ASSESSMENT OF THE RISK OF LOSS OF SUBSIDIZED MULTIFAMILY HOUSING, A SIMULATION OF NET CASH FLOW

By

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To my Sunshine

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The affordability gap between household income and the cost of rental housing has been an issue for many families, exacerbated by the loss of subsidized units due to deterioration or conversion to market-rate housing. Preventing the loss of affordable housing has been hindered by a lack of systematic risk analysis methods to identify and examine properties at risk of loss. The main research goal was to characterize the properties at heightened risk of loss. The purpose was twofold: To inform governments to allocate resources; and to provide a tool to target properties for preservation.

The research methodology was simulation modeling of the net cash flow of properties that received HUD project-based rental assistance in Duval and Miami-Dade County in Florida. Simulation modeling was performed as a tool to incorporate uncertain variables. A net cash flow approach was used, because net operating income (NOI) provides an indication of a property's financial and physical health. A fail-out risk model was created to identify properties at higher risk of deterioration and default, as measured by a lower NOI, debt coverage ratio below 1.0, or a failing HUD physical inspection score. An opt-out risk model was designed to analyze properties at higher risk of conversion, as measured by for-profit ownership, an increase in NOI of at least

20% if market rents are charged, rental assistance contract expiration by 2014, original contract term, and low poverty area.

Significance tests were performed to compare characteristics of higher and lower risk properties by risk model. Stepwise regression analysis was conducted to analyze the impact of variables on NOI. The conclusion was made that properties should be flagged at heightened fail-out risk according to three indicators: Project rent to Fair Market Rent (FMR) ratio (lower ratio, higher risk), year built (earlier year, higher risk) and HUD inspection score (below 60, higher risk).

The study also concluded that the key indicator for opt-out risk was project rent to FMR ratio (lower ratio, higher risk). Once a shortlist of properties is created based on this indicator, the shortlist could be refined by applying other criteria such as subsidy expiration year.

CHAPTER 1
INTRODUCTION

Statement of the Problem

The affordability gap between household income and the cost of rental housing has been an issue for many families across the country. The U.S. Census Bureau (2007a) estimated that almost 46% of renter households nationwide were cost-burdened, spending at least 30% of their income on housing; almost 23% pay at least half their income on rent. The U.S. Department of Housing and Urban Development (HUD) Secretary Shaun Donovan referred to the problem of affordability as a "persistent crisis that far too many low-income Americans face" (Rice 2009, 1). As reported by the Center on Budget and Policy Priorities, exacerbating the affordability issue has been the reduction in federal funding for rental assistance programs such as the Housing Choice Vouchers, and funding shortfalls for programs such as Section 8 Project-Based Rental Assistance (Rice 2009; Rice and Sard 2007).

On a national level, new construction of rental housing has slowed down year over year since 2000, despite a surge in the completion of new units in response to a stronger demand for rentals in various geographic pockets (Joint Center for Housing Studies 2008). While about 2.3 million new units in multifamily structures were added nationwide between 1993 and 2003, many of these were not affordable to low-income families for two reasons (Joint Center for Housing Studies 2006). First, much of the new construction of unassisted rental housing was in the form of high-cost luxury apartments (Katz and Austin Turner 2007). Second, the majority of new construction of subsidized rental housing was realized under the Low Income Housing Tax Credit program, which generally targets households at 60% of the area median income (AMI), not families in the lowest income brackets. New supply of rental housing cannot catch up to the demand for assistance (Joint Center for Housing Studies 2007).

Another challenge of the existing rental stock is that both unassisted and assisted (i.e., subsidized) units are lost each year. Between 1993 and 2003, more than 1.5 million units were removed from the affordable rental stock, either through abandonment, demolition or conversion (Joint Center for Housing Studies 2006). Subsidized rental properties have also experienced a loss of affordability due to the termination of subsidies. The National Housing Trust (2004) analyzed the loss of HUD-assisted project-based multifamily units during 1995 to 2003 throughout the country. It estimated a net loss of 300,000 units as a result of prepayment of subsidized mortgages and opt-out of rental assistance contracts. HUD has recognized the impact of the loss. The National Housing Law Project (1999, 7) reported that "for the first time, HUD's annual report on worst-case housing needs [in 1997] specifically cited the loss of HUD multifamily housing stock as a contributing factor in the growing gap between the nation's needs and available units."

While the need for affordable housing is growing, the supply is dwindling and new construction cannot keep pace, nor reach the lowest income households that have the greatest need. Therefore, the preservation of existing affordable rental properties is another strategy to address the need for housing. A significant hurdle to preservation has been that "there are no widely available standardized risk analysis tools to assist states and local governments in identifying and examining properties that may be facing expiration and/or opt-out situations so that preservation strategies can be built around the specific needs of each property" (Affordable Housing Study Commission 2005, 24). A related issue has been the lack of current and historical multifamily data that are publicly available and comprehensive. Data are necessary for "facilitating analysis of the portfolio and identification of at-risk properties (Center for Housing Policy 2008). The risk analysis and data hurdles may explain why the Joint Center for Housing

Studies reported that the country has seen "only piecemeal preservation efforts" (Joint Center for Housing Studies of Harvard University 2006, 29). However, in recent years, the research of the preservation issue as well as the funding of preservation projects have become a higher priority nationwide among state and local governments, foundations such as the MacArthur Foundation, research institutes such as the Center for Housing Policy and the Shimberg Center for Housing Studies, and advocacy bodies such as the National Low Income Housing Coalition.

Preservation Defined

Preservation of assisted multifamily housing means maintaining affordability for low-income households for an extended period, and keeping the properties in good physical and financial condition (The John D. and Catherine T. MacArthur Foundation 2007). Assisted properties have finite periods of affordability under the terms of their subsidies and use restrictions. Upon the prepayment or maturity of a subsidized mortgage, the expiration of a use restriction or the opt-out of a rental assistance program, the housing will likely be lost to low-income families unless other funding can be secured to keep it affordable. A property is also at risk of losing affordability if it faces large capital needs and repairs, but lacks the reserves, cash flow and/or owner motivation to address these. This situation can lead to mortgage default, foreclosure and displacement of tenants.

Research Goal, Purpose and Questions

The main goal of the dissertation research was to identify the types of properties at heightened risk of loss to the affordable assisted rental housing stock. Types of properties were categorized according to property, financial, subsidy and tenant characteristics.

The purpose of this research was twofold. The first purpose was to inform governments about the risk of displacement of low-income residents and the risk of community disinvestment in the case of deteriorating properties. This information can be used by policy-makers and

planners to allocate resources. The second purpose was to provide a tool for housing advocates to identify properties at heightened risk of loss. Advocates can approach these properties to offer assistance in the form of legal aid, financial resources, or financing and development expertise. Advocates can also target these properties for acquisition and preservation.

The following two main questions drove the research:

- What are the property, financial, subsidy and tenant characteristics of properties identified at fail-out risk, as measured by the financial or physical condition?
- What are the property, financial, subsidy and tenant characteristics of properties identified at opt-out risk, as measured by the opportunity to increase project rents and improve cash flow?

In order to address the main research questions, the literature review focused on addressing the following subset of questions:

- What are the terms and conditions of the major federal subsidy programs?
- What options are available to property owners concerning termination and continuation of subsidies and use restrictions?
- Which variables are indicators that a property is at risk of deterioration and default?
- Which variables are indicators that a property is at risk of conversion?
- Which risk assessment methods have been used to analyze the affordable housing stock?

Research Methodology

The research methodology that was applied to address the research questions was simulation modeling of the net cash flow of properties that received HUD project-based rental assistance in Duval and Miami-Dade County in Florida. A cash flow approach was used, because net operating income (NOI) provides an indication of the financial and physical health of a property. The financial and physical condition impacts the likelihood that an owner will opt-out of the housing subsidy program and convert the property to market rate housing. The condition also affects the likelihood of loss of the affordable housing due to physical deterioration and

mortgage default. As explained by Wallace et al. (1993, 2-25), "net cash flow is a key indicator of a property's viability." Achtenberg (2002, 43) also stated that "cash flow – the bottom line – is an important indicator of the overall health of the property." Simulation modeling was used, because many of the input variables to compose net cash flow statements were uncertain due to a lack of public information about the current and future financial and physical condition of subsidized properties. Missing property-level data included actual operating expenses, vacancy rates and capital needs. Simulation modeling allowed for the estimation of uncertain values according to probability distributions.

A database was composed of multifamily properties with project-based rental assistance contracts. From this database, development-level proformas were created, using actual as well as simulated data for rental income, operating expenses and debt service. Descriptive analysis, significance tests and regression analysis were performed to analyze the simulated net operating income data and to characterize the properties that were identified at heightened risk of loss to the affordable housing stock.

Programmatic and Geographic Scope

The programmatic scope of the research was on properties that received project-based rental assistance under the HUD Section 8 program. The reason for this focus was that rental assistance is considered a deep subsidy that targets the lowest income families. Households that receive project-based rental assistance generally pay no more than 30% of the gross household income on rent plus utilities. The rental assistance subsidy covers the difference between the collected rent and the actual cost of housing or the market rent, within limits established by the federal government (Rice 2009). The two other major federal rental assistance programs are Housing Choice Vouchers and Public Housing, both also providing deep subsidies. The Center on Budget and Policy Priorities reported that "there is strong evidence that rental assistance:

Alleviates poverty; frees up financial resources that poor families can use for other basic needs; and improves housing stability and reduces the risk of homelessness" (Rice and Sard 2009). However, "only one in four low-income households eligible for federal housing assistance receives it because of funding limitations" (Rice and Sard 2009, 4). Many other housing programs at the federal, state and local levels only impose income restrictions and in some cases maximum rent levels. These so-called shallow subsidies cannot prevent cost burden among the lowest income households. For example, the Low Income Housing Tax Credit program generally targets households at 50 to 60% of area median income. While households below these income limits are eligible to live in a tax credit property, they would spend more than 30% of income on housing (unless they have a Housing Choice Voucher). Without deep subsidies families in the lowest income brackets will experience cost burden. It is therefore essential to preserve the properties that receive project-based rental assistance.

The geographic focus was Miami-Dade and Duval County, because the number of properties and units with project-based rental assistance in these counties trumps that of all other individual counties in Florida (HUD 2008a). More than one third of properties and units covered under HUD rental assistance contracts in Florida were located in Miami-Dade or Duval. Preventing the loss of properties with rental assistance was considered important, because both counties housed renters that made less than 60% of the area median income and were paying more than 40% of income on housing; this group made up more than 30% of renter households in Miami-Dade and more than 21% in Duval (Shimberg Center for Housing Studies 2007).

Organization of the Study

The study first addresses the rationale for preservation in Chapter 1. This chapter includes a demand and supply analysis of affordable housing in Florida, and defines affordability and cost burden. Chapter 2 describes the major federal housing programs that contributed to the

construction and substantial rehabilitation of rental housing in the 1960s through 1980s. This chapter also outlines the first federal preservation legislation, as well as the programmatic reasons for the loss of subsidized properties. Chapter 3 addresses the definition of risk in the context of preservation, and reviews risk assessment methods that have utilized property data to estimate at-risk multifamily properties or to determine key indicators of risk. Chapter 4 explains the research methodology of the net cash flow approach and simulation modeling. The analysis results are presented in Chapter 5, followed by conclusions and recommendations in Chapter 6.

CHAPTER 2
THE RATIONALE FOR PRESERVATION OF AFFORDABLE HOUSING

Demographic Shifts and Implications for Housing Demand

The state of Florida has experienced a steady increase in population that is expected to keep pace in the decades ahead. The incline started with the adoption of air conditioning in homes in the 1950s. Since that time, growth was impacted by a large natural increase in population during the baby boom in the 1950s and 1960s, and the child-bearing years of the baby boomers in the 1970s and 1980s. But the most significant reason for Florida's growth in population has been migration from other states in the country, especially the northeastern states, and increasingly from foreign countries (Smith 2005). From a population of nearly five million in 1960, Florida increased to almost 16 million in 2000 and is expected to surpass 35 million residents by 2060, as graphed by Figure 2-1 (U.S. Census Bureau 1990; Zwick and Carr 2006). The U.S. Census Bureau (2005) projected that Florida together with California and Texas will account for almost one-half of the growth in U.S. population between 2000 and 2030 with Florida becoming the third most populous state in the country. Smith (2005, 6) predicted that, "if current projections prove to be accurate, net migration will account for all of Florida's population growth within 20-25 years."

The growth and composition of Florida's population have directly impacted the housing market. The groups that especially shaped the demand for affordable housing included the elderly, the workforce and foreign immigrants. Each of these groups is briefly discussed next.

Florida is home to many retirees who are settled in the state permanently, and to "snowbirds" who temporarily spend the winter months. Retirees and snowbirds typically include households at ages 55 and older with accumulated wealth and home equity, although recent changes in the capital markets may have eroded their spending power. For years, these

households were attracted to Florida for its warm climate and relatively affordable real estate, especially compared to the northeastern part of the United States. Their purchasing power contributed to a rise in the price and supply of homes in Florida until market conditions started to change in 2006.

Florida is also home to elderly residents who live on limited fixed incomes and are facing difficulty in finding and keeping housing that is affordable. Sixty percent of renter households that have a head of household at age 65 or older were estimated to be cost burdened (U.S. Census Bureau 2007b). The population group of households at age 65 and older was projected to almost double by 2025 (Shimberg Center for Housing Studies 2008a). The predicted growth of the elderly population as well as their relatively small household size will continue to spur demand for affordable housing units.

Florida's population growth also stemmed from an increase in its youth and working age population (White et al. 2005). Smith (2005) reported that the majority of people that migrated to Florida were younger (under 35) rather than older (65 and over). They were in pursuit of employment opportunities, which they found in construction, leisure, hospitality and retail (Nissen and Zhang 2006). These sectors offered low-paying jobs, which made housing affordability an issue for these young people when Florida's housing market was booming. As illustrated by Figure 2-2, Florida's workforce experienced stagnating incomes and increasing home prices until 2006. Even essential services personnel such as teachers, nurses, firefighters and policemen were confronted with an inability to afford to live in the community that they served. Especially in southern Florida, companies were finding it increasingly difficult to attract and retain employees (Rawls 2006).

While home prices have now stabilized or dropped in Florida's submarkets, this is not resolving the housing affordability challenge. Families are under financial pressure as they are faced with unemployment and foreclosure. The gap between house prices and flat wages continues to be large enough to make homeownership unattainable for many households, especially those in lower income brackets, on fixed income or with damaged credit scores.

Immigrants from other countries now represent one quarter of all people settling in Florida. In particular, Florida witnessed a rapid influx of Hispanics who include people from countries in Latin America and the Caribbean such as Cuba, Puerto Rico and Mexico. By the year 2000, Florida counted nearly 2.7 million Hispanics who were mostly concentrated in the southeastern part of the state (Smith 2005). Miami-Dade County had the largest cluster of Hispanics or Latinos at 57% of the county's total population. This was projected to increase to 70% by 2030 (Center for Urban and Environmental Solutions 2006). Foreign immigration has had an impact on housing demand. Foreign-born households have dominated the rental market, although they have also been finding opportunities to transition into homeownership. Between 1990 and 2000, foreign-born renter households made up over 60% of the increase in the total number of renter households in Florida. Foreign-born homeowners comprised just under 28% of the total growth in homeowner households in Florida for that same period (Myers and Yang Liu 2005).

Strong net migration continued in Florida during 2000-2007. The state experienced the highest domestic in-migration and the fourth largest number of international immigrants compared to the rest of the country (Joint Center for Housing Studies 2008).

Housing Supply Characteristics and Trends

Florida's housing stock is made up of single-family homes (as the predominant type), condominiums, multi-family rental developments and manufactured homes. The inventory is not

uniformly distributed throughout the state. There is a real diversity between urban and rural areas as well as coastal and non-coastal regions. The counties that are most urbanized and predominantly coastal are home to almost 94% of Florida's singly-family dwellings and more than 98% of its condominiums (White et al. 2009). Multi-family housing is also concentrated in urbanized areas. Florida's population of rural and interior counties is mostly housed in single-family homes, although the mobile home is also most common to the rural counties.

The state of Florida experienced a noticeable expansion and shift in housing supply since the late 1990s. It witnessed a substantial surge in new construction, particularly in coastal and metropolitan areas and in southern Florida. From 2001 to 2005, the number of single family homes authorized by building permits increased by 73.1%, compared to an increase of 22.9% between 1996 and 2000, as graphed in Figure 2-3 (HUD 1996-2008). Florida also underwent a wave of conversions of privately-owned, subsidized and non-subsidized rental apartments to condominiums. Condominiums offered ownership opportunities for first-time homebuyers who were encouraged by relatively low interest rates and favorable financing terms. Among the purchasers of new homes and condos were also investors; about a quarter or more of all home purchase loans were made to investors in 2005 and 2006 (HUD 2009).

In addition to the surge in new construction and the condo conversion craze, the volume of sales of existing single family homes almost doubled between 1996 and 2005, reaching a record level of close to 250,000 sales, as shown in Figure 2-2 (Florida Association of REALTORS® 1996-2008). Florida's homeownership rate reached 72.4% by 2005, compared to the national average of 68.9% (U.S. Census Bureau 2008).

The year 2006 marked a shift in Florida's housing market conditions: A drop in home sales and prices (Figure 2-2), a drop in the number of units authorized by building permits

(Figure 2-3), a rising unsold inventory of single-family homes and new condominiums, and a reconversion of condominiums back to rental properties (Joint Center for Housing Studies 2008). The situation worsened during 2007 and 2008, as signaled by the steep increase in home mortgage foreclosures.

Affordability and Cost Burden Defined

From the first half of the nineteenth century until the 1970s, the American concern with housing was focused on the problem of poor physical conditions, overcrowding and inadequate supply of units (Vidal 1997). By the 1980s, government housing policy had shifted from a supply-side focus to a demand-side emphasis when housing affordability had become a much greater concern than substandard conditions and overcrowding (Schwartz 2006; Vidal 1997). This shift was evidenced by the President's Commission's declaration in 1982: "Today… the largest problem is not the quality of housing in which most people live but its affordability" (Listokin 1991, 166).

From a simplistic perspective, housing affordability means that a household can afford to pay for the cost of housing from their income, while still financially able to meet other basic needs such as food, clothing and health care. Economists generally take another view. They believe that if a household is paying a given amount for housing, it implies that the household can afford to do so (Green and Malpezzi 2003). From a government policy and programmatic perspective, housing affordability usually means that a household pays no more than 30% of its annual gross income for housing. For renters, the cost of housing is considered the rental payments and utilities (excluding telephone); for homeowners, it includes principal, interest, property taxes and insurance. When a household spends more than 30% of its gross income on housing, it is regarded cost burdened; when spending more than 50%, a household is deemed severely cost burdened.

Prior to 1981, the 30% standard was 25% of income, as established by the Brook Amendment in 1969 to limit the rent and cost burden of tenants living in federally assisted housing (Eggers and Moumen 2008). Authors Eggers and Moumen (2008) as well as Belsky and Bogardus Drew (2006) concluded that the reasons for initially setting the standard at 25% – rather than another percentage – are unclear. They did explain that the standard was increased to 30% in order to reduce federal outlays for housing. Green and Malpezzi (2003, 137) argued that the 30% "or any fixed benchmark is always debatable." According to Schwartz (2006, 23), the current 30% and 50% cost burden thresholds "have no intrinsic meaning – until the 1980s the maximum acceptable cost burden was typically set at 25%; nevertheless, they are widely used."

Many housing programs impose income restrictions rather than rent restrictions. Under income restrictions a household will only be eligible to reside in the housing development if its income is below a specified percentage of the area median income.

Affordability in Florida

Florida's spur in new construction, conversion and sales was driven by a combination of factors: A decrease in interest rates, an increase in mortgage products with more flexible and favorable terms, a growth in population and number of households through migration from other states and foreign countries, and the emergence of investors and speculators. The demand and supply dynamics drove up the cost of land, the price of new and existing homes, property values and property taxes. While the cost of housing increased substantially, median income did not see much of a rise and the affordability gap widened, as was illustrated by Figure 2-2. Now that home prices have fallen, affordability remains an issue as a result of the economic downturn. Cost burden data presents insight into the issue of affordability in Florida.

The proportion of total households that was cost burdened was estimated at 40.5% or more than 2.8 million households in 2007. Cost burden data by tenure revealed that almost 52%

of renters paid more than 30% of household income on rent, which totaled more than 1 million households. This compared to almost 36% of homeowners that were cost burdened, which concerned more than 1.7 million households. Severe cost burden affected roughly a quarter of all renter households; more than half a million households were spending at least half their gross income on housing (U.S. Census Bureau 2007c).

Cost burdened households had lower levels of income and were thereby more challenged to meet other basic needs. About 80% of renter households with an annual income of less than $20,000 were cost burdened. Data confirmed that cost burden diminishes as income increases. Less than 4% of renter households that enjoy an annual income of at least $75,000 experienced cost burden (U.S. Census Bureau 2007d).

Cost burden affected people of all ages, but most noticeable was the proportional impact it had on the youngest and oldest generation of renters. Over 58% of renter households in the 15 to 24 age group were cost burdened (U.S. Census Bureau 2007b). This could be explained by their relatively low household income that results from their entry positions and predominant one-person household size. Cost burden also affected more than 60% of the renter households in the 65 and older cohort (U.S. Census Bureau 2007b). Many of these elderly live on fixed incomes and have a small household size.

The number of households that paid more than 40% of income for rent and that had an income at or below 60% of area median were estimated by county in the latest Rental Market Study that was conducted by the Shimberg Center for Housing Studies (2007). The data revealed that the households that met these income criteria were not geographically distributed evenly throughout Florida. Rather, more than 60% of the households are located in the state's seven largest counties: Broward, Duval, Hillsborough, Miami-Dade, Orange, Palm Beach and Pinellas.

These are urbanized counties that are home to many lower income households. These are also the counties that experienced a significant increase in the cost of housing. Miami-Dade and Broward housed 30% of Florida's cost burdened households, as defined in the Rental Market Study.

The number of cost burdened households does not equal demand for affordable housing units. But analysis of cost burden figures does provide insight into the severity of the affordability issue, as well as the characteristics of those households most impacted.

Rationale for Preservation

The rationale for preservation of subsidized housing is four-fold. First, preservation secures housing options for the lowest income households. More than 76% of the privately-owned units assisted by HUD were estimated to serve extremely low-income families that have a gross income of less than 30% of the area median income (HUD 2006). These households are at a relatively high risk of displacement, since the HUD properties are at a relatively high risk of loss.

Second, preservation protects assets that were built with public funds. Preservation and the prevention of subsidized mortgage default and foreclosure also minimize loss claims on the Federal Housing Administration insurance fund (National Housing Trust 2006a).

Third, preservation offers several advantages compared to new construction of affordable housing. While cost estimates vary, a general assumption is that rehabilitation of affordable units costs 40% less than new construction (Khadduri and Wilkins 2006). Also, preservation is not hindered by NIMBY-ism and regulatory barriers such as zoning.

Fourth, preservation can contribute to community revitalization. Many older federally-assisted properties are deteriorating and require capital improvements (Wilkins 2002). Dilapidated properties negatively impact the lives of residents and property values in the area. In a distressed neighborhood where conversion to market-rate housing is not a feasible option,

preservation can contribute to revitalization when mortgages are restructured and funds are made available for rehabilitation.

Obstacles to Preservation

While it is important to preserve the stock of assisted rental housing, preservation at any cost is not feasible. One obstacle to preservation is that a high infusion of capital is required, since many subsidized housing properties have substantial deferred capital needs or have to undergo major reconfiguration of the internal layout (Wilkins 2002). Rehabilitation can be extra costly and risky due to unknown conditions inherent to an older building structure. Unforeseen costs and repair needs can negatively impact a project's bottom line and construction schedule. Due to limited resources, it is not feasible to preserve every property. "Depending upon their overall quality, their locational desirability to tenants relative to other housing options, and their current annual subsidy costs (if assisted), it may be more cost effective to retire some of these especially high backlog properties from the stock of HUD-insured housing rather than to repair them" (Wallace et al. 1993, 3-32, 3-33).

Preservation cannot be achieved without the cooperation of the property owner. An owner could decide to terminate affordability and participation in a subsidy program, even if existing or new subsidies are available to continue to operate the property with use restrictions. An owner may be driven by financial motivations to convert a property to market-rate housing, or may seek relief from the administrative burden related to complex reporting requirements, especially if a property has multiple funding layers (Governor's Task Force for Housing Preservation 2004). An owner of an assisted property could also decide to not make substantial capital improvements. "For some distressed properties, lack of an owner willing to cooperate may make it impossible to undertake an effective program of physical improvements. HUD's

ability to assist properties depends upon the presence of a cooperative owner" (Wallace et al. 1993, 3-33).

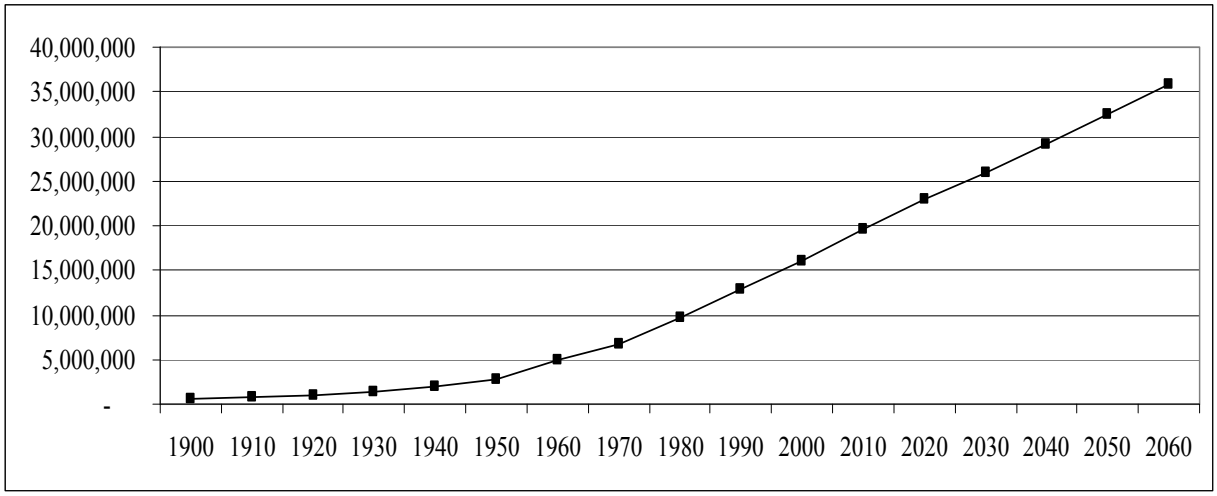


Figure 2-1. Population of the State of Florida, 1900-2060. Source: Zwick and Carr (2006); U.S. Census Bureau (1990).

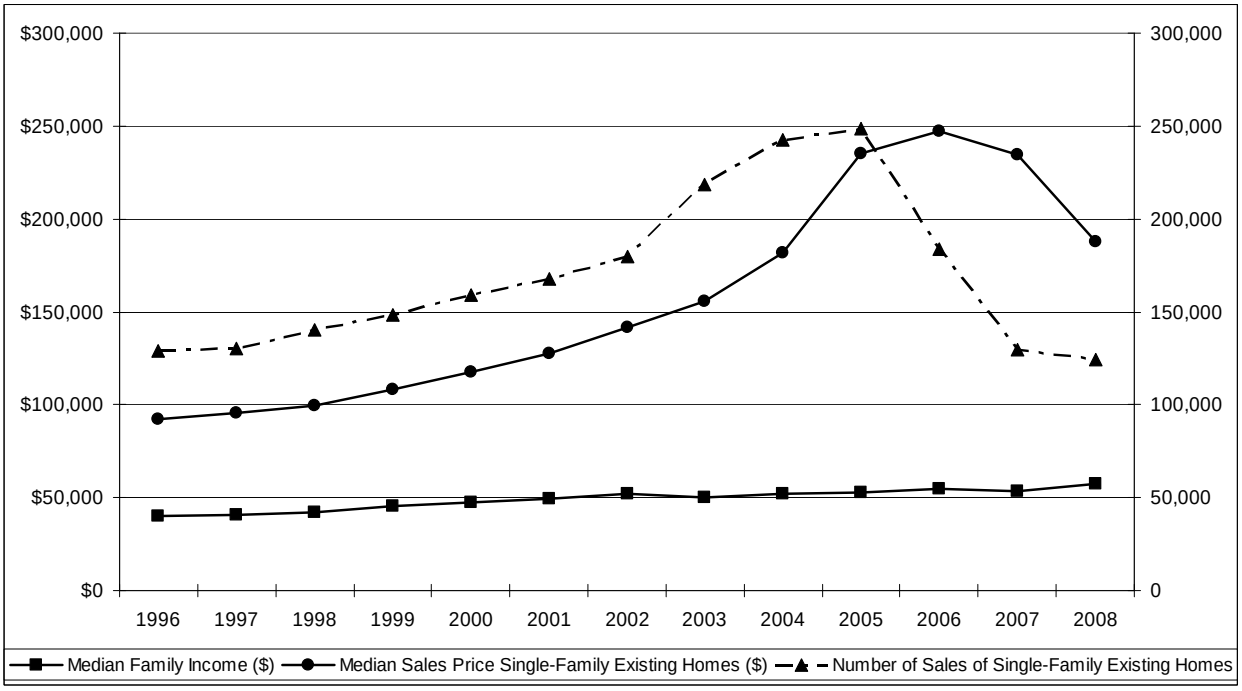


Figure 2-2. Median Family Income, Median Sales Price and Number of Sales of Existing Single-Family Homes in Florida, 1996-2008. Source: Florida Association of REALTORS® (1996-2008); U.S. Department of Housing and Urban Development (1996-2008).

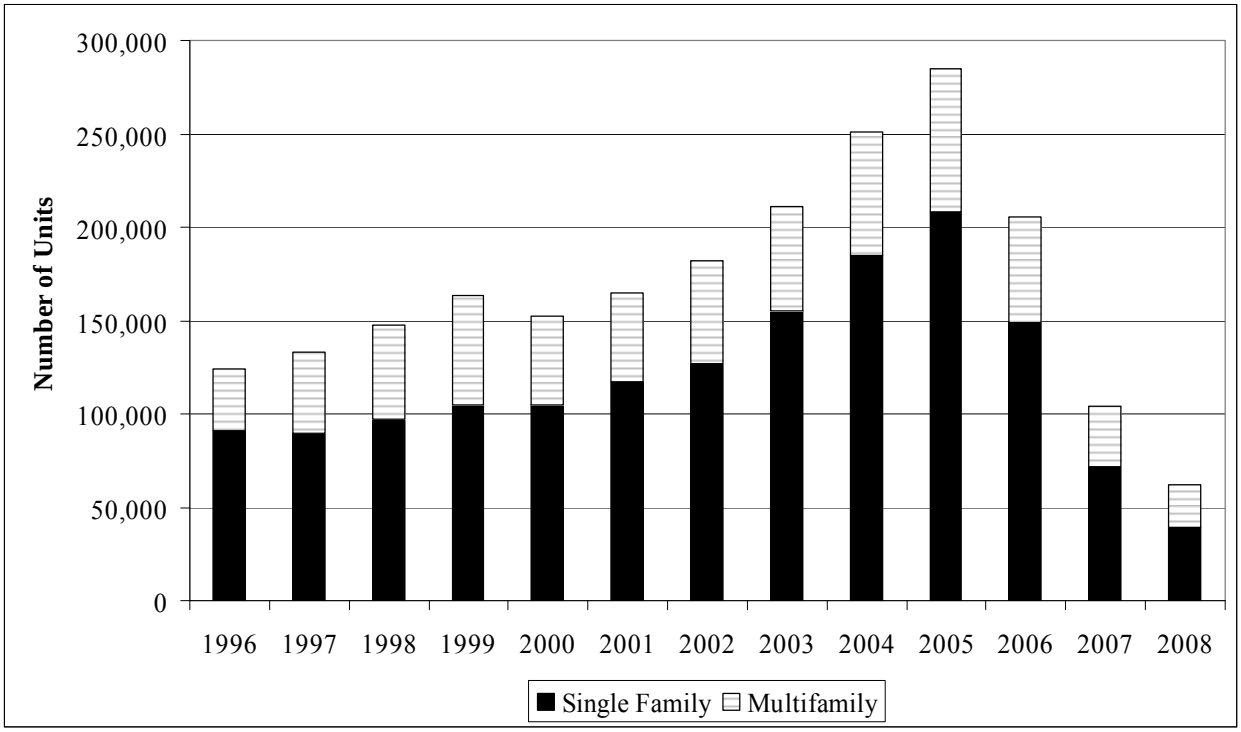


Figure 2-3. Units Authorized by Building Permits in Florida, 1996-2008. Source: U.S. Department of Housing and Urban Development (1996-2008).

CHAPTER 3
FEDERAL GOVERNMENT PROGRAMS AND IMPLICATIONS FOR OWNER CHOICES

First Government Involvement in Housing: Mortgage Insurance and Public Housing

Public concern with housing arose in the first half of the nineteenth century in reaction to poor housing conditions. Industrialization and employment opportunities attracted impoverished rural residents and foreign immigrants to American cities. Urbanization went hand-in-hand with the rise of substandard living conditions characterized by overcrowding, lack of sanitation and shoddy construction, which were believed to harm the poor (von Hoffman 1998). Public concern led to the housing reform movement that focused on the physical condition of structures, housing codes and legislation at local and state levels (Friedman 1985; von Hoffman 1998).

The U.S. government first became directly involved in housing during the Great Depression of the 1930s. The involvement was a reaction to a decline in housing starts and real estate values; high unemployment, especially in the building trades; large need for housing among poor, unemployed and evicted households; and bank failures as a result of increased withdrawals of deposits and mortgage defaults (Mitchell 1985). The position of the government was that these challenging conditions could be tackled by stimulating construction and thereby stimulating related industries, which would create employment, enlarge the housing stock and improve incomes. The government developed two major strategies to achieve this: Home mortgage insurance and public housing.

The Housing Act of 1934 was passed to establish the Federal Housing Administration (FHA). FHA was created as an independent agency that introduced mortgage insurance for private loans on single-family homes as a 100% guarantee against default. It was intended to encourage homeownership, fuel the construction industry and stabilize the mortgage market (Vandell 1995). It reduced lending risk for financial institutions and allowed them to replace

short-term, high down payment balloon notes by long-term, low down payment, fully amortized and level-payment mortgages (Hays 1995). The FHA-program was financed by insurance premiums that were deposited in an insurance reserve fund. The program did bring homeownership within reach of working class households, but it failed to target the poor that had no stable income.

Public housing was the second element of direct government response, as set out in the Housing Act of 1937. The objective of the public housing program was to generate employment opportunities in the construction industry, to provide housing for families who were temporarily unemployed, and to clear slums and blighted areas. Local public housing authorities (PHAs) were created under state legislations to build and operate housing developments. At the outset of the program, the capital cost of land and building construction was paid for by the federal government through annual installment repayments of bonds that PHAs issued to finance the realization of projects. Operating costs were expected to be financed in full by the PHAs from rent collections (Quercia and Galster 1997). But development was hindered by federal opposition against the public housing concept and by local opposition caused by negative perception of public housing tenants and resistance against poor curb appeal of the structures. By the 1960s, public housing authorities also faced financial challenges in supporting operating and maintenance costs. They were criticized for poor management, but according to Hays (1995) the financial distress was really caused by other factors. First, inflation was increasing expenses. Second, structures were aging and started to require repairs and capital improvements, but no cash reserves were available. Third, the composition of the public housing tenants changed from the temporarily unemployed to the long-term poor, resulting in declining tenant incomes and shortfall in rents to cover operating expenses. The government responded with the Brooke

Amendments in 1969, which limited rents to 25% of household income and provided for federal subsidies to bridge the gap between revenues and operating costs (Schnare 1991).

Between the 1930s and mid-1970s, housing built by the government – public housing – was the approach to address the need for affordable rental housing. The federal attitude to public housing shifted in a fundamental way when Kennedy took office in 1961. Kennedy was in support of housing the poor and wanted to stimulate the economy through construction. But he was concerned with the always troubled public housing program (Orlebeke 2000). He started to explore alternate approaches to housing production that would achieve two goals: To develop a housing program that would target households with incomes too high to be eligible for public housing but too low to acquire housing with FHA support; and to develop a housing program on the principle of public-private cooperation (Hays 1995).

Interest Rate Subsidy Programs: Section 221(d)(3) BMIR and Section 236

Section 221(d)(3) Below Market Interest Rate

The Kennedy Administration enacted the Section 221(d)(3) Below Market Interest Rate (BMIR) program under the National Housing Act in 1961. It enabled private lenders to originate mortgages on rental housing properties at a 3% interest rate by allowing them to sell these mortgages to Fannie Mae at market rate. The objective of the program was to promote construction of affordable housing by offering non-profit and for-profit developers the opportunity to obtain subsidized loans at an interest rate below market. The loans were also insured by the Federal Housing Administration to lower the risk to lenders. The amortization term of the mortgages issued under this program was 40 years. In general, non-profit owners had no option to prepay the mortgage. They had to maintain a 40-year use restriction until maturity. But most for-profit owners could prepay after 20 years and terminate the use restriction (Pedone 1991). The rate of return to property owners was restricted to 6% of their original equity, which

was generally 10% of the initial cost of the project. Public entities and non-profit developers were able to borrow up to 100% of the mortgage and were thereby not required to provide down payments. The first mortgage under this program closed in 1962 (U.S. Congress 1987).

Tax benefits were also provided to property owners as additional incentives to construct affordable rental properties. Owners were allowed to deduct mortgage interest payments and calculate accelerated depreciation, although a limited dividend restriction on their cash flow distribution was imposed (Achtenberg, 2002).

The program was aimed at families with incomes too high for public housing, but not sufficient to afford housing in the private rental market or the FHA-supported owner-occupied market. To determine eligibility, income limits were generally established at 95% of the area median income (Millennial Housing Commission 2002). The rent was usually set between the upper income limit for the public housing rent level and the area median income (Hays 1995). But without layering a rental assistance program or other additional funding on the mortgage subsidy, affordability of the units proved difficult to achieve (Affordable Housing Study Commission 2005).

Section 221(d)(3) BMIR required large capital outlays up front, since Fannie Mae would purchase each entire mortgage and absorb the difference between 3% and the market rate. Due to this budgetary impact, the program was eliminated and replaced by Section 236 in 1968 (Hays 1995).

According to HUD data for Florida, nineteen properties with more than 2,100 were built under the Section 221(d)(3) BMIR program during the 1960s and early 1970s (HUD 2009). Only one of these properties still has an original 221(d)(3) BMIR mortgage at present. The development contains 220 units, receives no other project-based funding and has a maturity date

of September 2012 (HUD 2009). The original Section 221(d)(3) BMIR mortgages on the 18 properties were terminated mostly because of prepayment or assignment[1].

Section 236

The Section 236 program became law under the Housing and Urban Development Act of 1968, which was enacted by the Johnson Administration. The government provided lenders with a monthly interest reduction payment (IRP) subsidy, which reduced the interest rate on loans to developers of rental housing from market rate to 1%. The amortization term of the mortgages issued under this program was the same as that for Section 221(d)(3) BMIR, 40 years with eligibility for most for-profit owners to prepay after 20 years (Clay and Wallace 1990). In addition to the mortgage subsidy, the government provided special tax advantages to the property owners such as accelerated depreciation, as well as FHA mortgage insurance to reduce lenders' risk. The rate of return to owners continued to be capped at 6% of original equity (Achtenberg 2002).

Households were eligible if their income did not exceed 80% of the area median. Tenants were to pay the higher of 30% of their income or basic rent that was set at the amount of operating expenses plus debt service at 1% (Achtenberg 2002). The rent could not exceed Fair Market Rent[2] (FMR) (HUD 2007).

In 1973, new funding under the Section 236 program came to a halt when Nixon's government placed a moratorium on all housing programs in reaction to rising costs and subsidy commitments, cash flow problems of public housing developments, program scandals and public

[1] Assignment means that HUD has taken over the loan after the property owner defaults. When this happens, HUD will attempt to work out the situation with the owner to get him back on track of mortgage payments. If this is not successful, the next step is foreclosure.

[2] Fair Market Rent is "HUD's estimate of the actual market rent for a comparable apartment in the conventional marketplace. Every year, HUD develops and publishes FMRs for every MSA and every apartment type" (Recapitalization Advisors, Inc. 2009, 1).

criticism (Mitchell 1985). Section 236 was abandoned and a new program (Section 8) was introduced to stimulate construction and rehabilitation of affordable rental housing by the private sector.

HUD data reported that 132 properties with more than 19,000 units were funded under Section 236 between 1969 and the early 1970s in Florida. Today, 49 properties of these properties with more than 8,000 units still have an original Section 236 mortgage. The majority will reach maturity by 2014; all mortgages are due to mature by 2017 (HUD 2009).

Rental Assistance Programs: Section 8

Under the Housing and Community Development Act of 1974, the federal government created a new program to stimulate construction of affordable rental housing by the private sector, called Section 8. It encompassed several rental assistance initiatives, both demand-side subsidies and supply-side subsidies.

Demand-side subsidies were provided under the Section 8 Existing Housing Program, which was considered the first national voucher program (Schwartz 2006). It offered tenant-based rental assistance for households to find housing in the private market. This program followed an experimental rental allowance program called Section 23 that offered the first form of tenant-based assistance and that was created by Congress in 1965 (Olsen 2000; Grigsby and Bourassa 2004). The Section 8 tenant-based program supplied rental certificates to households with an income at or below 80% of the area median. It limited the household's rent and utilities to 25% of gross income (increased to 30% in 1981). The property owner received a subsidy to cover the gap between collected rent and Fair Market Rent. Vouchers were administered by public housing authorities that were also in charge of waiting lists and inspections of units. A variant on the Section 8 certificate program was introduced in 1983, known as the Freestanding Voucher program (Schwartz 2006). This program also limited the household's rent to 30% of

income, although a household was allowed to spend more or less. The Section 8 certificate and voucher programs were merged into the Housing Choice Voucher program in 1998, which required that at least 75% of all vouchers issued each year are distributed to extremely low-income households that earn below 30% of the area median income (Schwartz 2006). The program has become "the nation's leading source of housing assistance for low-income elderly, people with disabilities, and families with children" (Rice, Sard and Coven 2007, 1). Vouchers currently serve about two million low-income families nationwide (Rice 2009). However, the number of households in need of financial support far exceeds the assistance that is available; more than eight million renter households were severely cost burdened in the United States in 2007 (U.S. Bureau of the Census 2007). More than 94,000 vouchers were administered by public housing authorities in Florida in 2007 (Shimberg Center for Housing Studies 2009).

Supply-side subsidies were introduced under various Section 8 project-based rental assistance programs. These programs provided a direct subsidy of rents through a contract between the property owner and the local public housing authority as the contract administrator. The subsidy covered the difference between the rent and 25% of household income (increased to 30% in 1981). Eligibility was initially set at 80% of the area median income, but later 40% of tenants admitted annually had to be classified as extremely low income (Millennial Housing Commission 2002). The major Section 8 project-based rental assistance programs were the Section 8 Loan Management Set Aside (LMSA) program, the Section 8 New Construction (NC) program and the Section 8 Substantial Rehabilitation (SR) program.

Properties built under Section 221(d)(3) BMIR and Section 236 were experiencing difficulty in meeting their mortgage obligations due to shortcomings in the rents received from tenants. The LMSA program was developed to supplement the rents on those properties (Bratt

1989). This would protect very-low income families and save the Federal Housing Administration the cost of loan defaults (Kochera, Redfoot, and Citro 2001). Project rents were budget-based, which means based on operating costs and a financial return on investment to owners. The initial term of the LMSA contracts was fifteen years with the option to renew or opt-out upon contract expiration (Recapitalization Advisors, Inc. 2009). In Florida, over 8,000 units continue to receive project-based rental-assistance under the LMSA program (HUD 2008), which is for the renewal of existing contracts; the program no longer provides new funding (Millennial Housing Commission 2002).

The Section 8 New Construction and Substantial Rehabilitation programs provided rental assistance to newly constructed or substantially rehabilitated privately-owned rental developments that were funded by any FHA-insured mortgage (HUD 1999). The contract rent was based on Fair Market Rent and subject to an annual adjustment factor. The initial contract term for assistance was set at 20 to 40 years with the option to renew or opt-out at the end of the contract term. It was up to the developers to decide on the type of financing such as a conventional loan or a below-market-rate mortgage. The Section 8 NC and SR programs were designed as an alternative to the interest rate subsidy programs (Section 221(d)(3) BMIR and Section 236) in order to provide more flexibility to owners and to reach lower-income families (Schwartz 2006). The programs offered an attractive tax benefit; owners could reduce their taxable income by using accelerated depreciation allowances (Schwartz 2006). The Section 8 NC and SR programs were repealed in 1983, but the federal government continues to fund the renewal of existing contracts. Current contracts provide rental assistance to almost 22,000 units in Florida (HUD 2009).

In Florida, the LMSA and NC/SR programs currently assist almost 80% of units that are covered under project-based rental assistance contracts. Roughly 14% of assisted units receive rental assistance in the form of Project Rental Assistance Contracts (PRACs) (HUD 2009). PRACs subsidize operating expenses of developments that are funded under the HUD Section 202 Capital Advance program for the elderly or the HUD Section 811 Capital Advance program for persons with disabilities (NLIHC 2009). The remaining 6% of project-based rental assistance units are funded by programs that are variants on the LMSA and NC/SR programs.

Due to a lack of information as well as data discrepancies, it is unclear how many units with HUD project-based rental assistance have been lost as a result of opt-out by the owner or non-renewal by HUD's decision.

Housing Preservation Act

By the 1980s, federal housing policy had shifted from a supply-side production approach to a demand-side subsidy system. After a substantial increase in the supply of affordable rental housing units during the previous two decades, new construction slowed down steadily under President Reagan's "antiproduction, voucher-only housing policy" (Orlebeke 2000, 509). Both homeowners and renters were starting to experience difficulty in finding affordable housing. The problem was most serious for renters (Hays 1995).

The 1980s also marked the 20th anniversary of the subsidized mortgages issued under the earliest federal programs, which placed assisted rental housing at risk of losing affordability restrictions if an owner would decide to prepay the mortgage. The extent of prepayments and the impact on residents were uncertain and had not been explored. In 1987, the Congressional Budget Office wrote, "As the twentieth anniversary dates on the first of [the 221(d)(3) and 236] projects have approached, concern is being expressed about whether the government should respond to the loss of a potentially significant number of these units from the assisted housing

stock and, if so, what form the response should take" (U.S. Congress 1987, 1). In the same year, the federal government introduced the Emergency Low Income Housing Preservation Act (ELIHPA) to prevent owners from converting to market rents. The Act placed a two-year moratorium on prepayments, while Congress developed a 'permanent' solution to protect affordable units. Various reports were produced by Congress and by government-initiated and independent task forces on the scope of the subsidized mortgage prepayment issue and the opt-out and expiry of Section 8 Project-based rental assistance contracts: 'The Potential Loss of Assisted Housing Units as Certain Mortgage-Interest Subsidy Programs Mature' (1987) by the Congressional Budget Office of the U.S. Congress; 'Preventing the Disappearance of Low Income Housing' (1988) by the National Low Income Housing Preservation Commission; 'The Preservation of Low and Moderate Income Housing in the United States of America' (1988) by the National Housing Preservation Task Force; and 'A Decent Place to Live (1988) by the National Housing Task Force. One of the reports predicted that 81% of the older HUD-assisted inventory would likely be impacted by prepayments or defaults from 1988 to 2002, assuming the expiry of Section 8 subsidies (Pedone 1991). Another overall conclusion was that the affected households were relatively poor and the threat of displacement of current tenants was substantial.

In 1990, ELIHPA was replaced by the Low-Income Housing Preservation and Resident Homeownership Act (LIHPRHA) that imposed 'permanent' prepayment restrictions. This Act was aimed at preserving privately owned subsidized properties as low-income housing for their remaining useful life (50 years). This new regulation placed several properties in challenging cash flow positions by prohibiting the increase to market rent. Owners were provided incentives to refinance their properties under the program or to sell to a 'qualified' purchaser, an entity with a mandate to keep the units affordable. Among the incentives were, "insured or direct capital

improvement financing, an equity takeout loan, an 8% return on preservation equity, access to reserves, increased Section 8 and non-Section 8 rents, and insured acquisition loans and grants to qualified purchaser" (Koebel and Baily 1992, 997). Conversion to market rate units or non-residential use was only allowed when public funding for preservation was inadequate or when a qualified purchaser could not be found (Koebel and Bailey 1992).

In 1996, the Clinton Administration adopted the Housing Opportunity Program Extension Act that restored the prepayment rights. In the subsequent year, all federal preservation funding under LIHPRHA was terminated (Peiser 1999). Eligible property owners were now allowed to prepay the mortgage at the 20th anniversary of the loan and prior to the 40 year maturity. This shift in policy followed the change in the federal focus from preservation of housing to protection of tenants against displacement (Achtenberg 2002).

In recent years, the research of the preservation issue as well as the funding of preservation projects have become a higher priority nationwide among state and local governments, foundations such as the MacArthur Foundation, research institutes such as the Center for Housing Policy and the Shimberg Center for Housing Studies, and advocacy bodies such as the National Low Income Housing Coalition.

Programmatic Reasons for Loss of Affordability and Owner Choices

A property is either lost as a result of deterioration and default, or conversion to market-rate housing, as discussed next.

The risk of loss of affordable units as a result of deterioration stems from the age of the structures and the need for capital improvements. As buildings have aged, replacement of such items as roofs, plumbing fixtures and heating-cooling equipment has become necessary. HUD properties built during the 1960s through 1980s are struggling with physical deterioration and deferred capital improvements. However, many subsidized multifamily properties have none or

limited capital reserves (Khadduri and Wilkins 2007; Wilkins 2002). As explained by Recapitalization Advisors (2008, 1), "Financial difficulties are inevitably tied up with physical deterioration: it is rare to find one without the other." An owner may default on a mortgage if it is no longer able to meet its mortgage obligation. Dilapidation and loan default lead to foreclosure if the government agency such as HUD cannot restore financial viability of a property in cooperation with the owner (Pedone 1991). Foreclosure can result in displacement of tenants if a new property owner cannot be found. The risk that a property is not maintained is highest in financially and socially distressed neighborhoods.

Conversion to market-rate rentals or condominiums can be a financially attractive option in a strong local housing market. An owner has this option when a subsidized property reaches a "discontinuity event," a term phrased by Recapitalization Advisors, Inc. (2002, 6). A discontinuity event is a point in time at which the terms of the funding allow the owner to make a choice about the future of a property's affordability. Discontinuity events include:

- Mortgage prepayment eligibility: A property owner with a mortgage under Section 221(d)(3) BMIR or Section 236 may be eligible to prepay the loan after 20 years from the origination of the loan and any time prior to maturity.
- Mortgage maturity: When the loan obligations are met at the end of the term, all affordability restrictions are lifted if no other funding programs or agreements are in place to keep the development affordable for a longer term.
- Expiration of rental assistance: Each rental assistance contract has a limited timeframe. Upon expiration of the contract, an owner has the choice to extend the contract and continue to receive rental assistance, or to opt-out.
- Expiration of use restriction: Some funding programs place a long-term use restriction on the property to keep units affordable. It is possible that such an affordability period extents beyond a loan maturity date.

Owners of subsidized properties have contractual rights and obligations that allow or force them to make a choice about the future of a property at the time of a discontinuity event such as eligibility of prepayment or mortgage maturity. Among the choices are to:

- Retain the property and maintain affordability by deferring prepayment of a mortgage, refinancing upon prepayment or mortgage maturity, or renewing the rental assistance contract.
- Retain the property, terminate affordability, and convert to market-rate rentals or condominiums by way of rehabilitation or by demolition and redevelopment.
- Sell the property to a preserving entity such as a non-profit organization that will maintain affordability and continue to serve the low-income tenants.
- Sell the property to a market buyer who will terminate affordability and convert to market-rate rentals or condominiums.

The choice that the owner will ultimately make is impacted by a wide variety of inter-connected motivations related to financial and market considerations, physical state of the property, availability of funding and relationship with the funding agency, and type of ownership.

Financial considerations may motivate an owner to terminate affordability and are impacted by market conditions. Cash flow is critical to the financial viability of a development. Marginal cash flow may be a motivation for a property owner to convert to market rate rentals in order to substantially increase rent revenues and improve the financial feasibility of a project. According to the National Housing Trust, the average rent hike in such a case is 45% (Bodaken and Heitlinger 2002). Although this is an average number from a number of years ago for conversions nationwide, it does provide a sense of the impact on rent and loss of affordability. A property owner may also choose to convert to condominiums as a way to quickly achieve a financial return on investment and abandon the long-term rental responsibilities of property management. Conversion to either market rate rentals or condominiums can be an attractive

option in a strong housing market or a gentrifying neighborhood that will support high rents or high home prices relative to current project rents. In a housing market where property values have appreciated, it can also be financially beneficial to sell a property. Especially if a property has a limited dividend restriction, the owner may be enticed to prepay or opt-out in order to improve return on equity, although substantial exit taxes on the capital gain may be due upon sale of a property.

The physical state of a property can impact an owner's decision. A structure may be deteriorating and in need of capital improvements due to owners' neglect or lack of capital reserves. If the structure is located in a strong housing market and a low-poverty neighborhood, an owner has an opportunity to raise cash by conversion to market rate rentals or condominiums. Alternatively, an owner can sell the property to a third party who recognizes the prospect of increased property value. Another aspect of the physical state of a property is its design and functionality. An older apartment building may hold large units with three and more bedrooms, whereas the market may demand one or two bedrooms to accommodate smaller households. Functional obsolescence can motivate an owner to sell the property or to redevelop and convert.

The availability of funding and the relationship with the funding agency are factors that can motivate an owner to change its current course. Additional funding might be necessary to improve the financial feasibility of a property and keep it from financial loss. Throughout the state of Florida, owners have seen their operating expenses increase as a result of higher property taxes and property insurance. But additional financial support seems unavailable. "After nearly 20 years of increases, growth in federal housing assistance ground to a halt in the second half of the 1990s" (Joint Center for Housing Studies of Harvard University 2006, 29). The relationship with the funding agency such as HUD can also be a factor in deciding whether to continue to

operate a property as affordable housing. An owner may no longer want to work within the complex system of regulations and administrative requirements. A recent study for HUD also cited "difficult relations with local HUD offices" (Finkel et al. 2006, 71) as a reason to opt-out.

The type of ownership and an organization's mission can also drive the decision about termination of affordability. The mandate of a non-profit owner will be to serve lower income families and supply housing that is adequate and affordable (U.S. Government Accountability Office 2004). The risk of conversion to market rate rentals or condominiums is therefore considered marginal, if housing is owned by a non-profit entity. For-profit owners who are driven by the financial bottom line will make business decisions accordingly. They are more likely to exit a funding program if it makes financial sense to do so. Personal motivations of management, such as retirement plans, can also impact the fate of a property.

CHAPTER 4
RISK AND RISK ASSESSMENT METHODS

Definition of Risk

In the general area of finance, risk is defined as the variability of a realized value from the forecasted value of a variable (Weaver and Michelson 2004; Van Horne and Wachowicz 2001). Variability is the result of "our imperfect knowledge of the future, a consequence of change" (Knight 1965, 198). While the knowledge about the future is imperfect, risk implies that previous knowledge about possible outcomes does exist. This previous knowledge makes risk measurable. Uncertainty, on the other hand, is not measurable and cannot be forecasted, since uncertainty assumes that any outcome is possible (UBC Real Estate Division 2001; Knight 1965). However, the concepts of risk and uncertainty are commonly used interchangeably (Slade 2006; Pyhrr 1973).

In real estate finance and investment analysis, risk is the variance about a forecasted value of variables such as rent, vacancy, operating expenses, cash flow, net present value and internal rate of return. Since the actual future values of variables can vary from the forecasted future values, risk is associated with the forecast (Weaver and Michelson 2004). Financial analysts and investors perform risk analysis to determine which investment decisions to make based on the forecasted values, the risk associated with the forecasts and their tolerance to risk (Albright, Winston, and Zappe 2006).

In the context of preservation, the concept of risk differs from its conventional meaning as applied in finance. In preservation research, risk analysis or risk assessment is commonly described as an approach to identify the properties or types of properties at risk of loss to the affordable housing stock. In this context, the word 'risk' takes on the definition as described by Knight (1965, 233): "The word "risk" is ordinarily used in a loose way to refer to any sort of

uncertainty viewed from the standpoint of the unfavorable contingency…; we speak of the "risk" of a loss." In other words, risk in preservation research does not refer to the variability in a value. Instead, it refers to the variability in the expectation about the continued affordability of an assisted property. More specifically, risk refers to the probability that a property loses its affordability as a result of:

- An owner's decision to opt-out of a rental assistance contract, prepay a subsidized mortgage or terminate a use restriction, and to convert the property to market-rate housing.
- Physical deterioration and mortgage default.

The Role of Property Data

To effectively target resources and preserve affordable housing, it is critical to know which properties are most likely to lose affordability. Therefore, the focus of data collection and analysis is to be on the property level. According to Recapitalization Advisors, Inc. (2002, 3), "Collecting and distilling data on the properties, the programs and financing structures that affect them, and establishing some basic definitions of prevalent terms would greatly facilitate the effective employment of our collective resources." But preservation efforts have been hampered by a limited knowledge about the characteristics of the subsidized housing stock and a lack of understanding of the motivations of property owners. Throughout the 1990s, several research papers identified the gap in information on multifamily housing and the weak multifamily housing datasets that lacked breadth and depth, especially compared to the research available on the single-family housing market (Follain 1994; Bogdon and Follain 1996). Follain (1994, 536, 564) stated that "the combination of a growing demand for information and a literature that has not placed great emphasis on multifamily housing has produced an information gap…. The study of multifamily housing is severely hampered by inadequate data." Researchers expressed the need for study of multifamily housing to address policy concerns such as loss of affordability

(Galster, Tatian, and Wilson 1999). Recapitalization Advisors, Inc. (2002, 3) echoed the need for data for policy purposes, claiming that "this lack of fundamental data handicaps the efforts of non-profit practitioners, governmental agencies and lenders who wish to assist in the effort to preserve the housing. It is difficult to know just where to apply resources and which category of housing has the greatest need and will be the most responsive to cost-effective preservation. Policy therefore tends to be driven by anecdote and headline rather than by a thoughtful strategy." Michael Bodaken, President of the National Housing Trust, also recognized the knowledge gap. He identified expanded funding for research, education and data gathering as one of the critical steps to address the preservation issue (Bodaken 2002).

Property-level data collection and data sharing have improved in recent years as a result of the preservation debate and HUD's initiative to publicize information on expiring Section 8 rental assistance contracts (Southern California Association of Governments 2000). Organizations at the national, state and local levels, including state housing finance agencies, advocacy coalitions and university research centers, have started to collect data to take an inventory of assisted developments within their jurisdictions. Such an inventory generally takes the shape of a development-level database that is populated with property data (e.g., address information, number of units, subsidy programs) collected from funding sources such as the U.S. Department of Housing and Urban Development, the U.S. Department of Agriculture Rural Development, state housing finance agencies and local governments. An inventory is often created to inform policy-makers, planners and advocates about the affordable housing supply. But several organizations have also started to use the inventory as a preservation tool by flagging the properties most likely to be lost. However, as expressed by Florida's Affordable Housing Study Commission (2005, 24), "There are no widely available standardized risk analysis tools to

assist states and local governments in identifying and examining properties that may be facing expiration and/or opt-out situations so that preservation strategies can be built around the specific needs of each property."

In order to develop a methodology to address the dissertation research questions and to identify critical data variables, an extensive review was performed of risk assessment methods that were designed to analyze the subsidized housing stock and the issue of preservation. Synthesis of the literature resulted in the classification of risk assessment methods by three types based on approach and objective. The sophistication of analysis and the depth of the data varied among the types of risk assessment methods, but property-level data were at the core of all three types.

The first type of risk assessment method identifies a handful of key indicators of risk (e.g., type of ownership, REAC Physical Inspection Score) and uses these to shortlist subsidized properties that meet the risk criteria. This type of method could also involve the rating of properties by level of risk. The objective of this approach is generally to flag specific properties in need of attention, or to assess the magnitude of properties at risk and in need of resources.

The second type of risk assessment method is the statistical analysis of housing data for properties with terminated subsidies and properties with current subsidies. The objective is to test which variables are significant indicators that a property is at risk of loss.

The third type of method is the simulation of property owner choices with the objective to estimate the number of units at risk of loss and to inform policy-makers of the implications of this loss.

Risk Assessment Method Type One: Target Inventory

General Description and Purpose

The most common risk assessment method is the target inventory. This approach uses the development-level database of assisted housing to identify properties at highest risk of loss as measured by the affordability expiration dates and a small number of other risk indicators. This method was found to be most common, because it is relatively simplistic and the data variables are most easily obtainable.

The purpose of creating a target inventory is generally to inform policy-makers about the extent of the potential loss of affordable housing units, to advocate for preservation legislation and funding, to flag individual at-risk properties, and to prioritize the allocation of preservation resources. The specific purpose is generally tied to the mission of the organization. For example, the Governor's Task Force for Housing Preservation in Wisconsin built an inventory of multifamily properties funded by HUD, RD and the Wisconsin Housing and Economic Development Authority with the mission "to identify and preserve those affordable rental housing units at greatest risk of loss where the tenant's residency is most threatened in order to maintain a positive impact on the stability of Wisconsin's residents and the continued sustained growth of Wisconsin's economy and to make recommendations on how to best preserve those units" (Governor's Task Force for Housing Preservation 2004, 3).

Methodology and Risk Indicators

Most target inventories are based on a small number of key risk indicators: Subsidy or affordability expiration dates, ownership type and strength of the market. Some inventories only use the expiration dates to identify the properties at highest risk of loss. This was the approach taken by the Community Economic Development Assistance Corporation (CEDAC). CEDAC (2008) listed all properties with federal or state subsidized or insured mortgages and properties

with HUD rental assistance that were at risk of leaving the stock by 2010 due to prepayment, full mortgage repayment or contract terminations. The City of Los Angeles (2002) also applied this method when analyzing at-risk housing for its Housing Element. It assessed the potential loss of federal, state and locally assisted housing between 2000 and 2010 according to the expiration year of affordability restrictions.

The key indicators generally include the following: Subsidy or affordability expiration dates, ownership type, and strength of the market. Expiration dates include the date of eligibility for prepayment of a subsidized mortgage, maturity date, rental assistance contract expiration date, or use restriction expiration date. If an expiration date is imminent, the risk of loss to the affordable housing stock is higher, because a property owner will soon have the option to terminate affordability. When a property has multiple funding layers, the expiration date of the most restrictive program is generally applied in the analysis. For example, if a property owned by a non-profit has a HUD rental assistance contract that expires in 2009 and a HUD Section 221(d)(3) BMIR mortgage that matures in 2012, the end date of 2012 is used under the assumption that the non-profit is not eligible to prepay the mortgage and that the rental assistance contract will get renewed (Shimberg Center for Affordable Housing 2007). Many target inventories define a timeframe for analysis in order to focus on the properties at highest risk of loss. For example, the National Housing Trust (2006b) reported on Section 8 contracts due to expire by the end of fiscal year 2011.

The type of ownership and an organization's mission can drive the decision about termination of affordability, hence its use as a key indicator. For-profit owners have a strong focus on the financial bottom line and aim for maximization of returns (Wallace 1995; Pedone 1991). A for-profit is more likely to exit the funding program and sell the property or convert to

market-rate housing if it makes financial sense to do so. The mandate of a non-profit owner is generally to serve lower income families in the community, and therefore the risk of conversion is considered marginal. A study prepared for HUD found that non-profits were less likely to opt out of a rental assistance contract compared to for-profits, because "nonprofit owners are often mission-driven to continue to provide affordable housing" (Finkel et al. 2006, ix). But the risk of deterioration was considered higher for properties owned by non-profits (Recapitalization Advisors, Inc. 2002).

The conditions in the local housing market can also impact the level of risk that a property will convert to market-rate housing. Conversion risk is considered higher in tight rental markets (Recapitalization Advisors, Inc. 2002). If a property is located in a distressed area with high poverty, the risk of deterioration and default is generally higher. The strength of the market can be measured by various indicators:

- Ratio of project rents to market rents. A weak ratio (below 1) is an indication of higher risk of loss, because an owner has greater opportunity to improve rental revenue through conversion (Finkel et al. 2006; Southern California Association of Governments 2000).
- Neighborhood characteristics such as area vacancy rate, poverty rate and median income. If vacancy and poverty rates are relatively low and median income is relatively high or improving, the local market is considered relatively strong (Finkel et al. 2006; United States General Accounting Office 2004).
- Home price appreciation. The year-over-year change in median home sales price provides another proxy for strength of the market. In a 2002 report for Cook County, Illinois, Recapitalization Advisors, Inc. (2002) categorized a market as strong if it had a positive change in median home sales price greater than 20% between 1997 and 2000, stable if it had a positive change of less than 20%, and weak in the case of a negative change.

Physical condition of the property is another indicator that was often mentioned as an important variable in the assessment of the risk of loss due to conversion or deterioration and default (United States General Accounting Office 2004). A property in good physical condition has a higher conversion potential (Achtenberg 2002). A deteriorated property that is in need of

capital improvements due to owners' neglect or lack of capital reserves is at a higher risk of mortgage default. Most target inventories do not incorporate physical condition as an indicator, because of the lack of data. Unless an organization has access to capital needs assessments for the assisted housing that it is tracking, the only publicly available information that can be used as a proxy for physical condition is the physical inspection score for HUD properties. The HUD Real Estate Assessment Center (REAC) performs inspections and assigns this score, referred to as the REAC score. HUD only started to make the REAC score publicly available on its website as of November 2007. But the United States General Accounting Office (GAO) had prior access to REAC data and incorporated this information in a state-by-state inventory of HUD properties with maturing mortgages and expiring rental assistance contracts (United States General Accounting Office 2004). GAO created a target inventory and included all properties with a maturity or expiration date between 2003 and 2013. In addition to general property information such as the number of units and the actual date of subsidy expiration, the inventory reported the REAC inspection score, ownership type, target population and economic occupancy rate.[1] This allowed for anyone to conduct a more thorough risk assessment of properties at risk by 2013, for example by narrowing down the list of properties to those with low REAC scores.

The year of construction or issuance of the certificate of occupancy could also be used as a proxy for the physical condition, assuming that older properties have greater capital needs. But this information is not commonly available from public datasets. In the case of HUD properties, the mortgage origination date could serve as a proxy. However, the age of the property is no indicator for the physical condition if a structure was rehabilitated.

[1] GAO described the economic occupancy rate as the income received from the rented units in a property divided by the income that would be received if all units were occupied.

Data Sources

A target inventory can be created for one or several types of funding programs. For example, the Housing Development Center (2006) in Portland, Oregon completed a risk assessment of Oregon's Low-Income Housing Tax Credit properties that were reaching the year fifteen of the use restriction between 2006 and 2011. More commonly, a target inventory is created for multiple programs such as HUD rental assistance, HUD insured mortgages and Rural Development loans. The availability of data and the purpose of analysis seemed to drive the focus of an inventory, whether it reported on one or several funding programs.

The following are data sources that are commonly used to build a target inventory:

- HUD Insured Multifamily Mortgages Database. This dataset is available online and updated quarterly. Some entities (e.g., Shimberg Center for Housing Studies) receive supplemental data from state HUD offices.
- HUD Multifamily Assistance and Section 8 Contracts Database. This dataset is available online and updated about every two months.
- HUD Low-Income Housing Tax Credit Database. This dataset is available online and currently reports on properties placed in service between 1987 and 2005.
- Rural Development. Data on RD loans and rental assistance are not available on the RD website, but can often be obtained from state RD offices or the Housing Assistance Council.
- State and local programs. Data on state-funded properties can be supplied by housing finance agencies (HFAs). State programs commonly include bonds, HOME and programs funded by housing trust funds. Some state HFAs provide data on tax credit properties, which are often more up to date than the information available through the HUD LIHTC Database. Data on locally-funded properties are available from municipal departments and local housing finance authorities. If the data collection entity has a broad geographic scope that spans multiple jurisdictions or even an entire state, gathering information on local programs and the properties that have been funded can be an intense process.
- Portfolio data. An entity that owns or manages a portfolio of assisted properties (e.g., a state housing finance agency) can use its own data to create a target inventory. It may use the public data sources to expand the inventory with information on other assisted developments in its jurisdiction.

- Market data. Information on home prices, median income, poverty rate, crime rate and other market and neighborhood characteristics can be retrieved from sources such as the U.S. Census Bureau, local realtor associations and property appraisers.

Output Format and Updates

The output format of a target inventory takes the form of a list of individual properties or aggregate counts of types of properties at risk. For example, the United States General Accounting Office (2004) published a state-by-state list of HUD properties with maturing mortgages and expiring rental assistance contracts by 2013. GAO also created tables and graphs to report the total number of properties and units by HUD funding program and by the year of mortgage maturity or rental assistance expiration. The output of the target inventory can also be mapped. LISC (2005) created maps for metropolitan areas, which plotted the location of federally-assisted properties and identified the type of ownership of each property (non-profit or for-profit) and timeframe of the rental assistance contract expiration (2005-2009 or after 2009). The maps also included median household income categories by census tracts.

While some target inventories are systematically updated on a regular basis (at least annually), others are the result of one-time or episodic efforts.

Risk Assessment Method Type One: Risk Rating

General Description and Purpose

Several entities have taken the target inventory approach one step further by categorizing each at-risk property by the level of risk of loss. The level of risk is generally determined by a small set of risk indicators such as subsidy expiration date and ownership type.

The purpose of rating properties by level of risk is the same as that of creating a target inventory: To inform policy-makers about the extent of the potential loss of affordable housing units, to advocate for preservation legislation and funding, to flag individual at-risk properties, and to prioritize the allocation of preservation resources. As a specific example, the California

Housing Partnership Corporation (CHPC) built a state-wide inventory of HUD and RD properties and classified each property as low risk, lower risk or at risk. CHPC's purpose for creating this inventory and risk assessment was derived from its mission, which was "to assist non-profit and government housing agencies to create, acquire and preserve housing affordable to lower income households, while providing leadership on housing preservation policy and funding" (California Housing Partnership Corporation 2006, 1).

Methodology and Risk Indicators

The level of risk is determined by a small set of risk indicators, which are the same indicators as those applied in the target inventory method: Subsidy or affordability expiration dates, ownership type and strength of the market. Some risk ratings may incorporate additional indicators.

Most risk ratings classify properties as lower risk, medium risk and higher risk. A property is generally considered at lower risk of loss if the affordability end date is not imminent and if it is owned by a non-profit. A weak local housing market can also be used as an indicator of lower risk. As an example, the Washington Low Income Housing Network[2] conducted a risk assessment of HUD properties with Section 8 project-based assistance in Washington State. Properties owned by non-profits with a housing mission or properties with use restrictions of 20 years or more were classified as preserved. Properties located in non-tight housing markets were deemed at lower risk. The rental vacancy rate was used to measure the condition of the market (non-tight market if above 6%). Where vacancy data were not available, the percentage change in the median home price was calculated for the past year to gauge the strength of the market (non-tight market if less than 10% change). For counties where median home prices were also

[2] In 2003, the Washington Low Income Housing Network merged with the Washington Low Income Housing Congress and formed the Washington Low Income Housing Alliance.

not available, the following data variables were used: Percentage changes in the number of home sales and building permits issued, and number of households paying more than 35% of income on rent. The Washington Low Income Housing Network also classified properties as lower risk if they had undergone a debt restructuring and project rent reduction under HUD's Mark-to-Market program (Farley 2002).

A property is often categorized as medium risk if the subsidy expiration is either imminent or if it is coming up in the medium term, and if the ownership is for-profit. The California Housing Partnership Corporation (CHPC 2006) considers these two indicators in its risk assessment of HUD and RD properties. According to CHPC, a property is at moderate risk if it can convert to market rate housing in five to ten years. If it is owned by a non-profit entity, the risk is reduced by one level. For example, a property with a subsidy expiring in five to ten years and with non-profit ownership is reduced to the lowest risk level. Some risk ratings also include the strength of the market as an indicator, which can be measured in various ways. CHPC (2001) performed a conversion risk analysis of tax credit properties that were constructed during the first years of the program (1987-1989) when the use restriction was only fifteen years. Due to a lack of other data, it used the county median income as a percentage of the statewide median income as a measure of the local market. Properties in median- or low-income counties were placed in the medium risk category if they also had non-profit ownership and no other affordability restrictions. The Southern California Association of Governments (SCAG 2000) used the project rent as a percentage of market rent to measure the strength of the market. SCAG assessed the risk of loss of properties with HUD project-based rental assistance and classified the following property types as moderate risk: HUD rental assistance contract expiration scheduled

to occur within five years, owner type is profit-motivated, and the project rent is between 105 and 120% of the estimated potential market rent in the area.

A property is typically classified as high risk if the affordability period is due to expire within the short term, if it is owned by a for-profit organization and if it is located in a strong housing market. These are the indicators incorporated in the risk assessment of properties with HUD project-based rental assistance by the Chicago Rehab Network (CRN 2003). CRN considered a property most at risk if it had a rental assistance contract due to expire within the year, if the owner was a for-profit entity, and if the property was located in a booming or gentrifying area. SCAG (2000) took a similar approach. A high risk property had a rental assistance contract that expired within five years, a for-profit owner, and a project rent that is 105% or less of the estimated potential rent in the area.

Data Sources

The data sources used to rate the risk level of assisted properties are the same as those discussed in the section on the target inventory risk assessment method.

Output Format and Updates

Similar to the target inventory, the results of the risk rating of properties are either presented in aggregate form or are provided for each development.

Risk ratings can be updated according to a regular schedule (at least annually), but are sometimes the result of one-time analysis.

Risk Assessment Method Type Two: Cross Tabulations

General Description and Purpose

Finkel et al. (2006) prepared a national study for HUD that assessed the characteristics of properties that left the assisted housing stock through mortgage prepayment or rental assistance opt-out and compared these to properties that have remained in the stock. As part of the

quantitative analysis, descriptive cross tabulations were created in order to examine the properties according to the following characteristics: Property, owner, financing, location, tenant, and physical and financial operating characteristics.

The purpose of the study was to identify the characteristics of properties that opted out or prepaid compared to those that remained assisted, and to assess the rents in lost properties. By gaining an understanding of the factors that impact the decision-making of owners, the study was able to present policy recommendations to HUD for preventing further loss of assisted housing. Cross tabulations were used as a method to determine the characteristics of properties that were more likely to opt out or prepay. The purpose of the cross tabulations was also to identify the explanatory variables to include in a regression analysis to assess the impact of variables on an owner's decision to opt-in or opt-out of a Section 8 rental assistance contract.

Methodology and Risk Indicators

The first step in the cross tabulations method applied by Finkel et al. (2006) was to divide the universe of HUD properties into categories of property types according to the original subsidy program and the current funding status. The final categories for analysis were opt-ins, opt-outs/prepays, foreclosure/enforcement, and all other. The next step was to statistically describe the characteristics of each of the property types. The characteristics that were described were considered potential factors in the decision-making of owners. A master file was created that included all the variables for 22,471 unique properties located throughout the country. These variables were organized as follows:

- Property: Development size in units, unit size in bedrooms, target population, building type, HUD program type, average percentage of assisted units, project rent to Fair Market Rent ratio, and building age.
- Owner: Ownership type and management review score.
- Financing: Primary form of financing and Housing Finance Agency-related properties.

- Location: Census division, metropolitan location, and neighborhood characteristics (e.g., median income, poverty rate, vacancy rate).
- Tenant: Length of residence, household size, percent minority-headed, percent household heads with disabilities, percent elderly-headed households, percent households with children, and household income as a percentage of area median income.
- Physical and financial operating: REAC physical inspection score, REAC financial performance score, financial ratios (e.g., expense-to-income ratio, debt-service-coverage), surplus cash level, reserve, vacancy rate, and operating expenses.

Percentages, means and medians were calculated for each of the four property types. The data were presented by characteristic in separate tables. Table 4-1 gives an example of a cross-tab.

Analysis of the cross tabulations concluded that properties were more likely to opt out if they were older, if they were occupied by families, if the owner was a non-profit entity, or if the project rents were substantially below the Fair Market Rent.

Data Sources

Since the study was commissioned by HUD, Finkel et al. had access to datasets and variables that are not publicly available. This allowed for a more rigorous analysis of the assisted housing stock compared to the target inventory and risk rating methods that generally rely on publicly available property data.

The data sources included the following:

- HUD Office of Housing's (FHA) Real Estate Management System (REMS) Data. This contained property- and contract-level information.
- HUD FHA's Multifamily DataMart (MPRD) files. These files included mortgage and contract data for active properties.
- HUD FHA's Multifamily Insurance System (MFIS) or F-47 data. Mortgage financing data was reported in this dataset.
- HUD Real Estate Assessment Center (REAC) Data. This was the source for physical condition and financial operating characteristics.

- Tenant Rental Assistance Certification System (TRACS). This system contained data on tenant characteristics.
- PIH Information Center (PIC) data. These data were used to retrieve information on rents.
- 1990 and 2000 Census of Population and Housing data. Neighborhood characteristics were based on Census data.
- FHA's List of Opt-out Properties (Opt-out List). This list reported the properties that completed the rental assistance contract opt-out process.

Output Format and Updates

The results of the cross tabulations were aggregated at the national level and presented by property type and characteristic for the entire national sample of 22,471 properties. The study was performed under contract with HUD as a one-time analysis.

Risk Assessment Method Type Two: Regression Analysis

General Description and Purpose

Regression analysis is another method that can be used to explain the correlation between an owner's decision (as the dependent variable) and characteristics of a development, its ownership, terms of the funding program and location (as the independent or explanatory variables). This method requires knowledge about the owner's decision or intent, as well as information on numerous property characteristics. Publicly available datasets contain only limited historical data that reflect owners' decisions (e.g., prepayment of HUD subsidized mortgages), a limited number of data variables, and no information on owners' intent. Because of these data limitations and because of the higher statistical complexity, regression analysis is not commonly performed by the entities that maintain assisted housing inventories. But this section will discuss two studies that used regression analysis to analyze the affordable housing stock and the decision of owners. Finkel et al. (2006) prepared a study for HUD and was provided with multiple datasets that enabled them to construct a multivariate logistic regression

model in order to analyze an owner's decision to opt-in or opt-out of a project-based rental assistance contract. Melendez, Schwartz, and de Montrichard (2007) conducted a survey of owners and developers of properties built under the Low-Income Housing Tax Credit program during 1987 to 1989. They developed an ordered logit model based on the extensive data collected on the owners' intent after expiration of the fifteen year compliance period, property characteristics, ownership structure and affordability restrictions.

The purpose of the multivariate regression analysis for the HUD properties was to test the observations that resulted from the cross tabulations (as discussed in the previous section), and to identify the characteristics of lost properties in order to enable policy-makers at HUD to predict and monitor which properties are most likely to opt-out of a rental assistance contract. The purpose of the ordered logit model for the tax credit properties was to "examine the primary determinants of risk [of losing affordability] for properties with credit allocated between 1987 and 1989" (Melendez, Schwartz and de Montrichard 2007, 1).

Methodology and Risk Indicators

The multivariate regression analysis only incorporated the decision to opt-in or opt-out of a HUD Section 8 project-based rental assistance contract. It excluded the decision about prepayment of a HUD subsidized mortgage. Finkel et al. (2006, 16) explained that "by narrowing the focus in this way, we avoided having to account for two different decisions (opting out of project-based Section 8 and mortgage prepayment) with the same model." The owner's decision was the dependent variable that took a value of 0 (opt-in) or 1 (opt-out). The explanatory variables in the model were derived from the cross tabulations and are listed in Table 4-2. The sample contained a total of 8,992 properties with non-missing values for all variables, of which 763 properties (8.5%) were opt-outs.

The regression model analyzed the relationship between each explanatory variable (each property characteristic) and an owner's decision, while keeping all other variables constant. The results were presented in odds ratio format, which means that a variable with an odds ratio estimate larger than 1.0 had a positive impact on the decision to opt-out; an odds ratio estimate smaller than 1.0 implies that the property characteristic reduced the likelihood of opting out (see Table 4-3). The regression analysis found that most variables were statistically significant. It also concluded that "the key explanatory variable yielded by the multivariate analyses appears to be the rent-to-FMR ratio: the lower the rent-to-FMR ratio, the higher the likelihood of opting out" (Finkel et al. 2006, 33). When the project rent is relatively low compared to the Fair Market Rent, the owner has a greater opportunity to improve rent revenues by opting out and converting to market rate housing. Another key variable was type of ownership; non-profit owners were significantly less likely to opt-out compared to other owners. Other findings included that properties with the following characteristics were more likely to opt-out (holding each other variable constant): 100% of the units have rental assistance; family-occupied; fewer than 50 units; unit mix with three or fewer bedrooms; older assisted properties; low-poverty rate census tracts; and central city or non-metropolitan locations.

For the ordered logit model, a telephone survey was completed for 164 tax credit properties placed in service between 1987 and 1989 in metropolitan areas throughout the country. The level of risk of losing affordability was the dependent variable and was ranked on a scale of 1 to 6. The level of risk was based on the owner's intent to continue the ownership of the property and to maintain affordability after the expiration of the fifteen year use restriction. The owner's intent was identified through the survey and categorized as follows (Melendez, Schwartz and de Montrichard 2007, 13):

- Affordability could be continued:
    - When the owner said that maintaining the property's affordability was very important.
    - When the owner said continued affordability was only somewhat or not too important.
    - When the owner intends to sell the property to an entity that will maintain affordability.

- Affordability may be lost:
    - When the owner plans to sell the property and is not interested in keeping it affordable or is undecided about what to do with the property.
    - When the owner plans to convert the property to market-rate occupancy, or when the property has already been sold and is at risk of converting to market rate.
    - When the property has already been sold without any affordability guarantees; this situation is thus ranked as having the highest risk on the scale.

The explanatory variables were also collected through the survey, and included data on the basic property characteristics, location, type of sponsor and ownership structure, additional affordability restrictions, occupancy rate, replacement reserves and rehabilitation needs.

The model analyzed the relationship between the risk level and each explanatory variable, while keeping all other variables constant. It found that a property had a lower risk of losing affordability if it had a non-profit sponsor, if additional affordability restrictions were in place beyond the year fifteen, or if the property had extensive rehabilitation needs. Contrary to the expectations of the researchers, a tax credit property located in a high rent housing market by itself was not found to be a factor in an owner's decision to convert.

Data Sources

Finkel et al. was able to achieve a relatively large sample size and conduct the regression analysis thanks to access to numerous HUD internal data sources with detailed property-level

information for both the lost and remaining assisted housing stock. Many of these data elements, especially for the lost units, are not publicly available. The data sources used for the regression analysis were the same as those for the cross-tabulations.

Melendez, Schwartz and deMontrichard relied on data from the HUD Low-Income Housing Tax Credit Database and conducted a telephone survey of owners and developers to collect detailed data on the owners' intent and characteristics of the properties. The researchers also held interviews with tax credit syndicators about acquisition, financing and rehabilitation of tax credit properties.

Output Format and Updates

The regression analysis was performed for the national sample. The results were presented in the table of coefficient estimates (Table 4-3). The study was carried out under contract with HUD as a one-time analysis.

The results of the logit model and a descriptive analysis of the tax credit properties were reported in the study and presented in tables. The study was recently released (2007) and does not make any reference to plans of updating the analysis.

Risk Assessment Method Type Three: Simulation Modeling

General Description and Purpose

Another method to assess the number of assisted properties at risk of loss is the simulation model, which is a model that simulates the decisions of owners to end or continue the affordability. This is a rather complex method, because it has to incorporate a large number of "possible interactions among owner decisions, economic trends, and HUD rules and funding availability" (Wallace 1995, 44). It also requires access to many data variables and the understanding of simulation software. Therefore, the simulation model is not used as a common risk assessment method by state and local entities that maintain assisted housing inventories. But

a simulation model was developed for the HUD portfolio of insured and assisted properties in the late 1980s; the model was refined during the early 1990s. In 1987, the National Low Income Housing Preservation Commission (1988) was created to assess the risk of loss of HUD-assisted properties built during the 1960s to early 1970s. The Commission contracted with Abt Associates, Inc. to create an economic model to simulate owners' decisions. Dr. James E. Wallace of Abt was the technical director for the Commission. The simulation model that was developed for the Commission was based on his doctoral thesis research (Wallace 1995). Wallace further refined the model under a contract with HUD in 1992, as discussed in this chapter.

The purpose of the simulation model for the HUD properties was to assess the number of units at potential risk of loss and the impact on tenants, and to analyze the costs and effects of policy solutions (Wallace 1995; National Low Income Housing Preservation Commission 1988).

Methodology and Risk Indicators

The model developed by Wallace was based on project-specific data and environment or context data to simulate the options that were available to property owners, under the assumption that owners make economically rational decisions. The following data variables were collected for a sample of 570 HUD properties, representing a total of 13,271 properties with mortgages insured or held by HUD:

- Property-specific data, including ownership type, mortgage amount and status, section of the federal housing act, annual income and expenses, cost of meeting physical needs (backlog of repairs and replacements needed, beyond normal maintenance, to restore a property to original working condition), expected accrual of future repair and replacement needs, highest and best use (or condominium prices), costs of upgrading to unassisted market use, and tenant income distributions.

- Environment or context data, including inflation rate for repairs and operating expenses, another inflation rate for rents and prices, discount rates, loan underwriting terms, and tax rates. Model parameters allow the user to specify a number of policy and budgetary conditions, such as the tenant income level eligible for new Section 8 Loan Management

Set Aside assistance, the funding priority score necessary to receive LMSA funding, and whether the Low-Income Housing Tax Credit is available.

The input data were first used to make basic projections for future potential revenues, operating costs and capital needs for each property. Next, the model tested the options that were available to owners, which included the following:

- Continued operation, either status quo or with the acceptance of federal preservation incentives.
- Disposition of the property through conversion to market-rate rentals by the current owner, through sale and subsequent conversion to market-rate rentals or condominiums by a new owner, through abandonment and deed-in-lieu of foreclosure, through sale as a Low-Income Housing Tax Credit project, or through transfer to a preserving entity.

For each property, the model simulated alternative paths for all the possible combinations of operation and disposition decisions that an owner can make until the maturity of a mortgage. Then Wallace (1992, A-2) made the assumption that a for-profit owner chooses "the path that yields the highest discounted present value of the stream of after-tax returns from annual operation and eventual disposition. Non-profit owners are assumed to operate through the mortgage term, if possible; otherwise to sell the property as a Low-Income Housing Tax Credit project, if possible; and, as a last alternative, to resign the property (submit the deed in lieu of foreclosure)," which is triggered by cumulative cash deficits.

The model also incorporated HUD rules and regulations related to the availability of supplemental assistance and the conditions for foreclosure. The ultimate path of a property over time was determined by the combination of owner and HUD choices. For this path, the model calculated the following three outputs: The predicted year of disposition, the characteristics of tenants, and the cost to the government.

The model predicted that during the 20-year timeframe, 33% of older assisted properties[3] would foreclose, 24% would sell to a non-profit buyer, and 38% continue operation. Only 4% were expected to convert to market-rate housing, because many older assisted properties did not have this option. Among newer assisted properties[4], 79% were predicted to continue operation and 20% were expected to convert to unassisted housing.

Model parameters such as inflation rates and the availability of government funding could be changed in order to assess the impact on the future of assisted properties.

Data Sources

The development of the simulation model was only possible because of the comprehensive data that were made available by HUD and that were gathered through intensive collection efforts. HUD provided several datasets from its computerized data systems, which contained basic information on the assisted developments such as occupancy type, funding program and total units. HUD also supplied property-level financial information related to mortgage terms, revenues and expenses, which was verified and supplemented by HUD field offices. To obtain information on the physical condition of properties, on-site inspections were performed. A survey of local real estate experts and HUD field offices was conducted to determine potential rents of unassisted properties and condominium sales prices, and to identify comparable properties. Property owners and managers were also surveyed to obtain missing financial information, tenant characteristics and ownership structure information.

[3] Properties built during the 1960s to mid-1970s under the following programs: Section 221(d)(3) Below Market Interest Rate, Section 236, Loan Management Set Aside, Rent Supplement or Rental Assistance Payment, and Section 8 Property Disposition.

[4] Properties built since the mid-1970s through the 1980s under the following programs: Section 8 New Construction, Section 8 Substantial Rehabilitation and Section 8 Moderate Rehabilitation.

Output Format and Updates

The model made annual predictions of the status of each of the properties in the sample over a 20 year timeframe, starting in 1990. The results were weighted up to the universe of more than 13,000 HUD properties nationwide. The report produced tables with a count of properties and units by property status (e.g., market conversion, foreclosure) at five year intervals under the baseline condition of current HUD funding[5] and under a full funding scenario[6]. Two excerpts of output tables are illustrated in Figures 4-1 and 4-2. The report also provided tables with predicted government costs for each property status under various scenarios of funding availability.

The study was carried out under contract with HUD as a one-time analysis.

Other Risk Indicators

The literature noted other variables that are indicators of risk of loss, in addition to those incorporated in the risk assessment methods discussed. But information for these variables was often not available to the entities that maintain assisted housing inventories, because it requires direct interaction with the owners or access to documentation that owners do not want to make public or that funding agencies cannot share under privacy rules.

Owner motivation is an example of another indicator. The Vermont Housing Finance Agency (1988, 7) suggested that it is important to "continue an active dialogue with the owners of properties in the higher risk categories to determine their needs, concerns and long-term objectives." The Wisconsin Governor's Task Force for Housing Preservation (2004, 5) also warned that "owner participation is critical" in achieving preservation of at-risk housing. Owners' decisions are driven by their motivations, which are impossible to pinpoint without

[5] Current HUD funding relates to the HUD obligations and rental assistance contracts that were in place at the time that the simulation analysis was performed.

[6] The full funding scenario assumed the addition of new rental assistance contracts and reduced-interest direct loans for all eligible properties.

direct interaction. Motivations are impacted by financial considerations such as tax benefits and ongoing federal funding, but also by personal motives such as retirement plans (Recapitalization Advisors, Inc. 2002). A property can be at higher risk of loss if tax benefits are exhausted, if ongoing funding is uncertain, or if an owner wants to scale back its portfolio or has plans to retire.

Ownership structure can provide additional insight into the risk of loss. Most assisted developments are owned by limited partnerships that consist of general partners who manage day-to-day operations and limited partners who are the investors (Achtenberg 2002). Limited and general partners can develop conflicting interests, which can impact the future of an assisted property. For example, the limited partner in a Low-Income Housing Tax Credit property may want to sell after the fifteen year compliance period expires and all tax credits have been received. But the general partner may be most interested in continuing to operate the property and serve low-income households. The general partner will have to buy out the limited partner, which could require a large amount of capital that may not be available (Melendez, Schwartz and de Montrichard 2007).

Portfolio risk is another indicator. Property owners with small portfolios may lack the resources, access to capital and expertise to effectively manage their assets, thereby increasing the risk of deterioration and default (Recapitalization Advisors, Inc. 2002). Owners with larger portfolios may have affiliated property management companies that rely on the portfolio for fees and may therefore be reluctant to sell (Achtenberg 2002; Recapitalization Advisors, Inc. 2002). Information on the size of an owner's portfolio is not easily obtainable, even though HUD reports owner names in its public datasets. Many properties are single-purpose entities with unique limited partnership names. The actual sponsor can therefore not be identified. But

Recapitalization Advisors (2002) explained that many properties are managed by the sponsor and made the broad assumption that the name of the management company can be used as a proxy for owner.

Compliance requirements and regulations can also impact an owner's decision. Subsidized properties are subject to compliance requirements and regulations as imposed by the funding entity. A factor in the decision of a property owner to terminate affordability can be its reluctance to continue to operate under complex rules. Achtenberg (2002, 38) called it "HUD fatigue" in the case of HUD properties. The Housing Development Center (2006) reported that even non-profit entities are looking to sell tax credit properties after the initial fifteen year compliance period expires, because of ongoing compliance requirements and reporting burdens. The administration of funding is especially complex when a property has various subsidy layers (Governor's Task Force for Housing Preservation 2004).

Exit taxes can play a big role in an owner's decision about the future use of a property. Exit taxes are payable by the owner on the capital gain when a property is sold. As explained by Achtenberg (2002, 40), the capital gain "consists of the cash proceeds realized on sale minus the owner's capital account. The capital account is the original cash investment adjusted by cumulative profits and tax losses to date. After 20 years, properties that have provided generous depreciation and interest deductions but limited dividends will typically have a negative capital account. In these cases, owners will owe taxes even if they realize no cash proceeds from the sale." Excessive exit taxes can provide an incentive to owners to retain the property and convert to market-rate rentals. If the local market is not strong enough to make conversion feasible, there is a risk of deterioration and default if the owner is reluctant or unable to inject cash into the property for repairs and renovations (Governor's Task Force for Housing Preservation 2004).

Financial condition is also regarded as a key indicator. If a property suffers from poor cash flow and low reserves, it may be difficult for the owner to meet its mortgage obligations, thereby increasing the risk of default. In a strong housing market or gentrifying neighborhood, poor cash flow can motivate the owner to sell or convert to market-rate housing in order to increase rent revenue and improve financial feasibility.

Lastly, information on capital needs and reserves would give important insight into the risk of loss. A lack of reserves poses the risk that capital improvements cannot be made and that no resources are available to cover financial shortfalls. The risk of deterioration and default is heightened if a property has capital needs and if reserves are limited or non-existent. A survey of tax credit properties reaching year fifteen between 2006 and 2011 found that 30% of respondents did not know if they had adequate reserves and almost 14% claimed not to have sufficient reserves (Housing Development Center 2006).

Table 4-1. Example of Cross Tabulations for Tenant Characteristics in HUD Properties

Average Tenant Characteristics	Opt-ins	Opt-outs/ Prepays	Foreclosure/ Enforcement	All Other	Total
Number of properties	11,126	1,715	2,385	7,245	22,471
Percent of properties	49.5%	7.6%	10.6%	32.2%	100%
Length of residence (years)	6.0	5.3	5.7	5.8	5.9
Household size	1.7	2.1	2.2	1.5	1.7
Percent minority-headed	42.1%	50.6%	72.7%	35.8%	42.4%
Percent household heads with disabilities	18.5%	12.5%	13.6%	29.9%	21.6%
Percent elderly-headed households	48.5%	27.9%	19.3%	47.5%	45.0%
Percent households with children	25.0%	42.8%	48.6%	16.8%	24.9%
Household income as a percentage of area median income (AMI)	27.7%	27.9%	23.8%	28.9%	27.8%

Source: Finkel et al. (2006).

Table 4-2. Regression Model Variables for the Logistic Regression Model of the Opt-out Decision

Variable	Variable Specification	Expected Direction of Impact
Development size in units	Less than 50 units (reference category) 50-99 units 100-199 units 200+ units	Unknown. On one hand, conversion to market rate may involve fixed costs; since larger projects have lower per-unit costs, this may increase their likelihood of opting out. On the other hand, large projects tend to be associated with other physical features that are less attractive to unassisted tenants.
Density	Percent of 3-bedroom-plus units	Negative. It may be harder to market projects with large units to unassisted tenants because these units may not be physically suitable for higher income singles and couples who could afford market rate units.
Family occupancy type	Family = 1 Elderly/disabled = 0	Positive. Elderly projects face competition from amenity-rich private market projects. Also, the income distribution among elderly and disabled households may not support many market rate units. In other words, family projects are more likely to opt out.
Building type	Detached or semi-detached = 1 Other = 0	Positive. Detached and semi-detached projects tend to be associated with other amenities and physical characteristics that are attractive to unassisted tenants.
Older Assisted HUD program types	Older assisted = 1 Newer assisted = 0	Positive. The older projects often have rents that are below market rate.
Ratio of rent-to-FMR	Rent-to-FMR ratio < 80% 80% < rent-to-FMR ratio < 100% 100% < rent-to-FMR ratio < 120% (reference category) 120% < rent-to-FMR ratio < 130% 130% < rent-to-FMR ratio < 140% 140% < rent-to-FMR ratio < 160% Rent-to-FMR ratio > 160%	Negative for projects with rents above local FMR. Projects with rents that are low relative to the FMR may be able to raise rents with little effect on vacancy rates. In other words, as rent-to-FMR ratio increases, we expect the property owner to be less motivated to opt out.
Ownership type	Nonprofit = 1 For-profit or limited dividend = 0	Negative. Nonprofits are less likely to opt out. By definition, for-profit owners are motivated to increase revenues.

Table 4-2. Continued

Variable	Variable Specification	Expected Direction of Impact
Not federally financed mortgage	Not federally financed = 1 Other = 0	Negative. This value is a proxy for projects financed by state Housing Finance Agencies (HFAs). HFAs may impose prepayment and/or opt-out restrictions.
Neighborhood poverty rate	Percent of persons in the surrounding census tract with incomes below poverty threshold in year 2000	Negative. Research has shown that tracts with high poverty rates typically have features that make them undesirable places to live and hence are less able to command high rents.
100-percent assisted	Projects with 100-percent units receiving HUD assistance =1 Other = 0	Positive. A project with a high percentage of unassisted tenants risks high turnover upon conversion to private market status because these tenants will not have enhanced vouchers and may not be able or willing to afford the higher rents. A high percentage of assisted tenants implies more opportunity for the owner to raise rents to market levels.
Metropolitan location	Suburb (reference category) Central city Non-metropolitan	Negative for central city. We expect owners in central cities to be less likely to opt out because markets may be unable to support unassisted housing. Positive for suburb. Suburban areas tend to have higher income renters to absorb market rate housing.
Census division	New England Mid Atlantic East North Central West North Central South Atlantic (reference category) East South Central West South Central Mountain Pacific	Positive for high rent regions such as New England, Mid-Atlantic, and Pacific.

Source: Finkel et al. (2006).

Table 4-3. Coefficient Estimates of the Logistic Regression Model of the Opt-out Decision

Explanatory Variable	Odds Ratio		T-statistic
Development size			
Less than 50 units (reference category)			
50-99 units	0.51	***	-6.04
100-199 units	0.38	***	-6.82
200 or more units	0.44	***	-3.06
Density			
Percent 3-bedroom-plus units in development	0.28	***	-5.88
Occupancy type			
Family occupancy type	2.30	***	6.84
Elderly/disabled (reference category)			
Building type			
Detached or semi-detached building type	1.13		0.75
Ownership type			
Nonprofit sponsor type	0.16	***	-10.65
Program characteristics			
Older Assisted Section 8	2.37	***	8.13
100% of project units are receiving HUD assistance	13.92	***	11.38
Not federally financed (proxy for HFA deals)	0.82		-1.47
Neighborhood characteristic			
Census tract poverty rate	0.97	***	-7.43
Rent-to-FMR ratio			
Rent-to-FMR ratio < 80%	11.56	***	16.55
80% < rent-to-FMR ratio < 100%	2.91	***	8.03
100% < rent-to-FMR ratio < 120% (reference category)			
120% < rent-to-FMR ratio < 130%	0.53	***	-2.65
130% < rent-to-FMR ratio < 140%	0.48	**	-2.48
140% < rent-to-FMR ratio < 160%	0.19	***	-4.17
Rent-to-FMR ratio > 160%	0.22	***	-2.86
Metropolitan location			
Central city	1.49	***	3.44
Non-metropolitan	1.29	*	1.65
Suburb (reference category)			
Census Division			
New England	0.95		-0.19
Mid Atlantic	1.32		1.17
East North Central	1.42	**	2.23
West North Central	1.44	*	2.02

Table 4-3. Continued

East South Central	0.88		-0.57
West South Central	1.78	***	3.19
Mountain	1.50	**	2.00
Pacific	1.45	**	2.33
South Atlantic (reference category)			
Other Regression Model Information		Value	
Opt-out = 1; opt-in = 0			
Total number of properties		8,992	
Number of opt-out properties		763	
Log-likelihood		-1701.20	
Pseudo R-square		0.35	

Notes:
*** indicates significance at the 0.01 level;
** indicates significance at the 0.05 level;
* indicates significance at the 0.10 level.

Source: Finkel et al. (2006).

	1990-1994 Number of Properties	1990-1994 Number of Units
Older Assisted		
As Is through Period	**4,727**	**527,858**
Market Conversion	**80**	**9,370**
Foreclosure or Deed-in-Lieu without Preservation Incentive	**951**	**97,270**
Foreclosure or Deed-in-Lieu with Preservation Incentive	**0**	**0**
Transfer	**278**	**39,728**
Extend through Term	**0**	**0**
Operation through Term without Extend Preservation Incentive	**0**	**0**
Tax Credit	**0**	**0**
Conversion Prior to Period	**0**	**0**

Figure 4-1. Predicted Number of Older Assisted HUD Properties and Units by Property Status under Current HUD Obligations for 1990-1994. Source: Wallace (1992).

	1990-1994 Number of Properties	Number of Units
Older Assisted		
As Is through Period	4,966	555,880
Market Conversion	53	8,275
Foreclosure or Deed-in-Lieu without Preservation Incentive	712	69,008
Foreclosure or Deed-in-Lieu with Preservation Incentive	0	0
Transfer	304	41,063
Extend through Term	0	0
Operation through Term without Extend Preservation Incentive	0	0
Tax Credit	0	0
Conversion Prior to Period	0	0

Figure 4-2. Predicted Number of Older Assisted HUD Properties and Units by Property Status under Full Funding Scenario for 1990-1994. Source: Wallace (1992).

CHAPTER 5
METHODOLOGY

Research Overview

The objective of the research was to address two main research questions related to fail-out risk and opt-out risk.

- What are the property, financial, subsidy and tenant characteristics of properties identified at fail-out risk, as measured by the financial or physical condition?
- What are the property, financial, subsidy and tenant characteristics of properties identified at opt-out risk, as measured by the opportunity to increase project rents and improve cash flow?

The research methodology that was applied to address the research questions was simulation modeling of the net cash flow of rental housing properties that receive HUD project-based rental assistance in Duval and Miami-Dade County. A cash flow approach was used, because net operating income provides an indication of the financial and physical health of a property. Simulation modeling was applied, because many of the input variables to compose net cash flow statements were uncertain due to a lack information about the current and future financial and physical condition of subsidized properties. Missing property-level data included actual operating expenses, vacancy rates and capital needs. Simulation modeling allowed for the estimation of uncertain values according to probability distributions.

Similar to the risk assessment methods discussed in Chapter 4, a database of properties was at the core of the net cash flow method. Data on assisted multifamily properties with project-based rental assistance contracts were collected and merged to compose a database. From this database, development-level proformas were created, using actual as well as simulated data for rent revenues, operating expenses and debt service. Descriptive analysis, significance tests and regression analysis were performed to analyze the simulated net operating income data and to

characterize the properties that were identified at heightened risk of loss to the affordable housing stock.

Net Cash Flow Approach to Fail-out Risk

The study used proforma analysis to assess the risk of fail-out as a result of physical deterioration and mortgage default. This approach was based on the link between the financial condition and the physical state of a property. According to Recapitalization Advisors, Inc. (2008, 1), "any property's Net Operating Income (NOI) is strongly affected by its physical status." Wallace et al. (1993, 1-10) made the same link and stated that "the current financial situation is particularly relevant in assessing whether a property is at risk of defaulting on its mortgage." As noted by Goodman (2004, 229), net operating income is used in several academic studies as "a trigger for mortgage default." Goodman (2004, 243) went on to state that "properties with negative cash flow have been shown to be the most likely to default on mortgages and ultimately be abandoned or otherwise removed from the housing stock." Wallace et al. (1993) also found that net cash flow was a predictor of a distressed property, which was defined as a property "whose combined physical and financial problems are severe enough to jeopardize tenant well-being, impair sound operations, and (if not corrected) lead to financial failure of the property" (Wallace et al. 1993, 1-2).

The consequences of insufficient cash flow include missed payments to reserve accounts and deferred repairs and capital improvements (Recapitalization Advisors, Inc. 2002; Wallace et al. 1993). Hence, "financial difficulties are inevitably tied up with physical deterioration: It is rare to find one without the other" (Recapitalization Advisors, Inc. 2008, 1).

Pedone (1991) also believed that properties with insufficient cash flows and limited reserves were at risk of deterioration and default. Under these financial conditions, owners are struggling to make mortgage payments and to address mounting repairs and capital needs.

Pedone claimed that some owners may purposely avoid default and allow their properties to deteriorate by not incurring expenses for repairs and not infusing cash from sources external to the property. An owner may make this disinvestment decision if a property is located in a weaker housing market and does not have a higher and best use that would be more profitable, and if exit taxes are owed upon foreclosure. Achtenberg (2002, i) echoed that "in weaker markets, subsidized housing is threatened by disinvestment, default, and foreclosure."

Net Cash Flow Approach to Opt-out Risk

This study also used proforma analysis to assess the risk of opt-out of a rental assistance contract in order to convert the property to market-rate housing. The reason for the net cash flow approach related to the link between an owner's decision to terminate affordability and the expected financial return that would result from this decision. In a study of the HUD-insured multifamily housing stock, Wallace et al. (1993, 2-57) stated that "the probability of an eligible owner converting from assisted to market use depends on the revenues and costs associated with each [prepayment or opt-out] option." Recapitalization Advisors, Inc. (2002) argued that owners were almost always motivated to prepay a subsidized mortgage or opt-out of a rental assistance contract if this action would result in a higher financial return on the property. This scenario was most realistic in very strong rental markets. Pedone (1991) also claimed that conversion to market-rate housing or another use can be a financially attractive option in tight housing markets where property owners have the opportunity to charge higher rents and improve profitability. Another condition for market conversion – in addition to a strong local market – was the financial state of a property. In an analysis by Wallace (1992), properties that were predicted to be feasible for a market conversion were in a healthy financial condition.

Wallace et al. (1993) did point out that conversion commonly required that costs were incurred for repairs and capital improvements. According to Pedone (1991, 247), "converting to

higher income use could be more profitable than continuing the current low-income use, even with rehabilitation costs, any other transition costs, and the costs of refinancing the mortgage at current interest rates, which will substantially exceed the subsidized interest rates."

A 2006 study that was conducted for HUD found a correlation between an owner's decision to terminate affordability and the financial motivation. Finkel et al. (2006) performed multivariate logistic regression analysis to assess the correlation between an owner's decision to opt-out of a HUD rental assistance contract (dependent variable) and characteristics of the property (independent variables). The study concluded that "the key explanatory variable yielded by the multivariate analyses appears to be the rent-to-FMR ratio: the lower the rent-to-FMR ratio, the higher the likelihood of opting out" (Finkel et al. 2006, 33). When the project rent was relatively low compared to the Fair Market Rent, the owner had a greater opportunity to improve rent revenues by opting out and converting to market rate housing.

Simulation Modeling of Net Cash Flow

Overview of Monte Carlo Simulation and Application to Real Estate

Simulation is a technique that can be used to quantitatively analyze decisions that involve uncertainty (Myerson 2005; Vose 1996). Monte Carlo is one type of simulation method. It differs from other simulation methods by attempting "to incorporate the random uncertainty of the real world" (Archer 2005, 1). In a Monte Carlo simulation computer model, a real-life situation is imitated and uncertainty is explicitly incorporated by assigning a range of possible values to input variables that are random, rather than using single-point estimates (Albright, Winston and Zappa 2006). Uncertain values are also referred to as stochastic values (Palisade Corporation 2008). The Monte Carlo method was developed for the nuclear industry during the 1940s (Schumann 2006; Vose 1996). Its name – Monte Carlo – originates from the city in Monaco in Southern France, known for its casino and gambling games such as roulette and dice, which are

based on random selections of numbers (Schumann 2006; UBC Real Estate Division 2001). Monte Carlo simulations are most commonly run in spreadsheets, as a result of the popularity of simulation add-in software programs such as @RISK and Crystal Ball that can be used in Excel (Albright, Winston and Zappa 2006; Vose 1996).

Simulation is used as a risk analysis technique in real estate to make investment decisions (Slade 2006; Pyhrr 1973). The use of simulation in real estate investment builds on the traditional discounted cash flow (DCF) method for the valuation of assets. Input variables that are common in real estate analysis relate to investment outlays (e.g., size and type of units, cost of land and construction), operations (e.g., rental revenue, operating expenses), financing (e.g., amount of debt, interest rate) and reversion (e.g., property sales price, holding period). The traditional DCF model is deterministic, because all input variables are single-point estimates and therefore the output variables are single-point estimates also (Pyhrr 1973). But in reality many input variables are random and therefore uncertain. For example, the vacancy rate for next year could be estimated with a single value, but vacancy is a random variable with uncertain future values.

It is common for the real estate investor or analyst to perform sensitivity and scenario analysis based on the single-point estimates. Sensitivity analysis typically estimates minimum and maximum values of variables to assess the impact on the outcome. But this approach does not recognize that the minimum and maximum values are less likely to occur compared to the single-point best guess value. Scenario analysis is usually based on a small number of scenarios, which are combinations of single-point estimates. However, several hundred scenarios could exist if the model has multiple variables (Vose 1996). It is "next to impossible to test the entire range of possible outputs" (Kelliher and Mahoney 2000, 49).

Simulation analysis addresses the limitations of deterministic, sensitivity and scenario analysis. The simulation risk analysis model incorporates the uncertainty of random variables, considers the probabilities of values, and runs hundreds of 'what if' scenarios in a matter of seconds.

Input and Output variables

The simulation risk analysis model is probabilistic in nature (Pyhrr 1973). In a simulation model, each random input variable has a probability density function, which is a range of possible values and a probability distribution for these values, as determined by the analyst. The simulation software samples a random variable from every probability density function and calculates the output value for the combination of inputs. This process is repeated a large number of times, e.g., 1,000 iterations. Each iteration can therefore be considered a separate 'what if' scenario. Since each random input variable has a range of possible values, the output of simulation analysis is not a single-value, but a distribution of outcomes (Albright, Winston and Zappa 2006). "While the simulation runs, all forecasts stabilize toward a smooth frequency distribution" (Schumann 2006, 13). The final output after multiple iterations includes summary statistics of the iterations (e.g., mean, median, standard deviation, minimum, maximum) and graphical displays (e.g., frequency charts) (Kelliher and Mahoney 2000).

Probability Distributions

For each uncertain variable, a type of probability distribution has to be selected. Vose (1996) identified three ways to categorize probability distributions: Continuous versus discrete; bounded versus unbounded; and parametric versus non-parametric. A continuous distribution is used when the variable can take any value within a defined range, implying that the value is infinitely divisible. The @RISK simulation software that was used in this research identified 31 types of continuous distributions such as the normal, logistic, gamma and uniform distributions.

A discrete distribution is selected when the variable can only take a finite number of values. Eight discrete distribution types are defined by @RISK, including binominal and Poisson distributions. Probability distributions are also either bounded or unbounded: A bounded distribution lies between two specific values, which is the case for uniform and triangular distributions. An unbounded distribution has an infinite minimum value and an infinite maximum value. This applies to distributions such as the normal and logistic distribution. A partially bounded distribution is also possible when either the minimum or the maximum value is constrained. The probability distributions can also be distinguished by parametric versus non-parametric. A parametric distribution is specific to a problem and is theoretically derived, relying on mathematics to model the problem (Vose 1996). An exponential or lognormal distribution can be parametric. A non-parametric distribution is considered a general distribution such as a discrete, triangular or cumulative distribution, for which few assumptions about the population distribution are required (Agresti and Finlay 1997). As described by Vose, "the defining parameters for general distributions are features of the graph shape" (1996, 56), which contrasts the parameters of parametric distributions "whose shape is borne of the mathematics describing a theoretical problem" (1996, 56).

Figure 5-1 illustrates the probability distributions as categorized by common, continuous and discrete distributions. The literature on the application of simulation to real estate investment analysis most commonly used the following probability distributions: Normal, lognormal, triangular and uniform (Schumann 2006; Hoesli, Jani, and Bender 2006; French and Gabrielli 2005). These distributions are least complex, widely applicable and generally understood among real estate analysts. However, both Schumann (2006) and French and Gabrielli (2005) made the argument that the triangular distribution was the most appropriate approach in real estate

valuation, even though normal distribution was more statistically robust. The authors explained that the triangular distribution reflects the thought process of the analyst who thinks in terms of best, worst and most likely figures.

Stochastic values have inherent uncertainty, hence the selection of probability distributions. To determine which type of probability distribution to select, the uncertainty can be quantified through research of each variable, which often involves the analysis of current and historical data, as well as the input of expert opinion. When a reliable data source is available for an uncertain variable, the simulation software can fit a probability distribution to the observed data. But Pyhrr expressed that "in real estate, where objective data is sparse, or often nonexistent, the decision maker is forced to use probability estimates that are highly subjective" (1973, 62). Kelliher and Mahoney also pointed out that "even when historical data is available, much of the distribution selection process is driven by subjective judgment, moderated by experience, with a final check for reasonableness" (2000, 51). Vose (1996, 153) presented the following reasons for data limitations and the difficulty in obtaining data to assess the uncertainty of variables:

- The data have simply never been collected in the past.
- The data are too expensive to obtain.
- Past data are no longer relevant (new technology, changes in political or commercial environment, etc.).
- The data are sparse, requiring expert opinion 'to fill in the holes.'
- The area being modeled is new.

Rationale for Simulation Modeling

Both Archer (2005) and Vose (1996) outlined criteria to be met if Monte Carlo simulation analysis is applied as a methodology. Archer explained that one of the following two conditions must exist. "First, if the stochastic behavior is complex and difficult to represent by

statistical models, then the flexibility of Monte Carlo can enable a closer fit to the real process. Second, if the main question depends on a threshold, such as with any option behavior (default, prepayment, lease renewal, etc.), Monte Carlo is well suited to examine the probability of crossing the decision threshold" (Archer 2005, 4). According to Vose (1996), two criteria must be met. First, it must be possible to model the problem. Second, the variables in the model have to be quantifiable. Simulation was considered a suitable method to address the research questions in this study, because all conditions as outlined by Archer and Vose were met: There were many uncertain input variables, which made the fail-out and opt-out processes complex; the main research questions depended on thresholds related to subsidy renewal and default; it was possible to model the risk of loss of affordable housing by using a cash flow approach; and the variables were quantifiable.

Research Design

Unit of Analysis, Population and Sampling Frame

The property was the unit of analysis. It was the unit of analysis for several reasons. First, project-based housing subsidies are made at the property level. Second, the property is the level at which owners commonly make decisions concerning investment, disposition and opt-out of subsidy programs. Third, physical deterioration directly or indirectly affects all units and thereby the entire property. Fourth, mortgages are secured by the real property and therefore mortgage default occurs at the property level.

The total population size was 119 properties. The population was defined as the properties that were located in Miami-Dade and Duval County, and that had an active contract under any HUD project-based rental assistance program (with one exception), which included the following programs

- Loan Management Set Aside
- Section 8 New Construction
- Section 8 Substantial Rehabilitation
- Section 8 Moderate Rehabilitation
- Property Disposition
- Preservation
- Rent Supplement

Excluded from this list are the Project Rental Assistance Contracts that subsidize operating expenses of developments that are funded under the HUD Section 202 Capital Advance program for the elderly or the HUD Section 811 Capital Advance program for persons with disabilities. These programs were outside the scope of the research.

The geographic focus was Miami-Dade and Duval, because the number of properties and units with project-based rental assistance in these counties trumped that of all other individual counties in Florida (HUD 2008a). More than one third of properties and units covered under HUD rental assistance contracts were located in Miami-Dade or Duval. Preventing the loss of properties with rental assistance was considered important, because both counties housed renters that made less than 60% of the area median income and were paying more than 40% of income on housing; this group made up more than 30% of renter households in Miami-Dade and more than 21% in Duval (Shimberg Center for Housing Studies 2007).

The sampling frame was the Assisted Housing Inventory (AHI), a property-level database of privately-owned rental properties in Florida that were funded under federal, state or local housing programs. These housing programs impose income and/or rent restrictions for all or a portion of the units, thereby offering affordable housing to lower income households. The AHI is a product of the Florida Housing Data Clearinghouse, which is part of the Shimberg Center for Housing Studies at the University of Florida. The AHI as the sampling frame was broader than

the population of research interest, because the AHI includes properties throughout the state of Florida and properties subsidized under programs other than HUD Section 8.

Data Collection and Database Design

The aim was to create a property-level database (herein referred to as 'the database') that contained the variables that were required for the analysis. The database was created in Excel with one row for each property. The Assisted Housing Inventory (Shimberg Center for Housing Studies 2008) was used as the starting point to identify the properties with HUD project-based rental assistance in Miami-Dade and Duval County. All variables that the AHI reported on were initially incorporated into the database. These included property characteristics such as address, number of units, bedroom configuration, target population, year built and housing programs. The AHI also reports on preservation-related variables such as type of ownership, Fair Market Rent, project rent to FMR ratio and expiration dates of the subsidy programs.

An advantage of the AHI was that it incorporated data from four major funding sources: HUD, the U.S. Department of Agriculture Rural Development, Florida Housing Finance Corporation and Local Housing Finance Authorities. As a result, the number and types of funding layers was known for each property in the AHI.

Excluded from the AHI were detailed data about the HUD rental assistance contracts such as the contract effective date and the type of rental assistance program. These were essential variables for the research, because they provided insight into the history of contract renewal and past owner decisions. Therefore, two datasets that were publicly available from HUD were merged with the database: The HUD Section 8 Contracts dataset and HUD Section 8 Properties dataset (HUD 2008a). Merging required the matching of properties by the HUD identification number, which is a unique ID that is assigned to each HUD-funded property.

Other important information not captured by the AHI concerned the mortgage data for HUD insured multifamily mortgages. This information was captured by the publicly available dataset called HUD Insured Mortgages (HUD 2008b), which provided details regarding the terms of the loan, the mortgage amount and the monthly payments. This information can add to the understanding of the financial status of a property. The insured mortgages dataset was merged with the database. Another publicly available dataset that was important for the verification of year built data was called HUD Terminated Mortgages (HUD 2008c). Both the HUD Insured Mortgages and HUD Terminated Mortgages datasets did not have a data field for HUD ID. Therefore, the merging with the database was more of a cumbersome process. It involved the matching of the properties to a third dataset that functioned as a reference dataset, because it contained the HUD ID. This other dataset was an annual Excel report from HUD in Jacksonville (HUD 2008d), which listed HUD-funded properties in Florida. The properties were matched by HUD Project Number (a number that is assigned to each HUD loan) or by property name. The HUD ID was then added to the HUD insured and terminated datasets. Then the variables in these datasets were merged into the database by matching properties by HUD ID.

HUD Physical Inspection Scores are part of the AHI. However, at the time of the database design, a recent dataset of scores was released, which was not yet reported in the AHI. Therefore, the recent scores were merged into the database, which was done through matching by HUD ID (HUD 2008e).

The properties in the database were also matched to the tenant and unit characteristics as published in the HUD Picture of Subsidized Households for 2000. This is the most recent year for which tenant data were available.

Once all the various datasets were merged, it was necessary to edit and clean the data, and to perform quality control. Each data field was examined by reviewing all cell contents. A pivot table of the database was created as an aide for quality control. This enabled a quick view of the data entries in order to detect anomalies and missing information. Several edits were made to the data fields and data entries. For example, the database initially contained one data field with the names of all housing programs that funded each property. Since this format was not conducive to efficient analysis, the names of the housing programs were parsed and placed in separate cells. As another example, discrepancies were found between AHI data and entries in the HUD datasets. For instance, for some properties the year built as reported by the AHI was almost a decade later than the year of HUD mortgage endorsement and start of loan payments for the terminated mortgage. Subsequent research on those properties found that the reported year built was actually the year of refinancing. The year built for those properties was therefore changed to the year of mortgage endorsement.

Another finding during the quality control stage was that the bedroom configuration and market rent data were not available for units in properties that had less than 100% of the units covered by project-based rental assistance. This was the case for 20 properties in the population. To fill the data gap, each property was contacted by telephone to collect data on the breakdown by bedroom size and on the rents by bedroom size for the non-rental assistance units.

As part of the data editing process, an adjustment was made to the monthly loan payment amounts for properties funded under the HUD Section 236 program. According to the terms of this program, property owners receive an interest subsidy that reduces the mortgage payments by lowering the interest rate to 1%. However, during the data review it was found that HUD calculated the Section 236 mortgage payments based on a market interest rate, rather than the

reduced rate. The actual debt service was therefore overstated. Since the HUD data that were incorporated into the database included figures on loan amount and the term of the mortgage, the monthly mortgage payments were recalculated for all Section 236 properties in the population, based on a 1% interest rate. Table 5-1 lists all datasets that were used to compose the database for the research.

Fail-out Risk: Structure of the Model and Methodological Assumptions

The Fail-out Risk Model was designed to address the research question concerning fail-out risk. This model made the initial assumption that all properties, regardless of type of ownership, were at risk of fail-out. Therefore, monthly net income statements were simulated for all 119 properties. Then the assumption was made that properties were at heightened risk of fail-out if they met at least one of the following conditions:

- REAC Physical Inspection Score of less than 60, or
- Median debt coverage ratio below 1.0, or
- Median Net Operating Income of less than $200 per unit per month.

As found in the research, all three conditions were considered indicators of financial or physical challenges. The first condition was based on the notion that a REAC Physical Inspection Score below 60 is a failing score. Properties with a score under 60 are referred to the HUD Departmental Enforcement Center (Achtenberg et al. 2005). The second condition was included, because a debt coverage ratio below 1.0 indicates that a property is experiencing difficulty covering the mortgage payments out of net income. The third condition was based on a benchmark adopted from a study completed for HUD by Abt Associates, Inc. (Finkel et al. 1999). The study included an analysis of the financial condition of HUD-insured properties. The analysis compared the mean and median annual net cash flow after debt service per 2-bedroom unit. Properties were classified as negative cash flow, low positive cash flow between $0 and

$500, high positive cash flow between $500 and $1,000, and very high positive cash flow over $1,000. For the purpose of the dissertation research, these benchmarks were converted to per month figures before debt service, since the simulation results for NOI were per month and debt service was missing for the majority (76%) of properties in the population. The first step in converting the benchmarks was to add back the mean debt service of $2,201 per year for HUD-insured properties, as was estimated by Abt (Finkel et al. 1999). The next step was to divide the figures by 12 to determine the benchmarks for the monthly NOI, as outlined in Table 5-2. Lastly, the assumption was made that a monthly per unit NOI of less than $200 was considered low.

At least one of the three conditions of fail-out risk was met by 32 properties or almost 27% of the population, as summarized in Table 5-3. These figures cannot be interpreted to mean that all these properties will be lost to the assisted housing stock within the next few years. These numbers were based on estimates of net cash flow and probability distributions. But they can be used to provide insight into the magnitude of properties that could be lost and that should receive attention from policy-makers and advocates. The analysis also informs the housing community of the characteristics of higher risk properties.

Opt-out Risk: Structure of the Model and Methodological Assumptions

The Opt-out Risk Model was designed to address the research question related to opt-out risk. This model relied on the initial assumption that properties under non-profit ownership were not subject to this type of risk, because non-profit entities have a mission to serve low income households. Therefore, monthly net income statements were simulated for properties with for-profit or limited-dividend ownership (both classified as for-profit for the purpose of analysis), a total of 83 properties. The simulation calculated two types of NOI values for for-profit properties: NOI values under the scenario that the properties continued to operate status quo with the same number of assisted (and non-assisted) units; and NOI values under the scenario that all

properties converted all units to market rate rents. The percentage change in NOI values was calculated in order to assess which properties would experience an increase in the bottom line and at what percentage. Next, the assumption was made that properties were at heightened risk of opt-out if they met all of the following conditions:

- NOI increase of at least 20%, and
- Expiration of the rental assistance contract by December 31, 2014, and
- Original contract term, and
- Not located in a low poverty census tract.

All these conditions were considered indicators of heightened risk of loss due to opt-out. An increase in NOI by at least 20% was established as an arbitrary benchmark above which properties would be enticed to convert to market-rate housing. The contract expiration by year end 2014 was selected as a condition, because owners of these contracts have an option to opt-out in the short-term. Properties that have a longer term contract in place were considered at a lower risk of imminent loss, because the contractual constraints extended beyond 2014. Original contract term was also one of the conditions, because the owners have not yet had an option to opt-out of the contract. They could decide to opt-out once they have the first opportunity to make such a decision. This was the experience in the late 1990s when the first Section 8 rental assistance contracts reached the end of the original contract term; a wave of opt-outs took place (HUD 2007). The assumption was made that properties that have had a chance to renew the rental assistance contract have not been interested in conversion. They would have opted out and converted to market rate housing when Florida's markets were booming in the first half of the current decade. Properties were also classified at greater risk of opt-out and conversion to market-rate housing if they were located in a low poverty census tract where they could command market rents.

The comparative cash flow approach (comparing status quo to 100% market units) was also taken in a recent paper that analyzed Low-Income Housing Tax Credit developments that were built during the early days of the program when the use restriction was only fifteen years (McClure and Grube 2007). The paper compared two scenarios of the operating performance for a tax credit development that was about to reach year fifteen of the use restriction. The first scenario was resyndication of the tax credits and continuation as a tax credit property with use restrictions. The second scenario was conversion to market rate housing.

A total of 27 properties or almost 33% of the for-profit properties met all conditions (Table 5-4). As was mentioned under the description of the fail-out risk model, these figures should not be interpreted to imply that all these properties will be lost to the affordable housing inventory within several years. These numbers were based on estimates of net cash flow and probability distributions. But they can be used to estimate the scale of the preservation challenge and to act as guide for policy-makers and advocates to determine the level and type of required resources to prevent loss of housing.

Input Variables and Probability Distributions

The input variables used to compose the net income statements had two types of values: Single-point or deterministic values and uncertain or probabilistic values. Single-point values were based on actual data as obtained through primary or secondary data collection (e.g., number of units). Probabilistic values were assigned to random variables (e.g., operating expense ratios). All random variables were expressed as a range of possible values and the likelihood of occurrence of each of these values as modeled by a probability distribution. All input variables and probability distributions that went into the simulation models are discussed in this section and summarized in Table 5-5.

The first element of the net income statement was the gross potential rental income, which was the sum of the potential rents on all occupied and vacant units. There were six input variables to calculate the gross potential rental income. The first two input variables were the number of units with project-based rental assistance by bedroom size and the project rents for these units. The number of units by bedroom configuration was provided by HUD and included in the database. The project rent was calculated as the product of the Fair Market Rent by bedroom size and the project rent to the FMR ratio for a property, as reported by HUD. Since the data on the units with project-based rental assistance were derived from actual HUD figures, these input variables were included in the models as single-point estimates.

The next two rent input variables were the number of units with income and/or rent restrictions under other subsidy programs by bedroom size and the corresponding rents. If the rental assistance contract did not cover 100% of the units and if another subsidy program imposed restrictions on the balance of the units, the number of other restricted units was calculated as the difference between total units and rental assistance units. Rent data for the other restricted units were not available through a public data source and were therefore collected directly at the property level. Property management provided rents either as single-point estimates or as a range with a minimum and a maximum rent value. The literature reported that rental income was commonly assumed to follow a normal, uniform or triangular distribution (Schumann 2006; French and Gabrielli 2005; Kelliher and Mahoney 2000). But for the dissertation research, the uniform distribution was deemed most appropriate for units for which a range of restricted rents was provided, because no data were available on most likely or average rents and standard deviations.

The last two rent input variables were the number of unrestricted units and market rents. If the rental assistance contract did not cover 100% of the units and if no other subsidy program funded the property, the number of unrestricted units was calculated as the difference between total units and rental assistance units. Actual market rent data for each property were not available through a public data source. For the fail-out model as well as the status quo scenario under the opt-out model, actual market rents were collected directly from the property. Rents by bedroom size were either provided as single-point estimates or as a range with a minimum and a maximum rent. A uniform probability distribution was selected if a range of rents was available. For the market-rate scenario under the opt-out model, the assumption was made that all units were rented at market. Government data sources for market rent (e.g., HUD, U.S. Census) have limitations in terms of the geographical scale (e.g., only county-level market rents or only market rents for a limited number of counties) and the time period (e.g., only market rents for several years ago). Private data sources may be available from appraisers or property management firms, but these data are often restricted to a small number of geographies, are kept for internal purposes only, or cannot be obtained through purchase. Due to these limitations, an alternate source of market rent information was relied upon, Zilpy.com. Zilpy is described as a ”free online rental market facts and analysis service dedicated to help you make better rental and investment decisions” (Zilpy LLC 2009). It collects rental data from a variety of sources, including newspaper classified ads, online classified ads and apartment rentals. Zilpy reported median rents by bedroom size, the number of rentals by bedroom size and average square footage by bedroom size for a specific address, zip code or city. For each query, Zilpy also provided a list of the top 100 most recent rentals with address details, unit configuration and building structure type. For each property in the opt-out model, Zilpy was used to find median

rents by zip code by bedroom size. The simulation software was then used to fit a probability distribution to the observed data for each bedroom size by county. The lognormal distribution was found to be the best fit.

In calculation of the gross potential rental income, other rental income was excluded due to a lack of data. Other income may include commercial rent, interest income from reserve accounts or forfeited tenant deposits (Wallace et al. 1993).

Another input variable was vacancy loss and bad debt allowance, which was calculated as a percentage of the gross potential rental income. This was an uncertain input variable for which no actual property-level data were publicly available. Hence, the models made the assumption that this input variable was uniformly distributed between 5-10%. Similar to the comparative analysis conducted by McClure and Grube (2007), the assumption was the same for the status quo scenario and market-rate scenario under the opt-out model. The uniform distribution was selected, because it was applied in other simulation research (Hoesli, Jani, and Bender 2006; Baroni, Barthélémy, and Mokrane 2005) and because it models Wilkins' suggestion that the allowance typically be 7-9% and not lower than 5% (2002). The range of 5-10% also considered the industry standard of 7%. According to Stan Fitterman at the Florida Housing Coalition (2007), a vacancy rate of 7% was the benchmark. Achtenberg (LISC 2005, 10) also explained that "the minimum vacancy and bad debt allowance required for first mortgage underwriting is generally 7%" for properties that were restructured under the HUD Mark-to-Market program. Slade (2006) used a triangular distribution to estimate vacancy rate, because he was modeling only one property and was able to make an assumption about the most likely vacancy rate; such an assumption was not deemed appropriate in this study.

The gross potential rental income less the vacancy loss and bad debt allowance equaled the effective gross income. Operating expenses, another input variable, were calculated as a percentage of effective gross income. None of the public data sources contained actual data on the operating expenses at the property level, because these data are considered proprietary. In lieu, operating expenses were estimated based on data from the Institute of Real Estate Management (IREM). Hecht (2006) in his book "Developing Affordable Housing, A Practical Guide for Nonprofit Organizations" suggested to rely on IREM data to project and compare operating costs if historical information is not available. IREM data are commonly used in real estate analysis to estimate operating expenses (Goodman 2004; Finkel et al. 1999; Bogdon and Follain 1996). As explained by IREM, the data can serve as inputs for feasibility studies and as benchmarks for comparison purposes (IREM 2007). IREM publishes an income and expense analysis report annually for various types of real estate, including federally assisted apartments funded under subsidy programs such as Section 236 and Section 8 project-based rental assistance. The report contains operating ratio data, which were used as the input variables in the risk models. Operating expenses divided by actual collections equaled the operating ratio. The IREM report presented the operating ratio data in two ways:

- Operating ratio by property age group and subsidy type. The properties in this study fall within two of the property age groups, 1965 to 1977 and 1978 to date.
- Operating ratio by region and subsidy types. Florida is part of Region 4, which consists of Kentucky, Tennessee, North Carolina, South Carolina, Mississippi, Alabama, Georgia and Florida.

Since operating expenses are random with uncertain values, the simulation analysis considered both sets of operating ratios. Additionally, the operating ratios were obtained for three consecutive years, rather than for one year, to take into account year over year fluctuations in operating expenses (Harvard University Graduate School of Design 2001; Finkel et al. 1999)

and in variations in the IREM sample base (IREM 2007). From among both sets of operating ratios over three years, the minimum and maximum values were recorded by subsidy type and age group. Depending on a property's funding layer and year built, the simulation analysis drew from the range of operating ratio values and assumed that these follow a uniform probability distribution. While other studies applied a triangular distribution to operating expenses (Hoesli, Jani, and Bender 2006; Kelliher and Mahoney 2000), this was not considered a suitable approach in this research due to the lack of property-specific information about operating expenses and most likely values. The assumptions pertaining to the operating expense estimates were the same for each model and all scenarios in this study, which was similar to the method use by McClure and Grube (2007) in their cash flow comparison of the status quo scenario to the market-rate scenario of a tax credit property.

Replacement reserves were another cost item and random input variable. Replacement reserves were estimated to follow a triangular distribution with a minimum value of $0, a most likely value of $26.50 and a maximum value of $62.50 per unit per month. These estimates were derived from an analysis of capital needs assessments and replacement reserve studies conducted by On-site Insight, Inc. during 1999 and 2000, which are the most recent studies. The analysis was conducted for a sample of 183 assisted properties funded by HUD or state housing finance agencies and located in eighteen different states. On-site Insight, Inc. (2001) reported a median annual contribution to the replacement reserve account of $26.50 per unit per month. The company published a histogram with annual replacement reserve contribution categories by number of properties. The categories ranged from $0-99 to $2,100-2,199. In order to estimate a probability distribution for the simulation analysis, a frequency table was created with the data from the histogram. The simulation software was then used to fit probability distributions to the

data. The triangular distribution provided the best fit. The minimum value was set to $0 and the most likely value was determined to be $26.50 (the median replacement contribution). The maximum value was established at $62.50 per unit per month, even though the histogram displayed observations with higher reserves. This maximum was considered appropriate for two main reasons. First, from $0 to $62.50 in annual replacement reserves covered almost 90% of all observations of the On-site Insight data. Second, at this maximum value, the mean value is $29.67, which approximates the benchmarks used within the industry. Khadurri and Wilkins (2007) assumed a replacement reserve of $25 per unit per month in simulation analysis of a tax credit property; Finkel et al. (1999) calculated average replacement reserve deposits at $27.58 per unit per month for HUD-assisted properties, compared to median reserves at $20.33 per unit per month; and LISC (2005) discussed a rule of thumb of $30 per unit per month. The assumptions for replacement reserves were the same for each model and all scenarios, which was also assumed in the comparative analysis by McClure and Grube (2007).

Debt service was the last input variable. Data on monthly mortgage payments were publicly available for properties funded with a HUD mortgage. These data were incorporated into the database and used to establish single-point estimates of the debt service for those properties. For all other properties, no debt service information was available. No inferences were made about the monthly mortgage payments for those other properties, due to the high level of uncertainty concerning this random variable.

The following input variables were the same for the fail-out risk model and the opt-out risk model with its two scenarios: Vacancy loss and bad debt allowance, operating expense ratios, and replacement reserve. All three input variables were modeled only once. The cash flow calculation for every property under each model linked to the same input cells for these random

variables. This was required in order to properly compare the outputs among all properties. If these three input variables were simulated for each property cash flow, the same variable (e.g., replacement reserve) would have a different value for every property in each single iteration (Vose 1996). Instead, the random values of these three input variables should be the same for all properties in each iteration. As explained by Vose (1996, 96), "every uncertain variable must be represented once only in the spreadsheet and any other cell that needs its value must make reference to the cell in which the distribution resides."

Output Variables

Each of the models had two output variables, net operating income and debt coverage ratio. Effective gross income less the operating expenses and replacement reserves totaled the net operating income, which was estimated for each property. Net operating income is a measure of financial condition (Wallace et al. 1993).

Debt coverage ratio was calculated as the net operating income divided by debt service. It was considered an indicator of financial health, because it measured if the net cash flow was sufficient to cover the mortgage payments (Bradley, Cutts, and Follain 2001). Since debt service information was not available for all properties, the debt coverage ratio could only be estimated for a subset of properties.

Data Analysis and Analytical Tools

Descriptive Analysis and Significance Tests

A simulation was run with 1,000 iterations to estimate the values of four categories of output variables: Net operating income at current rents; debt coverage ratio at current rents; net operating income at market rents; and debt coverage ratio at market rents.

For each property, the simulation analysis calculated the NOI based on the current project rents. For those properties for which mortgage data were available, the simulation also generated

values for the debt coverage ratio based on current project rents. The results of the simulation that was run with current project rents were used for the analysis of the fail-out risk. The results for the properties with for-profit ownership were also used in the assessment of the opt-out risk.

The simulation also calculated the NOI for for-profit properties with all market rents as the input variables. Additionally, the simulation estimated the debt coverage ratio under the scenario of market rents for for-profit properties for which mortgage payment information was available. The outcomes of the simulation based on market rents were compared to the simulation results based on current rents in order to analyze the opt-out risk.

The simulation results were summarized in tables and described for each risk model and by output variable. In addition to descriptive analysis, significance tests were performed for the opt-out risk model to compare the mean NOI values and to analyze the change in NOI if market rents are charged rather than contract rents.

For each risk model, the characteristics of the properties classified at a higher risk were compared to those of properties that were identified at lower risk. Four types of characteristics were described and summarized in cross-tabulations: Property, financial, subsidy and tenant characteristics. Where the difference in characteristics between the higher risk and lower risk groups seemed notable, a significance test was performed to assess if the difference was statistically significant.

If the data that described the characteristic were quantitative, the two groups were compared using a t-test of the null hypothesis that the means of the groups were the same (H_0: $\mu_1 = \mu_2$; H_a: $\mu_1 \neq \mu_2$). The t-test was selected as the significance test, because it is considered a robust statistical method. As explained by Agresti and Finlay (1997, 187), "even if the population is not normally distributed, two-sided tests and confidence intervals based on the *t*

distribution still work quite well. The *P*-values and confidence coefficients are fairly accurate, the accuracy being quite good when *n* exceeds about 15."

If a characteristic was described by qualitative data, the population proportions were compared by performing a z-test of the null hypothesis that the proportions were equal (H_0: $\pi_1 = \pi_2$; H_a: $\pi_1 \neq \pi_2$). Agrasti and Finlay (1997) suggested the z-test to compare population proportions if each category in each group contained more than five observations.

The significance level for all significance tests was set at 0.05 (5%). The P-value that was calculated by each test was compared to this significance level; a null hypothesis was rejected if a P-value was less than or equal to 0.05.

Correlation and Multiple Regression Analysis

Since NOI was considered a major indicator of the financial condition of a property, multiple regression analysis was conducted to assess which characteristics caused a lower NOI. The estimated mean NOI was the response (dependent) variable. The following explanatory (independent) variables were selected from the property and subsidy characteristics that were studied:

- Total number of units
- Target population (1=elderly; 0=family)
- Average unit size by number of bedrooms
- Year built
- Type of ownership (1=for-profit; 0=non-profit)
- REAC Physical Inspection Score
- Project rent to Fair Market Rent ratio
- Number of program layers
- Contract effective year
- Contract expiration year
- Original contract (1=not original contract; 0=original contract)

Prior to running the multiple regression analysis, each explanatory variable was regressed on the others to calculate the correlation between each pair of variables. Correlation statistics

were summarized in a correlation matrix and were analyzed to test for multicollinearity. The condition of multicollinearity exists when explanatory variables are highly correlated. A variable that is highly correlated becomes redundant in the regression model, because it has limited unique explanatory power. The effects of multicollinearity are problematic and can cause inflated standard errors, overly large P-values and wrong signs of the regression coefficients (Albright, Winston, and Zappe 2006; Agresti and Finlay 1997).

Variables that were highly correlated were excluded from further analysis. A multiple regression was run with the remaining explanatory variables. A stepwise regression was also performed. The stepwise procedure adds one explanatory variable to the model at a time. At each step, the variable that contributes most to R square is selected to be added. After a variable is added, the stepwise method also removes any variables that are no longer significant. The steps are repeated until no more variables can be added to improve R square (Agresti and Finlay 1997).

Scenario Analysis

For lack of a public data source with detailed and current market rents, the input values for the market scenario under the opt-out model were derived from the website Zilpy.com. The estimated market rents seemed reasonable, based on a comparison to the Fair Market Rent data. But since the reliability of Zilpy.com was unknown, the market scenario under the opt-out model was rerun with the 2009 Fair Market Rents as the input values for all units. The change in mean NOI was recalculated, analyzed and compared to the outcomes of the simulation that was based on the market rent data from Zilpy.

Analytical Tools

The cross-tabulations for the descriptive statistics and the significance tests were conducted in Microsoft Excel 2003. The analytical tool used to perform the t-test was the ‘t-Test:

Two-Sample Assuming Unequal Variance' in Excel. The correlation matrix and the multiple regression analysis (including the stepwise regression) were prepared in SPSS 16.0.

The simulation was performed with @RISK Version 5.0, which is a software system for risk analysis and Monte Carlo simulation. It is an add-in for Microsoft Excel. @RISK is produced by Palisade Corporation.

Limitations of Net Cash Flow Approach and Simulation Modeling

The net cash flow approach that was taken in this research had several limitations. One of the limitations was that random variables had to be used as input data. For most random variables no actual historical or current property-level data were available on which to base assumptions for the range of input values and probability distributions. This meant that if the quality of the inputs was low, the outputs would not be realistic (Li 2000; Vose 1996). To optimize the quality of the outputs, the uncertain inputs were therefore carefully researched in order to make realistic assumptions that could be justified.

Another limitation of the net cash flow approach was that this did not consider other major indicators of a property's viability. Wallace et al. (1993, 2-25) warned that "in assessing a property's viability, net cash flow must be examined concurrently with physical needs and property management. A property could have deceptively positive cash flow by failing to make necessary expenditures for repairs and replacements. Conversely, a property could have deceptively negative cash flow because a new owner or manager has begun a crash repair program to eliminate an accumulated backlog of physical needs." The fail-out model incorporated the REAC Physical Inspection Scores in lieu of publicly available data on capital needs, repairs and maintenance. The research did not consider any property management variables, due to a lack of information.

Type of ownership was a defining factor in the opt-out model, which only included properties with for-profit ownership. However, ownership type is only a general proxy of owner intent. Even though research showed that non-profit owners were less likely to opt-out compared to for-profit entities (Finkel et al. 2006), it would be possible for non-profit entities to decide to opt-out of a subsidy. Conversely, for-profits may have a 'double bottom line' and want to continue to serve low-income households, rather than converting to market-rate housing.

An owner's decision can be impacted by other factors that were not accounted for in the analysis. This may have resulted in an overstatement of the estimate of units at risk. It is clearly not possible to precisely predict an owner's decision. "[A]rmchair assessment can never be highly reliable as a predictor of owner behavior. Interacting with the owner and the property is, ultimately, the way to gauge the operative dynamics of the owner's decision making. Even then, predicting actual outcomes is difficult" (Recapitalization Advisors, Inc. 2002, 36).

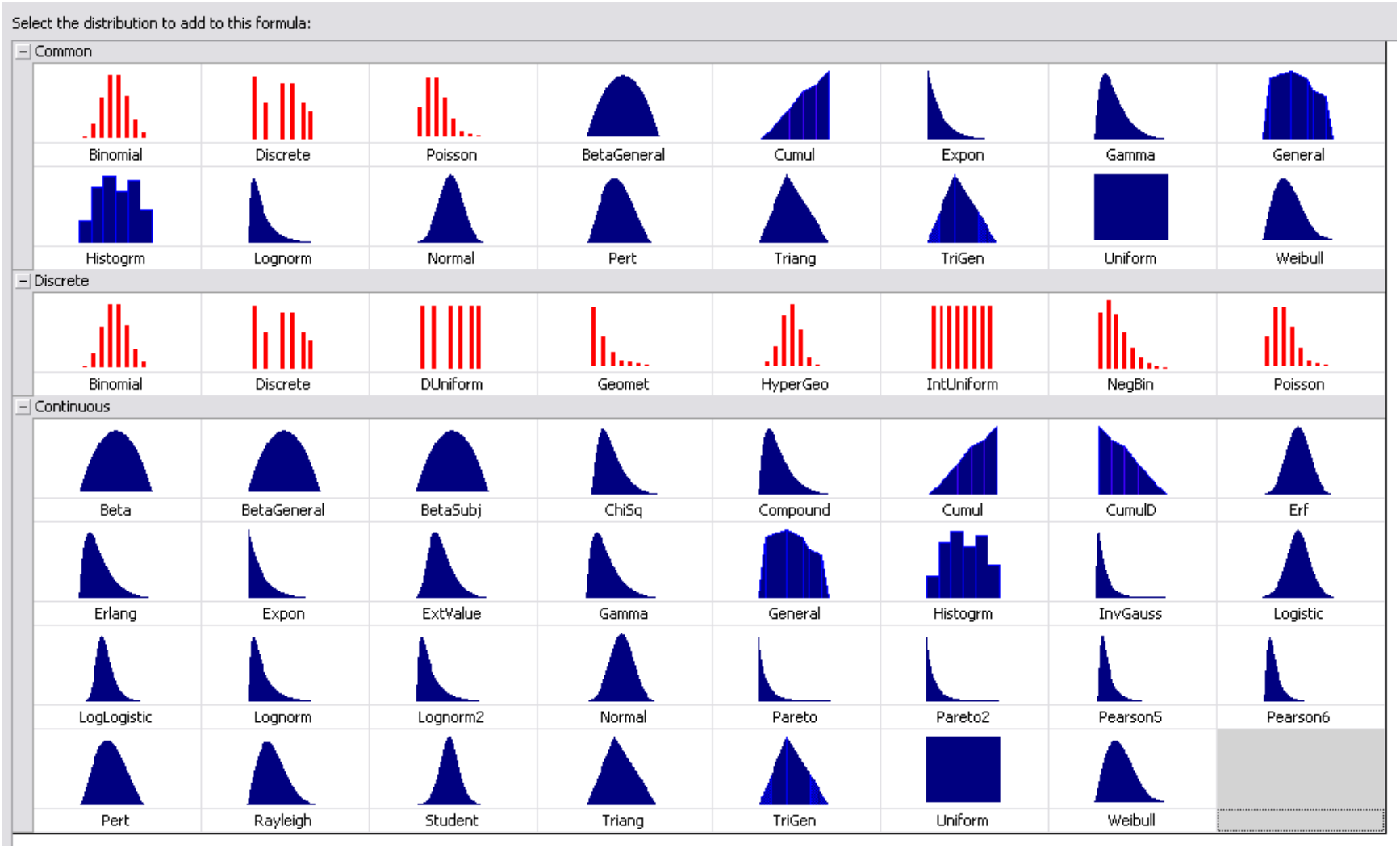


Figure 5-1. Probability Distributions.
Source: Palisade Corporation (2008).

Table 5-1. Datasets Used to Create the Database

Dataset	Source	Data as of Date
Assisted Housing Inventory	Shimberg Center for Housing Studies, University of Florida	September 2008
Multifamily Assistance and Section 8 Contracts Database	HUD DC	September 2008
Multifamily Assistance and Section 8 Properties Database	HUD DC	September 2008
Insured Multifamily Mortgages Database	HUD DC	June 2008
Terminated Multifamily Mortgages Database	HUD DC	June 2008
REAC Physical Inspection Scores	HUD DC	September 2008
Annual Database for Florida	HUD Jacksonville	January 2008
Picture of Subsidized Households	HUD DC	2000

Source: Shimberg Center for Housing Studies (2008b); U.S. Department of Housing and Urban Development (2008abcde); U.S. Department of Housing and Urban Development (2006).

Table 4-2. Net Operating Income Benchmarks

Benchmark and Amount	
Benchmarks of Annual Net Cash Flow after Debt Service per 2-Bedroom Unit:	
Low positive cash flow	$0-500
High positive cash flow	$500-1,000
Very high positive cash flow	>$1,000
Annual Mean Debt Service for Total HUD-Insured Properties per Property:	
$2,201	
Benchmarks of Annual Net Cash Flow before Debt Service:	
Low positive cash flow	$2,200-2,700
High positive cash flow	$2,700-3,200
Very high positive cash flow	>$3,200
Benchmarks of Monthly Net Cash Flow before Debt Service per Unit:	
Low positive cash flow	$183-225
High positive cash flow	$225-266
Very high positive cash flow	>$266
Research Assumption for Low Benchmark of Monthly Net Operating Income per Unit:	
<$200	

Source: Adapted from Finkel et al. (1999).

Table 5-3. Number of Properties by Condition for Higher Fail-out Risk

Condition	Properties
Mean NOI <$200	20
Mean DCR <1.0	1
REAC < 60	8
Mean NOI <$200 *AND* REAC < 60	2
Mean DCR <1.0 *AND* REAC < 60	1
Total properties that meet at least one condition	32

Table 5-4. Number of Properties by Condition for Higher Opt-out Risk

Condition	Properties
For-profit ownership	83
Not in low poverty census tract	74
Contract expiration by December 31, 2014	64
Mean NOI at least 20% higher	59
Original contract term	35
Total properties that meet all conditions	27

Table 5-5. Input Variables, Distributions and Parameters for the Fail-out and Opt-out Risk Models

Input Variable	Distribution	Parameters
Number of rental assistance units	Single-point	Property specific
Project rent (Fair Market Rent multiplied by project rent to FMR ratio)	Single-point	Property specific
Number of other restricted units	Single-point	Property specific
Rent for other restricted units	Single-point, uniform	Property specific
Number of unrestricted units	Single-point	Property specific
Market rent for unrestricted units	1) Fail-out Model and Opt-out Model/Assisted Scenario: Single-point, uniform 2) Opt-out Model/Market Scenario: lognormal	1) Fail-out Model and Opt-out Model/Assisted Scenario: Property specific 2) Opt-out Model/Market Scenario: Specific to county and bedroom size
Vacancy loss and bad debt allowance	Uniform	Minimum 5%, maximum 10%
Operating Expenses	Uniform	Specific to subsidy type and age group
Reserves	Triangular	Minimum $0, most likely $26.50, maximum $62.50
Debt Service	Single-point	Property specific

CHAPTER 6
DATA ANALYSIS

Input Variables and Simulation Results: Descriptive Analysis

A total of 41 input variables were simulated according to selected probability distributions. The table in Appendix 1 lists all input variables and the values that were generated in the 1,000 iterations performed by the simulation analysis. The table also notes the type of probability distribution and displays distribution graphs for all variables. Five categories of input variables were simulated: Vacancy loss and bad debt allowance; operating expense ratios; replacement reserve; current non-Section 8 rents; and market rents.

Vacancy loss and bad debt allowance was an input variable used in all models. A uniform probability distribution was assumed for this random variable. This distribution required that a minimum and maximum value were established. The simulation calculated a mean value of 7.5%. The percentiles show that there was an 80% probability that the vacancy loss and bad debt allowance is at least 6%; the probability was 20% that this variable amounted to more than 9%.

The operating expense ratios were a component of all models. The operating expense ratios were estimated by a uniform probability distribution rather than a triangular, normal or lognormal distribution, due to the lack of information that would provide insight into actual distribution patterns and most likely values. Five types of operating expense ratios were simulated. Each ratio was specific to a HUD subsidy program and year of construction. The minimum and maximum values for each type were determined based on a range of ratios calculated by the Institute of Real Estate Management for 2004 to 2006 (IREM 2007). The simulation calculated mean values that ranged from 55 to 62% for Section 8 properties, depending on target population and year built. For properties that also had a Section 236 mortgage, the mean operating expense ratio was estimated at 74%.

The replacement reserve was an input variable for each model. A triangular distribution was selected to compute the replacement reserve. The minimum, most likely and maximum values were based on the findings of a study of replacement reserves by On-site Insight, Inc. (2001). The simulation analysis calculated a mean replacement reserve of $29.67 per unit per month. According to the percentiles, the probability was 75% that the replacement reserve is at least $20.33 per unit per month. While the maximum value was set at $62.50, the results of the simulation show that the probability was 95% that the reserve is lower than $52.00.

For properties that contained units not covered by a HUD rental assistance contract, rental data were collected in the form of single-point estimates or ranges of rents with minimum and maximum values. Non-Section 8 rents were either market rents or rents restricted under the HUD Section 236 program. Where a range of rents was collected, a uniform distribution was assumed and the rental data were simulated at the property level for a total of 24 properties. The table in Appendix 1 summarizes the simulation results for those properties such as the mean rent. The simulation of these rental data was performed as part of the fail-out model and the assisted scenario under the opt-out model.

The market scenario under the opt-out model assumed that all units were leased at a market rent. Therefore, market rental data were the input variables that were estimated for each county by bedroom configuration. Market data were collected for all the zip codes of the properties in the population. A lognormal distribution was found to be the best fit to the market data. While this type of distribution is unbounded with an infinite minimum and maximum value, the simulation results showed that none of the minimum values were unreasonably low considering the unit type (lowest minimum value $427 for studio apartment in Duval); the maximum values were relatively high for the largest unit types in Miami ($8,395 for four

bedroom apartment), but the probability was less than 5% that the market rents would reach such levels.

NOI and DCR Output Analysis

Descriptive Analysis and Significance Tests

The NOI simulation results for the entire population are reported at the property-level in the table in Appendix 2 and summarized in Table 6-1. The estimated mean NOI ranged from $84 to $403 per unit per month, as graphed by Figure 6-1. The average of all 119 estimated mean NOI values amounted to $242; the median was $245. Table 6-2 compared these mean and median values to the mean and median NOI values that were reported for non-market rent properties in the metropolitan areas of Jacksonville and Miami (Urban Land Institute 2006). The mean and median NOI in these two areas ranged from $176 to $385.

Close to 19% of the 119 properties had an estimated mean NOI of less than $200 per unit per month; almost half of these had a mean NOI below $150, but not less than $84. More than 66% of the properties had a mean NOI between $200 and $299 and 15% had a mean NOI greater than $300.

Table 6-3 summarized the number and percentage of properties with an estimated NOI of below $200 by probability. For more than 68% of the properties the minimum NOI value that was estimated by the simulation was less than $200 and as low as $21. However, the percentiles showed that the probability was very small (less than 5%) that such a large proportion of properties had an NOI below this benchmark. At the 25th percentile, almost 32% of properties had an NOI less than $200. This implies that the probability was 75% that these properties had an NOI that exceeded the benchmark. Both the mean and median NOI calculation showed that almost 19% of the properties were below $200. For roughly 14% of the properties, there is a 75% probability that the NOI is below the benchmark and a 25% probability that the NOI will

rise above $200. For 10% of the properties, the probability is 95% that the NOI will be relatively low; a 5% probability exists that the NOI will reach at least $200.

The simulation analysis also estimated the debt coverage ratio, as outlined in Table 6-4. However, mortgage data were available for only 28 properties, which totaled less than 24% of the population. The majority of those properties had a mean DCR of at least 1.0; only two properties had a DCR less than 1.0, but not lower than 0.83. The mean DCR was less than 1.2 but greater than 1.0 for two properties. The calculation of maximum debt coverage ratios showed an outcome of 0.97 for one property and 1.05 for another property. The simulation estimates for the minimum DCR value resulted in a larger proportion of properties with a low debt coverage ratio; more than 39% of properties with debt service information (total of eleven properties) had a minimum DCR between 0.60 and 0.99. But the percentiles indicated that the probability was small that all eleven properties had a DCR below 1.0. For example, at the 5th percentile, only three properties have a DCR less than 1.0. This means that the probability was 95% that these properties had a DCR of at least 1.0.

Under the opt-out model, the simulation calculated the NOI values based on market rents for all units in properties with for-profit ownership. The simulation results were compared to the NOI values generated under the scenario of current project rents. Table 6-5 summarized the output values under each rent scenario. Under the assisted scenario, the majority of the properties had a mean NOI between $149 and $402. In comparison, the majority of the properties under the market scenario had a mean NOI that ranged from $190 to $529. A t-test was performed to compare the mean NOI values under both scenarios. The conclusion of the t-test was that the mean NOI values were statistically different (P-value of < 0.000), as presented in Table 6-6;

properties that charged market rents for all units (as opposed to restricted rents) yielded a higher net income.

To assess the impact on the bottom line of converting project rents to all market rents, the percentage change in estimated NOI values was calculated, as displayed in Table 6-7 and graphed in Figure 6-2. The mean NOI improved for more than 95% of the properties. For almost quarter of the properties, the mean NOI increased by up to 19.9%. Forty percent of properties experienced a rise in mean NOI between 20 and 39.9%, and for 30% of properties the estimated mean net income went up by 40 to 59.9%. According to the minimum values, there was a very small probability (less than 5%) for almost 41% of properties that the NOI dropped when project rents were calculated at to market rents. But less than 11% of properties experienced a decline in NOI at the 25th percentile, which means that the probability was 25% that the NOI was lower if all market rents were charged.

A drop in NOI would be possible for two reasons. First, some properties received project rents that were higher than the Fair Market Rent. Depending on the project rent to FMR ratio, a conversion to market rents can result in a smaller NOI. Second, for three of the bedroom sizes in Duval, the mean estimated market rents were lower than the Fair Market Rent. If the project rents for a property approximated FMR, the NOI can drop when revenues were calculated based on the simulated market rents.

Properties with a percentage change in mean NOI of at least 20% were considered at higher risk of conversion. According to the statistics presented in Table 6-8, roughly 71% of properties had an increase in mean NOI of at least 20%. For 60% of properties the probability was 50% that the NOI improved by at least 20%. For almost half of the properties, the probability was 75% that the NOI reached at least the 20% benchmark. The maximum NOI

values calculated by the simulation estimated that all properties experienced an increase in NOI of at least 32.8%. However, the probability of this was less than 5%.

The simulation could only estimate the debt coverage ratio for about 15% or 13 of the for-profit properties (Table 6-9). Under the assisted scenario, the mean DCR was below 1.0 for one property and was at a low of value between 1.0 and 1.19 for two properties. Under the market scenario, none of the properties had a mean DCR below 1.0, although the ratio was estimated at only 1.01 for one property.

Correlation and Multiple Regression Analysis

Multiple regression analysis was conducted to gain insight into the variables that impact net operating income. But first, a correlation matrix was generated to assess the correlation between each set of the following explanatory variables:

- Total number of units
- Target population (1=elderly; 0=family)
- Average unit size by number of bedrooms
- Year built
- Type of ownership (1=for-profit; 0=non-profit)
- REAC Physical Inspection Score
- Project rent to Fair Market Rent ratio
- Number of program layers
- Contract effective year
- Contract expiration year
- Original contract (1=not original contract; 0=original contract)

Analysis of the correlation statistics resulted in the exclusion of three explanatory variables from the regression analysis due to higher levels of correlation: Bedroom configuration, contract effective year and original contract. Bedroom configuration showed a very strong negative correlation of -0.803 with target population, implying a negative association between the average unit size by number of bedrooms and elderly as the target population. The bedroom variable was therefore removed from further analysis. The contract effective year was

also excluded from the regression analysis, because it was highly correlated with the original contract variable at 0.950. To a weaker degree, it was also correlated with total units at 0.529, number of program layers at 0.432 and year built at -0.412. The third explanatory variable that was not included in further analysis was the original contract variable, because it had a correlation of 0.524 with total units and -0.492 with year built.

A revised correlation matrix was prepared that excluded the three explanatory variables that had a relatively high correlation. The recalculated statistics indicated that no strong correlations were present; none of the correlations exceeded 0.379 (Table 6-10).

The first regression model included all eight explanatory variables. The results reported a coefficient of determination (R Square) of 0.513. In other words, 51.3% of the variation in the mean NOI was explained by this model. However, only two of the eight variables were calculated to significantly affect the NOI: Project rent to FMR and year built. Total units, target population, ownership type, REAC score, number of program layers and contract expiration year each had a relatively large P-value and small t-value, indicating no statistical significance.

To improve the regression model, a stepwise regression was completed with all eight explanatory variables. While six of the explanatory variables proved insignificant in the first regression, blindly excluding all these variables from a rerun of the regression analysis would not be appropriate. As explained by Albright, Winston, and Zappe (2006, 654), "it is possible that when one of these variables is excluded, another one of them will become significant." The stepwise procedure added one explanatory variable to the model at a time. At each step, the variable that contributes most to R square is selected to be added. After a variable is added, the stepwise method also removes any variables that are no longer significant. The steps are repeated until no more variables can be added to improve R square (Agresti and Finlay 1997). Table 6-11

revealed the outcome of the stepwise regression, reporting two variables that were significant: Project rent to FMR and year built. Compared to the first regression model, the R square dropped to 0.467 from 0.513. One of the statistical properties of R square is that it only increases when explanatory variables are added, hence the larger value in the first regression model. An alternative measure is the adjusted R square, which "adjusts R square for the number of explanatory variables in the equation. It is used primarily to monitor whether extra explanatory variables really belong in the equation" (Albright, Winston, and Zappe 2006, 590). The adjusted R square that resulted from the stepwise regression was 0.458, which was only slightly lower than the adjusted R square value of 0.477 as measured by the first regression model. In other words, 45.8% of the variation in the mean NOI was explained by only two explanatory variables.

The estimated regression coefficients of the stepwise model can be interpreted as follows:

- The predicted mean operating income will increase $221.88 when the project rent to FMR ratio is increased by 1%, keeping all other variables constant.
- The predicted mean operating income will increase $4.33 when the year built is increased by one year, keeping all other variables constant.

Fail-out Model: Descriptive Analysis and Significance Tests

Almost 27% of the properties (32 properties) were identified at higher risk of fail-out; 73% (87 properties) were considered at lower risk. Property characteristics seemed to differ between the higher and lower risk groups (Table 6-12). The majority of the properties in the higher risk group had either less than 50 units (25%) or more than 200 units (31%); more than half of the lower risk properties contained less than 100 units. On average, properties at higher risk had 124 units, compared to 99 units for the lower risk group. A significance test was performed to compare the groups. The P-value of the two-tail test was 0.123 (Table 6-13), which was greater than the significance level of 0.05. Therefore, the conclusion was made that there is no statistical difference in property size between the higher and lower risk properties.

The properties with higher fail-out risk seemed to contain smaller units by bedroom size. Seventy percent of units were studio or one-bedroom apartments; this figure amounted to 45% for the group of lower risk properties. The average number of bedrooms for the higher risk group was 1.1, compared to 1.5 for the lower risk properties. A t-test was run to examine the statistical difference in bedroom configuration. The P-value of the two-tail test was 0.023 (Table 6-14). Therefore, the null hypothesis was rejected and the conclusion was made that there was a statistical difference in the mean unit size; properties classified at higher fail-out risk had smaller units as measured by average number of bedrooms per unit.

The target population for the higher risk properties was fairly evenly distributed between family (44%) and elderly (56%). Almost 60% of the properties at lower risk targeted families. A significance test to compare the proportion of properties serving the elderly returned a P-value at 0.052 (Table 6-15), which meant no significant difference in target population at the 0.05 level.

The type of ownership for properties at higher risk of fail-out was evenly distributed between non-profits and for-profits. For properties at lower risk, 77% had for-profit ownership. The proportion of properties owned by non-profits was compared by applying a significance test. The P-value was calculated at 0.002 (Table 6-16), which implied that the null-hypothesis was rejected and that the difference in ownership type between higher and low risk properties was significant.

On average, properties in both groups were built in the 1970s; properties at higher risk had an average year built of 1974 compared to 1979 for those at lower risk. But the proportion of properties built by time period differed between the groups. More almost 69% of higher risk properties were constructed during 1970 to 1974 and almost 22% were erected between 1980 and 1984. In contrast, more than 56% of properties at lower risk were built during 1980 to 1984;

nearly 22% had a year of construction between 1970 and 1974. A t-test to compare the year built between the groups reported a P-value < 0.000 (Table 6-17). Therefore, the null hypothesis was rejected and the conclusion was drawn that the year built was statistically different; properties at higher risk of fail-out had an earlier year built.

The descriptive statistics showed that each risk group contained more than one third of properties with a REAC Physical Inspection Score of at least 90. But the proportion of properties for the score categories below 90 was different between the groups. All lower risk properties had a passing score of at least 60, while more than 34% of higher risk properties had a failing score below 60. This was the result of the approach that was taken to generate the list of properties at heightened risk of fail-out; a property was identified at risk if the REAC score fell below 60. A significance test confirmed the statistical difference between the risk groups; the P-value was 0.010 (Table 6-18).

The financial characteristics as summarized in Table 6-19 reflected the methodology of flagging properties at higher fail-out risk. Properties with a mean net operating income below $200 per unit per month or a mean debt coverage ratio below 1.0 were determined to be at higher risk. More than 31% of higher risk properties had an estimated mean NOI between $84 and $149; for almost 38% the mean NOI ranged between $150 and $199. Almost one third of the properties in the higher risk group were yielding a mean NOI greater than $200; these properties met either one of the other two conditions for inclusion in the higher risk group (REAC < 60 or DCR < 1.0). Almost 82% of the properties at lower fail-out risk had a mean NOI between $200 and $299.

The debt coverage ratio could only be calculated for 43% of the higher risk properties and less than 16% of the lower risk properties. Only two properties were estimated to have a DCR below 1.0. One of these also had a REAC score below 60.

The subsidy characteristics (Table 6-20) showed that for almost 91% of the properties in each risk group, the project rent to FMR ratio was below 100%. The proportion of properties with a rent to FMR below 80% was relatively large for properties at higher fail-out risk; it amounted to almost 66%, which contrasted to 31% for the lower risk group. On average the project rent to FMR was 78.7% for the higher risk group and 85.8% for the lower risk group. The significance test found that the project rent to FMR was statistically different between the groups; the P-value was calculated at 0.008 (Table 6-21).

The Loan Management Set Aside and Section 8 Substantial Rehabilitation programs were the largest categories of rental assistance programs for both higher and lower risk properties. More than 64% of properties at higher risk had a contract under the LMSA program and more than 18% were funded under Section 8 SR. Section 8 SR was the largest category for properties at lower risk (33%), followed by the LMSA program (almost 30%) and Section 8 New Construction (28%). A significance test was run to analyze the difference between the risk groups in the proportion of properties with a LMSA contract. At a P-value < 0.000, the test concluded that the difference was statistically significant; properties identified at higher risk had a larger proportion of contracts under the LMSA program (Table 6-22).

More than three quarters of the properties at higher risk no longer had a rental assistance contract in place under the original term; the contract was renewed at least once. In contrast, the lower risk group was fairly evenly divided between original contracts (more than 45%) and

renewed contracts (more than 54%). A statistically significant difference was detected between the groups in the contract renewal history (P-value at 0.017, Table 6-23).

The difference in current contract effective year was also found to be statically significant between the risk groups (P-value at 0.029, Table 6-24). More than 75% of properties at higher risk of fail-out had a contract effective year between 2000 and 2008; the contract effective year ranged between 1980 and 1989 for more than 18% of the higher risk properties. For lower risk properties, nearly 40% of the current contracts originated between 1980 and 1989 and more than 53% had a contract effective year of 2000 or later. The current contract effective year is related to the contract renewal history; contracts with an earlier effective year are still under their original term and have not yet been renewed.

The expiration year of the contract also varied between the higher and lower risk groups. Almost 94% of contracts for properties at higher risk of fail-out were due to expire by 2014. For lower risk properties, the percentage of expiring properties by 2014 was about 78%; almost 22% of properties had a contract expiration year between 2020 and 2025. The difference in expiration year was statistically significant between the groups at a P-value of 0.003 (Table 6-25).

A greater proportion of properties at higher fail-out risk had multiple program layers. Half of the higher risk properties had at least one other housing program in place in addition to the HUD rental assistance contract, most notably the HUD Section 236 program. About 31% of the properties in the lower risk group were covered by another housing program. The number of funding programs was compared between the risk groups. The significance test produced a P-value of 0.050 (Table 6-26). Therefore, it was inferred that the number of housing programs between the groups was statistically different; properties at higher fail-out had a greater number of housing programs in place.

Tenant characteristics were available for almost 67% of properties at higher risk of fail-out and 59% of properties in the lower risk group. The proportions in Table 6-27 were for the properties for which tenant data were available. The majority of properties classified at higher fail-out risk had a large proportion of tenants at age 62 and older and a smaller proportion of residents with a female head of household and children. Significance tests of the characteristics data confirmed a statistically significant difference between the risk groups in the proportion of households with a female head and children (P-value at 0.010, Table 6-28), and in the proportion of households at age 62 and older (P-value at 0.033, Table 6-29); the properties at higher risk of fail-out had a relatively greater number of households that were older than 61 and a relatively smaller number of single-mom family households.

At least 82% of households in each property in both risk groups were considered very low income at or below 50% of area median income. Both the higher risk and lower risk properties also served extremely low income households, those that were at or below 30% of AMI. Fifty to 74% of households were ELI for 40% of higher risk properties and more than 39% of lower risk properties; 75 to 100% of households were ELI for 50% of the higher risk group and almost 61% of the lower risk group. A t-test concluded that no significant difference existed between the proportions of ELI households served by the properties in each risk group (P-value at 0.092, Table 6-30).

Household income as a percentage of local median family amounted to less than 25% for almost 77% of lower risk properties, compared to 50% of those at higher risk. Income as a percentage of local median family income was between 25 and 49% for half of all higher risk properties and almost 24% of lower risk properties. Significance tests were performed to compare the household income as a percentage of local median family income (P-value at 0.346,

Table 6-31), as well as the annual household income (P-value at 0.101, Table 6-32). The conclusion was drawn that there was no significant difference in household income between the groups.

Two other variations between the risk groups were observed, which related to the proportion of minority households and overhoused households. From 75 to 100% of households were considered minority for nearly 73% of lower risk properties, compared to 45% of higher risk properties. A t-test was run and found a statistical difference in minority households (P-value at 0.033, Table 6-33); properties at higher risk of fail-out housed a lower proportion of minority households.

Less than 25% of households were overhoused in 65% of higher risk properties and in 33% of lower risk properties. The condition of overhousing may be explained by unit size; properties at higher fail-out risk are smaller in terms of number of bedrooms per unit. Therefore, overhousing is less likely to occur. A significance test concluded that the difference in overhousing between the risk groups was statistically significant (P-value at 0.018, Table 6-34); a smaller percentage of households in the higher fail-out group was overhoused.

Opt-out Model

Descriptive Analysis and Significance Tests

Table 6-35 with property characteristics showed that almost 78% of properties classified as higher risk of opt-out contained less than 50 units. The properties at lower opt-out risk were more evenly distributed among property size. On average, the higher risk group contained 47 units compared to 120 units in the lower risk group. A significance test confirmed that there was a statistical difference in the number of units between the groups (P-value < 0.000, Table 6-36); the properties in the higher risk group had a smaller number of units.

A large variation in target population also seemed apparent. The elderly were targeted by more than 66% of the higher risk properties and only 23% of the lower risk properties. A z-test was performed to compare the proportion of elderly by risk group. At a P-value of less than 0.000 (Table 6-37), the conclusion was drawn that the proportion of elderly was significantly different; a larger proportion of properties with a higher risk of opt-out targeted the elderly.

The difference in target population could also explain the variation in bedroom configuration between higher and lower risk properties. The majority of properties in the higher risk group had studio, 1 and 2 bedroom units, with an average number of bedrooms at 1.3. The smaller units are more appropriate for elderly households. Most of the properties in the higher risk group contained 1, 2 and 3 bedroom apartments, averaging 1.9 bedrooms per property. The difference in unit size was found to be statistically significant (P-value < 0.000, Table 6-38); higher risk properties had smaller units.

The majority of all for-profit properties were built during 1970-1974 or 1980-1984. The lower risk properties were mostly built during both time periods and average a year built of 1976. The higher risk properties were mainly constructed during 1980-1984 and had an average year built of 1981. The t-test concluded that a significant difference existed between the years built of the risk groups (P-value < 0.000, Table 6-39); properties at higher risk of opt-out were built in later years. It is likely that this finding was impacted by the condition that properties in the higher risk group had original contract terms. These could not have been built during the 1960s or 1970s, because most of those contracts would have already had an option to renew.

High REAC scores were achieved by both higher and lower risk properties. Nearly 67% of properties at higher opt-out risk and 79% of those at lower risk scored at least 80. A failing score of below 60 was observed for roughly 22% of the higher risk group and less than 4% of the

lower risk group. According to the results of a significance test, the REAC scores between the risk groups were statistically different (P-value at 0.04, Table 6-40); properties at higher risk had lower REAC scores.

The financial characteristics (Table 6-41) differed between the risk groups as a result of one of the criteria that were established to compose the list of properties at heightened risk of loss. Properties had to experience at least a 20% estimated increase in the mean NOI. For more than 55% of the higher risk properties, an increase of 20 to 39.9% was estimated; the increase in mean NOI was 40 to 59.9% for almost 41% of the properties. In the lower risk group, an increase of less than 20% was calculated for almost 45% of the properties. A significance test confirmed a statistical difference in the mean NOI change between the risk groups (P-value at 0.031, Table 6-42); the properties at higher risk of opt-out had a larger percentage increase in NOI when project rents are converted to market rents.

According to the subsidy characteristics (Table 6-43), the rent to Fair Market Rent ratio was below 100% for most higher risk and lower risk properties. Less than 19% of properties in the lower risk group had a project rent that was less than 80% of FMR, which compared to more than 39% of the properties in the lower risk group. On average, the project rent to FMR amounted to 86.4% for properties at higher risk and 84.7% for those at lower risk. At a P-value of 0.391 (Table 6-44), the difference in the project rent to FMR was not statistically different between the risk groups.

The prevailing types of rental assistance programs varied by risk group. More than 85% of properties at higher risk of opt-out were funded under the Section 8 Substantial Rehabilitation program and 11% under the Section 8 New Construction program. LMSA was the governing

program type among lower risk properties; almost 51% were funded under a LMSA contract. Section 8 NC and Section 8 SR each funded nearly 18% of lower risk properties.

Approximately 93% of higher risk properties had a current rental assistance contract effective year of 1980 to 1989 and a contract expiration year of 2008 to 2014. This large proportion was the result of the methodology that was applied to flag properties at higher risk of opt-out. To be identified at risk, properties had to be effective under the original contract term and have an expiration by year end 2014. In contrast, the majority of lower risk properties had a current contract year of 2000-2008 and an expiration year that varied from 2008 to 2025.

All but one of the properties in the higher risk group had the HUD rental assistance program as the only funding layer. More than 28% of lower risk properties had at least two housing programs, most notably a HUD insured mortgage without income restrictions in addition to the rental assistance program. The difference in number of funding programs between the groups was statistically significant (P-value 0.001, Table 6-45).

As illustrated by Table 6-46, tenant characteristics data were only available for four of the higher risk properties and 43 of those at lower risk. At least half of the households in almost 70% of the properties at lower risk of opt-out housed single-moms. The proportion of households with elderly tenants was small for the lower risk group; more than 69% of properties housed less than 25% elderly. This was in line with the observation that family – not elderly – was the major target population group for the lower risk properties. No further comparative analysis was conducted, because the sample of higher risk properties for which data were available was small.

Correlation and Scenario Analysis

An increase of at least 20% in NOI when assisted rents are converted to market rents was one of the conditions to be met for a property to be included in the group of properties at higher risk of opt-out. For more than 95% of the for-profit properties, the mean net operating income

improved under the scenario of all market rents. The reason for the increase in income was twofold. First, almost 93% of the properties had a project rent that was lower than the Fair Market Rent. Second, estimated mean market rents exceeded the Fair Market Rent for all the unit types in Miami-Dade and for two of the bedroom sizes in Duval.

For lack of a public data source with detailed and current market rents, the input values for the market scenario under the opt-out model were derived from Zilpy.com. The estimated market rents seemed reasonable, based on a comparison to the Fair Market Rent data. But since the reliability of Zilpy.com was unknown, the market scenario under the opt-out model was rerun with the 2009 Fair Market Rents as the input values for all units (in place of Zilpy rents). The mean NOI under the scenario of 2009 FMR was compared to the mean NOI under the scenario of assisted rents by calculating the change in mean NOI. Almost 88% of the properties saw an increase in NOI of at least 20%. This compared to 70% of the properties with market rents based on Zilpy, because the estimated Zilpy rents were lower than 2009 FMR for all of the unit sizes in Duval. Under the scenario of all 2009 FMR rents, only 2% of the properties (two properties) experienced a drop in mean NOI, compared to almost 5% (four properties) under the calculation with Zilpy-derived rents. The properties that had a project rent to FMR ratio that exceeded 100% did not achieve a positive change in NOI by at least 20% under the scenario with 2009 FMR rents.

The percentage change in the recalculated mean NOI was correlated to the project rent to FMR ratio. The outcome was a strong negative correlation at -0.876; a standard deviation increase in project rent to FMR ratio corresponded to a 0.876 decrease in the mean NOI change.

Table 6-47 compared the Fair Market Rents for 2008 and 2009 to the simulated mean rents (based on Zilpy) by county and bedroom size.

Table 6-1. Summary of Estimated Net Operating Income Values per Unit per Month for All Properties

Mean	Properties	Percentage
$83-149	10	8.4%
$150-199	12	10.1%
$200-249	42	35.3%
$250-299	37	31.1%
$300-349	13	10.9%
$350-403	5	4.2%
25th Percentile		
$66-99	7	5.9%
$100-149	6	5.0%
$150-199	25	21.0%
$200-249	43	36.1%
$250-299	28	23.5%
$300-349	7	5.9%
$350-387	3	2.5%
75th Percentile		
$100-149	7	5.9%
$150-199	10	8.4%
$200-249	30	25.2%
$250-299	45	37.8%
$300-349	18	15.1%
$350-399	6	5.0%
$400-419	3	2.5%

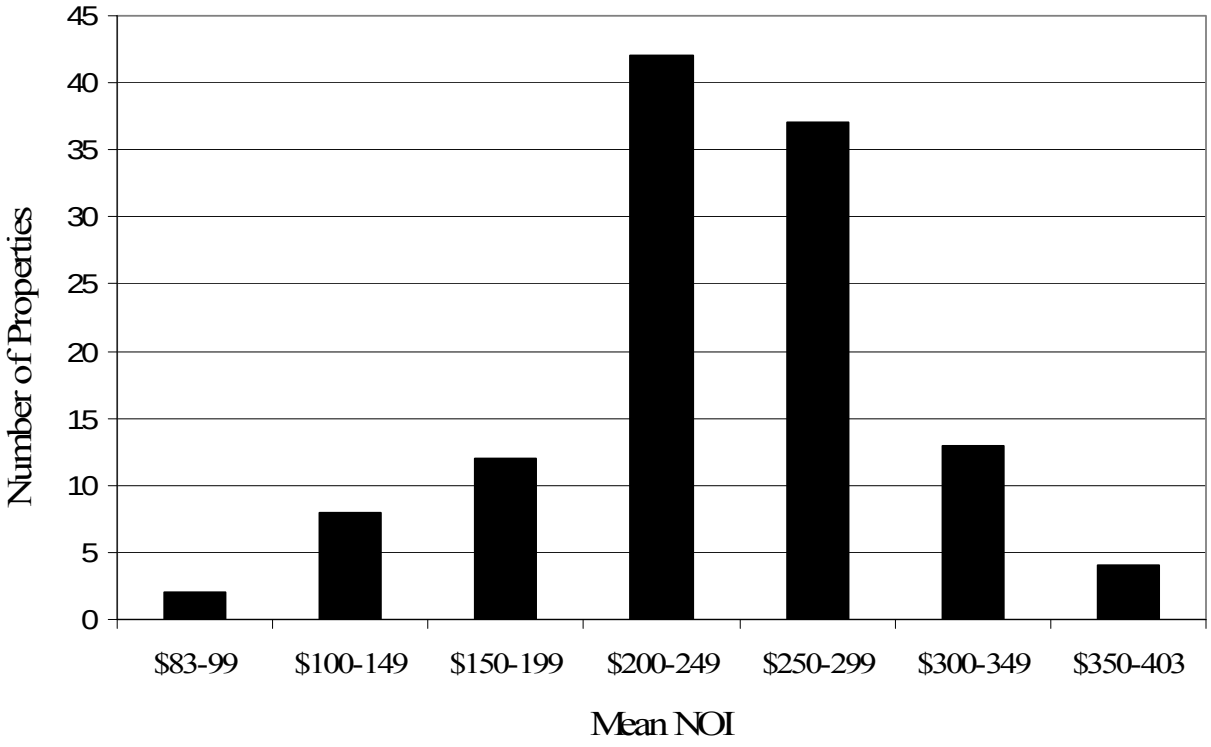


Figure 6-1. Mean Net Operating Income

Table 6-2. Comparison of the Simulated Mean and Median NOI Values to Reported NOI Values for Non-Market Rent Properties Per Unit per Month in Jacksonville MSA and Miami MSA

	Mean	Median	Properties	Units
Simulated NOI	$242	$245	119	12,570
Garden Properties, Jacksonville MSA	$223	$272	16	1,758
Elevator Properties, Jacksonville MSA	$176	$276	11	1,181
Garden Properties, Miami MSA	$261	$257	15	1,579
Elevator Properties, Miami MSA	$385	$334	59	6,969

Source: Urban Land Institute (2006).

Table 6-3. Number of Properties with an Estimated Net Operating Income Below $200 per Unit per Month by Probability for All Properties

	Properties	Percentage of 119 Properties
Mean	22	18.5%
Minimum	81	68.1%
5th percentile	56	47.1%
25th percentile	38	31.9%
50th percentile	22	18.5%
75th percentile	17	14.3%
95th percentile	12	10.1%
Maximum	7	5.9%

Table 6-4. Summary of Estimated Debt Coverage Ratio

Mean	Properties	Percentage
0.83-0.99	2	7.1%
1.0-1.19	2	7.1%
1.2-1.49	3	10.7%
1.5-1.99	2	7.1%
2.0-2.99	7	25.0%
3.0-3.99	7	25.0%
4.0-4.99	3	10.7%
5.0-6.68	2	7.1%
25th Percentile		
0.80-0.99	3	10.7%
1.0-1.19	1	3.6%
1.2-1.49	4	14.3%
1.5-1.99	5	17.9%
2.0-2.99	7	25.0%
3.0-3.99	6	21.4%
4.0-4.99	0	0.0%
5.0-6.03	2	7.1%
75th Percentile		
0.87-0.99	2	7.1%
1.0-1.19	0	0.0%
1.2-1.49	3	10.7%
1.5-1.99	3	10.7%
2.0-2.99	5	17.9%
3.0-3.99	7	25.0%
4.0-4.99	5	17.9%
5.0-7.03	3	10.7%

Table 6-5. Summary of Estimated Net Operating Income Values per Unit per Month by Rent Scenario for Opt-out Risk Model

	@ Assisted		@ Market	
Mean	Properties	Percentage	Properties	Percentage
$149-199	8	9.6%	1	1.2%
$200-249	35	42.2%	14	16.9%
$250-299	26	31.3%	17	20.5%
$300-349	12	14.5%	17	20.5%
$350-399	1	1.2%	20	24.1%
$400-449	1	1.2%	11	13.3%
$450-499	0	0.0%	0	0.0%
$500-529	0	0.0%	3	3.6%
25th Percentile				
$134-149	3	3.6%	0	0.0%
$150-199	19	22.9%	6	7.2%
$200-249	32	38.6%	23	27.7%
$250-299	23	27.7%	21	25.3%
$300-349	4	4.8%	20	24.1%
$350-399	2	2.4%	10	12.0%
$400-450	0	0.0%	3	3.6%
75th Percentile				
$165-199	4	4.8%	0	0.0%
$200-249	25	30.1%	3	3.6%
$250-299	34	41.0%	18	21.7%
$300-349	14	16.9%	14	16.9%
$350-399	5	6.0%	20	24.1%
$400-449	1	1.2%	16	19.3%
$450-499	0	0.0%	9	10.8%
$500-549	0	0.0%	0	0.0%
$550-588	0	0.0%	3	3.6%

Table 6-6. Significance Test of Mean NOI by Rent Scenario for Opt-out Risk Model

	Mean @ Assisted	Mean @ Market
Mean	252.0556965	329.4029134
Variance	2247.691523	5532.405399
Observations	83	83
Hypothesized Mean Difference	0	
df	139	
t Stat	-7.988978161	
P(T<=t) one-tail	2.33339E-13	
t Critical one-tail	1.655889868	
P(T<=t) two-tail	4.66678E-13	
t Critical two-tail	1.977177694	

Table 6-7. Percentage Change in Estimated NOI Value from Project Rents to Market Rents for the Opt-out Risk Model

	Mean		25th Percentile		75th Percentile	
	Properties	Percentage	Properties	Percentage	Properties	Percentage
-0.1%-16.0%	4	4.8%	9	10.8%	3	3.6%
0%-19.9%	20	24.1%	35	42.2%	18	21.7%
20.0%-39.9%	34	41.0%	21	25.3%	31	37.3%
40.0%-59.9%	17	20.5%	16	19.3%	23	27.7%
60.0%-79.0%	8	9.6%	2	2.4%	8	9.6%

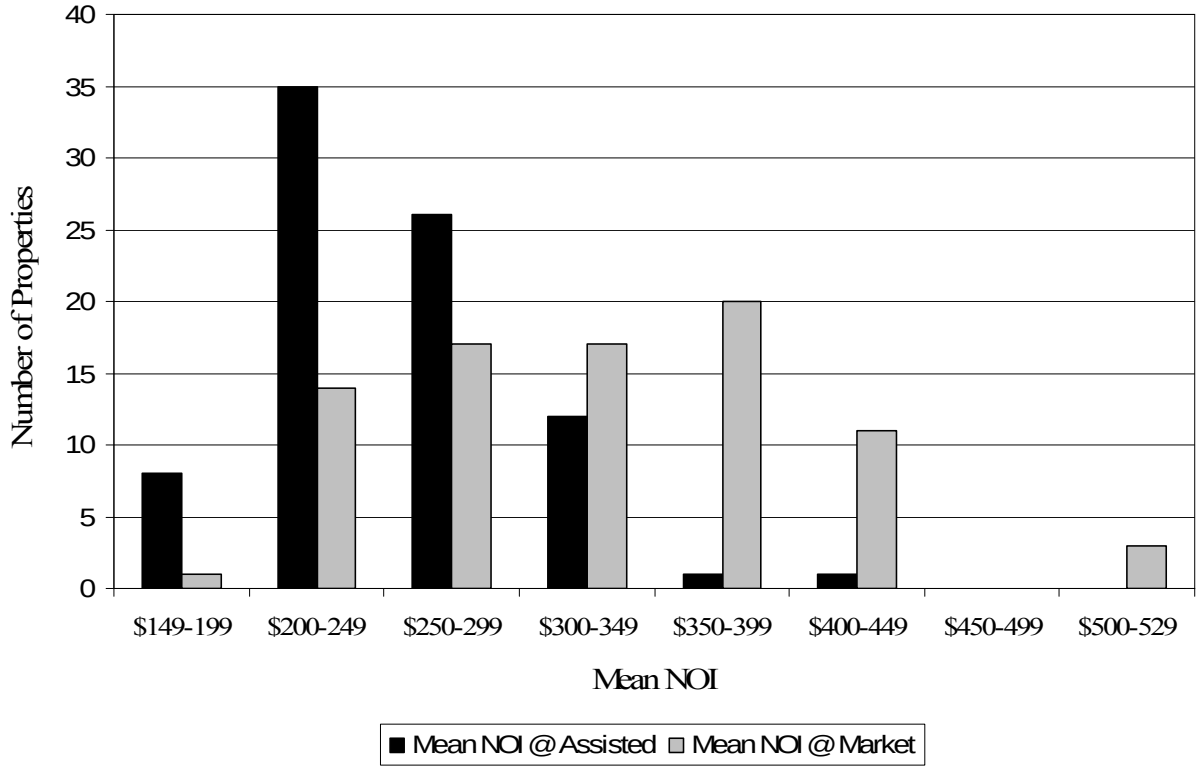


Figure 6-2. Mean Net Operating Income under Two Scenarios of Opt-out Model

Table 6-8. Number of Properties with an Estimated Change of Net Operating Income of At Least 20% by Probability for the Opt-out Risk Model

	Properties	Percentage of 83 Properties
Mean	59	71.1%
Minimum	21	25.3%
5th percentile	30	36.1%
25th percentile	39	47.0%
50th percentile	50	60.2%
75th percentile	62	74.7%
95th percentile	77	92.8%
Maximum	83	100.0%

Table 6-9. Summary of Estimated Debt Coverage Ratio for the Opt-out Risk Model

Mean	Properties	Percentage	Properties	Percentage
0.90-0.99	1	7.7%	0	0.0%
1.0-1.19	2	15.4%	1	7.7%
1.2-1.49	2	15.4%	3	23.1%
1.5-1.99	0	0.0%	1	7.7%
2.0-2.99	0	0.0%	0	0.0%
3.0-3.99	4	30.8%	0	0.0%
4.0-4.99	3	23.1%	1	7.7%
5.0-7.91	1	7.7%	7	53.8%
25th Percentile				
0.86-0.99	2	15.4%	1	7.7%
1.0-1.19	1	7.7%	3	23.1%
1.2-1.49	2	15.4%	0	0.0%
1.5-1.99	0	0.0%	1	7.7%
2.0-2.99	1	7.7%	0	0.0%
3.0-3.99	6	46.2%	1	7.7%
4.0-4.99	0	0.0%	2	15.4%
5.0-6.81	1	7.7%	5	38.5%
75th Percentile				
0.94-0.99	1	7.7%	0	0.0%
1.0-1.19	0	0.0%	1	7.7%
1.2-1.49	2	15.4%	3	23.1%
1.5-1.99	2	15.4%	0	0.0%
2.0-2.99	0	0.0%	1	7.7%
3.0-3.99	1	7.7%	0	0.0%
4.0-4.99	5	38.5%	1	7.7%
5.0-9.14	2	15.4%	7	53.8%

Table 6-10. Correlation Matrix

		NOI	Total_ Units	Target_ Pop	Year_ built	Ownership	Reac_score	FMR	Program_ lyr	Expiration_ dt
NOI	Pearson Correlation	1	-.262**	.128	.522**	.244**	-.029	.577**	-.152	.007
	Sig. (2-tailed)		.004	.166	.000	.008	.754	.000	.098	.940
	N	119	119	119	119	119	119	119	119	119
Total_Units	Pearson Correlation	-.262**	1	-.120	-.286**	-.194*	.110	-.098	.379**	-.060
	Sig. (2-tailed)	.004		.194	.002	.035	.235	.290	.000	.518
	N	119	119	119	119	119	119	119	119	119
Target_Pop	Pearson Correlation	.128	-.120	1	.299**	-.220*	.038	.272**	.075	-.304**
	Sig. (2-tailed)	.166	.194		.001	.016	.679	.003	.417	.001
	N	119	119	119	119	119	119	119	119	119
Year_built	Pearson Correlation	.522**	-.286**	.299**	1	.109	-.009	.299**	-.114	-.268**
	Sig. (2-tailed)	.000	.002	.001		.237	.918	.001	.218	.003
	N	119	119	119	119	119	119	119	119	119
Ownership	Pearson Correlation	.244**	-.194*	-.220*	.109	1	-.023	.162	-.287**	.239**
	Sig. (2-tailed)	.008	.035	.016	.237		.806	.077	.002	.009
	N	119	119	119	119	119	119	119	119	119
Reac_score	Pearson Correlation	-.029	.110	.038	-.009	-.023	1	.189*	.103	-.024
	Sig. (2-tailed)	.754	.235	.679	.918	.806		.039	.266	.793
	N	119	119	119	119	119	119	119	119	119
FMR	Pearson Correlation	.577**	-.098	.272**	.299**	.162	.189*	1	-.013	.034
	Sig. (2-tailed)	.000	.290	.003	.001	.077	.039		.885	.715
	N	119	119	119	119	119	119	119	119	119
Program_lyr	Pearson Correlation	-.152	.379**	.075	-.114	-.287**	.103	-.013	1	-.130
	Sig. (2-tailed)	.098	.000	.417	.218	.002	.266	.885		.160
	N	119	119	119	119	119	119	119	119	119
Expiration_dt	Pearson Correlation	.007	-.060	-.304**	-.268**	.239**	-.024	.034	-.130	1
	Sig. (2-tailed)	.940	.518	.001	.003	.009	.793	.715	.160	
	N	119	119	119	119	119	119	119	119	119

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 6-11. Results of Stepwise Regression for All Properties with Mean Net Operating Income as the Dependent Variable

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	FMR	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Year_built	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: NOI

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.577[a]	.333	.328	50.055
2	.683[b]	.467	.458	44.945

a. Predictors: (Constant), FMR

b. Predictors: (Constant), FMR, Year_built

ANOVA[c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	146501.335	1	146501.335	58.471	.000[a]
	Residual	293146.469	117	2505.525		
	Total	439647.804	118			
2	Regression	205323.497	2	102661.748	50.822	.000[b]
	Residual	234324.307	116	2020.037		
	Total	439647.804	118			

a. Predictors: (Constant), FMR

b. Predictors: (Constant), FMR, Year_built

c. Dependent Variable: NOI

Table 6-11. Continued

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.947	30.730		.324	.747
	FMR	276.825	36.202	.577	7.647	.000
2	(Constant)	-8498.348	1576.951		-5.389	.000
	FMR	221.884	34.063	.463	6.514	.000
	Year_built	4.326	.802	.383	5.396	.000

a. Dependent Variable: NOI

Excluded Variables[c]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Total_Units	-.208[a]	-2.821	.006	-.253	.990
	Target_Pop	-.031[a]	-.397	.692	-.037	.926
	Year_built	.383[a]	5.396	.000	.448	.911
	Ownership	.154[a]	2.042	.043	.186	.974
	Reac_score	-.143[a]	-1.885	.062	-.172	.964
	Program_lyr	-.145[a]	-1.938	.055	-.177	1.000
	Epriration_dt	-.013[a]	-.165	.869	-.015	.999
2	Total_Units	-.117[b]	-1.666	.098	-.154	.918
	Target_Pop	-.129[b]	-1.791	.076	-.165	.874
	Ownership	.131[b]	1.922	.057	.176	.970
	Reac_score	-.118[b]	-1.715	.089	-.158	.959
	Program_lyr	-.104[b]	-1.531	.129	-.141	.987
	Epriration_dt	.103[b]	1.457	.148	.135	.914

a. Predictors in the Model: (Constant), FMR

b. Predictors in the Model: (Constant), FMR, Year_built

c. Dependent Variable: NOI

Table 6-12. Property Characteristics for the Fail-out Model

	Higher Risk		Lower Risk		Total	
Property Characteristics:						
Number of Properties	32	26.9%	87	73.1%	119	100.0%
Number of Total Units	3,978	31.6%	8,592	68.4%	12,570	100.0%
Number of Assisted Units	3,978	32.9%	8,112	67.1%	12,090	100.0%
Property Size:						
Less than 50 units	8	25.0%	29	33.3%	37	31.1%
50-99 units	5	15.6%	19	21.8%	24	20.2%
100-149 units	4	12.5%	12	13.8%	16	13.4%
150-199 units	5	15.6%	13	14.9%	18	15.1%
more than 200 units	10	31.3%	14	16.1%	24	20.2%
Average number of units	124		99		106	
Bedroom Configuration:						
0 bedroom units	801	20.1%	689	8.0%	1,490	11.9%
1 bedroom units	1,987	49.9%	3,179	37.0%	5,166	41.1%
2 bedroom units	818	20.6%	2,924	34.0%	3,742	29.8%
3 bedroom units	344	8.6%	1,468	17.1%	1,812	14.4%
4 or more bedroom units	28	0.7%	332	3.9%	360	2.9%
Average number of bedrooms	1.1		1.5		1.4	
Target Population:						
Family	14	43.8%	52	59.8%	66	55.5%
Elderly	18	56.3%	34	39.1%	52	43.7%
Persons with Disabilities	-	0.0%	1	1.1%	1	0.8%
Type of Ownership:						
Non-profit	16	50.0%	20	23.0%	36	30.3%
For-profit	16	50.0%	67	77.0%	83	69.7%
Year Built:						
1967-1969	2	6.3%	4	4.6%	6	5.0%
1970-1974	22	68.8%	19	21.8%	41	34.5%
1975-1979	-	0.0%	10	11.5%	10	8.4%
1980-1984	7	21.9%	49	56.3%	56	47.1%
1985-1989	1	3.1%	3	3.4%	4	3.4%
1990-1994	-	0.0%	2	2.3%	2	1.7%
Average Year Built	1974		1979		1978	

Table 6-12. Continued

REAC Physical Inspection Score:						
13-29	3	9.4%	-	0.0%	3	2.5%
30-59	8	25.0%	-	0.0%	8	6.7%
60-69	1	3.1%	9	10.3%	10	8.4%
70-79	3	9.4%	10	11.5%	13	10.9%
80-89	6	18.8%	36	41.4%	42	35.3%
90-100	11	34.4%	32	36.8%	43	36.1%
Average REAC Score	71		85		81	
County:						
Duval	17	53.1%	30	34.5%	47	39.5%
Miami-Dade	15	46.9%	57	65.5%	72	60.5%
Metropolitan Location:						
Metropolitan/central city	14	43.8%	44	50.6%	58	48.7%
Suburb	16	50.0%	34	39.1%	50	42.0%
Non-metropolitan	2	6.3%	9	10.3%	11	9.2%
Low Poverty Census Tract:						
No	30	93.8%	76	87.4%	106	89.1%
Yes	2	6.3%	11	12.6%	13	10.9%

Table 6-13. Significance Test of Total Units per Property by Risk Group for the Fail-out Risk Model

	Total units higher risk	Total units lower risk
Mean	124.3125	98.75862069
Variance	6395.899194	5714.534082
Observations	32	87
Hypothesized Mean Difference	0	
Df	53	
t Stat	1.568117703	
P(T<=t) one-tail	0.061402686	
t Critical one-tail	1.674116237	
P(T<=t) two-tail	0.122805372	
t Critical two-tail	2.005745949	

Table 6-14. Significance Test of Average Unit Size by Risk Group for the Fail-out Risk Model

	Average br size higher risk	Average br size lower risk
Mean	1.14439346	1.53190707
Variance	0.60584367	0.76796959
Observations	32	87
Hypothesized Mean Difference	0	
Df	62	
t Stat	-2.32583226	
P(T<=t) one-tail	0.01165651	
t Critical one-tail	1.66980416	
P(T<=t) two-tail	0.02331302	
t Critical two-tail	1.9989715	

Table 6-15. Significance Test of Proportion of Elderly Properties by Risk Group for the Fail-out Risk Model

	Elderly	Family	Total	%
High risk	18	14	32	0.5625
Low risk	34	52	86	0.3953

Ho = $\pi 2 - \pi 1 = 0$

Estimate - null hypothesis value	-0.167151163
proportion of total sample	0.440677966
standard error	0.102803623
z=	-1.625926768
P-value	0.051982617

Table 6-16. Significance Test of Proportion of Non-profit Owners by Risk Group for the Fail-out Risk Model

	Non-profit	For-profit	Total	%
High risk	16	16	32	0.5000
Low risk	20	67	87	0.2299
Estimate - null hypothesis value	-0.270114943			
proportion of total sample	0.302521008			
standard error	0.094969073			
z=	-2.844241109			
P-value	0.002225867			

Table 6-17. Significance Test of Year Built by Risk Group for the Fail-out Risk Model

	Yr built higher risk	Yr built lower risk
Mean	1974.25	1978.701149
Variance	23.41935484	26.30499866
Observations	32	87
Hypothesized Mean Difference	0	
Df	58	
t Stat	-4.376909501	
P(T<=t) one-tail	2.54442E-05	
t Critical one-tail	1.671552763	
P(T<=t) two-tail	5.08885E-05	
t Critical two-tail	2.001717468	

Table 6-18. Significance Test of REAC Physical Inspection Score by Risk Group for the Fail-out Risk Model

	REAC higher risk	REAC lower risk
Mean	71.21875	84.551724
Variance	738.24093	90.017642
Observations	32	87
Hypothesized Mean Difference	0	
Df	34	
t Stat	-2.715664	
P(T<=t) one-tail	0.00516	
t Critical one-tail	1.6909242	
P(T<=t) two-tail	0.0103201	
t Critical two-tail	2.0322445	

Table 6-19. Financial Characteristics for the Fail-out Model

	Higher Risk		Lower Risk		Total	
Mean NOI:						
$84-149	10	31.3%	-	0.0%	10	8.4%
$150-199	12	37.5%	-	0.0%	12	10.1%
$200-249	4	12.5%	38	43.7%	42	35.3%
$250-299	4	12.5%	33	37.9%	37	31.1%
$300-349	1	3.1%	12	13.8%	13	10.9%
$350-403	1	3.1%	4	4.6%	5	4.2%
Mean DCR:						
0.83-0.99	2	6.3%	-	0.0%	2	1.7%
1.0-1.19	-	0.0%	2	2.3%	2	1.7%
1.2-1.49	-	0.0%	3	3.4%	3	2.5%
1.49-1.99	1	3.1%	1	1.1%	2	1.7%
2.0-2.99	7	21.9%	-	0.0%	7	5.9%
3.0-3.99	2	6.3%	5	5.7%	7	5.9%
4.0-4.99	1	3.1%	2	2.3%	3	2.5%
5.0-6.68	1	3.1%	1	1.1%	2	1.7%
Not available	18	56.3%	73	83.9%	91	76.5%

Table 6-20. Subsidy Characteristics for the Fail-out Model

	Higher Risk		Lower Risk		Total	
Percentage HUD RA Units:						
0-24%	-	0.0%	1	1.1%	1	0.8%
25-49%	1	3.1%	2	2.3%	3	2.5%
50-74%	4	12.5%	2	2.3%	6	5.0%
75-99%	5	15.6%	5	5.7%	10	8.4%
100%	22	68.8%	77	88.5%	99	83.2%
Average % HUD RA Units	92.4%		96.5%		95.4%	
Rent to FMR Ratio:						
50-59.9%	2	6.3%	2	2.3%	4	3.4%
60-69.9%	6	18.8%	2	2.3%	8	6.7%
70-79.9%	13	40.6%	23	26.4%	36	30.3%
80-89.9%	5	15.6%	36	41.4%	41	34.5%
90-99.9%	3	9.4%	16	18.4%	19	16.0%
100-109.9%	3	9.4%	4	4.6%	7	5.9%
110-119.9%	-	0.0%	2	2.3%	2	1.7%
120-129.9%	-	0.0%	1	1.1%	1	0.8%
130-139.9%	-	0.0%	-	0.0%	-	0.0%
140-142.2%	-	0.0%	1	1.1%	1	0.8%
Average Rent to FMR Ratio	78.7%		85.8%		83.9%	
Number of HUD RA Contracts per Property:						
1	31	96.9%	86	98.9%	117	98.3%
2	1	3.1%	1	1.1%	2	1.7%
HUD RA Program Type (by contract):						
Loan Management Set Aside	21	63.6%	26	29.5%	47	38.8%
Section 8 Substantial Rehab	6	18.2%	29	33.0%	35	28.9%
Section 8 New Construction	1	3.0%	25	28.4%	26	21.5%
HFDA/8 New Construction	1	3.0%	4	4.5%	5	4.1%
Property Disposition/8 Existing	2	6.1%	3	3.4%	5	4.1%
Property Disposition/8 Mod. Rehab	-	0.0%	1	1.1%	1	0.8%
Section 8 Preservation	1	3.0%	-	0.0%	1	0.8%
Rent Supplement	1	3.0%	-	0.0%	1	0.8%
Contract Renewal History (by contract):						
Original contract term	8	24.2%	40	45.5%	48	39.7%
Renewed contract	25	75.8%	48	54.5%	73	60.3%
Current Contract Effective Year:						
1970-1979	1	3.0%	4	4.5%	5	4.1%
1980-1989	6	18.2%	35	39.8%	41	33.9%
1990-1999	1	3.0%	2	2.3%	3	2.5%
2000-2008	25	75.8%	47	53.4%	72	59.5%

Table 6-20. Continued

	Higher Risk		Lower Risk		Total	
Expiration of Current Contract:						
2008-2009	13	39.4%	14	15.9%	27	22.3%
2010-2014	18	54.5%	54	61.4%	72	59.5%
2015-2019	-	0.0%	1	1.1%	1	0.8%
2020-2025	2	6.1%	19	21.6%	21	17.4%
Program Source:						
HUD	32	100.0%	87	100.0%	119	100.0%
RD	-	0.0%	-	0.0%	-	0.0%
FHFC	5	15.6%	8	9.2%	13	10.9%
LHFA	2	6.3%	4	4.6%	6	5.0%
No. of Program Layers:						
1	16	50.0%	66	75.9%	82	68.9%
2	11	34.4%	14	16.1%	25	21.0%
3	4	12.5%	4	4.6%	8	6.7%
4	1	3.1%	3	3.4%	4	3.4%
Average No. of Program Layers	1.7		1.4		1.4	
Funding Program Combinations:						
HUD RA Only	16	50.0%	66	75.9%	82	68.9%
HUD RA; HUD Section 236	8	25.0%	-	0.0%	8	6.7%
HUD RA; HUD Section 236; Elderly Housing Community Loan	2	6.3%	-	0.0%	2	1.7%
HUD RA; HUD Insured Mortgage – Unassisted	1	3.1%	11	12.6%	12	10.1%
HUD RA; HUD Insured Mortgage - Unassisted; Housing Credits 9%; SAIL	-	0.0%	2	2.3%	2	1.7%
HUD RA; HUD Insured Mortgage - Unassisted; State HOME; Elderly Housing Community Loan	1	3.1%	-	0.0%	1	0.8%
HUD RA; HUD Insured Mortgage - Unassisted; Bonds	2	6.3%	1	1.1%	3	2.5%
HUD RA; Housing Credits 9%	-	0.0%	1	1.1%	1	0.8%
HUD RA; Housing Credits 9%;State HOME	-	0.0%	1	1.1%	1	0.8%
HUD RA; Housing Credits 4%; Bonds	-	0.0%	1	1.1%	1	0.8%
HUD RA; State HOME	1	3.1%	-	0.0%	1	0.8%
HUD RA; SAIL	1	3.1%	1	1.1%	2	1.7%
HUD RA; Elderly Housing Community Loan; Bonds	-	0.0%	2	2.3%	2	1.7%
HUD RA; Bonds	-	0.0%	1	1.1%	1	0.8%

Table 6-21. Significance Test of Rent to Fair Market Rent Ratio by Risk Group for the Fail-out Risk Model

	Rent to FMR higher risk	Rent to FMR lower risk
Mean	0.787127	0.857636
Variance	0.015299	0.01545
Observations	32	87
Hypothesized Mean Difference	0	
Df	56	
t Stat	-2.753588	
P(T<=t) one-tail	0.003967	
t Critical one-tail	1.672522	
P(T<=t) two-tail	0.007933	
t Critical two-tail	2.003241	

Table 6-22. Significance Test of Proportion of Properties with a LMSA contract by Risk Group for the Fail-out Risk Model

	LMSA	Other	Total	%
High risk	21	12	33	0.6364
Low risk	26	62	88	0.2955
Estimate - null hypothesis value	-0.340909091			
proportion of total sample	0.388429752			
standard error	0.09948871			
z=	-3.426610844			
P-value	0.000305582			

Table 6-23. Significance Test of Proportion of Renewed Contracts by Risk Group for the Fail-out Risk Model

	Contract Renewed	Original Contract	Total	%
High risk	25	8	33	0.7576
Low risk	48	40	88	0.5455
Estimate - null hypothesis value	-0.212121212			
proportion of total sample	0.603305785			
standard error	0.099859884			
z=	-2.124188447			
P-value	0.016827194			

Table 6-24. Significance Test of Contract Effective Year by Risk Group for the Fail-out Risk Model

	Yr effective higher risk	Yr effective lower risk
Mean	1998.75	1993.64368
Variance	114.83871	140.185512
Observations	32	87
Hypothesized Mean Difference	0	
Df	61	
t Stat	2.23926221	
P(T<=t) one-tail	0.01439799	
t Critical one-tail	1.67021948	
P(T<=t) two-tail	0.02879599	
t Critical two-tail	1.99962357	

Table 6-25. Significance Test of Contract Expiration Year by Risk Group for the Fail-out Risk Model

	Expiration yr higher risk	Expiration yr lower risk
Mean	2010.8438	2013.1494
Variance	8.5877016	25.733226
Observations	32	87
Hypothesized Mean Difference	0	
df	95	
t Stat	-3.069735	
P(T<=t) one-tail	0.0013966	
t Critical one-tail	1.6610518	
P(T<=t) two-tail	0.0027931	
t Critical two-tail	1.985251	

Table 6-26. Significance Test of Number of Funding Layers by Risk Group for the Fail-out Risk Model

	Funding layers higher risk	Funding Layers lower risk
Mean	1.6875	1.356322
Variance	0.673387	0.534349
Observations	32	87
Hypothesized Mean Difference	0	
Df	50	
t Stat	2.008606	
P(T<=t) one-tail	0.024997	
t Critical one-tail	1.675905	
P(T<=t) two-tail	0.049995	
t Critical two-tail	2.008559	

Table 6-27. Tenant Characteristics for the Fail-out Model

	Higher Risk		Lower Risk		Total	
Properties with data	20	66.7%	51	58.6%	71.0	59.7%
Properties without data	10	33.3%	36	41.4%	46.0	38.7%
% Female Head with Children:						
0-24%	11	55.0%	17	33.3%	28.0	39.4%
25-49%	3	15.0%	3	5.9%	6.0	8.5%
50-74%	6	30.0%	19	37.3%	25.0	35.2%
75-100%	-	0.0%	12	23.5%	12.0	16.9%
% of All Persons with Disability:						
0-24%	19	95.0%	49	96.1%	68.0	95.8%
25-49%	1	5.0%	2	3.9%	3.0	4.2%
50-74%	-	0.0%	-	0.0%	-	0.0%
75-100%	-	0.0%	-	0.0%	-	0.0%
% 62 Year of Age or More:						
0-24%	7	35.0%	30	58.8%	37.0	52.1%
25-49%	2	10.0%	4	7.8%	6.0	8.5%
50-74%	1	5.0%	5	9.8%	6.0	8.5%
75-100%	10	50.0%	12	23.5%	22.0	31.0%
% Minority:						
0-24%	6	30.0%	1	2.0%	7.0	9.9%
25-49%	2	10.0%	5	9.8%	7.0	9.9%
50-74%	3	15.0%	8	15.7%	11.0	15.5%
75-100%	9	45.0%	37	72.5%	46.0	64.8%
Annual Household Income (rounded to $000's):						
$3,000	-	0.0%	1	2.0%	1.0	1.4%
$4,000	-	0.0%	-	0.0%	-	0.0%
$5,000	-	0.0%	2	3.9%	2.0	2.8%
$6,000	2	10.0%	1	2.0%	3.0	4.2%
$7,000	1	5.0%	16	31.4%	17.0	23.9%
$8,000	5	25.0%	9	17.6%	14.0	19.7%
$9,000	4	20.0%	9	17.6%	13.0	18.3%
$10,000	4	20.0%	7	13.7%	11.0	15.5%
$11,000	1	5.0%	3	5.9%	4.0	5.6%
$12,000	3	15.0%	3	5.9%	6.0	8.5%
% Very Low Income:						
0-24%	-	0.0%	-	0.0%	-	0.0%
25-49%	-	0.0%	-	0.0%	-	0.0%
50-74%	-	0.0%	-	0.0%	-	0.0%
75-100%	20	100.0%	51	100.0%	71.0	100.0%

Table 6-27. Continued

	Higher Risk		Lower Risk		Total	
% Extremely Low Income:						
0-24%	-	0.0%	-	0.0%	-	0.0%
25-49%	2	10.0%	-	0.0%	2.0	2.8%
50-74%	8	40.0%	20	39.2%	28.0	39.4%
75-100%	10	50.0%	31	60.8%	41.0	57.7%
Household Income as % of Local Median Family Income:						
0-24%	10	50.0%	39	76.5%	49.0	69.0%
25-49%	10	50.0%	12	23.5%	22.0	31.0%
50-74%	-	0.0%	-	0.0%	-	0.0%
75-100%	-	0.0%	-	0.0%	-	0.0%
Average Monthly Rent with Utilities:						
$97-149	3	15.0%	26	51.0%	29.0	40.8%
$150-199	10	50.0%	21	41.2%	31.0	43.7%
$200-249	5	25.0%	4	7.8%	9.0	12.7%
$250-275	2	10.0%	-	0.0%	2.0	2.8%
Average Years Since Moved in:						
2-5	12	60.0%	28	54.9%	40.0	56.3%
6-9	7	35.0%	19	37.3%	26.0	36.6%
10-13	1	5.0%	4	7.8%	5.0	7.0%
% of Households Overhoused:						
0-24%	13	65.0%	17	33.3%	30.0	42.3%
25-49%	2	10.0%	11	21.6%	13.0	18.3%
50-74%	4	20.0%	16	31.4%	20.0	28.2%
75-100%	1	5.0%	7	13.7%	8.0	11.3%

Table 6-28. Significance Test of Percentage of Female Heads of Household with Children by Risk Group for the Fail-out Risk Model

	% Female head with kids higher risk	% Female head with kids lower risk
Mean	23.6	44.98039
Variance	803.7263	1132.42
Observations	20	51
Hypothesized Mean Difference	0	
df	41	
t Stat	-2.706799	
P(T<=t) one-tail	0.004929	
t Critical one-tail	1.682878	
P(T<=t) two-tail	0.009858	
t Critical two-tail	2.019541	

Table 6-29. Significance Test of Percentage of Heads of Households at Age 62 or Older by Risk Group for the Fail-out Risk Model

	% 62 or more higher risk	% 62 or more lower risk
Mean	59.3	36.352941
Variance	1626.4316	1217.7929
Observations	20	51
Hypothesized Mean Difference	0	
df	31	
t Stat	2.2372753	
P(T<=t) one-tail	0.0162983	
t Critical one-tail	1.6955187	
P(T<=t) two-tail	0.0325967	
t Critical two-tail	2.0395134	

Table 6-30. Significance Test of Percentage of Extremely Low Income Households by Risk Group for the Fail-out Risk Model

	% ELI higher risk	% ELI lower risk
Mean	70.6	76.94117647
Variance	191.2	193.5764706
Observations	20	51
Hypothesized Mean Difference	0	
df	35	
t Stat	-1.73515334	
P(T<=t) one-tail	0.045756311	
t Critical one-tail	1.68957244	
P(T<=t) two-tail	0.091512622	
t Critical two-tail	2.030107915	

Table 6-31. Significance Test of Household Income as a Percentage of the Local Median Family Income by Risk Group for the Fail-out Risk Model

	HH inc. as % higher risk	HH inc. as % lower risk
Mean	22.9	21.470588
Variance	31.884211	33.094118
Observations	20	51
Hypothesized Mean Difference	0	
df	35	
t Stat	0.9544026	
P(T<=t) one-tail	0.1732128	
t Critical one-tail	1.6895724	
P(T<=t) two-tail	0.3464255	
t Critical two-tail	2.0301079	

Table 6-32. Significance Test of Annual Household Income by Risk Group for the Fail-out Risk Model

	HH inc. higher risk	HH inc. lower risk
Mean	9.1	8.2941176
Variance	3.2526316	3.4117647
Observations	20	51
Hypothesized Mean Difference	0	
df	36	
t Stat	1.6821043	
P(T<=t) one-tail	0.0506022	
t Critical one-tail	1.6882977	
P(T<=t) two-tail	0.1012045	
t Critical two-tail	2.028094	

Table 6-33. Significance Test of Percentage of Minority Households by Risk Group for the Fail-out Risk Model

	% minority higher risk	% minority lower risk
Mean	60	81.98039216
Variance	1664.842105	563.7796078
Observations	20	51
Hypothesized Mean Difference	0	
df	24	
t Stat	-2.263535982	
P(T<=t) one-tail	0.016462116	
t Critical one-tail	1.710882067	
P(T<=t) two-tail	0.032924233	
t Critical two-tail	2.063898547	

Table 6-34. Significance Test of Percentage of Overhoused Households by Risk Group for the Fail-out Risk Model

	% of hh overhoused higher risk	% of hh overhoused lower risk
Mean	21.1	40.6470588
Variance	873.357895	921.232941
Observations	20	51
Hypothesized Mean Difference	0	
df	36	
t Stat	-2.4878762	
P(T<=t) one-tail	0.00880874	
t Critical one-tail	1.68829769	
P(T<=t) two-tail	0.01761749	
t Critical two-tail	2.02809399	

Table 6-35. Property Characteristics for the Opt-out Model

	Higher Opt-out Risk		Lower Opt-out Risk		Total	
Property Characteristics:						
Number of Properties	27	32.5%	56	67.5%	83	100.0%
Number of Total Units	1258	15.8%	6694	84.2%	7952	100.0%
Number of Assisted Units	1258	16.6%	6341	83.4%	7599	100.0%
Property Size:						
Less than 50 units	21	77.8%	10	17.9%	31	37.3%
50-99 units	3	11.1%	13	23.2%	16	19.3%
100-149 units	1	3.7%	9	16.1%	10	12.0%
150-199 units	0	0.0%	12	21.4%	12	14.5%
more than 200 units	2	7.4%	12	21.4%	14	16.9%
Average number of units	47		120		96	
Bedroom Configuration:						
0 bedroom units	216	17.2%	294	4.4%	510	6.4%
1 bedroom units	603	47.9%	2093	31.3%	2696	33.9%
2 bedroom units	353	28.1%	2768	41.4%	3121	39.2%
3 bedroom units	74	5.9%	1385	20.7%	1459	18.3%
4 or more bedroom units	12	1.0%	154	2.3%	166	2.1%
Average number of bedrooms	1.3		1.9	0.0%	1.8	
Target Population:						
Family	9	33.3%	43	76.8%	52	62.7%
Elderly	18	66.7%	13	23.2%	31	37.3%
Persons with Disabilities	0	0.0%	0	0.0%	0	0.0%
Type of Ownership:						
Non-profit	0	0.0%	0	0.0%	0	0.0%
For-profit	27	100.0%	56	100.0%	83	100.0%
Year Built:						
1967-1969	0	0.0%	6	10.7%	6	7.2%
1970-1974	0	0.0%	23	41.1%	23	27.7%
1975-1979	2	7.4%	5	8.9%	7	8.4%
1980-1984	25	92.6%	17	30.4%	42	50.6%
1985-1989	0	0.0%	3	5.4%	3	3.6%
1990-1994	0	0.0%	2	3.6%	2	2.4%
Average Year Built	1981		1976		1978	
REAC Physical Inspection Score:						
13-29	2	7.4%	0	0.0%	2	2.4%
30-59	4	14.8%	2	3.6%	6	7.2%
60-69	1	3.7%	7	12.5%	8	9.6%
70-79	2	7.4%	3	5.4%	5	6.0%
80-89	11	40.7%	21	37.5%	32	38.6%
90-100	7	25.9%	23	41.1%	30	36.1%

Table 6-35. Continued

	Higher Opt-out Risk		Lower Opt-out Risk		Total	
Average REAC Score	74		84		81	
County:						
Duval	0	0.0%	33	58.9%	33	39.8%
Miami-Dade	27	100.0%	23	41.1%	50	60.2%
Metropolitan Location:						
Metropolitan/central city	15	55.6%	29	51.8%	44	53.0%
Suburb	8	29.6%	25	44.6%	33	39.8%
Non-metropolitan	4	14.8%	2	3.6%	6	7.2%
Low Poverty Census Tract:						
Yes	0	0.0%	9	16.1%	9	10.8%
No	27	100.0%	47	83.9%	74	89.2%

Table 6-36. Significance Test of Total Units per Property by Risk Group for the Opt-out Risk Model

	Total units low risk	Total units high risk
Mean	119.5357143	46.59259259
Variance	4667.744156	4996.404558
Observations	56	27
Hypothesized Mean Difference	0	
Df	50	
t Stat	4.452350773	
P(T<=t) one-tail	2.38696E-05	
t Critical one-tail	1.675905026	
P(T<=t) two-tail	4.77392E-05	
t Critical two-tail	2.008559072	

Table 6-37. Significance Test of Proportion of Elderly Properties by Risk Group for the Opt-out Risk Model

	Elderly	Family	Total	%
High risk	18	9	27	0.6667
Low risk	13	43	56	0.2321
Ho = $\pi 2 - \pi 1 = 0$				
Estimate - null hypothesis value	-0.4345238			
proportion of total sample	0.37349398			
standard error	0.11333592			
z=	-3.8339461			
P-value	6.3052E-05			

Table 6-38. Significance Test of Average Unit Size by Risk Group for the Opt-out Risk Model

	Average br size per property low risk	Average br size per property high risk
Mean	1.767384792	0.803010198
Variance	0.484078749	0.433132739
Observations	56	27
Hypothesized Mean Difference	0	
df	54	
t Stat	6.137881397	
P(T<=t) one-tail	5.12083E-08	
t Critical one-tail	1.673564907	
P(T<=t) two-tail	1.02417E-07	
t Critical two-tail	2.004879275	

Table 6-39. Significance Test of Year Built by Risk Group for the Opt-out Risk Model

	Yr built lower risk	Yr built higher risk
Mean	1976.428571	1980.925926
Variance	40.57662338	0.686609687
Observations	56	27
Hypothesized Mean Difference	0	
df	59	
t Stat	-5.193054216	
P(T<=t) one-tail	1.34339E-06	
t Critical one-tail	1.671093033	
P(T<=t) two-tail	2.68677E-06	
t Critical two-tail	2.000995361	

Table 6-40. Significance Test of REAC Physical Inspection Score by Risk Group for the Opt-out Risk Model

	REAC lower risk	REAC higher risk
Mean	84.14285714	73.59259259
Variance	123.0701299	613.4045584
Observations	56	27
Hypothesized Mean Difference	0	
Df	31	
t Stat	2.113591139	
P(T<=t) one-tail	0.021349135	
t Critical one-tail	1.695518742	
P(T<=t) two-tail	0.04269827	
t Critical two-tail	2.039513438	

Table 6-41. Financial Characteristics for the Opt-out Model

	Higher Opt-out Risk		Lower Opt-out Risk		Total	
Mean NOI Change:						
-0.1%-8.0%	0	0.0%	4	7.1%	4	4.8%
0%-19.9%	0	0.0%	21	37.5%	21	25.3%
20.0%-39.9%	15	55.6%	15	26.8%	30	36.1%
40.0%-59.9%	11	40.7%	10	17.9%	21	25.3%
60.0%-75.6%	1	3.7%	6	10.7%	7	8.4%

Table 6-42. Significance Test of the Mean NOI Change by Risk Group for the Opt-out Risk Model

	Mean % change lower risk	Mean % change higher risk
Mean	0.278078992	0.37676551
Variance	0.04577512	0.018419853
Observations	56	27
Pooled Variance	0.036994417	
Hypothesized Mean Difference	0	
Df	81	
t Stat	-2.189911565	
P(T<=t) one-tail	0.015703493	
t Critical one-tail	1.663883913	
P(T<=t) two-tail	0.031406986	
T Critical two-tail	1.989686288	

Table 6-43. Subsidy Characteristics for the Opt-out Model

	Higher Opt-out Risk		Lower Opt-out Risk		Total	
Funding Source:						
HUD	27	100.0%	56	100.0%	83	100.0%
RD	0	0.0%	0	0.0%	0	0.0%
FHFC	1	3.7%	4	7.1%	5	6.0%
LHFA	0	0.0%	4	7.1%	4	4.8%
No. of Program Layers:						
1	26	96.3%	40	71.4%	66	79.5%
2	0	0.0%	11	19.6%	11	13.3%
3	1	3.7%	3	5.4%	4	4.8%
4	0	0.0%	2	3.6%	2	2.4%
Average No. of Program Layers	1.1		1.4		1.3	
Percentage HUD RA Units:						
0-24%	0	0.0%	0	0.0%	0	0.0%
25-49%	0	0.0%	2	3.6%	2	2.4%
50-74%	0	0.0%	1	1.8%	1	1.2%
75-99%	0	0.0%	5	8.9%	5	6.0%
100%	27	100.0%	48	85.7%	75	90.4%
Average % HUD RA Units	100.0%		96.0%		97.3%	
Number of HUD RA Contracts per Property:						
1	27	100.0%	55	98.2%	82	98.8%
2	0	0.0%	1	1.8%	1	1.2%
HUD RA Program Type:						
HFDA/8 NC	0	0.0%	3	5.3%	3	3.6%
PD/8 MR	1	3.7%	0	0.0%	1	1.2%
LMSA	0	0.0%	29	50.9%	29	34.5%
PD/8 Existing	0	0.0%	4	7.0%	4	4.8%
Sec 8 NC	3	11.1%	10	17.5%	13	15.5%
Sec 8 SR	23	85.2%	10	17.5%	33	39.3%
Preservation	0	0.0%	1	1.8%	1	1.2%
Rent to FMR Ratio:						
67-79.9%	5	18.5%	22	39.3%	27	32.5%
80-89.9%	11	40.7%	23	41.1%	34	41.0%
90-99.9%	10	37.0%	6	10.7%	16	19.3%
100-109.9%	1	3.7%	3	5.4%	4	4.8%
110-121.0%	0	0.0%	2	3.6%	2	2.4%
Average Rent to FMR Ratio	86.4%		84.7%		85.2%	
Funding Program Combinations:						
HUD RA Only	26	96.3%	40	71.4%	66	79.5%
HUD RA; Bonds	0	0.0%	1	1.8%	1	1.2%
HUD RA: Bonds;HUD Insured Mortgage - Unassisted	0	0.0%	2	3.6%	2	2.4%
HUD RA; Housing Credits 4%;Bonds	0	0.0%	1	1.8%	1	1.2%
HUD RA; Housing Credits 9%	0	0.0%	1	1.8%	1	1.2%
HUD RA; Housing Credits 9%;SAIL;HUD Insured Mortgage - Unassisted	0	0.0%	2	3.6%	2	2.4%
HUD RA; Housing Credits 9%;State HOME	1	3.7%	0	0.0%	1	1.2%

Table 6-43. Continued

	Higher Opt-out Risk		Lower Opt-out Risk		Total	
HUD RA; HUD Insured Mortgage – Unassisted	0	0.0%	8	14.3%	8	9.6%
HUD RA; HUD Section 236	0	0.0%	1	1.8%	1	1.2%
Contract Renewal History:						
Original contract term	27	100.0%	8	14.0%	35	41.7%
Renewed contract	0	0.0%	49	86.0%	49	58.3%
Current Contract Effective Year:						
1970-1979	1	3.7%	0	0.0%	1	1.2%
1980-1989	25	92.6%	7	12.3%	32	38.1%
1990-1999	1	3.7%	1	1.8%	2	2.4%
2000-2008	0	0.0%	49	86.0%	49	58.3%
Expiration of HUD RA Contract:						
2008-2009	2	7.4%	9	15.8%	11	13.1%
2010-2014	25	92.6%	28	49.1%	53	63.1%
2015-2019	0	0.0%	1	1.8%	1	1.2%
2020-2025	0	0.0%	19	33.3%	19	22.6%

Table 6-44. Significance Test of Rent to Fair Market Rent Ratio by Risk Group for the Opt-out Risk Model

	Rent to FMR lower risk	Rent to FMR higher risk
Mean	0.84655797	0.863616578
Variance	0.011479136	0.005000712
Observations	56	27
Hypothesized Mean Difference	0	
Df	73	
t Stat	-0.863579079	
P(T<=t) one-tail	0.19532386	
t Critical one-tail	1.665996224	
P(T<=t) two-tail	0.390647721	
t Critical two-tail	1.992997097	

Table 6-45. Significance Test of Number of Funding Layers by Risk Group for the Opt-out Risk Model

	Funding Layers low risk	Funding layers high risk
Mean	1.410714286	1.074074074
Variance	0.573701299	0.148148148
Observations	56	27
Hypothesized Mean Difference	0	
Df	81	
t Stat	2.683978715	
P(T<=t) one-tail	0.004409663	
t Critical one-tail	1.663883913	
P(T<=t) two-tail	0.008819326	
t Critical two-tail	1.989686288	

Table 6-46. Tenant Characteristics for the Opt-out Model

	Higher Opt-out Risk		Lower Opt-out Risk		Total	
Properties with data	4	14.8%	43	76.8%	47	56.6%
Properties without data	23	85.2%	13	23.2%	36	43.4%
% Female Head with Children:						
0-24%	2	50.0%	9	20.9%	11	23.4%
25-49%	1	25.0%	4	9.3%	5	10.6%
50-74%	0	0.0%	22	51.2%	22	46.8%
75-100%	1	25.0%	8	18.6%	9	19.1%
% of All Persons with Disability:						
0-24%	4	100.0%	41	95.3%	45	95.7%
25-49%	0	0.0%	2	4.7%	2	4.3%
50-74%	0	0.0%	0	0.0%	0	0.0%
75-100%	0	0.0%	0	0.0%	0	0.0%
% 62 Year of Age or More:						
0-24%	1	25.0%	30	69.8%	31	66.0%
25-49%	0	0.0%	4	9.3%	4	8.5%
50-74%	1	25.0%	3	7.0%	4	8.5%
75-100%	2	50.0%	6	14.0%	8	17.0%
% 85 Year of Age or More:						
0-24%	4	100.0%	43	100.0%	47	100.0%
25-49%	0	0.0%	0	0.0%	0	0.0%
50-74%	0	0.0%	0	0.0%	0	0.0%
75-100%	0	0.0%	0	0.0%	0	0.0%
% Minority:						
0-24%	0	0.0%	0	0.0%	0	0.0%
25-49%	0	0.0%	5	11.6%	5	10.6%
50-74%	0	0.0%	8	18.6%	8	17.0%
75-100%	4	100.0%	30	69.8%	34	72.3%
Annual Household Income:						
3000	0	0.0%	1	2.3%	1	2.1%
4000	0	0.0%	0	0.0%	0	0.0%
5000	0	0.0%	2	4.7%	2	4.3%
6000	0	0.0%	2	4.7%	2	4.3%
7000	2	50.0%	11	25.6%	13	27.7%
8000	0	0.0%	8	18.6%	8	17.0%
9000	1	25.0%	8	18.6%	9	19.1%
10000	1	25.0%	7	16.3%	8	17.0%
11000	0	0.0%	1	2.3%	1	2.1%
12000	0	0.0%	3	7.0%	3	6.4%

Table 6-46. Continued

	Higher Opt-out Risk		Lower Opt-out Risk		Total	
% Very Low Income:						
0-24%	0	0.0%	0	0.0%	0	0.0%
25-49%	0	0.0%	0	0.0%	0	0.0%
50-74%	0	0.0%	0	0.0%	0	0.0%
75-100%	4	100.0%	43	100.0%	47	100.0%
% Extremely Low Income:						
0-24%	0	0.0%	0	0.0%	0	0.0%
25-49%	0	0.0%	0	0.0%	0	0.0%
50-74%	2	50.0%	18	41.9%	20	42.6%
75-100%	2	50.0%	25	58.1%	27	57.4%
Household Income as % of Local Median Family Income:						
0-24%	3	75.0%	34	79.1%	37	78.7%
25-49%	1	25.0%	9	20.9%	10	21.3%
50-74%	0	0.0%	0	0.0%	0	0.0%
75-100%	0	0.0%	0	0.0%	0	0.0%
Average Monthly Rent with Utilities:						
$97-149	2	50.0%	19	44.2%	21	44.7%
$150-199	2	50.0%	21	48.8%	23	48.9%
$200-249	0	0.0%	3	7.0%	3	6.4%
$250-275	0	0.0%	0	0.0%	0	0.0%
Average Years Since Moved in:						
2-5	0	0.0%	28	65.1%	28	59.6%
6-9	3	75.0%	12	27.9%	15	31.9%
10-13	1	25.0%	3	7.0%	4	8.5%
% of Households Overhoused:						
0-24%	2	50.0%	10	23.3%	12	25.5%
25-49%	1	25.0%	12	27.9%	13	27.7%
50-74%	1	25.0%	16	37.2%	17	36.2%
75-100%	0	0.0%	5	11.6%	5	10.6%

Table 6-47. Comparison of Rents by County and Bedroom Size

		0 br	1br	2br	3br	4br
Duval	FMR '08	616	701	816	1024	1173
	Simulated Market	628	628	790	976	1205
	FMR '09	685	779	907	1138	1304
Miami-Dade	FMR '08	753	853	1035	1324	1547
	Simulated Market	851	954	1294	1701	2160
	FMR '09	842	953	1156	1479	1728

CHAPTER 7
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Summary and Conclusions: Fail-out Risk

A property was classified as higher risk of fail-out if it met one of the following three criteria:

- Mean net operating income below $200 per unit per month, or
- Mean debt coverage ratio below 1.0, or
- REAC Physical Inspection Score below 60.

The majority of the higher risk group was composed of properties that only met the NOI condition. The significance tests found statistically significant differences in characteristics between the higher and lower risk groups. The analysis concluded that properties at higher risk of fail-out had the following characteristics compared to the lower risk properties:

- Smaller unit sizes by bedrooms
- Non-profit ownership
- Earlier year built
- Lower project rent to FMR ratio
- Larger proportion of contracts under LMSA program
- Contract renewed at least once (not original term)
- More recent contract effective year
- Earlier contract expiration year
- More additional program layers (Section 236)
- More households at age 62 and older
- Fewer households with a female head and children
- Smaller proportion of minority households
- Smaller proportion of overhoused households

Several of these variables were related. The LMSA program was designed to supplement the income of Section 236 properties, which were built by non-profits and limited dividend (for-profit) entities in the late 1960s and early 1970s. Contracts under the LMSA program generally had shorter terms than those under the Section 8 NC/SR programs, hence the finding that contracts have been renewed, which in turn can explain the more recent contract effective year.

The finding that the properties at higher risk served a larger number of tenants at age 62 can explain the smaller unit sizes and the lower number of single-mom families. The smaller unit size can explain the smaller proportion of overhoused households.

Higher risk properties were also found to have the following characteristics, which were similar (not statistically different) to those of properties at lower risk of fail-out:

- Family as well as elderly target population
- Smaller (less than 50 units) as well as larger (more than 200 units) property size
- All very low income households
- Large proportion of extremely low income households

To gain additional insight into the differences in characteristics between properties at higher risk of fail-out and those at lower risk, multiple regression analysis was conducted with the mean NOI as the dependent variable. Since almost 69% of the properties flagged at higher risk met the lower NOI condition, the regression analysis was expected to provide further insight into the variables that impacted the level of NOI. The analysis calculated that project rent to FMR and year built were statistically significant; the lower the project rent to FMR or the earlier the year built, the lower the mean NOI. The significance tests also found that the project rent to FMR and year built were statistically different between the properties at higher risk of fail-out and those at lower risk; the higher risk properties had a lower project rent to FMR and an earlier year built.

The findings that project rent to FMR and year built were significant were consistent with the outcomes of analysis by Abt Associates, Inc. In a national study for HUD (Finkel et al. 2006) and a Florida study for the University of Florida (Finkel and Lam 2008), Abt concluded that a larger percentage of HUD properties in distress or foreclosure had a lower project rent to FMR of below 80% and an earlier year built of before 1975. In both studies, Abt also found that the majority of these distressed properties were funded under older HUD mortgage programs such as

Section 236, had a rental assistance contract under the LMSA program, and had the lowest REAC Physical Inspection Score compared to other categories of properties.

To identify properties with project-based rental assistance at fail-out risk, the argument can be made that a risk assessment method can simply be based on a small number of key indicators: Project rent to Fair Market Rent ratio and year built. Based on the results of the significance tests, the stepwise regression analysis and the studies by Abt, these indicators could be sufficient to create a shortlist of properties at heightened risk. In addition, properties with a failing REAC score should be considered at risk. A more sophisticated or complex approach to flag properties may not add much value. It may also not be realistic, considering the current data limitations concerning the actual financial and physical conditions of properties.

A shortlist based on the three key indicators is a first step towards actual preservation of properties and protection of tenants. It could provide insight into the magnitude of properties that could be lost and that should receive attention from policy-makers and advocates. The next step is for policy-makers to acknowledge the need for preservation and to allocate resources. The next step is also for advocates to approach properties on the shortlist to assess the feasibility of preservation and the willingness of the owner to participate; it is during this step that detailed property-level data can be collected concerning items such as operating expenses, reserve accounts and capital needs, provided an owner is interested in participating or selling the property to a preserving entity.

Summary and Conclusions: Opt-out Risk

For the opt-out model, a property was considered at higher risk if it met all of the following criteria:

- For-profit ownership, and
- Increase in mean NOI by at least 20% when all market rents were charged, and

- Expiration of the rental assistance contract by year end 2014, and
- Original contract term, and
- Not located in a low poverty census tract.

The descriptive analysis and significance tests of the opt-out risk model found that the properties at higher risk had the following characteristics compared to those at lower risk:[1]

- Smaller property size
- Larger proportion of elderly households
- Smaller unit sizes by bedrooms
- Later year built
- Lower REAC scores
- More contracts funded under the Section 8 NC/SR program
- Smaller number of program layers

The properties at higher risk of opt-out were more likely to serve the elderly, which could also explain the smaller units. The later year built could be related to the smaller property size; in later years, properties were built with fewer units.

A significance test found no statistical difference in the project rent to FMR ratios between the risk groups. The majority of properties had project rents that were lower than FMR.

The finding that more properties at higher risk of opt-out had elderly as the target population was in contrast to the finding in the national report by Abt that elderly properties were less likely to opt-out than family properties (Finkel et al. 2006). However, the Abt analysis for the Florida sample did not indicate statistical significance of the target population to the opt-out decision (Finkel and Lam 2008).

The large number of elderly properties flagged at higher risk of opt-out can be explained by one of the conditions that had to be met as part of the opt-out risk model: Original contract term. This condition was established based on the assumption that properties that have had a chance to renew their current rental assistance contract at least once are not interested in the

[1] Not enough data were available to compare tenant characteristics.

conversion to market-rate housing, or they would have opted out of the contract. The condition was also based on the assumption that a wave of opt-outs will occur when rental assistance contracts with original terms hit their expiration dates and their first opportunity to make the opt-out/renew decision, as was experienced in the late 1990s. Analysis of the properties that had an original contract term revealed that almost 69% had elderly as the target population. This would explain the larger number of elderly properties in the higher risk group.

The characteristics found to be significantly different between the properties identified at higher and lower risk of opt-out were driven by the conditions that were established to determine level of risk. Therefore, these characteristics (e.g., elderly target population) should not be used as criteria to shortlist properties at risk of opt-out.

As was confirmed by the correlation statistics, the lower the project rent to FMR ratio, the larger the change in net operating income when all units are leased at market rent rather than project rent. Therefore, when identifying properties at risk of opt-out, the first key indicator should be the project rent to Fair Market Rent. Once a shortlist is created of properties by project rent to FMR, additional criteria can be applied to further specify the properties at risk of opt-out such as the expiration year and contract renewal history.

Project rent to FMR was found to be the key explanatory variable in both the national study and the analysis for Florida conducted by Abt. "The key explanatory variable … is the rent-to-FMR ratio. It explains the largest share of variations in the probability of opting out, suggesting that a property's pre-opt-out rent relative to the local market rent is the most important determinant of the owner's opt-out decision, controlling for all other characteristics. When the Section 8 rent is significantly below the market level (proxy by FMR), owners realize

that a conversion to market rate units can increase the rental revenues (and therefore profits) with little effect on vacancy rates" (Finkel and Lam 2008, 17).

Recommendations for Policy

The first policy recommendation is that the federal government allocate more funding to the Section 8 project-based rental assistance program. This is essential, considering the need for housing and the risk of losing part of the affordable stock. Additional funding will have two purposes. The first purpose is to provide incentives to current owners to renew the rental assistance contract upon expiration. Incentives could include financial resources for rehabilitation. Another incentive could be to adjust the project rent to 100% of the Fair Market Rent, if the project rent to FMR is currently lower. The second purpose is to provide funding to new owners for acquisition and rehabilitation of properties with a project-based rental assistance contract.

While additional funding is a valid recommendation, it may not be realistic considering today's economic climate and federal budget deficit. The Center on Budget and Policy Priorities estimated that approximately $8.2 billion is required for the Section 8 project-based rental assistance program in 2010; $7.9 billion for the renewal of existing contracts and the remaining funds to expand the program.

In lieu of the allocation of additional federal funds to expand the program, the recommendation is for the federal government to sustain the current level of funding for the renewal of contracts and to commit to making subsidy payments on time and in full. During 2008, HUD experienced insufficient appropriations to fund the renewal of rental assistance contracts for a full year and was also making late subsidy payments (Bodaken 2008). These conditions add another reason for property owners to consider opting out of a rental assistance contract, thereby increasing the opt-out risk.

A recommendation is also for governments to increase the accessibility to property-level data. Federal, state and local governments that administer housing programs collect massive amounts of data as part of the initial loan or contract origination process and the subsequent program compliance and contract renewal process. It is suggested that they make data publicly available in an accessible format for the purpose of research and preservation. These data should be at the property-level and are to be comprehensive in terms of the variables that are reported (including tenant data and financial data). The information should be current and updated regularly. Comprehensive historical data related to terminated subsidies and past property characteristics would also be essential, allowing for the research of historical patterns of fail-outs and opt-outs.

Recommendations for Future Research

It is recommended that the research is expanded to other geographical areas. Future research could focus on all metropolitan areas in Florida, or could encompass all counties in the state. Expanding the research to incorporate other jurisdictions would increase the primary data collection effort, but it would also provide insight into the level of risk of a larger population of properties with project-based rental assistance contracts. The research could even expand beyond Florida. Rental assistance contracts could be compared across metropolitan areas in multiple states or across entire states. The limitation is that many other areas outside of Florida do not have a database comparable to the Assisted Housing Inventory, which contains data that complement the HUD public datasets and that are essential to the research. Therefore, any comparative research on areas outside of Florida should focus on the jurisdictions that have extensive public data sources.

A related recommendation is to expand the research to other funding programs. Properties subsidized by other programs are also at risk of fail-out due to large capital needs and

deterioration or at risk of opt-out due to prepayment of mortgages or termination of use restrictions. All subsidized properties contribute to the much needed affordable housing stock, whether they provide deep or shallow subsidies. Therefore, the preservation of all types of subsidized properties is important. Expanding the research to other funding programs increases the complexity of the analysis, especially if many properties have multiple funding layers with multiple options for the termination of affordability. It also requires substantial property data collection, because public data sources are limited for programs under funding sources other than HUD; even the public HUD datasets do not report on several critical data fields and various housing programs.

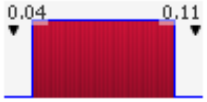
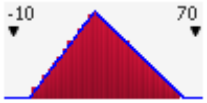
Another recommendation for future research is to pursue the collection of historical data on Section 8 project-based rental assistance contracts that have been terminated. These data would have to include detailed property-level information such as address, type of ownership, target population, REAC score, project rent to FMR ratio, original contract effective date, contract renewal dates and opt-out date. Data on the financial and physical condition of the property at the time of opt-out would also be valuable. The historical data would allow for the research of properties that already made a decision not to renew the contract. The analysis could provide insight into the indicators of actual loss. Abt Associates Inc. in a study for HUD (Finkel et al. 2006) conducted analysis of the Section 8 opt-outs and opt-ins, and compared property characteristics. Abt performed the same analysis for Florida under contract with the University of Florida (Finkel and Lam 2008). However, under the contractual agreement with HUD, Abt could not share the raw historical data. Therefore, to acquire the raw data would allow for additional research about the opt-outs. The historical data would have to be obtained from HUD.

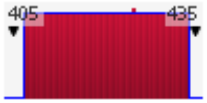
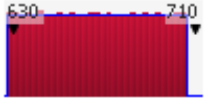
Alternatively, case studies can be conducted and property data can be collected from owners or property management firms.

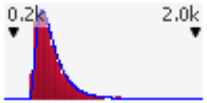
Validation of the risk assessment method applied in this research is also a recommendation. First, it is recommended that the outcomes presented in this study are compared to the results of other risk assessment tools that have analyzed the assisted housing stock in Florida. This comparative analysis can assess if the various methods identify the same properties, the same types of properties in terms of characteristics, and the same magnitude of properties at risk. Second, if detailed historical data can be obtained about the properties that already opted out of a rental assistance contract, the risk assessment method could be tested to assess if the properties would have been identified at higher risk of loss.

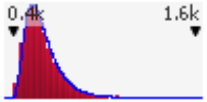
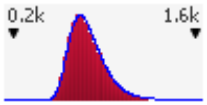
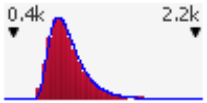
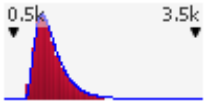
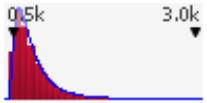
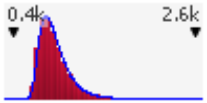
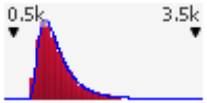
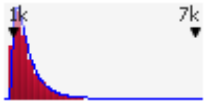
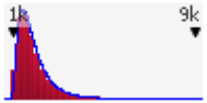
APPENDIX A
INPUT VARIABLES AND SIMULATION RESULTS

Table A-1. Input variables and simulation results

Input Variable	Model/ Scenario	Probability	Graph	Mean	Min	5%	25%	50%	75%	95%	Max
Vacancy Loss and Bad Debt Allowance	All	Uniform		7.50%	5.00%	5.25%	6.25%	7.50%	8.75%	9.75%	10.00%
Operating Expense Ratio: Section 236	All	Uniform		73.80%	65.71%	66.50%	69.75%	73.79%	77.84%	81.09%	81.89%
Operating Expense Ratio: Section 8 - Family (1965-77)	All	Uniform		62.10%	55.60%	56.24%	58.84%	62.09%	65.34%	67.95%	68.59%
Operating Expense Ratio: Section 8 - Family (1978-06)	All	Uniform		61.35%	54.11%	54.82%	57.72%	61.34%	64.97%	67.87%	68.59%
Operating Expense Ratio: Section 8 - Elderly/Persons w Disab. (1965-77)	All	Uniform		55.20%	50.71%	51.15%	52.95%	55.19%	57.45%	59.25%	59.69%
Operating Expense Ratio: Section 8 - Elderly/Persons w Disab. (1978-06)	All	Uniform		53.75%	50.70%	51.00%	52.22%	53.75%	55.27%	56.49%	56.80%
Replacement Reserve	All	Triangular		29.67	1.24	9.07	20.33	28.93	38.78	51.88	61.50
Cathedral Terrace - S. 236 Rent - 1 br	Fail-out	Uniform		594.50	518.07	525.54	556.17	594.49	632.72	663.25	670.94
Fannie E. Taylor Home For The Aged - S. 236 Rent - 1 br	Fail-out	Uniform		597.00	550.01	554.66	573.43	596.92	620.46	639.27	643.98
Florida Christian Home - S. 236 Rent - 0 br	Fail-out	Uniform		538.50	505.01	508.31	521.72	538.48	555.20	568.64	571.97

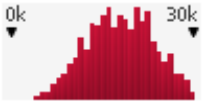
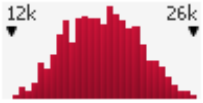
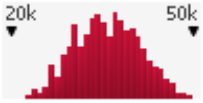
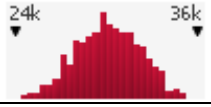
Florida Christian Home - S. 236 Rent - 1 br	Fail-out	Uniform		596.00	563.05	566.26	579.45	595.95	612.46	625.70	628.95
Miami Beach Marian Towers - S. 236 Rent - 1 br	Fail-out	Uniform		508.00	490.02	491.78	498.97	507.97	516.99	524.18	525.97
Mt Carmel Gardens - S. 236 Rent - 0 br	Fail-out	Uniform		420.50	408.00	409.23	414.23	420.48	426.74	431.75	432.98
Mt Carmel Gardens - S. 236 Rent - 1 br	Fail-out	Uniform		511.00	494.01	495.68	502.50	510.97	519.47	526.27	527.97
Pablo Towers - S. 236 Rent - 1 br	Fail-out	Uniform		667.50	631.06	634.58	649.20	667.47	685.73	700.28	703.96
Riverside Presbyterian Apartments - S. 236 Rent - 0 br	Fail-out	Uniform		515.50	476.07	479.94	495.74	515.48	535.25	551.05	554.96
Riverside Presbyterian Apartments - S. 236 Rent - 1 br	Fail-out	Uniform		669.50	618.09	623.09	643.68	669.45	695.21	715.83	720.98
The Towers Of Jacksonville - S. 236 Rent - 1 br	Fail-out	Uniform		661.50	555.08	565.47	608.09	661.48	714.66	757.29	767.79
Town Park Plaza South, Inc. - S. 236 Rent - 1 br	Fail-out	Uniform		457.00	418.06	421.87	437.43	456.98	476.46	492.09	495.94
Town Park Plaza South, Inc. - S. 236 Rent - 2 br	Fail-out	Uniform		474.00	435.03	438.86	454.44	473.96	493.46	509.04	512.98
Town Park Plaza South, Inc. - S. 236 Rent - 3 br	Fail-out	Uniform		510.00	468.07	472.16	488.98	509.99	530.92	547.72	551.95

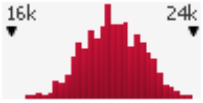
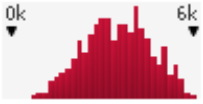
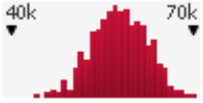
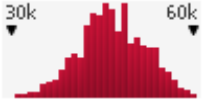
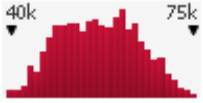
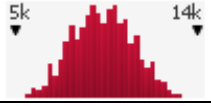
Town Park Plaza South, Inc. - S. 236 Rent - 4 br	Fail-out	Uniform		513.50	471.07	475.20	492.19	513.48	534.74	551.71	555.94
Town Park Village I - Market Rent - 3 br	Fail-out	Uniform		631.50	621.01	622.05	626.23	631.49	636.74	640.94	641.98
Caroline Arms Apartments - Market Rent - 2 br	Fail-out; Opt-out @ Assisted	Uniform		550.00	516.04	519.39	532.99	549.99	566.94	580.58	584.00
Caroline Arms Apartments - Market Rent - 3 br	Fail-out; Opt-out @ Assisted	Uniform		563.50	529.06	532.43	546.25	563.48	580.69	594.52	597.98
Caroline Arms Apartments - Market Rent - 4 br	Fail-out; Opt-out @ Assisted	Uniform		580.00	545.03	548.46	562.45	580.00	597.47	611.49	614.94
Fieldcrest Apartments - Market Rent - 2 br	Fail-out; Opt-out @ Assisted	Uniform		834.00	789.05	793.46	811.43	833.96	856.41	874.42	879.00
Monaco Arms Apartments II - Market Rent - 1 br	Fail-out; Opt-out @ Assisted	Uniform		497.00	480.01	481.67	488.47	497.00	505.50	512.29	513.97
Monaco Arms Apartments II - Market Rent - 2 br	Fail-out; Opt-out @ Assisted	Uniform		554.00	535.02	536.88	544.49	554.00	563.49	571.08	572.98
Monaco Arms I - Market Rent - 1 br	Fail-out; Opt-out @ Assisted	Uniform		498.00	480.01	481.79	488.97	497.97	506.97	514.20	516.00
Monaco Arms I - Market Rent - 2 br	Fail-out; Opt-out @ Assisted	Uniform		550.50	535.00	536.54	542.73	550.49	558.24	564.42	566.00
Duval - Market Rent - 0 br	Opt-out @ Market	Lognormal		628.11	427.55	473.43	529.84	592.28	684.99	899.54	1,862.10

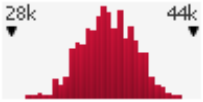
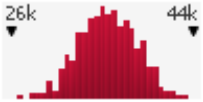
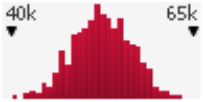
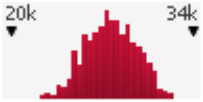
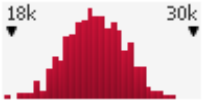
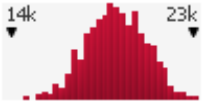
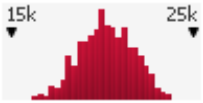
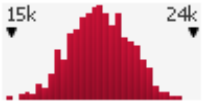
Duval - Market Rent - 1 br	Opt-out @ Market	Lognormal		628.10	456.45	501.72	553.13	605.45	677.15	829.08	1,447.24
Duval - Market Rent - 2 br	Opt-out @ Market	Lognormal		789.47	521.48	619.29	698.45	770.14	858.84	1,025.23	1,419.63
Duval - Market Rent - 3 br	Opt-out @ Market	Lognormal		976.05	693.77	772.08	859.19	944.20	1,056.84	1,285.10	2,053.03
Duval - Market Rent - 4 br	Opt-out @ Market	Lognormal		1,205.10	824.08	921.60	1,034.10	1,151.52	1,314.48	1,667.36	3,018.24
Miami-Dade - Market Rent - 0 br	Opt-out @ Market	Lognormal		850.67	552.20	602.87	680.67	777.30	933.26	1,338.67	2,997.22
Miami-Dade - Market Rent - 1 br	Opt-out @ Market	Lognormal		954.34	673.71	750.21	834.36	919.04	1,033.28	1,274.98	2,447.00
Miami-Dade - Market Rent - 2 br	Opt-out @ Market	Lognormal		1,293.63	891.11	980.06	1,095.82	1,223.27	1,409.64	1,839.09	3,261.29
Miami-Dade - Market Rent - 3 br	Opt-out @ Market	Lognormal		1,701.16	1,140.87	1,239.33	1,382.77	1,561.39	1,853.14	2,623.12	6,682.37
Miami-Dade - Market Rent - 4 br	Opt-out @ Market	Lognormal		2,160.59	1,244.49	1,454.71	1,703.34	1,987.04	2,413.53	3,429.07	8,395.87

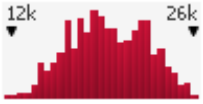
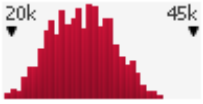
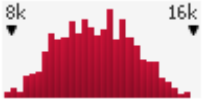
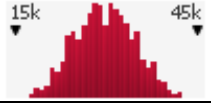
APPENDIX B
OUTPUT RESULTS BY PROPERTY, OUTPUT, VARIABLE AND MODEL

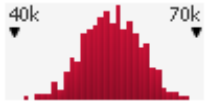
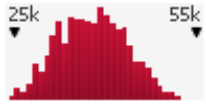
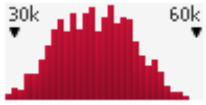
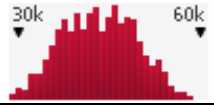
Table B-1. Output results by property, output variable and model

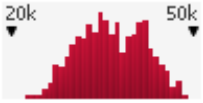
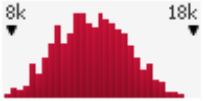
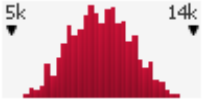
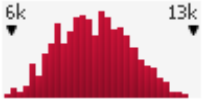
Output Variable	NOI or DCR	Model/Scenario	Graph	Mean	Min	5%	25%	50%	75%	95%	Max
Duval / NOI 1	NOI	Fail out		108.46	41.73	61.79	87.13	108.71	129.59	152.92	173.13
Duval / NOI 1	NOI	Fail out		173.38	119.40	143.99	161.38	172.52	186.03	202.48	219.04
Duval / NOI 1	NOI	Fail out		87.76	23.10	47.45	70.36	88.33	105.93	127.90	143.82
Duval / NOI 1	NOI	Fail out		109.43	40.18	63.67	87.70	109.03	129.99	153.94	173.68
Duval / NOI 1	NOI	Fail out		145.30	64.86	90.08	118.45	144.98	171.04	198.97	218.66
Duval / NOI 1	NOI	Fail out		121.64	47.41	72.69	98.72	121.85	144.68	170.07	190.29
Duval / NOI 1	NOI	Fail out		131.69	53.71	79.88	106.77	131.39	155.65	181.97	203.77
Duval / NOI 1	NOI	Fail out		190.95	127.04	149.48	172.22	190.81	209.59	232.71	258.32
Duval / NOI 1	NOI	Fail out		180.19	117.88	139.98	162.31	179.92	198.11	220.29	245.59
Duval / NOI 1	NOI	Fail out		286.71	208.64	233.14	258.82	286.69	312.20	341.58	371.61
Duval / NOI 1	NOI	Fail out		290.70	230.97	261.25	277.59	290.37	304.12	320.47	344.05

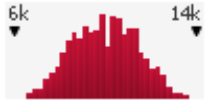
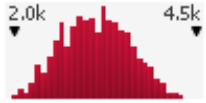
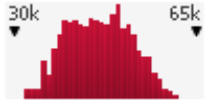
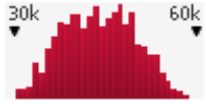
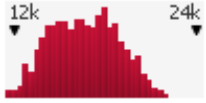
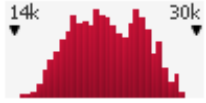
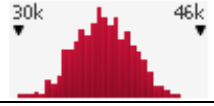
Duval / NOI 1	NOI	Fail out		233.51	163.30	187.18	210.69	232.77	255.06	280.78	308.66
Duval / NOI 1	NOI	Fail out		394.14	325.23	359.91	378.07	393.64	410.13	428.88	455.92
Duval / NOI 1	NOI	Fail out		200.53	135.20	158.12	180.77	200.37	219.73	243.89	269.65
Miami-Dade / NOI 1	NOI	Fail out		204.11	125.05	156.44	183.38	203.13	227.00	248.98	270.01
Miami-Dade / NOI 1	NOI	Fail out		120.42	46.47	71.36	97.43	120.83	143.02	168.13	189.39
Miami-Dade / NOI 1	NOI	Fail out		116.04	43.41	68.36	94.33	116.12	138.04	162.81	182.44
Miami-Dade / NOI 1	NOI	Fail out		83.80	20.91	44.25	66.86	84.26	100.85	123.07	140.74
Miami-Dade / NOI 1	NOI	Fail out		245.42	189.72	218.32	233.42	245.19	257.96	273.09	295.08
Miami-Dade / NOI 1	NOI	Fail out		172.00	117.62	142.71	160.34	171.39	184.52	201.38	218.98
Miami-Dade / NOI 1	NOI	Fail out		259.80	185.70	209.42	234.55	259.75	283.42	310.85	339.77
Miami-Dade / NOI 1	NOI	Fail out		156.87	98.00	119.39	140.59	156.80	173.06	194.13	218.00

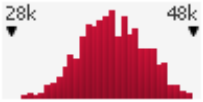
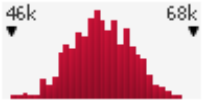
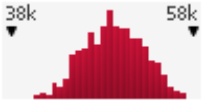
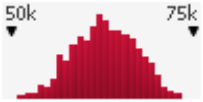
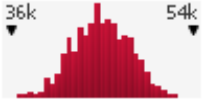
Miami-Dade / NOI 1	NOI	Fail out		362.64	296.53	329.80	347.46	362.29	377.98	395.79	421.86
Miami-Dade / NOI 1	NOI	Fail out		237.49	182.49	210.75	225.69	237.37	249.92	265.03	286.51
Miami-Dade / NOI 1	NOI	Fail out		263.39	206.09	235.32	250.83	263.07	276.34	291.57	314.52
Miami-Dade / NOI 1	NOI	Fail out		277.47	218.92	248.69	264.65	277.20	290.61	306.44	329.75
Miami-Dade / NOI 1	NOI	Fail out		236.61	181.69	209.87	224.84	236.51	249.05	264.11	285.55
Miami-Dade / NOI 1	NOI	Fail out		255.98	199.34	228.31	243.65	255.84	268.62	283.93	306.50
Miami-Dade / NOI 1	NOI	Fail out		270.92	212.95	242.44	258.20	270.73	283.79	299.43	322.66
Miami-Dade / NOI 1	NOI	Fail out		259.28	202.35	231.43	246.93	259.12	272.12	287.28	310.07
Miami-Dade / NOI 1	NOI	Fail out		314.60	252.75	284.17	300.82	314.15	328.88	345.38	369.90
Miami-Dade / NOI 1	NOI	Fail out		245.75	160.07	192.87	220.15	244.47	272.37	296.77	320.74
Miami-Dade / NOI 1	NOI	Fail out		270.76	180.14	213.64	242.43	269.42	299.99	325.60	350.60

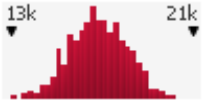
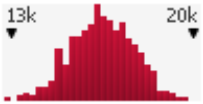
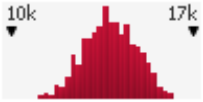
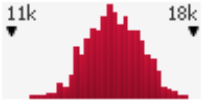
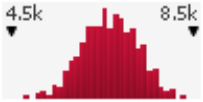
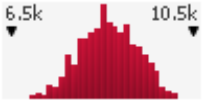
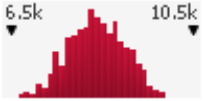
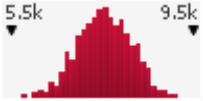
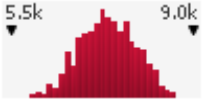
Miami-Dade / NOI 1	NOI	Fail out		261.99	173.10	206.13	234.61	260.42	290.19	315.45	340.13
Miami-Dade / NOI 1	NOI	Fail out		271.37	180.63	214.18	242.98	270.02	300.68	326.31	351.33
Miami-Dade / NOI 1	NOI	Fail out		371.22	260.75	299.34	333.62	369.60	408.95	443.63	470.50
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		237.33	154.87	185.60	212.05	236.70	263.34	288.61	313.11
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		203.54	126.20	156.75	182.49	202.59	226.50	248.04	270.37
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		215.75	148.39	171.91	194.41	214.96	235.87	260.57	287.73
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		203.43	137.67	160.67	183.38	203.13	222.89	247.13	273.08
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		210.56	143.68	165.97	190.16	210.18	230.49	255.13	280.33
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		224.18	155.17	179.16	202.17	223.77	245.26	270.09	297.40
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		224.90	155.97	179.59	202.74	224.49	245.87	271.08	298.48
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		149.75	91.93	113.11	134.15	149.64	165.31	186.16	209.57

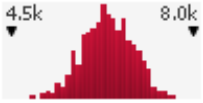
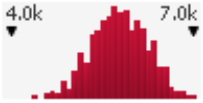
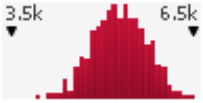
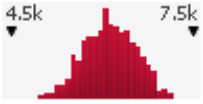
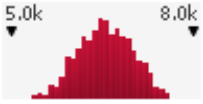
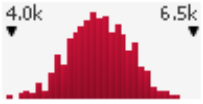
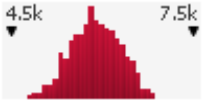
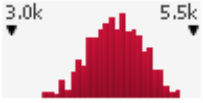
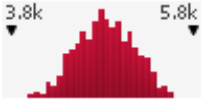
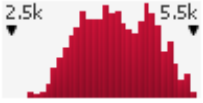
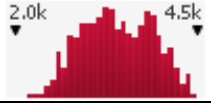
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		212.64	145.52	168.79	191.89	212.22	232.75	257.06	283.98
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		255.85	168.18	201.11	229.13	254.38	283.50	308.45	332.80
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		255.68	168.04	200.98	228.99	254.22	283.33	308.26	332.61
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		204.60	127.05	157.61	183.43	203.63	227.68	249.28	271.63
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		230.24	147.63	179.25	206.34	228.64	255.51	278.36	302.24
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		224.89	171.01	198.28	213.13	224.95	237.22	251.79	272.87
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		212.71	145.58	168.85	191.95	212.28	232.82	257.14	284.06
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		191.45	127.47	149.92	172.67	191.32	210.12	233.30	258.92
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		248.42	176.01	200.02	224.01	247.91	271.09	297.60	326.30
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		218.58	150.58	174.02	197.14	218.01	239.12	263.93	291.00
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		218.53	150.54	173.98	197.11	217.97	239.08	263.88	290.95

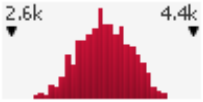
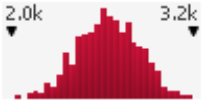
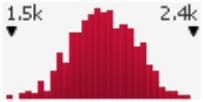
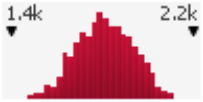
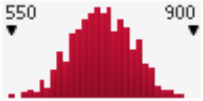
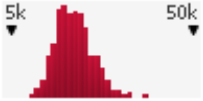
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		226.59	144.70	176.25	203.07	225.06	251.53	274.02	297.88
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		230.94	161.11	184.91	208.48	230.26	252.33	277.93	305.62
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		223.46	154.74	178.32	201.49	222.98	244.33	269.41	296.77
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		243.80	158.51	191.20	218.39	242.65	270.20	294.43	318.42
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		205.98	139.85	162.92	185.79	205.70	225.53	249.85	276.10
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		268.09	192.77	216.67	241.84	267.81	292.26	320.46	349.57
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		216.44	148.76	172.14	195.27	215.91	236.87	261.46	288.48
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		174.72	113.22	135.15	157.48	174.43	192.11	214.15	239.12
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		158.25	99.18	120.61	141.84	158.14	174.62	195.68	219.63
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		181.57	119.05	141.20	163.52	181.32	199.62	221.83	247.22
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		242.90	157.78	190.42	217.58	241.79	269.26	293.35	317.34

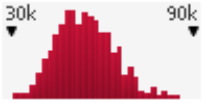
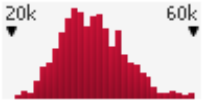
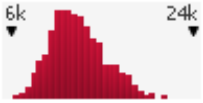
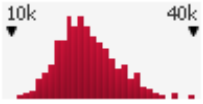
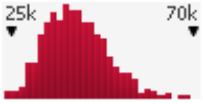
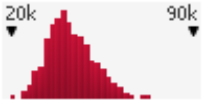
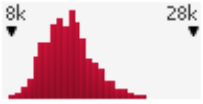
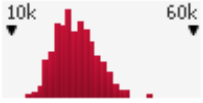
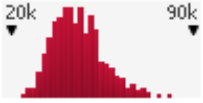
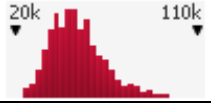
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		209.96	143.24	166.43	189.49	209.61	230.05	254.10	280.81
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		222.73	141.60	173.00	199.72	221.35	247.44	269.55	293.27
Duval / NOI 1	NOI	Fail out; Opt-out @ Assisted		185.10	122.06	144.31	166.69	184.75	203.39	225.80	251.40
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		266.69	191.58	215.43	240.61	266.44	290.69	318.88	347.92
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		281.54	204.23	228.61	253.98	281.61	306.63	335.72	365.49
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		302.04	221.70	246.12	272.24	301.78	328.60	358.98	389.74
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		253.14	180.03	203.92	228.37	252.93	276.25	303.10	331.89
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		258.83	184.88	208.63	233.66	258.82	282.39	309.73	338.62
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		301.28	204.64	240.02	270.16	299.79	333.34	361.62	387.03
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		176.34	85.93	113.68	144.37	175.67	206.87	237.85	260.32
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		342.56	278.23	310.70	327.91	342.14	357.44	374.65	400.14

Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		280.31	213.51	243.60	263.77	279.29	296.72	317.02	337.62
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		378.09	310.61	344.70	362.43	377.71	393.87	412.00	438.57
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		327.21	264.24	296.27	313.02	326.71	341.65	358.62	383.54
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		257.79	183.99	207.76	232.78	257.81	281.28	308.51	337.39
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		270.93	180.28	213.79	242.58	269.59	300.18	325.79	350.80
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		300.18	239.61	270.41	286.69	299.72	313.72	330.48	354.31
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		292.15	197.31	232.20	261.82	290.38	323.08	350.92	376.13
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		296.73	200.98	236.22	266.03	295.22	328.19	356.36	381.60
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		240.96	156.23	188.77	215.82	239.78	267.25	291.04	315.04
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		336.71	233.06	269.89	302.15	335.25	372.20	403.08	429.32
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		402.68	333.01	367.86	386.46	402.15	418.95	437.92	465.15

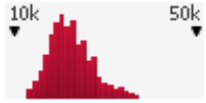
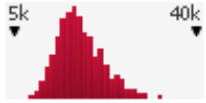
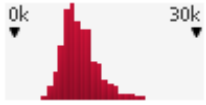
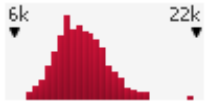
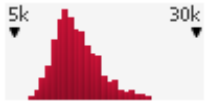
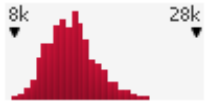
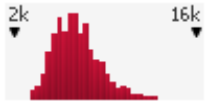
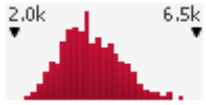
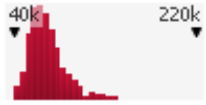
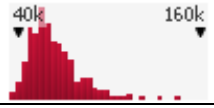
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		276.99	218.48	248.22	264.16	276.73	290.09	305.91	329.22
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		285.17	225.93	255.94	272.26	284.80	298.55	314.61	338.06
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		238.63	154.36	186.76	213.78	237.34	264.74	288.24	312.25
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		271.29	213.29	242.79	258.57	271.11	284.16	299.81	323.06
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		305.61	244.56	275.57	291.94	305.09	319.51	336.09	360.18
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		196.65	145.28	171.04	185.10	196.98	208.14	222.33	242.34
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		270.58	212.64	242.12	257.87	270.38	283.46	299.07	322.29
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		263.06	205.79	235.00	250.49	262.72	275.98	291.22	314.15
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		252.69	196.34	225.20	240.43	252.46	265.31	280.60	302.95
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		263.39	206.09	235.32	250.83	263.07	276.34	291.57	314.52
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		227.45	173.35	200.83	215.74	227.46	239.76	254.50	275.65

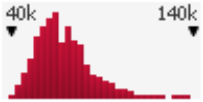
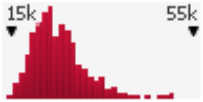
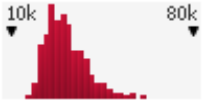
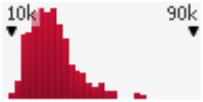
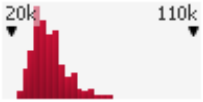
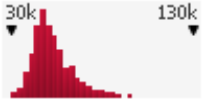
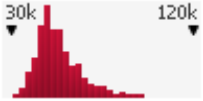
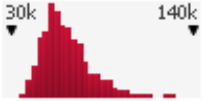
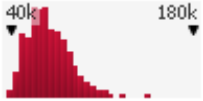
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		265.67	208.17	237.48	253.08	265.38	278.60	293.95	316.98
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		241.21	185.88	214.26	229.30	241.02	253.63	268.89	290.53
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		220.18	166.72	193.74	208.49	220.35	232.43	246.81	267.78
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		292.65	232.75	263.12	279.50	292.27	306.08	322.52	346.15
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		312.94	251.24	282.58	299.22	312.40	327.13	343.66	368.10
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		248.72	192.72	221.44	236.58	248.52	261.36	276.45	298.65
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		296.33	236.11	266.75	283.01	295.90	309.78	326.38	350.14
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		222.49	168.82	195.92	210.76	222.64	234.74	249.25	270.28
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		346.42	281.74	314.37	331.64	345.90	361.34	378.72	404.31
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		303.58	206.48	241.96	272.27	302.18	335.93	364.26	389.77
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		262.28	173.34	206.37	234.87	260.72	290.54	315.78	340.48

Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		272.05	213.98	243.50	259.32	271.88	284.94	300.60	323.88
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		252.76	165.70	198.60	226.38	251.27	280.21	304.93	329.12
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		209.24	130.77	161.58	187.58	208.29	232.76	254.68	277.17
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		264.76	207.34	236.61	252.17	264.46	277.70	293.00	316.00
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		245.25	159.68	192.45	219.71	244.01	271.81	296.18	320.16
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		245.42	189.72	218.32	233.42	245.19	257.96	273.09	295.08
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		302.89	242.08	272.99	289.34	302.37	316.65	333.28	357.24
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		322.12	221.36	257.89	288.53	320.85	356.42	385.67	411.90
Miami-Dade / NOI 1	NOI	Fail out; Opt-out @ Assisted		242.43	186.99	215.46	230.48	242.20	254.88	270.10	291.84
Duval / NOI 2	NOI	Opt out @ Market		232.76	111.87	172.03	202.27	228.77	259.16	302.34	501.45
Duval / NOI 2	NOI	Opt out @ Market		223.29	103.06	159.82	191.38	219.97	250.74	295.19	478.55

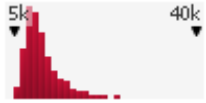
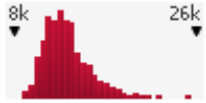
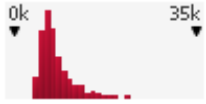
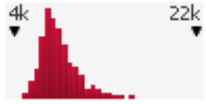
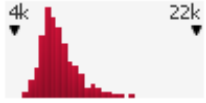
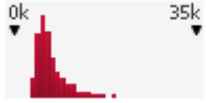
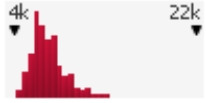
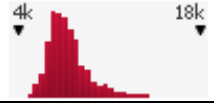
Duval / NOI 2	NOI	Opt out @ Market		271.43	163.59	207.88	240.83	269.49	299.92	342.51	411.83
Duval / NOI 2	NOI	Opt out @ Market		257.92	151.24	192.90	226.11	254.87	287.35	332.20	401.00
Duval / NOI 2	NOI	Opt out @ Market		230.94	124.35	165.64	199.50	225.36	258.41	310.77	406.16
Duval / NOI 2	NOI	Opt out @ Market		228.99	122.13	164.37	198.12	223.51	255.51	306.86	395.03
Duval / NOI 2	NOI	Opt out @ Market		275.46	169.03	207.32	242.06	272.35	305.31	354.86	447.04
Duval / NOI 2	NOI	Opt out @ Market		221.34	113.41	159.46	191.96	215.88	246.47	293.57	406.61
Duval / NOI 2	NOI	Opt out @ Market		307.46	181.06	233.30	271.91	305.42	336.54	399.19	546.87
Duval / NOI 2	NOI	Opt out @ Market		239.92	119.64	176.77	207.33	236.76	268.24	314.93	477.85
Duval / NOI 2	NOI	Opt out @ Market		278.79	157.85	205.29	240.51	273.75	310.89	370.80	480.11
Duval / NOI 2	NOI	Opt out @ Market		253.29	133.12	188.67	218.74	248.70	282.56	331.15	471.23
Duval / NOI 2	NOI	Opt out @ Market		252.82	133.62	172.95	210.98	246.90	284.67	360.09	529.35

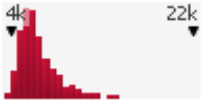
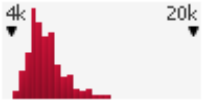
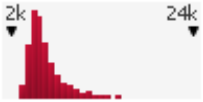
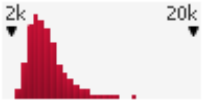
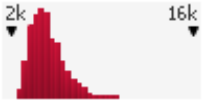
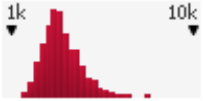
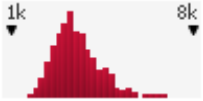
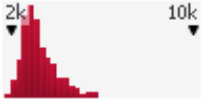
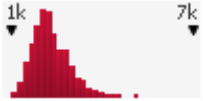
Duval / NOI 2	NOI	Opt out @ Market	20k 160k	239.03	120.63	176.25	204.28	232.03	263.31	325.24	577.60
Duval / NOI 2	NOI	Opt out @ Market	30k 90k	275.79	169.76	206.77	241.52	271.84	305.86	357.57	447.86
Duval / NOI 2	NOI	Opt out @ Market	30k 100k	278.97	173.38	207.40	243.05	274.68	309.30	368.69	491.62
Duval / NOI 2	NOI	Opt out @ Market	30k 100k	281.24	174.89	208.50	244.09	277.34	312.49	371.41	494.65
Duval / NOI 2	NOI	Opt out @ Market	30k 120k	289.11	178.62	215.12	250.49	283.52	319.56	387.80	549.63
Duval / NOI 2	NOI	Opt out @ Market	30k 120k	289.11	178.62	215.12	250.49	283.52	319.56	387.80	549.63
Duval / NOI 2	NOI	Opt out @ Market	20k 90k	267.67	146.67	199.24	232.22	262.00	297.74	351.06	499.73
Duval / NOI 2	NOI	Opt out @ Market	25k 70k	276.21	169.88	207.74	242.37	273.09	305.56	356.12	448.03
Duval / NOI 2	NOI	Opt out @ Market	10k 60k	247.14	122.88	168.78	209.01	239.72	278.63	346.83	498.92
Duval / NOI 2	NOI	Opt out @ Market	10k 50k	247.26	127.16	183.83	213.32	243.07	275.21	325.07	469.98
Duval / NOI 2	NOI	Opt out @ Market	10k 45k	241.11	126.76	167.98	206.73	235.12	271.55	333.93	464.38

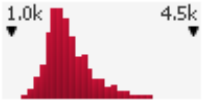
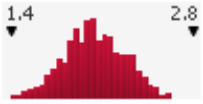
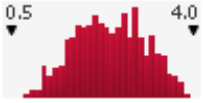
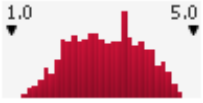
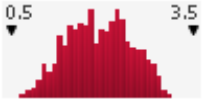
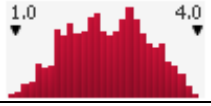
Duval / NOI 2	NOI	Opt out @ Market		293.04	180.49	218.35	254.01	286.76	323.73	397.45	577.13
Duval / NOI 2	NOI	Opt out @ Market		247.14	122.88	168.78	209.01	239.72	278.63	346.83	498.92
Duval / NOI 2	NOI	Opt out @ Market		215.63	106.91	156.78	188.26	210.41	239.32	286.04	421.11
Duval / NOI 2	NOI	Opt out @ Market		190.42	78.20	131.71	158.23	182.89	213.30	272.90	485.22
Duval / NOI 2	NOI	Opt out @ Market		239.39	131.19	180.86	211.79	236.28	264.66	305.83	417.18
Duval / NOI 2	NOI	Opt out @ Market		282.02	158.98	206.23	241.48	273.13	314.87	383.77	572.98
Duval / NOI 2	NOI	Opt out @ Market		307.46	181.06	233.30	271.91	305.42	336.54	399.19	546.87
Duval / NOI 2	NOI	Opt out @ Market		252.82	133.62	172.95	210.98	246.90	284.67	360.09	529.35
Duval / NOI 2	NOI	Opt out @ Market		232.09	128.44	173.72	203.85	228.70	258.09	295.32	358.08
Miami-Dade / NOI 2	NOI	Opt out @ Market		446.23	273.92	328.49	383.96	430.16	491.13	623.01	1151.53
Miami-Dade / NOI 2	NOI	Opt out @ Market		440.06	264.36	318.65	372.76	419.08	486.81	623.29	950.26

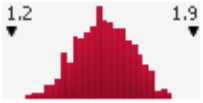
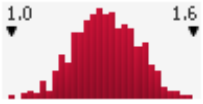
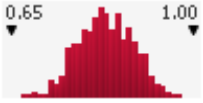
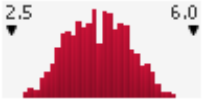
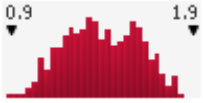
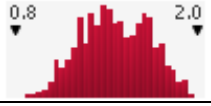
Miami-Dade / NOI 2	NOI	Opt out @ Market		518.83	315.05	376.88	443.38	496.79	571.27	733.32	1608.08
Miami-Dade / NOI 2	NOI	Opt out @ Market		406.40	246.07	300.07	350.53	391.82	447.39	550.35	772.79
Miami-Dade / NOI 2	NOI	Opt out @ Market		406.05	245.61	299.72	350.04	391.18	447.15	551.71	769.32
Miami-Dade / NOI 2	NOI	Opt out @ Market		438.70	248.56	314.93	371.29	424.01	490.79	615.55	1054.07
Miami-Dade / NOI 2	NOI	Opt out @ Market		289.69	119.02	175.70	227.93	277.34	334.97	459.47	803.90
Miami-Dade / NOI 2	NOI	Opt out @ Market		378.44	239.54	280.99	326.48	362.31	411.03	531.92	969.30
Miami-Dade / NOI 2	NOI	Opt out @ Market		322.86	169.08	208.30	251.93	294.28	359.76	538.96	1166.86
Miami-Dade / NOI 2	NOI	Opt out @ Market		367.30	228.44	280.08	322.73	355.85	399.18	498.56	794.18
Miami-Dade / NOI 2	NOI	Opt out @ Market		366.72	227.67	280.01	321.91	354.58	398.77	498.09	784.96
Miami-Dade / NOI 2	NOI	Opt out @ Market		421.35	255.24	310.75	362.26	405.50	464.75	577.83	855.02
Miami-Dade / NOI 2	NOI	Opt out @ Market		373.69	222.19	267.44	315.82	362.57	419.22	510.93	847.68

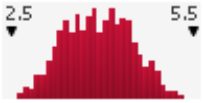
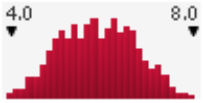
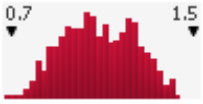
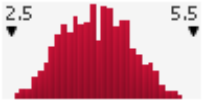
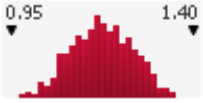
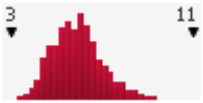
Miami-Dade / NOI 2	NOI	Opt out @ Market	40k 220k	378.44	239.54	280.99	326.48	362.31	411.03	531.92	969.30
Miami-Dade / NOI 2	NOI	Opt out @ Market	50k 350k	444.22	252.15	321.57	377.33	429.62	494.14	610.43	1018.71
Miami-Dade / NOI 2	NOI	Opt out @ Market	50k 300k	529.13	296.34	387.98	450.41	516.12	587.43	717.72	1339.29
Miami-Dade / NOI 2	NOI	Opt out @ Market	20k 180k	311.54	158.28	214.65	259.87	300.60	352.27	441.23	802.37
Miami-Dade / NOI 2	NOI	Opt out @ Market	20k 110k	410.64	243.67	300.32	349.84	396.94	459.61	550.83	921.90
Miami-Dade / NOI 2	NOI	Opt out @ Market	20k 100k	370.54	232.68	282.43	324.56	357.89	402.82	502.79	845.03
Miami-Dade / NOI 2	NOI	Opt out @ Market	10k 50k	357.40	215.47	269.96	310.94	340.67	391.27	485.10	782.43
Miami-Dade / NOI 2	NOI	Opt out @ Market	10k 55k	350.97	207.05	261.31	298.82	332.47	385.56	499.97	918.86
Miami-Dade / NOI 2	NOI	Opt out @ Market	5k 45k	311.54	158.28	214.65	259.87	300.60	352.27	441.23	802.37
Miami-Dade / NOI 2	NOI	Opt out @ Market	10k 50k	378.44	239.54	280.99	326.48	362.31	411.03	531.92	969.30
Miami-Dade / NOI 2	NOI	Opt out @ Market	10k 45k	372.12	234.75	282.73	325.04	357.95	403.41	505.46	869.89

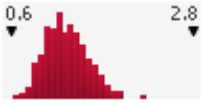
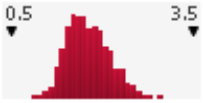
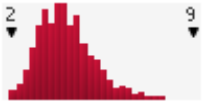
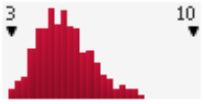
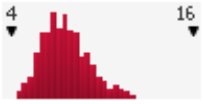
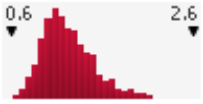
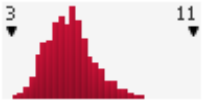
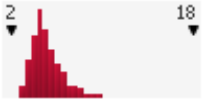
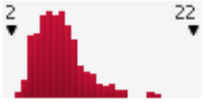
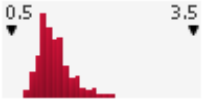
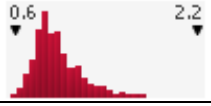
Miami-Dade / NOI 2	NOI	Opt out @ Market		340.69	193.59	236.06	278.48	315.38	372.30	520.07	1136.98
Miami-Dade / NOI 2	NOI	Opt out @ Market		370.14	232.16	281.81	324.20	358.04	403.20	502.42	838.82
Miami-Dade / NOI 2	NOI	Opt out @ Market		426.08	299.64	340.29	379.12	415.16	459.47	552.02	782.59
Miami-Dade / NOI 2	NOI	Opt out @ Market		378.44	239.54	280.99	326.48	362.31	411.03	531.92	969.30
Miami-Dade / NOI 2	NOI	Opt out @ Market		334.18	184.34	218.24	262.05	305.75	371.27	548.63	1275.08
Miami-Dade / NOI 2	NOI	Opt out @ Market		334.18	184.34	218.24	262.05	305.75	371.27	548.63	1275.08
Miami-Dade / NOI 2	NOI	Opt out @ Market		371.06	233.37	282.73	325.10	357.62	403.19	504.00	853.32
Miami-Dade / NOI 2	NOI	Opt out @ Market		371.06	233.37	282.73	325.10	357.62	403.19	504.00	853.32
Miami-Dade / NOI 2	NOI	Opt out @ Market		334.18	184.34	218.24	262.05	305.75	371.27	548.63	1275.08
Miami-Dade / NOI 2	NOI	Opt out @ Market		378.44	239.54	280.99	326.48	362.31	411.03	531.92	969.30
Miami-Dade / NOI 2	NOI	Opt out @ Market		385.97	251.47	303.06	341.01	374.78	415.72	515.00	819.67

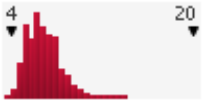
Miami-Dade / NOI 2	NOI	Opt out @ Market		346.82	201.63	251.51	290.87	324.92	383.12	509.70	1006.76
Miami-Dade / NOI 2	NOI	Opt out @ Market		378.44	239.54	280.99	326.48	362.31	411.03	531.92	969.30
Miami-Dade / NOI 2	NOI	Opt out @ Market		338.60	190.86	231.56	273.63	312.57	372.59	529.34	1181.17
Miami-Dade / NOI 2	NOI	Opt out @ Market		399.23	268.11	310.19	352.72	386.83	431.00	531.19	893.97
Miami-Dade / NOI 2	NOI	Opt out @ Market		433.35	231.08	292.49	350.54	410.83	486.60	651.65	1325.17
Miami-Dade / NOI 2	NOI	Opt out @ Market		405.24	232.72	284.49	337.19	389.02	454.45	580.13	1100.20
Miami-Dade / NOI 2	NOI	Opt out @ Market		340.99	193.98	236.61	279.46	316.01	372.64	519.67	1130.60
Miami-Dade / NOI 2	NOI	Opt out @ Market		311.54	158.28	214.65	259.87	300.60	352.27	441.23	802.37
Miami-Dade / NOI 2	NOI	Opt out @ Market		302.31	156.08	212.12	255.56	292.51	339.54	412.54	657.60
Miami-Dade / NOI 2	NOI	Opt out @ Market		351.88	208.25	262.54	301.38	334.32	387.06	494.46	899.43
Miami-Dade / NOI 2	NOI	Opt out @ Market		311.54	158.28	214.65	259.87	300.60	352.27	441.23	802.37

Miami-Dade / NOI 2	NOI	Opt out @ Market		334.18	184.34	218.24	262.05	305.75	371.27	548.63	1275.08
Miami-Dade / NOI 2	NOI	Opt out @ Market		363.69	223.71	278.50	319.16	350.53	397.07	497.53	737.34
Miami-Dade / NOI 2	NOI	Opt out @ Market		505.68	281.71	358.28	419.15	487.42	566.21	717.01	1605.20
Miami-Dade / NOI 2	NOI	Opt out @ Market		334.18	184.34	218.24	262.05	305.75	371.27	548.63	1275.08
Duval / DCR 1	DCR	Fail out		3.06	1.18	1.74	2.46	3.07	3.66	4.32	4.89
Duval / DCR 1	DCR	Fail out		2.06	1.42	1.71	1.92	2.05	2.21	2.40	2.60
Duval / DCR 1	DCR	Fail out		2.49	0.65	1.34	1.99	2.50	3.00	3.62	4.07
Duval / DCR 1	DCR	Fail out		2.42	0.89	1.41	1.94	2.41	2.87	3.40	3.83
Duval / DCR 1	DCR	Fail out		3.10	1.38	1.92	2.53	3.10	3.65	4.25	4.67
Duval / DCR 1	DCR	Fail out		1.98	0.77	1.18	1.61	1.98	2.35	2.77	3.10
Duval / DCR 1	DCR	Fail out		2.54	1.04	1.54	2.06	2.54	3.00	3.51	3.93

Duval / DCR 1	DCR	Fail out		3.25	2.37	2.65	2.94	3.25	3.54	3.88	4.22
Duval / DCR 1	DCR	Fail out		1.56	1.24	1.40	1.49	1.56	1.63	1.72	1.85
Duval / DCR 1	DCR	Fail out		6.68	4.67	5.36	6.03	6.66	7.30	8.04	8.84
Miami-Dade / DCR 1	DCR	Fail out		2.84	1.09	1.68	2.29	2.85	3.37	3.96	4.46
Miami-Dade / DCR 1	DCR	Fail out		2.51	0.94	1.48	2.04	2.51	2.99	3.52	3.95
Miami-Dade / DCR 1	DCR	Fail out		2.40	0.60	1.27	1.91	2.41	2.88	3.52	4.02
Miami-Dade / DCR 1	DCR	Fail out		1.31	1.02	1.17	1.25	1.31	1.38	1.46	1.58
Miami-Dade / DCR 1	DCR	Fail out		0.83	0.68	0.76	0.80	0.83	0.87	0.91	0.97
Duval / DCR 1	DCR	Fail out; Opt-out @ Assisted		4.19	2.87	3.33	3.78	4.19	4.59	5.07	5.60
Duval / DCR 1	DCR	Fail out; Opt-out @ Assisted		1.41	0.92	1.10	1.26	1.40	1.56	1.69	1.83
Duval / DCR 1	DCR	Fail out; Opt-out @ Assisted		1.47	0.91	1.13	1.31	1.46	1.63	1.79	1.95

Duval / DCR 1	DCR	Fail out; Opt-out @ Assisted		3.89	2.49	3.03	3.48	3.86	4.32	4.70	5.10
Duval / DCR 1	DCR	Fail out; Opt-out @ Assisted		3.96	2.72	3.15	3.57	3.95	4.33	4.78	5.27
Duval / DCR 1	DCR	Fail out; Opt-out @ Assisted		5.94	4.09	4.73	5.36	5.93	6.50	7.18	7.91
Duval / DCR 1	DCR	Fail out; Opt-out @ Assisted		1.09	0.71	0.86	0.98	1.09	1.21	1.32	1.43
Duval / DCR 1	DCR	Fail out; Opt-out @ Assisted		3.93	2.68	3.12	3.55	3.92	4.31	4.76	5.26
Miami-Dade / DCR 1	DCR	Fail out; Opt-out @ Assisted		3.25	2.38	2.65	2.93	3.24	3.53	3.86	4.19
Miami-Dade / DCR 1	DCR	Fail out; Opt-out @ Assisted		4.81	2.35	3.10	3.94	4.79	5.65	6.49	7.10
Miami-Dade / DCR 1	DCR	Fail out; Opt-out @ Assisted		1.18	0.96	1.07	1.13	1.18	1.23	1.29	1.38
Miami-Dade / DCR 1	DCR	Fail out; Opt-out @ Assisted		0.90	0.73	0.81	0.86	0.90	0.94	0.99	1.05
Miami-Dade / DCR 1	DCR	Fail out; Opt-out @ Assisted		4.14	2.80	3.29	3.71	4.12	4.58	4.97	5.32
Duval / DCR 2	DCR	Opt out @ Market		6.06	3.57	4.60	5.36	6.02	6.64	7.87	10.79

Duval / DCR 2	DCR	Opt out @ Market		1.32	0.66	0.97	1.14	1.30	1.47	1.73	2.62
Duval / DCR 2	DCR	Opt out @ Market		1.81	0.95	1.35	1.57	1.78	2.02	2.37	3.38
Duval / DCR 2	DCR	Opt out @ Market		4.27	2.26	2.92	3.56	4.17	4.81	6.08	8.94
Duval / DCR 2	DCR	Opt out @ Market		5.23	3.23	3.89	4.53	5.13	5.78	7.02	9.95
Duval / DCR 2	DCR	Opt out @ Market		7.86	4.86	5.85	6.81	7.71	8.69	10.55	14.95
Duval / DCR 2	DCR	Opt out @ Market		1.27	0.71	0.93	1.09	1.23	1.42	1.73	2.58
Duval / DCR 2	DCR	Opt out @ Market		5.76	3.39	4.37	5.09	5.72	6.30	7.47	10.24
Miami-Dade / DCR 2	DCR	Opt out @ Market		5.58	3.39	4.05	4.77	5.34	6.14	7.88	17.29
Miami-Dade / DCR 2	DCR	Opt out @ Market		7.91	3.25	4.80	6.22	7.57	9.14	12.54	21.94
Miami-Dade / DCR 2	DCR	Opt out @ Market		1.30	0.82	0.97	1.12	1.25	1.41	1.83	3.34
Miami-Dade / DCR 2	DCR	Opt out @ Market		1.01	0.63	0.77	0.89	0.97	1.10	1.37	2.16

Miami-Dade / DCR 2	DCR	Opt out @ Market		7.38	4.13	5.41	6.28	7.20	8.19	10.01	18.67

Note: The amounts noted in the graphs are per property.

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BIOGRAPHICAL SKETCH

Patricia E. Roset-Zuppa was born and raised in the Netherlands. She studied human geography at Utrecht University and specialized in urban planning. As part of her graduate studies in Utrecht, she participated in an international exchange program with the University of Florida for one semester in 1996. She completed her thesis research in Toronto in 1997. Upon graduation, Ms. Roset-Zuppa worked as a researcher at the Canadian Urban Institute in Toronto for several years. In 2000-2002, she pursued a Master of Business Administration with a specialization in real property development at York University in Toronto. During this time, she worked as a real estate credit analyst at Scotiabank for one summer. Upon completion of the MBA degree, Ms. Roset-Zuppa worked at Diamante Development, a Toronto-based builder, where she was charged with the planning approvals process. Her subsequent position was as project manager in the international office of the Canadian Urban Institute in Toronto, managing capacity building projects for local governments in Cuba and the Philippines. Ms. Roset-Zuppa also worked for Monarch Corporation, a land developer and homebuilder in Southern Ontario, where she was responsible for feasibility analysis and the due diligence process of land acquisition. While pursuing a Ph.D. in urban and regional planning at the University of Florida (2005-2009), she was a research and policy analyst at the Shimberg Center for Housing Studies. Upon completion of her doctoral studies, Ms. Roset-Zuppa joined the Canada Mortgage and Housing Corporation as a senior policy analyst at its national office in Ottawa.