Risk in Housing Markets

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prepared for *International Encyclopedia of Housing and Home,* Elsevier

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1 Introduction

Although risk is notoriously difficult to define, economists have, for more than half a century, relied on a surprisingly uniform mathematical characterization of the concept of risk. This characterization assigns a single number to quantify risk in housing markets—and virtually all other contexts in which random variables can be used to represent unknown quantities—based on the expected distance between housing prices that are observed and the prices that were expected before actual prices were observed.

This is the standard definition of housing risk. Its simplicity is attractive because it allows analysts to abstract away from ambiguity surrounding the everyday usage of the word "risk." By assigning a single number to characterize risk in settings with many dimensions along which differences could be measured, this device based on expected distance (i.e., square root of expected squared deviation, or the so-called standard deviation) allows for unambiguous rankings of risky conditions across various settings. Unfortunately, what is lost in this abstraction is frequently of critical importance.

We want to be explicit in acknowledging a disconnect between much of the academic analysis of housing market risk and what virtually any non-academic would think of when mentioning the phrase "housing market risk." To a non-expert, this phrase likely conjures thoughts about recent economic crises: headlines about foreclosures, record drops in home values, commercial real estate ventures leading to rental properties with virtually no tenants, or frequently discussed theories about how the unwinding of a housing market bubble propagated risk to other sectors of the economy leading to crises across multiple markets, including housing and labor. The quantifications of risk described below, although ubiquitous in economics, finance and real estate research, bear very little resemblance to notions of housing risk that one reads about in newspapers or surveys of non-economists. It is quite likely that mis-use of single-number quantifications of risk may even be responsible for clouding the judgment of analysts who ignored many warning signs of the housing market crisis that US Federal Reserve officials began responding to in late 2008.

Before describing weaknesses and alternatives to the standard measure of housing market risk, an example is introduced here to illustrate the expected-distance measure of risk. Notice that this formulation of risk mentions "expectations" twice: the expected distance between actual price and expected price. To an economist or statistician, an expectation is typically thought of as a probability-weighted average (assuming all outcomes and their associated probabilities are known). Or when estimating without knowledge of a particular probability distribution, expectations are typically estimated as the arithmetic average over a large number of experiments conducted under identically controlled conditions.

One might begin by observing a few thousand homes with identical features—same number of square feet, same lot size, same number of bathrooms, same neighborhood conditions, same school quality, etc. After observing the market value or price of each of these homes at two points in time separated by a duration of one year, we could compute a realized percentage return for each: (last observed price minus earlier price)/(earlier price). Finally, the "expected return" for any home with this particular list of features could then be estimated by taking the simple average of all the percentage returns observed.

The previous paragraph describes one way to estimate expected return. Risk, however, is typically defined as the expected (i.e., average) distance between the percentage return actually observed and the percentage return that was expected before the actual return was observed. For example, suppose an actual percentage return of 11 percent was observed after having expected a return of 8 percent one year before. The gap between actual and expected return would be 3 percentage points. If, after observing many actual and expected returns, we found that the typical gap were around three percentage points, then housing market risk could be quantified as this average distance. Often the average squared distance—referred to as *variance* as opposed to its square root, which is referred to as *standard deviation*—is the focus of studies of housing market risk.

2 Measuring housing risk

2.1 Defining risk

Suppose a time series of housing prices is observed, $p_0, p_1, \ldots, p_T$, where p_t represents the price of a single property, or an index value, observed at time t. The return at time $t+1$ is defined as:

$$r_{t+1} = p_{t+1}/p_t - 1. \tag{1}$$

Alternatively, the return can be calculated as an approximation using natural logarithms, $\ln(p_{t+1}) - \ln(p_t)$, which is explained further in a subsection below.

If there were a well specified probability distribution for returns, then we could compute the theoretical expected return as $\mathrm{E}[r_t] = \int_{\infty}^{\infty} r_t f(r_t) dr_t$, which involves calculating an integral (assuming r_t is a continuous rather than discrete variable) under the known distribution function $f(\cdot)$. More commonly, however, there is no known distribution of prices or returns, and analysts analyze averages, interpreted as estimated moments of the unknown distribution, together with the effects of observable exogenous factors on those expected housing market returns. To estimate the expected return with the sample of returns, $r_1, r_2, \ldots, r_T$, a simple arithmetic average is computed:

$$\text{estimated expected return} = \bar{r} = \sum_{t=1}^{T} r_t/T. \tag{2}$$

Statistical variance (rather than theoretical variance, which would be based on a known probability distribution for r_t) is computed as:

$$\text{estimated variance of housing returns} = s^2 = \sum_{t=1}^{T} (r_t - \bar{r})^2/(T-1). \tag{3}$$

Standard deviation is then computed as:

$$\text{estimated standard deviation of housing returns} = s = \sqrt{(s^2)}. \tag{4}$$

Putting aside the thorny problems of observing housing prices and computing returns in a way that controls for factors like quality improvements that make observed price changes difficult to interpret, the technique described above is the industry standard for baseline descriptive data analysis of housing risk. Some variant of standard deviation is probably used well more than 95% of the time by economists and housing market analysts when attempting to characterize housing market risk. The formula for standard deviation given above, based on observed dispersion from the arithmetic mean, is, however, not the only technique. Problems and alternatives to standard deviation are discussed in subsequent sections of this chapter, and a variety of techniques for computing standard deviation itself (e.g., implicit volatility measures based on the Black Scholes model) can be found in the economics of housing literature. Another term for risk one frequently encounters in the housing literature is volatility, which is an approximate, or sometimes perfect, synonym for the distance measure of standard deviation defined above. The terms standard deviation, volatility, and dispersion, all refer to how scattered, or spread out, percentage returns are relative to the average return.

An important lacuna in the account of housing market risk described so far concerns price observations and where they actually come from. Other chapters provide critical information about publicly available housing market data and techniques for computing housing price indexes.

2.2 Returns versus price levels

Note that the standard deviation measure of risk in the definition above is stated in terms of returns rather than price levels. This standard methodological step is very common in housing risk analyses and significantly affects quantitative measures of risk. Therefore, it is worthwhile understanding the advantages and possible drawbacks of measuring risk in units of percentage returns rather than price levels. We discuss some examples to consider how risk measured as dispersion of price levels would, in contrast to dispersion of percentage returns, affect the usefulness of risk measures computed in different markets, or for two individual houses' time series.

Suppose, for example, that prices fluctuated mostly within a 10% range in two neighborhoods, the first of which has an average home value of \$100,000, and the second of which has an average home value of \$1,000,000. In this case, standard deviation of price levels would be 10 times larger in the high-price neighborhood and variance would be 100 times higher, even though the percentage changes are identical across both neighborhoods. Here, the unequal units of measurement make it difficult to compare numerical measures of risk computed in different markets or at different times, because standard deviation of price levels is, by construction, proportional to those price levels. Standard deviation of percentage returns, on the other hand, need not bear any relation to price levels: in principle, high priced neighborhoods could have higher or lower annual returns than average returns, and either higher or lower risk as measured by standard deviation of annual returns.

Using price levels generates a confound between price levels and risk. This would mean, for example, that markets or time periods with relatively high prices would tend to look riskier, or more volatile, simply because the units used to measure risk increase proportionally with price levels, and not because of any intrinsic difference in volatility in percentage terms. Therefore, most economists prefer to transform the price time series, p_0, p_1, . . ., p_T, to an annual return time series, r_1, r_2, . . ., r_T, before risk analysis begins. Returns can be computed analogously for any time increment, but, for simplicity, all the examples in this chapter suppose that each period represents an annual observation of a one-year return.

2.3 Percentage return and its natural logarithm approximation

To see the advantage of rates of return over changes in price levels (i.e., risk measured as percentages instead of in dollars) starting from price data for individual houses, consider the time series for three houses presented in Table 1. The columns labeled "price levels" are constructed so that each home price is observed for six consecutive years (times denoted 0, 1, 2,. . ., 5) during which each home price increases by exactly the same amount each year: \$20,000 in year 1; \$30,000 in year 2; \$5,000 in year 3; \$2,000 in year 4; and \$33,000 in year 5.

If price fluctuations were measured as dispersion of price levels in units of dollars, then the statistics describing these three homes' price appreciation would be identical. However, House 1 requires twice the initial investment as House 2, which makes the economic value of their identical dollar gains a little less straightforward to compare. Using percentage returns instead of changes in price level provides standardized units—in the form of dollar gains per dollar invested—which facilitates easy comparisons of housing and other investments on a per-dollar-invested basis.

The problem of difficult-to-compare units of analysis when using price levels (as opposed to percentage return) carries over to risk measures. If one were to compute the statistical variance of the price-level time series $p_0, p_1, \ldots, p_T$ for the three houses in Table 1, the lower-priced House 2 would have much smaller variance, simply because it is cheaper, even though the magnitude of its price changes were exactly the same as the other two houses. When we switch to percentage returns, however, we see that the same-magnitude dollar gain is a smaller percentage change, the more expensive is the house, so that the standard deviation of the more expensive houses will be lower.

Table 1 illustrates several commonly found differences in measurement methodology that can influence the numbers resulting from even the most standard quantification of risk: standard deviation of annual returns. The example data in Table 1 are not designed to maximize differences among different measurement techniques. The reported differences in Table 1 should nevertheless serve to alert users of housing risk measures about the sensitivity of those measures to methodological choices concerning the units in which price fluctuations are measured.

A commonly used natural logarithm approximation that attenuates or dampens the effect of extreme percentage changes is $\log(p_{t+1}) - \log(p_t)$. To understand the mathematics underlying this approximation, one should first note that the Taylor approximation of the natural logarithm function can be expressed as $\log(x) = x - 1 + \text{error}$, where the error term goes to zero as x approaches 1. If x is the gross return p_{t+1}/p_t, then $\log(p_{t+1}/p_t) \approx p_{t+1}/p_t - 1$. The left hand side of this expression is the log difference $\log(p_{t+1}) - \log(p_t)$, and the right hand side is the exact percentage return. When percentage returns are near zero, the gross return p_{t+1}/p_t is close to 1, and the approximation approaches perfection. As percentage returns stray further and further from zero, the approximation rapidly looses precision, with the particular effect that natural log approximated returns are shifted closer to zero than the exact percentage returns really are. Large positive percentage returns become smaller under the log approximation, and large magnitude negative percentage returns are less severely negative, again shifted closer to zero.

At the bottom of each House's price and returns data in Table 1 are each House's average return over the 5-year period using two distinct averaging formulas, arithmetic and geometric average return, which are described in the next subsection. Comparing percentage and log returns from left to right under these two headings, one sees that the percentage returns are noticeably larger than the log returns. The bottom row in Table 1 shows the standard deviation of percentage versus log returns for each house, demonstrating that the log approximation does indeed attenuate volatility: 10.8 versus 12.3; 17.0 versus 20.6; and 10.5 versus 11.8 percentage points.

2.4 Arithmetic versus geometric mean

The arithmetic mean of percentage changes or log returns is the simple average. Because of the potentially powerful effects of compounding returns over time, however, the geometric average can provide a more representative statistical characterization of price change in a typical year. For example, suppose a house price produces returns of $r_1 = r_2 = 0$, $r_3 = 0.50$, and $r_4 = r_5 = 01.00$. The arithmetic average return is $(0.00 + 0.00 + 0.50 + 1.00 + 1.00)/5 = 0.50$. If one simply adds up the percentage changes of 50 and 100, and then 100 percentage points again, one might mistakenly surmise that every dollar invested would at the end of these five years be worth \$2.50. But because of compounding, the 5-year gross return would be $(1)(1)(1.50)(2)(2) = 6$. In other words, every dollar invested at time $t = 0$ would be worth \$6.00 at the end of these five years.

If the arithmetic average return is used to estimate the 5-year gross return, a distortion in the opposite direction occurs: $1.50^5 = 7.5938$. Every dollar invested at the outset did not in fact turn into \$7.59. To correct this distortion, the geometric average provides a characterization that properly accounts for compounding returns over time: $((1)(1)(1.50)(2)(2))^{\frac{1}{5}} - 1 = 0.4310$. In other words, each dollar invested grew by around 43 percent each year. Compounding annual returns of 43 percent over five years produces the exact 5-year gross return, because $1.4310^5 = (1)(1)(1.50)(2)(2)$.

Table 1 presents 5-year arithmetic and annualized geometric mean returns for each of the three houses. The geometric mean is generally smaller than the arithmetic mean return. Note, too, that the standard deviation risk measure is based on average distance from the arithmetic rather than geometric mean.

2.5 Median versus mean

The final two blocks of columns in Table 1 illustrate differences between mean price and median prices computed at each period in time, and risk measures (below) computed as the standard deviation of these price index time series. Table 1 shows that there are few valid generalizations when describing the relationship between median and mean prices. The average house's 5-year arithmetic mean was lower than that of the median house, but the average house's 5-year annualized geometric mean return was larger than that of the median house. Whereas researchers and textbooks often point to the median's insensitivity to outliers as an advantage over the mean, Table 1 shows that volatility of the median return index was actually larger than that of the average house index.

2.6 Longrun/shortrun distinction

Economists usually define the long run as the minimum period of time required so that all inputs in a production process, or all choice variables, are free to vary through the complete feasible range. In the statistical analysis of home prices, however, the longrun/shortrun distinction re-emerges in discussion of hedging risk. According to one common view, there is a stable long-run trend line along which home prices move, with short-run fluctuations around this trend line averaging out to zero. Some suggest that shortrun fluctuations around longrun trends are of secondary importance. However, there is no direct evidence that the primary factors generating observed price data follow a steady longterm path, and less evidence still that people benefit by ignoring allegedly shortrun phenomena such as year-to-year or day-to-day volatility. It may sound elegant to ignore, say, the financial crisis that began at the end of 2008 as a mere shortrun fluctuation, or to admonish ourselves to remain focused on the long term. In this case, however, any distance separating elegance and arrogance begins to blur, and the role of overly simple statistical models based on straight-line extrapolations is clearly complicit in bolstering misplaced confidence in adages to focus on hypothesized longrun equilibria to the exclusion of so-called short-run phenomena that have profound impact on many people's lives.

3 Problems with and alternatives to standard deviation

3.1 Risky for whom?

In contrast to the apparent simplicity of the algebraic formula for standard deviation, it is, both mathematically and in everyday language, very difficult to define risk. In everyday language, "risk" refers to a variety of ideas with differences that are potentially important to economics and housing science. Even with a concrete event such as the decline in a home's value by 10%, it is less than obvious which part should be described as risk. Does risk refer to the bad event (i.e., the price decline) itself? Does risk refer to the probability of this event? The standard definition of risk based on distance from expected value asserts, in this case, that risk can be measured as the distance between -10% and whatever percentage return had expected. Thus, if a 10% decline had been expected, the annual return of negative 10% would be quantified as zero risk!

Psychologists who study risk note that risk is experienced differently by different people, with different intensities according to contextual factors, such as the degree to which one has control over various contingencies. Therefore, a single number quantifying risk across many different kinds of people, or across many different situations that entail risk, (e.g., any common scalar-valued index of risk such as standard deviation) may be too much of an abstraction, failing to include inter-personal variation and contextual differences from the perspective of even a single individual needed to make correct predictions and effective policy. Nevertheless, in academic analyses of risk, this uniformity of standard deviation as the nearly universal definition of risk is thought by many economists to be beneficial, precisely because it allows for apparently clear-cut comparisons of risk across many diverse contexts.

There is certainly room for debate about the value of cross-contextual comparisons of risk, because potentially predictive context-specific information is necessarily ignored. Nevertheless, the universality of standard deviation remains pervasive throughout much of the academic and private-sector research worlds, in banking, finance and beyond. Researchers in economics, psychology and finance are, however, beginning to augment this virtually singular methodological toolkit—quantifying risk based on standard deviation of a known probability distribution as the sole metric of risk—with alternative quantifications of risk described below.

The scientific microscope can be focused variously to bring out different layers of the same phenomenon, enabling us to observe different layers and different gradations of detail. In studying housing markets, it may be useful to focus on different categories or perspectives: home owners living in their own homes, real estate investors investing in properties at which they do not reside, real assets as a single aggregated category in sector-by-sector comparisons of the macroeconomy, or real estate as an aggregate category in the eyes of individuals and firms trying to balance investment portfolios that contain combinations of stocks, bonds and housing-related assets. Thus, in analyzing housing risk, it is critical to define clearly whose perspective the risk analysis applies to. The question, "Risky for whom?," is a preliminary yet fundamental scientific question that can unfortunately be too easily glossed over thanks to the availability of context free risk measures such as standard deviation. Regardless of how this question is answered and in whose perspective the risk analysis is intended to apply, the tool of standard deviation will likely be among the first techniques to consider. One of the most important problems, however, is its symmetry, which remains in any context. The symmetry problem is described next and motivates the alternative risk measures, introduced subsequently, that have begun to appear in the economics and finance literatures.

3.2 Symmetry problem

The symmetry of standard deviation and related measures based on volatility, or spread of a probability distribution, is troubling in the eyes of many observers, because it conflicts with a fundamental asymmetry in the way most people experience upward and downward fluctuations of random payoffs. Whether a home price turns out to be 5 percentage points higher or 5 percentage points lower than expected, in both cases the real world deviates from prior expectations by 5 percentage points. Symmetric risk measures such as standard deviation penalize both these errors—5 percentage points too high and 5 percentage points too low—by exactly the same amount, which is almost surely wrong as a model of humans' subjective experience of risk. Here, one sees the intuition for why distance-based measures of risk build in an unnatural symmetry that grossly violates the subjective experience of risk (which is what a good economic model of risk, or technique for measuring it, aims to capture). The key element of the subjective experience of risk that all symmetric risk measures fail to capture is that unexpected losses are more unpleasant than unexpected gains. Unexpected gains may be so pleasant that they should not be counted as contributing to risk at all.

Nevertheless, the symmetry of the standard deviation unavoidably implies that, given an expected return of 15%, the much more favorable outcome of positive 25% contributes the same amount to "risk" as the unfavorable outcome of 5%. Using any symmetric risk measure, in fact, the contribution of these two outcomes toward risk is identical, because they are equally distant from the expected value of 15%.

3.3 Alternative risk measures

3.3.1 Singular or well-defined events as risk

The events listed as follows can all be described as "risks." My house burns down. Half the homes in my neighborhood go into foreclosure. The schools in my attendance zone receive failing assessments from my state's regulators of education quality. The soil in my neighborhood turns out to contain toxins that cause brain damage in children. The owners of the mineral drilling rights on my property set up drills and begin a mining operation in my front yard. My company goes bankrupt. I lose all my money. I do not have enough savings to send my child to college. A nuclear bomb explodes in my city.[1]

It is perfectly natural in everyday language to refer to the events described above as "risks." Notice that there are no probabilities, no expectations, and therefore no distances from expectations in defining these risks. Consequently, these risks are importantly distinct from those that can be modeled using standard deviation. Future research in economics and housing science will determine whether these well-defined risks are taken up and whether new technical machinery for analyzing such risk, without the notion of symmetric distance from expectations, will be discovered.

[1]See Kaneko (2009) for more on the infrequently examined economic significance of nuclear holocaust in the much broader field of economic wellbeing, welfare analysis and utility theory.

3.3.2 Probability of a specific negative outcome

Given a well-defined negative outcome such as those listed in the subsection above, risk can be quantified as the probability that a specific outcome occurs. Factors that increase the probability naturally increase risk when measured as such. Furthermore, when analyzing an objective function that seeks to minimize risk measured as the probability of a negative event, nonlinear cost transformation functions, or loss functions, can be applied to map different probabilities of the bad event occurring into different magnitudes of subjective loss.

For example, following Tversky and Kahneman (1981), the idea that there is a large and discontinuous jump in psychic loss when the probability of a bad event moves from zero to any positive probability has gained widespread acceptance in economics. The intuition appeals to many people, or many behavioral economists to be more specific—that moving from a chance of 0 to a chance of, say, 0.01 (that a negative outcome occurs) produces a much larger drop in psychic well being than does shifting from a chance of 0.01 to 0.02. This nonequivalence of equal-magnitude changes in risk, measured as probabilities, is sometimes referred to as the *certainty effect* (Tversky and Kahneman, 1981).

In the context of housing risk, this could have several interesting implications about residents' willingness to pay for risk mitigation as well as required compensation for bearing new risks. According to the certainty effect, residents might require infinite compensation when plans emerge to build a new nuclear power plant in their neighborhood with a 0.01 chance of an accident over its operating lifetime. And yet, these same residents might require only a modest compensation to locate a second nuclear power plant in their neighborhood given the presence of the first one. Similarly, these residents might have a relatively small willingness to pay to reduce an existing risk from 0.02 to 0.01, while requiring enormous compensation for accepting an increase of an existing risk from 0.01 to 0.02.

3.3.3 Downside risk

Given the symmetry problem described above, a few researchers have attempted to construct explicitly asymmetric risk measures that penalize only those outcomes that fall below expectations while ignoring those outcomes that exceed expectations. For a continuous probability distribution with pdf $f(x)$ and mean $\mu \equiv \int_{-\infty}^{\infty} x f(x) dx$, the kth-order lower partial moment is defined as:

$$\int_{-\infty}^{\mu} (x - \mu)^k f(x) dx. \tag{5}$$

To define the empirical or statistical analog of the kth-order partial moment, one defines the operator $[x]^-$, which is equal to x whenever x is negative, and 0 otherwise. Given a sample of housing returns $r_1, \ldots, r_T$, with arithmetic mean $\bar{r}$, the kth-order lower partial moment can be defined as:

$$\sum_{t=1}^{T} ([r_t - \bar{r}]^-)^k / T. \tag{6}$$

When $k = 2$, these lower partial moment formulas provide a non-negative and asymmetric risk measure, scoring higher levels of risk for distributions with larger negative deviations from the mean. Finance researchers in particular have recognized the potential of this tool for asymmetric quantification of risk, which penalizes negative deviations and ignores positive deviations, perhaps more than economists have so far. Downside risk and the many as-yet unexplored variations based upon it that readily come to mind, represent an expanding frontier for further research.

3.3.4 Unknown probability distribution

The inherent limitations of probability distribution theory have been apparent to economists going back at least to Frank Knight (1921), who distinguished "risk" when referring to random variables with known probability distributions, from "uncertainty" when referring to situations where some or all of the probability distribution was altogether unknown. For example, should a global financial market crisis be modeled as a regularly, although infrequently, occurring event to which a stable probability can be assigned? Or should every financial crisis be regarded as a singular, one-off event, rendering historical frequencies irrelevant? A similar issue arises concerning the applicability—or inapplicability, as the case may be—of historical frequencies when quantifying the probability of wars, political events, and even weather. Aragones et al. (2005) pose the question, for example, "What is the chance of going to war with Iran in the next year?" This probability could plausibly affect housing markets, and yet assigning a probability between 0 and 1 based on a weighted average of historical data may be just as arbitrary as assigning a subjective belief.

3.3.5 Control as determinant of perceived risk

Starr (1972), Slovic et al. (1974), Slovic et al. (1982), and Slovic (1987) provide evidence that our sense of control (or lack thereof) has a profound impact on the subjective experience of risk. For homeowners, this control factor could play an especially important role. For example, planting a rare kind of grass with a 50% chance of causing a $40,000 drop in the market value of one's home, because it is under the decision maker's control, could be a more acceptable risk to homeowners than a 30% chance of a pornography vendor setting up shop nearby, which would lead to a $20,000 drop in the market value of one's home. Although this would seem to violate standard monotonicity assumptions that lower-probability and smaller-magnitude drops in home values are always preferred over higher-probability and larger-magnitude drops, the control factor documented by Slovic and colleagues offers important insights and predictions for housing risk research.

4 Local factors and externalities that affect housing risk

Within a metropolitan area, housing values reflect more than just home-specific characteristics like the number of bathrooms and square footage measuring the size of the living area. Prices also capture the values of local (or neighborhood) public goods, defined as goods that are at least somewhat nonrival and/or nonexcludable in consumption. For example, the values of amenities such as access to employment centers, an ocean, a golf course, or a wooded recreation area are generally capitalized into home values. Local school quality and crime rates usually top the list of concerns among potential buyers and builders of housing. These local public goods are not under the direct control of homeowners. Therefore, unlike characteristics such as the size of the living area, these factors reflect important externalities that significantly affect home values and fluctuate without the specific consent (or even knowledge) of homeowners. In other words, the behavior of others aside from homeowners can influence housing prices. One only needs to look at the values of homes surrounding poorly maintained foreclosures to get a glimpse of the importance of neighborhood quality.

In their classic analyses of housing market equilibrium, Rosen (1974) and Freeman (1974) employed the ideas of Lancaster (1966) and proposed a regression methodology for disentangling the multiple factors that influence home prices. The result is a technique for measuring factor-specific price effects, measuring the change in expected home value resulting from a one unit change in a single factor, assuming that other factors are held constant. Referred to as hedonic prices, these price effects (expected changes in home values), in theory, reveal consumer and producer marginal valuations for various housing attributes. Since there are no explicit markets where local public goods such as clean air or low crime rates can be bid upon and traded among buyers and sellers, researchers do not have access to direct price observations for many important factors that affect home values. Therefore, the Rosen-Freeman approach based on indirect observation of hedonic prices generated a huge number of valuation studies based on real estate data. Virtually all measurable phenomena that might conceivably influence housing prices have been studied using this technique, an important subset of which is various measures of risk.

To the extent that the Rosen-Freeman technique is valid, researchers interested in housing can learn about the relative value of different forms of risk, in the eyes of buyers and sellers of homes, by looking at a given risk factor's hedonic price. This technique reveals risk premiums (e.g., the discount on an otherwise identical house that happens to be located in a more risky location) as well as the social value of distinct forms of uncertainty, some of which are mentioned below. Most of these studies suggest that homeowners face substantial risk to what is often a significant portion of their wealth, owing to the behavior of individuals and institutions outside their control. However, as noted by Durlauf et al. (2004), the identification and magnitude of these neighborhood effects is still an active area for controversy in the economics literature.

4.1 Foreclosures

Foreclosures impose costs not only on individuals in default and the lending institutions that lent those individuals money, but also on nearby neighbors. It is relatively straightforward to measure the costs that fall upon the individuals and institutions directly involved in the mortgage transaction and subsequent legal proceedings in a typical home foreclosure (see, for example, Capone (2001) and Kau and Keenan (1995)). But the neighborhood externalities that result from home foreclosures (i.e., reductions in home valuations experienced by neighbors who happen to live nearby a foreclosed home) are another matter. Immergluck and Smith (2006) found that a foreclosure causes a 0.9 percent decline in values for all homes within an eighth of a mile radius after a one year period. Lin et al. (2009) found that a foreclosure reduces sale prices by 8.7% for closely neighboring properties and that this effect lasts for up to five years after the foreclosure. Leonard and Murdoch (2009) found an almost 1% impact on homes very close to foreclosures, even after spatially filtering for cascading effects. Although fractional percentages might sound small, these foreclosure effects are both statistically and economically significant, reaching very large magnitudes in dollar terms for two reasons. First, real estate assets tend to have large valuations, so that a small percentage is still a significant amount of money for the homeowners who are affected. More importantly, the total external cost of a even a single foreclosure effect that measures less than one percent can reach a staggeringly large magnitude because this total cost is an aggregate effect after summing over potentially many neighbors affected by the single foreclosure. These values are substantial, and the risk is difficult to manage at the individual level. Moving away from foreclosures only drives prices lower. It is not surprising then that many observers and stakeholders in assets that could be negatively affected by foreclosures are looking for tighter regulatory controls on lenders.

4.2 School quality

Presumably, the value of an equity asset traded on stock markets rises and falls due, in no small measure, to the leadership of the firm. Similarly, housing values can rise and fall due to the leadership of local school administration. This raises the question of the extent to which housing values really respond to school quality.

Hayes and Taylor (1996) found that housing prices do indeed respond to school quality and, more intriguingly, that the aspect of school quality that most affects home values is the size of the school's effect on educational performance. Thus, it appears that the housing market is savvy enough to filter out well-known socio-economic confounds in education research where high levels of school performance can be the result of well-to-do and highly educated parents rather than the effect of the school system per se. This finding suggests that housing markets capitalize into home values the portion of students' test scores that is not predicted by those students' socioeconomic backgrounds.

School quality premiums can disappear quickly because of public policy. Recent initiatives, including vouchers, school choice, and equalization of funding, seem to affect good schools differently than bad schools. Therefore, the effects of these policies on home values depend importantly on pre-policy characteristics of schools and neighborhoods. If everyone had an equivalent education, then prices for homes in the historically good districts would fall, while those in historically bad would rise. According to the hedonic price model, homeowners with beneficial school quality premiums capitalized into their home values stand to lose home value, just as homeowners in attendance zones with below-average schools stand to gain, from policies that aim to shrink historical differences between neighborhoods by equalizing school quality. In fact, this is close to what Brunner et al. (2002) found in their study of real estate markets in California over a 25-year period. This points to another interesting question regarding how homeowners in good districts might strategize to insure against losses in their school quality premiums. Although their results were inconclusive, Brunner et al. (2001) speculated that voters in good school districts would work to defeat a statewide voucher program in California.

4.3 Environmental factors

Most of the initial hedonic studies concerned the hedonic price of one particular environmental characteristic. Environmental characteristics studied in this way range from natural hazards (e.g., earthquakes, floods, wildfires and landslides) to man-made hazards (e.g., toxic releases, ambient air pollution, and jetliner noise). Boyle and Kiel (2001), Jackson (2001), and Simons (2006) provide fairly complete reviews of this literature. More recently, several papers have used environmental events to study how people (and housing markets) respond. For example, Gayer et al. (2000, 2002) looked at hedonic prices based on distance to superfund sites before and after the announcements of estimated health risks associated with the sites. The negative impact of being close to the superfund sites shrank after more information about risks was provided by the estimates in the public announcements, which indicates that uncertainty about the risk, as well as the risk itself, was priced into housing values. Murdoch and Thayer (1988) found a similar premium associated with the uncertainty (measured as statistical variance) of ambient air quality and Beron et al. (1997) used the 1898 Loma Prieta earthquake as "information" to the housing market about the true risk of an event, in this case, an earthquake. Like Gayer, et al., they found a reduction in the magnitude of the hedonic price of earthquake risk after the release of the information.

There is some fear that environmental events "stigmatize" an area (Gregory et al., 1995). If so, environmental policies that mitigate environmental hazards may be less beneficial because the price-depressing stigma persists after environmental improvements have been accomplished, holding prices down and reducing the beneficial price appreciation that was predicted to follow from those environmental improvements. Dale et al. (1999) looked at this issue by studying property values before, during and after the announcement, and remediation of, an environmental hazard in Dallas, Texas. They found some evidence of stigma (lower housing values even though the hazard was remediated). However, after a period of several years, the stigma disappeared and environmental improvements appeared to be fully capitalized into home values. Case et al. (2006) analyze a similar case in Phoenix, Arizona. They find that the effects of negative environmental factors on housing markets disappear soon after environmental hazards are announced. This area of research would seem to benefit greatly from further research that draws on recent contributions from behavioral economics and psychology. Yet another amenity that might be considered as a component of the "environment" is access to fresh food, which suggests still another dimension of housing risk connected to nutrition, sometimes referred to as the problem of food security (Berg and Murdoch, 2008).

5 Macro dimensions of housing risk

5.1 Interest rates and the monetary authority

Observers of housing markets frequently emphasize the important role that interest rates play in housing market dynamics. Insofar as the market for mortgage home loans and housing are complementary goods, then the price of mortgages is an obvious factor that generates fluctuations in home prices (Gramlich, 2007). Apart from origination, appraisal and titling fees that are not directly proportional to the magnitude of home loans, the interest rate is often interpreted as the price per year, per dollar of loaned funds. Sowell (2009) argues that people who were charged higher rate of interest also foreclosed or defaulted more frequently, which would imply that at least in a rough qualitative sense that mortgage markets properly assess repayment risks associated with home loans.

In general terms, factors that stabilize real interest rates, or stabilize rates of inflation, both of which affect borrowers and lenders, will tend to reduce housing market risk. However, this general perspective has many subtler nuances and is vulnerable to changes in many other factors. While providing a useful rule of thumb, it cannot be regarded as complete. This section, very far from exhaustive, introduces a handful of macroeconomic studies of housing market risk from the perspective of homeowners, suppliers of mortgages, and investors aiming to use real estate as one component of a well-diversified investment portfolio (e.g., Berg et al. (2007)).

5.2 Housing is consumption and investment

Housing is unique among the various categories of consumption and among the various categories of investments, because housing is *both* consumption and investment, at least for homeowners who live in the homes they buy. Specifically, the consumption aspect of housing is special because, unlike most other forms of consumption, housing is durable. As an investment, housing is special because, unlike other assets which are usually pieces of paper that entitle their owners to a future cashflow, housing as an investment additionally provides a flow of housing services and has a material presence in addition to the paper deed that confers ownership.

The interconnected aspects of housing—as a flow of real services, and as an investment—relate in important ways to sources of fluctuations in housing markets and the propagation of housing risk more generally. The durability of housing services is a key benefit enjoyed by homeowners that is priced into home values. This very durability—coupled with the fact that consuming those housing services requires the owner to reside in a single location—implies less flexibility in matching services that a home provides with consumers of those services than would be the case for a single-period housing service contract in the form of, for example, a one-year lease.

Because homes are place specific and subject to idiosyncratic shocks while at the same time being indivisible and representing a large share of homeowners' wealth, the risks associated with home ownership when conceived of purely as an investment are much harder to diversify. This has led to a large literature on hedging, or reducing housing risk, by building portfolios of commonly traded financial assets. And because this hedging problem has turned out to be so difficult to solve using liquid assets available to most homeowners, an innovative line of research aimed at designing new institutions, most often, neighborhood- or city-specific housing index futures contracts, had developed, inspiring the creation of new financial derivatives based on more finely disaggregated housing indexes.

A key factor underling housing risk is the correlation between national income, which at least in theory shifts housing demand up and down, and home prices. The correlation between income and housing exacerbates the diversification problem associated with housing, because income and the housing component of personal wealth tend to both fall during recessions and financial crises. Gallin (2006) finds that, although fundamentals such as income may affect housing prices in levels, this co-movement disappears in longrun structural models that measure co-movement in terms of the statistical concept of cointegration.

Gan and Hill (2008) posit and find a linear relationship between income and housing prices based on data from several cities. They go on to argue that this holds more generally. For the relationship between income and home prices to be co-integrated, the relationship would need to be stable over time, which is unlikely, given important changes in financial markets, demographics (such as levels of immigration), supply factors (such as zoning laws), and other external factors. For most individuals, housing is one among, if not the most important asset (Himmelberg et al., 2005).[2] This theoretical relationship would imply that individuals with higher variation in income will purchase less housing, a pattern that enjoys empirical support as well (Davidoff, 2006)

5.3 Housing and real estate in portfolio choice

Regarding the connection between fluctuations in the consumption and investment components of housing demand, Brueckner (1997) shows that insofar as housing consumption is constrained by investors' decisions about how much to invest in housing, then the optimal investment portfolio is mean-variance inefficient. Homeowners face a different set of costs and benefits than non-homeowner housing investors do, which leads homeowners to make combined consumption/investment decisions that differ from what would be predicted if these decision were based solely on housing's investment component (Flavin and Yamashita, 2002). These authors point out that young households make riskier investment decisions out of necessity, because of their larger ratio of real-estate holdings to net wealth. Thus, the optimal portfolio according to Brueckner's theory varies over homeowners' life cycles. In a related vein, (Henderson and Ioannides, 1983) analyzes various consumption and investment effects of tax policies that subsidize home mortgages. And in a panel study, Case et al. (2005) reports significant connections between changes in household wealth and consumption of housing, which has stark implications about mechanisms that propagate risk from sector to sector in the macroeconomy.

The risks associated with being a homeowner are one reason why some individuals may be better off as renters rather than homeowners. Surprisingly, much of US housing policy (and policies in some other countries as well) seems to take as its point of departure the view that higher rates of

[2]According to Himmelberg (2005), 68% of non-pension assets in Americans' retirement savings accounts consist of real estate equity.

home ownership are always socially desirable, while ignoring the substantial risks that homeowners face and the economic benefits of renting.[3]

5.4 Home mortgage tax deductions

Nobel Laureate, Edmund Phelps, is an adamant critic of policies that favor home ownership over other ownership patterns in the market for housing services. Phelps worries about unsustainable feedback loops in run-ups of housing prices that give rise to housing bubbles, linking this phenomenon to a larger change in preferences over the span of a generation favoring spending over saving: [4]

> Of course, while house prices were going up, that [home] became a substitute for saving. People would refinance their homes, take the profit and spend that, hoping that prices would go up again. And then they would do the same thing and spend that. . . . I'm old enough to remember in the 1930s and the 1940s when thrift, frugality was considered an important virtue. In those days we all knew Benjamin Franklin's aphorism, "A penny saved is a penny earned." Today, the official doctrine seems to be that a penny spent is a penny earned.
>
> - Edmund Phelps

Phelps' opposition to subsidies for home mortgages is shared by a number of other economists, who tend to dislike policies that seek to lower or raise prices. US policy's preference for homeowners over renters raises the possibility of over-investment in housing, a scenario that Taylor (1998) argues is supported by the available US housing market data. Passmore (2005) argues that government sponsored enterprises such as Fannie Mae and Fredie Mac are implicitly assumed to be government backed, are able to sell their bonds at lower interest rates, and therefore should be considered as further government subsidies to homebuyers that make home mortgages less expensive than they would be otherwise. Insofar as tax assessments of home values are uncertain (Berg, 2006), this fluctuation in annual taxes owed on home equity is another component of housing risk that is relatively infrequently discussed in the housing risk literature. Porterba and Sinai (2008) also analyze the

[3]For example, in 1997 and 2002, Democrats and Republicans, respectively, pushed for increases in the rate of home ownership by providing new incentives to loan or borrow money for the purpose of buying a home.

[4]Retrieved from:http://housingcrashhub.com/why-home-ownership-is-us-obsession

unequal or unfair incidence of the mortgage tax subsidy with respect to age, based on the observation that home mortgage debt is concentrated among younger homeowners.

5.5 Cross-country housing market correlations

From the point of view of an investor attempting to minimize variance of investment returns while holding expected return constant, or maximizing expected return while holding variance constant, housing markets as an investment device provide an opportunity to diversify or possibly hedge other forms of risk. In this context, the portion of housing market returns that are uncorrelated—or better yet, negatively correlated, with other major asset categories such as stocks and bonds, provide valuable portfolio diversification services. Thus, a rather large literature has arisen, analyzing optimal proportions of housing in a typical investor's portfolio, and been applied to region-specific risk diversification problems as well (Berg, 2003).

Gyourko, Mayer and Sinai (2006) argue that rising incomes in cities with housing that is inelastically supplied and in very high demand (referred to sometimes as superstar cities) bring about above average rates of growth in home prices. Ong and Yong (2000) links the real estate risk premium in Hong Kong to its relative land scarcity. Such imbalances across cities or countries could, in theory, be traded away by international real estate investors. Therefore, the presence of these imbalances in real world housing market data puts an interesting challenge to equilibrium theory based on standard assumptions of perfect competition.

It remains an open question the extent to which real estate shocks are reflected in publically traded equity markets. This connection, in turn, suggests the possibility that real estate shocks spill over from one geographic region to another through international banking and equity market channels. In a recent working paper, Kuethe and Pede (2009) find evidence suggesting that macroeconomic shocks to US states do indeed spill over to neighboring states—most importantly, personal income and employment levels in neighboring states affect in-state housing prices. Such significant spillovers underscore just how difficult it is for individual homeowners to avoid risks that may originate from distant geographic regions and indirect causes. Some have tried to make the case that housing risk, viewed in conjunction with price volatility, is primarily an urban phenomenon (Sinai, 2008), although the relationship between regions and their specific risk levels is complex and probably far from being describable with anything approaching a consensus point of view or interpretation.

Homeowners' reactions to re-zoning proposals and their potential to lower home values is discussed by (Fischel, 1999). Development of financial instruments such as the Case-Shiller derivatives[5] aim to decouple the dual consumption and investment components of housing, providing new tools for diversifying housing risk. Housing price index futures (Shiller and Weiss, 1999) would allow homeowners to place bets on national or regional home prices to hedge against their own home's price fluctuations. Yet another proposal is housing partnerships. Caplin (1997) propose that "housing finance entail an institutional investor that provides equity capital for the house in exchange for a portion of the ultimate sale price." This would reduce mortgage expenses for individual home buyers and also provide diversification tools to financial investors by providing a new asset with direct exposure to real estate markets. Incentives for maintenance by homeowners would, however, likely require new enforcement mechanisms. As with other instruments that provide insurance services, the thorny problem of moral hazard remains. More recently, Caplin et al. (2007) propose the use of shared-equity mortgages. Shiller (2007) cites psychological factors as a key to understanding transaction inefficiency and the absence of stop-loss strategies in housing markets. Simultaneous evolution of expectations and psychological responses is an exciting area for housing market researchers.

6 Behavioral trends in housing science

6.1 Cost-benefit model of constrained utility maximization fails

According to the standard cost-benefit model of neoclassical economics, a homebuyer's choice of housing should be a special case of the utility maximization problem. According to this model, the consumer instantaneously sees the complete feasible set—a list of all assets on the globe that provide housing services, including homes, leases and possibly other choice options, that his or her budget can afford.

The next step is to assign scores to each element of this feasible set, reflecting a weighted average of the benefits and costs associated with this element reflecting the various attributes of different homes such as square feet, number of bathrooms, school quality, distance from work, air quality, etc. Finally, after exhaustively scanning through the affordable set, the best feasible alternative is selected.

[5] See www.macromarkets.com for a fuller explanation of the Case-Shiller derivatives.

This process would require more than a lifetime of arithmetic. No home buyer goes through such an ordeal. Instead, heuristics are employed that quickly shrink this massive feasible set down to a manageable size. Non-compensatory heuristics for shrinking choice sets and their superior power of prediction relative to standard linear statistical models that unnecessarily weight all product features are analyzed by Yee et al. (2007).

6.2 Behavioral trends

As behavioral economics, or psychology and economics, provides more insights about the factors that influence decisions by consumers, investors, governments and private firms, social science's explanations for high stakes housing decisions will likely evolve to account for these behavioral dimensions. A house is, after all, one of the biggest assets that people typically own in their lifetimes, and the model of exhaustive search and systematic weighting of all product features seems, to many, to be manifestly wrong. Sociological studies call into question the standard economic view that market prices provide the proper normative benchmark for evaluating the real private economic value and social value of a home (Smith et al., 2006). Emotions emanating from fear, such as apprehension and anticipation, undoubtedly follow interesting dynamics that reflect social interdependencies, and these basic emotions clearly have effects on home prices (Christie et al., 2008).

Any market—and perhaps the housing market in particular—depends on a complex mix of subjective perceptions and emotional processes underlying the buying and selling processes. The role of emotions and well documented psychological factors in the demand and supply of housing will undoubtedly be important topics for future researchers. Relative to the singularity and universality of standard deviation for measuring risk, allowing for just one or two additional dimensions of heterogeneity represents a substantive step forward in terms of incorporating more psychological realism into models of housing market dynamics.

6.3 Disposition effect

One specific example of behavioral ideas contributing to housing research is the work of Ong et al. (2008), which examines seller behavior using data that include foreclosed sales. The disposition effect refers to the tendency for individuals to hold on to assets that have lost value relative to the reference point of their initial purchase price (i.e., a reluctance to sell losers) as well as an excessive readiness to sell assets that have gained value relative to the initial purchase price. Homeowners' selling behavior is not well described by standard rational choice models based only on the so-called fundamentals (Case and Shiller, 1988). Perhaps the time is now right for housing research to expand and elaborate on Shiller's (2005) idea of irrational exuberance with more specific models of emotion, the process by which perceptions that influence housing demand are formed, the role of institutions that comprise "the housing market," and more veridical descriptions of the decision making processes and social interdependencies that drive key outcomes in those housing markets.

6.4 Future research

As is hopefully clear by now, the housing risk research literature is rife with open questions. Prospects for progress in addressing these open questions are many, and therefore provide substantive grounds for excitement and optimism among those aiming to contribute to this literature. Among the outstanding questions that would seem to have large magnitude stakes hanging in the balance are the following.

Are expected price changes capitalized into home values? Whether one's point of departure is newspaper anecdotes of homebuyers who purchased homes almost solely in anticipation of future price gains, or intricate mathematical models of pricing bubbles, a key channel for understanding the phenomenon being described is the idea that average price is a function of expected future price change. Should this be the case, then this feedback loop would predict much higher levels of volatility and more persistence in time series data than is predicted by equilibrium models based on standard assumptions of perfect competition.

Another high stakes question for housing risk researchers is how to quantify social inter-dependencies that undoubtedly influence market prices. Here, one can think about buying into a neighborhood based on its reputation. Whether this kind of buying behavior leads to place-specific price differentials that lock in at a difficult-to-budge status quo with large degrees of socio-economic inequality, or whether this process leads to profound price instability over time, depends on a number of auxiliary assumptions about which no consensus has yet emerged. Given the pervasiveness of home buying based on neighborhood reputation, this would seem to be an important priority for researchers studying housing risk.

Finally, as the shortcomings of standard deviation as a single-number summary of housing risk described above make clear, housing risk research stands to benefit from the bold analysis of new risk measures. Risk measures ideally would correspond to intuitive notions of risk that better overlap with meanings of this term in everyday language. New risk measures would, perhaps most importantly, tell observers something more meaningful than standard deviation has so far about how to avoid environments where many simultaneous housing market changes occur in a direction that hurts a significant and correlated subset of stakeholders. If future risk research can also lead to the design of new institutions (Bennis et al., 2010) that reduce fear, anxiety and other psychic costs associated with consuming and investing in housing, then this increasingly important area of research will indeed be making a contribution to wellbeing.

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