texts at the zip code-year level and the zip code-quarter level, respectively. Standard errors are clustered at the zip code-quarter level and in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2: Real House Price Growth and Real Consumption Growth

	Period	Real HP Growth		Real Cons. Growth			
		Mean	Std. Dev.	Mean	Std. Dev.	Correlation	Cons. beta
Australia	1901-2009	2.51%	12.1%	1.51%	4.99%	0.102	0.248
Belgium	1975-2009	2.92%	6.06%	1.59%	1.51%	0.439	1.761
Canada	1975-2009	2.38%	7.69%	1.61%	1.73%	0.433	1.929
Denmark	1975-2009	1.99%	9.24%	0.98%	2.71%	0.538	1.838
Finland	1975-2009	2.17%	8.70%	2.07%	2.79%	0.710	2.214
France	1840-2009	2.06%	11.8%	1.49%	6.32%	-0.054	-0.101
Germany	1975-2009	-0.45%	2.33%	1.64%	1.52%	0.494	0.755
Italy	1975-2009	1.28%	8.10%	1.75%	2.18%	0.165	0.614
Japan	1975-2009	0.02%	4.45%	1.97%	1.60%	0.503	1.394
Netherlands	1814-2009	2.79%	20.8%	1.57%	7.49%	0.078	0.215
New Zealand	1975-2009	2.46%	8.09%	1.00%	2.30%	0.580	2.044
Norway	1830-2009	1.77%	11.6%	1.78%	3.83%	0.243	0.737
Singapore	1975-2009	7.18%	19.5%	3.43%	4.03%	0.348	1.685
South Africa	1975-2009	1.13%	10.1%	0.92%	3.02%	0.707	2.365
South Korea	1975-2009	0.58%	7.93%	4.62%	4.49%	0.370	0.652
Spain	1975-2009	3.14%	8.07%	1.56%	2.60%	0.593	1.837
Sweden	1952-2009	1.55%	6.04%	1.63%	1.99%	0.536	1.627
Switzerland	1937-2009	0.47%	7.17%	1.48%	3.82%	0.187	0.350
U.K.	1952-2009	2.89%	9.55%	2.26%	2.11%	0.700	3.169
U.S.	1890-2009	0.49%	7.36%	1.84%	3.41%	0.148	0.320

Note: The table shows time series properties of annual growth rates of real house prices (as described in Appendix A.3.1) and real consumption, as collected by Barro and Ursua (2008). Column 1 shows the sample considered. Columns 2 and 3 show the mean and standard deviation of real house price growth. Columns 4 and 5 show the mean and standard deviation of real consumption growth. Column 6 shows the correlation of real house price growth and real consumption growth. Column 7 shows the consumption beta of house prices.

Table 3: Real House Price Growth and Personal Disposable Income Growth

	Real HP Growth		Real PDI Growth			
	Mean	Std. Dev.	Mean	Std. Dev.	Correlation	PDI beta
Australia	3.54%	6.67%	1.37%	2.10%	0.156	0.495
Belgium	2.53%	5.50%	0.92%	2.30%	0.431	1.031
Canada	2.91%	7.49%	1.35%	2.18%	0.466	1.604
Switzerland	1.12%	4.58%	1.17%	1.53%	0.425	1.275
Germany	0.07%	2.52%	1.28%	1.64%	0.237	0.365
Denmark	1.73%	8.58%	1.13%	2.29%	0.224	0.839
Spain	-0.09%	10.6%	0.81%	2.27%	0.409	1.909
Finland	1.90%	7.71%	1.92%	2.97%	0.470	1.219
France	2.28%	5.13%	1.12%	1.61%	0.332	1.056
U.K.	3.47%	8.49%	2.05%	2.26%	0.420	1.575
Ireland	3.36%	9.44%	1.89%	3.33%	0.574	1.627
Italy	0.33%	8.15%	0.89%	2.48%	0.363	1.195
Japan	-0.39%	4.24%	1.49%	1.44%	0.622	1.835
South Korea	0.64%	7.36%	3.97%	4.38%	0.245	0.412
Luxembourg	4.16%	6.40%	2.76%	3.63%	0.067	0.117
Netherlands	2.31%	9.12%	0.74%	3.01%	0.467	1.414
Norway	2.65%	6.92%	2.22%	2.05%	0.037	0.126
New Zealand	2.90%	7.73%	1.13%	3.41%	0.486	1.103
Sweden	2.00%	7.01%	1.40%	2.39%	0.467	1.371
U.S.	1.36%	3.88%	1.59%	1.54%	0.322	0.812
South Africa	0.49%	9.13%	0.34%	2.37%	0.474	1.824
Croatia	1.16%	12.3%	8.79%	27.0%	-0.345	-0.158
Israel	3.05%	8.83%	2.74%	7.37%	0.129	0.155

Note: This table shows time series properties of quarterly frequency annual growth rates of real house prices and personal disposable income between 1975 and 2016, as collected by Mack and Martínez-García (2011). Columns 1 and 2 show the mean and standard deviation of real house price growth. Columns 3 and 4 the mean and standard deviation of real personal disposable income growth. Column 5 shows the correlation of real house price growth with real personal disposable income growth. Column 6 shows the personal disposable income beta of house prices.

Table 4: Expected Returns and Rental Growth

	United States										United Kingdom					Singapore
	Price/Rent					Balance Sheet					Price/Rent		Balance Sheet			Price/Rent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Gross Return	10.2%	9.7%	8.9%	9.4%	10.0%	9.7%	9.3%	9.1%	8.9%	8.7%	9.5%	9.6%	10.2%	9.9%	9.7%	9.9%
Rental Yield	9.5%	8.9%	8.1%	8.9%	9.0%	7.1%	7.1%	7.0%	7.0%	7.0%	6.8%	6.9%	7.0%	6.9%	6.9%	5.6%
Capital Gain	0.8%	0.8%	0.8%	0.5%	1.0%	2.7%	2.3%	2.1%	1.8%	1.6%	2.7%	2.7%	3.3%	3.0%	2.8%	4.2%
Depreciation	2.5%	2.5%	2.5%	2.5%	2.5%	2.3%	2.3%	2.3%	2.3%	2.3%	2.5%	2.5%	2.4%	2.4%	2.4%	2.5%
Taxes	0.67%	0.67%	0.67%	0.67%	0.67%	1.1%	1.1%	1.1%	1.1%	1.1%	0%	0%	0%	0%	0%	0.6%
Net Return	**7.1%**	**6.5%**	**5.7%**	**6.3%**	**6.8%**	**6.3%**	**5.9%**	**5.7%**	**5.5%**	**5.2%**	**7.0%**	**7.1%**	**7.9%**	**7.6%**	**7.4%**	**6.8%**
Rent Growth	0.7%	0.7%	0.7%	0.7%	0.9%	-	-	-	-	-	1.4%	1.4%	-	-	-	-0.4%
Baseline-P/R	Trulia	Trulia$^-$	Bal	Trulia$^-$	Trulia$^-$	-	-	-	-	-	Bracke	Bal	-	-	-	iProp
Price Index	CS	CS	CS	FHFA	CS	-	-	-	-	-	LR	LR	-	-	-	URA
Rent Index	CPI-S	CPI-S	CPI-S	CPI-S	PCE-H	-	-	-	-	-	CPIH	CPIH	-	-	-	URA
Stock Adj.	-	-	-	-	-	Pop	Units	Floor	Reval	QI	-	-	Pop	Units	QI	-
Sample	1953-2016										1988-2016					1990-2016

Note: This table shows our estimates for net real returns to housing and real rent growth in the U.S., the U.K., and Singapore based on the price-rent approach and the balance-sheet approach. The *price-rent approach* starts from a price-rent ratio estimated in a baseline year and constructs a time series of returns by combining a house price index and a rental price index. Baseline-P/R is the source of the baseline price-rent ratio – either a direct estimate or based on the balance-sheet approach (Bal). In the U.S., Trulia$^-$ includes an adjustment for utilities possibly included in Trulia's gross rents. CS is the Case-Shiller house price index, FHFA is the FHFA house price index, CPI-S is the shelter component of the CPI, and PCE-H is the housing component of the PCE price index. In the U.K., LR stands for Land Registry, and CPIH is the housing component of the consumer price index including housing. In Singapore, iProp stands for iProperty.com, and URA stands for Urban Redevelopment Authority. In the *balance-sheet approach*, the total value of the residential housing stock is used to estimate the value of housing, and net capital income earned on the housing stock is used to estimate net rents. To estimate the return on a representative property, changes in the total housing stock are controlled for by the growth in population (Pop), housing units (Units), housing floor space (Floor), or quality-adjusted quantity indexes (QI). The U.S. Financial Accounts also publish aggregate holding gains for each sector in the economy in the revaluation accounts (Reval), which directly hold the aggregate stock of housing constant. See Appendix A.4 for further details on the estimation procedures and the underlying data sources used. Numbers may not add up due to rounding.

"Climate Change and Long-Run Discount Rates: Evidence from Real Estate"

Online Appendix

Stefano Giglio Matteo Maggiori Krishna Rao Johannes Stroebel Andreas Weber

A.1 Discounting: The Role of Risk and Horizon

How should policymakers decide whether a particular investment in climate change abatement is worth pursuing? A common approach is to conduct a cost-benefit analysis to determine the societal net present value (NPV) of an investment project that is costly *today* and provides a stream of potentially uncertain *future* benefits (cash flows), with positive NPVs indicating socially beneficial projects. Discount rates play a central role in determining NPVs, since even small changes in discount rates can dramatically alter the NPVs of investments with long horizons (see e.g., Arrow et al., 2013; Dietz, Gollier and Kessler, 2015; Dreze and Stern, 1987; Moyer et al., 2014).

In this section, we review the basic theoretical concepts for our empirical and structural analysis in Sections 2. Section A.1.1 describes how the appropriate rate for discounting a particular cash flow depends on both the riskiness and the maturity of that cash flow. Section A.1.2 highlights what this implies for learning about the appropriate discount rates for climate change policies from observable assets that pay cash flows with different riskiness and maturity. The main body of the paper uses insights from the term structure of discount rates for one particular asset, real estate, to guide the choice of appropriate discount rates for investments in climate change abatement.

To introduce our basic notation, let us represent an investment at time t as a claim to a stream of future benefits (cash flows), D_{t+k}, $k = 1, 2..., n$, where n is the final maturity of the cash flows. For example, an investment to avoid one ton of CO_2 emissions today provides benefits in terms of mitigated climate change in each future period for hundreds of years. Each of these benefits, D_{t+k}, is stochastic and depends on the state of the world at time $t + k$. For example, the future benefits of reducing CO_2 emissions today could depend on how much the economy grows in the future. We denote the state of the world at time $t + k$ as $\omega_{t+k} \in \Omega_{t+k}$ and stress the dependence of benefits on its stochastic realization with the notation $D_{t+k}(\omega_{t+k})$. The set Ω_{t+k} includes all possible states of the world at time $t + k$, which can differ along many dimensions, including the health of the aggregate economy and the degree of environmental damage. In what follows, we will sometimes refer to general assets with maturity n that could pay cash flows such as dividends or rents at any point in time up to their maturity; these will simply be referred to with superscript n. A subset of these assets is the set of claims to a single cash flow at a specific point in time, maturity n; we will refer to these with superscript (n).

A.1.1 The Value of a Single-Cash-Flow Investment

We begin our analysis by studying the value of an investment that pays only one cash flow, at a specific point in time: t+n. This cash flow is not predetermined: it might be different in different states of the world, $\omega_{t+n} \in \Omega_{t+n}$. We denote the present value of the claim to this benefit as $P_t^{(n)}$. A classic tenet of asset pricing is that, under the relatively mild assumptions of no arbitrage and the law of one price, $P_t^{(n)}$ can be expressed as the weighted expected value of that cash flow across scenarios ω_{t+n}, where a benefit paid in each scenario is weighted by the importance investors assign to benefits in that state (see Hansen and Richard (1987), and Cochrane (2005) for a textbook treatment). Let $M_{t,t+n}(\omega_{t+n}) > 0$ denote the value that investors attach at time t to benefits in state ω_{t+n}. An asset is considered more *risky* if it pays off primarily in states of the world in which investors value that payoff less. If investors value benefits paid out earlier more than benefits paid out later, the weighting $M_{t,t+n}$ will also adjust for this time discounting. We can then write the value of an investment that yields D_{t+n} as:

$$P_t^{(n)} = \sum_{\omega_{t+n} \in \Omega_{t+n}} M_{t,t+n}(\omega_{t+n}) D_{t+n}(\omega_{t+n}) \pi_{t,t+n}(\omega_{t+n}) = E_t \left[M_{t,t+n} D_{t+n} \right], \tag{A.1}$$

where $\pi_{t,t+n}(\omega_{t+n})$ is the conditional probability of state ω_{t+n}. The object $M_{t,t+n}$ is called the *stochastic discount factor* (SDF). In economic terms, the SDF reflects the marginal utility of a payoff in different states of the world. The value of the asset thus reflects both the physical properties of the asset (when and how much it pays in each state ω_{t+n}) and the preferences of investors (how much they value payoffs in each scenario ω_{t+n}).

An equivalent representation of $P_t^{(n)}$, which is more prevalent in policy analysis, is in terms of *discount rates*. The time and risk adjustments are then expressed using a per-period discount rate $\bar{r}_t^n$:

$$P_t^{(n)} = E_t \left[M_{t,t+n} D_{t+n} \right] = \frac{E_t \left[D_{t+n} \right]}{(1 + \bar{r}_t^n)^n}. \tag{A.2}$$

Put differently, we can think of prices as the expected value of the cash flow discounted at a per-period discount rate $\bar{r}_t^n$. The appropriate discount rate will differ across investments depending on which states of the world an investment pays benefits in, and the relative valuation of benefits across states of the world: more risky investments are valued less, and thus discounted at higher per-period discount rates.

A.1.2 The Importance of Horizon-Specific Risk Adjustments

We now consider a multi-period-payoff investment project that pays stochastic benefits at different points in time up to maturity n. Any such asset can be thought of as the combination of many single cash-flow assets, each paying at specific points in time, $t+1, t+2, ..., t+n$. Therefore, the value of a multi-period-payoff investment project is the sum of the values of the individual single-period-payoff projects:

$$P_t^n = P_t^{(1)} + P_t^{(2)} + ... + P_t^{(n)}$$

Since the two representations discussed above for the one-period case also apply to the multi-period case, the value P_t^n can be written as:

$$\begin{aligned} P_t^n &= E_t\left[M_{t,t+1}D_{t+1} + M_{t,t+2}D_{t+2} + ... + M_{t,t+n}D_{t+n}\right] && \text{(A.3)} \\ &= \frac{E_t\left[D_{t+1}\right]}{1+\bar{r}_t^1} + \frac{E_t\left[D_{t+2}\right]}{(1+\bar{r}_t^2)^2} + ... + \frac{E_t\left[D_{t+n}\right]}{(1+\bar{r}_t^n)^n}. && \text{(A.4)} \end{aligned}$$

These two representations differ from the valuation formula that is often applied in cost-benefit analyses, which discounts each cash flow at the *same* per-period discount rate $\bar{r}_t$:

$$P_t^n = \frac{E_t\left[D_{t+1}\right]}{1+\bar{r}_t} + \frac{E_t\left[D_{t+2}\right]}{(1+\bar{r}_t)^2} + ... + \frac{E_t\left[D_{t+n}\right]}{(1+\bar{r}_t)^n}. \tag{A.5}$$

Representations A.3 and A.4 are always correct and equivalent; the last one is *only* correct if the discount rate $\bar{r}_t$ is chosen to match the risk and maturity of a particular asset. Therefore, $\bar{r}_t$ can only be applied to value the benefits of a project with exactly the same risk characteristics and exactly the same maturity as the asset from which $\bar{r}_t$ was derived in the first place. For the purpose of discounting the benefits of a project with different characteristics, the full term structure of discount rates $\bar{r}_t^1, \bar{r}_t^2, ..., \bar{r}_t^n$ needs to be known and appropriately adjusted for differences in risk characteristics. We highlight the importance of this by considering the valuation of three different investment projects below: A project with the same risk and payoff horizon as those of an observed traded asset (whose average per-period discount rate is $\bar{r}_t$); a project with the same risk properties but a different payoff horizon; and a project with different risk properties but the same payoff horizon.

Case 1: Same Risk, Same Horizon. Consider first an observable asset with maturity n and stochastic cash flows D_{t+1}, D_{t+2},..., D_{t+n} (if the asset has infinite maturity as in the case of the stock market, then $n = \infty$). Imagine we are able to observe the average discount rate of this asset, $\bar{r}_t$. Put differently, given an asset with maturity n and some risk profile, $\bar{r}_t$ is defined as the constant discount rate consistent with the asset's price. Now consider the case in which an investment in climate change abatement pays cash flows $\tilde{D}_{t+1}, ..., \tilde{D}_{t+n}$ that are different from the cash flows of the observed asset, but have the same risk characteristics (i.e., the same dependence on the state of the world ω_{t+n}). This is the only case in which cash flows from climate change abatement can be discounted at the *same* average rate as those from the observable asset. The value of the climate change investment, C_t^n, will be:

$$C_t^n = \frac{E_t\left[\tilde{D}_{t+1}\right]}{1+\bar{r}_t} + \frac{E_t\left[\tilde{D}_{t+2}\right]}{(1+\bar{r}_t)^2} + ... + \frac{E_t\left[\tilde{D}_{t+n}\right]}{(1+\bar{r}_t)^n}.$$

Case 2: Same Risk, Different Horizon. Since the risk preferences captured by $M_{t,t+k}$ potentially depend on the horizon, using average discount rates from one asset to discount cash flows from another investment is no longer valid if those cash flows materialize over different horizons. Take our example from above and assume that the asset's cash flows have the same riskiness as the cash flows from the investment in climate change abatement at each horizon. Assume further that the observable asset yields benefits in every period between time t and time $t+n$, while the investment in climate change abatement only yields benefits after maturity $\underline{n} > 1$. Since the riskiness of the cash flows of both investments is the same, one may be tempted to use the observed average discount rate $\bar{r}_t$ from the observable asset to discount climate change project cash flows. This turns out to be incorrect, however. The correct price is obtained as below:

$$C_t^{(\underline{n},n)} = \frac{E_t\left[\tilde{D}_{t+\underline{n}}\right]}{(1+\bar{r}_t^{\underline{n}})^{\underline{n}}} + \frac{E_t\left[\tilde{D}_{t+\underline{n}+1}\right]}{(1+\bar{r}_t^{\underline{n}+1})^{\underline{n}+1}} + ... + \frac{E_t\left[\tilde{D}_{t+n}\right]}{(1+\bar{r}_t^{n})^{n}},$$

where each dividend is discounted at the horizon-specific discount rate, $\bar{r}_t^{\underline{n}}, \bar{r}_t^{\underline{n}+1}, ..., \bar{r}_t^{n}$. Since $\bar{r}_t$ was obtained as the discount rate that applies to the observable asset, it reflects an average of *all* the horizon-specific discount rates $\bar{r}_t^1, \bar{r}_t^2, ..., \bar{r}_t^n$, including the ones for maturities up to $\underline{n}-1$. Since the climate change project does not accrue benefits at those horizons, its value should not depend on the discount rates between $t+1$ and $\underline{n}-1$.

To see this more clearly, suppose that investors are only worried about the states of the world in which the relatively near cash flows are being paid out (horizons 1 to $\underline{n} - 1$), while they are not worried about risks for horizons higher than $\underline{n}$: for long maturities, investors only care about the expected payout from the asset, not the state of the world, in which it is paid out. They will discount the short-term cash flows at high rates, $\bar{r}_t^1, \bar{r}_t^2, ..., \bar{r}_t^{\underline{n}-1}$, but the longer-maturity cash flows at lower rates, $\bar{r}_t^{\underline{n}}, \bar{r}_t^{\underline{n}+1}, ..., \bar{r}_t^{n}$, reflecting their risk-neutrality at those horizons. The term structure of discount rates for this particular asset is thus downward-sloping. The claim to all cash flows may have a relatively high implied average discount rate, in particular if many of the cash flows accrue before $\underline{n}$. At the same time, if the benefits from a climate change investment had the same risk properties, but only accrued after $\underline{n}$, the correct present value for such an investment should *only* depend on the low discount rates $\bar{r}_t^{\underline{n}}, \bar{r}_t^{\underline{n}+1}, ..., \bar{r}_t^{n}$. It would thus be higher than under the relatively high *average* discount rate $\bar{r}_t$.

Case 3: Different Risk, Same Horizon. Beyond the timing of cash flows, a second potentially important difference between an observed asset's discount rates and those that apply to some investment project is the relative riskiness of the payoffs *at the same horizon*. As outlined before, riskiness here refers to whether an asset mostly pays in states of the world ω_{t+k} where payments are least valuable for the investor. Consider our example from above again. Assume that the asset as well as the climate change investment project only pay a single cash flow in period $t+n$. Further assume that the observed asset's cash flow is riskier than the investment's cash flow: for example, equities generally pay off in states of the world where the economy is doing well, while investments that mitigate the impact of climate disasters would pay off in states of the world where the economy is not doing well. The discount rate implied by the observable price of the asset will then be different from the appropriate discount rate for the investment project.

For concreteness, assume that there are only two equally likely states of the world – a good one (ω_{t+n}^G) and a bad one (ω_{t+n}^B). Assume that marginal utility in the good state of the world is lower than marginal utility in the bad state of the world, and assume that the observed asset pays out in the good state of the world only, while the investment project only pays out in the bad state of the world; both pay out the same amount if they pay out. This implies that $E_t \left[M_{t,t+n} D_{t+n} \right] < E_t \left[M_{t,t+n} \tilde{D}_{t+n} \right]$. It then follows from equation A.2 that the investment project should be discounted at a lower rate than the asset.

A.2 Estimating the Climate Risk Exposure of Real Estate

In this section, we provide additional information related to our analysis of the climate-risk exposure of real estate in Section 1.1. We first provide additional information on the construction of the "Climate Attention Index" before discussing the hedonic regressions in more detail.

A.2.1 Construction of Climate Attention Index

To construct the Climate Attention Index, we conduct a textual analysis of the descriptions of properties in our for-sale listings data. First, we convert every word to lowercase letters before using the *stopwords* function of the *nltk* Python package to remove prepositions, articles, pronouns, and punctuation marks. We flag the listing of a property as "one" if it contains at least one of the climate-related words or bigrams from Table A.1 and as "zero" if none of them is used. More specifically, for single words, we simply check if any one of them matches with the textual description of the listing. For bigrams, we check whether the combination of two words in different orders matches with the description. For instance, for the bigram *sea level*, we check if either *sea level* or *level sea* appears in the sequence of words of the description as *level of sea* will be stripped of the preposition due to the textual analysis function. We also check whether the names of the deadliest and costliest hurricanes since 2000 appear in the description.

Appendix Tables A.2, A.3, A.4, and A.5 list the most common words indicating attention to climate change in each state. In Florida, the most common term is "hurricane", occurring in about 3.3% of all property listings, while in the other states the most common term is "storm." We next present a number of examples of property listings that would be flagged using our algorithm.

> Example 1: Diamond in the Rough on water with pier and dock! **Owner holds letter of expemption from FEMA, stating high elevation, flood insurance may not be required,** minutes to area beaches, Close to Jacksonville and Wilmington.
>
> Example 2: Adorable home in Archdale situated on 1.43 acres!! Features include vinyl replacement windows, large bonus room perfect for extra bedroom, den or game room, fenced backyard, large outbuilding and two driveways for extra parking room. **Creek is in 500 year flood plain, left side of lot is in 100 year flood plain. House is not in a flood zone to our knowledge. Flood insurance has never been required.**

Example 3: SUPERIOR CONSTRUCTION, UPGRADES GALORE & STUNNING BAY VIEWS SET THIS HOME A PART FROM THE OTHERS! You'll have a hard time finding a higher quality constructed home in Destin. **In addition, because of its construction and location on high & dry ground (17-20 FT ABOVE SEA LEVEL), IT'S HOMEOWNERS INSURANCE & FLOOD INSURANCE COSTS ARE SOME OF THE LOWEST IN THE AREA! ALTHOUGH FLOOD INSURANCE IS NOT REQUIRED (HOME IS IN ZONE X), THIS HOME IS NOT IN THE COBRA ZONE AND IS ONE OF THE FEW BAY FRONT HOMES IN DESTIN ELIGIBLE FOR $348 PER YEAR FEDERAL FLOOD INSURANCE. ALL OF THE HOMES IN KELLY PLANTATION, REGATTA BAY, EMERALD LAKES, EMERALD BAY AND MOST OF DESTINY ARE IN THE COASTAL BARRIER ZONE AND ARE NOT ELIGIBLE FOR FEDERAL FLOOD INSURANCE. This is a huge benefit because private flood insurance for homes in those neighborhoods can cost between $8,000 and $20,000 per year! This home's Insulated Concrete Form (ICF) construction provides superior storm protection,** is resistant to mold & termites, can reduce this home's heating & cooling bills up to 50%, & delivers LOW homeowners insurance.

Example 4: Looking for a family home that's ready to move in and only 6 years old? This 4 bedroom 2 1/2 bath plus office/hobby room is in a great neighborhood in the award-winning Carolina Forest school district and is priced to sell! A new home in 2011, it has a private office area away from the upstairs bedrooms, a fireplace, a screened porch, and even a low HOA with a community pool! Loads of storage space,a 2 car garage, an upstairs laundry room, and an open living area with lots of natural light add to the value of this beauty. All the items in the garage convey- such as lawn mower, freezer, safe, hurricane coverings for windows, edger, etc. **Not in a flood zone, it's high and dry!** Close to Coastal University, Carolina Forest, Tanger outlets,and Hwy 31. A quick back route available using Hwy 544 when Hwy 501 is too busy. Only 15 minutes to the beach. **Not in a flood zone.** Great for a family residence, or a good investment for long term rentals. Come and see!

Example 5: Now selling just 6 lots left EMERALD COAST Yacht Club; **FLOOD ZONE X:** This beautiful neighborhood faces West for the most spectacular sunsets; **21 feet above sea level**; This is a rare find in the Panhandle WOW! **No**

> **Flood insurance this will save you $5-$6000 annually**. Underground utilities on site; All permits for dock had been received however some have expired for dock and 14'x30' Boat Slips. All Neighborhood HOA Documentation will convey with sale. Permits and plans attached. Should HOA members decide to proceed with Dock construction, all funding for permit resubmittals and construction must be agreed to and paid for by HOA members.

Importantly, most of these property listings include descriptions that highlight that a specific property is *less* exposed to climate risk. We believe that this is sensible: if you were selling a property with particular exposure to climate risk, for example because it sits in a flood zone, you would not highlight this negative feature in a property listing. However, if you are selling a house that is *not* exposed to climate risk, this is something worth highlighting in a property listing, in particular in areas and at times when potential buyers pay more attention to these risks.

After identifying all listings that suggest particular attention is paid to climate risks, the Climate Attention Index is then constructed as the share of listings with these climate-related texts at the zip code-quarter and zip code-year level. To explore how this Climate Attention Index varies across regions, Figures A.1, A.2, and A.3 show heatmaps that are similar as that in Panel A of Figure 2. As before, the Climate Attention Index is particularly high in those zip codes near the coast line.

A.2.2 Coefficients on Control Variables in Hedonic Regression

In our main hedonic regression specification, equation 1, we control for a large number of property characteristics that could affect the value of the property. While the coefficients on these characteristics are not of primary interest for our work, in this section we discuss the relationship between each control variable and transaction prices (Appendix Figure A.4) and rental prices (Appendix Figure A.5), controlling for the other hedonic characteristics.

We see a consistently increasing positive impact of a larger finished square footage, lot size, and number of bathrooms on the transaction price and rental price. The effect of the number of bedrooms on transaction values and rental values is an inverted U-shape. This is consistent with our empirical understanding of the real estate market in which, at some point, home buyers prefer having a larger common area to having more bedrooms for the same property size: for most households, having six tiny bedrooms and a small living room is less desirable than having four larger bedrooms and a larger living room. We also observe an increasing negative effect of older remodel ages on prices. For property age, we see an initial negative impact as age increases, but after a certain point property age impacts prices positively. We find it reasonable that people prefer a mid-century house to a house built in the 1990s (especially holding the remodeling age fixed) that is neither new nor old enough for its age to be appealing.

Overall, these relationships are highly consistent with those estimated in the literature (see, e.g., Stroebel, 2016), which highlights the quality of our transaction and property characteristics data.

A.3 Details on the Riskiness of Housing

A.3.1 The Riskiness of Housing – Details on Main Analyses

This section provides the details underlying the analysis carried out in Section 1.3. Section A.3.2 will provide additional evidence for the riskiness of housing.

Table A.7 reports the availability of house price data and the associated financial crises and rare disasters. The first column in Table A.7 shows the time coverage of house price indices for each country. For some countries, we can go far back in time; for example, we sourced data as far back as 1819 for Norway, 1890 for the U.S., and 1840 for France. The second and third column report the dates of any banking crises or rare consumption disasters that occur in each country over the time period provided in the first column. Banking crises dates for all countries, except Singapore, Belgium, Finland, New Zealand, South Korea, and South Africa, are from Schularick and Taylor (2012). Banking crises dates for the countries not covered by Schularick and Taylor (2012) are from Reinhart and Rogoff (2009).[1] Rare disaster dates in the last column indicate the year of the trough in consumption during a consumption disaster as reported by Barro and Ursua (2008).

For each country, we obtained the longest continuous and high-quality time series of house price data available. To make the data comparable across countries and time periods, we focus on real house prices at an annual frequency. Finally, to increase historical comparability across time within each time series, we report each index for the unit of observation, for instance a city, for which the longest possible high quality time series is available. For example, since a house price index for France is only available since 1936, but a similar index is available for Paris since 1840, we focus on the Paris index for the entire history from 1840-2012. We stress, however, that for each index and country we have carried out an extensive comparison with alternative indices, in particular with

[1]For this second set of countries and dates, we have also consulted Bordo et al. (2001), who confirm all dates in Reinhart and Rogoff (2009), except 1985 for South Korea and 1989 for South Africa.

indices available for the most recent time period, in order to ensure that we are observing consistent patterns in the data. In the following, we detail the sources for each of the 20 countries in our sample:

- **Australia**: Real annual house price indices are from Stapledon (2012). For our analysis, we use the arithmetic average of the indices (rebased such that 1880 = 100) for Melbourne and Sydney.

- **Belgium, Canada, Denmark, Finland, Germany, Japan, Italy, New Zealand, South Africa, South Korea, and Spain**: Real annual house price indices are from the Federal Reserve Bank of Dallas.[2] The sources and methodology are described in Mack and Martínez-García (2011).

- **France**: Nominal annual house price index and CPI are available from the Conseil Général de l'Environnement et du Développement Durable (CGEDD).[3] We obtain the real house price index by deflating the nominal index using the CPI. For our analysis, we use the longer time series available for the Paris house price index.

- **Netherlands**: Nominal annual house price index for Amsterdam and CPI for the Netherlands are available from Eichholtz (1997) and Ambrose, Eichholtz and Lindenthal (2013).[4] We obtain the real house price index by deflating the nominal index using the CPI.

- **Norway**: Nominal annual house price index and CPI are from the Norges Bank.[5] We obtain the real house price index by deflating the nominal index using the CPI.

- **Singapore**: Nominal annual house price index for the whole island is from the Urban Redevelopment Authority (`http://www.ura.gov.sg`). CPI is from Statistics Singapore. We obtain the real house price index by deflating the nominal index using the CPI.

- **Sweden**: Nominal house price index for one-or-two-dwelling buildings and CPI are from Statistics Sweden. We obtain the real house price index by deflating the nominal index by CPI.

[2] The data are available at: `http://www.dallasfed.org/institute/houseprice/`, last accessed February 2018.

[3] `http://www.cgedd.developpement-durable.gouv.fr/les-missions-du-cgedd-r206.html`, last accessed February 2014.

[4] Part of the data are available on Eicholtz' website at: `http://www.maastrichtuniversity.nl/web/Main/Sitewide/Content/EichholtzPiet.htm`, last accessed February 2014.

[5] `http://www.norges-bank.no/en/price-stability/historical-monetary-statistics/`, last accessed February 2014.

- **Switzerland**: Nominal house price index for Switzerland is available from Constantinescu and Francke (2013). Among the various indices the authors estimate, we focus on the local linear trend (LLT) index. The data are available for the period 1937-2007. We update the index for the period 2007-2012 by using the percentage growth of the house price index for Switzerland available from the Dallas Fed.[6] The CPI index for Switzerland is from the Office fédéral de la statistique (OFS). We obtain the real house price index by deflating the nominal index using the CPI.

- **U.K.:** Annual nominal house price data are from the Nationwide House Price Index. We divide the nominal index by the U.K. Office of National Statistics "long term indicator of prices of consumer goods and services" to obtain the real house price index. The Nationwide index has a missing value for the year 2005, for that year we impute the value based on the percentage change in value of the house price index produced by the England and Wales Land Registry.

- **U.S.**: Real annual house price data are originally from Shiller (2000). Updated data are available on the author's website.[7]

For all countries, the real annual consumption data are from Barro and Ursua (2008) and available on the authors' website.[8]

Figure 3 is produced by combining the time series of house prices and consumption described in the previous subsection with the dates for banking crises and rare disasters in Table A.7. When taking averages across countries in Panel A of Figure 3 for the 6 year windows around a banking crisis, the following countries have missing observations for the house price series: France data are unavailable for the year 2011 following the 2008 crisis, Netherlands data are unavailable for the years 2010 and 2011 following the 2008 crisis, and South Africa data are unavailable for the year 1974 before the 1977 crises. In these cases, the crises are still included in the sample but the average reported in the figure excludes these missing country-year observations.[9]

A.3.2 The Riskiness of Housing – Additional Evidence

In this section, we provide additional details and evidence for the riskiness of real estate to complement the analysis in Section 1.3.

[6]This source is described in the second bullet point above.

[7]Available at: `http://aida.wss.yale.edu/~shiller/data.htm`, last accessed February 2018.

[8]Available at: `https://scholar.harvard.edu/barro/data_sets`, last accessed February 2018.

[9]In unreported results, we have verified that the result is essentially unchanged if we exclude the 2008 crisis for France and the Netherlands and the 1975 crisis for South Africa from the data.

Figure A.9 plots the growth rates of rents and personal consumption expenditures (PCE) in the U.S. since 1929. In periods of falling PCE, in particular the Great Depression, rents also fell noticeably. The bottom panel shows a (weak) positive relationship between the growth rates of rents and personal consumption expenditures. This suggests that housing rents tend to increase when consumption increases and marginal utility of consumption is low. Figure A.10 indicates that rents in London are positively correlated with house prices in London, but more volatile.

A.4 Details on Average Returns to Residential Real Estate

This section describes the methodology and data used to compute average real returns and rent growth for residential properties for the price-rent approach and for the balance-sheet approach presented in Section 1.3.1.

A.4.1 Details on the Price-Rent Approach

United States. For the U.S., we calculate returns between 1953 and 2016. For consistency with the balance-sheet approach, we use Q4-indices. We follow Favilukis, Ludvigson and Van Nieuwerburgh (2017) and use the house price index from Shiller (2000), which combines data from two sources in its current version: The home purchase component of the U.S. CPI from 1953 to 1975, and the *S&P CoreLogic Case-Shiller Home Price Index* thereafter.[10]

For rent growth, we also follow Favilukis, Ludvigson and Van Nieuwerburgh (2017) and use the shelter index from the BLS (the component of CPI related to shelter, item *CUUR0000SAH1* from the Federal Reserve Bank of St. Louis). However, for the period up until 1985, we substitute for the BLS shelter index with the adjusted rental index from Crone, Nakamura and Voith (2010). We do not use the BLS shelter index up until 1985 for two reasons: First, as documented by Gordon and vanGoethem (2007) and Crone, Nakamura and Voith (2010), there appears to be a significant downward bias in all rental CPIs published by the BLS up until the mid-80s, most likely due to a non-response bias for units that were vacant or where tenants changed. Second, while we are interested in housing as an unlevered asset, mortage interest rates directly affected BLS rental indices until 1982 (see, e.g., Reed, 2014). For the same reasons, we use the *CPI for All Urban Consumers* excluding shelter as our inflation measure before 1986 (item *CUUR0000SA0L2*),

[10] A continuously updated series is published on Shiller's website `http://www.econ.yale.edu/~shiller/data.htm`, last accessed February 2018.

and including shelter (item *CPIAUCNS*) thereafter. The downside of this substitution is that the rental index of Crone, Nakamura and Voith (2010) does not include (imputed) owner-occupied rents, but at least since the BLS shelter index methodology has been updated with regard to the treatment of mortgage interest in the mid-80s, the BLS shelter index and the BLS rent index have tracked each other closely.

Unlike Favilukis, Ludvigson and Van Nieuwerburgh (2017), we choose 2012 as a baseline year for our rent-to-price ratio, which we estimate to be 10%; the choice of the baseline year is motivated by the availability of high-quality data obtained from real estate portal Trulia that allows us to directly estimate rent-to-price ratios for the U.S. Figure A.6 shows the distribution of rent-to-price ratios across the 100 largest MSAs provided by Trulia and Figure A.7 suggests that these rent-to-price ratios are close to their long-run average.[11]

In robustness checks, we use several complementary time series. First, our benchmark rent-to-price ratio from Trulia might include rental properties where some utilities are covered by the monthly rent. Using data from the balance-sheet approach (described in detail in Section A.4.2), the "utilities yield" for water and gas for all residential real estate was 0.6% in 2012. In a robustness check, we therefore reduce our gross rental yield estimate by this amount. Alternatively, we use the 2012 gross rent-to-price ratio implied by our preferred balance sheet approach specification that adjusts for revaluation-implied housing stock growth as discussed in Section A.4.2. This estimate is slightly lower than our Trulia estimate, at 8.6%.

Second, we use the FHFA house price index (formerly OFHEO house price index, item *USSTHPI* from the Federal Reserve Bank of St. Louis) for the period since 1975. The FHFA house price index differs on four main dimensions from the Case-Shiller House Price Index: While the latter is only based on purchase prices, the former also includes refinance appraisals. While the Case-Shiller HPI relies on transaction information obtained from county assessor and recorder offices, the FHFA HPI relies on data from conforming mortgages provided by Fannie Mae and Freddie Mac. Moreover, while the Case-Shiller HPI is value-weighted, the FHFA HPI is equal-weighted. Finally, the FHFA's geograhic coverage includes all U.S. states, while the Case-Shiller HPI does not.[12]

In a third robustness check, we use the BEA price index for personal consumption

[11]We thank Jed Kolko and Trulia for providing these data. Trulia observes a large set of both for-sale and for-rent listings. The rent-to-price ratio is constructed using an MSA-level hedonic regression of $\ln(price)$ on property attributes, zip-code fixed effects, and a dummy for whether the unit is for sale or for rent. The rent-to-price ratio is constructed by taking the exponent of the coefficient on this dummy variable.

[12]For additional details, see `https://www.fhfa.gov/Media/PublicAffairs/Pages/Housing-Price-Index-Frequently-Asked-Questions.aspx#quest11`, last accessed February 2018.

expenditure on housing (*NIPA Table Table 7.4.4. Line 1*) in place of the BLS shelter index for the years since 1985; for internal consistency, we use the BEA price index for personal consumption expenditure to deflate nominal returns (*NIPA Table 2.3.4. Line 1*) instead of the BLS CPI for this time period in this specification. While the BLS price indices are the most widely known inflation measures, the Federal Reserve states its goal for inflation in terms of the PCE price index. Both measures follow similar trends, but differ along four key dimensions: First, CPI weights are based on a survey of what households are buying, while PCE price index weights are based on surveys of what businesses are selling. Second, the CPI only includes out-of-pocket expenditures, while the PCE price index also includes expenditures indirectly paid for, e.g. insurance payments through employer-provided medical insurance. Finally, the PCE price index reflects substitution between goods when relative prices change, while the CPI does not.[13]

We assume a property tax impact of 0.67% for a representative household for the price-rent approach. Property taxes in the U.S. are levied at the state level and, while there is variation across states, are generally around 1% of house prices. Property taxes, however, are deductible from federal income tax. We assume that the deductibility reflects a marginal U.S. federal income tax rate of 33%. The net impact is therefore $(1 - 0.33) * 0.01 = 0.67\%$.

United Kingdom. For the U.K., we calculate returns between 1988 and 2016.[14] For consistency with the balance-sheet approach, we use Q4-indices. We use the house price index from the U.K. Land Registry (series *K02000001*) to compute price appreciation. This new house price index has been introduced in 2016 in an effort to provide a "single definitive House Price Index (HPI)" that replaces the previously and separately published house price indices by the Land Registry and the Office of National Statistics (ONS).[15] It addresses a number of limitations of the previous house price indices, namely: It has increased coverage and is therefore more representative of the overall U.K. housing market, it is less sensitive to extreme prices, and it is internally consistent and therefore fully comparable across time.[16]

[13]For additional details, see `https://www.clevelandfed.org/newsroom-and-events/publications/economic-trends/2014-economic-trends/et-20140417-pce-and-cpi-inflation-whats-the-difference.aspx`, last accessed February 2018.

[14]The data provided by the ONS would allow us to include 1987 as well, but housing returns were extraordinary high in that year – in fact the inclusion of this one year would increase our return estimates by almost a full percentage point. We therefore decided to drop it from our sample.

[15]For more details, see `https://www.ons.gov.uk/economy/inflationandpriceindices/methodologies/developmentofasingleofficialhousepriceindex`, last accessed February 2018.

[16]Overall, growth rates are mostly comparable with the two outdated house price indices from the Land Registry and the ONS. For more details, see

To compute rent growth, we combine three rental indices from the ONS: For the years before 1996, we use the *RPI Component Housing Rent* (series *DOBP*). For the years between 1996 and 2005, we use the *CPI Component Actual Rents for Housing* (series *D7CE*). For the years since 2005, the ONS has included owner-occupied housing into its CPI measures and calls these enriched series CPIH. For this period, we combine the *CPIH Component Actual Rents for Housing* (series *L536*) with the *CPIH Component Owner Occupiers' Costs for Housing* (series *L5P5*) following the methodology outlined by the ONS in its *Consumer Price Indices Technical Manual* ONS (2014). In particular, we calculate weighted arithmetic means using the relevant COICOP weights for the respective current year (series *L5E5, L5PA*) at the monthly level, and average across quarters to get to quarterly indices.[17] We use the *CPI for All Items* for the period before 2005 (series *D7BT*) and the *CPIH for All Items* for the period since 2005 (series *L522*) to adjust for inflation.

For the baseline rent-to-price ratio, we rely on estimates for matched properties that are both sold and rented out within six months in London from Bracke (2015), who finds a median rent-to-price ratio of 5% between 2006 and 2012. In our setting, this translates into a rent-to-price ratio of 5.2% in 2012. Since properties in city centers tend to have lower rent-to-price ratios on average, we consider this a conservative estimate for the average U.K. housing stock. Nevertheless, it is close to the rent-to-price ratio of 5.3% that we estimate using the balance-sheet approach for 2012. Since U.K. rents typically do not cover any utilities (see Bracke, 2015), we do not correct gross rent-to-price ratios for utilities.

Singapore. For Singapore, we calculate returns between 1990 and 2016. For consistency with the U.S. and the U.K., we use Q4-indices. We obtain time series of price and rental indices for the whole island from the Urban Redevelopment Authority (the government's official housing arm: ura.gov.sg). Both series are published by the Department of Statistics Singapore (series *M212261* and *M212311*). We obtain the CPI from the same source (series *M212191*). To estimate the baseline rent-to-price ratio, we use data from for-sale and for-rent listings provided by iProperty.com, Asia's largest online property listing portal in 2012. We observe approximately 105,000 unique listings from 2012, about 46% of which are for-rent listings. To estimate the rent-to-price ratio, we run the following regression, which pools both types of listings. The methodology is similar to the one used to construct

`https://www.ons.gov.uk/economy/inflationandpriceindices/articles/explainingtheimpactofthenewukhousepriceindex/may2016`, last accessed February 2018.

[17] COICOP stands for "Classification of Individual Consumption according to Purpose"; it is a reference published by the U.N. Statistics Division and followed by the ONS that divides individual consumption expenditures into standardized divisions and groups. *Housing, Water, Electricity, Gas and Other Fuels* is Division (04), and *Actual Rentals for Housing* and *Imputed Rentals for Housing* are groups (04.1) and (04.2).

rent-to-price ratios for the U.S. in Figure A.6:

$$\ln\left(ListingPrice\right)_{i,t} = \alpha + \beta_i ForRent_i + \gamma Controls_{i,t} + \epsilon_{i,t} \tag{A.6}$$

The dependent variable, *ListingPrice*, is equal to the list-price in "for-sale" listings, and equal to the annual rent in "for-rent" listings. $ForRent_i$ is an indicator variable that is equal to one if the listing is a for-rent listing. The results are reported in Table A.6. In column 1, we control for postal code by quarter fixed effects. The estimated coefficient on β_i suggests a rent-to-price ratio of $e^{\beta_i} = 4.5\%$. In columns 2–4, we also control for other characteristics of the property, such as the property type, the number of bedrooms, bathrooms as well as the size, age, and the floor of the building. In columns 3 and 4, we tighten fixed effects to the month by postal code level and the month by postal code by number of bedrooms level respectively. In all specifications, the estimated rent-to-price ratio for 2012 is 4.4% or 4.5%.

We calibrate the property tax-impact to be 0.6%. Before 2003, Singapore levied a 10% annual tax on the estimated rental income of the property. A lower tax rate of 4% applied to owner-occupied properties. Starting in 2011 for owner-occupiers and in 2014 for landlords, Singapore has introduced increasingly progressive tax schemes that start at 0% and cap out at 16% for owner-occupiers, and start at 10% and cap out at 20% for landlords since 2015. Even though homeownership rates are around 90% during our sample period (numbers based on series *M810401 - Resident Households By Tenancy* as published by Statistics Singapore on its website `http://www.singstat.gov.sg`), we use the more conservative (higher) rate of 10% for rental properties as it has prevailed for most of our sample period. The tax impact on returns is the tax rate times the average rent-price ratio, estimated at around 6%. Hence, $\tau = 0.1 * 0.06 = 0.6\%$.[18]

A.4.2 Details on the Balance-Sheet Approach

United States. For the U.S., we calculate returns between 1953 and 2016. We focus on owner-occupied housing and tenant-occupied housing in the nonfinancial noncorporate sector, the most representative sectors of the U.S. housing market (both sectors accounted for more than 90% of the value of residential housing on average during our sample period, and for roughly 95% towards the end of our sample period). Our data for the U.S. come from two main sources, the *Financial Accounts of the United States (FAUS)* for

[18]For details, see `https://www.iras.gov.sg/irashome/Property/Property-owners/Working-out-your-taxes/Property-Tax-Rates-and-Sample-Calculations/`, last accessed February 2018.

housing wealth (published by the Federal Reserve Board, FRB), and the *National Income and Product Accounts (NIPA)* for rents (published by the Bureau of Economic Analysis, BEA). In total, we calculate six objects: (1) The value of the housing stock, (2) net rents, (3) depreciation, (4) maintenance and other intermediate inputs, (5) taxes, and (6) varying measures of the physical housing stock. We add (3) & (4) to get a measure of depreciation gross of maintenance. For each object, we describe in detail below how we perform the sectoral match between NIPAs and FAUS to ensure that our rental yields are internally consistent. The details are as follows:[19]

- **Value of the Housing Stock**: For the value of the housing stock, we use data obtained from the FAUS. In particular, we sum *Owner-Occupied Real Estate at Market Value* (*FL155035013*) and *Residential Tenant-Occupied Real Estate at Market Value* in the *Nonfinancial Noncorporate Business* sector (*FL115035023*).

- **Net Rents**: To calculate net rents, we start from Mayerhauser and Reinsdorf (2006), and sum *Rental Income of Persons with Capital Consumption Adjustments* of owner-occupied housing (*NIPA Table 7.12. Line 164*) less mobile homes (*NIPA Table 7.9. Line 12*) and of tenant-occupied housing in the nonfinancial noncorporate sector with *Proprietor's Income with Inventory Valuation and Capital Consumption Adjustments* (*NIPA Table 7.4.5. Line 20*),[20] where "with capital consumption adjustment" means after depreciation. For rental income in the tenant-occupied nonfinancial noncorporate sector, we subtract rental income of persons with capital consumption adjustments for owner-occupiers and for nonprofits (*NIPA Table 7.9. Line 14*) from all rental income of persons with capital consumption adjustments in the housing sector (*NIPA Table 7.4.5. Line 21*).

  Since we are interested in housing as an unlevered asset, we also add back mortgage interest. For owner-occupied housing, we follow Piketty and Zucman (2014) and use *Monetary Interest Paid* (*NIPA Table 7.11. Line 16*).[21] For tenant-occupied nonfinancial noncorporate housing, we compute monetary interest paid in two steps. First,

[19] Some time series that are used in a supportive function to derive key objects have missing data points for the first few years in our sample. In those cases, we extrapolate back using a decadal trailing average of yearly growth rates. All results are robust to setting these values to zero instead.

[20] (Nonfarm) proprietors are unincorporated (nonfarm) businesses that are included in the nonfinancial noncorporate sector in the FAUS (for details, see Bond et al. (2007) and Bureau of Economic Analysis (2017), Chapter 11).

[21] We effectively assume that the share of mobile homes corresponds to its share in owner-occupied structure values based on FAUS data (*FL155012013* for mobile homes and *FL155012665* for all other owner-occupied structures; the FAUS only publish structure values for mobile homes), and reduce the resulting series accordingly. Mobile homes accounted for less than 3.5% of owner-occupied structure values over our sample period and all results are robust to including mobile homes instead in our capital stock.

note that the NIPA table for the housing sector lists *Net Interest* (*NIPA Table 7.4.5. Line 18*) instead of monetary interest paid.[22] We calculate net interest for tenant-occupied housing as the difference between all net interest in the housing sector (*NIPA Table 7.4.5. Line 18*) and net interest paid by owner-occupiers (*NIPA Table 7.12. Line 160*). Second, to calculate monetary interest paid by tenant-occupied housing, we assume that the percent difference between total interest and net interest is the same for owner-occupied and tenant-occupied housing.[23] To infer the share of nonfinancial noncorporate tenant-occupied housing among all tenant-occupied housing, we use its share in mortgages on tenant-occupied housing using data from the FAUS (*FL113165105*, *FL113165405*, *FL153165105*, *FL893065105*, *FL893065405*).

Finally, to arrive at net operating surplus, i.e. our measure of net rents, we add back *Current Transfer Payments*, which mainly consist of insurance settlements (see Mayerhauser and Reinsdorf, 2006).[24] For owner-occupiers, we use *NIPA Table 7.12. Line 163*.[25] For nonfinancial noncorporate tenant-occupied housing, we calculate current transfer payments to all tenant-occupied housing as the difference between current transfer payments to all housing (*NIPA Table 7.4.5. Line 19*) and current transfer payments to owner-occupied housing, and infer the share of nonfinancial noncorporate tenant-occupied housing among all tenant-occupied housing based on its share in tenant-occupied housing wealth using data from the FAUS again (*FL105035023*, *FL115035023*, *FL165035023*).[26]

---

[22]The difference between monetary interest paid and net interest is imputed interest. In the housing sector, imputed interest essentially stems from mortgage borrowing and property insurance: Homeowners and landlords that have financed their homes with mortgages are consuming financial intermediation services. These are called "Financial Services Furnished Without Payments" in the NIPAs. They are treated as intermediate inputs (i.e., maintenance and other intermediate inputs) instead of interest, and are typically imputed as the margin between mortgage interest rates and a reference rate at which the lender refinances itself. In a similar spirit, insurance premiums paid by homeowners and landlords are often supplemented through interest earned as insurers invest these premiums, called "Premium Supplements for Property and Casualty Insurance", which is treated as earned interest in the NIPAs.

[23]The percent difference of total interest and net interest was 7% for owner-occupiers during our sample period.

[24]Since our measure of maintenance and other intermediate inputs includes incurance payments, we symmetrically include insurance settlements as a benefit accruing to the homeowner. It is by far the smallest of the above items and all results are robust to its removal.

[25]As before, we effectively assume that the share of mobile homes corresponds to its share in owner-occupied structure values and reduce the resulting series accordingly.

[26]Note that while NIPA housing flows include the government sector, the FAUS' residential wealth measures do not. To correct for this, we use data from the BEA *Fixed Assets Accounts (FAA)* to scale up FAUS values for the non-profit sector using the ratio of non-profit to government sector values in the FAAs. For example, for the value of real estate, we use the *Current-Cost Net Stock of Residential Fixed Assets* (*FAA Table 5.1, Lines 6 & 8*), and for depreciation we use *Current-Cost Depreciation of Residential Fixed Assets* (*FAA Table 5.4, Lines 6 & 8*). These allocations affect our measures of rents only marginally.

- **Depreciation**: To calculate depreciation, we rely on data for the consumption of fixed capital from the FAUS. For owner-occupiers, we use *FU156320063*, and for nonfinancial noncorporate tenant-occupied housing, we use *FU116320065*.

- **Maintenance and Other Intermediate Inputs**: To calculate maintenance and other intermediate inputs, we start from Mayerhauser and Reinsdorf (2006) as before. For owner-occupiers, we use *Intermediate Goods and Services Consumed* (*NIPA Table 7.12. Line 155*). We infer the share of mobile homes among all owner-occupied housing by assuming that the ratio of depreciation plus maintenance and other intermediate inputs over housing wealth is constant across owner-occupied housing sectors, and reduce the series by that share. For nonfinancial noncorporate tenant-occupied housing, we proceed in two steps. First, we calculate intermediate goods and services consumed by all tenant-occupied housing as the difference between intermediate goods and services consumed by all housing (*NIPA Table 7.4.5. Line 6*) and intermediate goods and services consumed by owner-occupied housing. We then infer the share of nonfinancial noncorporate tenant-occupied housing among all tenant-occupied housing by assuming that the ratio of depreciation plus maintenance and other intermediate inputs over housing wealth is constant across tenant-occupied housing sectors. To do so, we calculate tenant-occupied housing wealth as described above and tenant-occupied consumption of fixed capital using data from the FAUS (*FU106320065, FU116320065, FU166320063*). Second, we add the cost for compensation of employees to arrive at maintenance and other intermediate inputs for nonfinancial noncorporate tenant-occupied housing. We start by assuming that all compensation of employees (*NIPA Table 7.4.5. Line 14*) is paid by tenant-occupied housing, and allocate the share of nonfinancial noncorporate tenant-occupied housing among all tenant-occupied housing based on its share in tenant-occupied housing wealth again. Finally, we remove the imputed interest that we added to net rents above from both, owner-occupied and nonfinancial noncorporate tenant-occupied maintenance and other intermediate inputs.

- **Taxes**: We calculate net taxes of owner-occupiers as *Taxes on Production and Imports* (*NIPA Table 7.12. Line 158*) minus *Subsidies* (*NIPA Table 7.12. Line 159*).[27] For nonfinancial noncorporate tenant-occupied housing, we conservatively assume that the remainder of all housing-related taxes is paid by tenant-occupied for-profit sectors, and calculate these taxes as the difference between all taxes on production and

[27] As before, we effectively assume that the share of mobile homes corresponds to its share in owner-occupied structure values and reduce the resulting series accordingly.

imports to housing (*NIPA Table 7.4.5. Line 15*), and taxes on production and imports to owner-occupied housing. To calculate net taxes, we assume that the ratio of taxes to subsidies is constant across owner-occupied and for-profit tenant-occupied sectors (the implied assumption is that a large share of subsidies accrues to the non-profit sector). Finally, we infer net taxes for nonfinancial noncorporate tenant-occupied housing based on its share in for-profit tenant-occupied housing wealth based on data from the FAUS again.

- **Housing Stock**: We adjust for the growth in the housing stock in various ways and rely on a variety of data sources: *Population* estimates are based on U.S. Census data and sourced from the Federal Reserve Bank of St. Louis (item *POP*). *Housing Unit* estimates are based on Moura, Smith and Belzer (2015) for the years before 2010 and on the Census Housing Vacancy Survey Supplement of the Current Population Survey (CPS/HVS) otherwise. *Floor Space* estimates are inferred from Moura, Smith and Belzer (2015).[28] *Holding Period Gains* are taken from the FAUS Revaluation Accounts. We use *FR155035013* for owner-occupiers and *FR115035023* nonfinancial noncorporate tenant-occupied housing.[29] *Quantity indices* are taken from Davis and Heathcote (2007). To be consistent with our price-rent approach, we use the quantity indices derived from the Case-Shiller-Weiss price index for the period after 1975.[30]

We use the BEA price index for personal consumption expenditure to deflate nominal returns (*NIPA Table 2.3.4. Line 1*) to be consistent with our housing consumption source data. Consistent with our yearly flow and stock data, all price and quantity indices are Q4-indices.

United Kingdom. For the U.K., we calculate returns between 1988 and 2016.[31] We focus on the *Household Sector (S.14)*, the most representative sector of the U.K. housing market (it accounted for close to 90% of residential housing on average during our sample period). Since the U.K. National Accounts are based on the *System of National Accounts (SNA)*, the household sector includes activities associated with tenant-occupied housing (these are

[28] We extrapolate using a decadal trailing average of yearly growth rates for the years after 2011.

[29] We thank Eric Nielsen from the FRB for clarifying details of the Revaluation Accounts for us.

[30] Quantity indices are a widely used concept in national accounts and aim to capture changes in the value of an asset that are not driven by (constant-quality) price changes. Quality changes are treated as changes in quantity in such a decomposition. See Bureau of Economic Analysis (2017) for more details.

[31] The data provided by the ONS would allow us to include 1987 as well, but housing returns were extraordinary high in that year – in fact the inclusion of this one year would increase our return estimates by almost a full percentage point. We therefore decided to drop it from the sample. As we can see from Figure A.8, our net return series for the U.K. starts around its long-run mean in 1988.

included in the nonfinancial noncorporate business sector in the U.S.).[32] Moreover, since all our data (except some measures of the physical housing stock) are based on the U.K. National Accounts as published by the Office of National Statistics (ONS), ensuring a sectoral match between housing wealth and rental flows is more straight forward for the U.K. than for the U.S. However, for the period before 1995, the ONS does not provide separate statistics for the household sector, but combined statistics for the *Household & Nonprofit Institutions Serving Households (HH & NPISH) Sector (S.14 & S.15)*, which we use to extrapolate levels from the household sector backwards (between 1995 and 2015, the household sector accounted for around 98% of housing wealth in the combined sector).[33] Overall, we calculate five objects: (1) The value of the housing stock, (2) net rents, (3) depreciation, (4) maintenance and other intermediate inputs, and (5) varying measures of the physical housing stock. We add (3) & (4) to get a measure of depreciation gross of maintenance. Since there is no property tax in the U.K., we set taxes to zero. The details are as follows:

- **Value of the Housing Stock**: For the period since 1995, we add the value of residential structures, (*Dwellings*, *E46V*) and the value of residential land, (*Land*, *E44N*), to calculate the total value of residential housing in the household sector. For the period before 1995, the ONS only reported a combined value of structures and land for residential housing for the HH & NPISH sector (series *CGRI*), which we use to extrapolate levels backwards.

- **Net Rents**: To calculate net rents, we follow Piketty and Zucman (2014) and start from *Gross Operating Surplus* in the household sector (series *HABM*).[34] Note that gross operating surplus includes net interest, so we do not need to add it back as we do for the U.S. However, following Piketty and Zucman (2014) again, to fully correct our measure of net rents for mortgage-related interest payments, we need to add back imputed interest, called *Financial Intermediation Services Indirectly Measured (FISIM)* in the U.K. National Accounts.[35] But, unlike Piketty and Zucman

[32] See Bond et al. (2007) for details.

[33] The ONS started to report values for the household sector separately with the 2017 edition of the Blue Book, following guidelines of the European System of Accounts 2010 (ESA 2010); most time series we are interested in were updated back to 1995 only.

[34] Gross operating surplus in the household sector is essentially gross rents minus intermediate consumption and payment of employees. Indeed, the depreciation we record for housing in the household sector is higher than the depreciation allocated to gross operating surplus in the household sector in the U.K. National Accounts. If anything, this suggests that we may miss some of the surplus generated by housing in the household sector.

[35] See our discussion for the U.S. on imputed interest, i.e., the difference between net interest and monetary interest paid.

(2014), we take a more conservative approach and consider that secured debt should command lower interest rates than unsecured debt. Therefore, instead of calculating the share of financial liabilities secured on dwellings amongst all financial liabilities in the household sector and allocating FISIM back proportionally, we use data on household-mortgage-related FISIM published by the ONS on its website for the years since 2005.[36] Between 2005 and 2016, the difference between FISIM markups on loans secured on dwellings and all other household debt was fairly constant at 3.6 percentage points on average. We assume that this difference also holds for the years before 2005 and calculate household-mortgage-related FISIM using data on all household-debt-related FISIM (series *CRNB*), all household debt (series *NIWJ*), and household loans secured on dwellings (series *NIWV*) accordingly.[37] Finally, we subtract depreciation as calculated below to arrive at net rents.

- **Depreciation**: To calculate depreciation rates, we use data on the *Consumption of Fixed Capital* (series *MJX9*) in the household sector. For the period before 1995, we combine the corresponding series for the consumption of fixed capital (series *CIHB*) with housing wealth (series *CGRI*) in the HH & NPISH sector. For the time period where both series overlap (1995 to 2009), depreciation was around 0.5 percentage points higher in the updated data series. Therefore, we conservatively increase our depreciation estimates for the years before 1995 by 0.5 percentage points each year.

- **Maintenance and Other Intermediate Inputs**: To calculate *Maintenance and Other Running Costs*, we subtract net rents, depreciation, and net taxes from total personal consumption expenditure in the household sector. We proceed in two steps to calculate personal consumption expenditure on housing in the household sector: First, we calculate total personal consumption expenditure on housing across all

[36] We use the non-risk-adjusted FISIM allocated to households as owners of dwellings underlying Figure 19 of the article "Financial intermediation services indirectly measured (FISIM) in the UK revisited", retrieved from `https://www.ons.gov.uk/economy/grossdomesticproductgdp/articles/financialintermediationservicesindirectlymeasuredfisimintheukrevisited/2017-04-24`, last accessed February 2018.

[37] We calculate FISIM markups on loans secured on dwellings as household-mortgage-related FISIM divided by loans secured on dwellings. FISIM markups on all other household debt are calculated as the difference between all household-debt-related FISIM and household-mortgage-related FISIM, divided by the difference between all household debt and loans secured on dwellings. While fairly constant overall, the difference between household-mortgage-related FISIM markups and other household-debt FISIM markups tends to vary somewhat with overall FISIM markup levels between 2005 and 2016 (at an average markup of 3.6 percentage points, the standard deviation was 0.5 percentage points). However, since the average overall FISIM markup before 2005 is lower than the average overall FISIM markup since 2005 (if slightly at 1.4 vs. 1.9 percentage points) and much less volatile (with a standard deviation of 0.2 vs. 0.7 percentage points), our estimate for household-mortgage-related FISIM before 2005 should be slightly conservative if anything.

sectors as the sum of *Actual Rentals for Housing* (series *ADFT*), *Imputed Rentals for Housing* (series *ADFU*), and *Maintenance and Repair of the Dwelling* (series *ADFV*). Second, we allocate this total across all sectors based on the fraction of housing wealth in the household sector vs. all remaining sectors.[38]

- **Housing Stock**: We adjust for the growth in the housing stock in various ways and rely on a variety of data sources again: *Population* estimates are retrieved from the ONS (series *UKPOP*). *Housing Unit* estimates are based on dwelling stock data from the DCLG for the U.K. until 2013 (*Table 101*) and for England thereafter (*Table 104*). *Quantity Indexes* are derived following the baseline methodology outlined in Davis and Heathcote (2007), that is, we discount the value of the housing stock with a (constant-quality) house price index.[39]

To be consistent with our housing consumption source data and our approach for the U.S., we use the ONS price index for personal consumption expenditure to deflate nominal returns (series *CRXB*). Consistent with our yearly flow and stock data, all price and quantity indices are Q4-indices.

A.4.3 Consistency Across Rent-Price and Balance-Sheet Approaches

Appendix Figure A.8 plots the net housing returns for the balance-sheet and the price-rent approach for the U.S. and the U.K. (top row), the correlation between net housing returns from the balance-sheet and the price-rent approach for the U.S. and the U.K. (middle row), and housing depreciation (gross of maintenance) and tax yields from the balance-sheet approach for the U.S. and the U.K. (bottom row; there are no taxes in the U.K.). The U.S. results are based on specifications 2 and 9 in Table 4. The U.K. results are based on specifications 11 and 15 in the same table. We can see that both approaches yield similar net return time series that are highly correlated. Moreover, depreciation and taxes as derived from the balance-sheet approach have been fairly stable and trending around their long-run averages over our sample periods, which verifies our constant-adjustment approach for depreciation and taxes for the price-rent approach.

---

[38] We think that this is a conservative assumption, since rental yields tend to be higher in the household sector than in other sectors. Note however that this assumption has no impact on our results for net rents as we derive these directly from gross operating surplus.

[39] See our discussion of data sources for the price-rent approach for details on the U.K. house price index.

A.5 Price and Quantity of Risk Across the Term Structure

Section 1 showed empirically that the term structure of discount rates for real estate – a risky asset – is steeply downward-sloping. In this section, we apply asset pricing theory to discuss a decomposition of this term structure into its building blocks: risk and return across the term structure. This decomposition will help us understand the forces that drive discount rates at different horizons, and provides a link between discount rates observed on tradable assets and investments in climate change abatement.

A.5.1 Per-Period Discount Rates and Expected One-Period Returns

Most of the insights of asset pricing theory are clearest to interpret when thinking about one-period expected returns, independent of the maturity of the asset. Since any asset can be bought, held for one period, and then sold at the end of that period (before its maturity), looking at the one-period return is one way to reduce assets of different maturities to a common horizon. This allows us to compare their risk and return properties.

We start by introducing our main notation and by linking together the concepts of returns to maturity and one-period returns. In what follows, we will sometimes refer to general assets with maturity n that could pay cash flows such as dividends or rents at any point in time up to maturity; these will simply be denoted with superscript n. A subset of these assets is the set of claims to single cash flows at a specific point in time, maturity n; we will denote these with superscript (n).

Define the one-period (gross) return per dollar spent on any security with maturity n as the total amount obtained from buying the security and liquidating it after one period:

$$R^n_{t,t+1} \equiv \frac{P^{n-1}_{t+1} + D_{t+1}}{P^n_t},$$

Note that at the time the asset is sold, its maturity has shortened to $n-1$. The return to holding the security over multiple periods (and reinvesting all intermediate cash flows) can be found by compounding the one-period returns. For example, the return to maturity of any investment with maturity n is

$$R^n_{t,t+n} = \prod_{k=0}^{n-1} R^{n-k}_{t+k,t+1+k}.$$

Of particular interest to us are the one-period returns and discount rates for claims to a single cash flow D_{t+n}. In this case, the one-period returns in all but the last period are entirely driven by price movements (since D_{t+k} is zero for all k, except for $k = n$, the last cash flow at maturity). What makes the return to this security of particular interest is its intimate link to our per-period discount rates for horizon-specific cash flows, $\bar{r}_t^n$. To see this, we can rewrite the return to maturity of such a claim as:

$$R_{t,t+n}^{(n)} = \frac{D_{t+n}}{P_t^{(n)}};$$

we can do this since there are no dividends to be reinvested over the life of this security. Taking expectations on both sides, and then rearranging, we obtain:

$$P_t^{(n)} = \frac{E_t[D_{t+n}]}{E_t[R_{t,t+n}^{(n)}]}.$$

Comparing this equation with equation A.2 in Section A.1, we immediately see that the n-period expected return to maturity of a claim to a single dividend at $t + n$ is exactly the compounded discount rate to be applied to that security: $E_t[R_{t,t+n}^{(n)}] = (1 + \bar{r}_t^n)^n$.

Next, we want to link these quantities to the one-period expected return, for which we are able to provide a very intuitive risk-return decomposition. The focus of this paper is on the *average* shape of the term structure of discount rates. Time-variation in discount rates, while important in the asset pricing literature, plays a second-order role in thinking about climate change investments. We therefore derive the link between one-period expected returns $E_t[R_{t,t+1}^{(n)}]$ and per-period discount rates $\bar{r}_t^n$ under the assumption that per-period discount rates for a cash flow with a particular maturity are constant over time; relaxing this assumption would complicate the intuition without adding any economically relevant elements to the analysis. If expected returns are constant over time (though they may be different across maturities, such that the term structure of discount rates is not necessarily flat at each point in time), we have

$$E_t[R_{t,t+n}^{(n)}] = \prod_{k=0}^{n-1} E_t[R_{t,t+1}^{(n-k)}],$$

where all the returns are for claims to single cash flows, D_{t+k}, at different horizons k. The formula shows that in this case, not only the realized but also the expected returns are linked through compounding. Since $E_t[R_{t,t+n}^{(n)}]$ is directly linked to $\bar{r}_t^n$ as shown above, we can then easily substitute and take logs (and recall that $\ln(1+x) \simeq x$), to obtain:

$$\bar{r}_t^n \simeq \frac{1}{n} \sum_{k=1}^{n} \ln(E_t[R_{t,t+1}^{(k)}]). \tag{A.7}$$

Therefore, the discount rate for a particular horizon n is simply the average of the one-period expected returns for claims to cash flows at each horizon. A flat term structure of discount rates must then imply a flat term structure of expected one-period returns across maturities; in fact, expected one-period returns and discount rates across maturities would all be equal. In Section A.5.2, we will build on this decomposition to further elaborate on the forces that shape the term structure of discount rates.

A.5.2 Decomposing the Term Structure of Expected One-Period Returns

Now that we have clarified the link between one-period returns and per-period discount rates, we focus on the one-period returns of securities with maturity n. We start by using the fundamental asset pricing equation introduced in Section A.1.1 to decompose the expected one-period returns $R_{t,t+1}^{(n)}$ into a component that reflects time discounting and a component that reflects the riskiness of the underlying cash flow. It follows from:[40]

$$1 = E_t[M_{t,t+1} R_{t,t+1}^{(n)}]$$

that:

$$E_t[R_{t,t+1}^{(n)}] = R_{t,t+1}^f - Cov_t[R_{t,t+1}^{(n)}, M_{t,t+1}] R_{t,t+1}^f,$$

where the first component $R_{t,t+1}^f = E_t[M_{t,t+1}]^{-1}$ is the one-period risk-free rate that reflects time discounting, and the second component reflects an additional discount compensating the investor for bearing risk (the covariance with the SDF reflects whether this asset primarily pays off in good states of the world that have a low marginal utility of consumption). The risk premium has the opposite sign of the covariance between the stochastic discount factor (SDF) and the one-period return, $Cov_t[M_{t,t+1}, R_{t,t+1}^{(n)}]$. This reflects the fact that a claim with a higher return in states of the world in which extra resources are less valuable (i.e., when marginal utility $M_{t,t+1}$ is low) is less valuable to the investors, and thus has a positive risk premium. Finally, to highlight the fact that only *innovations* in the SDF matter for the purpose of understanding risk premia (rather than

[40] The fundamental asset pricing equation introduced in Section A.1.1 (equation A.1) can be restated as $P_t^{(n)} = E_t\left[M_{t,t+1} P_{t+1}^{(n-1)}\right]$, which implies $1 = E_t\left[M_{t,t+1} \frac{P_{t+1}^{(n-1)}}{P_t^{(n)}}\right] = E_t\left[M_{t,t+1} R_{t,t+1}^{(n)}\right]$.

its mean, which instead pins down the risk-free rate), we can rewrite excess returns as:

$$E_t[R^{(n)}_{t,t+1}] - R^f_{t,t+1} = -Cov_t[R^{(n)}_{t,t+1}, M_{t,t+1} - E_t[M_{t,t+1}]]R^f_{t,t+1}.$$

As is common in asset pricing theory, we make the additional assumption that log returns $r^{(n)}_{t,t+1} \equiv \ln(R^{(n)}_{t,t+1})$ as well as the log stochastic discount factor $m_{t,t+1} \equiv \ln(M_{t,t+1})$ are at least approximately jointly normally distributed, which allows us to simplify our expression for the risk premium to the covariance term alone (see, for example, Campbell and Vuolteenaho, 2004):

$$E_t[R^{(n)}_{t,t+1}] - R^f_{t,t+1} \simeq -Cov_t[r^{(n)}_{t,t+1}, m_{t,t+1} - E_t[m_{t,t+1}]], \tag{A.8}$$

The above notation highlights again that only *innovations* in the (log-)SDF, $m_{t,t+1} - E_t[m_{t,t+1}]$, matter for expected returns.

To highlight the forces that shape the term structure of expected one-period returns, we will focus on analyzing the set of linear and log-linear consumption-based asset pricing models, in which the stochastic discount factor is a function of consumption growth. This class of models encompasses the vast majority of modern asset pricing models, in particular those employed in climate change analysis, such as power utility models as in Lucas (1978), long-run risk models with Epstein–Zin preferences as in Bansal and Yaron (2004), and rare disaster models as in Barro (2006) and Gabaix (2012). As noted in Dew-Becker and Giglio (2013), these asset pricing models can be nested in the following general representation for the SDF innovations:[41]

$$m_{t,t+1} - E_t[m_{t,t+1}] = -\sum_{k=0}^{\infty} z_k \cdot (E_{t+1} - E_t)\Delta c_{t+1+k}, \tag{A.9}$$

where $\Delta c_{t+1} - E_t \Delta c_{t+1}$ (the first term of the sum, i.e. for $k = 0$) is the shock to current consumption growth, while $(E_{t+1} - E_t)\Delta c_{t+1+k}$ with $k > 0$ is *news* about future consumption growth at horizon k, received during the holding period (between t and $t + 1$).

The terms z_k depend only on the parameters of the utility function (not on the consumption growth process), and represent risk aversion regarding news about consumption growth at a particular horizon. They can be thought of as horizon-specific risk prices. Substituting equation A.9 into equation A.8, we can write the expected return of any asset

[41]More precisely, all of these models produce this representation of the SDF depending only on consumption growth news as long as the variance of consumption growth and higher moments are constant; the decomposition easily generalizes to cases with arbitrary affine processes.

by decomposing it across horizons:

$$
\begin{aligned}
E_t[R^{(n)}_{t,t+1}] - R^f_{t,t+1} &\simeq z_0 Cov_t[r^{(n)}_{t,t+1}, \Delta c_{t+1}] \\
&+ z_1 Cov_t[r^{(n)}_{t,t+1}, (E_{t+1} - E_t)\Delta c_{t+2}] \\
&+ z_2 Cov_t[r^{(n)}_{t,t+1}, (E_{t+1} - E_t)\Delta c_{t+3}] \\
&+ \ldots. \qquad \text{(A.10)}
\end{aligned}
$$

The above decomposition holds for *any* asset, and therefore holds for all claims to cash flows at one particular point in the future, D_{t+n}, which jointly characterize the term structure of discount rates. It highlights that the shape of the term structure of expected one-period returns (and thus ultimately of horizon-specific discount rates) can be attributed to the interaction of two forces:

1. The term structure of horizon-specific *risk prices* z_k, i.e., how much agents care about long-term news relative to short-term news. The higher z_k is for long maturities, the more worried agents are about long-run risks in the economy.

2. The term structure of *risk quantities*, i.e. how much news about future consumption growth there is in the economy, and how it affects claims at different maturities. If there is no news about future consumption growth, for example if consumption growth is *iid*, all the news terms $(E_{t+1} - E_t)\Delta c_{t+n}$ and hence all of the respective covariances will be equal to zero. If instead there is long-horizon consumption risk (that is if consumption growth is predictable, for example because cash flows are persistently mean-reverting), then the news terms $(E_{t+1} - E_t)\Delta c_{t+n}$ are non-zero. Moreover, the returns to claims of different horizons $r^{(n)}_{t,t+1}$ are then differentially exposed to shocks at different horizons.

A.5.3 Explanations for a Downward-Sloping Term Structure of Discount Rates for Risky Assets – Preferences vs. Cash Flows

We can put the above decomposition to work and ask what mechanisms can generate a downward-sloping term structure of discount rates. As we can see from equation 14 of our model as presented in Section 2, $z_0 = \gamma$, but all z_k's are zero for $k > 0$ in equation A.10 for an agent with power utility preferences. Put differently, such an agent is *only* worried about one-period innovations in consumption. For an Epstein–Zin investor by contrast, $z_0 = \gamma$ like in the power utility case, but $z_k = (\gamma - \frac{1}{\psi})\theta^k$ for $k > 0$, where ψ is the elasticity of intertemporal substitution and θ a parameter close to 1 related to the time discount factor. Epstein–Zin parameterizations with $\gamma > \frac{1}{\psi}$, as in standard calibrations of the long-run risk model, thus imply that agents are worried *both* about immediate consumption growth *and* pure news regarding future consumption. Since claims to long-run cash flows D_{t+n} are naturally exposed to *all* dividend growth shocks from t to $t+n$ ($D_{t+n} = D_t \exp[\Delta d_{t+1} + ... + \Delta d_{t+n}]$), claims become *more exposed* to long-run shocks as their maturity increases. Accordingly, their risk premium grows with maturity as more and more of the positive covariance terms in equation A.10 are added up with positive weights. Therefore, introducing Epstein–Zin preferences would push the slope of the term structure of discount rates upwards. To match the data on a downward-sloping term structure of discount rates for risky assets, we would require an even stronger mean reversion in cash flows as a consequence in our model presented in Section 2. More generally, we are not aware of a standard representation of preferences that would push towards a downward-sloping term structure of discount rates for risky assets.

As we can see again from equation 14, what we require for a downward-sloping term structure of discount rates for risky assets are declining exposures of claims of different maturity $r^{(n)}_{t,t+1}$ to the consumption shock Δc_{t+1}, i.e. *risk quantities*. In our setting presented in Section 2, mean reversion in cash flows makes growth in the economy predictable and implies that a climate disaster that strikes today has larger effects on immediate cash flows than on distant cash flows, which exposes short-run returns more than long-run returns to a consumption shock.

A.6 Details on the Model

This section presents details on our model. We derive the prices of claims to consumption and rents at different horizons and all results presented in Section 2.

A.6.1 Assumptions and Parameter Restrictions

Throughout, we are going to evaluate the term structure of discount rates and expected returns at the ergodic mean of all variables, i.e. evaluated when $\lambda_t = E[\lambda_t] \equiv \bar{\lambda}$, $x_t = E[x_t] \equiv \bar{x}$, and $y_t = E[y_t] \equiv \bar{y}$. We assume that x and y have mean zero, which implies:

$$\mu_x = -\bar{\lambda}\phi\xi \qquad \text{and} \qquad \mu_y = -\bar{\lambda}\psi\xi.$$

The unconditional mean of λ_t is:

$$\bar{\lambda} = \frac{\mu_\lambda}{1 - \alpha - \chi\xi} > 0.$$

The long-run growth rate of consumption is:

$$\mu - \bar{\lambda}\xi > 0.$$

We further assume that consumption and rents have the same long-run growth rates, requiring:

$$\mu_d = \mu + (\eta - 1)\,\bar{\lambda}\xi.$$

Our calibration is discussed in Section 2.2 and summarized in Table A.8.

A.6.2 Pricing Claims to Single-Period Cash Flows

In Section A.7.1, we derive the prices of claims to arbitrary cash flows Z_{t+1} at different horizons. This section presents the results. We start by generalizing the cash flow process to:

$$\Delta z_{t+1} = \mu_z + \pi_z y_t - \eta_z J_{t+1},$$

where y_t still captures persistent changes in the growth rate of the cash flows and J_{t+1} is the underlying economic shock. Including separate and flexible loadings on persistent changes in the growth rate of cash flows, π_z, as well as the underlying economic shock, η_z, will allow us to nest the dynamics of all assets and liabilities relevant to our discussion in Section 2. This allows us to solve the model once and parameterize the solution as needed. The solution is recursive and takes the following form:

$$p_{z,t}^{(n)} = a_n^z + b_n^z x_t + e_n^z y_t + f_n^z \left(\lambda_t - \bar{\lambda}\right), \tag{A.11}$$

where $p_{z,t}^{(n)}$ is the log price-dividend ratio of a claim to the cash flow n periods ahead (in levels, we write $PD_{z,t}^{(n)}$). The full recursive expressions of the coefficients in terms of primitives are as follows:

$$
\begin{aligned}
a_n^z &= \ln\delta - \gamma\mu + \mu_z + a_{n-1}^z + b_{n-1}^z\mu_x + e_{n-1}^z\mu_y + f_{n-1}^z\left(\mu_\lambda + \bar{\lambda}\left(\alpha - 1\right)\right) \\
&+ \ln\left[1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^z\phi + e_{n-1}^z\psi + f_{n-1}^z\chi\right)\xi\right\} - 1\right)\right] \\
b_n^z &= -\gamma + b_{n-1}^z\rho + f_{n-1}^z\nu \\
e_n^z &= e_{n-1}^z\omega + \pi_z \\
f_n^z &= f_{n-1}^z\alpha + \frac{\exp\left\{\left(\gamma - \eta_z + b_{n-1}^z\phi + e_{n-1}^z\psi + f_{n-1}^z\chi\right)\xi\right\} - 1}{1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^z\phi + e_{n-1}^z\psi + f_{n-1}^z\chi\right)\xi\right\} - 1\right)}.
\end{aligned}
$$

with $a_0^z = b_0^z = e_0^z = f_0^z = 0$. The prices of all assets and liabilities we discuss in Section 2 can be derived based on various parameterizations of the above solution.

Consumption: To derive claims to consumption, we need $\Delta z_{t+1} = \Delta c_{t+1}$, i.e. $\mu_z = \mu$, $\pi_z = 1$, and $\eta_z = 1$. Also note that we need to replace y_t with x_t as a consequence, i.e. μ_y with μ_x, ω with ρ, and ψ with ϕ. The price of a consumption strip claim is then:

$$
p_{c,t}^{(n)} = a_n^c + b_n^c x_t + f_n^c\left(\lambda_t - \bar{\lambda}\right). \tag{A.12}
$$

Note that we can sum b_n^z and e_n^z to get b_n^c as x and y are the same for a consumption claim. The full recursive expressions of the coefficients in terms of primitives are as follows: $a_0^c = b_0^c = f_0^c = 0$, and

$$
\begin{aligned}
a_n^c &= \ln\delta + (1-\gamma)\mu + a_{n-1}^c + b_{n-1}^c\mu_x + f_{n-1}^c\left(\mu_\lambda + \bar{\lambda}\left(\alpha - 1\right)\right) \\
&+ \ln\left[1 + \bar{\lambda}\left(\exp\left\{\left(-(1-\gamma) + b_{n-1}^c\phi + f_{n-1}^c\chi\right)\xi\right\} - 1\right)\right] \\
b_n^c &= (1-\gamma) + b_{n-1}^c\rho + f_{n-1}^c\nu \\
f_n^c &= f_{n-1}^c\alpha + \frac{\exp\left\{\left(-(1-\gamma) + b_{n-1}^c\phi + f_{n-1}^c\chi\right)\xi\right\} - 1}{1 + \bar{\lambda}\left(\exp\left\{\left(-(1-\gamma) + b_{n-1}^c\phi + f_{n-1}^c\chi\right)\xi\right\} - 1\right)}.
\end{aligned}
$$

Risk-Free Bond: To derive claims to a risk-free bond with maturity n, we need $Z_{t+n} = 1$ and zero otherwise. We set $\mu_z = 0$, $\pi_z = 0$, and $\eta_z = 0$. The price of a risk-free strip claim is then:

$$
b_{f,t}^{(n)} = a_n^f + b_n^f x_t + f_n^f\left(\lambda_t - \bar{\lambda}\right). \tag{A.13}
$$

Note that y and hence e_f drops as a result of the above parameterization. The full recursive expressions of the coefficients in terms of primitives are as follows: $a_0^f = b_0^f = f_0^f = 0$, and

$$
\begin{aligned}
a_n^f &= \ln\delta - \gamma\mu + a_{n-1}^f + b_{n-1}^f \mu_x + f_{n-1}^f \left(\mu_\lambda + \bar{\lambda}\left(\alpha - 1\right)\right) \\
&\quad + \ln\left[1 + \bar{\lambda}\left(\exp\left\{\left(\gamma + b_{n-1}^f \phi + f_{n-1}^f \chi\right)\xi\right\} - 1\right)\right] \\
b_n^f &= -\gamma + b_{n-1}^f \rho + f_{n-1}^f \nu \\
f_n^f &= f_{n-1}^f \alpha + \frac{\exp\left\{\left(\gamma + b_{n-1}^f \phi + f_{n-1}^f \chi\right)\xi\right\} - 1}{1 + \bar{\lambda}\left[\exp\left\{\left(\gamma + b_{n-1}^f \phi + f_{n-1}^f \chi\right)\xi\right\} - 1\right]}.
\end{aligned}
$$

Rents: To derive claims to rents, we need $\Delta z_{t+1} = \Delta d_{t+1}$, i.e. $\mu_z = \mu_d$, $\pi_z = 1$, and $\eta_z = \eta$. The price of a rent strip claim is then:

$$
p_{d,t}^{(n)} = a_n^d + b_n^d x_t + e_n^d y_t + f_n^d \left(\lambda_t - \bar{\lambda}\right). \tag{A.14a}
$$

The full recursive expressions of the coefficients in terms of primitives are as follows: $a_0^d = b_0^d = e_0^d = f_0^d = 0$, and

$$
\begin{aligned}
a_n^d &= \ln\delta - \gamma\mu + \mu_d + a_{n-1}^d + b_{n-1}^d \mu_x + e_{n-1}^d \mu_y + f_{n-1}\left(\mu_\lambda + \bar{\lambda}\left(\alpha - 1\right)\right) && \text{(A.14b)} \\
&\quad + \ln\left[1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta + b_{n-1}^d \phi + e_{n-1}^d \psi + f_{n-1}^d \chi\right)\xi\right\} - 1\right)\right] \\
b_n^d &= -\gamma + b_{n-1}^d \rho + f_{n-1}^d \nu && \text{(A.14c)} \\
e_n^d &= e_{n-1}^d \omega + 1 && \text{(A.14d)} \\
f_n^d &= f_{n-1}^d \alpha + \frac{\exp\left\{\left(\gamma - \eta + b_{n-1}^d \phi + e_{n-1}^d \psi + f_{n-1}^d \chi\right)\xi\right\} - 1}{1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta + b_{n-1}^d \phi + e_{n-1}^d \psi + f_{n-1}^d \chi\right)\xi\right\} - 1\right)}. && \text{(A.14e)}
\end{aligned}
$$

Damages: To derive claims to damages, we need $\Delta z_{t+1} = \Delta q_{t+1}$, i.e. $\mu_z = \mu_q$, $\pi_z = -\pi_q$, and $\eta_z = -\eta_q$. The price of a damage strip claim is then:

$$
p_{q,t}^{(n)} = a_n^q + b_n^q x_t + e_n^q y_t + f_n^q \left(\lambda_t - \bar{\lambda}\right). \tag{A.15}
$$

The full recursive expressions of the coefficients in terms of primitives are as follows: $a_0^q = b_0^q = e_0^q = f_0^q = 0$, and

$$\begin{aligned} a_n^q &= \ln\delta - \gamma\mu + \mu_q + a_{n-1}^q + b_{n-1}^q\mu_x + e_{n-1}^q\mu_y + f_{n-1}^q\left(\mu_\lambda + \bar{\lambda}\left(\alpha - 1\right)\right) \\ &+ \ln\left[1 + \bar{\lambda}\left(\exp\left\{\left(\gamma + \eta_q + b_{n-1}^q\phi + e_{n-1}^q\psi + f_{n-1}^q\chi\right)\xi\right\} - 1\right)\right] \\ b_n^q &= -\gamma + b_{n-1}^q\rho + f_{n-1}^q\nu \\ e_n^q &= e_{n-1}^q\omega - \pi_q \\ f_n^q &= f_{n-1}^q\alpha + \frac{\exp\left\{\left(\gamma + \eta_q + b_{n-1}^q\phi + e_{n-1}^q\psi + f_{n-1}^q\chi\right)\xi\right\} - 1}{1 + \bar{\lambda}\left(\exp\left\{\left(\gamma + \eta_q + b_{n-1}^q\phi + e_{n-1}^q\psi + f_{n-1}^q\chi\right)\xi\right\} - 1\right)}. \end{aligned}$$

A.6.3 Per-Period Discount Rates

We derive per-period discount rates for claims to arbitrary cash flows Z_{t+1} at different horizons again and parameterize those accordingly to derive implied discount rates for all assets and liabilities discussed in Section 2. Remember from Section A.5.1 that per-period discount rates $\bar{r}_{z,t}^n$ are implicitly defined by:

$$P_{z,t}^{(n)} = \frac{E_t\left[Z_{t+n}\right]}{\left(1 + \bar{r}_{z,t}^n\right)^n}.$$

In Section A.7.2, we show that expected cash flows can be expressed as:

$$E_t\left[Z_{t+n}\right] = Z_t \exp\left\{n\mu_z + \pi_z\frac{1-\omega^n}{1-\omega}y_t + \pi_z\mu_y\sum_{s=0}^{n-1}\frac{1-\omega^s}{1-\omega}\right\}A_{z,n,t}, \tag{A.16}$$

where the second and third term inside the curly brackets are related to persistent changes in the growth rate of the economy, and $A_{z,n,t}$ is a term that captures the history of (path-dependent) jump events. Formally, $A_{z,n,t}$ is defined as:

$$A_{z,n,t} \equiv E_t\left[\exp\left\{\sum_{i=0}^{n-1} J_{t+n-i}\left(\pi_z\psi\frac{1-\omega^i}{1-\omega} - \eta_z\right)\right\}\right]. \tag{A.17}$$

These expectations can be computed in closed form for short horizons, but are best computed numerically for longer horizons. We outline a numerical solution algorithm in Section A.7.3. Rearranging and substituting for $E_t\left[Z_{t+n}\right]$ using equation A.16, we get:

$$\left(1 + \bar{r}_{z,t}^n\right)^n = \frac{\exp\left\{n\mu_z + \pi_z\mu_y\sum_{s=0}^{n-1}\frac{1-\omega^s}{1-\omega} + \pi_z\frac{1-\omega^n}{1-\omega}y_t\right\}A_{z,n,t}}{\exp\left\{p_{z,t}^{(n)}\right\}}.$$

Taking logs and approximating $\ln(1+x) \simeq x$, we get:

$$\bar{r}^n_{z,t} \simeq \frac{1}{n}\left[n\mu_z + \pi_z\mu_y \sum_{s=0}^{n-1}\frac{1-\omega^s}{1-\omega} + \pi_z\frac{1-\omega^n}{1-\omega}y_t + \ln A_{z,n,t} - p^{(n)}_{z,t}\right].$$

Substituting for $p^{(n)}_{z,t}$ using equation A.11, we get:

$$\bar{r}^n_{z,t} \simeq \mu_z + \frac{1}{n}\left[\pi_z\mu_y \sum_{s=0}^{n-1}\frac{1-\omega^s}{1-\omega} + \pi_z\frac{1-\omega^n}{1-\omega}y_t + \ln A_{z,n,t}\right] \tag{A.18}$$

$$-\frac{1}{n}\left[a^z_n + b^z_n x_t + e^z_n y_t + f^z_n\left(\lambda_t - \bar{\lambda}\right)\right],$$

with a^z_n, b^z_n, e^z_n, and f^z_n are defined as in equation A.11, and $A_{z,n,t}$ is defined as above.

Consumption: To derive per-period discount rates for consumption, we need $\Delta z_{t+1} = \Delta c_{t+1}$, i.e. $\mu_z = \mu$, $\pi_z = 1$, and $\eta_z = 1$. Also note that long-run dynamics in consumption are driven by x instead of y, and so we also need to replace y_t with x_t as a consequence, i.e. μ_y with μ_x, ω with ρ, and ψ with ϕ. The per-period discount rate is then:

$$\bar{r}^n_{c,t} \simeq \mu + \frac{1}{n}\left[\mu_x \sum_{s=0}^{n-1}\frac{1-\rho^s}{1-\rho} + \frac{1-\rho^n}{1-\rho}x_t + \ln A_{c,n,t} - \left(a^c_n + b^c_n x_t + f^c_n\left(\lambda_t - \bar{\lambda}\right)\right)\right],$$

with a^c_n, b^c_n, and f^c_n defined as in equation A.12 (note that we can sum b^z_n and e^z_n to get b^c_n as x and y are the same for a consumption claim), and $A_{c,n,t}$ is defined as:

$$A_{c,n,t} = E_t\left[\exp\left\{\sum_{i=0}^{n-1} J_{t+n-i}\left(\phi\frac{1-\rho^i}{1-\rho} - 1\right)\right\}\right].$$

Risk-free rate: The risk-free rate in the economy is given by:

$$R^f_{t,n} = 1/B^{(n)}_t,$$

and linked to the risk-free discount rate by $R^f_{t,n} = \left(1 + r^f_{t,n}\right)^n$. Approximating $\ln(1+x) \simeq x$, we have:

$$r^f_{t,n} \simeq \frac{1}{n}\ln R^f_{t,n} = -\frac{1}{n}\ln B^{(n)}_t = -\frac{1}{n}b^{(n)}_{f,t} = -\frac{1}{n}\left(a^f_n + b^f_n x_t + f^f_n\left(\lambda_t - \bar{\lambda}\right)\right),$$

where a_n^f, b_n^f, and f_n^f are defined as in equation A.13. The risk-free rate increases in x_t and decreases in the severity and probability of disasters.

Rents: To derive per-period discount rates for rents, we need $\Delta z_{t+1} = \Delta d_{t+1}$, i.e. $\mu_z = \mu_d$, $\pi_z = 1$, and $\eta_z = \eta$. The per-period discount rate is then:

$$\bar{r}_{d,t}^n \simeq \mu_d + \frac{1}{n}\left[\mu_y \sum_{s=0}^{n-1} \frac{1-\omega^s}{1-\omega} + \frac{1-\omega^n}{1-\omega} y_t + \ln A_{d,n,t} - \left(a_n^d + b_n^d x_t + e_n^d y_t + f_n^d\left(\lambda_t - \bar{\lambda}\right)\right)\right].$$

where a_n^d, b_n^d, e_n^d, and f_n^d are defined as in equations A.14b to A.14e, and $A_{d,n,t}$ is defined as:

$$A_{d,n,t} \equiv E_t\left[\exp\left\{\sum_{i=0}^{n-1} J_{t+n-i}\left(\psi\frac{1-\omega^i}{1-\omega} - \eta\right)\right\}\right].$$

Damages: To derive claims to damages, we need $\Delta z_{t+1} = \Delta q_{t+1}$, i.e. $\mu_z = \mu_q$, $\pi_z = -\pi_q$, and $\eta_z = -\eta_q$. The per-period discount rate is then:

$$\bar{r}_{q,t}^n \simeq \mu_q + \frac{1}{n}\left[-\pi_q\mu_y \sum_{s=0}^{n-1} \frac{1-\omega^s}{1-\omega} - \pi_q\frac{1-\omega^n}{1-\omega} y_t + \ln A_{q,n,t}\right]$$
$$- \frac{1}{n}\left[a_n^q + b_n^q x_t + e_n^q y_t + f_n^q\left(\lambda_t - \bar{\lambda}\right)\right], \tag{A.19}$$

where a_n^q, b_n^q, e_n^q, and f_n^q are defined as in equation A.15, and $A_{q,n,t}$ is defined as:

$$A_{q,n,t} \equiv E_t\left[\exp\left\{\sum_{i=0}^{n-1} J_{t+n-i}\left(-\pi_q\psi\frac{1-\omega^i}{1-\omega} + \eta_q\right)\right\}\right].$$

A.6.4 Expected Returns and Return Decomposition for Rent Strips

In this section, we derive expressions for expected returns to rent strips and decompose rent strip returns following the methodology outlined in Section A.5.2.

A.6.4.1 Expected Returns on Rent Strips

The return on a rent strip is given by:

$$R_{d,t,t+1}^{(n)} = \frac{P_{d,t+1}^{(n-1)}}{P_{d,t}^{(n)}}.$$

Consequently, the log return on the strip is simply:

$$r_{d,t,t+1}^{(n)} = \ln P_{d,t+1}^{(n-1)} - \ln P_{d,t}^{(n)} = p_{d,t+1}^{(n-1)} - p_{d,t}^{(n)} + \Delta d_{t+1}$$

for $n > 1$, and $\Delta d_{t+1} - p_{d,t}^{(1)}$ for $n = 1$ (for the first return, we just set $p_{d,t}^{(0)} = 0$; note that we have to adjust for Δd_{t+1} because we denote by p the log price-dividend ratio, not just the log price). Substituting for the log price-dividend ratio and for dividend growth, we get:

$$\begin{aligned} r_{d,t,t+1}^{(n)} = & \left[a_{n-1}^d + b_{n-1}^d x_{t+1} + e_{n-1}^d y_{t+1} + f_{n-1}^d \left(\lambda_{t+1} - \bar{\lambda}\right)\right] \\ & - \left[a_n^d + b_n^d x_t + e_n^d y_t + f_n^d \left(\lambda_t - \bar{\lambda}\right)\right] + \left[\mu_d + y_t - \eta J_{t+1}\right]. \end{aligned}$$

Substituting for x_{t+1}, y_{t+1}, and λ_{t+1} and collecting shock terms, we get:

$$\begin{aligned} r_{d,t,t+1}^{(n)} = & \left[a_{n-1}^d + b_{n-1}^d \left(\mu_x + \rho x_t\right) + e_{n-1}^d \left(\mu_y + \omega y_t\right) + f_{n-1}^d \left(\mu_\lambda + \alpha \lambda_t + \nu x_t - \bar{\lambda}\right)\right] \\ & - \left[a_n^d + b_n^d x_t + e_n^d y_t + f_n^d \left(\lambda_t - \bar{\lambda}\right)\right] + \left[\mu_d + y_t\right] \\ & + \left(b_{n-1}^d \phi + e_{n-1}^d \psi + f_{n-1}^d \chi - \eta\right) J_{t+1}. \end{aligned} \tag{A.20}$$

For the expected return of the rent strip, we have:

$$\begin{aligned} E_t\left[R_{d,t,t+1}^{(n)}\right] & = E_t\left[\exp\left\{r_{d,t,t+1}^{(n)}\right\}\right] \\ = \exp & \left\{\left[a_{n-1}^d + b_{n-1}^d \left(\mu_x + \rho x_t\right) + e_{n-1}^d \left(\mu_y + \omega y_t\right) + f_{n-1}^d \left(\mu_\lambda + \alpha \lambda_t + \nu x_t - \bar{\lambda}\right)\right]\right\} \\ & \times \exp\left\{-\left[a_n^d + b_n^d x_t + e_n^d y_t + f_n^d \left(\lambda_t - \bar{\lambda}\right)\right] + \left[\mu_d + y_t\right]\right\} \\ & \times \left[1 + \lambda_t \left(\exp\left\{\left(b_{n-1}^d \phi + e_{n-1}^d \psi + f_{n-1}^d \chi - \eta\right) \xi\right\} - 1\right)\right], \end{aligned} \tag{A.21}$$

where the last line follows from J_{t+1} only taking value $\xi \in (0, 1)$ with probability λ_t and zero else, and therefore:

$$\begin{aligned} & E_t\left[\exp\left\{\left(b_{n-1}^d \phi + e_{n-1}^d \psi + f_{n-1}^d \chi - \eta\right) J_{t+1}\right\}\right] \\ & = (1 - \lambda_t) + \lambda_t \exp\left\{\left(b_{n-1}^d \phi + e_{n-1}^d \psi + f_{n-1}^d \chi - \eta\right) \xi\right\}. \end{aligned}$$

A.6.4.2 Return Decomposition for Rent Strips

As discussed in Section A.5, in our model with power utility, we have $z_0 = \gamma$ and $z_k = 0$ for $k > 0$, and thus equation A.10 simplifies to:

$$E_t[R^{(n)}_{d,t,t+1}] - R^f_{t,t+1} \simeq \gamma Cov_t\left[r^{(n)}_{d,t,t+1}, \Delta c_{t+1}\right].$$

Substituting for consumption growth $\Delta c_{t+1} = \mu + x_t - J_{t+1}$ and the log strip return from equation A.20, and dropping constant terms, we get:

$$\gamma Cov_t\left[r^{(n)}_{d,t,t+1}, \Delta c_{t+1}\right] = \gamma Cov_t\left[\left(b^d_{n-1}\phi + e^d_{n-1}\psi + f^d_{n-1}\chi - \eta\right) J_{t+1}, -J_{t+1}\right].$$

Since $Var_t\left[J_{t+1}\right] = \xi^2 \lambda_t \left(1 - \lambda_t\right)$, we obtain:

$$\gamma Cov_t\left[r^{(n)}_{d,t,t+1}, \Delta c_{t+1}\right] = \gamma\left[\eta - \phi b^d_{n-1} - \psi e^d_{n-1} - \chi f^d_{n-1}\right]\xi^2 \lambda_t \left(1 - \lambda_t\right),$$

and therefore:

$$\begin{aligned} E_t[R^{(n)}_{d,t,t+1}] - R^f_{t,t+1} &\simeq \gamma\, Cov_t[r^{(n)}_{d,t,t+1}, \Delta c_{t+1}] \\ &= \gamma\left[\eta - \psi e^d_{n-1} - \phi b^d_{n-1} - \chi f^d_{n-1}\right]\xi^2 \lambda_t (1 - \lambda_t). \end{aligned} \tag{A.22}$$

where b^d_{n-1}, e^d_{n-1}, and f^d_{n-1} are defined in equations A.14c to A.14e.

A.6.5 Price-Rent Ratio Semi-Elasticity to Disaster Probability

The price-rent ratio of the freehold is simply the sum of the price-rent ratios of strips across all maturities:

$$PD^{fh}_{d,t} = \sum_{n=1}^{\infty} PD^{(n)}_{d,t} = \sum_{n=1}^{\infty} \exp\left\{p^{(n)}_{d,t}\right\}.$$

After substituting for the log price-rent ratio for the strips from equation A.14a, we can see that the semi-elasticity of the price-dividend ratio with respect to the disaster probability λ_t is:

$$\frac{\partial p_{d,t}}{\partial \lambda_t} = \frac{1}{PD^{fh}_{d,t}} \sum_{n=1}^{\infty} PD^{(n)}_{d,t} f^d_n.$$

It tells us by how much the price dividend-ratio moves (in percent) if the probability of a disaster increases by one percentage point. Note that this semi-elasticity is affected by two opposing forces: As the disaster probability increases, the risk-free rate falls for precautionary motives, while the risk premium increases. To isolate the effect of an increase in disaster probabilities (without a disaster having occurred) on the risk premium, we can look at properties that are differentially exposed to the disaster risk. In particular, the difference between the semi-elasticity of two properties, one with high and one with low loadings on climate risk ($\eta_d^H > \eta_d^L$) is:

$$\frac{\partial \left(p_{d,t}^H - p_{d,t}^L\right)}{\partial \lambda_t} = \frac{1}{PD_{d,t}^H} \sum_{n=1}^{\infty} PD_{d,t}^{H(n)} f_d^{n,H} - \frac{1}{PD_{d,t}^L} \sum_{n=1}^{\infty} PD_{d,t}^{L(n)} f_d^{n,L}.$$

Intuitively, we expect this number to be negative – all else equal, the risk premium of a property with higher disaster-risk exposure should increase by more than the risk premium of a property with lower disaster-risk exposure as disaster risk increases (and hence the price of a property with higher disaster-risk exposure should decrease relative to the price of a property with lower disaster-risk exposure).

A.6.6 Expected Returns and Risk Premia for the Freehold

The return on the freehold is:

$$E_t\left[R_{d,t,t+1}^{fh}\right] = \sum_{n=1}^{\infty} \left[\frac{PD_{d,t}^n}{PD_{d,t}^{fh}} E_t\left[R_{d,t,t+1}^{(n)}\right]\right].$$

The risk premium for the freehold then is:

$$E_t\left[R_{d,t,t+1}^{fh} - R_{t,t+1}^f\right] = \sum_{n=1}^{\infty} \left[\frac{PD_{d,t}^{(n)}}{PD_{d,t}^{fh}} E_t\left[R_{d,t,t+1}^{(n)} - R_{t,t+1}^f\right]\right].$$

A.7 Solving the Model

A.7.1 Cash Flow Strip Prices

We are going to derive prices of arbitrary cash flows Z_{t+1} here, where

$$\Delta z_{t+1} = \mu_z + \pi_z y_t - \eta_z J_{t+1},$$

and where y_t captures persistent changes in the growth rate of the cash flows and J_{t+1} is the underlying economic shock. Including separate and flexible loadings on persistent changes in the growth rate of cash flows, π_z, as well as the underlying economic shock, η_z, will allow us to nest the dynamics of all assets and liabilities relevant to our discussion in Section 2. This allows us to solve the model once and parameterize the solution as needed. The solution is recursive:

For maturity 1: We can price a claim to next period's cash flow (i.e., the first cash flow strip) as:

$$P_{z,t}^{(1)} = E_t \left[M_{t+1} Z_{t+1} \right],$$

or:

$$\frac{P_{z,t}^{(1)}}{Z_t} = E_t \left[M_{t+1} \frac{Z_{t+1}}{Z_t} \right].$$

Rewriting in logs and substituting for the log stochastic discount factor, we have:

$$\exp\left\{ p_{z,t}^{(1)} \right\} = E_t \left[\exp\left\{ \ln\delta - \gamma\Delta c_{t+1} + \Delta z_{t+1} \right\} \right],$$

and substituting for the consumption and cash flow growth rates, and collecting terms, we have:

$$= E_t \left[\exp\left\{ \ln\delta - \gamma\left(\mu + x_t\right) + \mu_z + \pi_z y_t + \left(\gamma - \eta_z\right) J_{t+1} \right\} \right].$$

We can now pull time-t information out of the expectation:

$$= \exp\left\{ \ln\delta - \gamma\left(\mu + x_t\right) + \mu_z + \pi_z y_t \right\} E_t \left[\exp\left\{ \left(\gamma - \eta_z\right) J_{t+1} \right\} \right],$$

and recall that J_{t+1} only takes value ξ with probability λ_t and zero else, and therefore:

$$E_t \left[\exp\left\{ \left(\gamma - \eta_z\right) J_{t+1} \right\} \right] = \left(1 - \lambda_t\right) + \lambda_t \exp\left\{ \left(\gamma - \eta_z\right)\xi \right\}.$$

After taking logs, we get:

$$p_{z,t}^{(1)} = \ln\delta - \gamma\left(\mu + x_t\right) + \mu_z + \pi_z y_t + \ln\left[1 + \lambda_t \left(\exp\left\{ \left(\gamma - \eta_z\right)\xi \right\} - 1\right)\right].$$

Via Taylor expansion of the last term around the unconditional mean of λ_t, $\bar{\lambda}$, we obtain:

$$\ln\left[1 + \lambda_t \left(\exp\left\{ \left(\gamma - \eta_z\right)\xi \right\} - 1\right)\right]$$

$$\simeq \ln\left[1 + \bar{\lambda}\left(\exp\left\{ \left(\gamma - \eta_z\right)\xi \right\} - 1\right)\right] + \frac{\exp\left\{ \left(\gamma - \eta_z\right)\xi \right\} - 1}{1 + \bar{\lambda}\left(\exp\left\{ \left(\gamma - \eta_z\right)\xi \right\} - 1\right)} \left(\lambda_t - \bar{\lambda}\right).$$

Thus:

$$p_{z,t}^{(1)} = \ln\delta - \gamma\left(\mu + x_t\right) + \mu_z + \pi_z y_t$$

$$+\ln\left[1+\bar{\lambda}\left(\exp\left\{\left(\gamma-\eta_z\right)\xi\right\}-1\right)\right]+\frac{\exp\left\{\left(\gamma-\eta_z\right)\xi\right\}-1}{1+\bar{\lambda}\left(\exp\left\{\left(\gamma-\eta_z\right)\xi\right\}-1\right)}\left(\lambda_t-\bar{\lambda}\right),$$

or:

$$p_{z,t}^{(1)}=a_1^z+b_1^z x_t+e_1^z y_t+f_1^z\left(\lambda_t-\bar{\lambda}\right), \tag{A.23}$$

with

$$\begin{aligned}
a_1^z &= \ln\delta-\gamma\mu+\mu_z+\ln\left[1+\bar{\lambda}\left(\exp\left\{\left(\gamma-\eta_z\right)\xi\right\}-1\right)\right]\\
b_1^z &= -\gamma\\
e_1^z &= \pi_z\\
f_1^z &= \frac{\exp\left\{\left(\gamma-\eta_z\right)\xi\right\}-1}{1+\bar{\lambda}\left(\exp\left\{\left(\gamma-\eta_z\right)\xi\right\}-1\right)}.
\end{aligned}$$

For arbitrary maturity n: For arbitrary maturities, we conjecture that all $p_{z,t}^{(n)}$ will follow the recursion:

$$p_{z,t}^{(n)}=a_n^z+b_n^z x_t+e_z^d y_t+f_n^z\left(\lambda_t-\bar{\lambda}\right),$$

where a_1^z, b_1^z, e_1^z, and f_1^z are defined as above. We can price a claim to an n-period cash flow (i.e., the n-th dividend strip) as:

$$P_{z,t}^{(n)}=E_t\left[M_{t+1}P_{z,t+1}^{(n-1)}\right],$$

or:

$$\frac{P_{z,t}^{(n)}}{Z_t}=E_t\left[M_{t+1}\frac{P_{z,t+1}^{(n-1)}}{Z_{t+1}}\frac{Z_{t+1}}{Z_t}\right].$$

Rewriting in logs and substituting for the log stochastic discount factor, we have:

$$\exp\left\{p_{z,t}^{(n)}\right\}=E_t\left[\exp\left\{\ln\delta-\gamma\Delta c_{t+1}+\Delta z_{t+1}+p_{z,t+1}^{(n-1)}\right\}\right],$$

and substituting for the consumption and cash flow growth rates and the log price-dividend ratio, and collecting terms, we have:

$$=\exp\left\{\ln\delta-\gamma\left(\mu+x_t\right)+\mu_z+\pi_z y_t\right\}$$

$$\times E_t\left[\exp\left\{\left(\gamma-\eta_z\right)J_{t+1}+a_{n-1}^z+b_{n-1}^z x_{t+1}+e_{n-1}^z y_{t+1}+f_{n-1}^z\left(\lambda_{t+1}-\bar{\lambda}\right)\right\}\right].$$

Substituting for x_{t+1}, y_{t+1} and λ_{t+1}, and collecting a few terms and all shocks, we get:

$$=\exp\left\{\ln\delta-\gamma\mu+\mu_z+a_{n-1}^z+b_{n-1}^z\mu_x+e_{n-1}^z\mu_y+f_{n-1}^z\left(\mu_\lambda+\bar{\lambda}\left(\alpha-1\right)\right)\right\}$$

$$\times \exp\left\{\left(-\gamma + b_{n-1}^{z}\rho + f_{n-1}^{z}\nu\right) x_t + \left(\pi_z + e_{n-1}^{z}\omega\right) y_t + f_{n-1}^{z}\alpha\left(\lambda_t - \bar{\lambda}\right)\right\}$$
$$\times E_t\left[\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right) J_{t+1}\right\}\right].$$

Recall that J_{t+1} only takes value ξ with probability λ_t and zero else, and therefore:

$$E_t\left[\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right) J_{t+1}\right\}\right]$$
$$= (1-\lambda_t) + \lambda_t \exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right)\xi\right\}.$$

After taking logs, we get:

$$\begin{aligned} p_{z,t}^{(n)} &= \ln\delta - \gamma\mu + \mu_z + a_{n-1}^{z} + b_{n-1}^{z}\mu_x + e_{n-1}^{z}\mu_y + f_{n-1}^{z}\left(\mu_\lambda + \bar{\lambda}\left(\alpha - 1\right)\right) \\ &+ \left(-\gamma + b_{n-1}^{z}\rho + f_{n-1}^{z}\nu\right) x_t + \left(\pi_z + e_{n-1}^{z}\omega\right) y_t + f_{n-1}^{z}\alpha\left(\lambda_t - \bar{\lambda}\right) \\ &+ \ln\left[1 + \lambda_t\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right)\xi\right\} - 1\right)\right]. \end{aligned}$$

Via Taylor expansion of the last term around the unconditional mean of λ_t, $\bar{\lambda}$, we obtain:

$$\ln\left[1 + \lambda_t\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right)\xi\right\} - 1\right)\right]$$
$$\begin{aligned} &\simeq \ln\left[1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right)\xi\right\} - 1\right)\right] \\ &+ \frac{\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right)\xi\right\} - 1}{1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right)\xi\right\} - 1\right)}\left(\lambda_t - \bar{\lambda}\right). \end{aligned}$$

Thus:

$$\begin{aligned} p_{z,t}^{(n)} &= \ln\delta - \gamma\mu + \mu_z + a_{n-1}^{z} + b_{n-1}^{z}\mu_x + e_{n-1}^{z}\mu_y + f_{n-1}^{z}\left(\mu_\lambda + \bar{\lambda}\left(\alpha - 1\right)\right) \\ &+ \ln\left[1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right)\xi\right\} - 1\right)\right] \\ &+ \left(-\gamma + b_{n-1}^{z}\rho + f_{n-1}^{z}\nu\right) x_t + \left(\pi_z + e_{n-1}^{z}\omega\right) y_t + f_{n-1}^{z}\alpha\left(\lambda_t - \bar{\lambda}\right) \\ &+ \frac{\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right)\xi\right\} - 1}{1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^{z}\phi + e_{n-1}^{z}\psi + f_{n-1}^{z}\chi\right)\xi\right\} - 1\right)}\left(\lambda_t - \bar{\lambda}\right). \end{aligned}$$

Matching coefficients, we get the following expression for the log price-dividend ratio:

$$p_{z,t}^{(n)} = a_n^{z} + b_n^{z} x_t + e_n^{z} y_t + f_n^{z}\left(\lambda_t - \bar{\lambda}\right), \tag{A.24}$$

with:

$$\begin{aligned}
a_n^z &= \ln\delta - \gamma\mu + \mu_z + a_{n-1}^z + b_{n-1}^z\mu_x + e_{n-1}^z\mu_y + f_{n-1}^z\left(\mu_\lambda + \bar{\lambda}\left(\alpha - 1\right)\right) \\
&+ \ln\left[1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^z\phi + e_{n-1}^z\psi + f_{n-1}^z\chi\right)\xi\right\} - 1\right)\right] \\
b_n^z &= -\gamma + b_{n-1}^z\rho + f_{n-1}^z\nu \\
e_n^z &= e_{n-1}^z\omega + \pi_z \\
f_n^z &= f_{n-1}^z\alpha + \frac{\exp\left\{\left(\gamma - \eta_z + b_{n-1}^z\phi + e_{n-1}^z\psi + f_{n-1}^z\chi\right)\xi\right\} - 1}{1 + \bar{\lambda}\left(\exp\left\{\left(\gamma - \eta_z + b_{n-1}^z\phi + e_{n-1}^z\psi + f_{n-1}^z\chi\right)\xi\right\} - 1\right)},
\end{aligned}$$

and $a_0^z = b_0^z = e_0^z = f_0^z = 0$.

A.7.2 Expected Cash Flows

The expected flow from a strip of arbitrary maturity n is:

$$E_t\left[Z_{t+n}\right] = Z_t E_t\left[\exp\left\{\Delta z_{t+1} + ... + \Delta z_{t+n}\right\}\right].$$

To compute $E_t\left[\exp\left\{\Delta z_{t+1} + ... + \Delta z_{t+n}\right\}\right]$, we iterate forward:

For $n = 1$: For $n = 1$, we have:

$$E_t\left[\exp\left\{\Delta z_{t+1}\right\}\right] = E_t\left[\exp\left\{\mu_z + \pi_z y_t - \eta_z J_{t+1}\right\}\right]$$

$$= \exp\left\{\mu_z + \pi_z y_t\right\} E_t\left[\exp\left\{-\eta_z J_{t+1}\right\}\right]$$

Recall that J_{t+1} only takes value ξ with probability λ_t and zero else, and therefore:

$$E_t\left[Z_{t+1}\right] = Z_t \exp\left\{\mu_z + \pi_z y_t\right\}\left[\left(1 - \lambda_t\right) + \lambda_t \exp\left\{-\eta_z\xi\right\}\right].$$

For $n = 2$: Iterating forward to $n = 2$, we have:

$$E_t\left[\exp\left\{\Delta z_{t+1} + \Delta z_{t+2}\right\}\right] = E_t\left[\exp\left\{\left(\mu_z + \pi_z y_t - \eta_z J_{t+1}\right) + \left(\mu_z + \pi_z y_{t+1} - \eta_z J_{t+2}\right)\right\}\right],$$

substituting for y_{t+1} and collecting terms, we get:

$$= \exp\left\{2\mu_z + \pi_z\left(1 + \omega\right) y_t + \pi_z\mu_y\right\} E_t\left[\exp\left\{\left[\pi_z\psi - \eta_z\right] J_{t+1} - \eta_z J_{t+2}\right\}\right].$$

Note that the jump events are not independent unless λ_t is constant and define:

$$A_{z,2,t} \equiv E_t \left[\exp\left\{[\pi_z\psi - \eta_z] J_{t+1} - \eta_z J_{t+2}\right\}\right].$$

Thus:

$$E_t [Z_{t+2}] = Z_t \exp\left\{2\mu_z + \pi_z (1+\omega) y_t + \pi_z \mu_y\right\} A_{z,2,t}.$$

For $n = 3$: Iterating forward to $n = 3$, we have:

$$E_t \left[\exp\left\{\Delta z_{t+1} + \Delta z_{t+2} + \Delta z_{t+3}\right\}\right]$$

$$= E_t \left[\exp\left\{(\mu_z + \pi_z y_t - \eta_z J_{t+1}) + (\mu_z + \pi_z y_{t+1} - \eta_z J_{t+2}) + (\mu_z + \pi_z y_{t+2} - \eta_z J_{t+3})\right\}\right],$$

substituting for y_{t+1} and y_{t+2} iteratively and collecting terms, we get:

$$= \exp\left\{3\mu_z + \pi_z \left(1 + \omega + \omega^2\right) y_t + \pi_z [1 + (1+\omega)] \mu_y\right\}$$

$$\times E_t \left[\exp\left\{[\pi_z (1+\omega)\psi - \eta_z] J_{t+1} + [\pi_z\psi - \eta_z] J_{t+2} - \eta_z J_{t+3}\right\}\right].$$

As before, define:

$$A_{z,3,t} \equiv E_t \left[\exp\left\{[\pi_z (1+\omega)\psi - \eta_z] J_{t+1} + [\pi_z\psi - \eta_z] J_{t+2} - \eta_z J_{t+3}\right\}\right].$$

Thus:

$$E_t [Z_{t+3}] = Z_t \exp\left\{3\mu_z + \pi_z \left(1 + \omega + \omega^2\right) y_t + \pi_z [1 + (1+\omega)] \mu_y\right\} A_{z,3,t}.$$

For arbitrary n: We conclude that cash flow growth is given by:

$$E_t [Z_{t+n}] = Z_t \exp\left\{n\mu_z + \pi_z \frac{1-\omega^n}{1-\omega} y_t + \pi_z \mu_y \sum_{s=0}^{n-1} \frac{1-\omega^s}{1-\omega}\right\} A_{z,n,t}, \tag{A.25a}$$

with

$$A_{z,n,t} \equiv E_t \left[\exp\left\{\sum_{i=0}^{n-1} J_{t+n-i} \left(\pi_z \psi \frac{1-\omega^i}{1-\omega} - \eta_z\right)\right\}\right]. \tag{A.25b}$$

These expectations can be computed in closed form for short horizons, but are best computed numerically for longer horizons. We outline a numerical solution algorithm in Section A.7.3.

A.7.3 Solution method for $A_{z,n,t}$

In this section, we describe our numerical solution method for $A_{z,n,t}$. Remember that $A_{z,n,t}$ is defined as:

$$A_{z,n,t} \equiv E_t \left[\exp \left\{ \sum_{i=0}^{n-1} J_{t+n-i} \left(\pi_z \psi \frac{1-\omega^i}{1-\omega} - \eta_z \right) \right\} \right],$$

and captures the history of (path-dependent) jump events that go into cash flow growth. More generically, we want to compute:

$$A_{z,n,t} = E_t \left[\exp \left\{ \beta_1^z J_{t+1} + \beta_2^z J_{t+2} + ... + \beta_n^z J_{t+n} \right\} \right]$$

for arbitrary constants $\beta_1^z ... \beta_n^z$ and arbitrary maturity n, where J_{t+1} is a variable that, conditional on time-t information (particularly λ_t), has value ξ with probability λ_t and zero else, and where

$$\lambda_{t+1} = \mu_\lambda + \alpha \lambda_t + \nu x_t + \chi J_{t+1},$$

with

$$x_{t+1} = \mu_x + \rho x_t + \phi J_{t+1}.$$

To solve for $A_{z,n,t}$ numerically, we start from the last period n. By the law of iterated expectations, we have:

$$E_t \left[\exp \left\{ \beta_1^z J_{t+1} + \beta_2^z J_{t+2} + ... + \beta_n^z J_{t+n} \right\} \right]$$

$$= E_t \left[E_{t+n-1} \left[\exp \left\{ \beta_1^z J_{t+1} + \beta_2^z J_{t+2} + ... + \beta_n^z J_{t+n} \right\} \right] \right]$$

$$= E_t \left[\exp \left\{ \beta_1^z J_{t+1} + \beta_2^z J_{t+2} + ... + \beta_{n-1}^z J_{t+n-1} \right\} E_{t+n-1} \left[\exp \left\{ \beta_n^z J_{t+n} \right\} \right] \right].$$

Note that the jumps J_{t+1} to J_{t+n-1} are all known by time $t+n-1$, so we can pull them outside the internal expectation. Next, we can solve for the internal expectation:

$$E_{t+n-1} \left[\exp \left\{ \beta_n^z J_{t+n} \right\} \right] = (1 - \lambda_{t+n-1}) + \lambda_{t+n-1} \exp \left\{ \beta_n^z \xi \right\}.$$

We can think of this as a sort of binomial tree where jump probabilities change over time – each period either a jump is realized or not, and that outcome also changes λ for the next node. Note that the above expression is only a function of λ, call it $f_{n-1}(\lambda, x)$ for consistency with later steps:

$$f_{n-1}(\lambda, x) \equiv (1 - \lambda) + \lambda \exp \left\{ \beta_n^z \xi \right\}.$$

We compute $f_{n-1}(\lambda, x)$ on a grid of possible values for λ and x and store it for later use. Updating our expression for $A_{z,n,t}$, we have:

$$A_{z,n,t} = E_t\left[\exp\left\{\beta_1^z J_{t+1} + \beta_2^z J_{t+2} + ... + \beta_{n-1}^z J_{t+n-1}\right\} f_{n-1}\left(\lambda_{t+n-1}, x_{t+n-1}\right)\right].$$

Next, we iterate back, and condition on the information set at $t+n-2$:

$$E_t\left[E_{t+n-2}\left[\exp\left\{\beta_1^z J_{t+1} + \beta_2^z J_{t+2} + ... + \beta_{n-1}^z J_{t+n-1}\right\} f_{n-1}\left(\lambda_{t+n-1}, x_{t+n-1}\right)\right]\right] =$$

$$E_t\left[\exp\left\{\beta_1^z J_{t+1} + ... + \beta_{n-2}^z J_{t+n-2}\right\} E_{t+n-2}\left[\exp\left\{\beta_{n-1}^z J_{t+n-1}\right\} f_{n-1}\left(\lambda_{t+n-1}, x_{t+n-1}\right)\right]\right].$$

Note again that the internal expectation is only a function of λ_{t+n-2} and x_{t+n-2}. In particular:

$$E_{t+n-2}\left[\exp\left\{\beta_{n-1}^z J_{t+n-1}\right\} f_{n-1}\left(\lambda_{t+n-1}, x_{t+n-1}\right)\right] =$$

$$E_{t+n-2}\left[\exp\left\{\beta_{n-1}^z J_{t+n-1}\right\} f_{n-1}\left(\mu_\lambda + \alpha\lambda_{t+n-2} + \nu x_{t+n-2} + \chi J_{t+n-1}, \mu_x + \rho x_{t+n-2} + \phi J_{t+n-1}\right)\right]$$

$$= \left(1-\lambda_{t+n-2}\right)\left[f_{n-1}\left(\mu_\lambda + \alpha\lambda_{t+n-2} + \nu x_{t+n-2}, \mu_x + \rho x_{t+n-2}\right)\right]$$

$$+\lambda_{t+n-2}\left[\exp\left\{\beta_{n-1}^z \xi\right\} f_{n-1}\left(\mu_\lambda + \alpha\lambda_{t+n-2} + \nu x_{t+n-2} + \chi\xi, \mu_x + \rho x_{t+n-2} + \phi\xi\right)\right],$$

where the last expression reflects the fact that J_{t+n-1} is ξ with probability λ_{t+n-2} and zero else. As before, call this function $f_{n-2}(\lambda, x)$:

$$f_{n-2}(\lambda, x) \equiv (1-\lambda)\left[f_{n-1}\left(\mu_\lambda + \alpha\lambda + \nu x, \mu_x + \rho x\right)\right]$$

$$+\lambda\left[\exp\left\{\beta_{n-1}^z \xi\right\} f_{n-1}\left(\mu_\lambda + \alpha\lambda + \nu x + \chi\xi, \mu_x + \rho x + \phi\xi\right)\right].$$

We compute $f_{n-2}(\lambda, x)$ on a grid of possible values for λ and x again and store it for later use. Note that we are using the function f_{n-1} that we had computed in the previous iteration to compute f_{n-2}.

Next, we iterate back once more, and condition on the information set at $t+n-3$:

$$A_{z,n,t} = E_t\left[\exp\left\{\beta_1^z J_{t+1} + \beta_2^z J_{t+2} + ... + \beta_{n-2}^z J_{t+n-2}\right\} f_{n-2}\left(\lambda_{t+n-2}, x_{t+n-2}\right)\right] =$$

$$E_t\left[\exp\left\{\beta_1^z J_{t+1} + ... + \beta_{n-3}^z J_{t+n-3}\right\} E_{t+n-3}\left[\exp\left\{\beta_{n-2}^z J_{t+n-2}\right\} f_{n-2}\left(\lambda_{t+n-2}, x_{t+n-2}\right)\right]\right].$$

We keep iterating this way until we condition on the information set t, which only depends on λ_t (and x_t).

Appendix References

Ambrose, Brent W., Piet Eichholtz, and Thies Lindenthal. 2013. "House Prices and Fundamentals: 355 Years of Evidence." *Journal of Money, Credit and Banking*, 45(2-3): 477–491.

Arrow, Kenneth, Maureen Cropper, Christian Gollier, Ben Groom, Geoffrey Heal, Richard Newell, William Nordhaus, Robert Pindyck, William Pizer, Paul Portney, Thomas Sterner, Richard S. J. Tol, and Martin Weitzman. 2013. "Determining Benefits and Costs for Future Generations." *Science*, 341(6144): 349–350.

Bansal, Ravi, and Amir Yaron. 2004. "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles." *Journal of Finance*, 59(4): 1481–1509.

Barro, Robert J. 2006. "Rare Disasters and Asset Markets in the Twentieth Century." *Quarterly Journal of Economics*, 121(3): 823–866.

Barro, Robert J., and Jose F. Ursua. 2008. "Macroeconomic Crises since 1870." *Brookings Papers on Economic Activity*, 39(1): 255–350.

Bond, Charlotte Anne, Teran Martin, Susan Hume McIntosh, and Charles Ian Mead. 2007. "Integrated macroeconomic accounts for the United States." *Survey of Current Business*, 87(11): 14–31.

Bordo, Michael, Barry Eichengreen, Daniela Klingebiel, and Maria Soledad Martinez-Peria. 2001. "Is the Crisis Problem Growing More Severe?" *Economic Policy*, 16(32): 51–82.

Bracke, Philippe. 2015. "House Prices and Rents: Microevidence from a Matched Data Set in Central London." *Real Estate Economics*, 43(2): 403–431.

Bureau of Economic Analysis. 2017. "Concepts and Methods of the U.S. National Income and Product Accounts."

Campbell, John Y, and Tuomo Vuolteenaho. 2004. "Bad Beta, Good Beta." *American Economic Review*, 94(5): 1249–1275.

Cochrane, John H. 2005. *Asset Pricing.* Princeton, NJ:Princeton University Press.

Constantinescu, Mihnea, and Marc Francke. 2013. "The Historical Development of the Swiss Rental Market - A New Price Index." *Journal of Housing Economics*, 22(2): 135 – 145.

Crone, Theodore M., Leonard I. Nakamura, and Richard Voith. 2010. "Rents have been rising, not falling, in the postwar period." *The Review of Economics and Statistics*, 92(3): 628–642.

Davis, Morris A., and Jonathan Heathcote. 2007. "The Price and Quantity of Residential Land in the United States." *Journal of Monetary Economics*, 54(8): 2595–2620.

Dew-Becker, Ian, and Stefano Giglio. 2013. "Asset Pricing in the Frequency Domain: Theory and Empirics." National Bureau of Economic Research Working Paper 19416.

Dietz, Simon, Christian Gollier, and Louise Kessler. 2015. "The Climate Beta." *Centre for Climate Change Economics and Policy Working Paper No. 215.*

Dreze, Jean, and Nicholas Stern. 1987. "The Theory of Cost-Benefit Analysis." In *Handbook of Public Economics*. Vol. 2, , ed. A. J. Auerbach and M. Feldstein, Chapter 14, 909–989. Elsevier.

Eichholtz, Piet. 1997. "A Long Run House Price Index: The Herengracht Index, 1628–1973." *Real Estate Economics*, 25(2): 175–192.

Favilukis, Jack, Sydney C. Ludvigson, and Stijn van Nieuwerburgh. 2010. "The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk-Sharing in General Equilibrium." National Bureau of Economic Research Working Paper 15988.

Gabaix, Xavier. 2012. "Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance." *Quarterly Journal of Economics*, 127(2): 645–700.

Gordon, Robert J., and Todd vanGoethem. 2007. "Downward Bias in the Most Important

CPI Component: The Case of Rental Shelter, 1914–2003 - Chicago Scholarship." In *Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches.* , ed. Ernst R. Berndt and Charles R. Hulten, 153–195. Chicago, IL:University of Chicago Press.

Hansen, Lars Peter, and Scott F Richard. 1987. "The Role of Conditioning Information in Deducing Testable Restrictions Implied by Dynamic Asset Pricing Models." *Econometrica*, 55: 587–614.

Lucas, Robert E, Jr. 1978. "Asset Prices in an Exchange Economy." *Econometrica*, 46(6): 1429–45.

Mack, Adrienne, and Enrique Martínez-García. 2011. "A Cross-Country Quarterly Database of Real House Prices: A Methodological Note." Federal Reserve Bank of Dallas Globalization and Monetary Policy Working Paper 99.

Mayerhauser, Nicole, and Marshall Reinsdorf. 2006. "Housing Services in the National Economic Accounts." *US Bureau of Economic Analysis*.

Moura, Maria Cecilia P., Steven J. Smith, and David B. Belzer. 2015. "120 Years of U.S. Residential Housing Stock and Floor Space." *PLOS ONE*, 10(8): e0134135.

Moyer, Elisabeth J., Mark D. Woolley, Nathan J. Matteson, Michael J. Glotter, and David A. Weisbach. 2014. "Climate Impacts on Economic Growth as Drivers of Uncertainty in the Social Cost of Carbon." *The Journal of Legal Studies*, 43(2): 401 – 425.

ONS. 2014. "Consumer Price Indices - Technical Manual."

Piketty, Thomas, and Gabriel Zucman. 2014. "Capital is Back: Wealth-Income Ratios in Rich Countries 1700-2010." *The Quarterly Journal of Economics*, 129(3): 1255–1310.

Reed, Stephen B. 2014. "One hundred years of price change: the Consumer Price Index and the American inflation experience." *Monthly Lab. Rev.*, 137: 1.

Reinhart, Carmen M., and Kenneth S. Rogoff. 2009. *This Time is Different: Eight Centuries of Financial Folly.* Princeton University Press.

Schularick, Moritz, and Alan M. Taylor. 2012. "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises." *American Economic Review*, 102(2): 1029–1061.

Shiller, Robert. 2000. *Irrational Exuberance.* Princeton University Press, Princeton.

Stapledon, Nigel. 2012. "Trends and Cycles in Sydney and Melbourne House Prices from 1880 to 2011." *Australian Economic History Review*, 52(3): 293–317.

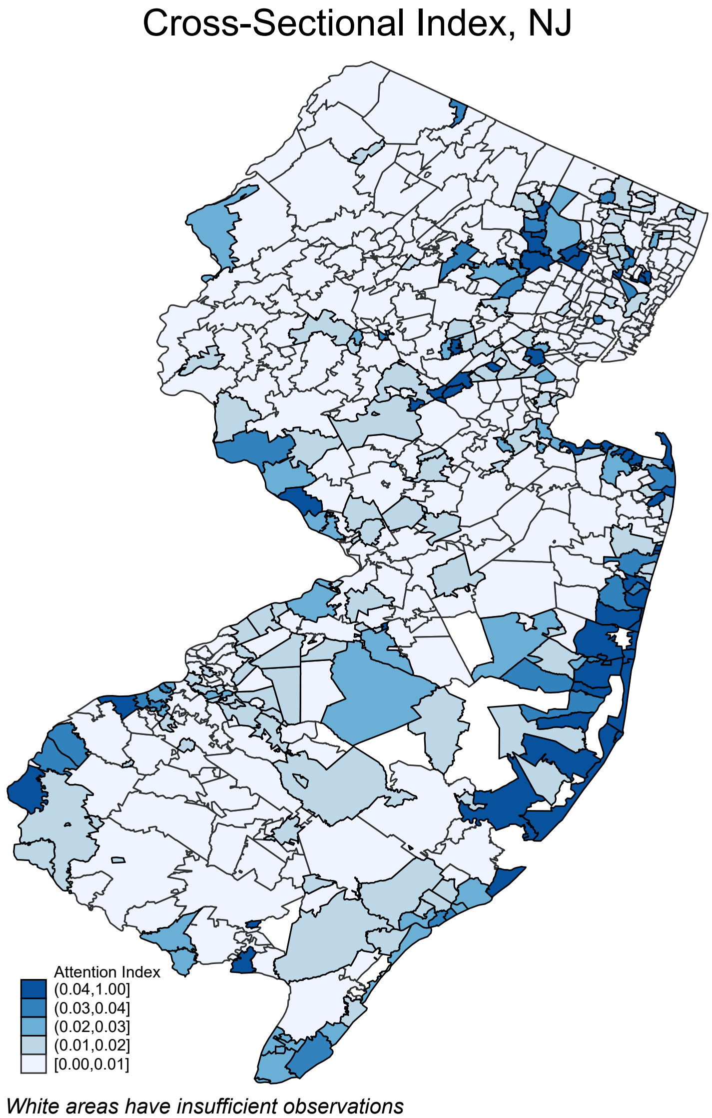
Stroebel, Johannes. 2016. "Asymmetric information about collateral values." *The Journal of Finance*, 71(3): 1071–1112.

van Benthem, Arthur. 2015. "What is the Optimal Speed Limit on Freeways?" *Journal of Public Economics*, 124: 44 – 62.

Weisbach, David A. 2014. "Distributionally Weighted Cost-Benefit Analysis: Welfare Economics Meets Organizational Design." *Journal of Legal Analysis*, 7(1): 151 – 182.

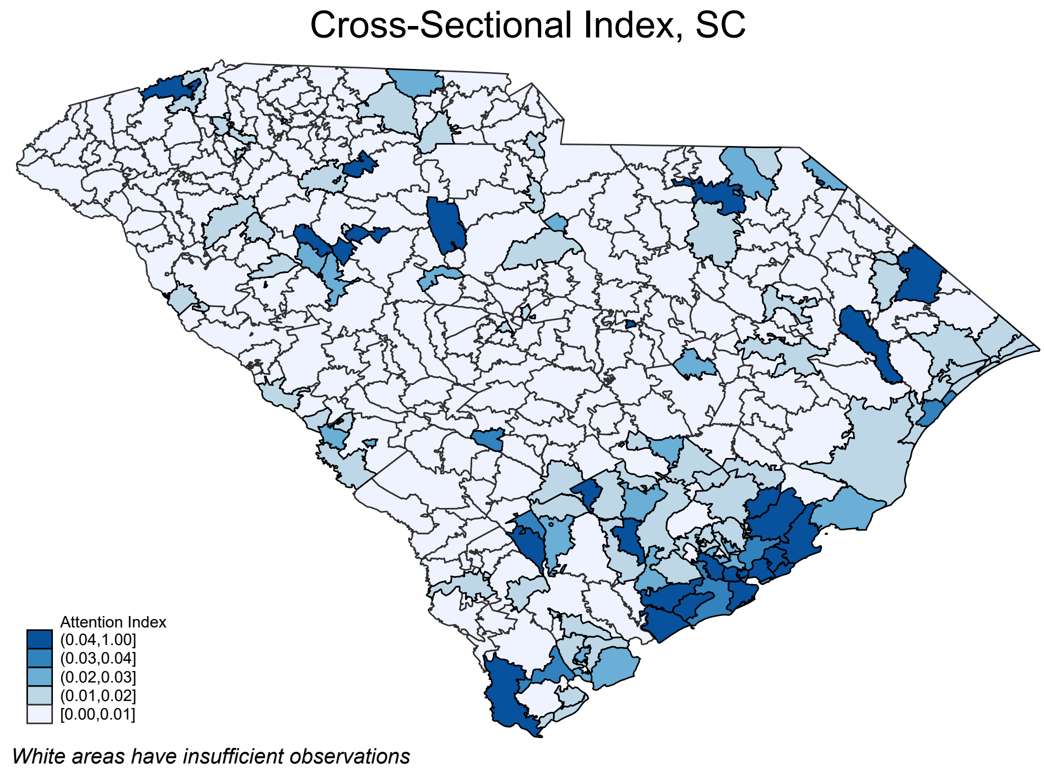
Appendix Figures

Figure A.1: Heatmap of Climate Attention Index in New Jersey



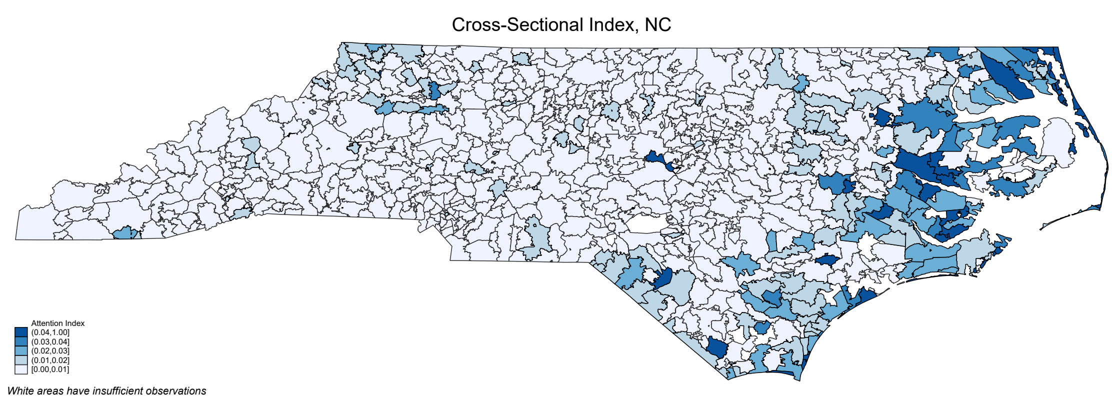
Note: Figure shows a heatmap of our "Climate Attention Index" in New Jersey at the zip-code level. The "Climate Attention Index" is defined as the fraction of for-sale listings whose description includes climate-related text for the period from 2008Q1 to 2017Q2.

Figure A.2: Heatmap of Climate Attention Index in South Carolina



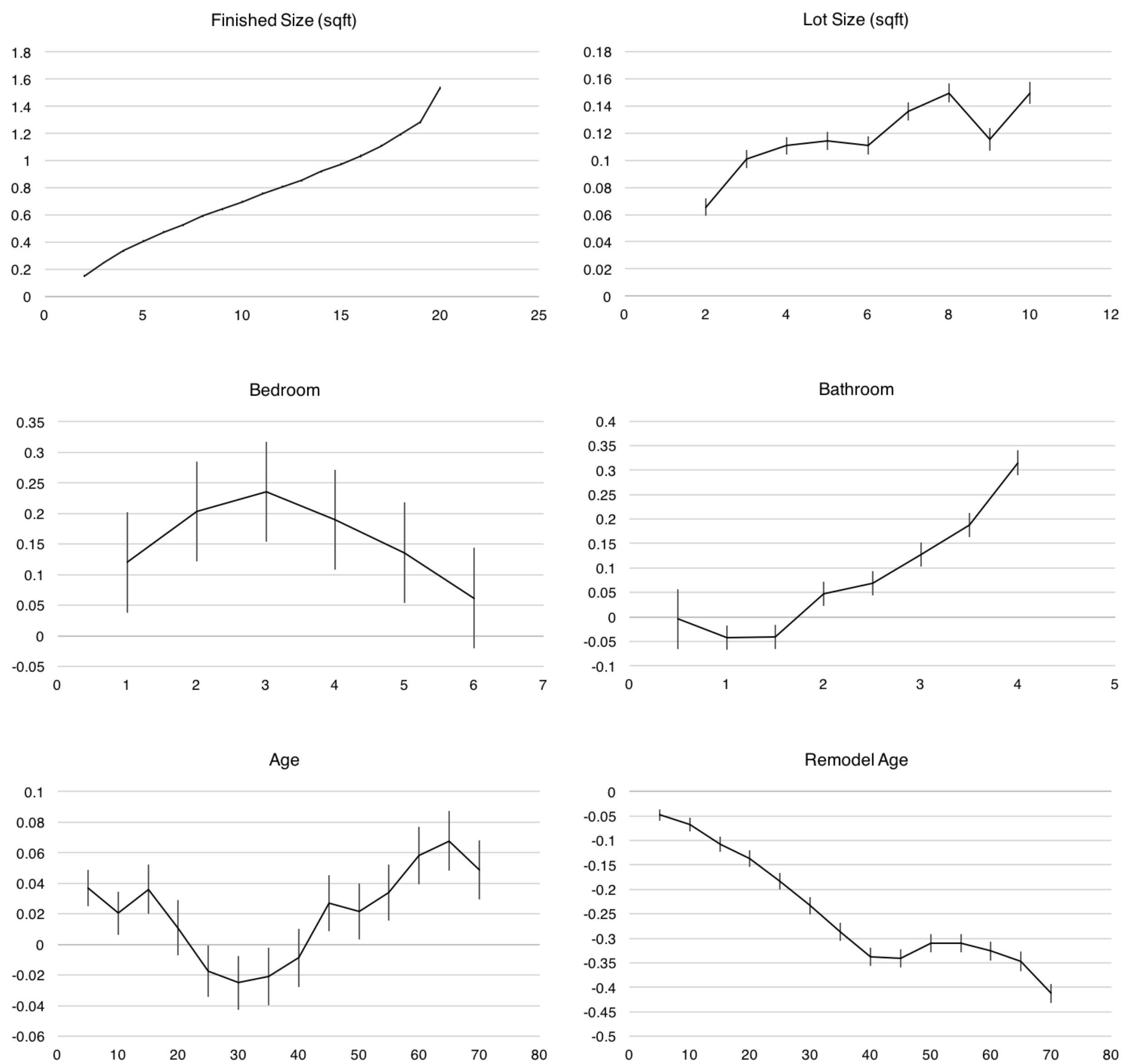
Note: Figure shows a heatmap of our "Climate Attention Index" in South Carolina at the zip-code level. The "Climate Attention Index" is defined as the fraction of for-sale listings whose description includes climate-related text for the period from 2008Q1 to 2017Q2.

Figure A.3: Heatmap of Climate Attention Index in North Carolina



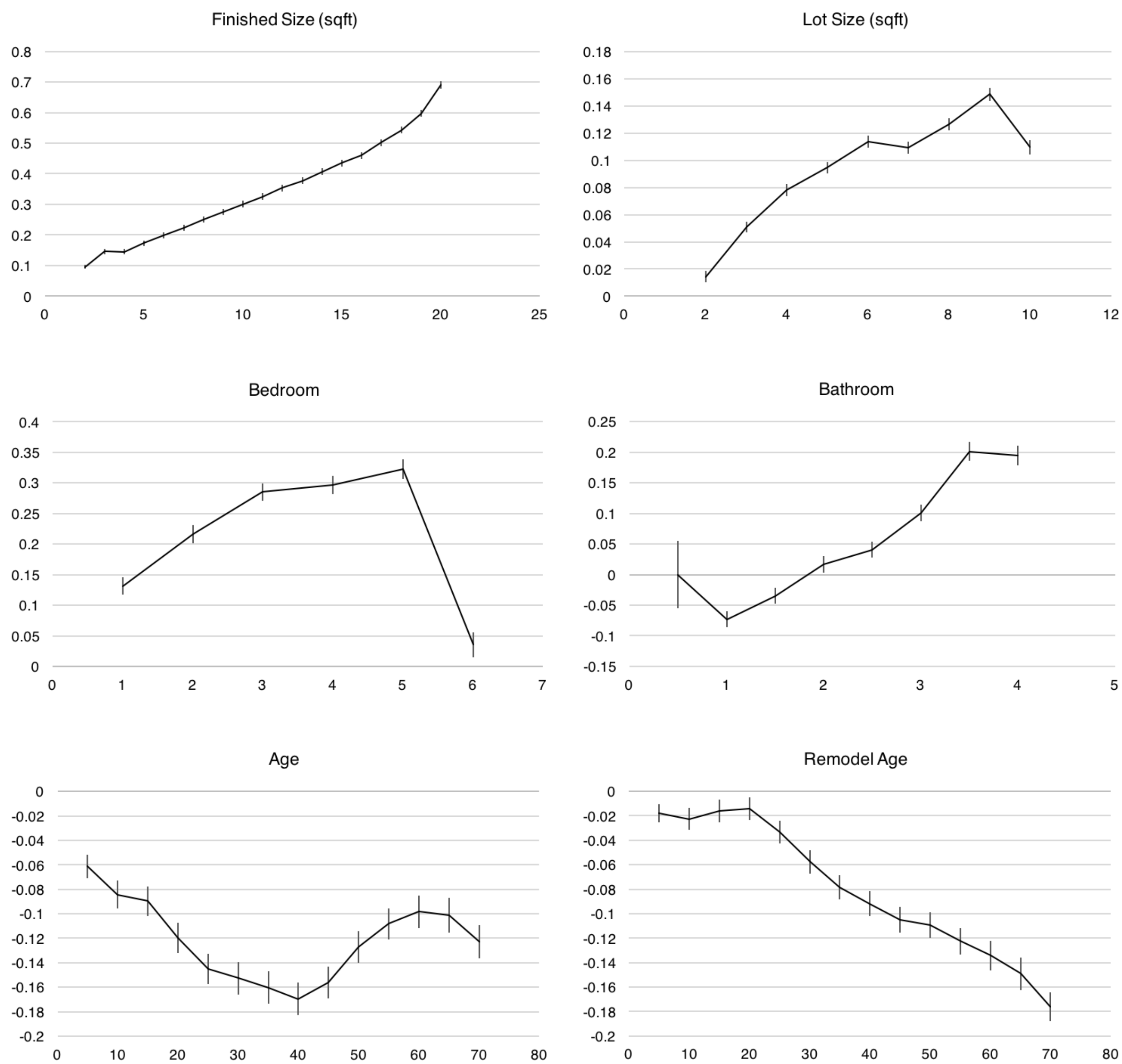
Note: Figure shows a heatmap of our "Climate Attention Index" in North Carolina at the zip-code level. The "Climate Attention Index" is defined as the fraction of for-sale listings whose description includes climate-related text for the period from 2008Q1 to 2017Q2.

Figure A.4: Hedonic Coefficients in Transaction Regression



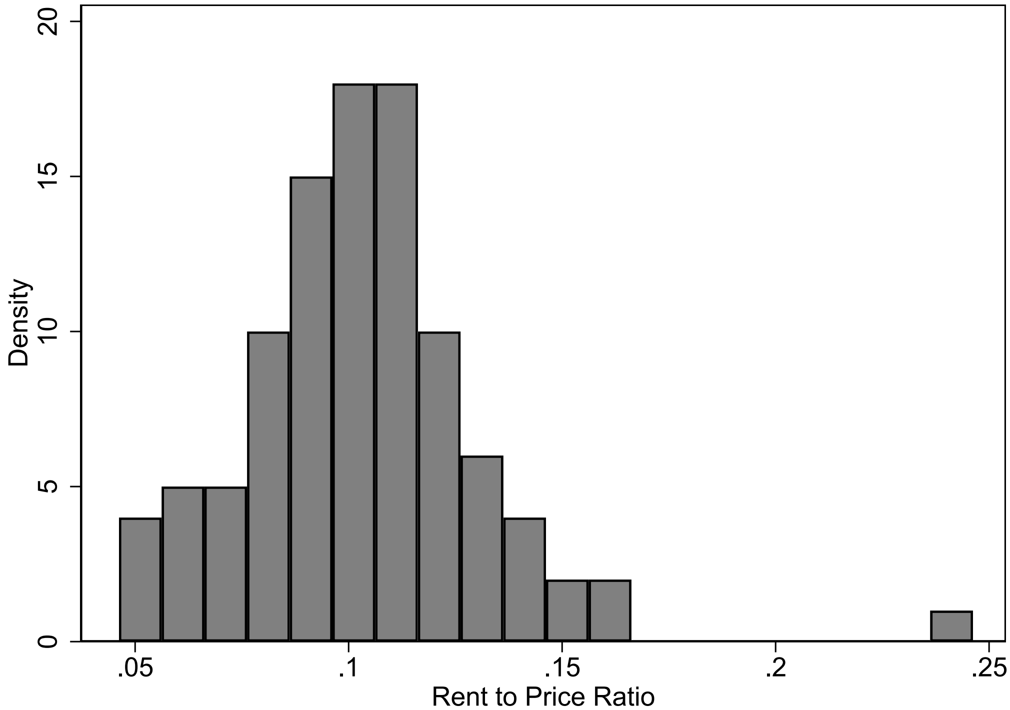
Note: Figures show coefficients on hedonic controls from regression 1. The dependent variable is the log price paid. Starting from the top left, the different panels show the coefficients on (i) indicators for ventiles of property size, (ii) indicators for deciles of lot size, (iii) indicators for the number of bedrooms, (iv) indicators for the number of bathrooms, (v) indicators on property age, and (vi) indicators on the time since the last major remodeling of the property. The regression includes other control variables and fixed effects as in Column 1 of Panel A, Table 1. The bars show 95% confidence intervals for standard errors clustered at the zip-code-quarter level.

Figure A.5: Hedonic Coefficients in Rental Regression



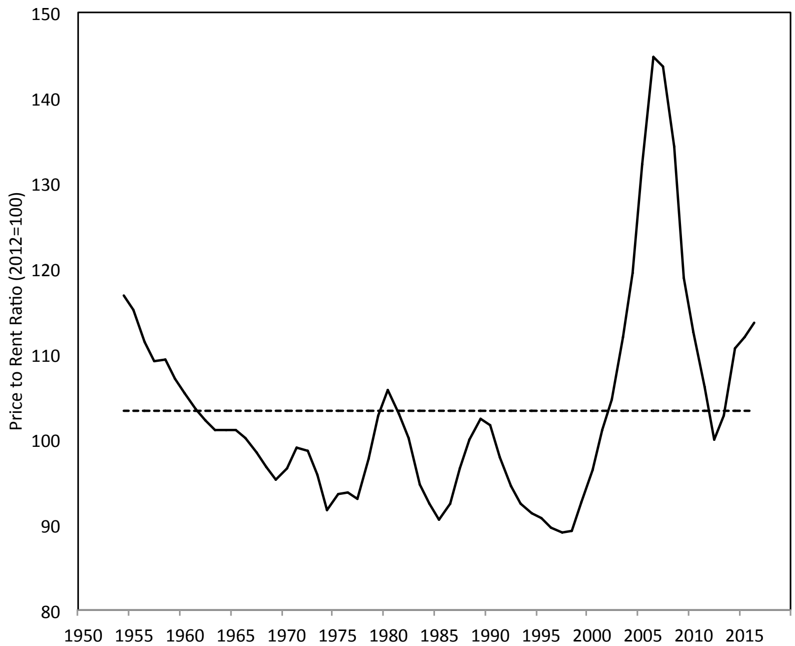
Note: Figures show coefficients on hedonic controls from regression 1. The dependent variable is the log of the rental listing price. Starting from the top left, the different panels show the coefficients on (i) indicators for ventiles of property size, (ii) indicators for deciles of lot size, (iii) indicators for the number of bedrooms, (iv) indicators for the number of bathrooms, (v) indicators on property age, and (vi) indicators on the time since the last major remodeling of the property. The regression includes other control variables and fixed effects as in column 1 of Panel B, Table 1. The bars show 95% confidence intervals for standard errors clustered at the zip-code-quarter level.

Figure A.6: Cross-Sectional Distribution of the Rent-to-Price Ratio in the U.S.



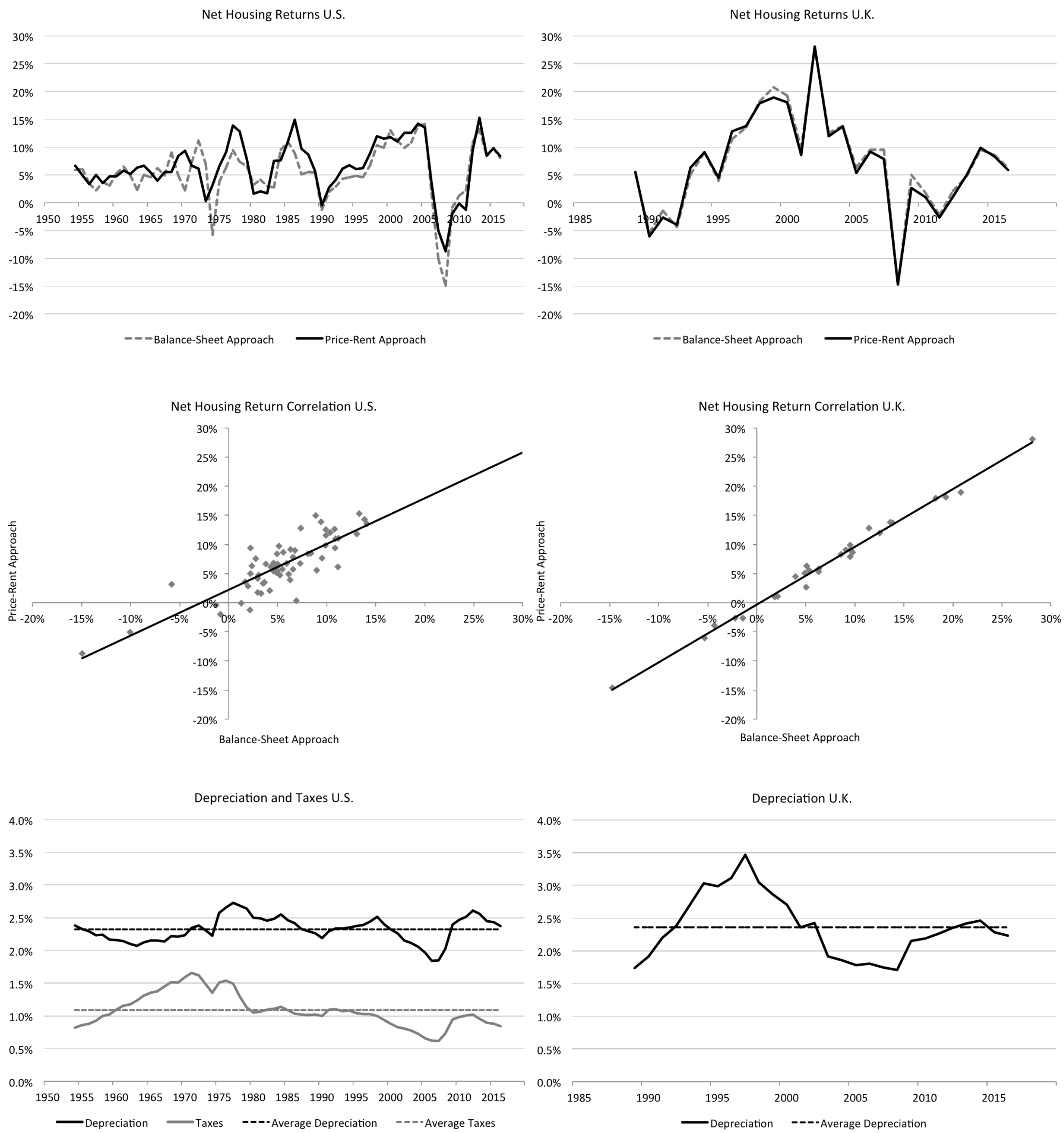
Note: The figure shows the distribution of the rent-to-price ratio for the 100 largest MSAs in the U.S. in 2012 as constructed by Trulia, which observes a large set of both for-sale and for-rent listings. It is constructed using a metro-level hedonic regression of log price on property attributes, zip-code fixed effects, and a dummy for whether the unit is for rent. The rent-to-price ratio is constructed by taking the exponent of the coefficient on this dummy variable.

Figure A.7: Price-to-Rent Ratio Time-Series in the U.S.



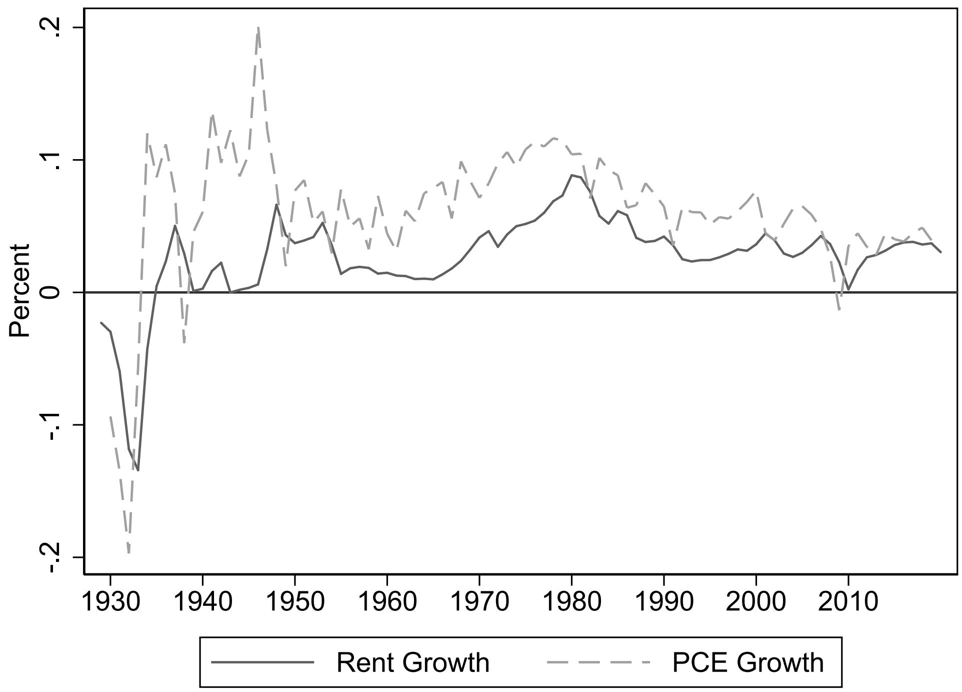
Note: The figure shows the time series of the price-rent ratio in the U.S., constructed as the ratio of the Case-Shiller House Price Index and a rental price index that is constructed as discussed in Section A.4.1. The index ratio is normalized to 100 in 2012.

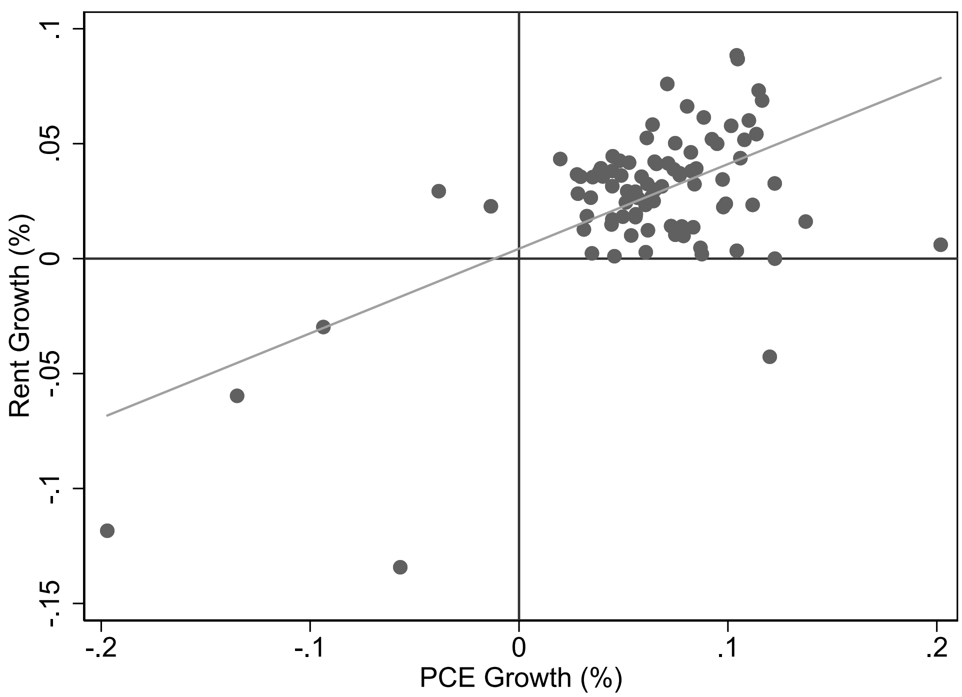
Figure A.8: Housing Return Estimates – Consistency Across Approaches



Note: Figures show the net housing returns for the balance-sheet and the price-rent approach for the U.S. and the U.K. (top row), the correlation between net housing returns from the balance-sheet and the price-rent approach for the U.S. and the U.K. (middle row), and housing depreciation (gross of maintenance) and tax yields from the balance-sheet approach for the U.S. and the U.K. (bottom row; there are no property taxes in the U.K.). The U.S. results are based on specifications (2) and (9) in Table 4. The U.K. results are based on specifications (12) and (15) in the same table.

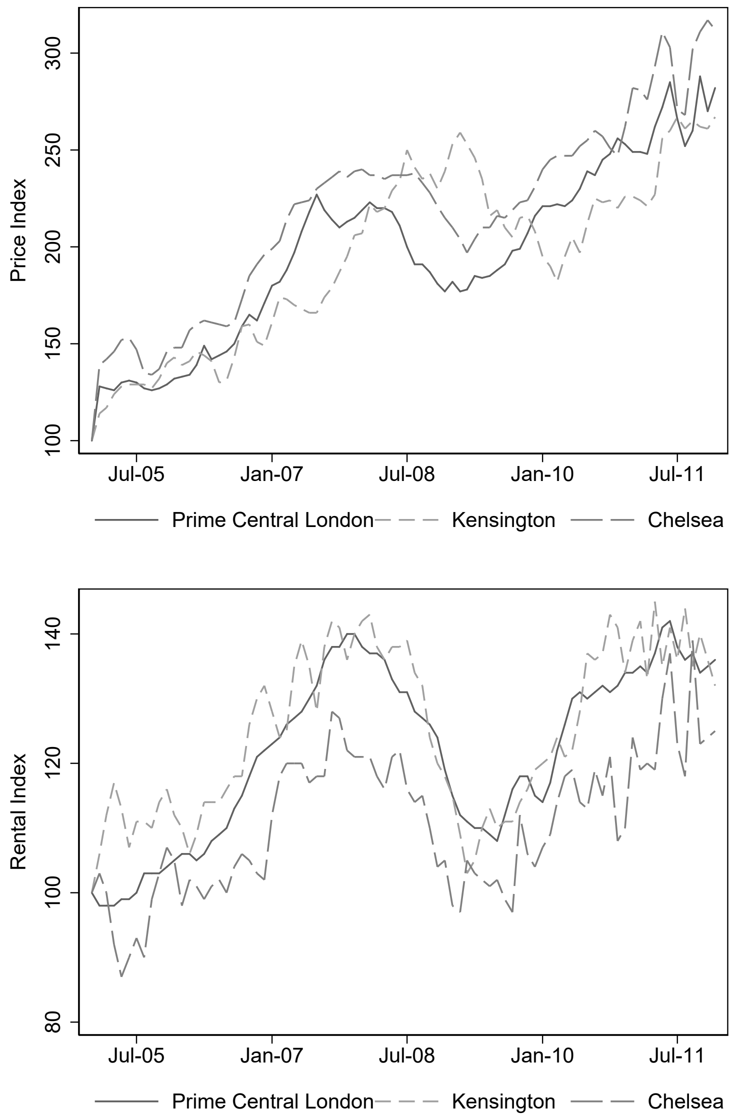
Figure A.9: Rent Growth vs. PCE Growth in the U.S.





Note: The figure shows the annual growth rates of the "Consumer Price Index for All Urban Consumers: Rent of Primary Residence" (FRED ID: CUUR0000SEHA) and "Personal Consumption Expenditure" (FRED ID: PCECA) since 1929.

Figure A.10: House Prices and Rents in Prime Central London Areas during the 2007-09 Financial Crisis



Note: The figure shows the time series of house prices and rents for Prime Central London, Kensington, and Chelsea for the period January 2005 to January 2012. The series are monthly and available from John D Wood & Co. at `http://www.johndwood.co.uk/content/indices/london-property-prices/`, last accessed February 2014.

Appendix Tables

Table A.1: Dictionary for Climate Attention Index

Text Type	Text
Single Words	’storm’,’storms’,’superstorm’,’hurricane’,’hurricanes’, ’fema’, ’tornado’, ’tornadoes’,’floodplain’
Pairs	(’flood’,’risk’),(’flood’,’insurance’),(’flood’,’ins’),(’flood’,’plain’),(’flood’,’risk’), (’flood’,’damage’),(’flood’,’zone’),(’flood’,’zones’),(’flood’,’protection’), (’flood’,’safe’),(’hurricane’, ’zone’),(’hurricane’, ’zones’),(’hurricane’,’shutter’), (’hurricane’,’shutters’),(’hurricane’,’shelter’),(’hurricane’,’shelters’), (’hurricane’,’protection’),(’hurricane’,’safe’),(’hurricane’,’impact’), (’hurricane’,’curtains’), (’sea’,’level’),(’storm’,’zone’),(’storm’,’zones’), (’storm’, ’window’),(’storm’, ’windows’),(’storm’,’door’),(’storm’,’doors’), (’storm’,’water’),(’storm’,’protection’),(’storm’,’safe’),(’tornado’,’shutter’), (’tornado’,’shutters’),(’tornado’,’shelter’),(’tornado’,’shelters’)
Hurricane Names	’keith’,’allison’,’iris’,’michelle’,’isidore’,’lili’,’fabian’,’isabel’,’juan’,’charley’, ’frances’,’ivan’,’jeanne’,’dennis’,’katrina’,’rita’,’stan’,’wilma’,’dean’,’felix’, ’noel’,’gustav’,’ike’,’paloma’,’igor’,’tomas’,’irene’,’sandy’,’ingrid’,’erika’, ’joaquin’,’matthew’,’otto’

Note: The table shows the dictionary used to construct the “Climate Attention Index”.

Table A.2: Top Climate Words in Florida

Words	Number of Listings Containing the Word	Frequency
hurricane(s)	465,308	3.309%
hurricane shutter(s)	241,812	1.720%
storm(s)	114,893	0.817%
hurricane impact	66,485	0.473%
flood insurance	57,737	0.411%
flood zone(s)	45,696	0.325%
hurricane protection	18,285	0.130%
storm door(s)	13,286	0.094%
storm window(s)	7,692	0.055%
storm protection	5,644	0.040%
sea level	3,808	0.027%
FEMA	3,448	0.025%
hurricane safe	1,798	0.013%
flood plain	1,684	0.012%
storm water	971	0.007%
hurricane shelter(s)	603	0.004%
storm safe	491	0.003%
tornado(es)	457	0.003%
flood risk	373	0.003%
flood damage	235	0.002%
hurricane zone(s)	178	0.001%
hurricane curtains	171	0.001%
flood protection	117	0.001%
tornado shelter(s)	74	0.001%
storm zone(s)	30	0.000%
flood safe	9	0.000%
tornado shutter(s)	1	0.000%
Total number of listings	14,059,936	

Note: The table shows the most commonly occurring words signaling increased attention paid to climate change in the state of Florida.

Table A.3: Top Climate Words in New Jersey

Words	Number of Listings Containing the Word	Frequency
storm(s)	20,702	0.602%
flood insurance	15,342	0.446%
flood zone(s)	14,354	0.417%
storm door(s)	10,020	0.291%
hurricane(s)	5,842	0.170%
FEMA	5,253	0.153%
storm window(s)	2,316	0.067%
flood risk	1,395	0.041%
flood damage	834	0.024%
flood plain	678	0.020%
superstorm	529	0.015%
storm water	369	0.011%
sea level	326	0.009%
hurricane shutter(s)	213	0.006%
hurricane impact	68	0.002%
storm protection	27	0.001%
flood protection	25	0.001%
storm zone(s)	17	0.000%
hurricane protection	9	0.000%
storm safe	9	0.000%
flood safe	3	0.000%
hurricane zone(s)	2	0.000%
Total number of listings	3,441,094	

Note: The table shows the most commonly occurring words signaling increased attention paid to climate change in the state of New Jersey.

Table A.4: Top Climate Words in North Carolina

Words	Number of Listings Containing the Word	Frequency
storm(s)	18,160	0.376%
flood zone(s)	11,788	0.244%
storm door(s)	11,075	0.229%
flood insurance	8,587	0.178%
hurricane(s)	5,232	0.108%
storm window(s)	4,161	0.086%
flood plain	4,215	0.087%
hurricane shutter(s)	2,639	0.055%
sea level	1,169	0.024%
FEMA	635	0.013%
storm water	385	0.008%
tornado(es)	211	0.004%
storm protection	107	0.002%
hurricane protection	74	0.002%
hurricane impact	74	0.002%
flood damage	55	0.001%
tornado shelter(s)	42	0.001%
flood risk	32	0.001%
flood protection	22	0.000%
hurricane shelter(s)	22	0.000%
storm safe	10	0.000%
hurricane safe	8	0.000%
hurricane zone(s)	6	0.000%
storm zone(s)	1	0.000%
Total number of listings	4,827,756	

Note: The table shows the most commonly occurring words signaling increased attention paid to climate change in the state of North Carolina.

Table A.5: Top Climate Words in South Carolina

Words	Number of Listings Containing the Word	Frequency
storm(s)	11,354	0.472%
hurricane(s)	7,243	0.301%
storm door(s)	6,406	0.266%
flood insurance	5,340	0.222%
flood zone(s)	3,848	0.160%
hurricane shutter(s)	2,531	0.105%
storm window(s)	2,305	0.096%
flood plain	614	0.026%
sea level	422	0.018%
hurricane protection	343	0.014%
FEMA	300	0.012%
hurricane impact	182	0.008%
tornado(es)	175	0.007%
flood damage	165	0.007%
storm water	160	0.007%
hurricane zone(s)	103	0.004%
storm protection	101	0.004%
tornado shelter(s)	97	0.004%
hurricane shelter(s)	29	0.001%
hurricane safe	21	0.001%
flood risk	19	0.001%
storm safe	18	0.001%
flood safe	8	0.000%
flood protection	3	0.000%
Total number of listings	2,406,832	

Note: The table shows the most commonly occurring words signaling increased attention paid to climate change in the state of South Carolina.

Table A.6: Rent-to-Price Ratio Singapore - 2012

	(1)	(2)	(3)	(4)
For-Rent Dummy	-3.095***	-3.131***	-3.123***	-3.107***
	(0.044)	(0.019)	(0.014)	(0.025)
Fixed Effects	Quarter × Postal Code	Quarter × Postal Code	Month × Postal Code	Month × Postal Code × Bedrooms
Controls	·	✓	✓	✓
Implied Rent-to-Price Ratio	4.5%	4.4%	4.4%	4.5%
R-squared	0.804	0.873	0.872	0.872
N	106,145	105,189	105,189	105,189

Note: This table shows results from regression (A.6). The rent-to-price ratio is constructed by taking the exponent of the coefficient on this dummy variable. The dependent variable is the price (for-sale price or annualized for-rent price) for properties listed on iProperty.com in Singapore in 2012. Fixed effects are included as indicated. In columns 2 to 4, we also control for characteristics of the property: we include dummy variables for the type of the property (condo, house, etc.), indicators for the number of bedrooms and bathrooms, property age, property size (by adding dummy variables for 50 equal-sized buckets), information on the kitchen (ceramic, granite, etc.), which floor the property is on, and the tenure type for leaseholds. Standard errors are clustered at the level of the fixed effect. Significance levels are as follows: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

Table A.7: House Prices, Banking Crises, Rare Disasters

	House Price Index Time Period	Banking Crises	Rare Disasters
Australia	1880 - 2013	1893, 1989	1918, 1932, 1944
Belgium	1975 - 2012	2008	
Canada	1975 - 2012		
Denmark	1975 - 2012	1987	
Finland	1975 - 2012	1991	1993
France	1840 - 2010	1882, 1889, 1907, 1930, 2008	1871, 1915, 1943
Germany	1975 - 2012	2008	
Italy	1975 - 2012	1990, 2008	
Japan	1975 - 2012	1992	
Netherlands	1649 - 2009	1893, 1907, 1921, 1939, 2008	1893, 1918, 1944
New Zealand	1975 - 2012	1987	
Norway	1819 - 2013	1899, 1922, 1931, 1988	1918, 1921, 1944
Singapore	1975 - 2012	1982	
South Africa	1975 - 2012	1977, 1989	
South Korea	1975 - 2012	1985, 1997	1998
Spain	1975 - 2012	1978, 2008	
Sweden	1952 - 2013	1991, 2008	
Switzerland	1937 - 2012	2008	1945
U.K.	1952 - 2013	1974, 1984, 1991, 2007	
U.S.	1890 - 2012	1893, 1907, 1929, 1984, 2007	1921, 1933

Note: The table shows the time series of house price indices used in the first column. The second and third column report dates of banking crises or rare consumption disasters for each country in the time period provided in the first column. Banking crisis dates for all countries, except Singapore, Belgium, Finland, New Zealand, South Korea, and South Africa, are from Schularick and Taylor (2012). Banking crisis dates for the countries not covered by Schularick and Taylor (2012) are from Reinhart and Rogoff (2009). Rare disaster dates indicate the year of the trough in consumption during a consumption disaster as reported by Barro and Ursua (2008).

Table A.8: Parameters of the Calibrated Model

Calibrated Variables		Value
δ	Time discount rate	0.99
γ	Risk aversion	10
μ	Average consumption growth	2%
ρ	Consumption growth persistence	0.85
ϕ	Consumption growth after disaster	0.025
η	Exposure of rents to disaster	3
ω	Rent growth persistence	0.915
ψ	Rent growth after disaster	0.24
$\bar{\lambda}$	Unconditional mean of disaster probability	3%
α	Disaster probability persistence	0.75
ν	Relation between disaster probability and consumption growth	0.1
χ	Exposure of disaster probability to disaster	0.05
ξ	Consumption drop after disaster	21%

Note: The table summarizes the calibration of the model in Section 2. Time discount rate δ, risk aversion γ, the drop in consumption following a disaster ξ, the exposure of risky cash-flows to the climate shock η, and average consumption growth in the absence of a disaster μ are set following the standard asset pricing literature. All other parameters are calibrated to match some of our new moments estimated in Section 1. The remaining parameters of the consumption process are chosen to generate a recovery in consumption growth after disasters ($\phi > 0$) and persistent growth rates ($\rho > 0$). The magnitude of these parameters targets a term structure of real interest rates that is slightly upward-sloping with a level of around 1.0%. The remaining parameters of the rent process are chosen to generate a recovery in rent growth after disasters ($\psi > 0$) and persistent rent growth ($\omega > 0$). The magnitudes of these parameters are chosen to match the shape and the level of the observed term structure of discount rates in the housing market as described in Section 1. The steady-state conditional probability of disasters, $\bar{\lambda}$ is set based on estimates in Barro (2006), and the remaining parameters for the λ-process are chosen to obtain economically reasonable interactions between the real economy and the disaster probability, while at the same time matching the term structure of the risk-free rate (which is directly affected by the disaster probability dynamics through the precautionary savings channel). In particular, the disaster probability is persistent (α), increases after a jump (χ), and increases when expected consumption growth is above its trend (ν). x and y are assumed to have mean zero, which implies: $\mu_x = -\bar{\lambda}\phi\xi$ and $\mu_y = -\bar{\lambda}\psi\xi$. The unconditional mean of λ pins down μ_λ as $\bar{\lambda} = \frac{\mu_\lambda}{1-\alpha-\chi\xi} > 0$. Consumption and rents are assumed to have the same long-run growth rates, requiring: $\mu_d = \mu + (\eta - 1)\,\bar{\lambda}\xi$. Further details of the calibration are discussed in Section 2.2. Parameter restrictions are discussed in Section A.6.1.