HEDGING HOUSING RISK IN THE NEW ECONOMY: IS THERE A CONNECTION, AND SHOULD FIRMS CARE?

Nathan Berg, University of Texas at Dallas, USA

ABSTRACT

This paper analyzes housing price dynamics in and outside of Telecom Corridor, a region near Dallas, Texas, with a high concentration of new economy firms. Using separate home price indexes in and outside this region, the paper tests whether home values are more volatile in the new economy area and compares mean-variance efficient portfolio weights on housing. The problem of hedging housing price volatility appears to be more severe in the high tech sector, suggesting that new economy firms may benefit by offering workers various forms of home price insurance in lieu of cash wages.

I. INTRODUCTION

There is abundant evidence that imperfections in residential real estate markets burden homeowners with unwanted risk. These imperfections include housing market illiquidity, high transactions costs, predictability of housing market returns and, perhaps most important, the absence of financial instruments with which to hedge against declines in home values. Empirical evidence of housing market imperfections and theoretical discussions of hedging instruments are discussed in Englund, Hwang and Quigley (2002), Flavin and Yamashita (2002), Clayton (2001), Case and Shiller (1996, 1990).

This paper explores whether previously documented imperfections in housing markets are more severe for stakeholders in the so-called "new economy," i.e., for workers, owners, and property-owning neighbors near firms with a high degree of co-investment in human and financial capital, or a high degree of real option characteristics. The central empirical question is whether housing markets in areas with high concentrations of new economy firms operate differently from housing markets in other locations. In the context of comparing new and old economy housing markets, a related normative issue arises as to whether new economy firms and workers might mutually benefit from experimenting with labor contracts that feature a housing market option component. Gu and Kuo (2002), Iacoviello and Ortalo-Magne (2002), and Brown (2000) describe a variety of option contracts and other financial instruments designed for the purpose of hedging home price risk.

The following is an overview of this paper. Section 2 discusses theoretical reasons for suspecting that housing markets behave differently in areas with high concentrations of new economy firms. Section 2 also introduces the normative issue at stake — how to hedge housing risk, and whether new economy firms are in a special position to innovate and possibly profit by providing home price insurance to workers. Section 3 introduces the empirical component of the analysis, drawing on a sample of more than 300,000 home sales from Dallas County, 1979-2000, which includes a highly concentrated new economy sector, Telecom Corridor. A descriptive profile of that area, details on price index methodology, and a number of statistical tests are presented. Section 4 uses return and volatility measures within a standard mean-variance portfolio framework to analyze and compare optimal weights on housing in new and old economy areas. Finally, Section 5 attempts to link differences in the severity of the housing risk problem as revealed by portfolio analysis to specific policy prospects for new economy firms.

II. HOUSING MARKETS IN THE NEW ECONOMY

There are several reasons to suspect that residential housing markets with concentrations of new economy workers might be more volatile than housing markets in other areas. More than other firms, new economy firms have attempted to tie their employees' earnings to the market value of the firm. In so far as this shift has led to greater volatility in aggregate personal earnings through time, it seems likely that new economy workers' demand for housing, which theory suggests should depend on anticipated lifetime earnings, would fluctuate more widely, too. Assuming that the market supply curve for housing is positively sloped rather than flat, wider fluctuations in the market demand curve would therefore cause wider variation in the price of residential housing.

A second reason why geographic areas containing new economy firms might see unusually large fluctuations in housing prices stems from the importance of "flexibility" as a core managerial principle at such firms. The flexibility principle when applied to decisions about hiring and lay-offs (or simply manifest in a workplace culture that encourages workers to actively seek new positions within the firm that entail geographic relocation), would seem to lead directly to shorter than average residential tenure and more turnover in the housing market. High turnover, if it is lumpy in the sense that surprise hiring and lay-off decisions are of large magnitude and concentrated at certain points in time, implies greater volatility in housing price returns.[1]

Thus, the conjecture is that new economy human resources practices make old housing market problems worse.[2] On the other hand, there is also reason to hope that new economy firms may by well positioned to introduce innovative labor contracts with home price risk sharing features that potentially improve the efficiency of housing markets. New economy firms are highly invested in human capital. They have a proven track record using options and innovative forms of non-cash employee compensation — these include greater work time flexibility (e.g., telecommuting, non-standard working hours, time off for elder car), tax friendly payroll services (e.g., medical savings accounts and 401K retirement accounts), and upscale lifestyle amenities (e.g., onsite exercise trainers, masseuses and gourmet chefs). New economy firms also tend to be financially sophisticated, accustomed to using derivatives markets in dealing with risk.

The possibility that new economy firms will find it in their interest to offer their employees risk sharing benefits associated with home ownership finds support in the following observations. First, workers at new economy firms bear a portion of the housing market volatility that their employers cause. In equilibrium, workers will demand a wage premium to locate in new economy areas as compensation for bearing greater housing market risk. Seen in this light, additional housing market risk is an indirect cost associated with accomplishing other profit-enhancing objectives. Because the firm internalizes a portion of the volatility costs it imposes on its neighbors, it has an incentive to take action in moderating the costs of housing market risk. Creating new risk sharing opportunities for workers who want to be homeowners can be viewed as part of the broader objective of cutting costs.

The question of whether cost-effective risk sharing mechanisms are actually feasible depends on workers' willingness to accept lower cash wages in exchange for firm-administered home price insurance (workers' degree of risk aversion), the tax treatment of firm-administered insurance, and the firm's ability to price housing risk and find mechanisms for hedging the additional risk it assumes by writing labor contracts with home insurance provisions. In so far as new economy housing market volatility results in a wage premium that new economy firms must pay, and to the extent that new economy firms have a greater propensity to innovate when it comes to human resources and non-cash compensation, then such firms must be considered among the leading candidates for improving housing market efficiency. In particular, there may be scope for mutually beneficial employee benefits packages that provide insurance against housing market risk while reducing overall labor costs. This broader normative issue is discussed again in the Section 5 and motivates the empirical investigation that follows.[3]

III. THE NEW ECONOMY SECTOR OF DALLAS COUNTY

The data presented in this paper consist of all single-family home sales recorded in the multiple listing service of Dallas County in the State of Texas from 1979-2000. Dallas County is the heart of the 12-county Dallas/Fort Worth Consolidated Metropolitan Area (CMSA) which has a labor force of 2 million and a population of 5 million, making it the 9th largest CMSA in the U.S. The latest Census shows high rates of population growth in the area that outpace the national average. Population projections indicate that the area will be the 4th largest CMSA by 2010.

The "new economy" aspect of Dallas is substantial. The composition of its business sector is heavily weighted toward technology-based services, high-tech manufacturing, retail and other services. Relatively little heavy manufacturing takes place in the area. The volume of economic activity in the Dallas area is large, both in absolute terms and in proportion to its population. According to the Greater Dallas Chamber of Commerce, if the Dallas CMSA were a country, its GDP would rank 24th in the world (http://www.gdc.org).

Although there are several "business parks" in the Dallas area, the largest and most precisely defined (in terms of geographical boundaries and its emphasis on high-tech business enterprise) is Telecom Corridor. Telecom Corridor is a "T"-shaped region comprised of two 10-mile vertical and horizontal stretches centered on Richardson, Texas, a northern suburb of the City of Dallas, about 10 miles north of downtown. The high-tech orientation of the region to the north of Dallas owes in large part to the founders of the Texas Instruments Corporation who located company headquarters there in the 1960s. They also helped found a technology-based research university (now University of Texas at Dallas) and played an instrumental role in attracting telecommunications firms like MCI WorldCom and Nortel to the area.

In 1988, when the Fujitsu Corporation announced it would establish a 100 acre corporate campus in the area, the *Dallas Morning News* first referred to the area as "Telecom Corridor." The Richardson Chamber of Commerce eventually trademarked the phrase in 1992. Today, Telecom Corridor is home to over 600 high-tech companies and contains the largest concentration of telecommunications firms in the U.S. Among these are Hewlett Packard, Compaq, Nortel, Alcatel, and Cisco Systems.

Table 1 presents the number of home sales in the Dallas County data together with median size and age-of-home statistics by year, for transactions in and out of the disc-shaped area (covering Telecom Corridor's "T" with a 5 mile radius) referred to here as the "Telecom" region. The price

Table 1: Number of Sales, Median Size and Age by Year

	Telecom Corridor Area				Non-Telecom Corridor Areas			
Year	Number of Sales	Median Price	Median Square Feet	Median Age of Dwelling	Number of Sales	Median Price	Median Square Feet	Median Age of Dwelling
1979	1,264	68,000	1,928	1	6,675	46,200	1,432	14
1980	2,197	78,500	1,877	5	8,664	54,337	1,420	18
1981	1,086	70,590	1,705	7	6,834	60,000	1,444	19
1982	1,683	98,500	2,022	7	4,578	65,000	1,480	13
1983	2,946	110,000	2,049	8	10,371	73,500	1,503	18
1984	2,933	119,000	2,088	9	11,136	81,317	1,547	19
1985	2,478	118,000	2,038	10	11,135	86,000	1,556	20
1986	2,634	122,500	2,059	11	10,505	84,499	1,540	17
1987	2,217	125,000	2,142	11	9,011	89,000	1,657	15
1988	2,212	112,000	2,130	11	8,912	83,500	1,651	15
1989	2,487	109,000	2,128	12	11,042	82,000	1,664	13
1990	2,465	107,563	2,100	14	10,827	83,000	1,671	17
1991	2,230	104,333	2,047	15	10,902	79,000	1,649	18
1992	2,530	103,000	2,028	16	13,087	77,500	1,630	19
1993	2,753	105,000	2,020	17	14,925	79,000	1,630	20
1994	2,747	103,000	2,007	18	15,291	78,900	1,614	22
1995	2,471	106,000	2,002	20	14,251	84,000	1,662	23
1996	2,498	115,950	2,102	21	14,191	91,896	1,717	24
1997	2,676	125,000	2,164	21	14,657	96,500	1,725	24
1998	3,009	130,000	2,140	22	16,040	102,000	1,726	24
1999	2,935	132,000	2,064	24	16,131	103,000	1,674	26
2000	3,147	139,500	2,032	24	18,436	114,500	1,703	22
All Years	53,598	112,000	2,048	16	257,601	84,000	1,623	19
# Properties		34,294				175,095		

data in Table 1 are unadjusted for inflation. Telecom area houses are noticeably larger (in terms of interior square feet, but not lot size), newer, and have higher prices. The total number of sales in the sample is 311,199. Because many of the homes in the sample are sold more than once in the time interval 1979.1 through 2000.12, the number of unique dwellings in the sample is considerable lower: 34,294 in the Telecom area and 175,095 in the non-Telecom area. Although the sales data in Table 1 are broken out by year, the date of each sale is observed to the nearest month, making it possible to construct monthly, quarterly, 6-month, or annual price indexes from which a representative "return on housing" can be computed.

Price Index Methodology

The estimation of representative price series for the Telecom and the non-Telecom areas, respectively, serves as a preliminary step toward computing expected real returns, covariance matrices (for housing returns and other assets such as stocks and bonds), and ultimately minimum-variance portfolio weights. In spite of its intermediate status within the overall architecture of that research agenda, the methodological challenges surrounding residential real estate indexing are daunting and require extra attention. The technical issues that thwart aggregation of individual home sales into a reasonable summary or spot price for real estate have in the past and continue to occupy the attention of leading real estate economists. Englund, Quigley and Redfearn (1999), Zabel (1999), and Wang and Zorn (1997) contain discussions that provide an overview of home price index methodology and its outstanding problems.

Perhaps the biggest problem in choosing a summary statistic for home values has to do with disentangling changes in the quality of homes from changes in the market price for a representative house, holding quality constant. For example, if new homes in a particular area are twice as big as existing homes, and the average price of a home increases as a result, it does not follow that owners of smaller homes can now sell their homes at a higher price. In other words, changes in the average sales price may be a poor indicator of changes in the value of the average house. Newer homes built with better technology, depreciation due to wear and tear, and improvements to existing homes (or beneficial environmental change such as the growth of attractive tree cover) are just some of the factors that create problems for measuring housing market returns.

Techniques for computing a housing price index generally fall into one of four categories: summary, repeat sales, hedonic and hybrid (Wang and Zorn, 1997). Probably the most widely sited summary measures of home prices in the aggregate are per-period mean and median prices. For example, the National Board of Realtors reports the median price of existing home sales each month, and this statistic is widely cited in the news media. Repeat sales indexes, on the other hand, measure change in home values by comparing sales prices for identical homes sold at different points of time. The repeat sales technique attempts to control for difficult-to-measure changes in quality by limiting price comparisons to pairs of same-home sales prices arranged chronologically through time (see Shiller, 1991; Case and Quigley, 1987; and Bailey, Muth and Nourse, 1963, for details). Unlike the repeat sales technique, the hedonic method uses additional data about the characteristics of individual homes, such as number of bathrooms, square feet, proximity to good schools and other amenities. The strategy of the hedonic method is to explicitly control for variation in home features that otherwise make it difficult to compare prices. Hybrid techniques combine repeat sale and hedonic price models in an attempt to use all available information and more precisely estimate changes in aggregate home prices.

Fortunately, the Dallas data contain enough information to construct different price indexes and compare their performance. From sales price data, monthly means and medians are straightforward to compute. The properties in the sample have unique id numbers from which same-house sales can be linked for the purpose of computing the repeat sale index. The data also include an abundance of housing characteristic controls, including year built, number of bathrooms, square feet, wet bars, appraisal value of swimming pools and saunas, etc. In addition, the data are geo-coded and linked to census tract data on tract-specific demographic information such as median age, racial composition, the fraction of housing units that are rentals, and the average size of a household.

Table 2 presents mean values for some of the most important among the numerous housing characteristic variables in the Dallas data. The average Telecom-area home is bigger, newer, possesses more in-house amenities, and is located in a neighborhood that is whiter, younger, and more affluent. It is important to realize, however, that it is unclear based on Table 2 whether a physically identical home located in a Census tract with identical demographic characteristics would be worth more in the Telecom or Non-Telecom area. In other words, the difference in average price in Table 2, by itself, provides no help in determining whether Telecom homes sell for more because they are in the Telecom area or because they happen to be homes with a greater quantity of amenities which would be valuable in any location.

Table 2 also presents means grouped according to whether a particular property appears more than once in the sample. It is worthwhile to compare so-called repeat sale homes to those involved in only a single sale. When considering the external validity with which changes in the repeat-sales price index may be used to make inferences about the population of all home sales, paying attention to systematic differences between those two categories is crucial. The average repeat sale home is larger and worth more. The large sample sizes lead to very small root-N adjusted standard errors, and many statistically significant differences among the four subgroups broken out in Table 2.

Table 2: Mean Housing Characteristics and Standard Errors

Variables	Telecom		Non-Telecom		Single Sale Transactions		Repeat Sale Transactions		All Sales	
	mean	s.e.	mean	s.e.	mean	s.e.	mean	s.e.	mean	s.e.
Attributes of Individual Dwellings										
price	134,630	387.635	120,691	298.464	114,139	356.876	129,859	358.413	121,006	256.106
square feet	2,153.28	3.317	1,810.10	1.657	1,805.51	2.255	1,917.34	2.008	1,869.20	1.503
age of house	17.11	0.047	23.10	0.035	22.11	0.047	22.04	0.041	22.07	0.031
fireplaces	0.88	0.002	0.76	0.001	0.72	0.001	0.82	0.001	0.78	0.001
full baths	2.25	0.003	1.92	0.001	1.91	0.002	2.02	0.002	2.10	0.001
half baths	0.29	0.002	0.23	0.001	0.24	0.001	0.25	0.001	0.24	0.001
wetbars	0.29	0.002	0.11	0.001	0.11	0.001	0.17	0.001	0.14	0.001
pool appraisal	2,776.46	21.412	1,374.30	8.111	1,206.25	10.290	1,925.36	11.042	1,615.81	7.719
miles from downtown	11.92	0.008	10.46	0.008	10.91	0.010	10.57	0.009	10.71	0.007
Telecom	1.00	0.000	0.00	0.000	0.19	0.001	0.15	0.001	0.17	0.001
Single Sale Transaction	0.37	0.002	0.44	0.001	1.00	0.000	0.00	0.000	0.43	0.001
Census Tract Variables										
percent black	0.09	0.000	0.15	0.000	0.16	0.001	0.12	0.000	0.14	0.000
percent asian	0.09	0.000	0.04	0.000	0.04	0.000	0.05	0.000	0.05	0.000
percent hispanic	0.12	0.000	0.22	0.000	0.23	0.001	0.19	0.000	0.21	0.000
percent 18 or under	0.25	0.000	0.28	0.000	0.28	0.000	0.27	0.000	0.27	0.000
median age (tract residents)	36.78	0.021	33.50	0.013	33.24	0.019	34.69	0.014	34.07	0.012
average household size	2.65	0.002	2.76	0.001	2.79	0.002	2.69	0.001	2.74	0.001
percent owner occupied	0.66	0.001	0.66	0.000	0.66	0.001	0.66	0.000	0.66	0.000
Number of Sales	53,598		257,601		133,967		177,232		311,199	

Note: a number of independent variables used in estimating the hedonic price index are not listed above. These include 164 (=22x12) month-year time dummies, dummy variables for each of 14 school districts located in Dallas County (aside from the Dallas Independent School District), and up to fourth-order polynomial transforms of two variables: age of house and distance from downtown.

House Price Index Models

Define the sample of all home sales prices to be $\{V_{it}\}_{i=1,\ldots,N_t}^{t=1,\ldots,T}$, where the time index t runs from 1 to 264 (which corresponds to 1979.01 to 2000.12) and N_t is the number of sales at month t. The mean and median price indexes are straightforward:

$$P_t^{mean} = (V_{1t} + V_{2t} + ... + V_{N_t})/N_t, \tag{1}$$

$$P_t^{med} = \text{median}(V_{1t}, V_{2t}, ..., V_{N_t}). \tag{2}$$

Let the symbol $v_{ut} \equiv \log(V_{ut})$. The hedonic price index can be expressed as

$$P_t^{hed} = e^{\lambda_t}, \tag{3}$$

where the parameters $\lambda_1, ..., \lambda_T$ are estimated from

$$v_{it} = \beta' x_{it} + \sum_{s=1}^{T} \lambda_t \, 1(s = t) + \epsilon_{it}, \tag{4}$$

$1(\cdot)$ is the identity function, and x_{it} is a vector of dwelling-specific characteristics such as square feet, age of home, and proximity to down town. The error term ϵ_{it} is assumed to be uncorrelated, with zero conditional mean, and the parameters are estimated using ordinary least squares. For the hedonic index, as well as the mean and median indexes, all observed home sales are incorporated into the calculations resulting in a sample size of $\sum_{t=1}^{T} N_t = 307,741$.

The repeat-sales index, on the other hand, discards properties from the sample that are sold only once. In contrast to the other indexes in which each observation corresponds to an individual sale, the sampling unit in the repeat sales model is a pair of consecutive same-home sales. A home sold k times generates $k - 1$ pairs. If one re-labels the sales data so that u identifies unique *properties* as opposed to sales (u=1,...,209,389), and k_u is the number of times property u is sold, then the sample size can be computed as:

$$N^{rep} = \sum_i (k_u - 1) = \text{total number of sales} - \text{unique dwellings}. \tag{5}$$

That means the sample size is $307,741 - 209,389 = 77,629$.

Let the symbol $\tau_u(t)$ represent the last period before t when property u was sold. Define

$$D_{us} = \begin{cases} 1 & \text{if } s = t \\ -1 & \text{if } s = \tau_u(t) \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

The repeat sales price index can be expressed:

$$P_t^{rep} = e^{\phi_t}, \tag{7}$$

where the parameters $\phi_1, ..., \phi_T$ are estimated from the equation

$$v_{ut} - v_{u\tau(t)} = \sum_{s=1}^{T} \phi_s D_{us} + \mu_{ut}, \tag{8}$$

with uncorrelated although heteroskedastic, zero conditional mean μ_{it}. The parameters ϕ_s can be efficiently estimated using generalized least squares, utilizing information about the dependence of $\mathrm{E}\mu_{ut}^2$ on t and τ. See Shiller (1991) or the appendix on "Weighted Repeat Sales Method" in Englund, Quigley and Redfearn (1999). Unlike the hedonic model, the repeat-price index requires only prices, dates of sale, and a way to link properties through time.

Figure 1 plots the four monthly price indexes for non-Telecom home sales in Dallas County. Figure 2 plots the indexes for sales in the Telecom area. The two Figures are scaled identically to facilitate comparison of levels and volatility. Comparing the two, price appreciation in the non-Telecom area appears to be greater than in the Telecom area. However, according to the hedonic index, price appreciation from 1979 through 2000 is actually greater in the Telecom area, increasing by a factor of 2.5 rather than 2.4 in the non-Telecom area.

The four measures of aggregate price level are normalized so that all indexes equal 1 when $t = 1$, in the period 1970.01. The four indexes appear to track one another fairly well, although there are systematic differences in their levels, which could be potentially important to risk/return analyses of the two respective markets. Correlation matrices among the four price indexes (not presented here due to space considerations) show a high degree of inter-relatedness, with correlations mostly in the 90% range and never lower than 86% in the non-Telecom region. The price indexes in the Telecom area, however, are less consistent, with correlations as low as 70%. In both areas, the repeat sales index is noticeably less correlated than the other three measures.

In Figures 1 and 2, the mean and median price indexes give the highest estimate of price appreciation in the housing market, while the repeat sales index gives the lowest. This would appear to be the logical result of the fact that the mean and median price indexes conflate improved aggregate quality (e.g., bigger, better built homes featuring more amenities) with price appreciation of a uniform-quality unit of housing. The fact that median sales are consistently less than mean sales in Figure 1 reflects the influence of several multi-million dollar home sales each period in older upscale areas located in the non-Telecom area. Explaining why the hedonic index shows higher aggregate price levels than the repeat sales index is less obvious. This may result from differences in the two subpopulations — single-sales versus repeat-sales homes. In an encompassing hedonic regression in which repeat sale and non-repeat sale homes are allowed to have different parameters, the data soundly rejects the hypothesis that the models are the same, with

Figure 1: Non-Telecom Housing Price Indexes, 1979-2000

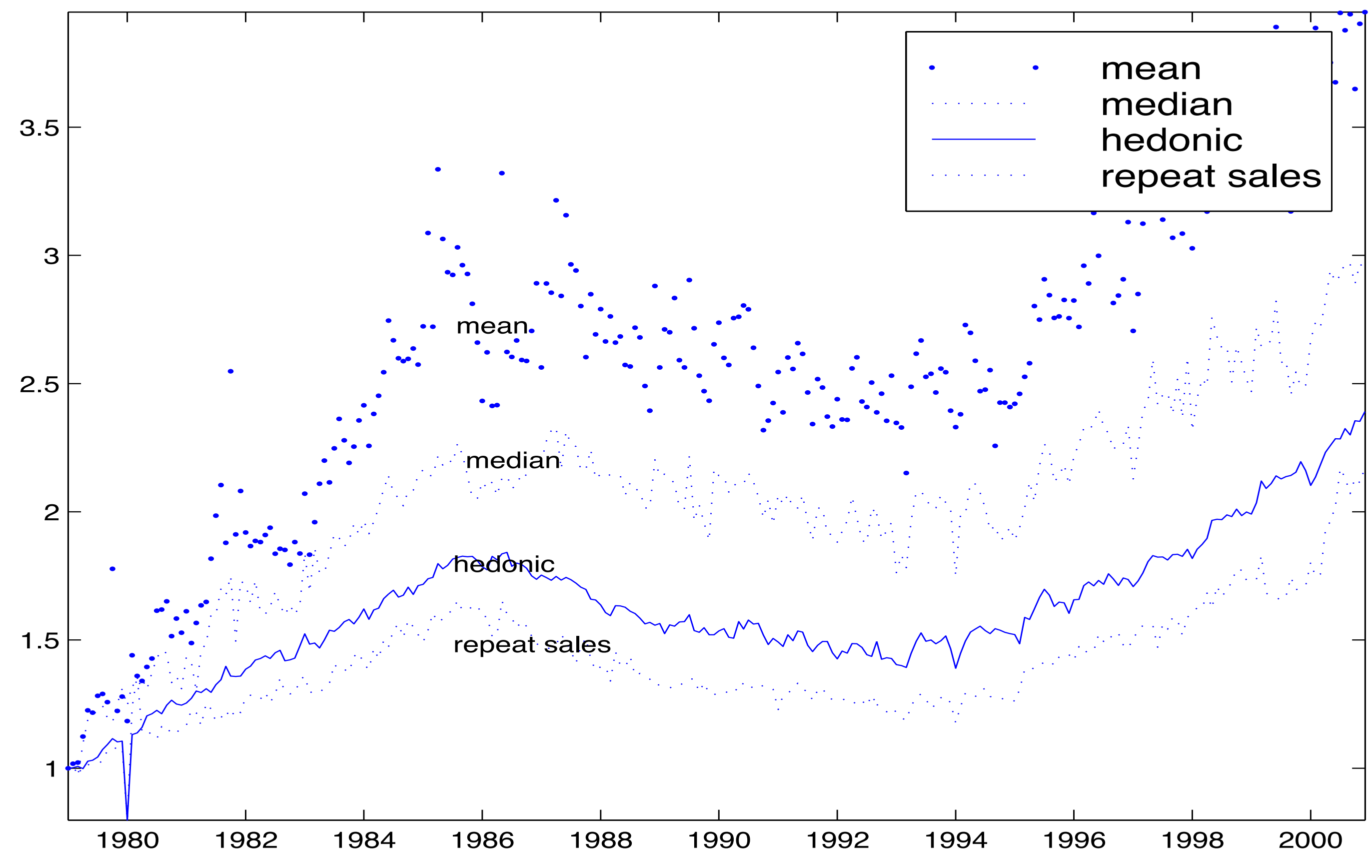
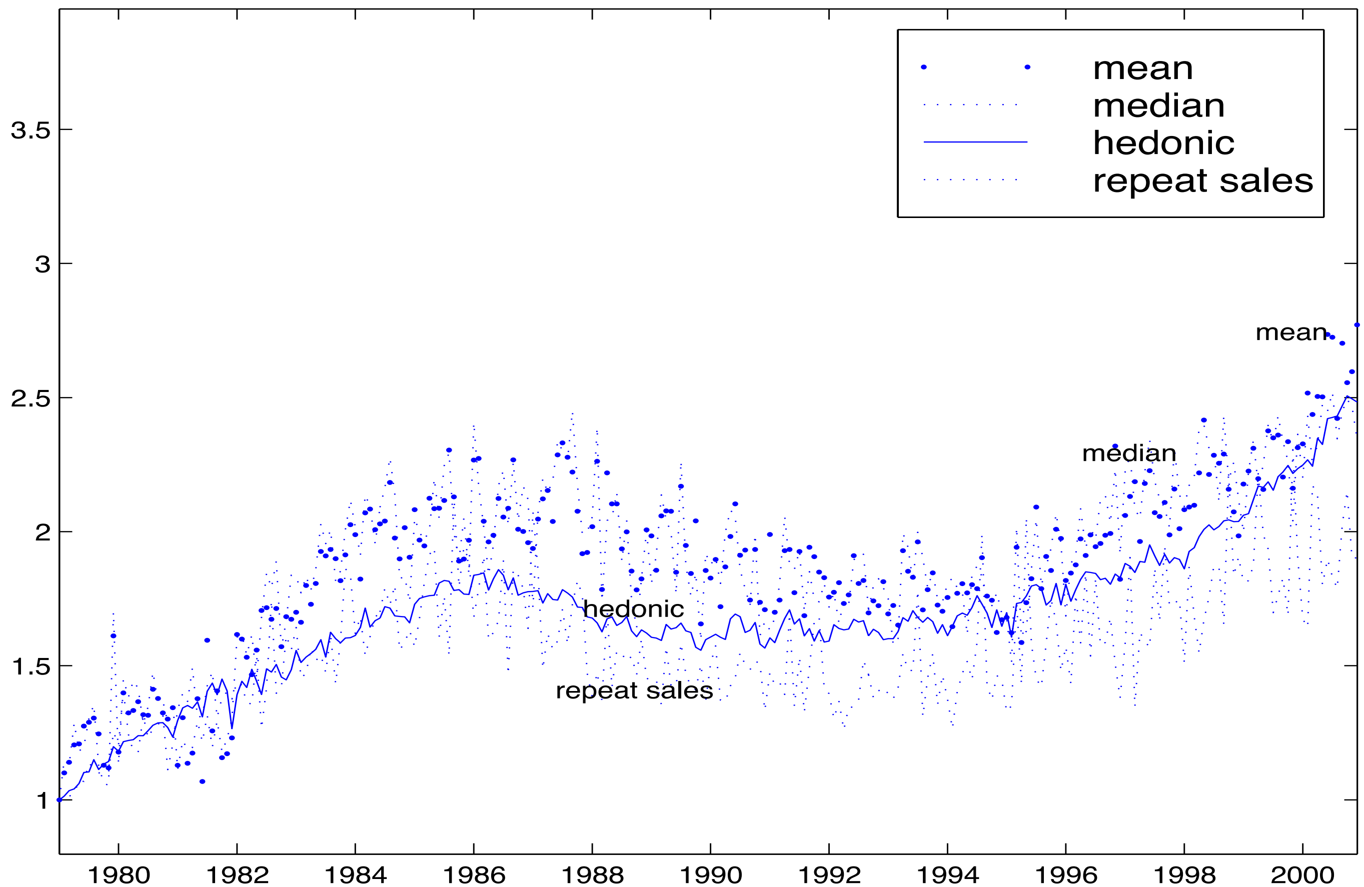


Figure 2: Telecom Housing Price Indexes, 1979-2000



a $\chi^2(304)$ Wald test statistic of 4779.0. The technique of Oaxaca decomposition (originally applied to wage differentials in empirical labor studies (Oaxaca, 1973)) reveals that the gap in expected price between repeat and non-repeat sale homes is 17% attributable to coefficients and 83% attributable to regressors. The estimate of 17% is statistically significant with a $\chi^2(304)$ Wald test statistic of 504.1, meaning that both market differences and, to a greater extent, different x values play a role in explaining the different behavior of the repeat-sale price index.

An important feature of the hedonic index in both Figures is its relative smoothness. Apparently, changes in the mix of houses sold from one month to another (which are netted out in the hedonic index), rather than fluctuations in the market price for a standard-characteristic home, accounts for most of the month-to-month fluctuation in average and median home prices. This is consistent with previous findings, such as those in Case and Shiller (1987) comparing repeat sales and median indexes. In principle, changes in the mix of homes sold should not affect the repeat sale index either, and the repeat sales index should appear as smooth as the hedonic index. This is precisely the case in Figure 1, but not in Figure 2.[4] Discrepancies in sample sizes between Telecom and non-Telecom areas, and between repeat-sale and other price indexes, should be kept in mind in interpreting Figures 1 and 2. The average number of repeat sales occurring each month is 127 in the Telecom area and 545 in the non-Telecom area. The corresponding average sample sizes for price indexes that do not exclude single-sale homes are 203 and 975.

The remainder of the empirical analysis in this paper addresses the question of whether Figures 1 and 2 reflect genuinely different price processes in the Telecom and non-Telecom areas, i.e., different enough to matter in a substantive way to potential homeowners considering whether to move to one area or the other. In a statistical sense, the two areas are clearly distinct. An unconditional t test of the hypothesis that log prices are equal has magnitude 87.1; a Telecom area dummy variable in a single hedonic regression using the entire sample has a large and statistically significant coefficient; and an equality of coefficients test from two separate hedonic regressions on the Telecom and non-Telecom samples leads to a $\chi^2(304)$ Wald test statistic of 2152.8. Further evidence that Telecom and non-Telecom areas are statistically differentiated can be seen in the monthly percentage changes in the (unconditional) average price series. Figure 3 presents these monthly changes, and Figure 4 shows the standard deviation of log prices in both areas. The two figures, combined with a highly significant equality of variance F(203,203) test statistic of 1.66 (corresponding to the percentage change series), indicate greater unconditional volatility in the Telecom area.[5]

Thus, every statistical test that was attempted rejects the hypothesis that Telecom and non-Telecom price processes are identical. However, the issue of whether hedging opportunities in the two regions are substantively different requires a further set of comparisons. Using inflation-adjusted percentage changes in the different aggregate measures of house prices, the following sections compare average real returns, volatility of returns, and the correlations between returns on housing and other assets.

IV. RETURNS ON HOUSING AND OTHER ASSETS

Defining "Returns on Housing"

Having constructed four monthly housing price indexes, the next step is to compute a corresponding real return series by taking monthly percentage changes (not difference of logs) and subtracting the percentage change in the monthly CPI-U for the U.S. By itself, this calculation of "returns on housing" neglects potentially important costs and benefits associated with home ownership. The rental or consumption value of residing on the property one owns is an important benefit. And the tax advantages of home ownership can be substantial (e.g., both mortgage interest payments and capital gains from owner-occupied home sales generally receive favorable tax treatment in the U.S.). Homes also require periodic expenditures on maintenance and, in most places in the U.S., create a tax liability for their owners. The "return" on housing clearly depends on these annual flows of costs and benefits in addition to capital gains, i.e., price appreciation.

The problem is analogous to computing the time series of returns on a common stock. Given a price series, it is easy to compute capital gains over any time horizon. But dividends must be added in somehow in order to accurately state the return on one share. In the case of investing in a home, one needs to add in the flow of net benefits apart from capital gains to compute the investment's return. The approach here follows Flavin and Yamashita (2002).

The following three equations represent the rental value (or home dividend) D_t, the costs of maintenance COM_t, and the annual return on housing R_t for a homeowner with marginal income tax rate ϕ:

$$\begin{aligned}
D_t &= (i+d)P_{t-1} + PropertyTax_t & (9)\\
COM_t &= dP_{t-1} + (1-\phi)PropertyTax_t & (10)\\
R_t &= \frac{P_t + D_t - COM_t - P_{t-1}}{P_{t-1}} & (11)\\
&= P_t/P_{t-1} + i + \phi PropertyTax_t/P_{t-1} - 1. & (12)
\end{aligned}$$

The symbol i is the short-term real interest rate (assumed in Flavin and Yamashita (2002) to equal 5%); d is the physical rate of depreciation (borne equally by renters and owners). Flavin and Yamashita argue that the rental value equation (9) derives from the zero profit condition facing landlords, and operationalize the system of equations by plugging in reasonable values for the various parameters: $i = .05$, $\phi = .28 + .05$ (federal plus state marginal tax rates facing the average investor), and $PropertyTax_t/P_{t-1} = 0.025$. Just how "reasonable" these values are, however, is open to question.

In the case of Dallas County, the Flavin and Yamashita numbers require adjustments for several reasons. For one thing, there is no state income tax in Texas, and high property tax rates are relatively high (as a result). It should be noted that the problem of dealing with taxes is relevant when computing the returns on other assets, too. Therefore consistent conventions for making adjustments for taxes are required if the results are to be compared meaningfully. For example, Flavin and Yamashita compare all asset returns on an after-tax basis. They apply the marginal income tax rate ϕ to interest income and stock dividends, and treat capital gains on stocks as if they were unrealized and therefore untaxed.

Because tax rates differ for different investors and change through time, it would be ideal to include detailed income and property tax data to more accurately quantify the symbols in the algebraic expression for housing market return. Absent this information, however, I adopted the following strategy. I simply tested a variety of assumptions about the value of $i + \phi(PropertyTax)/P$ and tried to develop some understanding of the degree to which the ultimate results are sensitive to their manipulation. By inspecting the real annual return on housing (R_t) equation above, it is obvious that different assumptions about i, ϕ and $PropertyTax/P$ amount to changing the entire 'percentage change in real price' series by a constant. Fortunately changing the constant does not lead to any change in the covariance matrices needed to compute efficient portfolios.

Unfortunately, however, different choices of values for that constant directly affect the expected return data which are critical inputs in the portfolio weight calculation. The portfolio weights reported in the next section are highly sensitive to a one percentage point change in this quantity. However, the relative weight on housing between Telecom and non-Telecom portfolios is consistent even when the levels of the weights change as a result of changing $i + (PropertyTax)/P$. Of course, by choosing a higher value of $i + (PropertyTax)/P$, the expected return on housing increases, and optimal portfolios shift to contain more housing. Because the correlation of housing returns and other assets is unchanged, however, minimum-variance portfolios in the Telecom versus non-Telecom areas broadly retain their relationship to one another. For example, if Telecom homeowners' portfolios contain half the housing in non-Telecom homeowners' portfolios when $i + (PropertyTax)/P = 0.06$, then the same will hold when $i + (PropertyTax)/P = 0.07$, even though both portfolios will contain more housing.

To keep the comparisons as straightforward as possible, my analysis is taken on a pre-tax basis. In other words, I make no adjustments for taxes. I also lower i to .04 in order to reflect the lower real interest rates experienced in the U.S. in the 1990s. Flavin and Yamashita's choice of $i = 0.05$ strikes me as too high (although possibly appropriate for the

1968-1992 data they used). They describe i as a short-term interest rate. Conceptually, it represents the opportunity cost of tying up capital in a home, together with the assumption that the next best alternative to home ownership is short term bonds earning 5%.[6]

Empirical Estimates of Return and Risk

Table 3 presents average returns for housing (according to four different indexes) in the Telecom and non-Telecom areas, as well as stocks (S&P 500 index), bonds (10-year constant maturity Treasury rate), and the Wilshire REIT (Real Estate Investment Trust) index.[7] Average returns at monthly, quarterly, 6-month and annual time horizons (adjusted to an annual basis) are presented, based on geometric summation of monthly percentage changes. For example quarterly returns are constructed as $(1 + r_t)(1 + r_{t+1})(1 + r_{t+2}) - 1$, and then converted to an annual basis by multiplying times 4. Each time-horizon specific block in Table 2 contains three rows: the (arithmetic) average return, the standard deviation of the (time-horizon specific) return, and the standard deviation of the *average* return, which simply involves division by the square root of the number of non-overlapping time-horizons in the sample minus one. Because the Wilshire REIT index begins in December 1982, all calculations in the remainder of this paper are based on monthly returns series which are truncated to begin on that date, leaving only 18 instead of 22 years of data.

Comparing the first and third rows of each time horizon block in Table 3, one finds only a few statistically significant disagreements in expected return among the four indexes within and between each of the two geographical regions. The hedonic index has the smallest standard errors, formally demonstrating its smoothness which was apparent in Figures 1 and 2. Another point worth mentioning is that annual returns are less volatile than monthly returns (times 12), a fact at odds with the random walk model. This suggests that more complex dynamics may underlie the housing price process.

Table 4 produces statistics that are analogous to those in Table 3, but this time under the assumption that each asset follows a univariate AR(1) process, where the time increment t variously represents one month, three months, six months, or 12 months. The expected return statistics represent the arithmetic average of one-period ahead conditional expectations. Under the assumption that the error process is ergodic, the time average approaches the unconditional expectation (which could have been estimated directly by plugging in estimates of α and ρ into $\frac{\alpha}{1-\rho}$). Empirical values for the standard errors are computed on the basis of squared forecasting errors, taken as the difference between each period's conditional expectation and realized value.

The monthly returns in Table 4 are significantly autocorrelated, with large negative autocorrelation coefficients ("rho" in Table 4). Reverting

Table 3: Random Walk Model --- Arithmetic Mean Real Returns on Housing and Other Assets

	Telecom				Non-Telecom				Other Assets		
	Mean	Median	Hedonic	Repeat-Sale	Mean	Median	Hedonic	Repeat-Sale	S&P 500	10-year T Bill	REIT
Monthly, T=217											
Er x 12	0.068	0.074	0.040	0.102	0.077	0.052	0.038	0.041	0.105	0.040	0.076
sigma_r x 12	0.892	1.082	0.257	1.455	0.841	0.509	0.216	0.333	0.515	0.028	0.433
sigma_r x 12/(T-1)^0.5	0.061	0.074	0.017	0.099	0.057	0.035	0.015	0.023	0.035	0.002	0.029
Quarterly, T=72											
Er x 4	0.048	0.049	0.040	0.063	0.062	0.047	0.037	0.038	0.104	0.040	0.075
sigma_[(1+r_t)(1+r_{t+1})(1+r_{t+2})] x 4	0.355	0.391	0.121	0.620	0.337	0.208	0.123	0.149	0.296	0.022	0.277
sigma_[…]/(T-1)^0.5	0.042	0.046	0.014	0.074	0.040	0.025	0.015	0.018	0.035	0.003	0.033
6-month, T=36											
Er x 2	0.041	0.044	0.040	0.036	0.060	0.047	0.037	0.038	0.103	0.041	0.077
sigma_[(1+r_t)...(1+r_{t+5})] x 2	0.195	0.243	0.075	0.281	0.211	0.143	0.073	0.099	0.191	0.018	0.211
sigma_[…]/(T-1)^0.5	0.033	0.041	0.013	0.048	0.036	0.024	0.012	0.017	0.032	0.003	0.036
Annual, T=18											
Er	0.037	0.035	0.040	0.026	0.053	0.047	0.038	0.039	0.105	0.041	0.081
sigma_[(1+r_t)...(1+r_{t+11})]	0.102	0.107	0.054	0.138	0.090	0.092	0.062	0.091	0.136	0.017	0.169
sigma_[…]/(T-1\)^0.5	0.025	0.026	0.013	0.034	0.022	0.022	0.015	0.022	0.033	0.004	0.041

Table 4: AR(1) Model --- Average Expected Real Returns Using AR(1) Models on Housing and Other Assets

	Telecom				Non-Telecom				Other Assets		
	Mean	Median	Hedonic	Repeat-Sale	Mean	Median	Hedonic	Repeat-Sale	S&P 500	10-year Bond	REIT
Monthly Returns x 12 for the "t = 1 Month" AR(1) Model, T=217											
E_t r_{t+1} x 12	0.032	0.040	0.025	0.052	0.049	0.034	0.033	0.030	0.103	0.058	0.082
sigma_t(r_{t+1}) x 12	0.788	0.995	0.244	1.275	0.784	0.481	0.215	0.325	0.513	0.030	0.425
sigma / (T-1)^0.5	0.054	0.068	0.017	0.087	0.053	0.033	0.015	0.022	0.035	0.002	0.029
rho in Monthly AR(1)	-0.474	-0.403	-0.328	-0.489	-0.373	-0.345	-0.056	-0.214	-0.053	0.448	0.163
t stat for rho	-7.928	-6.496	-5.110	-8.248	-5.925	-5.419	-0.820	-3.224	-0.789	7.379	2.433
Quarterly Returns x 4 for the "t= 1 Quarter" AR(1) Model, T=72											
E_t r_{t+1} x 4	0.026	0.028	0.031	0.032	0.046	0.036	0.031	0.036	0.093	0.049	0.071
sigma_t(r_{t+1}) x 4	0.311	0.360	0.117	0.509	0.322	0.203	0.121	0.148	0.294	0.023	0.275
sigma / (T-1)^0.5	0.037	0.043	0.014	0.060	0.038	0.024	0.014	0.018	0.035	0.003	0.033
rho in Quarterly AR(1)	-0.489	-0.390	-0.181	-0.569	-0.290	-0.190	-0.132	-0.053	-0.077	0.232	0.000
t stat for rho	-4.756	-3.599	-1.563	-5.867	-2.568	-1.643	-1.133	-0.450	-0.651	2.025	0.003
6-Month Returns x 2 for the "t = 6 Months" AR(1) Model, T=36											
E_t r_{t+1} x 2	0.015	0.013	0.032	0.021	0.017	0.027	0.045	0.050	0.085	0.061	0.059
sigma_t(r_{t+1}) x 2	0.156	0.190	0.072	0.240	0.159	0.131	0.070	0.095	0.186	0.026	0.198
sigma / (T-1)^0.5	0.026	0.032	0.012	0.041	0.027	0.022	0.012	0.016	0.031	0.004	0.033
rho in Six-Month AR(1)	-0.604	-0.617	-0.110	-0.518	-0.637	-0.360	0.269	0.316	-0.113	0.521	-0.091
t stat for rho	-4.549	-4.710	-0.664	-3.635	-4.962	-2.315	1.676	1.997	-0.684	3.664	-0.549
Annual Returns for the "t = 1 Year" AR(1) Model, T=18											
E_t r_{t+1}	0.035	0.024	0.066	0.009	0.052	0.032	0.056	0.038	0.081	0.061	0.064
sigma_t(r_{t+1})	0.098	0.098	0.046	0.125	0.081	0.080	0.050	0.088	0.135	0.025	0.160
sigma / (T-1)^0.5	0.024	0.024	0.011	0.030	0.020	0.019	0.012	0.021	0.033	0.006	0.039
rho in Annual AR(1)	0.116	-0.032	0.761	-0.396	0.162	-0.106	0.657	0.098	-0.209	0.593	-0.061
t stat for rho	0.495	-0.138	4.975	-1.830	0.698	-0.453	3.700	0.416	-0.907	3.124	-0.259

behavior is especially severe in the Telecom area. The importance of autocorrelation, however, seems to dissipate with longer time horizons, and the sign of many of the housing index autocorrelation coefficients switches from negative to positive. Expected returns in Table 4 based on the AR(1) model are in general lower, and reveal sharper differences among the different housing indexes than in the random walk model.

How Different Are Telecom and Non-Telecom Regions?

By the two standard deviation criterion, very few significant differences between expected returns in the Telecom and non-Telecom areas can be seen in Tables 3 and 4. The data easily reject formal (Wald) tests of the hypothesis that parameter values across the two samples are equal. Housing market volatility as measured by standard deviation appears slightly greater in the Telecom area, which would confirm one of the main hypotheses proposed in the introduction. However, without consulting a formal measure of precision for the estimated standard deviation, Tables 3 and 4 by themselves do not add much weight to the claim that new economy housing markets are distinctly risky. Although there is ample statistical evidence to differentiate the two regions, whether those differences translate into something substantively important for homeowners in new economy areas is another question.

The outlined diagonals in Table 5 contain the same-index correlations for the Telecom and non-Telecom areas. By all measures, monthly returns in the two areas are weakly correlated, never reaching more than 38%. Annual or 12-month returns are more correlated, but not uniformly: the repeat sale price indexes in the two areas in the random walk model, for example, have 0% correlation. Comparing the degree to which home prices are correlated with stocks, bonds, and REITs in the two areas, one find several large magnitude and opposite-sign disagreements.

Overall, Tables 3, 4 and 5 paint a pessimistic picture with respect to the goal of estimating risk and return for investments in the housing market. Different investment horizons and different assumptions about the returns process lead to significantly different quantifications of risk and return. Nevertheless, those differences are finite, and we can proceed by discussing a representative case and analyzing the sensitivities to changes in index, time horizon, and error structure.

How Much Housing Belongs in Minimum-Variance Portfolios?

This section computes the share of wealth allocated to housing in a minimum-variance portfolio. It is well known that the equivalent goals of minimizing variance subject to a target level of expected return, and of maximizing expected return subject to a target level of variance, together with normality assumptions, correspond to preferences represented by the constant absolute risk aversion expected utility function. Table 6 contains minimum-variance portfolio weights (on housing, stocks, bonds and REITs)

Table 5: The Correlation of Real Returns

		Telecom				Non-Telecom				Other		
		Mean	Median	Hedonic	Repeat-Sale	Mean	Median	Hedonic	Repeat-Sale	S&P 500	10-year T Bill	REIT
	One-Month Returns Monthly Random Walk Model											
Telecom	Mean	1.00										
	Median	0.72	1.00									
	Hedonic	0.37	0.41	1.00								
	Repeat-Sale	0.14	0.01	0.26	1.00							
Non-Tele.	Mean	0.17	0.07	0.15	0.07	1.00						
	Median	0.18	0.14	0.19	-0.01	0.50	1.00					
	Hedonic	0.16	0.14	0.37	0.16	0.25	0.45	1.00				
	Repeat-Sale	0.13	0.16	0.18	0.10	0.10	0.19	0.29	1.00			
Other	S&P 500	0.02	0.06	0.10	-0.02	0.15	0.01	-0.03	-0.07	1.00		
	10-year T Bill	-0.04	-0.02	0.10	0.07	-0.05	0.04	0.08	0.04	0.12	1.00	
	REIT	0.06	0.01	0.03	-0.05	0.01	0.06	-0.06	-0.09	0.10	0.08	1.00
	12-month Returns Using Monthly Random Walk Model											
Telecom	Mean	1.00										
	Median	0.66	1.00									
	Hedonic	0.56	0.63	1.00								
	Repeat-Sale	0.00	0.18	0.42	1.00							
Non-Tele.	Mean	0.52	0.43	0.65	0.26	1.00						
	Median	0.68	0.65	0.61	-0.02	0.75	1.00					
	Hedonic	0.46	0.41	0.84	0.51	0.75	0.50	1.00				
	Repeat-Sale	0.56	0.58	0.74	0.04	0.70	0.78	0.71	1.00			
Other	S&P 500	0.03	0.13	0.11	0.60	0.23	-0.07	0.38	0.02	1.00		
	10-year T Bill	0.03	0.17	0.19	0.11	0.36	0.16	0.20	0.07	0.20	1.00	
	REIT	0.39	0.50	0.20	-0.18	0.30	0.30	0.25	0.21	0.23	0.41	1.00
	"t = 1 Month" AR(1) Model											
Telecom	Mean	1.00										
	Median	0.72	1.00									
	Hedonic	0.41	0.44	1.00								
	Repeat-Sale	0.10	0.01	0.22	1.00							
Non-Tele.	Mean	0.21	0.14	0.19	0.02	1.00						
	Median	0.27	0.21	0.24	0.01	0.54	1.00					
	Hedonic	0.21	0.15	0.38	0.21	0.35	0.51	1.00				
	Repeat-Sale	0.16	0.20	0.23	0.14	0.15	0.24	0.32	1.00			
Other	S&P 500	0.04	0.05	0.12	-0.02	0.13	0.03	-0.02	-0.09	1.00		
	10-year T Bill	0.02	-0.05	0.16	0.20	-0.07	-0.02	0.09	0.06	0.08	1.00	
	REIT	0.07	0.01	0.07	-0.03	0.01	0.03	-0.07	-0.14	0.12	0.03	1.00
	"t = 1 Year" AR(1) Model											
Telecom	Mean	1.00										
	Median	0.62	1.00									
	Hedonic	0.22	0.42	1.00								
	Repeat-Sale	0.19	0.26	0.55	1.00							
Non-Tele.	Mean	0.43	0.31	0.15	0.28	1.00						
	Median	0.65	0.56	0.19	0.07	0.70	1.00					
	Hedonic	0.25	0.12	0.42	0.47	0.58	0.22	1.00				
	Repeat-Sale	0.52	0.55	0.49	0.12	0.64	0.79	0.49	1.00			
Other	S&P 500	0.02	0.12	0.10	0.60	0.27	-0.03	0.46	0.00	1.00		
	10-year T Bill	0.02	0.12	0.14	0.11	0.11	-0.07	0.04	0.05	0.18	1.00	
	REIT	0.25	0.43	-0.20	-0.20	0.19	0.21	0.05	0.16	0.21	0.51	1.00

Table 6: Optimal Portfolio Weights --- Telecom Versus Non-Telecom Homeowners

Target Return	Telecom Corridor Area Housing	Telecom Corridor Area Stocks	Telecom Corridor Area Bonds	Telecom Corridor Area REITS	Non-Telecom Corridor Areas Housing	Non-Telecom Corridor Areas Stocks	Non-Telecom Corridor Areas Bonds	Non-Telecom Corridor Areas REITS	Telecom - Non-Telecom Weight
Monthly Random Walk Model									
0.000	0.086	-0.443	1.671	-0.314	0.002	-0.442	1.755	-0.315	0.084
0.010	-0.170	0.883	-0.345	0.632	0.015	0.881	-0.531	0.636	-0.185
0.020	-0.427	2.209	-2.360	1.578	0.027	2.204	-2.817	1.587	-0.454
0.030	-0.684	3.535	-4.376	2.525	0.040	3.526	-5.104	2.538	-0.723
0.040	-0.940	4.860	-6.391	3.471	0.052	4.849	-7.390	3.489	-0.992
0.050	-1.197	6.186	-8.406	4.417	0.064	6.172	-9.676	4.440	-1.261
0.060	-1.453	7.512	-10.422	5.363	0.077	7.494	-11.962	5.391	-1.530
0.070	-1.710	8.838	-12.437	6.309	0.089	8.817	-14.248	6.342	-1.799
0.080	-1.967	10.163	-14.452	7.256	0.101	10.140	-16.534	7.293	-2.068
0.090	-2.223	11.489	-16.468	8.202	0.114	11.462	-18.820	8.244	-2.337
0.100	-2.480	12.815	-18.483	9.148	0.126	12.785	-21.106	9.195	-2.606
0.120	-2.993	15.466	-22.514	11.040	0.151	15.430	-25.678	11.097	-3.144
0.140	-3.506	18.118	-26.545	12.933	0.176	18.076	-30.251	12.999	-3.682
0.160	-4.019	20.769	-30.575	14.825	0.201	20.721	-34.823	14.901	-4.220
0.180	-4.532	23.421	-34.606	16.718	0.225	23.366	-39.395	16.804	-4.758
0.200	-5.046	26.072	-38.637	18.610	0.250	26.012	-43.967	18.706	-5.296
0.300	-7.612	39.330	-58.790	28.072	0.374	39.238	-66.828	28.216	-7.986
0.400	-10.178	52.588	-78.944	37.534	0.498	52.465	-89.689	37.727	-10.676
0.500	-12.744	65.845	-99.098	46.996	0.622	65.691	-112.550	47.237	-13.365

for a range of levels of target expected return. The expected return and covariance matrix come from the hedonic index and the monthly random walk model. After examining similar tables for other indexes, time horizons and error structures, the weights in Table 6 are representative in at least two senses. The optimal weight on housing is usually quite different in the Telecom area than in the non-Telecom area. When assumptions are changed that elevate the expected return of housing, both areas' housing weights shift toward housing, but the relative differences persist. For example, given a particular covariance matrix, if Telecom portfolios start out with less housing in them, then even after housing becomes more attractive in terms of expected return, Telecom portfolios remain comparatively short on housing.

Table 6 shows that efficient portfolios over reasonable ranges of expected return contain negative amounts of housing.[8] The hedonic index, which typically is the least volatile among the housing indexes, and frequently has one of the highest returns, is a good basis for comparison because it is, for the most part, the most favorable among the indexes for housing. Even under favorable circumstances (relatively low risk and high return) for housing investment, the wise homeowner (in a frictionless world with complete markets in risk) will not hold positive quantities net investment in housing. The last column shows the difference between optimal weights on housing for the two areas, demonstrating that Telecom homeowners should hold much less housing than non-Telecom homeowners. One may propose the following generalization: the housing-risk hedging problem is more severe for new economy workers, because their optimal portfolio decisions in a world without constraints imposed by market imperfections contain far less housing than those of homeowners in traditional real estate markets.

V. Discussion and Conclusions

The housing market in Telecom Corridor, one of Dallas County's greatest concentrations of new economy firms, has "new economy" features of its own. Telecom Corridor homes earn an investment return that is more volatile and more correlated with common stocks than housing returns in other areas. The correlation between Telecom and non-Telecom housing returns is weak. For most model specifications and expected-return targets, the optimal weight on housing (in a mean-variance efficient portfolio) is negative, and Telecom area portfolios generally contain less (more negative) weight on housing than in other areas. Even when this is not the case, efficient portfolios across the two areas are quite different.

According to the portfolio model, home ownership requires new economy homeowners to mover farther away from their optimal behavior under perfect market conditions than is the case for homeowners in other areas. This implies that workers at new economy firms may be among the most highly motivated to adopt new hedging instruments provided by their employers. In other words, new economy workers may be willing to pay more for contracts that insure against house price declines.

Unfortunately, existing classes of assets do not offer feasible hedging opportunities for homeowners. The evidence is mixed as to whether the city- or region-wide price indexes presented in this paper could be used as effective tools for hedging. One way to quantify the hedging value of a single price index is to regress individual home sale returns (using the repeat-sale sample) on a constant and the "market return" given by the price index over a corresponding time horizon. Following the textbook approach, return volatility can then be decomposed into systematic and idiosyncratic components (Shiller and Weiss, 2000; Case and Shiller, 1989). If more sophisticated housing future contracts incorporating the hedonic approach were made available, then it might be possible to hedge a greater fraction of home price volatility by exploiting additional information about the characteristics of individual homes. In that case, the idiosyncratic component would be smaller and the error term in the hedonic regression, or $1 - R^2$, would provide an estimate.

If demand for insurance is strong in new economy areas, as the argument above suggests, it is reasonable to hypothesize that risk-neutral new economy firms could profit by offering labor contracts which include some form of home price insurance and an offsetting reduction in cash wages. For example, a firm might consider writing a put option that has fair market value of $\$20,000$ (a valuation possibly provided by the firm's lenders who will be keen to monitor the balance sheet effects of any housing option activity).[9] The firm then offers its employees the option of switching to a labor contract that delivers possession of the put to the employee in exchange for accepting $\$25,000$ less in cash compensation over a period of several years. The firm receives 20% more for the put than its fair or risk-neutral valuation. And sufficiently risk averse employees will be made better off.

The trade-off between cash wages and put option insurance is not zero sum, because a worker's risk aversion leads to a willingness to pay function that is nonlinear in risk. Modeling this in detail is left for future study. Current tax rules may provide additional support for the idea that firms are the logical institution to offer home price insurance. Because of lenient and ambiguous accounting rules concerning option contracts as employee compensation, it may be possible that workers "pay" for employer provided insurance with pre-tax dollars. This would make the proposals discussed above even more attractive and encourage risk averse employees to overcome any hesitation in participating in a novel compensation plan.

Of course, writing put options on homes levers the firm with increased downside risk in the event that their own misfortune coincides with declining home values in their vicinity. However, the firm stands to gain nevertheless, because workers who are more risk averse than the firm, and who enjoy additional tax benefits by reducing their cash compensation, will pay more than the firm's valuation of home puts in terms of reduced cash wages. Providing that workers who are holders of home put options enjoy precedence over other debtors in the event of default, the risk pricing expertise of banks and other investors would come into play. In fact, one way to price housing risk would be to approach a firm's creditors with the wage plan described above and ascertain how their borrowing costs would rise as a result of taking on an additional unit of employee-housing liability. Future work in this direction should attempt to embed home insurance risk into a two-sided economic model of workers and firms, derive a home put pricing formula, and explore the possible tax advantages to workers and firms who exchange home price insurance for labor.

ENDNOTES

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Berg: Cecil and Ida Green Assistant Professor of Economics, University of Texas at Dallas, GR 31 211300, Box 830688, Richardson, Texas 75083-0688. Phone 1-972-883-2088, Fax 1-972-883-2735, Email nberg@utdallas.edu

1. Pyhrr, Roulac and Brown (1999) review a large body of empirical studies that demonstrate evidence of cyclicity in real estate markets.

2. This paper assumes throughout that homeowners are better off, *ceteris paribus,* the less exposed to housing market volatility they are. In contrast, Nordvik's (2001) life-cycle model demonstrates that home prices can be increasing in risk even in a market populated by risk-averse homeowners. This possibility greatly complicates the welfare analysis of risk in housing markets and is not considered further in this analysis.

3. There has been substantial commercial and academic interest in the development of new institutions for helping homeowners convert illiquid and risky home equity to other uses and/or reduce exposure to real estate risk (Shiller and Weiss, 2000, 1999; Caplin, Chan, Freeman and Tracy, 1997; Sheffrin and Turner, 2001). The novel aspect of the normative discussion in this paper is its focus on the exchange of housing risk by employers and employees.

4. Clapp and Giacotto (2002) compare repeat sale and hedonic indexes by different measures of forecasting efficiency, finding that the hedonic index is the more efficient of two.

5. Measures of volatility in a panel data set such as this are somewhat sensitive to specification. For example, the Telecom area sample has many more observations in later years, whereas the non-Telecom sample is more evenly balanced. Being more uniformly spread through time makes the non-Telecom prices have greater dispersion by some measures. Another problem is that same-period price dispersion can reflect a housing market with a greater variety of homes rather than greater price volatility associated with individual homes of a particular quality level. Another possibility left here to future research is time-varying volatility, i.e., the use of GARCH of stochastic volatility models, in the analysis of housing market risk. Yet another approach is that of He and Winder (1999) who analyze cointegrating relationships and apply Granger causality tests using home price data from two adjacent housing markets.

6. Although the measurement problems described here are formidable, the real estate finance literature has devoted considerable attention to the empirical question of whether real estate investment delivers excess returns. That almost inevitably means comparing actual capital gains on a tax-adjusted basis with theoretical rates of return based on various modeling assumptions. De Wit (1997) formally demonstrates the link between excess returns, conceived of as a risk premium paid to investors willing to hold an imperfectly diversified portfolio, and the degree to which returns on individual properties are correlated. Thus, real-estate risk premiums represent another theoretically distinct flow to account for in addition to the stream of benefits considered here.

7. The short-term risk-free rate of interest is excluded from the universe of assets. Liang, Myer and Webb (1996) find that its inclusion lowers the weight on real estate in mean-variance efficient portfolios. This would only strengthen the finding of low weights on housing presented subsequently in this paper. Furthermore, the mutual fund theorem implies that investors with mean-variance preferences can separately decide the questions, "How much in real estate relative to other risky assets," and "How much in the risk free asset."

8. The low weights on housing are consistent with Mok's (2002) finding that, in a two-asset equilibrium model, most homeowners prefer to own less housing than they do. Chinloy (1999) also finds the optimal weight on housing to be negative.

9. It should be acknowledged that put options are motivated by a concern over downside risk, which reflects a hedging motive distinct from

the traditional portfolio framework where risk is conceptualized as variance.

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