Portfolio Diversification across U.S. Gateway and Non-Gateway Real Estate Markets*

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Abstract

Using simulation analysis and property-level data for the U.S., we compare performance metrics for portfolios containing varying proportions of gateway and non-gateway markets. Risk-adjusted performance is found to be similar across types of markets. Gateway markets have higher appreciation and total returns, while non-gateway markets exhibit higher income returns even after accounting for capital expenditures. Downside risk appears to be slightly greater for gateway markets than for non-gateway markets; however, full drawdown and recovery lengths tend to be shorter for gateway markets. Systematic risk is found to be constant across types of markets. We show that discriminating between gateway and non-gateway markets is useful for mixed-asset diversification purposes, with the former type of markets being useful in risky portfolios and the latter in low-risk portfolios. By considering a large spectrum of performance metrics in a realistic investment setting, the results should provide investors with valuable information when allocating funds across gateway and non-gateway markets. The paper also provides insights regarding how best to define gateway markets.

Keywords: Commercial Real Estate; Gateway Markets; Non-Gateway Markets; Diversification; Risk-Adjusted Performance; Downside Risk
JEL Codes: R33; C63; G11; G23

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1. Introduction

Consistent with studies that have documented the positive impacts of holding real estate assets in a mixed-asset portfolio (Pagliari, 2017; Delfim and Hoesli, 2019), survey results indicate that investors have a strong appetite for the asset class (PREA, 2021). Against this background, an important issue for investors is that of how to structure their exposure to commercial real estate. Much research, for instance, focuses on comparing listed and direct investment performance (Hoesli and Oikarinen, 2012; Ling and Naranjo, 2015; Ling et al., 2018). For large investors, such as institutional investors and sovereign wealth funds, direct investments constitute the preferred route given the flexibility and the control that such investments provide, as well as the diversification benefits associated with holding properties directly. Those investors, but of course also REIT and fund managers, have a keen interest in assessing how best to diversify a portfolio of real estate assets.

Much of the early research in this area has looked at the benefits of investing across property types versus investing across geographies, defined in various ways. Using National Council of Real Estate Investment Fiduciaries (NCREIF) data, Fisher and Liang (2000) show that diversification across sectors is more effective than geographic diversification using four broadly defined areas. For the U.K., Byrne and Lee (2011) also find that sectors dominate regions, however defined. The authors also report that functional groups of regions provide greater risk reduction than administrative areas.

Going beyond the analysis of portfolio diversification by sector and region, an important dimension in the portfolio allocation process is that of asset selection. This paper seeks to expand this line of research. Many investors, in particular institutional investors, tilt their real estate holdings towards quality assets, as documented both for domestic (Malpezzi and Shilling, 2000) and international investors (McAllister and Nanda, 2015; Devaney et al., 2019). This process involves selecting assets in gateway markets, purchasing larger and newer properties, and focusing on CBD locations. It is posited that such strategy is rational as prime assets and locations should exhibit lower risk, largely because those markets are more liquid and transparent (Riddiough et al., 2005; Ling et al., 2018). Using NCREIF data, Plazzi et al. (2011) show that the optimal portfolio weights are tilted towards high capitalization rate, low vacancy rate, and high value properties when compared to a portfolio that holds these properties in proportion to their appraisal values. This is consistent with the results reported by Beracha et al. (2017) who find that high capitalization rate properties outperform low capitalization rate properties on a risk-adjusted basis.

Gateway and non-gateway markets have also been examined in the context of REIT portfolios. Ling et al. (2018) find evidence of U.S. REIT managers being able to time allocation decisions ahead of Metropolitan Statistical Area (MSA) outperformance, this effect being most prevalent in non-gateway markets. Wang and Zhou (2021) examine property sell-offs by U.S. REITs and find a negative relationship between the distance from the seller's headquarters to the sold properties and stock market reactions for non-gateway markets but not for gateway markets. Finally, using a broad set of 25 "gateway" markets in the U.S., Milcheva et al. (2020) show that REITs with a low exposure to those markets have a higher return to compensate for a higher risk.

While research suggests that non-gateway markets have higher levels of information asymmetry and are less efficient than gateway markets, it is unclear what this implies in terms of diversification of a portfolio across both types of markets. Using simulation analysis and property-level data sourced from NCREIF, we analyze the implications of holding a portfolio with various weights of gateway and non-gateway markets on risk-adjusted returns, the breakdown of total returns in appreciation and income returns, downside risk, systematic risk, and portfolio diversification. Although not looking specifically at gateway versus non-gateway markets, some papers are related to ours. Using NCREIF data, Gang et al. (2020) report that core properties have higher returns and lower systematic risk than noncore properties. Fisher et al. (2020) find that U.S. REITs with holdings in high-density locations earn higher risk-adjusted returns and carry higher real estate systematic risk than their peers in low-density locations. Also using REIT data, Feng et al. (2021) report that geographic diversification is associated with higher REIT values for firms that are more transparent (i.e., that have high levels of institutional ownership or invest in core property types), whereas higher values are associated with more geographic concentration for less transparent firms.

Our results show that gateway markets have a higher total return and standard deviation than their non-gateway counterparts, translating in comparable risk-adjusted performance across types of markets. We further show that the differences in standard deviations are not attributable to differences in systematic risk given that the latter is comparable across market types. The breakdown of total returns into income and appreciation components highlights that non-gateway markets have a higher income return and a lower standard deviation of those returns than gateway markets. This holds true after accounting for capital expenditures. In contrast, gateway markets have a higher appreciation return and standard deviation than non-gateway markets. Gateway markets appear to have slightly higher downside risk than their non-gateway counterparts; however, recovery times are faster for the former than for the latter, consistent with the higher appreciation returns for gateway markets. Non-gateway markets are shown to be useful in diversifying low-risk portfolios, while their gateway counterparts constitute the entire real estate allocation in portfolios with higher levels of risk. The conclusions pertaining to market performance are shown to be robust to holding sectoral weights constant across the two types of markets and to using various sizes of assets under management. A comparison of results with alternative numbers of gateway markets leads us to conclude that markets are best differentiated when our initial set of six gateway markets is considered.

The paper contributes to the literature in the following ways. First, the use of simulation analysis makes it possible to derive return and risk metrics and their distribution that are an accurate depiction of portfolio performance. Indeed, as replicating an index is not possible for direct real estate investors, return and risk measures calculated from that index are inappropriate. Second, we propose an innovative way of correcting values for appraisal smoothing and the escrow lag, while also incorporating the effects of the uncertainty stemming from any unobserved characteristics on property values. By using a randomly selected quantile of the sale price to appraised value ratio, instead of a central tendency measure of the ratio, we take full advantage of the information available concerning property sales during any given quarter. A further contribution pertains to how best to classify markets in gateway or non-gateway markets from an investment standpoint. We use various subsets of markets and test which classification produces the most clear-cut discrimination of markets based on performance metrics. Finally, our approach aims at mimicking real world investment constraints in that we explicitly model the cash management process, in particular properties' acquisitions and dispositions.

The paper has the following practical implications. Our results show the effects of investing varying proportions of a portfolio to gateway and non-gateway markets on total, income, and appreciation returns and standard deviations. This permits to assess portfolio risk-adjusted performance for various levels of diversification across gateway and non-gateway markets. Our paper also provides evidence on the type of market that offers high and recurrent income returns. In addition, our findings should help investors be better aware of the combinations of assets that minimize downside risk and recovery times after a drawdown. It also provides insights regarding how best to diversify a portfolio containing also stocks and bonds across gateway and non-gateway real estate markets.

The remainder of the paper is organized as follows. In the next section, we discuss our data. The following section presents our method. We then discuss our results, before providing some concluding remarks in a final section.

2. Data

We first discuss the various filters that we have implemented to clean the database, before presenting the method that we use to correct the reported property values.

2.1 Data Cleaning

All real estate data are sourced from NCREIF. The data pertain to the properties held by NCREIF constituents that form the basis for constructing their appraisal-based property index (NPI). After scrutinizing the data and reviewing a number of papers that have relied on NCREIF data, in particular Plazzi et al. (2011) and Sagi (2020), we implemented filters to discard data points presenting anomalies or deemed inappropriate for our study. Properties were deleted if:

1) They had less than four quarters of data;
2) They had one quarter or more of missing data;
3) The CBSA was missing;
4) The CBSA changed during the period;
5) They did not have at least two external appraisals or one external appraisal and a sale price;[1]
6) They were classified as hotels for at least one quarter;

[1] We only consider sales that are classified by NCREIF as being true sales.

7) The sales code suggested that they are not investment-grade;

8) They had a total or capital return below -99.9% in any quarter;

9) The absolute value of the net operating income (NOI) exceeded 20% of market value in any quarter;

10) The absolute value of capital expenditures or partial sales exceeded 50% of market value in any quarter.

We use data for the period 2003Q1-2020Q1. Some quarters of data are needed to calculate forward- or backward-looking metrics; hence, the period considered for our simulations is 2004Q1-2019Q4. After the filtering out of anomalous data, the number of properties in our dataset is 1,683 as of 2004Q1 and 4,065 as of 2019Q4. Table 1 contains descriptive statistics by sector and market type as of the beginning and end of our time period. The breakdown by type of market is 478 (1,477) properties for gateway markets and 1,205 (2,588) for non-gateway markets as of 2004Q1 (2019Q4). The relative importance of gateway markets (in value) has risen from 42% to 51%. Gateway market properties are on average almost twice the value of non-gateway properties. Capitalization rates declined significantly during the time period, this being particularly true for gateway markets (Figure 1). This results on average in a 58 basis point lower capitalization rate for gateway markets.

A total of 11,632 properties fulfill the criterion of having at least one year's worth of data. There is much turnover in the dataset as 9,949 properties entered and 8,229 properties exited the dataset during the period (including 5,694 properties exiting due to an arm length's transaction). A total of 199 properties were in the dataset for the entire 16-year period, 1,731 properties were in the sample for at least 10 years, and 5,031 properties were in the dataset for at least five years. Figure 2 depicts the number of entries, exits, and properties over time. The sample size increased during the period. Given that properties need to be in the dataset for at least one year, the numbers of sales and exits are equal to zero at the beginning of the period.[2] Given the lack of external valuations subsequent to the end of the time period that are necessary to conduct the property value adjustments, a large number of properties exit the dataset during the last three quarters.

2.2 Property Value Adjustments

It is well known that appraised values suffer from smoothing and lagging (Geltner, 1993; Delfim and Hoesli, 2021). Given that the analyses will be biased because of this, it is important to adjust values so that they more accurately reflect market conditions. We use a sale price to appraisal method that is akin to that used until recently by NCREIF to construct their transaction-based indices (Geltner, 2011; Plazzi et al., 2011).[3] The NCREIF database contains an indicator specifying the nature of the quarterly market value: internal appraisal, external appraisal, or value not recalculated.[4] We only consider external appraisals and fill the gaps by linearly interpolating between appraised values net of any capital expenditures or partial sales that have occurred between two appraisals. Thus, we allocate linearly to each period any capital gain (or loss) above the effects of capital expenditures or partial sales. The adjusted estimated values are obtained by reinstating the effect of capital expenditures and partial sales.

For each quarter, we then calculate the ratio of sale price to adjusted estimated value two quarters ago for each property that was sold and for which the sale is classified by NCREIF as a true sale:

[2] Exits refer to properties that leave the dataset and that are not identified as sales or with a sale code that does not allow us to ascertain that such sales are arm's length transactions.
[3] Due to the lack of transactions in 2020, the NCREIF transaction-based index has been discontinued.
[4] In the latter case, the value is that of the previous quarter adjusted for any capital expenditures or partial sales.

$$SPAEV_{p,q} = \frac{SP_{p,q+1}}{AEV_{p,q-1}} \quad (1)$$

where $SPAEV_{p,q}$ is the sale price to adjusted estimated value ratio for property p at quarter q, $SP_{p,q+1}$ is the sale price of property p in quarter $q-1$, and $AEV_{p,q-1}$ is the adjusted estimated value at time $q-1$. We use a two-quarter lag between the sale price and the adjusted estimated value to ensure that the appraisal is independent from the subsequent sale. Figure 3 shows the number of sales in the cleaned dataset over the period. Whereas more than 150 sales occurred during some quarters, there were only 16 sales across all property types during 2009Q1. To smooth out some of the quarterly variations in the ratios of sale prices to appraised values, the ratio for each period is the average over three quarters (the previous, current, and next quarters). Figure 4 depicts the medians and selected quantiles for this ratio.[5] Focusing on the median ratios, appraised values appear to be 5% below transaction prices prior to the Global Financial Crisis (GFC), while properties transacted some 15% below their estimated value at the height of the GFC. After the GFC, prices again slightly exceeded appraised values. This is consistent with the much documented smoothing and lagging of appraisals and the effects of these throughout the cycle.

We use the empirical distribution of ratios at time q to determine the expected sale price of unsold properties at time q rather than $q+1$ as in the production of the NCREIF transaction-based index (NTBI). This is to take into account the well-documented escrow lag in commercial real estate; transaction prices were agreed upon several weeks prior to their recording. The one quarter lag we use is consistent with the 90-day escrow lag that is discussed in Hoesli et al. (2015). Given the selected quantile order (Q_o), the expected sale price of unsold properties is calculated as:

[5] We also calculated the ratio of sale price to the lagged appraised value for gateway and non-gateway markets separately. Given that there were no meaningful differences in the times series of the ratio across the two types of markets, we use the overall ratio.

$$ESP_{p,q} = AEV_{p,q-1} \cdot Q_o(SPAEV_q) \quad (2)$$

where $ESP_{p,q}$ is the expected sale price of property p at time q, $AEV_{p,q-1}$ is the adjusted estimated value of property p at time $q-1$, and $Q_o\left(SPAEV_q\right)$ is the empirical quantile of order o of the ratio of sale prices to adjusted estimated values for quarter q.

3. Method

In this section, we first discuss the classification between gateway and non-gateway markets. We then discuss how we construct the simulated portfolios, before presenting the performance metrics that are computed for our simulated portfolios. We then present our mixed-asset portfolio analyses. Finally, we discuss the method we use to analyze systematic risk across market types.

3.1 Gateway vs. Non-Gateway Markets

Gateway cities can be defined as cities with wide appeal to international investors. Such cities have large international airports, diversified economies, and status. We use conventional wisdom and prior research (Devaney et al., 2019) and consider Boston, Chicago, New York, Los Angeles, San Francisco, and Washington, D.C. as our initial set of gateway markets. Looking at GDP figures at the MSA level, those cities rank in the top three (New York, Los Angeles, and Chicago), fifth (Washington, D.C.), sixth (San Francisco), and ninth (Boston) in the country.

An important consideration is whether the whole MSAs should be considered as gateway or only some divisions. For the six markets and for each property type (apartment, industrial, office, and retail), we analyzed capitalization rates and percent leased to assess whether divisions within an MSA were homogenous or not. With the exception of Los Angeles, there are clear differences within MSAs, indicating that only parts of those are to be considered gateway markets. Appendix 1, Panel A shows our classification of divisions for the six gateway markets.

For robustness check purposes, we consider two expanded sets of gateway markets using 2003 GDP figures at the MSA level from the Bureau of Economic Analysis.[6] The first set considers markets that account for at least 2.4% of national GDP. This results in Dallas and Philadelphia being added to the initial six gateway markets. The second set uses a threshold of 2.2%. This leads to Atlanta, Houston, and Miami being also considered to be gateway markets. Appendix 1, Panel B shows the classification of divisions for those additional markets. We also consider two more restricted sets of markets. The first one only includes the three largest markets (New York, Los Angeles, and Chicago), while the second set additionally considers Washington, D.C.

3.2 Portfolio Simulations

Appendix 2 presents the flowchart of our simulation process. For a given amount of assets under management (AUM), we use Monte Carlo simulations to construct hypothetical portfolios with various weights of gateway and non-gateway markets. We start with gateway markets only, and modify weights by 10% increments until reaching portfolios with non-gateway markets only.[7] For each set of weights, we construct 1,000 hypothetical portfolios. Given the stringent filtering rules used to clean up the database, the population from which the portfolios are drawn is representative of the institutional investment universe and hence we do not apply any stratification to the sampling scheme above that concerning location. Hence, we construct *N* (=1,000) portfolios of *P* properties

[6] We use 2003 figures to avoid look-ahead bias.
[7] We allow for a 1% margin of error in weights for initial portfolios.

(varies depending on AUM assumption) for each of the *W* (=11) weighting schemes. Note that a specific property can be included in multiple portfolios but only once in a given portfolio.

A crucial parameter in the simulation analyses is AUM. We start by considering an amount of USD 5 billion to be invested as of the beginning of 2004. We also use an amount of 2.5 and 7.5 billion, respectively, to assess whether portfolio size impacts upon the results. The amount invested is incremented to reflect the growth in assets managed by institutional investors over time. To proxy for such growth, we use data concerning U.S. total retirement assets as published by the Investment Company Institute.[8] We then estimate the value of real estate holdings by applying the allocations to real estate by all plan sponsors as published in various Pension Real Estate Association (PREA) reports and remove the effect of commercial real estate capital returns as measured by NCREIF index returns. We obtain an average annual growth in real estate holdings from 2004 to 2019 of 5.5%; hence, we apply a quarterly rate of increase of 1.35% to the invested capital at the beginning of the quarter. This results in a compound increase in invested capital that is independent from portfolio performance. We use a constant rather than time-varying rate to insure that our results are not affected by market timing. The increases in invested capital lead to additional properties being incorporated in our portfolios. This is desirable given the significant increase in the number of properties in the NCREIF database.

In addition to the growth in invested capital over time, we also take into account properties that exit the dataset without there being a true sale.[9] These properties are removed from portfolios as of the quarter prior to their exiting the dataset at their expected sale price. As explained in section

[8] https://www.ici.org/.

[9] Some properties exit the dataset and are not identified as sales or have a sale code that does not allow us to ascertain that such sales are arm's length transactions. These include the following sale codes: *Consolidation*, *No longer qualifies*, *Owner exited database*, *Split into multiple properties*, and *Transfer of ownership*. There are also a number of properties for which we do not have an external appraisal (as such appraisals would be subsequent to the period under review).

2.2, the expected sale price of property p at time q is calculated by multiplying the adjusted estimated value at time $q-1$ by the empirical quantile of order o of the ratio of sale prices to adjusted estimated values for quarter q. At each portfolio inception, we draw for each property the order o that will be used to sample empirical quantiles for the entire lifespan of the property. For example, if the selected order for a given property is 0.5 (i.e., the median), then we use the median of the ratios of sale price to adjusted estimated value computed for each quarter. So, for this example, we compute the expected sale price for quarter q on the basis of the median of the ratios pertaining to that period. Note that the order of the quantile is drawn randomly without taking into account the characteristics of properties. As such, the quantile for a given property will change with each iteration. Despite the fact that we do not take into account the attributes of properties, using quantiles rather than a measure of central tendency is useful to generate heterogeneity in simulation results, making it possible to explore more widely the solution space.

In the case of true sales, properties exit our portfolios at the reported sale price. For those properties, we know the true ratio of sale price to adjusted market value. We can thus determine the quantile order of the ratio within the distribution of ratios for that quarter. We use this quantile order to calculate the expected sale price of that property for previous quarters.

The proceeds from the sale and exiting of properties are combined with the increase in investment capital as well as the other items affecting cash flows and added to the initial cash balance to determine the funds available for purchases for a given quarter:

$$FAP_{n,q} = CB_{n,q-1} + \Delta IC_q + PSE_{n,q} + OCF_{n,q} \qquad (3)$$

where $FAP_{n,q}$ are the funds available for purchases for portfolio n during quarter q, $CB_{n,q-1}$ is the cash balance at the beginning of quarter q, ΔIC_q is the change in invested capital during quarter q,

$PSE_{n,q}$ are the proceeds from the sale and exiting of properties during quarter q, and $OCF_{n,q}$ are the other items affecting cash flows during quarter q. The other items affecting cash flows include NOIs, capital expenditures, and partial sales. Provided that the funds available exceed USD 50 million, they are used to purchase additional properties, maintaining portfolio weights for gateway and non-gateway markets as close as possible to targets.

At the end of the simulations, we check for the amount of cash held in portfolios as well as for the weights of gateway and non-gateway markets. Specifically, we remove any portfolio containing more than 2% of AUM in cash in absolute value or whose gateway weight deviates by more than five hundred basis points in absolute value from its target allocation.

3.3 Performance Metrics

Various portfolio performance metrics are calculated for the 11 sets of 1,000 portfolios, and we compare metric distributions across the 11 sets. We first calculate portfolio annualized total, income, and appreciation returns for each simulated portfolio. Returns are calculated using the NCREIF methodology, substituting their market values for our expected sale prices. Considering return distributions makes it possible to analyze both the standard deviation within and across market weightings. We also consider portfolio standard deviations, which provide for an analysis of variations through time. We further calculate the following metrics: the Sharpe ratio, value-at-risk (VaR), and maximum drawdown (MDD). The Sharpe ratio is calculated for all three types of returns (total, income, and appreciation), whereas the downside risk measures are only computed for appreciation returns. For the Sharpe ratios, we use the three-month Treasury rate sourced from the Federal Reserve Bank of St. Louis. VaR_{α} is calculated as the return level for which we expect a proportion

$1 - \alpha$ of the returns to be below that threshold. So, computing VaR_α involves solving the following equation for a given level of α:

$$P\,[Return < VaR_\alpha] = 1 - \alpha \tag{4}$$

where we define $Return$ as the trailing appreciation return compounded over four quarters. We consider both 95% and 99% confidence levels. MDD is the maximum capital loss from a peak to a trough over the simulation period:

$$MDD = \max_{t\,\in(0,T)} \left\{ -\frac{(C_t - RunMax_t)}{RunMax_t} \right\} \tag{5}$$

where $RunMax_t$ is the highest peak (i.e., running maximum) observed during the period going from 0 to t and C_t is the capital value at time t. Examples of the limited use of those downside risk measures for direct real estate investments include Gordon and Tse (2003), Hamelink and Hoesli (2004), and Amédée-Manesme et al. (2015).

We also calculate the recovery and drawdown cycle lengths. The recovery length is the number of years needed for the capital value to regain its pre-drawdown level from the trough. The drawdown cycle length is the number of years from the start of the drawdown to full recovery of capital losses. The cycle length thus contains both the length from peak to trough and that from trough to restoration of the capital back to the high-water mark.

3.4 Portfolio Analyses

As a further means of investigating the usefulness of diversifying across gateway and non-gateway markets, we construct efficient frontiers with stocks, bonds, and gateway and non-gateway real estate. For stocks, we use the MSCI USA total return index, while the Bloomberg Barclays U.S. Government 10-year total return index is used for bonds. The analysis is first undertaken using median total returns from our simulations for the two types of real estate markets. For gateway markets, access to market information is likely to be homogeneous for domestic and international investors (Devaney et al., 2019) and hence we maintain that all investors will achieve a return akin to that of the simulation median returns. For non-gateway markets, however, information asymmetry is likely to occur, with local players at an advantage. To reflect varying information levels for non-gateway markets, we also perform portfolio analyses using the returns for the 0.65 and 0.35 percentiles, respectively, for non-gateway markets. The 0.65 (0.35) percentile highlights the performance of an investor having an information advantage (disadvantage) on non-gateway markets. The underlying intuition is that an investor with an information advantage will be able to select properties in such a way that portfolio performance will exceed the median. The reverse reasoning applies to an information disadvantage.

3.5 Systematic Risk

We consider systematic risk across types of markets by estimating, for each weighting scheme, the following regression:

$$TR_n - r_f = \beta_0 + \beta_1(Mkt - r_f) + \varepsilon_n \qquad (6)$$

where TR_n is the vector of quarterly total returns for portfolio n, r_f is the vector of risk free rates over the same period, and Mkt is the vector of market returns. The market is a capitalization-weighted composite index of U.S. stocks, government bonds, corporate debt, securitized debt, and real estate. The real estate weight is approximated using a fixed percentage (42.9%) between the value of real estate and GDP. The percentage is calculated based on the figures contained in various issues of the *Total Markets Table* as published by EPRA. We use the following indexes to proxy for asset class returns: *MSCI USA Index*, *Bloomberg Barclays U.S. Treasury Index*, *Bloomberg Barclays U.S. Securitized: MBS/ABS/CMBS and Covered Index*, and *Bloomberg Barclays U.S. Corporate Bond Index*. Real estate returns are computed from our sample of properties using the median ratio of the sale price to adjusted estimated value to account for appraisal smoothing. We also performed the regressions using an index both as the dependent variable and as the real estate component in the composite index. The indexes include the NPI, the NTBI, and an index constructed using our method to adjust for appraisal smoothing. The models are estimated using OLS.

4. Results

We first present descriptive statistics and graphs for our simulated portfolios. The performance analyses for portfolios containing varying weights of gateway and non-gateway markets are discussed next. The following subsection contains various robustness checks, while a fourth subsection provides our portfolios analyses. A final subsection provides a discussion of systematic risk.

4.1 Simulated Portfolios

Appendix 3 contains descriptive statistics concerning the number of properties in our simulated portfolios both at the beginning (Panel A) and at the end (Panel B) of our time period. As of 2004Q1, the median number of properties in the full portfolios ranges from 83 (when the portfolio is entirely invested in gateway properties) to 151 (when the entire allocation is in non-gateway markets). Some sub-portfolios contain only a limited number of properties when the weight of the related market type is small. For instance, if 10% of a portfolio is allocated to gateway markets, the median number of gateway properties is only 11 and the minimum is one. However, in most instances, portfolios contain a sufficient number of properties to achieve proper diversification. At the end of the time period, the median number of properties in portfolios is markedly larger (in the 215-369 range), reflecting the growth of AUM over time, and the minimum number of properties in sub-portfolios is never below 16.

Figure 5 shows appreciation returns for 50 portfolios for gateway markets (Panel A) and non-gateway markets (Panel B), as well as returns for the NPI and the NTBI. The figure shows return patterns that are consistent with the well-documented cyclical nature of commercial real estate markets. Our portfolio returns are more volatile than NPI returns. This is to be expected given that the NPI is appraisal-based, whereas the values of the properties in our portfolios are adjusted. On the other hand, as we implemented a method to filter out the noise resulting from the highly variable number of sales over time, our portfolio returns are less volatile than those of the NTBI. Figure 5 shows a similar pattern for returns in gateway and non-gateway markets, despite some differences in return magnitudes.

4.2 Performance Analysis

Figure 6 depicts the distributions of portfolio average annual total returns (Panel A), standard deviations (Panel B), and Sharpe ratios (Panel C) for the 11 weighting schemes. Each boxplot shows the median (thick line) and the 25% and 75% percentiles (the edges of the box). The whiskers represent the most extreme data points or one and a half the interquartile range, depending on which one is the least extreme. Any observation lying outside of the whiskers can be considered an outlier. Panel A shows that the median portfolio total return diminishes monotonously as a larger weight is allocated to non-gateway markets (median return of 8.40% for gateway markets versus 7.65% for non-gateway markets). Panel A also shows that the distribution of gateway total returns is almost symmetrical (skewness of 0.05). On the other hand, as we move to a larger weight for non-gateway markets, distributions exhibit positive asymmetry (skewness for non-gateway markets of 0.63). In line with median returns, the standard deviations also diminish as a larger fraction of a portfolio is allocated to non-gateway markets (median standard deviation of 5.33% and 4.92% for gateway and non-gateway markets, respectively). Also, the dispersion of portfolio standard deviations diminishes as the weight of non-gateway markets increases. As a result, the portfolio Sharpe ratios do not vary depending on the share of gateway and non-gateway markets (Panel C). It is interesting to contrast our results with those of Beracha et al. (2017) who find that high capitalization rate properties dominate low capitalization rate properties on a risk-adjusted basis. Our results suggest that there is no difference in performance across non-gateway and gateway markets, although the former have higher capitalization rates than the latter, with the exception of a few quarters at the beginning of the time period. Those diverging results are likely due to differences in time periods (1978-2015 for Beracha et al., 2017, and 2004-2019 for us) and data filtering rules (our filtering rules do not accommodate for value-add properties).

We now turn to analyzing the two components of total returns. Figure 7, Panel A shows that median income returns are 50 basis points larger for non-gateway markets (5.77%) than for gateway markets (5.27%). Income returns exhibit a slight negative asymmetry (skewness from -0.12 to -0.32), with no clear trend with respect to the market type weight. Negative asymmetry would be expected for income returns as NOI surprises are more likely to be on the downside than the upside. Income returns for non-gateway markets are also less volatile than their gateway counterparts (Figure 7, Panel B). This leads to higher income return Sharpe ratios for non-gateway markets relative to gateway markets (Figure 7, Panel C). Income returns represent a share of 63% of total returns for gateway markets, whereas this figure is 69% for a portfolio with equal weights of both types of markets, and 75% for non-gateway markets. On the other hand, gateway markets offer a higher total return but as much as 37% of that return stems from capital appreciation.

Given that the NOI does not provide the full picture regarding the cash flow generating ability of assets, we calculated the free cash flow return as the NOI minus capital expenditures divided by the property's market value at the beginning of the period. Free cash flow returns are approximately 150 basis points lower than income returns, with capital expenditures only 12 basis points higher for non-gateway markets. Hence, non-gateway markets offer significantly higher recurrent returns than gateway markets even after accounting for capital expenditures. These results should be of interest to institutional investors looking for sizeable and recurrent cash flows to meet their commitments.

Focusing on the appreciation return component, Appendix 4, Panel A shows that gateway markets have a 123 basis point larger median return (3.01%) than their non-gateway counterparts (1.78%). Bearing in mind that the average compound inflation rate during the 2004-2019 period was 2.08%, non-gateway markets on average did not provide capital protection in real terms. This is a clear disadvantage of investing in those markets, at least for the period under review. A minimum allocation of 30% in gateway markets would have been warranted to insure preservation of the invested capital in real terms. The shape of the total return distribution is largely inherited from that of appreciation returns. Gateway capital returns also come with a somewhat larger dispersion than for non-gateway markets (Panel B), resulting in capital return Sharpe ratios being in favor of gateway markets (Panel C).

Figure 8, Panel A indicates that the 95% VaR is somewhat greater for gateway markets (19.6%) than for non-gateway markets (18.0%). This is confirmed by the 99% VaR figures (Panel B) of 25.2% and 23.8% for gateway and non-gateway markets, respectively. The MDD results (Panel C) further suggest that downside risk is greater for gateway markets (31.5%) than for non-gateway markets

(30.4%). Unsurprisingly, these drawdowns occurred during the GFC. The lack of evidence of negative skewness or of differences in dispersion across market types suggests that VaR and MDD medians are robust estimates of downside risk. From a practical perspective, this analysis does not indicate material differences in downside risk across gateway and non-gateway markets. Nevertheless, gateway markets have a higher exposure to downside risk given that a larger fraction of total return originates from capital appreciation.

For investors, capital loss measures, albeit important, are not sufficient in ascertaining the riskiness of portfolios. Two complementary items are the recovery length, i.e., the number of years needed to revert to the pre-drawdown portfolio high-water mark and the drawdown cycle length, i.e., the number of years from the high-water mark to restoring that level. Those two measures are depicted in Figure 9. Panel A shows that the median recovery length is shorter for gateway markets (5.5 years) than for non-gateway markets (7.1 years). The shorter recovery length for gateway markets is a consequence of the greater appreciation returns for gateway markets. The recovery length standard deviations are lower for gateway markets, which reinforces the idea that those markets are quicker to recover. Nonetheless, portfolios that are heavily tilted towards gateway markets exhibit stronger positive skew than their non-gateway counterparts as evidenced by the outliers in Panel A. The length of full drawdown cycles (Panel B) confirms this result, with a shorter cycle for gateway markets (7.3 years versus 9.0 years). Portfolios that are heavily tilted towards non-gateway markets could be problematic in an asset-liability management (ALM) framework, as asset values will take longer to regain the level of the associated liabilities. This is even more of an issue for leveraged investors, especially if the lender is monitoring closely the loan-to-value ratio as part of the agreed covenants.

The analysis of the performance of gateway and non-gateway markets would be incomplete without a comparison of the liquidity of the two types of markets. Figure 10 depicts the turnover ratio for both gateway and non-gateway markets, based on the sales in the cleaned NCREIF dataset. The ratios are calculated as the dollar volume of sales during any given year divided by the value of assets at the end of the year. The measures are likely to constitute a conservative assessment of real estate turnover given the buy-and-hold policies of many NCREIF contributing members. Nonetheless, the ratios are broadly in line with those reported by Devaney and Scofield (forthcoming) for New York using Real Capital Analytics data. Figure 10 shows slightly higher levels of turnover for non-gateway markets than for gateway markets.[10] Whereas the turnover ratios were in a 6-14% range prior to the GFC, they declined markedly during the crisis, and have stabilized after the recovery at 4-9%. Hence, there does not appear to be any meaningful differences in liquidity across the two types of markets.

4.3 Robustness Checks

The first set of robustness checks pertains to the definition of gateway markets, the second to the size of AUM, and the third to sectors.

We consider five sets of gateway markets, ranging from a three-market definition to an 11-market definition. For each set of markets, we report in Table 2 various performance metrics for three types of portfolios (gateway weight of 100%, 50%, and 0%, respectively). For each metric, the table also shows the difference in performance between 100% gateway and 100% non-gateway portfolios. Overall, the performance spreads have the same sign and are of similar magnitude, suggesting that our results are robust to the definition being used. Widening the definition of gateway markets from our base case leads to more muted differences between gateway and non-gateway

[10] The same pattern is observed for simulation turnovers that consider both sales and exits from the database.

markets. Narrowing the definition of markets from the original set shows that the four-market set provides slightly less discrimination across markets, while the three-market definition is comparable with the base case. We conclude that the original set of six gateway markets is appropriate, corroborating the conventional wisdom. A set of six markets has the further advantage of widening the universe of investment opportunities.

We formally tested the difference in performance between gateway and non-gateway markets by undertaking analyses of variance (ANOVAs). Such tests allow to measure and compare discrimination between market types for all market definitions. Tests were performed on the metrics presented in Table 2, considering various univariate and multivariate settings. Overall, the results (not reported) validate our prior observation that the six-market definition leads to the best discrimination between gateway and non-gateway markets. It also confirms that the three-market definition offers the second best discrimination. We also performed Kolmogorov–Smirnov tests which aim to investigate whether two probability distributions are statistically identical. These tests yield results in line with the ANOVAs and provide further support for the six-market definition.

A second robustness check consisted in using an initial AUM of 2.5 billion and 7.5 billion, respectively, rather than the original 5 billion. The results (not reported) remain by and large unchanged. The median of full drawdown cycle and recovery lengths, however, appear to be slightly longer for an AUM of 2.5 billion. We attribute this to the better performance of some larger properties that are less likely to be included in smaller portfolios.

The discussion of performance metrics in section 4.2 refers to portfolios that can include assets of any sector. We now take sectors into account which is useful for at least two reasons. First, some types of investors may favor a given sector over others, e.g., if they have developed an expertise that is specific to a sector. Second, considering all sectors simultaneously may reveal differences in performance that are attributed to the type of markets (gateway versus non-gateway), whereas they can be explained by different sector weights. The analyses are undertaken for an AUM of USD 2.5 billion to account for the smaller pool of properties available at the sector level.

Results (not reported) point to noteworthy differences across sectors. Whereas the total return spread between gateway and non-gateway markets is 87 basis points in the overall analysis, the spread is markedly higher for office and industrial properties (210 and 169 basis points, respectively). For retail, the spread is in line with the overall spread. Interestingly, the total return for apartments is greater for non-gateway than for gateway markets (spread of 37 basis points). A similar pattern emerges for appreciation returns. The main conclusion pertaining to downsize risk, i.e., that gateway markets tend to be slightly riskier than non-gateway markets holds across sectors, with the exception of apartments which tend to be slightly riskier in non-gateway markets. Finally, the difference in income returns between non-gateway and gateway markets is of similar magnitude across all sectors.

We also consider a sectoral composition for both gateway and non-gateway markets that is equal to the sectoral composition of the entire sample (rather than that by type of market) at the beginning of each quarter. By doing so, any differences in performance will be due purely to the type of market. This results mainly in a lower weight for office properties and a higher allocation for retail in gateway markets, while the changes in allocations are in the opposite direction for non-gateway markets. The analysis yields that the superiority of gateway markets over their non-gateway counterparts with respect to total and appreciation returns is reinforced. For instance, whereas gateway markets has an 87 basis points higher return than their non-gateway counterparts when sectoral composition is not constrained, the spread is 114 basis points when sector constraints are implemented. Hence, our conclusions are robust to changes in sectoral composition.

4.4 Portfolio Analyses

Figure 11, Panel A depicts the composition of portfolios containing stocks, bonds, and both gateway and non-gateway markets. Median returns from our simulations are used for the two types of real estate markets. The allocation to real estate in mixed-asset portfolios is large, with non-gateway markets appearing in low-risk portfolios while gateway markets constitute the preferred investment route for medium- to high-risk portfolios.

To analyze the effects of information asymmetry on non-gateway markets, we consider both an information disadvantage (Panel B) and an information advantage (Panel C). An information disadvantage does not lead to any differences in portfolio allocations. Non-gateway markets are still useful in low-risk portfolios and this remains true even for high information disadvantages (i.e., the 0.05 percentile). Non-local investors, who are more likely to be at a disadvantage on such markets, should still consider non-gateway markets. On the other hand, an information advantage leads to a substitution of gateway markets by non-gateway markets up to the middle of the frontier. Hence, an investor with even a slight information advantage should increase markedly the allocation to non-gateway markets. This result is reinforced as one moves to higher percentiles and for top-tier performers (i.e., percentiles equal or over 0.7) the allocation should be entirely to non-gateway markets.

4.5 Analysis of Systematic Risk

This section contains a discussion of regression results for Equation (6). Figure 12 depicts the distributions of regression adjusted R-squared (Panel A) and of estimated coefficients for systematic risk over the whole sample period (Panel B) for 11 weighting schemes. It also shows (Panel C), for three weighting schemes, the estimated coefficients for systematic risk for two time periods (2004Q1-2011Q4 and 2012Q1-2019Q4). The adjusted R-squared amount to approximately 0.15 and increase slightly with the weight allocated to non-gateway markets. Systematic risk appears to be the same across market types and its median value across samples is 0.47, with all coefficients significant at the 5% level. Panel B also shows that in-sample variation is less for non-gateway than for gateway markets. When performing the regressions at the index level, we obtain median beta coefficients of 0.29 (NPI), 0.34 (NTBI), and 0.45 (our desmoothing method), respectively. Those results are consistent with the well-known smoothing bias of appraisal-based indexes and the potential issues of the NTBI, which lead to lower measures of systematic risk. We also classified portfolios based on their total return, rather than by market type, and again found no differences between groups.

Although systematic risk is constant across markets, it exhibits much variability over time (Panel C). As would be expected, during the first subperiod (which includes the GFC), median betas are much higher (0.72) than during the second subperiod (0.05), highlighting the fact that during a crisis asset returns tend to be much more correlated. There are no material differences across the three types of markets.

5. Conclusions

Using simulation analysis and property-level data, we compare various return and risk metrics for portfolios with varying exposures to gateway and non-gateway markets. The sample distributions of performance metrics are an accurate depiction of the return and risk of the different types of real estate markets. We also analyze how best to diversify a mixed-asset portfolio across gateway and non-gateway markets. All analyses are conducted using property values that have been corrected using an innovative procedure to reflect market values more accurately.

Our results show that gateway markets have a higher total return and standard deviation than their non-gateway counterparts, leading to comparable risk-adjusted performance across types of markets. Differences in standard deviations are not attributable to differences in systematic risk given that the latter is comparable across market types. Non-gateway markets have a significantly higher income return than gateway markets, even after accounting for capital expenditures. On the other hand, gateway markets exhibit higher appreciation returns. Gateway markets appear to have slightly higher downside risk than their non-gateway counterparts; however, recovery times are shorter for the former than for the latter, consistent with the higher appreciation returns for gateway markets. Non-gateway markets are useful in diversifying low-risk mixed-asset portfolios, while gateway markets should constitute the entire allocation for riskier portfolios. An information disadvantage on non-gateway markets does not alter this conclusion, but an information advantage leads to a substitution of gateway markets by their non-gateway counterparts.

Changing the set of gateway markets does not alter our main findings, although a six-market definition has most appeal, corroborating a common practice of institutional investors. Our results are also shown to be robust across alternative assumptions pertaining to AUM and when sectoral weights are held constant across the two types of markets. Income returns are consistently larger for non-gateway markets than for gateway markets across all sectors. On the other hand, total and appreciation returns are larger for gateway than for non-gateway markets in all sectors, except apartments.

There are various ways in which our knowledge of commercial real estate gateway markets could be expanded. First, it would be interesting to analyze how the importance of a metropolitan area can change over time. Obvious examples of metropolitan areas that have grown fast during the period are San Francisco, Dallas, or Houston. Second, a more granular set of areas than metropolitan divisions could be used to delineate markets in order to capture the effects of micro-location more precisely. Finally, a fruitful avenue for future research would be to analyze whether our main conclusions hold for other regions or globally. There are many international gateway markets, such as Toronto, Paris, London, or Tokyo, and comparing commercial real estate performance between those cities and more regional markets should prove informative.

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Table 1. Sample Descriptive Statistics by Sector and Market Type

Panel A. Beginning of Time Period (2004Q1)

	Apartment	Industrial	Office	Retail	All
# Properties					
All CBSAs	399	518	521	245	1,683
Gateway	72	159	182	65	478
Non-Gateway	327	359	339	180	1,205
Aggregate Value of Properties (USD billion)					
All CBSAs	15.0	10.4	28.4	16.7	70.5
Gateway	5.0	3.6	15.9	5.4	29.9
Non-Gateway	10.0	6.8	12.5	11.3	40.5
Average Property Value (USD million)					
All CBSAs	37.5	20.1	54.6	68.0	41.9
Gateway	69.4	22.7	87.5	83.3	62.6
Non-Gateway	30.5	19.0	36.9	62.5	33.6
Capitalization Rates (%)					
All CBSAs	5.20	7.30	7.07	6.98	6.69
Gateway	4.92	7.61	6.94	7.03	6.70
Non-Gateway	5.34	7.13	7.24	6.95	6.67
Spread in Capitalization Rates between Non-Gateway and Gateway Markets (bps)					
	42	-48	30	-8	-2

Panel B. End of Time Period (2019Q4)

As of 2019Q4	Apartment	Industrial	Office	Retail	All
# Properties					
All CBSAs	901	1,752	710	702	4,065
Gateway	316	582	353	226	1,477
Non-Gateway	585	1,170	357	476	2,588
Aggregate Value of Properties (USD billion)					
All CBSAs	87.2	63.5	145.2	95.4	391.3
Gateway	40.1	23.4	104.8	32.1	200.4
Non-Gateway	47.2	40.1	40.4	63.3	190.9
Average Property Value (USD million)					
All CBSAs	96.8	36.2	204.5	135.8	96.3
Gateway	126.8	40.3	269.8	141.8	135.7
Non-Gateway	80.6	34.2	113.1	133.0	73.8
Capitalization Rates (%)					
All CBSAs	4.25	4.48	4.26	4.60	4.37
Gateway	3.98	4.28	4.02	4.31	4.09
Non-Gateway	4.47	4.60	4.86	4.75	4.67
Spread in Capitalization Rates between Non-Gateway and Gateway Markets (bps)					
	49	32	83	44	58

Table 2. Selected Performance Metrics for Various Sets of Gateway Markets

	Total Returns (%)				Income Returns (%)			
Gateway Weight	**1.0**	**0.5**	**0.0**	**Δ**	**1.0**	**0.5**	**0.0**	**Δ**
3 Markets	8.4	8.1	7.8	65	5.2	5.5	5.7	-48
4 Markets	8.2	8.1	7.9	29	5.3	5.5	5.7	-44
6 Markets (Base Case)	8.4	8.0	7.6	75	5.3	5.6	5.8	-50
8 Markets	8.2	8.0	7.8	49	5.3	5.6	5.8	-46
11 Markets	8.1	7.9	7.7	41	5.4	5.6	5.8	-40
	Standard Deviation of Total Returns (%)				**Standard Deviation of Income Returns (%)**			
Gateway Weight	**1.0**	**0.5**	**0.0**	**Δ**	**1.0**	**0.5**	**0.0**	**Δ**
3 Markets	5.4	5.1	5.0	48	0.4	0.4	0.4	3
4 Markets	5.4	5.1	5.0	40	0.4	0.4	0.4	3
6 Markets (Base Case)	5.3	5.1	4.9	41	0.4	0.4	0.3	7
8 Markets	5.2	5.0	4.9	29	0.4	0.4	0.3	5
11 Markets	5.2	5.0	4.9	24	0.4	0.3	0.3	3
	Maximum Drawdown (%)				**95% VaR (%)**			
Gateway Weight	**1.0**	**0.5**	**0.0**	**Δ**	**1.0**	**0.5**	**0.0**	**Δ**
3 Markets	-31.9	-31.0	-30.3	-167	-19.8	-19.3	-18.4	-138
4 Markets	-30.4	-30.6	-30.8	37	-18.8	-18.8	-18.8	-6
6 Markets (Base Case)	-31.5	-30.8	-30.4	-111	-19.6	-19.0	-18.0	-159
8 Markets	-31.1	-30.7	-30.4	-71	-19.3	-18.8	-18.2	-114
11 Markets	-30.7	-30.7	-30.4	-28	-19.1	-18.8	-18.3	-80

Notes: Δ denotes the spread in basis points between 100% gateway and 100% non-gateway markets. 3 Markets = New York, Los Angeles, and Chicago; 4 Markets = New York, Los Angeles, Chicago, and Washington D.C.; 6 Markets = New York, Los Angeles, Chicago, Washington D.C., Boston, and San Francisco; 8 Markets = New York, Los Angeles, Chicago, Washington D.C., Boston, San Francisco, Dallas, and Philadelphia; and 11 Markets = New York, Los Angeles, Chicago, Washington D.C., Boston, San Francisco, Dallas, Philadelphia, Atlanta, Houston, and Miami.

Figure 1. Capitalization Rates for Gateway and Non-Gateway Markets

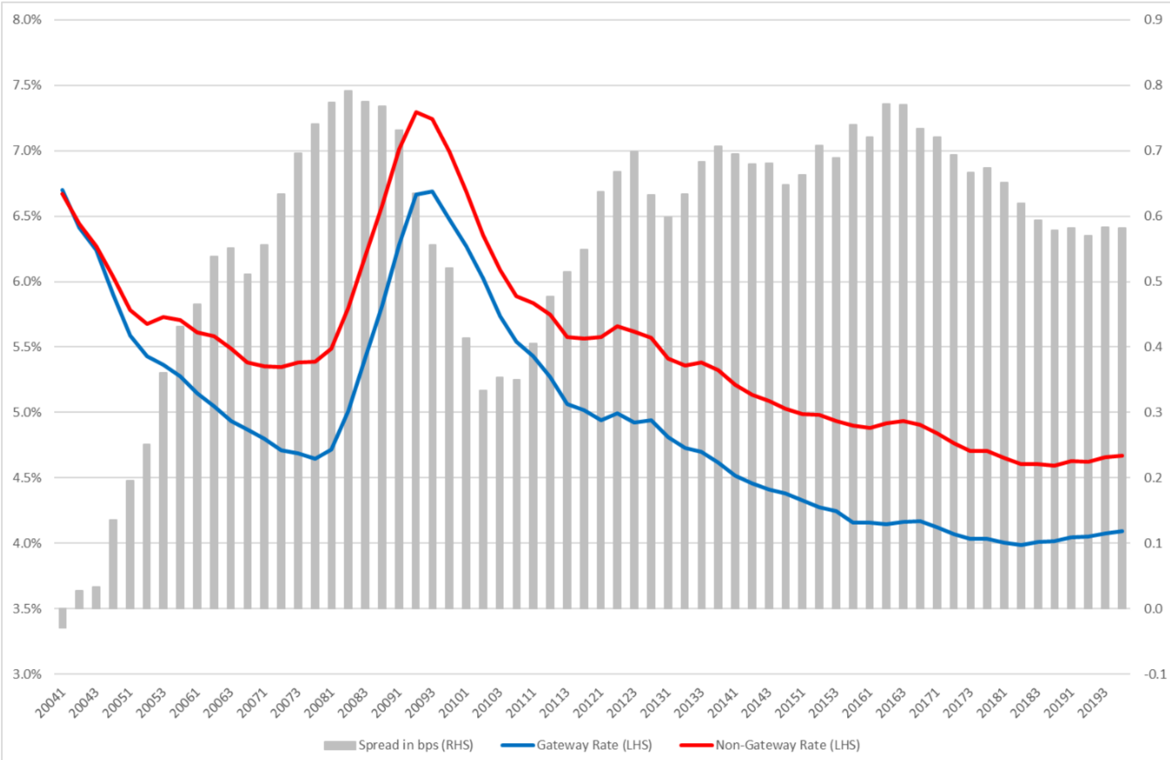
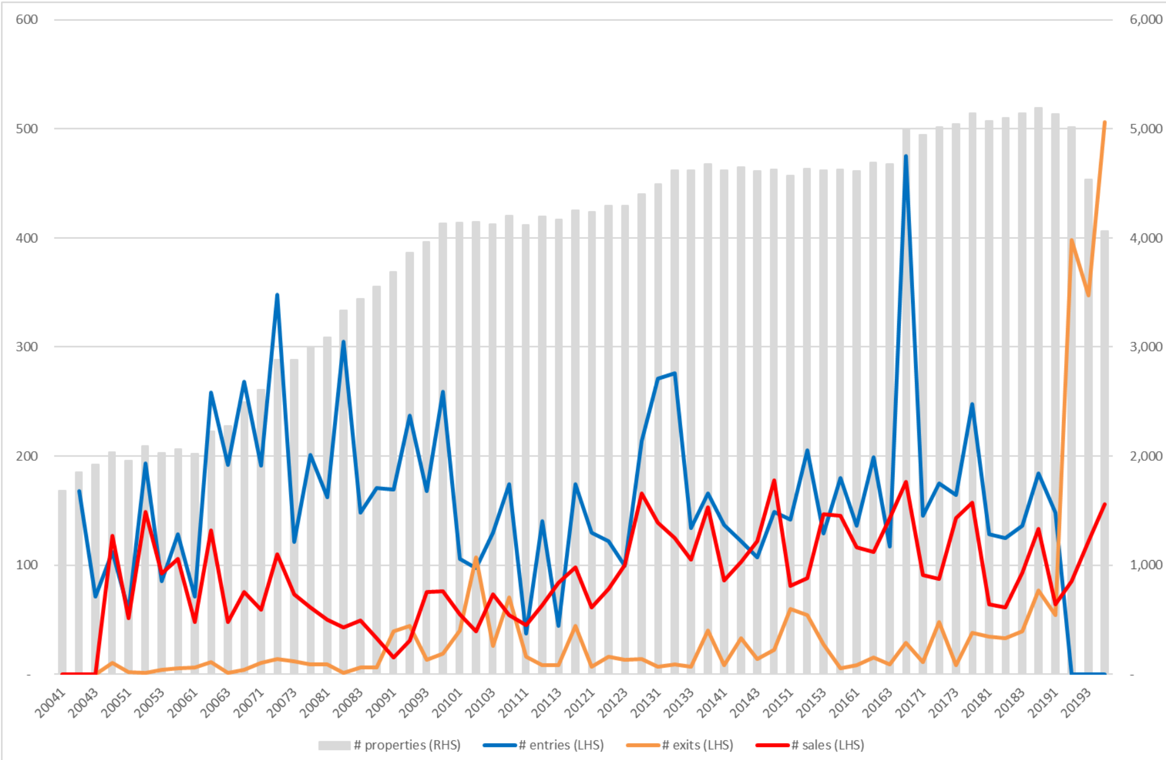
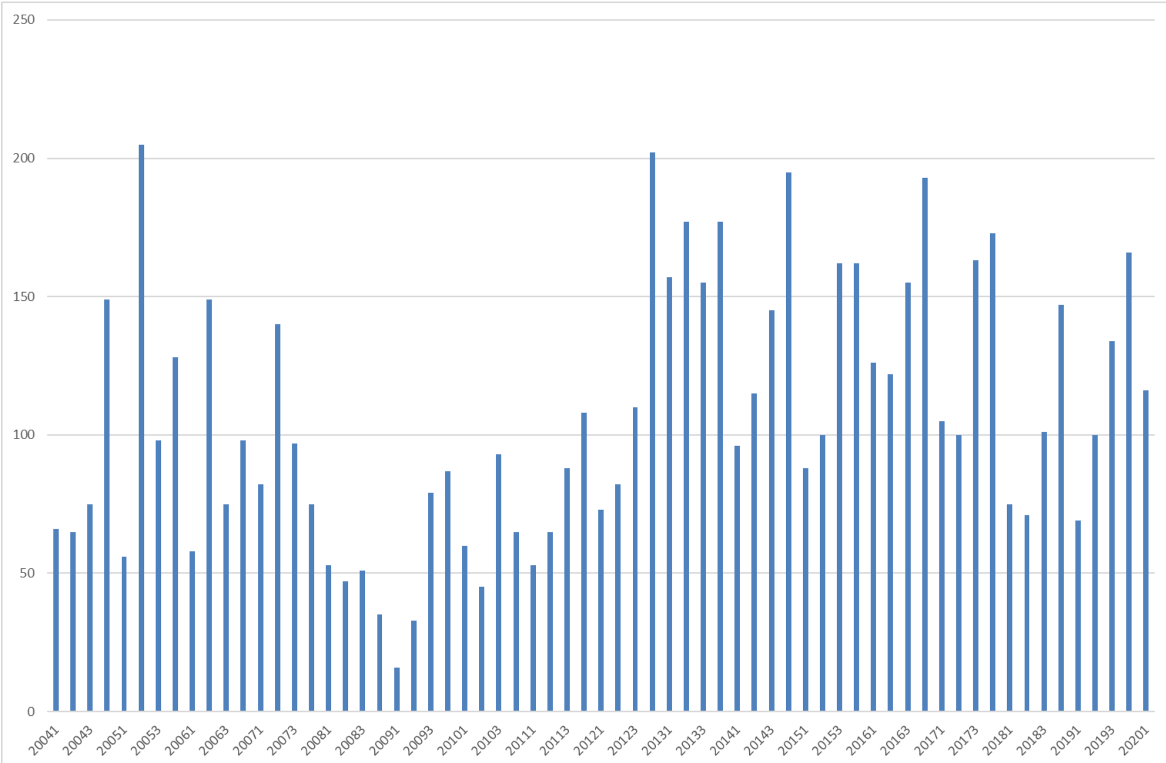


Figure 2. Properties Entering and Exiting the Database and Number of Properties in the Database



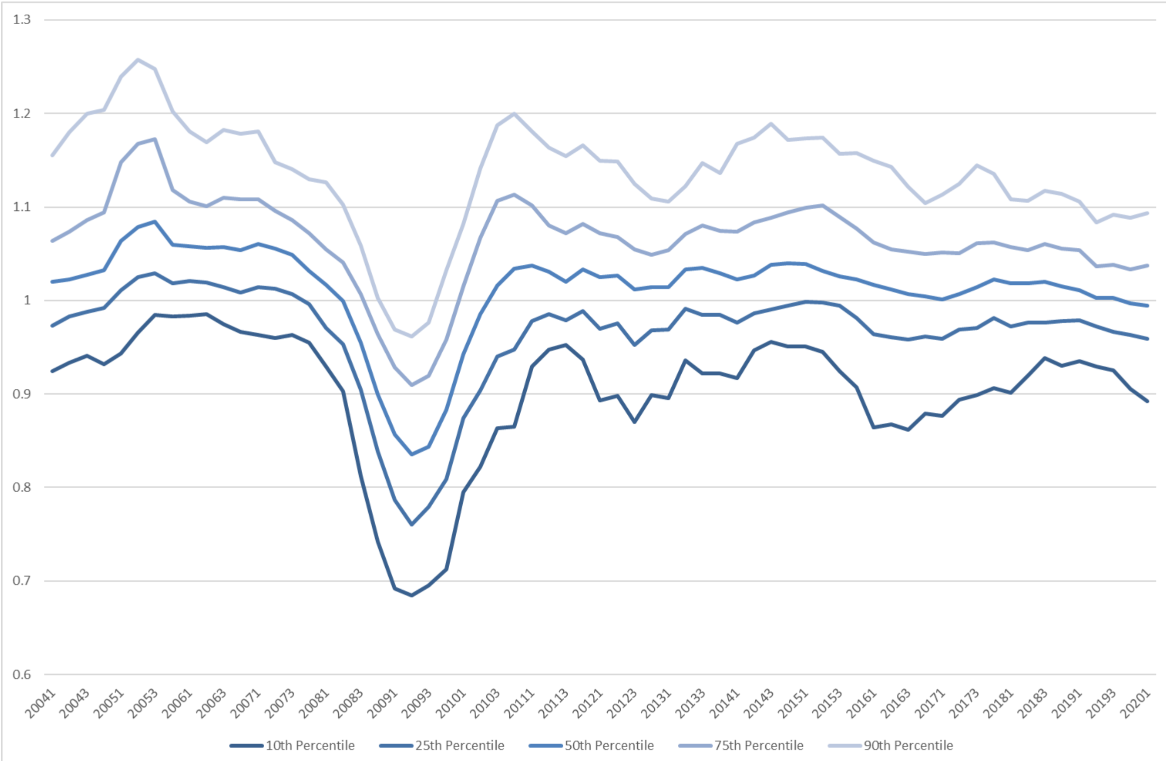
Note: The number of exits refers to the number of properties that leave the dataset and that are not identified as sales or with a sale code that does not allow us to ascertain that such sales are arm's length transactions.

Figure 3. Number of Sales



Note: The figure displays the number of true sales in the cleaned dataset.

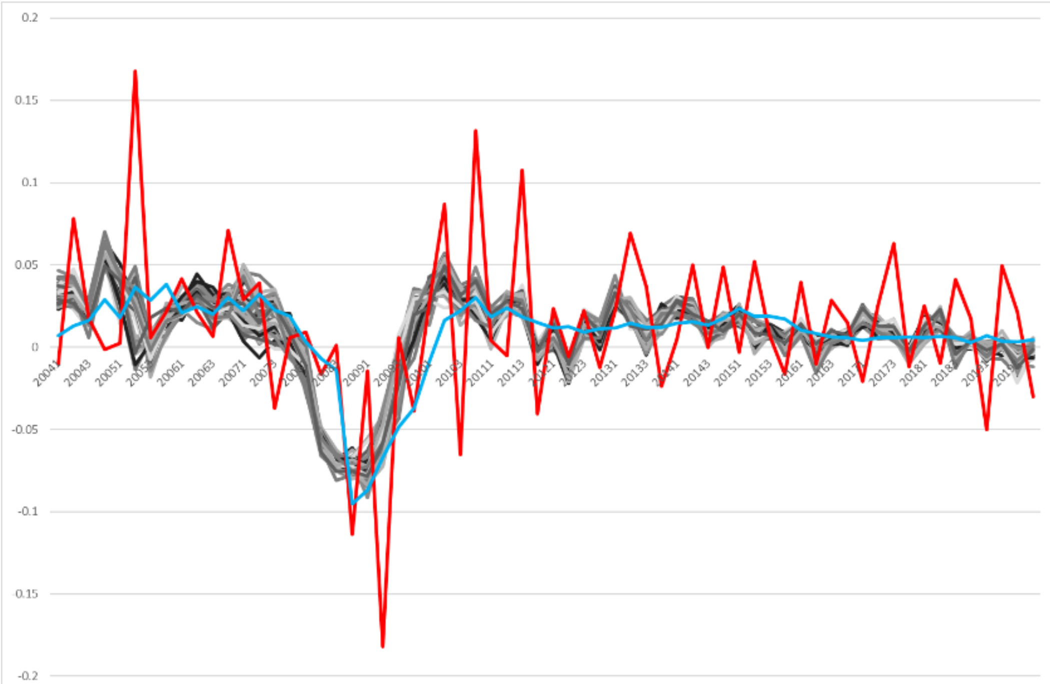
Figure 4. Ratios of Sale Prices to Appraised Values



Note: The figure depicts the median (50th percentile) of the three-quarter average of the ratio of sale price to the lagged appraised value as well as the 10th, 25th, 75th, and 90th percentiles.

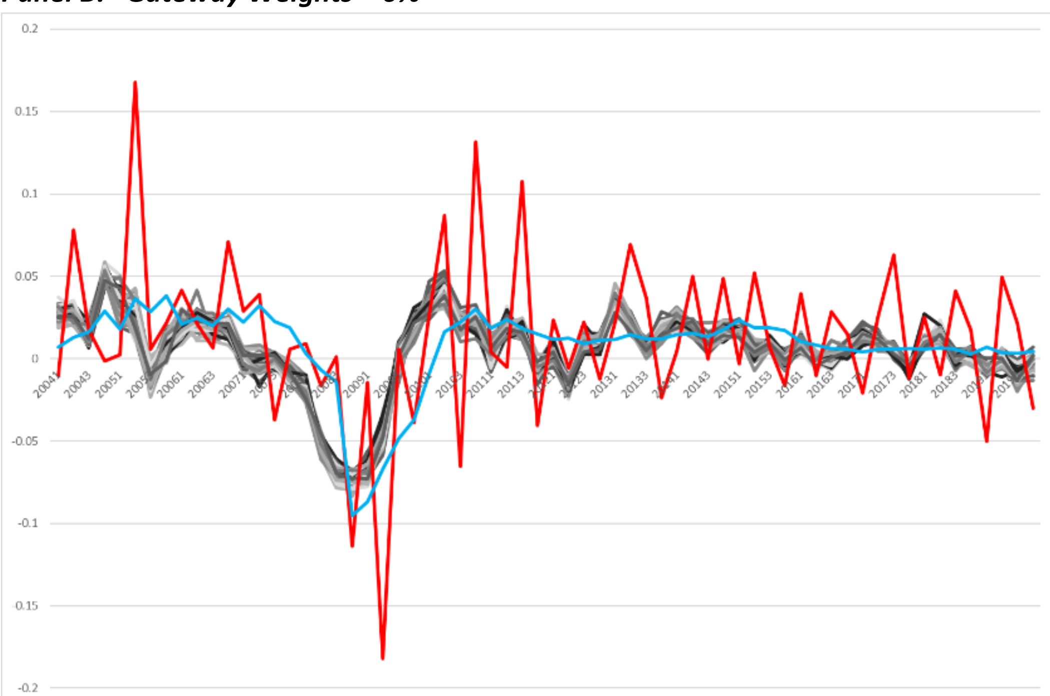
Figure 5. Portfolio and Market Appreciation Returns

Panel A. Gateway Weights = 100%



Note: The grey lines are the returns of 50 randomly-selected portfolios, the blue line is the NCREIF Property Index (NPI), and the red line the value-weighted NCREIF Transaction-Based Index (NTBI).

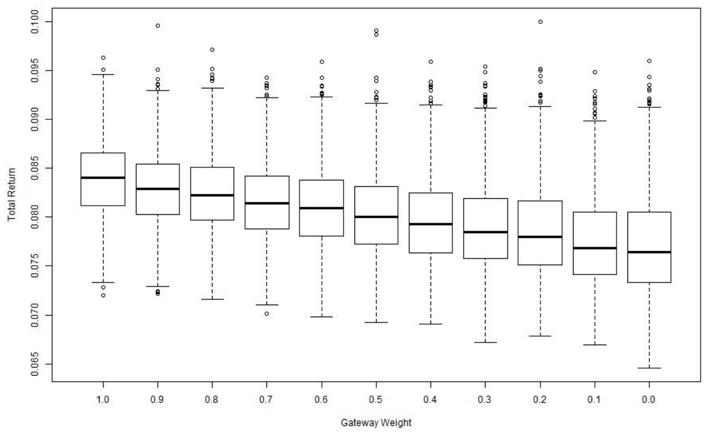
Panel B. Gateway Weights = 0%



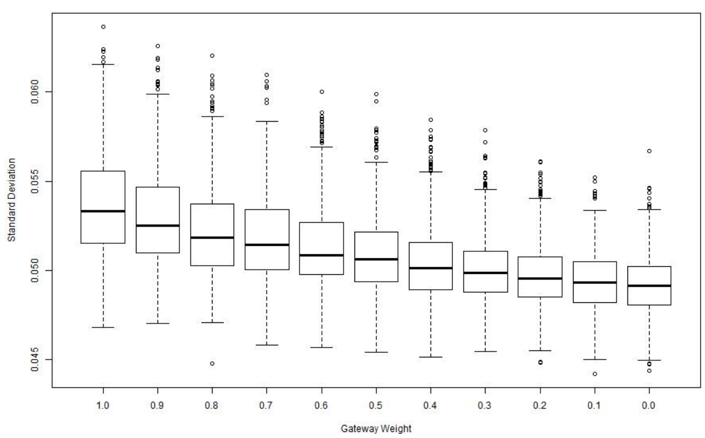
Note: The grey lines are the returns of 50 randomly-selected portfolios, the blue line is the NCREIF Property Index (NPI), and the red line the value-weighted NCREIF Transaction-Based Index (NTBI).

Figure 6. Distributions of Portfolio Total Returns, Standard Deviations, and Sharpe Ratios

Panel A. Annualized Total Returns



Panel B. Standard Deviations



Panel C. Sharpe Ratios

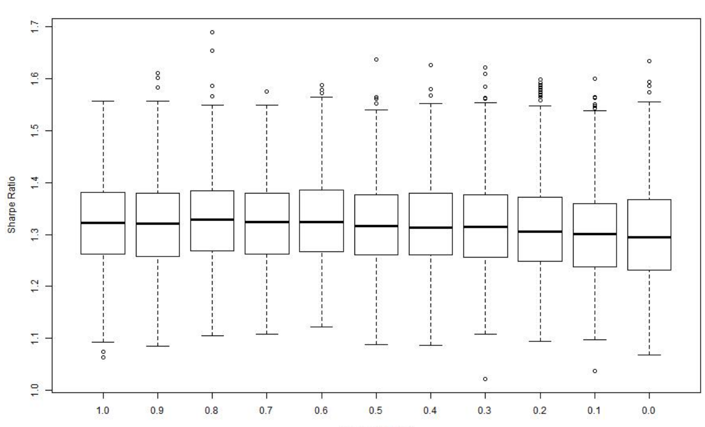
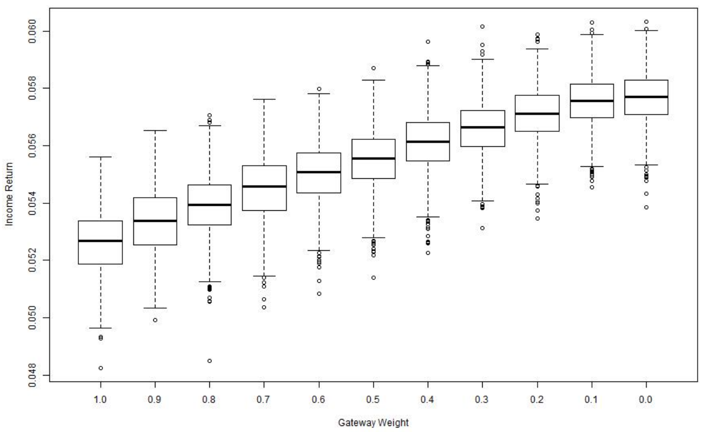
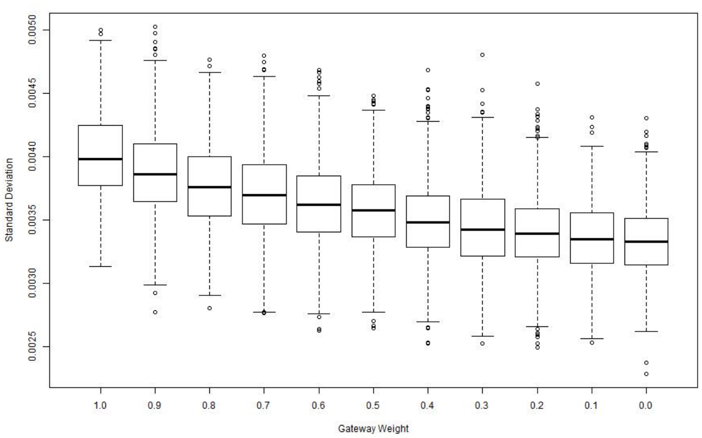


Figure 7. Distributions of Portfolio Income Returns, Standard Deviations, and Sharpe Ratios

Panel A. Annualized Income Returns



Panel B. Standard Deviations



Panel C. Sharpe Ratios

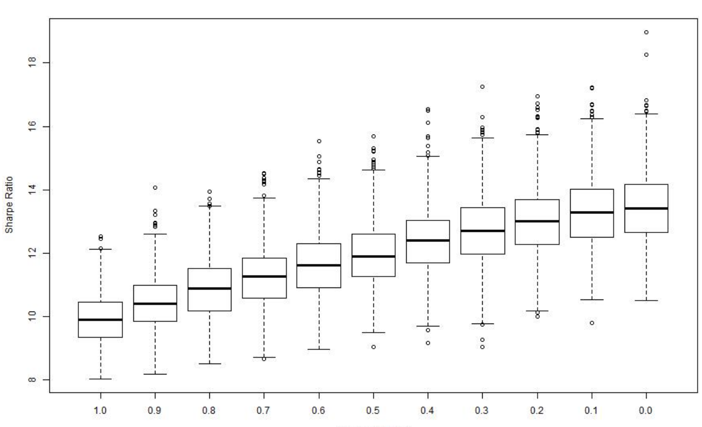
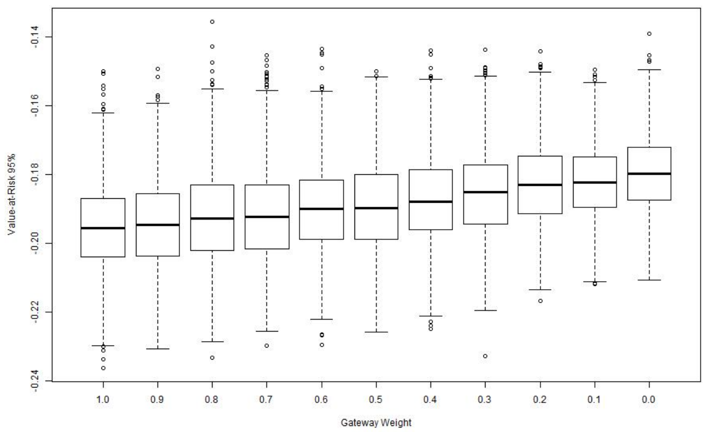
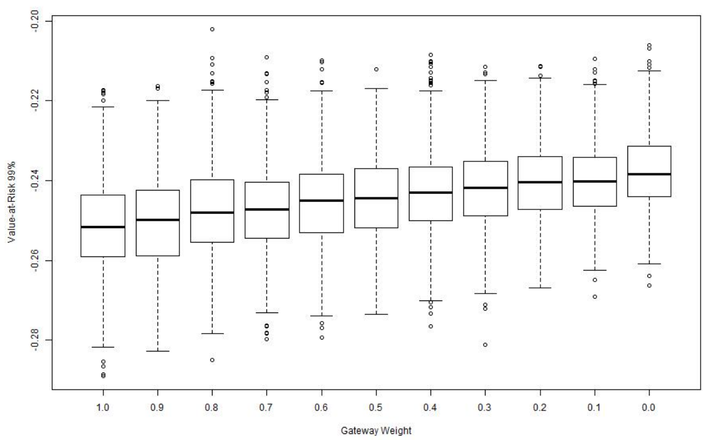


Figure 8. Portfolio Downside Risk Measures

Panel A. 95% Value-at-Risks



Panel B. 99% Value-at-Risks



Panel C. Maximum Drawdowns

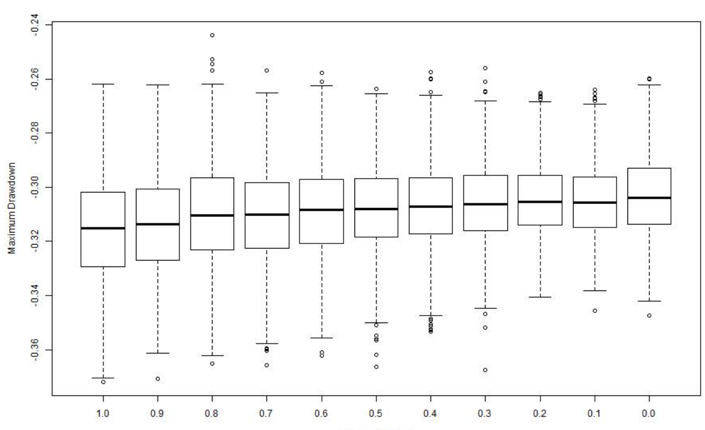
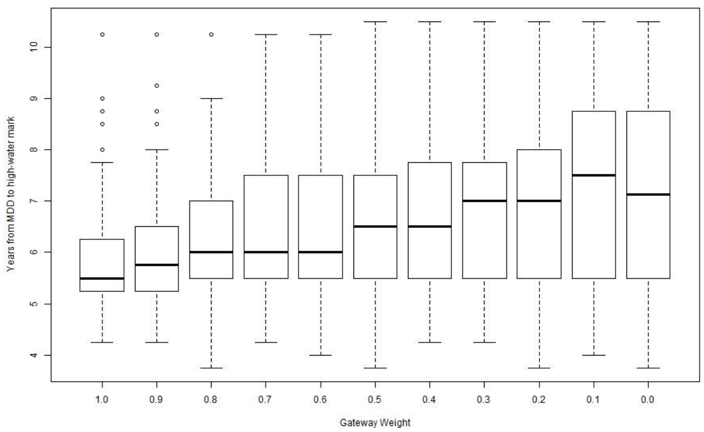


Figure 9. Portfolio Recovery and Drawdown Cycle Lengths

Panel A. Recovery Lengths



Panel B. Drawdown Cycle Lengths

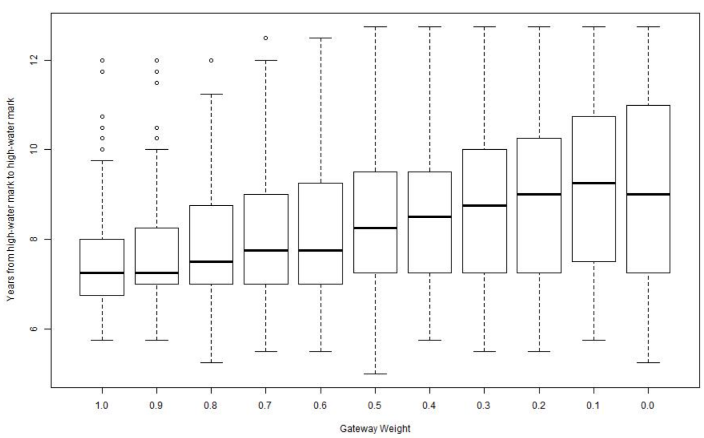
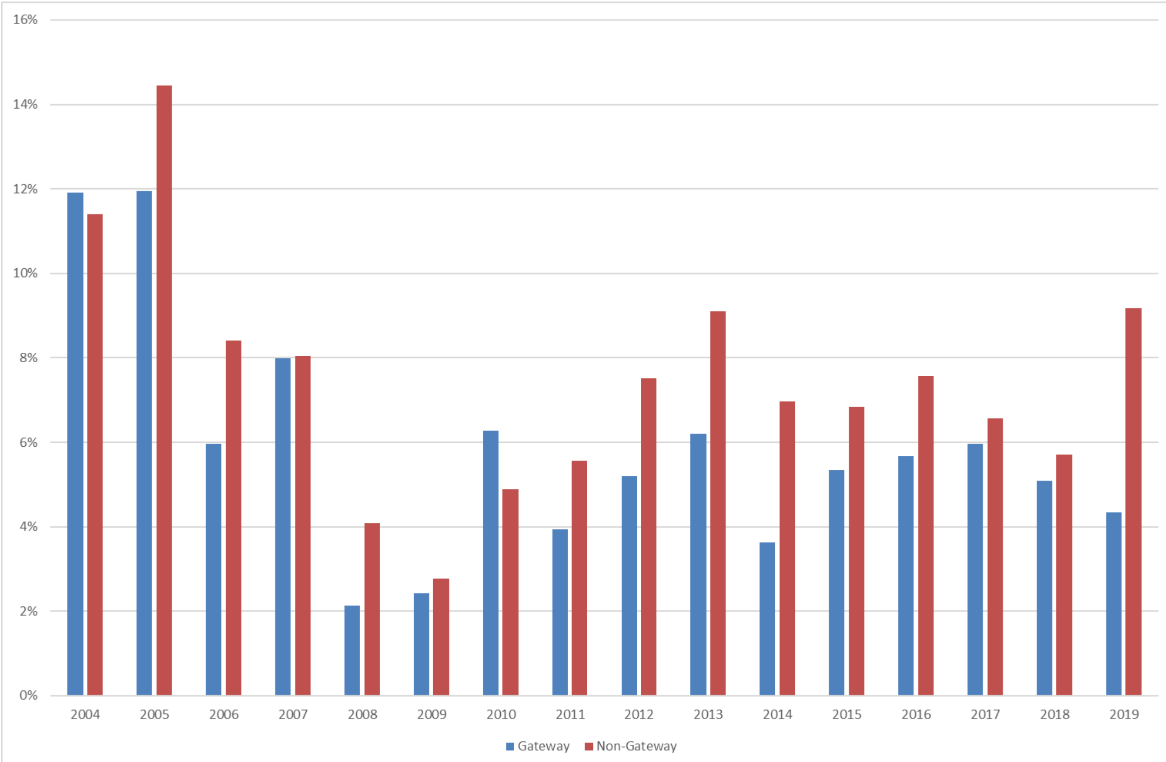


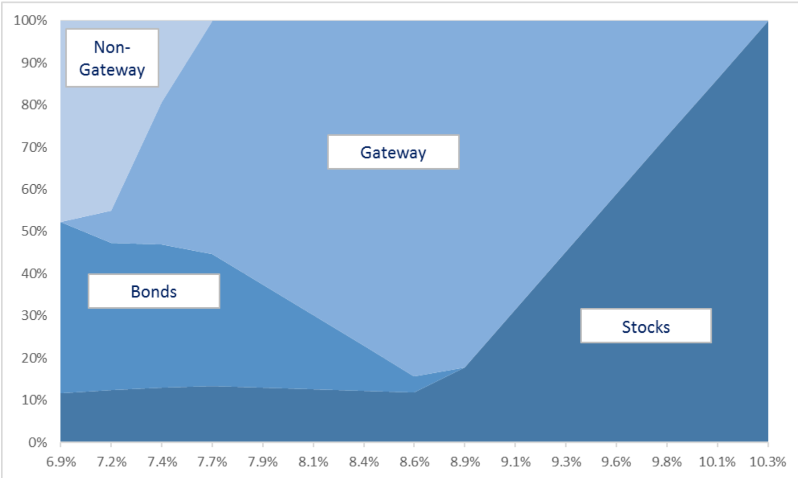
Figure 10. Turnover Ratios for Gateway and Non-Gateway Markets



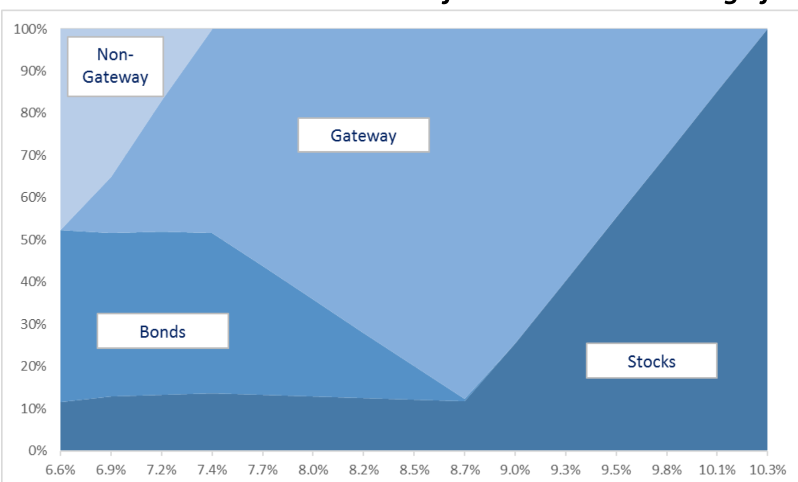
Note: The ratios are calculated as the dollar volume of sales during any given year divided by the value of assets at the end of the year.

Figure 11. Composition of Mixed-Asset Portfolios

Panel A. With Median Returns for Gateway and Non-Gateway Markets



Panel B. For an Investor with an Information Disadvantage for Non-Gateway Markets



Panel C. For an Investor with an Information Advantage for Non-Gateway Markets

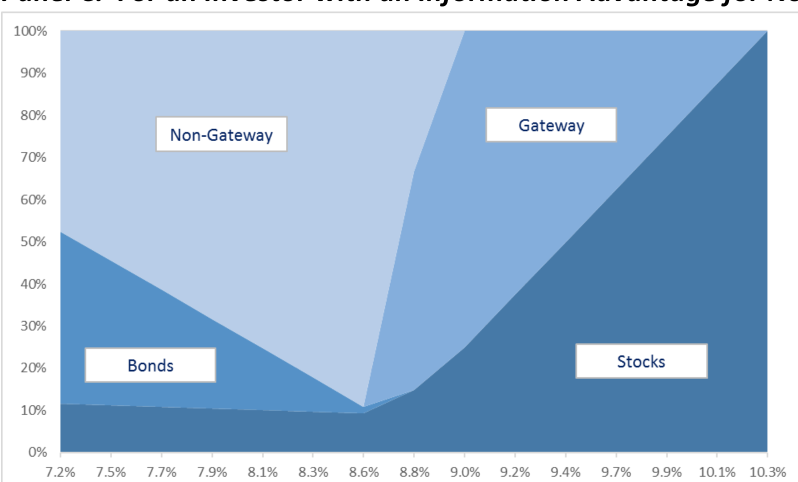
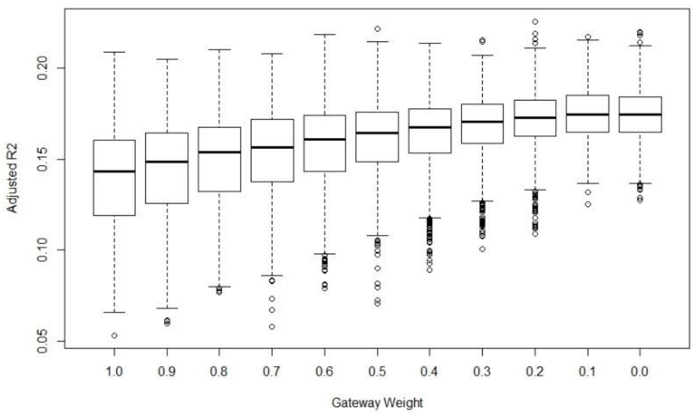
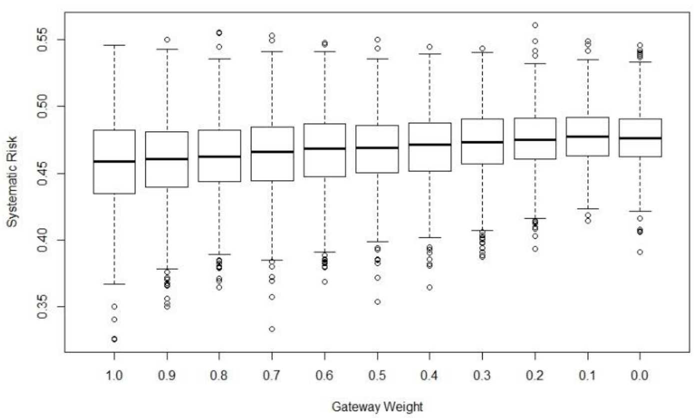


Figure 12. Distributions of Adjusted R-Squared and Portfolio Betas

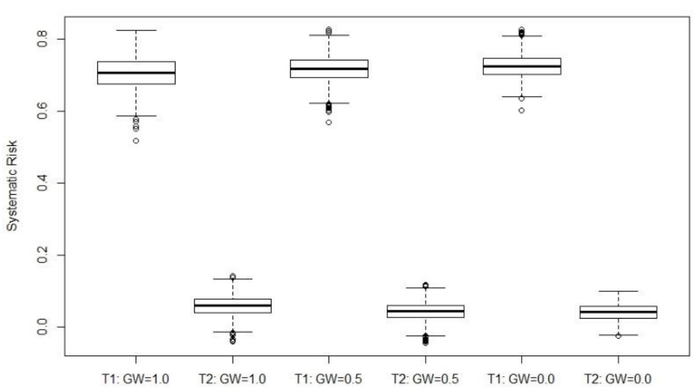
Panel A. Distributions of Adjusted R-Squared



Panel B. Distributions of Portfolio Betas



Panel C. Distributions of Portfolio Betas by Subperiod



Note: T1 = 2004Q1-2011Q4 and T2 = 2012Q1-2019Q4.

Appendix 1. Classification of Divisions

Panel A. Six Gateway Markets

MSA	CBSA	Div.	CBSA Name	Apart.	Ind.	Office	Retail
Boston	14460	14454	MA-Boston	G	G	G	G
Boston	14460	15764	MA-Cambridge-Newton-Framingham	G	G	G	G
Boston	14460	40484	NH-Rockingham County-Strafford County	N-G	N-G	N-G	N-G
Chicago	16980	16974	IL-Chicago-Naperville-Arlington Heights	G	G	G	G
Chicago	16980	20994	IL-Elgin	N-G	N-G	N-G	N-G
Chicago	16980	29404	IL-WI-Lake County-Kenosha County	N-G	N-G	N-G	N-G
Chicago	16980	23844	IN-Gary	N-G	N-G	N-G	N-G
Los Angeles	31080	11244	CA-Anaheim-Santa Ana-Irvine	G	G	G	G
Los Angeles	31080	31084	CA-Los Angeles-Long Beach-Glendale	G	G	G	G
New York	35620	35084	NJ-PA-Newark	N-G	N-G	G	N-G
New York	35620	20524	NY-Dutchess County-Putnam County	N-G	N-G	N-G	N-G
New York	35620	35004	NY-Nassau County-Suffolk County	N-G	N-G	N-G	N-G
New York	35620	35614	NY-NJ-New York-Jersey City-White Plains	G	G	G	G
San Francisco	41860	36084	CA-Oakland-Hayward-Berkeley	G	G	G	G
San Francisco	41860	41884	CA-San Francisco-Redwood City-South San Francisco	G	G	G	G
San Francisco	41860	42034	CA-San Rafael	N-G	N-G	N-G	N-G
Washington DC	47900	47894	DC-VA-MD-WV-Washington-Arlington-Alexandria	G	G	G	G
Washington DC	47900	43524	MD-Silver Spring-Frederick-Rockville	N-G	N-G	N-G	N-G

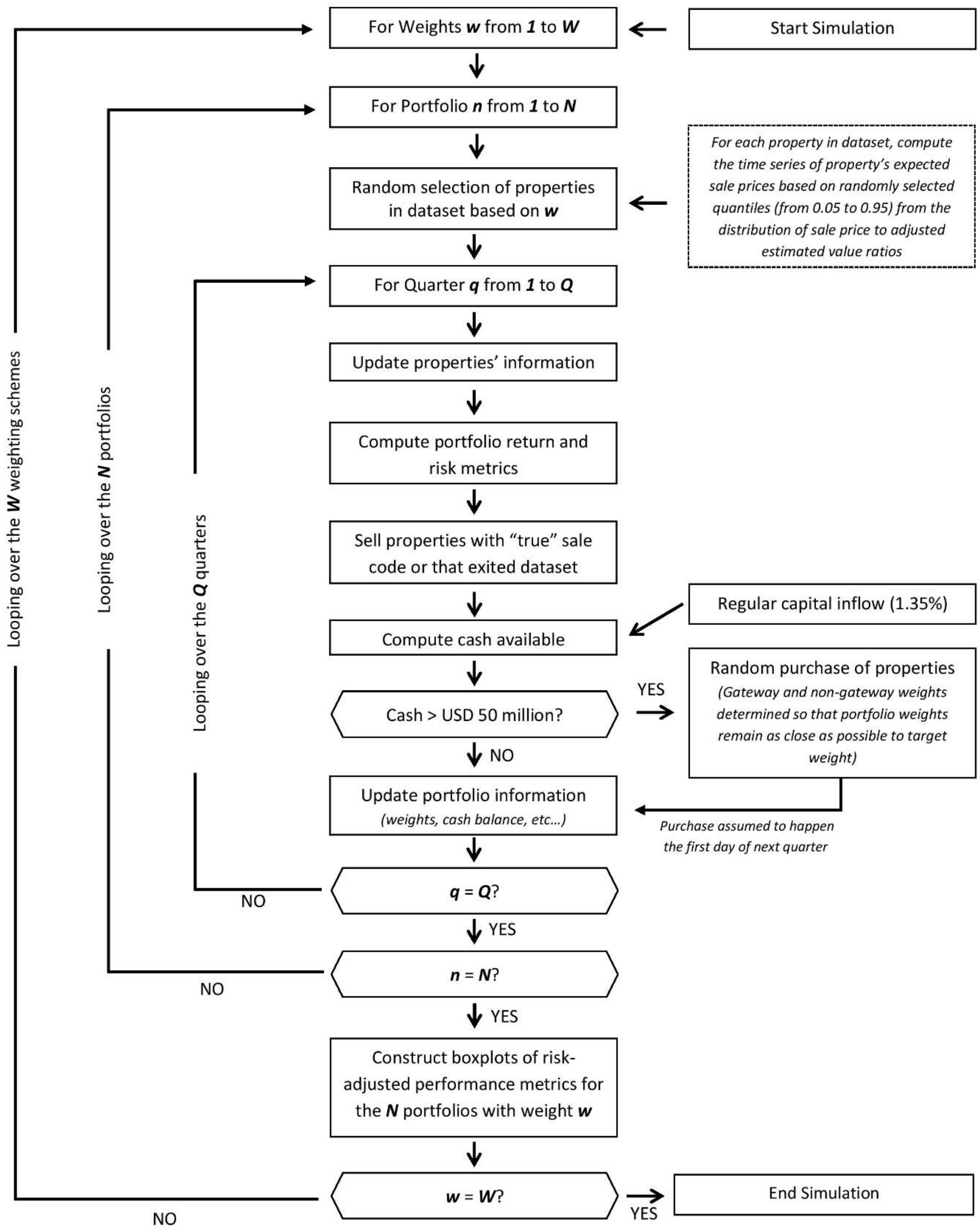
Note: G = Gateway; N-G = Non-Gateway.

Panel B. Additional Markets

MSA	CBSA	Div.	CBSA Name	Apart.	Ind.	Office	Retail
Atlanta	12060	12060	GA-Atlanta-Sandy Springs-Roswell	G	G	G	G
Dallas	19100	19124	TX-Dallas-Plano-Irving	G	G	G	G
Dallas	19100	23104	TX-Fort Worth-Arlington	G	G	N-G	N-G
Houston	26420	26420	TX-Houston-The Woodlands-Sugar Land	G	G	G	G
Miami	33100	22744	FL-Fort Lauderdale-Pompano Beach-Deerfield Beach	G	G	G	G
Miami	33100	33124	FL-Miami-Miami Beach-Kendall	G	G	G	G
Miami	33100	48424	FL-West Palm Beach-Boca Raton-Delray Beach	G	G	G	G
Philadelphia	37980	15804	NJ-Camden	G	G	N-G	N-G
Philadelphia	37980	33874	PA-Montgomery County-Bucks County-Chester County	G	G	G	G
Philadelphia	37980	37964	PA-Philadelphia	G	G	G	G
Philadelphia	37980	48864	DE-MD-NJ-Wilmington	N-G	N-G	N-G	N-G

Note: G = Gateway; N-G = Non-Gateway.

Appendix 2. Flowchart of Simulation Process



Appendix 3. Portfolio Descriptive Statistics

Panel A. Beginning of Time Period (2004Q1)

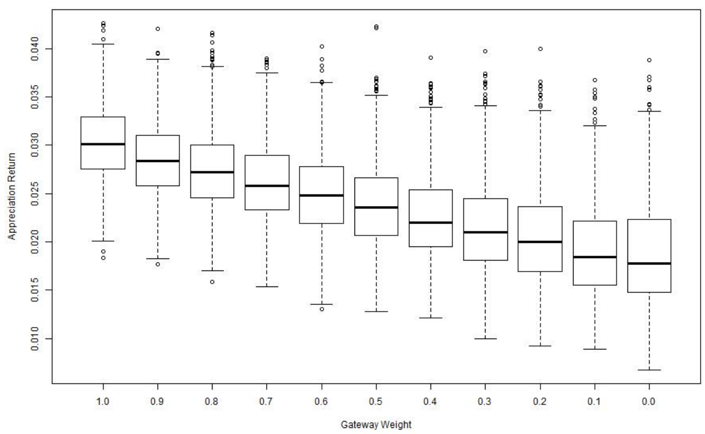
Number of Properties in Portfolio (AUM = 5bn)											
					Full Portfolio						
Gateway Weight	**1.0**	**0.9**	**0.8**	**0.7**	**0.6**	**0.5**	**0.4**	**0.3**	**0.2**	**0.1**	**0.0**
Median	83	93	100	107	114	121	128	133	140	149	151
Mean	84	93	100	108	114	120	127	133	140	148	150
St. Dev.	13	13	14	14	16	16	17	18	17	18	19
Maximum	123	136	153	149	160	172	175	183	187	204	201
Minimum	48	52	47	57	70	71	75	66	89	95	89
					Gateway Sub-Portfolio						
Gateway Weight	**1.0**	**0.9**	**0.8**	**0.7**	**0.6**	**0.5**	**0.4**	**0.3**	**0.2**	**0.1**	**0.0**
Median	83	75	67	59	51	43	35	27	19	11	0
Mean	84	75	68	59	51	43	35	27	19	11	0
St. Dev.	13	12	11	11	10	9	8	7	6	4	0
Maximum	123	115	105	92	87	74	60	48	37	21	0
Minimum	48	37	36	22	22	17	9	6	3	1	0
					Non-Gateway Sub-Portfolio						
Gateway Weight	**1.0**	**0.9**	**0.8**	**0.7**	**0.6**	**0.5**	**0.4**	**0.3**	**0.2**	**0.1**	**0.0**
Median	0	19	33	49	63	77	93	106	122	138	151
Mean	0	18	33	48	63	77	92	106	121	137	150
St. Dev.	0	5	8	10	12	14	14	17	17	18	19
Maximum	0	32	56	78	95	116	130	150	168	195	201
Minimum	0	2	6	15	26	36	55	52	69	82	89

Panel B. End of Time Period (2019Q4)

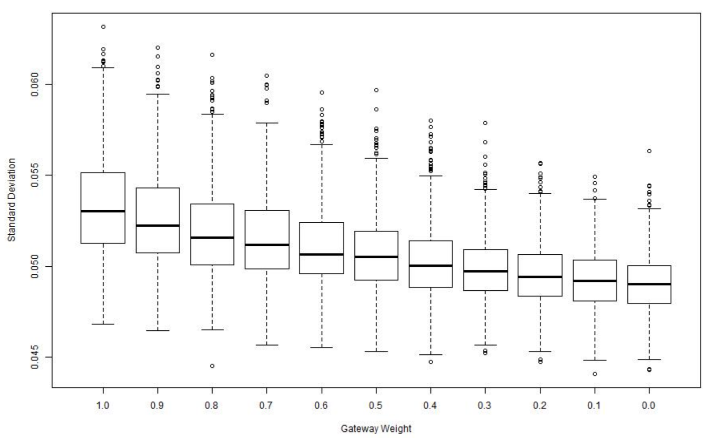
Number of Properties in Portfolio (AUM = 5bn)											
Full Portfolio											
Gateway Weight	**1.0**	**0.9**	**0.8**	**0.7**	**0.6**	**0.5**	**0.4**	**0.3**	**0.2**	**0.1**	**0.0**
Median	215	255	282	302	317	332	345	355	365	369	348
Mean	216	254	281	301	317	332	345	355	364	368	348
St. Dev.	17	18	21	20	21	22	24	23	26	27	27
Maximum	273	309	347	357	369	405	438	425	433	444	430
Minimum	161	185	214	222	244	260	252	268	267	279	258
Gateway Sub-Portfolio											
Gateway Weight	**1.0**	**0.9**	**0.8**	**0.7**	**0.6**	**0.5**	**0.4**	**0.3**	**0.2**	**0.1**	**0.0**
Median	215	197	180	162	144	126	106	88	68	45	0
Mean	216	197	180	162	144	126	107	88	68	45	0
St. Dev.	17	16	15	15	13	12	12	10	9	6	0
Maximum	273	245	239	215	183	171	147	117	92	59	0
Minimum	161	148	138	117	107	89	70	59	37	16	0
Non-Gateway Sub-Portfolio											
Gateway Weight	**1.0**	**0.9**	**0.8**	**0.7**	**0.6**	**0.5**	**0.4**	**0.3**	**0.2**	**0.1**	**0.0**
Median	0	58	103	141	174	207	239	267	297	324	348
Mean	0	58	101	140	173	206	238	267	296	323	348
St. Dev.	0	9	14	16	18	19	21	22	25	26	27
Maximum	0	78	139	183	217	267	297	332	368	398	430
Minimum	0	17	44	73	106	149	156	183	217	238	258

Appendix 4. Distributions of Portfolio Appreciation Returns, Standard Deviations, and Sharpe Ratios

Panel A. Annualized Appreciation Returns



Panel B. Standard Deviations



Panel C. Sharpe Ratios