Snowblind:
The importance of climate information for recreational real estate

Draft[1]

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[1]All results are preliminary and subject to change. Although every attempt has been made to accurately describe the data cleaning and analysis process, omissions and errors may exist.

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1 Introduction

Seasonal climate forecasting has made substantial gains in recent years. In many parts of the world, forecasters can now provide high quality spatially explicit probabilistic predictions of precipitation and temperature for the coming season (Zebiak, 2003). These forecasts allow optimizers address variability in climate on monthly and seasonal timescales, whether it is driven by anthropogenic or natural processes.

Work on the importance of seasonal climate forecasting and variability is primarily limited to narrowly focused agronomic agricultural and fishery production decision modeling or to computable general equilibrium calculations of economy wide impacts (Mjelde et al., 2003; Costello et al., 1998). The literature valuing climate tends to focus on long term global climate change, conceptualizing the problem in terms alternate steady state climates without not addressing the utility of forecasting (Timmins, 2003; Maddison and Bigano, 2003).

The bulk of the literature on information valuation tends to address unique information shocks without focusing on climate forecasts or repeated draws from an observable distribution (Foster and Just, 1989; Freeman, 1989; Teisl et al., 2001; Leggett, 2002). Recent work on disaster forecasting explicitly models disasters as draws from an observable distribution, studying risk and information through a natural experiment resulting from a hurricane (Carbone et al., 2004). Although somewhat related to the problem I am studying, it investigates a single event, a disaster, (as opposed to repeated draws of typical variations in seasonal climate) and values a fundamentally different type of technology, hurricane track forecasting (instead of monthly and seasonal climate forecasts).

Since climate forecasting technologies are quite new, it is difficult to value them by studying the impacts of existing systems. In pursuing the research necessary to develop and refine these technologies it is worthwhile to know if they have any benefit before their implementation. My goal in this manuscript is to determine if there is any pre-implementation evidence that new forecasting technologies could provide non-zero benefits, and to illustrate an approach that has potential for rough valuation of information systems before their implementation. I will also discuss intriguing results for parameters introduced in order to control for confounding impacts that suggest rents on geographic information asymmetries.

In my work, I will discuss the link between curvature of an optimized expected utility or profit function, risk aversion, and the value of information. I will study the value of forecasts by econometrically estimating the cost of unanticipated seasonal ex-post climate shocks as draws from an observable ex-ante distribution, and assuming that the value of information is equivalent to the cost of uncertainty. I make no attempt to identify the mechanism driving the forecast information value or distinguish between impacts due to production, preferences, or other factors. I build upon the literature on information value and valuation of climate amenities, separating the cost of risk in expected optimization from the value of improved probabilistic information. I use sale prices for ranchettes (seasonal and retirement vacation properties) in Yavapai county, Arizona and a remotely sensed climate amenity proxy, Normalized Difference Vegetation Index (NDVI) which has been identified as a useful proxy for climate amenities, and for which there are emerging skillful forecasting technologies.

2 Methodology

The penalty from an unanticipated climate shock is revealed through the standard risk aversion calculus. Say an optimizing agent can select a piece of land to lease with a level of climate amenity q. Assume the consumer maximizes a twice differentiable increasing quasiconcave optimization function leading to a maximized expected optimization function $M(q)$, and faces unanticipated ex-post shock (Δq) in the climate amenity. The second order expansion of equation 1 demonstrates the standard penalty to uncertainty. In expectation, $\Delta q = 0$ and Δq^2 is the variance of the disturbance ($\sigma^2_{\Delta q}$) and the approximate expected penalty due to uncertainty is $\frac{1}{2}M''(q)\sigma^2_{\Delta q}$.

$$\begin{aligned} M(q+\Delta q) &\approx M(q) + \tfrac{1}{1!}M'(q)\Delta q + \tfrac{1}{2!}M''(q)\Delta q^2 \\ \implies E[\Delta M] &\approx \tfrac{1}{2}M''(q)\sigma^2_{\Delta q} \end{aligned} \tag{1}$$

The cost of uncertainty is driven by the curvature of the expected utility or profit function the agent is optimizing.[1] There are therefore a multitude of processes that may lead to the the curvature of $M(q)$. For example, the optimizer may not make appropriate investments in order to take advantage of an ex-post outcome. For a rancher, this could be stocking an incorrect number of cattle. Without forecast information, the rancher does not know to stock more cattle in wet years to take advantage of the increased greenness and fewer in dry years to reduce losses. On average the gains from unanticipated wet years are less than the losses in unanticipated dry years. For a seasonal vacationer, these investments might involve travel choices, or the choice between investments that extract utility from different types of climates in different locations. Temporal processes may be to blame if there are increasing costs to borrowing. Utility driven risk aversion may also lead to the penalty from uncertainty. Although it may be possible to disentangle these separate phenomena, that task is beyond the scope of the current paper, in which I merely attempt to detect the aggregate signal pertaining to risk penalties and to roughly quantify the magnitude of the value of information.

If the climate amenity q is connected to a piece of land, the component of the rental rate of the property that is due to the climate amenity is, $M(q)$, the climate based utility or profit that the consumer can obtain from the parcel. For land markets, this penalty is capitalized into prices. Since land is the net present value of rents, discounting issues must be accounted for in order to extract the penalty from price data. A convenient way to do this is to phrase sales pair data in terms of the log rate of return for a parcel, which is $\frac{1}{t}\left(\ln\left(p_2\right) - \ln\left(p_1\right)\right)$, the difference in log prices divided between the time between sales.[2] Climate driven deviations in the rate of return between sales pairs provide a measure of the cost of the uncertainty, or the value of forecasts that predict deviations.

Unanticipated climate shocks are ex-post draws from an observable ex-ante distribution (long term climate) as opposed to a single shock in an otherwise deterministic system. Because the long term climate distribution is observable, it is possible for agents to select a preferred level of risk and to make choices that reduce their exposure to the risks they face.

I control for exogenous factors (z), exante climate distribution information using the long term mean and variance (μ_q, σ^2_q), and mean deviations over the period between sales ($\mu_{\Delta q}$). The penalties due to

[1] In his textbook presentation of risk, the Hal Varian wrote that "concavity of the expected utility function is equivalent to risk aversion" (Hal R. Varian, 1992).

[2] The choice to sell a property is assumed to be exogenous to climate events.

unforeseen climate shocks are approximated through the coefficient for the monthly variance during the time between sales ($\sigma^2_{\Delta q}$). I arrive at the regression specification of equation 2.

$$\frac{1}{t}\left(\ln\left(p_2\right)-\ln\left(p_1\right)\right)=\sigma^2_{\Delta q}\beta_{\sigma^2\Delta q}+\mu_{\Delta q}\beta_{\mu\Delta q}+\mu_q\beta_{\mu q}+\sigma^2_q\beta_{\sigma^2 q}+\boldsymbol{z}\boldsymbol{\beta_z}+\epsilon \tag{2}$$

Because mean deviations average out over time and the timescale for observing rates of return cannot be optimized by the experimenter,[3] the parameter for average deviations from the mean ($\beta_{\mu\Delta q}$) is difficult to recover. Fortunately, the parameter of interest is $\beta_{\sigma^2\Delta q}$, the cost of unanticipated climate variation, which does not tend towards zero and can be calculated for monthly deviations, the timescale of interest for the experiment.

The estimation strategy is to eliminate and control for as much confounding information as possible in order to reduce potential for spurious detection of $\beta_{\sigma^2\Delta q}$. In addition to phrasing sales in a useful form, the log of rate of return regression is a convenient specification for eliminating impacts of parcel specific factors that do not change over time since it is the difference of log prices. As with a fixed effects regression, own effects are subtracted out so time invariant impacts on prices, both observed or unobserved, are removed from the estimation. Since long term climate information is time invariant for the timescale of my study, the first order impacts of this information are automatically removed from the regression, leaving its observable impacts to interactions and higher order effects.

Spatial error processes may exist, potentially driven by unobserved variables that vary systematically over space. This can lead to biased results for quality of fit. One approach to dealing with this problem is to assume the structure of the spatial error process and explicitly correct for it (Anselin, 1988). However, the assumed spatial process imposes a great deal of structure on the estimation. If misspecified, these assumptions may lead to spurious results. This is of particular concern in the study area, in which 1800's era land allocation policy has led to a highly structured "checkerboard" of parcels. In a diagnostic application of the spatial configuration of ranchettes in Yavapai county to non-correlated randomly generated data, several diagnostics falsely detected spatial autocorrelation (Osgood and Moreno, 2000). The price difference specification provides an alternative strategy for addressing spatial error processes since it subtracts out the impacts from unobserved variables, including those with unobserved spatial structure. The price difference therefore attenuates the potential bias in quality of fit estimates from unobserved spatial error processes without requiring explicit specification of potentially inappropriate spatial error processes.

3 Ranchettes and NDVI

Hobby agricultural operations, such as ranchettes, have become a major force driving rural and exurban real estate markets. Typically, a ranchette is an owner's secondary property and is used as a seasonal or retirement escape from cold northern climates.[4] Across the west, "ghost subdivisions" of secondary properties that are used for seasonal recreation have consumed the landscape (William E. Riebsame, 1997). Ranchettes and other hobby farms represent a large share of all agricultural operations. Almost 70% of Arizona agricultural operators surveyed reported that a production operation should be defined as having

[3] Sale timing is determined by the real estate market as opposed to being chosen by the experimenter.

[4] Yavapai county ranchettes are often used as weekend escapes from the hot Phoenix climate as well.

more than ten thousand dollars worth of sales (Farm Foundation, 2001). Under this definition, more than 60% of agriculture in the United States would be categorized as hobby operations. The impacts of the high-value ranchette market now drive other related land markets. Only 27% of the value of a ranch in the most productive areas of New Mexico is due to cattle productivity. Instead, aesthetic, recreational, and trophy components drive value (Xu et al., 1994).

The Arizona ranchettes real estate market provides an ideal laboratory to study climate information because it is a market for seasonal climate amenities reflecting climate based migration and decisionmaking. Although a particular market is studied, this market has features that are evident in other contexts. It is climate driven and characterized by processes such as seasonal migration, migration networks, and the location and timing of investments that compliment climate. Because of these commonalities, the ranchette market may provide insight into other situations, such as that of agricultural labor migration, so long as one does not take analogies too far.

A ranchette does function as an escape from harsh winters, but the Arizona desert can look barren to someone from a wetter climate. Green vegetation has been shown to provide a substantial premium for Arizona real estate (Bark et al., 2005a; Bark et al., 2005b; Sengupta and Osgood, 2003). Although a seasonal visitor from a cold climate can find a reliable escape from the cold, the visitor cannot count on the vacation property to be reliably pretty, since vegetation varies dramatically with precipitation. This variation drives the identification of my experiment. I use NDVI as a proxy for unanticipated shocks in natural vegetative “beauty” to identify of the value of information.

NDVI is a satellite measured index of the level of photosynthesis occurring in plants. It is a dimensionless index, ranging from -1 (low photosynthesis levels) to 1 (vigorous photosynthesis activity). It has been used for many applications, ranging from crop productivity to forage estimation to malaria prediction. Although it is not necessarily the most accurate vegetative measure, it is the benchmark that more sophisticated indices are compared to. Its utility is due, in part to its availability. Bi-weekly global NDVI data is available at 1km resolution[5] from 1981 to the present in a calibrated, standardized form (Tucker et al., 2004).

NDVI can reflect fundamentally different processes in different regions. In the Midwest, NDVI might indicate productivity (vigor) of farmland. It has been found to be a strong predictor of Midwestern farm prices (Nivens et al., 2002). In arid lands such as the Southwest, NDVI may be more representative of percentage vegetative cover (Nagler et al., 2001). In Arizona, NDVI has been found to be significant for amenity based recreational and residential land prices (Sengupta and Osgood, 2003; Bark et al., 2005a).

These papers were cross sectional price regressions as opposed to price difference or rate of return studies, and serve mostly to motivate further work using NDVI. They did not investigate variation in NDVI or changes over time. One of the works used NDVI only as a proxy to control for confounding variation in Ranchettes due to environmental amenities to improve the quality of estimation of other amenities. The most proxy most useful for controlling for variation was the average NDVI for the year preceding the sale of a ranchette (Sengupta and Osgood, 2003). Another work used a single, high spatial resolution image to measure impacts of NDVI in single family homes (Bark et al., 2005a), paying particular attention to the biological processes reflected in NDVI in Arizona. The work studying Midwestern farmland used a lagged average of NDVI for the three years before a parcel sold, using NDVI as a proxy for farmland productivity (Nivens et al., 2002).

[5]This is a useful resolution for attenuating potential endogeneity. If it is possible for a ranchette owner to manipulate the NDVI of a parcel, an individual ranchette sized parcel is negligible compared to a 1 km pixel.

Because it measures different effects in for different places, NDVI can be problematic when used as an index for comparing climate across regions. Thus, I restrict NDVI use to comparisons in changes over time within a single county, and make no assumptions about the processes that NDVI changes reflect except that they are correlated with some climate based amenity.

NDVI is a particularly interesting climate proxy to study because new forecasting technologies are demonstrating considerable skill in its prediction. One forecast attempt has explained 57 percent of the variation in NDVI in Kenya[6] (Indeje et al., 2004). Thus, evidence that suggests a non-zero value to explaining variation in NDVI might be used to motivate the value of a potentially available forecasting technology.

4 Data

The Yavapai County MIS office provided georeferenced boundary data for the more than one hundred thousand parcels in the county. A ranchette was defined as being between 2 and 40 acres[7]. Sales from 1991 to 2000 were provided by the Yavapai County Assessors office and were associated with the parcel dataset using parcel ID number. The sales dataset included sale dates, prices, assessed value of improvements, and name and mailing address of the purchaser. The sales dataset includes approximately 70,000 ranchette sales, or about 1000 repeat ranchette sales pairs. For a sales pair, the owner following the original sale is classified as the seller (owner a), and the owner following the second sale is classified as the buyer (owner b). The log rate of return was calculated using reported sale prices and dates (logr).

Typically, regressions on amenity value in real estate are preformed on single family homes, controlling for the characteristics of the home with a multitude of descriptive variables, and assuming that there is, at most, a negligible change in housing supply during the study period. The benefit of this approach is that a homogeneous class of real estate is looked at and data on house characteristics can control for much of the variation seen in prices. In addition, the reader can gain intuition into the regression behavior by observing if parameters for house characteristics are reasonable. One problem with the approach is that housing may be endogenous, a bay window may have been built to take advantage of a bay view, and the house may have been built (changing the housing supply) because of the value of amenities at that site. In addition, house characteristics are often highly correlated, making it difficult to isolate their individual impacts.

In this ranchette study, many parcels have no improvements at all. Others have improvements that have characteristics that are difficult to compare, since one may have a house with bedrooms and fireplaces and another may have only a corral and driveway. In addition, for Yavapai county, very little information is available about the characteristics of improvements outside of urban areas. Therefore an alternate strategy is used. The focus of the analysis is on land as opposed to houses. The disadvantages of this strategy are that parcels with fundamentally different structures are included in the same regression, and that improvement characteristics are not explicitly controlled for.

Because the analysis is a difference in log prices, the contributions of improvements that do not

[6] In this work, as in much of the climate forecast literature I cite, skill is presented in terms of a normalized correlation parameter equal to 0.76, which, when squared, represents the R^2, or fraction of variance explained by the forecast.

[7] This follows the literature on ranchettes, which uses a size classification based on recommendations from assessors and realtors because tax or zoning classifications for ranchettes are highly diverse and unreliable (Sengupta and Osgood, 2003).

change between the sales should be subtracted out. In addition, by focusing on land instead of house characteristics, much of the potential endogeneity of the regression is avoided. The assessed value of all improvements on the property is available from the sales dataset (bimpfcv). In theory, this variable should control for most of the impacts that would be accounted for with explicit inclusion of improvement characteristics in a house oriented hedonic regression. Because of its potential benefits as a control and its potential for endogeneity, results are presented with and without this variable.

Because of the difference regression structure, most of the effects of variables that do not change over time is subtracted out. I develop several site specific time invariant variables because they are useful in interaction with time varying variables. Since they are commonly included in price regressions, I will include them in one regression specification as a robustness test to see if any significant detections of a penalty from expost shocks disappear as additional variables are included. The locations of zip codes, major road, rivers, cities, public land, elevation, and other geographical information was obtained from the Environmental Systems Research Institute and the Arizona Regional Image Archive. The centroid of the parcel was used in the GIS to calculate distance from the parcel to the nearest major road (dist2road), river (dist2river), and city (dist2city) in meters. Adjacency of a parcel to publicly owned land was calculated using parcel boundaries (aveopensp).

Parcel centroids were used to link the parcels to elevation data (aveelevat) and for association with the NDVI dataset. To represent long term climatology, the NDVI dataset was queried through the IRI data library to calculate mean and variance for each parcel centroid for the entire history of NDVI data (ndviave, ndvivar). The sale dates were used by the IRI data library to calculate the deviation from average and variance during the time between the sale pairs for the parcel (deltandvi, ndvidvar).[8]

The states associated with the zip code of owners were determined. A dummy variable was set if the zip code of the owner was outside of Arizona (aoutaz, boutaz) and another was set if the owners were from the same state (abeqst). To proxy experience in the local real estate market, the sales dataset was queried to determine the number of times each owner's name appeared and a dummy variable was set if the owner was listed more than once (amult, bmult).

The centroid of the owner's reported zip codes was associated with temperature data.[9] Temperature was used instead of NDVI for two reasons. First, NDVI will reflect vastly different processes across the United States, so it is not clear what value a cross country comparison has. Second, Arizona real estate provides multiple amenities, One, a relatively reliable escape from cold climates (reflected through temperature) and the other aesthetically pleasing vegetation (proxied by NDVI). In an attempt to proxy the geographic climate characteristics driving seasonal demand preferences, the January average temperature was calculated at each owner zip code centroid (aziptemp, bziptemp). The geographic and temporal selection and averaging involved was performed using an automated query to the IRI data library. The out of state dummies (aoutaz, boutaz) were interacted with the climate variables to yield the interacted NDVI anomalies (aoutdeltandvi, boutdeltandvi, aoutdvidvar, boutndvidvar) and January temperatures (aoutziptemp, boutziptemp).

Sale pairs with missing data were removed from the dataset as were sales with zero prices and the same buyer and seller. Since rate of return parameters are sensitive to dramatic changes in price that occur

[8]The data library allows one to query a database using a URL that contains the lat, lon, time period, and a desired statistical operation.

[9]The CRU05 0.5 Degree 1901-1995 Monthly Climate Time-Series (New et al., 2000) pixel that the zip code centroid fell inside was identified.

over short periods in time, a small number of atypical sales can dominate the regression.[10] Sale pairs with rates of return exceeding 200 percent and rates below 50 percent were therefore removed from the dataset. The resulting dataset had 691 observations. For the final dataset the mean value for each variable is reported in table 1.

5 Results

To illustrate the level of robustness of results and to aid in interpretability, two regressions are presented. One is designed with a conservative approach to variable selection, and the other with a large number of variables and interactions to control for as much information as possible. The log specification is presented.[11]

Table 2 presents the minimal regression equation. This regression does not include any interactions, time invariant variables, or potentially endogenous variables, eliminating potential complications due to these variables. It ignores information that might improve the quality of fit, improve the identification of the parameters, control for variation that is wrongly attributed to the climate deviation variability parameter, and variables that might aid in interpretation of results. Not surprisingly, the variance explained is low, and few of the results are significant. In spite of the low power of the regression, the parameter of interest describing the variance between the sales (ndvidvar) is significant and negative, providing evidence of a significant cost from uncertainty.

The results of adding time invariant variables, potentially endogenous variables, and interactions, are presented in table 3. The experiment variable (ndvidvar) remains consistent in sign and significance between the minimal and expanded regression. Even with the additional controls, a significant parameter for mean deviation (deltandvi) is not detected. As would be expected, the bulk of the time invariant parameters are not significant. Although their impacts on prices may be substantial (and estimated in other work), any impacts they may have on *changes* in prices, (the rate of return) are not detectable. These include distances to roads, rivers, parcel size, elevation, bordering public land, and the long term climate mean and variance parameters. Interestingly, the distance to a city does impact the rate of return, showing that the rate of growth in real estate prices is lower as a parcel is further from a city. The parameter for assessed improvements at the second sale reflects a positive premium on returns for investments on a ranchette property.

Instead of the additional variables diminishing the information parameter (ndvidvar), the magnitude has increased. Most likely, this effect is due to the interactions with the dummy for out of state buyers, which yield intriguing results. For a parcel with an out of state buyer, a higher average climate driven greenness yields higher rates of return to the seller (boutazndviave). This finding is not surprising if NDVI is an effective proxy for aesthetic beauty of vegetation on a parcel. Once one has escaped from a cold climate, there may be a premium for having beautiful lush vegetation as opposed to barren desert. More perplexing, a parcel with higher variance between sales yields a substantially higher rate of return to the seller if sold to an out of state buyer (boutndvidvar), indicating a premium for unforeseen variability.

One potential explanation for this effect is an information story. It could be that sellers can collect rent

[10] A parcel that doubles in price in 1 month has a rate of return of almost a half a million.

[11] Linear model specifications behave similarly in terms of signs, magnitudes and significance of the experiment variables.

on information asymmetries if the buyer is from out of state. In other contexts, authors have discussed how agents might take advantage of asymmetries in climate related information to extract rents (Pfaff et al., ; Sheriff and Osgood, 2005). This would also be consistent with price studies of ranchette properties in which average NDVI for the year *preceding* a sale was found to be a strong predictor of prices (Sengupta and Osgood, 2003).[12] If a buyer's perception of the greenness of a property is determined in a visit to the property prior to sale, a Realtor could schedule visits to follow especially wet monthly precipitation anomalies. In this way, a seller could take advantage of variance in greenness to increase the perceived value of the property, since a property with more anomalies would provide more opportunities for the seller to portray the parcel as having lush vegetation.

The signs and significance of other variables are consistent with this explanation. The dummy variable indicating that a buyer has participated in more than one sale in the ranchette market (bmult) is significant and negative. Therefore experience in the market may potentially provide information to a buyer, leading to more realistic expectations and reducing the information asymmetry. None of the interactions with the seller are significant, and the sales experience of the seller is not significant, which is consistent with the premium on greenness variability being driven by an information asymmetry gained, so long as the information can be gained through ranchette ownership. Finally, none of the variables that might proxy impacts driven by migration networks (outeqst, abeqst) or preferences for ranchettes (aziptemp, bziptemp, aoutziptemp, boutziptemp) are significant, further suggesting that the premium on variance driven by out of state buyers might be due to information asymmetries as opposed to other processes.

6 Implications to forecast value

Given the findings of the previous sections, there is preliminary evidence that a forecast might have a non-zero value. If a forecast with the skill of the Kenya forecast was hypothetically possible for Arizona, it is interesting to have a rough idea of its approximate value. [13]

For a strong set of assumptions, it is possible to utilize the econometric findings to gauge the rough magnitude of benefits if a hypothetical forecast was available. Assume that the recovered parameter reflecting the cost of uncertainty (ndvidvar) is equivalent to the value of forecast information and that the objective function of agents is to maximize the return on investment.

The marginal impact of a reduction in uncertainty ($\sigma^2_{\Delta q}$) for the average sale pair is about 19.6 using the parameter from the full regression.[14] A forecast that explains 57 percent of the variance would reduce unexplained variance by approximately 0.0016, which when applied to the derived $\frac{\partial r}{\partial ndvidvar}$ leads to an increase in returns of about 0.032, or three percent of the average property value per year. For the minimal

[12] In this work, the role of NDVI was to proxy and for otherwise unobserved environmental amenities, and the most convenient and powerful proxy was chosen. Since the regression was not designed to determine the most useful important timing of an NDVI average in driving sales prices it is not a test of the timing of NDVI and prices. Nevertheless, the results in the paper are consistent with an information asymmetry story.

[13] There is no reason to believe that 1km resolution NDVI in Yavapai County would be forecast with the same skill as reported in Kenya (Indeje et al., 2004). Nevertheless, the most simplistic precipitation forecasts, based only on correlation analysis with weather stations and global forecast models, are able to explain on the order of 15 percent of the variance of for precipitation in Arizona (Hartmann et al., 1999).

[14] Because a log-linear specification was used, the marginal impact on r of a continuous explanatory variable x is $\frac{\partial r}{\partial x} = \beta_x e^{x\beta_x}$. Since the average for $\sigma^2_{\Delta q}$ is 0.00280, $\frac{\partial r}{\partial x} = -19.6$. For the smaller minimal regression parameter, this result is approximately a third of the impact, or about -7.6.

regression, this would be approximately one percent.[15] Using the regression parameter from the minimal regression and assuming a forecast explains only 15 percent of the variance, the value is roughly a quarter of a percent of the property value per year.

These impacts are subtle, being only a small fraction of property value. For the regression dataset, the average price is slightly over ten thousand dollars per acre. Therefore, the value of a forecast the skill of the Kenya explaining about half of the variance could have a rough value from one to three hundred dollars per acre per year, and a forecast explaining only fifteen percent of the variance might have a value of about twenty five to seventy five dollars per acre per year.

However, since there are approximately one million acres of ranchette sized parcels in Yavapai county, when aggregated, the annual benefits are nontrivial. They are of a magnitude that could exceed the cost of implementing a forecasting system, even if the potential benefits presented here are overstated by a factor of ten.

7 Conclusion

In this manuscript I have outlined an approach for estimating the impacts of a forecasting system prior to a system's implementation. Applying this approach to study the potential impacts of NDVI forecasts for ranchettes in Arizona, I have found preliminary evidence that there is a cost to uncertainty, and that information has a subtle, but nonzero value. In controlling for potentially confounding effects, an intriguing premium on variance was found for transactions that involved out of state buyers, a premium that is consistent with transfers driven by rent collection on information asymmetries. In general, the cost of uncertainty outweighs this premium.

Because this is an exploratory analysis, there is much work to be done. First, a great deal of the variation that identifies the risk parameter in the regression is cross sectional. Since the response to information is largely temporal, the relationship between the estimated risk parameter and the value of a forecast would be strengthened by a regression in which climate shocks could be estimated using temporal variation in characteristics. In future work, it may be possible to take advantage of the difference between anticipated calendar variation and unanticipated shocks to better identify the risk parameter in terms of temporal processes.

In addition, it is worthwhile to refine controls and interactions to improve parameter estimation and to better explain the premium on variance. Potentially useful variables include census based characteristics of the buyer and seller and temperature anomalies during the year of sale using the zip codes of the buyer and seller. Perhaps the most appealing extension of this work would be to collaborate with a climate scientist to study the impacts of an NDVI forecast system explicitly applied to the study area.

The philosophy of the methodology in this work, using climate moments to identify Taylor series terms in the objective function of the optimizer, contrasts much of the work in valuation, for which a functional form is assumed. Because climate distributions are rich in higher moments, potential future work could extend this moment based approach, using moments in distributions of both quantity shocks (such as NDVI) and price shocks to approximate optimization functions, derive the properties of demand

[15] This lower parameter may reflect a the cost of variability less the transfers to out of state buyers due to rents on information asymmetries.

curves, and potentially disentangle income and substitution effects.

Variable	Mean
r	1.158276
logr	.1303868
deltandvi	-.0031623
ndvidvar	.0028048
aoutdeltan i	-.0007947
aoutndvidvar	.0006719
boutdeltan i	-.0007994
boutndvidvar	.000445
ndviave	.3084191
ndvivar	.002695
aoutazndvi e	.2351654
aoutazndvi r	.0020682
boutazndvi e	.0522667
boutazndvi r	.0004569
aziptemp	5.164007
aoutziptemp	1.055364
bziptemp	5.26413
boutziptemp	.531546
amult	.3746398
aoutaz	.2449568
bimpfcv	31624.71
bmult	.3126801
boutaz	.1743516
dist2road	2000.988
dist2river	5936.81
dist2city	9132.533
outeqst	.0129683
abeqst	.6527378
dacres	7.099977
aveelevat	1413.359
aveopensp	.20317

Table 1: Variable means

parm	estimate	stderr	t	p
deltandvi	.0626232	.4967639	.1260624	.8997197
ndvidvar	-7.734053	4.464219	-1.732454	.0836442
aziptemp	-.0020839	.0015303	-1.361792	.1737126
bziptemp	-.0003587	.0017323	-.2070831	.8360067
aoutaz	-.038894	.0268614	-1.447952	.1480893
boutaz	-.0113196	.0259328	-.4364965	.6626145
abeqst	.0032548	.0290452	.1120608	.9108081
cons	.1744192	.0334032	5.221632	2.36e-07

Table 2: Diagnostic minimal rate regression results (Adj R2 = 0.0065)

parm	estimate	stderr	t	p
deltandvi	.0431492	.6255699	.0689758	.9450297
ndvidvar	-20.78534	6.826282	-3.0449	.0024201
aoutdeltandvi	-.7225877	1.161639	-.6220414	.5341292
aoutndvidvar	18.50339	12.39798	1.492452	.1360578
boutdeltandvi	.2955868	1.266972	.2333018	.8155993
boutndvidvar	38.06536	18.65847	2.040111	.0417362
ndviave	-.2361606	.1861976	-1.268333	.2051255
ndvivar	17.57166	21.52306	.8164112	.4145591
aoutazndviave	.0265363	.1999561	.1327106	.8944626
aoutazndvivar	1.355692	23.85736	.0568249	.9547018
boutazndviave	.5947202	.2228817	2.668322	.0078101
boutazndvivar	-24.82405	29.41249	-.8439969	.3989765
aziptemp	.0001861	.0030582	.0608565	.9514919
aoutziptemp	-.0005214	.0035145	-.1483557	.8821073
bziptemp	-.0008511	.00283	-.3007486	.7637008
boutziptemp	.002651	.0036531	.7256836	.4682896
amult	.001393	.0145198	.0959403	.923597
aoutaz	-.0520992	.0815792	-.6386332	.5232828
bimpfcv	4.48e-07	1.16e-07	3.873011	.0001182
bmult	-.0259779	.0151128	-1.718934	.0860946
boutaz	-.2154812	.0871056	-2.473792	.0136189
dist2road	2.74e-06	2.39e-06	1.146912	.2518331
dist2river	-1.15e-06	1.53e-06	-.753648	.451329
dist2city	-1.16e-06	6.30e-07	-1.834469	.0670336
outeqst	-.0954287	.0933705	-1.022043	.3071344
abeqst	.0206748	.0424446	.4871009	.6263483
dacres	.0003547	.0010757	.3297561	.7416887
aveelevat	-9.71e-06	.0000256	-.3792652	.7046127
aveopensp	.00225	.0175077	.128513	.8977821
cons	.2128209	.0655519	3.246602	.0012269

Table 3: Preliminary rate regression results (Adj R2 = 0.0457)

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