No Encore for Non-core? Property-level Returns in the Private Real Estate Market

By:

Dr. Matthew Cypher*
Atara Kaufman Professor of Real Estate
Director - Steers Center for Global Real Estate
McDonough School of Business
Georgetown University
Matthew.Cypher@georgetown.edu

Dr. Lee Pinkowitz
Associate Professor
McDonough School of Business
Georgetown University
Lee.Pinkowitz@georgetown.edu

Sara R. Rutledge, MS
Managing Director
StratoDem Analytics
Chicago, IL
sara@stratodem.com

* Contact Author

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I. Introduction

Investment managers charged with allocating institutional capital to private equity real estate are fundamentally focused on the relationship between the risk and return of a prospective investment. As additional risk is undertaken, there is a reasonable expectation that they are compensated through an ex-post return, appropriately adjusted for the risk. The expectation that increased risk will be compensated through additional return is sacrosanct in the industry, but prior research is beginning to suggest that while the investment may underwrite to these return levels, the realized return might be a different (and less attractive) story altogether. Complicating this story are negative real global bond yields that are driving investors further out on the risk curve in an economic expansion that is exceptionally long in the historic tooth.

Real estate investors utilize investment styles commonly identified as core, value-add and opportunistic to roughly articulate the risk level taken on any one investment (Kaiser, 2005; Peyton, 2008). The extant real estate literature has typically considered value-add and opportunistic to be non-core strategies as these represent elevated risk given that they involve significant renovation to an existing asset or ground-up development of a new asset. Higher levels of leverage are also standard for these strategies because they tend to be total return driven. Conversely, the core risk class represents stabilized assets in high quality markets with long-term, creditworthy tenants and minimal debt, representing a lower overall risk profile. Core investors are long-term income focused so they view this strategy as providing consistent cash flow with less of the total return dependent on capital appreciation, which is the opposite of non-core strategies.

While the industry's conceptual understanding of the relative risk associated with each of these investment strategies and the resultant implications on underwritten returns is quite clear, there is room within the literature and the industry to explore whether investors in non-core strategies are truly compensated ex-post for what is often meaningfully higher risk relative to core assets.

Our research builds upon work conducted by Shilling and Wurtzebach (2012) and Peng and Thibodeau (2013) who both utilized property-level return data from the National Council of Real Estate Investment Fiduciaries (NCREIF) to consider the relative performance of each risk class and whether investors earn risk-adjusted returns for non-core strategies. The findings are somewhat mixed, but the overall thesis is that investors are not always rewarded with a risk-adjusted total return. It is our hope that this paper offers new insights beyond the prior research through analysis of property-level data from NCREIF that employs a different methodological approach.

The importance of this research and our focus on risk and return dynamics of private real estate investing remains as relevant today as ever. Institutional Real Estate, Inc (IREI) and Kingsley Associates, for instance, released their 2019 Annual Investor Study in May of 2019. A total of 205 institutional investors (134 U.S. and 71 foreign) with $9.52 trillion of aggregate assets under management responded to the survey regarding their anticipated allocations to real estate for 2019. The headline finding is that 2019 could represent a pull-back in capital flows to real estate with roughly half of the respondents indicating that flows to real estate will be less than 2018. These same investors still anticipate total capital flows to real estate of $59 billion, 9% less than the prior year. Only 8% of total respondents felt that real estate underperformed expectations over the prior year, which was meaningfully less than other asset classes, demonstrating strong support for real estate. Core and non-core strategies remain attractive as U.S. investors anticipate 31% of total 2019 allocations will be in U.S. core real estate while 61% of their non-core allocation will be target European investments.

In this paper, we examine property level cash flow data and construct returns for assets within the NCREIF property database. We define assets within the database as either core or non-core and document that even in raw returns, core properties outperform non-core properties. The surprising result is widespread and robust. Core properties outperform across a wide range of property characteristics as well as across time. The results hold using either quarterly property-level returns or calculating property-specific IRRs. Overall, our results provide strong evidence that even on an absolute return basis, core properties seem to outperform non-core properties.

II. Literature Review

The relative performance of core versus non-core investments has been the subject of prior research at both the property and fund level, but the fund-level analysis has been particularly prominent. It is our hope that this property-focused research will be of service to the industry and notably to the investment management firms charged with constructing diversified real estate portfolios for their client capital. In some respects, we feel like much of the prior literature was beneficial to the pension fund, endowment or foundation who must allocate capital across managers, whereas this research is in service to the investment professionals such as the portfolio managers who are overseeing various strategies. There is much that can be taken from the prior and current research that will make the investment managers better fiduciaries of their client capital, many of who provide for the retirement needs of some of society's most vital members – teachers, firefighters and police officers.

An early example of property focused research is Shilling and Wurtzebach (2012) who considered the relative performance of core, value-add and opportunistic investments through an analysis of leveraged return data from NCREIF for all sold assets during the time period 1978 to 1Q 2009. Assets were ranked by total return and segmented into four return categories – less than 8%, 8% - 12%, 12% - 18% and greater than 18%. They then used discriminate analysis to determine which variables were principally responsible for the property belonging to one of the four return categories. While they found that non-core strategies have higher returns and were viewed as riskier than core investments, they conclude that the excess returns were due principally to the acquisition timing within the real estate cycle and the use of low-cost debt. Investments made during periods of recession had a higher likelihood of being classified in a higher return category, which was the same finding for higher leverage levels during lower interest rate environments.

Peng and Thibodeau (2013) also performed a property-level study to address the question of whether valued-added investments outperform core investments on a risk-adjusted basis and generally find no evidence that this occurs within their dataset. They evaluated property-level returns within the NCREIF database from 1977 to 2012 through a categorization of assets into core or value-add buckets. Value-add investments were defined as those assets that experienced "building capital improvements" during the hold period, while core assets were those that did not experience any capital improvements. The final dataset was comprised of 6,780 total properties with 3,129 properties classified as value-add and 3,651 as core. All assets within the dataset were acquired and sold within the period of analysis. The authors controlled for bias associated with location and time by using a difference in differences approach that determined the extra added return for core and value-add investments through benchmarking against two indices. The first comparison was the NCREIF property type capital appreciation indices that provided individual indexes for office, industrial, retail and apartment assets while the second benchmark was the core Business Statistical Area (CBSA) level capital appreciation indices also by property type. The authors employed t-tests to evaluate the equality of the means of extra returns and found no evidence for higher returns on value-add investments versus core.

Fisher and Hartzell (2016) conducted an empirical analysis of risk classifications in real estate private equity funds that utilized ex-post returns to determine whether class is effective in differentiating fund performance. Fund level data from Burgiss were employed to evaluate limited partner cash flows in value-add and opportunistic funds raised between 1980 and 3Q 2013 that made direct investments in real estate. After considering the performance of individual funds with vintages years ranging from 1980 to 2008, they conclude that there is not a discernible difference in performance between value-add and opportunistic funds. Of particular relevance to our research paper, when the author's compared aggregate value-add and opportunistic fund performance to NCREIF's Open End Diversified core Equity (ODCE) index, they found that these funds did outperform the core index from 1980 to 2003 but under-performed from 2004 – 2008. This demonstrates the influence and importance of vintage year relative to the outperformance of non-core strategies.

The consideration of fund-level performance by risk class is furthered by Pagliari (2020) where he considers the after-fee performance of value-add and opportunistic funds against a levered core return based on the NCREIF-Townsend Fund Returns data. Ultimately, he was focused on determining whether the non-core strategies justified the additional fee load relative to simply levering to the same volatility, a more economical core investment vehicle. The findings suggest that, on average, value-add funds underperformed levered core funds by 180 basis points per year. A particularly interesting finding concerns time-period-specific results of core versus value-add risk-adjusted returns in that the value-add funds index rarely produced positive alpha relative to the levered core index over all time periods from 1996 to 2012. This finding suggests that strong vintage year value-add investing does not necessarily produce outsized risk-adjusted returns relative to simply increasing the leverage level within a core investment. The research also considers the relative performance of levered core to opportunistic investments and while the headline is that opportunistic investments generally performed on par with a levered core investment, significant data issues exist that cause concern as to the reliability of this finding.

In a follow-on study to Pagliari (2020), Bollinger and Pagliari (2019) utilize a similar methodology that employs different data sources with longer time series to consider again whether investors in non-core fund strategies are compensated through risk-adjusted, net-of-fee returns relative to the core alternative[1]. The authors utilize financial leverage and the law of one price to effectively lever core funds to a point where the risk/return profile is akin to non-core alternatives. As such, non-core funds that demonstrate performance over and above the levered core strategy are effectively producing positive alpha while those below the levered core level create negative alpha. Their findings suggest that over the course of the 2000-2017 student period, value-add funds generated negative alpha of 326 basis points while the opportunistic funds performed slightly better with -2.85% alpha. Most strikingly, investment managers would have saved roughly $7.5 billion per year in non-core fund fees had they simply leveraged core investments.

[1] The non-sequential publication dates are due to the time required for Pagliari (2020) to be assigned an issue. The paper was accepted for publication in 2016.

Farrelly and Stevenson (2016) also consider the performance of private real estate funds focused on value-add and opportunistic strategies through fund-level data provided by The Townsend Group. The data considered 396 total funds managed by 181 unique fund managers, spanning vintage years of 1990 to 2008 with performance data through the end of 2012. The overarching research objective was to understand fund performance through evaluation of fund characteristics and other drivers of influence. Similar to other studies (Fisher & Hartzell, 2016) they used the public market equivalent (PME) methodology to examine relative performance of the fund-level data to a benchmark. The NCREIF Fund Index-Open-End Diversified core Equity (ODCE) was selected for one of the PME analyses such that the performance of the Townsend fund data was compared to this core index. Their finding was that the Townsend fund data outperformed the ODCE by roughly 0.65% per annum, which they considered, "well below the target outperformance of funds" in their sample. It is important to note that this analysis considered leveraged returns and that the underlying Townsend fund data would be leveraged to a higher level than the ODCE, which suggests that property level outperformance was likely even less than observed at the fund level.

Others have considered fund-level performance of real estate investments relative to investment strategy as well as manager. Bond and Mitchell (2010) find little support for the notion that active management in the real estate fund space systematically adds alpha in the medium and long-term. Interestingly, they also do not find that investment managers systematically produce poor performance over the same time periods.

III. Data

Our data come from the property level dataset of NCREIF. We use unlevered property quarter returns for the period 1988Q1 until 2019Q1 for a total of 125 quarters. We define the quarterly return for the property as the total return including both the income and capital return components (NCREIF data item *totret*).

To mitigate the influence of major outliers, we winsorize the return data at the 0.5% tails.[2] We drop any observations if they are missing data for market value or the market value in the prior period. We also drop any observations if the real market value, in 2000Q1 dollars, is less than $100,000. Properties which end up being classified as hotels (NCREIF data item *propertytype* equal to two) are eliminated from the sample because the daily occupancy structure and high operational costs of hotels lend the property type to different standards for core/non-core classification than other commercial property types. In addition, hotels are the smallest subset of NCREIF properties by type, representing 1.8% of total property quarters available for this analysis. Finally, there are 22 properties which appear to switch CBSA locations through time. We eliminate these properties concerned that the data may be erroneous. Our final sample is 34,445 properties comprising 650,353 property quarters, representing every state except Wyoming. The economic importance of our sample is significant. The total market value of the 34,445 properties adjusted to 2019 dollars exceeds more than $1.5 trillion, using the value of the property in the first quarter it enters the data. Figure 1 shows the distribution of property values across the country. Unsurprisingly, California, Texas, and New York contain the most total market value, each with more than $100 billion in property. However, this cumulative total does not necessarily align with average property value, as the total is driven both by value per property as well as the number of properties in that state. California's $331 billion in property represents over 7,000 individual properties, while New York's $125 billion is the based on only 894 individual properties.

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[2] The winsorized returns have a mean of 1.71% with a standard deviation of 5.98%, skewness of 0.6 and kurtosis of 13.3 with a minimum of -26% and a maximum of 34%. While the mean of the raw returns is close at 1.84%, the standard deviation is 21.4% with a skewness of 261, a kurtosis of 139,398 with a minimum of -3,764% and a maximum of 11,465.

To examine the performance of core and non-core properties, we classify the properties as either core or non-core based on the following four criteria. A property can be considered core if:

1. It is leased at 85% or better (NCREIF data item *percentleased*) at any point within the first four quarters it appears in the dataset.
2. It has a lifecycle (NCREIF data item *lifecycle*) listed as operating sometime within the first four quarters it appears in our dataset.
3. It has a property type of either Apartment, Industrial, Office, or Retail (NCREIF data item *propertytype* equal to either 1, 3, 5, or 6) sometime within the first four quarters it appears in the dataset.
4. Has capital expenditures in its first four quarters in the dataset totaling less than 5% of the market value of the property as it was reported in the first quarter the property is in the dataset.

If a property satisfies all four of the criteria, it is classified as core. Any property which does not satisfy every one of those is considered non-core. Once a property is classified, it does not switch classification throughout the entire sample period. Thus, even though properties may change their percentage leased, their lifecycle, and possibly even their property type, once a property is considered core it remains that way throughout our analysis. This is done to ensure our analysis evaluates core and non-core property performance based upon the initial investment premise without bias as to the property's actual performance. On average, about 2/3 of our properties are classified as core. Figure 2 shows how our distribution of core properties appears by state. The percentage of properties classified as core is relatively separate from the cumulative value of the properties in our data. In fact, the correlation between cumulative value and percentage of properties which are core in a state is only 0.11. Additional data on macroeconomic variables is retrieved from the FRED database at the St. Louis Federal Reserve Bank.

IV. Core and Non-Core Performance

A. Univariate Comparisons

Table 1 shows the summary statistics of the property quarters split into core and non-core categories. Nearly 2/3 of our properties (21,658 out of 34,445) and property quarters (430,882 out of 650,353) are classified as core. The mean return for core property quarters is about 1.8% per quarter. This is significantly larger than the 1.5% per quarter mean for non-core property quarters. Most investors consider core properties to be less risky than non-core and thus the outperformance in raw returns is even more impressive. In total risk terms, measured by standard deviation, non-core properties are in fact riskier with a quarterly standard deviation of 7% versus about 5.4% for core properties. While we examine all our results using raw returns unadjusted for risk, this means that our documented outperformance of core is conservative. The relative risk-adjusted outperformance of core to non-core would be even greater.

In addition to the full sample, Table 1 shows univariate comparisons across different cross-sectional splits of our data which show that the outperformance of core properties is pervasive. First, we examine the results across different geographic splits. Gateway cities are the six major urban cities (CBSA numbers in parentheses) in the US: Boston (14454), Chicago (16974), Los Angeles (31084), New York (35614), San Francisco (41884), and Washington D.C. (47894). We see that in both gateway and non-gateway cities, the core outperformance appears to be similar. Moreover, we find that the outperformance of core is evident across all four regions of the country as defined by NCREIF.

We also show the results within different property types. While core outperforms non-core across each type of property, it is statistically significant only for Industrial, Office, and Retail.[3] We also show results based on whether the property was no longer in the NCREIF dataset as of 2019Q1 or if it was still actively reported. The outperformance of core is driven by the properties which were no longer in the database at the end of the sample.[4]

Whether the property is one which is held in an open-end fund or not, core significantly outperforms non-core. The same is true regardless of the type of appraisal that underlies the quarterly return.

Different properties based on market value are likely to have different return patterns and thus, we examine our properties broken into three large buckets. We segment all our property quarters based on real market value into the smallest 25%, the middle 50%, and the 25% which were the highest valued. The outperformance of core properties is evident across all size buckets, but the returns of the largest properties are not significantly different.

While we have return data each quarter for each property, most of those returns are not based on an actual market transaction, rather they are based on either an internal or external appraisal. We examine whether the outperformance of core properties is driven by some systematic difference in the way core and non-core properties are appraised. The outperformance of core is evident across all categories of appraisal.

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[3] While properties are not allowed to switch between core and non-core categories, they do switch property types through time. Thus, the sum of the core properties across property types (21,909) is larger than the 21,658 number of unique core properties because a single property can be in different type categories across its time in the dataset. This is also the reason that we have about 180 property quarters which are categorized as land and yet still considered core. The roughly 20 properties there were originally core and then the property was converted to land.

[4] A property can leave the sample for many reasons other than a hard sale. In fact, only 3,562 of our properties have a hard sale as a reason to exit the sample, and we examine those separately later. Other possibilities include a partial sale, a transfer of ownership, the property is consolidated into another, etc. The NCREIF dataset includes the variable *salecode* to identify the disposition type of a property.

In addition to cross-sectional splits, we also examine a single time-series break. We split our sample into quarters which fall inside a National Bureau for Economic Research (NBER) Business Cycle Dating Committee recession and those which do not. Clearly the performance in both categories is better in growth times than in a recession, with negative average returns in a recession for both core and non-core. However, the outperformance of core properties is evident in both parts of the economic cycle. While the average return for core is negative in a recession, it is significantly higher (less negative) than that of non-core properties.

An additional way to examine the time-series performance between core and non-core is to create portfolios each quarter of all the properties in that category. Each quarter we construct a portfolio of core properties as well as a portfolio of non-core properties and measure the relative performance of the two by subtracting the non-core return from the core return. This is essentially equivalent to going long the core portfolio and short the non-core portfolio.

Figure 3 shows the results of this exercise under two different assumptions about the portfolio weights. First, we construct value-weighted portfolios where the weights in each portfolio are based on the market value of the property as a percentage of the total market value of all the portfolio properties in that quarter. Portfolios are rebalanced each quarter as market values change and properties enter or leave the sample. In addition, we calculate our results using an equal-weighted portfolio, which is also rebalanced every quarter. When the core portfolio outperforms, the difference in the returns is positive and indicated by the green bars. When the non-core portfolio has a higher quarterly return than the core portfolio, the result is negative and shown by the red bars.

The consistent outperformance of core is readily apparent in Figure 3. With value-weighting, the core portfolio beats the non-core portfolio in nearly two-thirds of the quarters between 1988 and 2019. Across the 125 quarters, the mean level of outperformance is about 17 basis points per quarter for the value-weighted portfolio and about 28 basis points for the equal-weighted portfolio, which roughly matches the difference between core and non-core in Table 1. Both are statistically significant using the time-series standard error. The fact that outperformance is slightly better with equal weighting is not surprising, as Table 1 shows that the outperformance of core is higher with smaller properties.

B. Regression Analysis

The results in both Table 1 and Figure 3 are univariate without controlling for any variables which might systematically impact returns and could also be correlated with the classification of a property as core. As such, we examine regressions with quarterly returns as the dependent variable and a variety of cross-sectional and time-series control variables.

Regression (1) in Table 2 includes the most basic form of the regression which simply controls for time using calendar quarter fixed effects. In equation form we estimate $return_{i,t} = \alpha_t + \delta Core_i + \varepsilon_{i,t}$. The coefficient on core represents the difference between core and non-core property quarters controlling for simple time-variation. To control for correlated errors through time, all our regressions use standard errors clustered at the property level. The first regression shows that core properties significantly outperform non-core by about 20 basis points per quarter, which is similar to what the results were from Figure 3.

However, our rich dataset allows us to control for a wide variety of observable and potentially unobservable characteristics. For instance, the return on a property may be heavily influenced by the manager and thus controlling for manager identity might be useful. Regression (2) shows our analysis if we simply include manager fixed effects, while regression (3) includes both manager fixed effects as well as calendar quarter fixed effects. Regression (3) essentially looks at the return data along three dimensions: return for property *i*, managed by manager *j*, in quarter *t*. The estimation equation is: $return_{i,j,t} = \alpha_t + \lambda Manager_j + \delta Core_i + \varepsilon_{i,j,t}$. Including both manager and time effects has little impact on the coefficient and core outperforms by 19 basis points per quarter.

Given the significance of asset location relative to financial performance, we need to control for geography as well. Regression (4) includes dummy variables as to whether the property is located in a gateway city as well as across US regions. While region is typically reported in NCREIF indices, our property level data allow us to get far more granular and estimate the effect using county-level fixed effects, which is shown in regression (5). Regression (5) provides the baseline for the rest of our regression results by segmenting the data into another measurable dimension. Each quarter *t*, we have an observation of return for property *i*, managed by manager *j*, located in county *c* and estimate:

$$return_{i,j,t,c} = \alpha_t + \lambda_j Manager_{i,j,t,c} + \gamma_c county_{i,j,t,c} + \delta_i Core_{i,j,t,c} + \Gamma X_{i,j,t,c} + \varepsilon_{i,j,t,c}$$

The estimates on the time, manager, and county fixed effects (i.e. the α, λ, and γ coefficients respectively) are not reported as they are only meant to control for observable and unobservable variation which could affect the return on core and non-core properties.[5] Our focus is on the delta coefficient which represents the differential performance of core and non-core properties. While we can continue to estimate the effect of gateway on returns, the county fixed effects fully absorb region and those are omitted from regression (5) and onward. The results of (5) show that, for

[5] The regression is estimated in STATA using the reghdfe command. The number of observations in regression (5) is smaller than the full sample because there are nine observations which become fully specified by the fixed effects and thus are not included in the estimation of the coefficient on core.

properties in the same quarter, managed by the same manager, in the same county of the US, on average, core still outperforms by 16 basis points per quarter. Recall that these are raw returns and thus, the deck should be stacked against us finding a positive coefficient since with higher risk, non-core properties would be expected to have higher returns.

Regressions (6)-(10) include additional variables to control for the property type, whether the property is active or was sold, the value of the property, the type of appraisal that produced the quarterly return, or whether the property was included in an open end fund.[6] In addition to all the fixed effects, no matter what control variables are included the coefficient on core remains positive and significant.

The final regression includes all the fixed effects and all the control variables simultaneously. The coefficient on core remains statistically significant although the magnitude falls to about 5 basis points. The implication though is that, on average, core properties outperform non-core properties by 5 basis points even after controlling for calendar time, manager identity, county, property type, value of the property, appraisal type and whether the investment is held in an open-end fund. Regression (11) provides compelling evidence that investments in core properties are a better use of funds than investing in non-core properties.

The large number of fixed effects in Table 2 allow us to rule out that the results are due to managerial skill, macroeconomic conditions, and locality. However, we now attempt to be even more restrictive by estimating our regressions with interactions among our fixed effects. In regression (1) of Table 3, we allow for fixed effects for each county/calendar quarter pair. This effectively allows for the regression to account for time variation in local macroeconomic

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[6] There are 3,055 quarterly observations where appraisal is missing. When missing, we recode it as "No appraisal" to keep the observation in the regression.

conditions. Doing so lowers the outperformance of core to 4 basis points per quarter, but not only is it still positive, it remains significant.

Our manager fixed effects allow us to control for unobserved managerial skill, but the prior regressions implicitly assume that managerial skill is unchanging through time. If managers were able to learn from their prior investments and/or managers were hiring different people, we could see skill changing through time. Regression (2) allows for this by including manager/quarter fixed effects as well as the county/quarter effects. If managerial skill is allowed to vary through time, we still see the outperformance of core properties and the estimate increases to 6 basis points per quarter.

Managerial skill might be localized however, and our prior regressions assume that the skill of a manager is constant across geography. Regression (3) allows managerial skill to vary across regions, while (4) allows managerial skill to vary not only across regions, but across time. In both cases, the coefficient on core remains significantly positive at 4 or 5 basis points. Perhaps managerial skill is more localized than region however and thus in (5) we allow managerial skill to vary at the CBSA level, while (6) allows it to vary at both the CBSA level and through time. core still outperforms by 3 basis points per quarter, but we are finally able to eliminate the statistical significance of the estimate. Of course, we are asking a lot of the core coefficient given the extensive fixed effects as well as clustering the standard errors by property.[7] Moreover, for completeness, we also estimate regression (7) allowing managerial skill to vary at the county level and regression (8) which is a fully interacted fixed-effect model with controls for each combination of manager/county/calendar quarter.

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[7] Additionally, we are calculating p-values on the basis of a two-tail test. It is not unreasonable for the null hypothesis to be that non-core should outperform core in raw returns which would then imply a one-tailed test that core<non-core, which would increase the significance of the results.

Utilizing the full panel of data in Table 2 allows us to examine the results with extensive fixed effects and controls. However, it also assumes that the coefficients on the control variables and the fixed effects are constant through time. Table 3 alleviates some of that constraint by allowing the fixed effects to vary through time, but the other coefficients are assumed to be constant through time. Thus, we estimate regression (11) in Table 2 for every quarter in our dataset and then, using the time-series of 125 coefficients, draw our inferences (see Fama Macbeth (1973)). Of the 125 quarterly coefficients on core, we find that 60% of them are positive and they have a mean of 14 basis points which is significantly greater than zero at the 5% level.[8] The median of the distribution is also 14 basis points and that is significantly different than zero at the 1% level.

Figure 4 shows each of the coefficients and the 95% confidence interval surrounding them. Quarterly coefficients which are significantly greater than zero are depicted in blue, while those which are significantly negative are depicted in red. The confidence intervals in gray indicate that the coefficient on core is insignificant at the 5% level. Figure 4 is similar to Figure 3, except that this represents the difference in core vs non-core controlling for many factors. However, the figures not only look similar, the correlation between the 125 quarterly point estimates in Figures 3 and 4 is 0.58 for the value-weighted portfolio returns and 0.81 for the equal-weighted returns.

On average, core outperforms no matter how we measure it, but does that mean there are not types of properties where non-core outperforms? We examine regressions on subsets of the data either geographically or cross-sectionally. While our main regressions included dummy variables as controls for these characteristics, using the subsets allows the estimates of the fixed effects to be specific to that property characteristic. One can consider these tests as a way to show

[8] Significance levels for the Fama-MacBeth procedure are done using Newey-West standard errors accounting for four lags of autocorrelation to account for annual seasonality.

fully interacted regressions. To avoid collinearity, the characteristic itself is removed from the control variables in the regression. For instance, when looking at the gateway or non-gateway subsets, the indicator variable for gateway is removed from the regression specification. When the subsets are based on property type (i.e. Apartment, Office, etc.) the property type dummy variables are removed. For ease of reporting, in Table 4, we only report the coefficient on core.

Using this method allows us to determine exactly where the core outperformance is coming from. We see clear cross-sectional differences along geographic, property type, and fund type dimensions. The core outperformance is driven by non-gateway cities and primarily the Midwest region. Core outperformance comes primarily from Retail and Office properties, while we estimate a significant negative coefficient on the apartment subset. Lastly, the core outperformance appears to be more prevalent in properties held outside of open-end funds. Overall, of the 12 different subcategory regressions, we find that nine of them have positive coefficients, five of which are significant. Of the three negative coefficients, only one is significant. However, it is somewhat surprising that we are able to detect any significant difference between core and non-core performance in Table 4 given that the specification controls for all types of managerial skill related to that property characteristic (managerial fixed effects within the category), all local impact of that property characteristic (county effects within the category), quarterly general economic impact related to that characteristic (calendar quarter fixed effects within the category), as well as other controls whose coefficients are estimated solely on that characteristic.

C. Property-level Internal Rates of Return

While the NCREIF data provides quarterly returns for all properties, we can also examine the performance of core and non-core properties using the internal rate of return (IRR). For each property, we construct the IRR using quarterly cash flows. The initial cost of the property is assumed to be the market value of the property in the first quarter it enters our data. The subsequent quarterly net cash flows are calculated as the net operating income less capital expenditures plus cash from partial sales of the property (NCREIF data items *NOI-CAPEX+PSALES*). The terminal cash flow of the property assumes that the sales price of the property equals the market value and thus, the final quarter cash flow is net operating income less capital expenditures plus cash from partial sales of the property plus market value of property.[9]

Table 5 shows the distribution of property-level IRRs in our sample. We can compute the IRR for 30,610 properties, of which 20,921 are classified as core and 9,689 are classified as non-core. The mean quarterly IRR for core properties is 2.1% which is 20 basis points larger than the mean IRR for non-core properties, a difference that is both economically and statistically significant. The results are similar when we examine the medians. We again see that the returns to non-core properties are more volatile with the standard deviation being significantly larger and nearly twice that of the core IRRs.[10]

We again notice cross-sectional differences in the outperformance. Core properties are more likely to have higher IRRs in non-gateway cities, with marginally better IRRs in the East and

[9] Implicitly, our calculations assume that the properties are purchased at the end of the first quarter it enters our dataset and sold at the end of the final quarter it is in our dataset. Thus, the IRR calculations implicitly assume that there is no operating income earned or capital expenditures paid in the initial quarter. However, the terminal quarter includes both income and expenditures in that quarter. This timing is done to match the assumptions used to construct the indices which we benchmark our IRRs against.

[10] Because of this, the univariate t-tests between core and non-core are estimated assuming unequal variances across the two subsamples.

Midwest regions. Core IRRs are larger for offices and retail properties as well as those which were sold by the first quarter of 2019. Core properties which are not in open-end funds have higher IRRs, while for properties in open-end funds, non-core properties significantly outperform, the lone instance where we observe that. Core IRRs are significantly larger than non-core for larger properties, those which are held for a longer period, and those which were never held in a separate account. Interestingly, the medians indicate that the outperformance of core IRRs is much more pervasive than the means imply, which seems to suggest that there are some non-core properties with large enough IRRs to affect the mean results.

Raw IRRs are a way to examine performance slightly different from our quarterly returns. However, IRRs are clearly dependent on the time frame over which they are calculated. Moreover, aggregating IRRs makes for difficult interpretations due to the differences in scale across various properties. To control for these issues, we construct "excess IRRs" where we compare the property IRR to the IRR of an index of similar properties held over the same time interval. We do so using a similar procedure as Geltner (2003). For inclusion in the index, we drop all properties which are held in separate accounts (NCREIF data item *fundtype* equal to 6) as well as any properties which ended up being classified as something other than Apartments, Industrial, Retail, or Office. Our index construction follows where we separately compute the cash flow return of the index and the price return of the index based on the aggregate levels of net operating income, capital expenditures, partial sales prices, and market values of all properties in the index. The quarterly cash flow return is calculated as the aggregate net operating income less the aggregate capital expenditures all divided by the aggregate prior-quarter market value of all properties in the index. The price return of the index is computed as the aggregate market value plus the aggregate amount of partial sales in a quarter all divided by the aggregate prior-quarter market value of all properties in the index. The "price level" of the index is calculated assuming a starting value of $100. The initial cost of acquiring the index is assumed to be 100 multiplied by (1+ price return) in the initial quarter.[11] Each quarter, the price level of the index is assumed to increase by the price return, and the sales price of the index is assumed to be the price level of the index in the last quarter. The interim "cash flows" of the index are estimated as the cash flow return of the index applied to the prior quarter's price level of the index.

Separate indices are computed in our sample for each group of geographic region and property type at every possible time combination.[12] Thus, for a property which is of type *i* in region j bought in quarter t and sold in quarter T, the excess IRR is calculated as $IRR_{i,j,t,T} - IndexIRR_{i,j,t,T}$.[13] Table 6 shows the summary statistics for the excess IRRs.

The results in Table 6 are intriguing for several reasons. First, the pervasive outperformance of core properties is not only absent, but it appears that the reverse holds with excess IRRs. The mean non-core excess IRR is significantly larger than the average core excess IRR, although the economic magnitude is quite small at about 2 basis points.

Second, the results using medians do not support the results with the means. The median core excess IRR is significantly larger, although economically indistinguishable, from the median non-core excess IRR. Combined this suggests a few things. First, it is clear the performance of indices which are matched against core properties is better than the performance of indices matched against non-core properties. As the indices are matched based on region, property type, and time frame, this suggests that core properties tend to be purchased more frequently in places

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[11] This assumes that the index is essentially purchased at the "end" of the first quarter of construction and is the reason we calculate property IRRs with this same assumption.
[12] This gives us 124,000 unique indices. There are 16 possible region/property type groups and there are 7,750 unique time horizons in the period 1988Q1 to 2018Q4.
[13] For properties which were not sold as of 2018 Q4, the IRRs are calculated assuming the property was sold at that time at the market value contained in the NCREIF database.

and at times where general economic performance is better. Given that one of the criteria for core is whether a property is leased at 85% or better in any of the first four quarters it appears in the NCREIF data, this might not be that surprising, since it may suggest better overall economic times. Second, the results based on the medians exhibit the pattern where core relatively outperforms non-core both as a whole and across a variety of cross-sectional characteristics. This again suggests that the mean results are potentially driven by some outliers in the non-core sample which experience very strong performance.

Table 7 provides insights into this by showing the full distribution of IRRs for our properties split by their investment style classification. Panel A demonstrates that the property level IRRs have both a mean and median larger for core properties than non-core. However, as we move deep into the right tail, the discrepancies between the core and non-core IRRs become apparent. The 90^{th} percentile for core IRR is 4.16% and 5.44% for non-core, roughly a 25% difference. At the 95^{th} percentile, non-core is about 50% more than core at 7.83% versus 5.34% and, at the 99^{th} percentile, non-core nearly doubles the performance of core at 19.6% versus 10.2%.

Panel B shows the distribution of the IRRs of the indices matched to each of our properties. The indices matched to our core properties have a higher mean than those matched to the non-core properties, which explains the reversal of results from Table 5 to Table 6. The benchmarks against which core properties are judged are consistently higher and importantly, we do not see dramatic outliers in the core or non-core indices. The lack of outliers is not surprising since each index is the aggregation of many properties. Finally, Panel C shows the full distribution of excess IRRs, showing that the outliers from property IRRs are driving these results. As in Table 6, the mean excess IRR is higher for non-core properties, while the median is lower. We see that the outperformance of non-core is being completely driven by the upper 10% of the IRR distribution.

If investors are more likely to talk about their winners when they "hit a home run", it is possible that the bias about non-core outperformance comes from this upper tail.

Interestingly, the results in Tables 5 and 6 show that the split based on whether or not the property had a hard sale as of 2019Q1 has a significant impact on our inferences. Looking back at Table 5, for the nearly 3,500 properties which have an actual sale, the average IRR is 2.3% per quarter for core properties and only 0.7% for non-core. For the roughly 27,000 properties which either are currently held or exited the dataset due to something other than a true sale, the mean IRR for core is 2.1% and the mean for non-core is 2.0%. This is also evident in Table 6 where sold core properties have significantly higher excess IRRs than sold non-core properties. The results are basically reversed for the properties without a hard sale. Given that the property IRR may be heavily determined by the exit value, we re-examine only on the subset of properties where we have a hard sale with the view that the IRR for sold properties is likely to be measured more accurately.

For completeness, we redo our raw IRR and excess IRR analyses using only the sample of properties for which we have a hard sale. Table 8 shows the raw IRR results, while Table 9 shows the excess IRR results.

Table 8 shows that the outperformance of core is significant and widespread across nearly every category of property for which we have an actual sale. These results are consistent with those of our whole sample in Table 5, but the outperformance of core is considerably larger for the sale properties. Interestingly, the excess IRRs of the sale properties shown in Table 9 confirm that for properties which we have an actual sales price, the IRRs of core properties outperform those of non-core even controlling for a composite index matched on region, property type, and holding period.

Taken together, the IRR results indicate that the outperformance of core properties remains and is consistent with our results using quarterly returns. However, our analysis in Table 7 does show that the composite indices which are matched to core properties tend to do better than the indices which are matched to non-core properties. Additionally, in the extreme tails, the performance of non-core properties far exceeds that of core properties. Those two factors appear to explain Table 6 which is the lone example we could find of non-core outperforming core properties in raw returns, with no adjustment made for risk.

V. Conclusion

The idea that investments with higher levels of risk should earn greater returns represents the fundamental tradeoff in finance. We examine the performance of core and non-core real estate and document that, despite non-core properties having higher standard deviations, core properties outperform non-core even in simple raw returns. We document that this outperformance cannot be explained by observable or unobservable property or manager characteristics. We show that our results hold whether we look at quarterly returns or examine property-level IRRs. Our regression results show that for a core and non-core property of the same type which is held by the same manager, in the same US County, in the same calendar quarter, and has similar observable characteristics, the core property outperforms by an average of 5 basis points per quarter. Given that one basis point per quarter on $1.5 trillion of property translates to more than $600 million per year, the implication seems clear.

The academic community has been steadily questioning the relative value of core versus non-core real estate investment and this research is yet another in that line. As the competition for institutional quality real estate has increased and returns decreased, fund managers have had to work exceptionally hard to deliver performance to their client capital. An example of this effort is the "value-add bucket" found in most open-end core funds. The intent of this bucket is to allow fund manages to deploy a slice of fund capital in higher risk strategies such as development. These investments have often followed a build-to-core strategy, which allows for the development of product that is otherwise difficult to acquire on the open market, such as multifamily and industrial assets. These same managers might be well suited to rethink their approach to incrementing fund-level returns by simply incurring a higher leverage level, which we believe will offer better return and lower risk to their client capital.

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Table 1: Core and Non-core returns by subsamples

The table shows the sample composition with the number of properties and property quarters for each of the subsamples split by core and non-core NC. It also shows the mean, median, and standard deviation of property quarter returns split by core and non-core. *, **, *** (+,++,+++) indicate that the mean (standard deviation) between core and non-core returns is different at the 10%, 5%, and 1% level, respectively. For ease of comparison, the stars (plus signs) are placed on the larger mean (standard deviation). Subsample groups are shaded together.

	Core Quarters	Core Properties	Mean Core Returns	Median Core Returns	Std Dev Core Returns	Noncore Quarters	Noncore Properties	Mean Noncore Returns	Median Noncore Returns	Std Dev Noncore Returns
Full Sample	430,882	21,658	0.018***	0.010	0.054	219,471	12,787	0.015	0.010	0.070+++
Nongateway	329,772	16,849	0.018***	0.010	0.054	171,223	10,075	0.015	0.010	0.070+++
Gateway	101,110	4,809	0.019***	0.010	0.055	48,248	2,712	0.016	0.010	0.069+++
East	95,910	4,906	0.017***	0.010	0.053	52,435	3,068	0.015	0.010	0.069+++
Midwest	59,715	2,973	0.014***	0.010	0.052	32,909	1,849	0.012	0.010	0.068+++
South	118,630	6,124	0.017***	0.010	0.052	66,639	3,889	0.015	0.010	0.070+++
West	156,627	7,655	0.021***	0.010	0.056	67,488	3,981	0.018	0.010	0.072+++
Apartment	92,689	4,763	0.019	0.010	0.047	33,434	2,081	0.018	0.010	0.064+++
Industrial	169,491	8,882	0.020***	0.010	0.056	69,816	4,107	0.018	0.010	0.069+++
Land	178	19	0.007	-0.002	0.092+++	17,511	1,517	0.003	-0.000	0.088
Office	93,570	4,664	0.014***	0.010	0.059	48,871	2,896	0.011	0.010	0.069+++
Retail	74,276	3,514	0.017***	0.010	0.050	24,805	1,245	0.015	0.010	0.065+++
Other	678	67	0.023	0.010	0.061	25,034	1,844	0.021	0.010	0.071+++
Out of dataset: 2019Q1	264,948	15,137	0.016***	0.010	0.058	138,635	8,633	0.012	0.010	0.073+++
Active as of 2019Q1	165,934	6,521	0.021	0.010	0.047	80,836	4,154	0.021	0.010	0.064+++
Not in Open End Fund	259,034	14,638	0.019***	0.010	0.056	119,369	8,007	0.015	0.010	0.072+++
In Open End Fund	171,848	7,235	0.017***	0.010	0.051	100,102	4,927	0.016	0.010	0.068+++
Bottom 25% Size	93,214	6,260	0.019***	0.020	0.063	71,293	5,932	0.014	0.010	0.080+++
Middle 50% Size	223,859	12,671	0.018***	0.010	0.053	100,818	7,701	0.016	0.010	0.067+++
Top 25% Size	113,809	6,240	0.017	0.010	0.047	47,360	3,172	0.016	0.010	0.058+++
External Appraisal	148,251	15,080	0.021***	0.010	0.064	78,608	8,493	0.020	0.010	0.083+++
Internal Appraisal	163,085	13,681	0.017***	0.010	0.055	83,174	8,302	0.014	0.010	0.070+++
No Appraisal	119,546	11,960	0.016***	0.010	0.034	57,689	6,027	0.011	0.010	0.045+++
No recession	382,419	21,491	0.022***	0.010	0.051	194,899	12,532	0.019	0.010	0.068+++
Recession	48,463	8,965	-0.009***	0.010	0.064	24,572	4,651	-0.014	0.005	0.079+++

Table 2: Full panel regressions

Dependent variable is quarterly return (winsorized at the 0.5% tails). When calendar quarter and/or county dummies are included, the constant is not reported. Shaded boxes indicate that the variable is fully absorbed by the dummy variables in that particular regression. Standard errors are clustered at the property level and *, **, *** indicate significantly different from zero at the 10%, 5%, and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Core	**0.0020*****	**0.0025*****	**0.0019*****	**0.0017*****	**0.0016*****	**0.0009*****	**0.0014*****	**0.0017*****	**0.0012*****	**0.0016*****	**0.0005****
Gateway				0.0014***	-0.0016	-0.0026*	-0.0021	-0.0022*	-0.0016*	-0.0016	-0.0033***
Midwest				-0.0028***							
South				0.0004							
West				0.0037***							
Industrial						0.0004*					-0.0003
Land						-0.0136***					-0.0143***
Office						-0.0050***					-0.0051***
Retail						-0.0019***					-0.0024***
Other						0.0037***					0.0022***
Active							0.0026***				0.0024***
Middle 50% Size								-0.0002			-0.0008***
Top 25% Size								-0.0024***			-0.0029***
External Appraisal									0.0110***		0.0120***
Internal Appraisal									0.0042***		0.0043***
In Open End Fund										-0.0013***	-0.0045***
Calendar Quarter Fixed Effects	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects					Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0923	0.0078	0.0957	0.0970	0.0990	0.1012	0.0993	0.0992	0.1023	0.0991	0.1053
N	650,353	650,353	650,353	650,353	650,344	650,344	650,344	650,344	647,289	650,344	647,289

Table 3: Full panel regressions – High dimensional fixed effects

Dependent variable is quarterly return (winsorized at the 0.5% tails). Fixed effects indicate which effects are included in the regression. - indicates interaction thus County-Qtr means separate fixed effects for each county/calendar quarter pair in the dataset. Sample size changes because singleton observations within a fixed effect(s) are removed. Manager is the identity of the manager (i.e. Principal, Stockbridge, Invesco). Standard errors are clustered at the property level and *, **, *** indicate significantly different from zero at the 10%, 5%, and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Core	**0.0004****	**0.0006*****	**0.0004****	**0.0005****	**0.0003**	**0.0003**	**0.0003**	**0.0002**
Industrial	0.0001	0.0001	0.0001	0.0003	-0.0000	0.0008**	0.0002	0.0013***
Land	-0.0144***	-0.0139***	-0.0145***	-0.0138***	-0.0139***	-0.0129***	-0.0136***	-0.0123***
Office	-0.0047***	-0.0047***	-0.0047***	-0.0046***	-0.0040***	-0.0039***	-0.0036***	-0.0035***
Retail	-0.0019***	-0.0019***	-0.0018***	-0.0018***	-0.0018***	-0.0016***	-0.0016***	-0.0010**
Other	0.0021***	0.0017**	0.0019***	0.0018**	0.0010	0.0009	0.0004	0.0003
Active property	0.0021***	0.0022***	0.0021***	0.0022***	0.0020***	0.0021***	0.0020***	0.0020***
Gateway	-0.0013	0.0006	-0.0035	-0.0038	-0.0033	-0.0093	-0.0044	-0.0212
Middle 50% Size	-0.0005**	-0.0007***	-0.0005**	-0.0007***	-0.0009***	-0.0005*	-0.0010***	-0.0004
Top 25% Size	-0.0027***	-0.0025***	-0.0027***	-0.0024***	-0.0034***	-0.0024***	-0.0040***	-0.0023***
External Appraisal	0.0126***	0.0159***	0.0127***	0.0164***	0.0132***	0.0186***	0.0135***	0.0186***
Internal Appraisal	0.0047***	0.0073***	0.0047***	0.0077***	0.0049***	0.0090***	0.0049***	0.0087***
In Open End Fund	-0.0047***	-0.0052***	-0.0046***	-0.0052***	-0.0047***	-0.0057***	-0.0049***	-0.0056***
Fixed Effects	Mgr County-Qtr	Mgr-Qtr County-Qtr	Mgr-region County-Qtr	Mgr-region-Qtr County-Qtr	Mgr-cbsa County-Qtr	Mgr-cbsa-Qtr County-Qtr	Mgr-county County-Qtr	Mgr-county-qtr
Adjusted R^2	0.1393	0.1809	0.1398	0.1919	0.1434	0.2381	0.1450	0.2575
N	634,082	633,881	634,075	631,853	633,945	565,988	633,892	505,540

Table 4: Subgroup regressions

Dependent variable is quarterly return (winsorized at the 0.5% tails). All regressions are as in (11) from Table 2 but the sample is conditional on property location or type or characteristic. To avoid collinearity, the characteristic itself is removed from the control variables in the regression. For instance, when looking at the Gateway or Nongateway subsets, the indicator variable for gateway is removed from the regression specification. When the subsets are based on property type (i.e. Apartment, Office, etc.) the property type dummy variables are removed. All regressions include manager, calendar quarter, and county fixed effects. Only the coefficient on core are reported. Standard errors are clustered at the property level and *, **, *** indicate significantly different from zero at the 10%, 5%, and 1% level respectively.

	Nongateway	Gateway	East	Midwest	South	West	Apartment	Industrial	Office	Retail	In Open End	Not in Open End
Core	0.0007***	-0.0006	0.0000	0.0012**	0.0006	0.0004	-0.0020***	0.0003	0.0007*	0.0021***	-0.0005	0.0015***
Adjusted R^2	0.1011	0.1259	0.1002	0.0844	0.0952	0.1346	0.1489	0.1134	0.1226	0.1048	0.1446	0.0831
N	500,986	149,358	148,336	92,621	185,265	224,114	126,117	239,300	142,437	99,075	271,943	378,393

Table 5: Property level IRRs

We calculate the IRR using quarterly cash flows calculated as net operating income – Capital expenditures + partial sales of the property. In the final quarter of the property, we also add on the net sales price. The initial cost is assumed to be the market value of the property at the beginning of the quarter it enters the sample. The table shows the mean, median, and standard deviation of property IRRs split by core and non-core. *, **, *** indicate that the mean between core and non-core IRRs is different at the 10%, 5%, and 1% level, respectively. For ease of comparison, the stars are placed on the larger mean. Subsample groups are shaded together. Property types are based on the last quarter (i.e. the sale quarter) for each property.

	Core Properties	Mean Core IRR	Median Core IRR	Std Dev Core IRR	Noncore Properties	Mean Noncore IRR	Median Noncore IRR	Std Dev Noncore IRR
Full Sample	20,921	0.021***	0.021^^^	0.027	9,689	0.019	0.018	0.057+++
Nongateway	16,259	0.021***	0.021^^^	0.028	7,577	0.018	0.018	0.057+++
Gateway	4,662	0.021	0.021^^^	0.026	2,112	0.021	0.017	0.057+++
East	4,743	0.020*	0.020^^^	0.026	2,234	0.018	0.017	0.052+++
Midwest	4,743	0.020*	0.020^^^	0.026	2,234	0.018	0.017	0.052+++
South	5,914	0.021	0.020^^^	0.026	2,931	0.020	0.018	0.054+++
West	7,387	0.023	0.023^^^	0.029	3,128	0.023	0.020	0.066+++
Apartment	4,538	0.021	0.020	0.023	1,943	0.022	0.020	0.053+++
Industrial	8,616	0.023	0.022^^^	0.024	3,854	0.023	0.018	0.061+++
Office	4,377	0.018***	0.018^^^	0.036	2,718	0.014	0.014	0.057+++
Retail	3,390	0.020***	0.020^^^	0.026	1,174	0.014	0.017	0.050+++
Hard Sale by 2019Q1	2,410	0.023***	0.020^^^	0.041	1,050	0.007	0.011	0.068+++
Not hard sale	18,511	0.021	0.021^^^	0.025	8,639	0.020	0.018	0.056+++
Not in Open End Fund	13,873	0.022***	0.021^^^	0.029	6,127	0.018	0.016	0.058+++
In Open End Fund	7,048	0.019	0.020	0.024	3,562	0.021**	0.020	0.055+++
Bottom 25% Size	5,030	0.023	0.023^^^	0.033	3,715	0.023	0.019	0.073+++
Middle 50% Size	10,795	0.021***	0.021^^^	0.026	4,427	0.017	0.017	0.047+++
Top 25% Size	5,096	0.018***	0.018^^^	0.022	1,547	0.015	0.016	0.035+++
Short Hold	8,520	0.024	0.021^^^	0.038	4,382	0.023	0.017	0.081+++
Medium Hold	4,260	0.019***	0.021^^^	0.020	2,130	0.015	0.018	0.031+++
Long Hold	8,141	0.019***	0.020^^^	0.013	3,177	0.015	0.018	0.019+++
In Separate Account	7,714	0.022	0.022^^^	0.024	3,090	0.021	0.019	0.056+++
Never in Separate	13,207	0.020***	0.020^^^	0.029	6,599	0.018	0.017	0.058+++

Table 6: Property level excess IRRs

We calculate the excess IRR as the IRR less the IRR of the relevant index. Separate indices are computed in our sample for each group of geographic region and property type at every possible time combination. For a property which is of type i in region j bought in quarter t and sold in quarter T, the excess IRR is calculated as $IRR_{i,j,t,T}$ – $IndexIRR_{i,j,t,T}$. IRR using quarterly cash flows is calculated as net operating income – Capital expenditures + partial sales of the property. In the final quarter of the property, we also add on the net sales price. The initial cost is assumed to be the market value of the property at the beginning of the quarter it enters the sample. The table shows the mean, median, and standard deviation of property IRRs split by core and non-core. *, **, *** indicate that the mean between core and non-core IRRs is different at the 10%, 5%, and 1% level, respectively. For ease of comparison, the stars are placed on the larger mean. Subsample groups are shaded together. Property types are based on the last quarter (i.e. the sale quarter) for each property.

	Core Properties	Mean Core IRR	Median Core IRR	Std Dev Core IRR	Noncore Properties	Mean Noncore IRR	Median Noncore IRR	Std Dev Noncore IRR
Full Sample	20,921	-0.001	-0.001^^^	0.025	9,689	0.001***	-0.001	0.056+++
Nongateway	16,259	-0.001	-0.001^^	0.025	7,577	0.001**	-0.001	0.057+++
Gateway	4,662	0.001	0.000	0.023	2,112	0.003	-0.000	0.054+++
East	4,743	0.000	0.001^^	0.024	2,234	0.003**	-0.000	0.054+++
Midwest	4,743	0.000	0.001^^	0.024	2,234	0.003**	-0.000	0.054+++
South	5,914	0.000	-0.000	0.024	2,931	0.002**	-0.000	0.053+++
West	7,387	-0.001	-0.001	0.026	3,128	0.001**	-0.002	0.063+++
Apartment	4,538	0.001	0.000	0.021	1,943	0.009***	0.004^^^	0.053+++
Industrial	8,616	-0.002	-0.002	0.023	3,854	0.000**	-0.002	0.059+++
Office	4,377	0.000	-0.000^^^	0.032	2,718	-0.001	-0.003	0.056+++
Retail	3,390	0.001***	0.002^^^	0.024	1,174	-0.004	-0.001	0.050+++
Hard Sale by 2019Q1	2,410	0.003***	0.002^^^	0.037	1,050	-0.007	-0.003	0.065+++
Not hard sale	18,511	-0.001	-0.001	0.023	8,639	0.002***	-0.001	0.055+++
Not in Open End Fund	13,873	0.000	0.000^^^	0.026	6,127	0.001	-0.002	0.058+++
In Open End Fund	7,048	-0.002	-0.001	0.021	3,562	0.001***	-0.000^^^	0.052+++
Bottom 25% Size	5,030	-0.000	-0.001	0.031	3,715	0.003***	-0.000	0.072+++
Middle 50% Size	10,795	-0.001	-0.000^^	0.024	4,427	0.000	-0.001	0.046+++
Top 25% Size	5,096	-0.001	-0.001^^^	0.019	1,547	-0.002	-0.002	0.032+++
Short Hold	8,520	-0.000	-0.002	0.036	4,382	0.005***	-0.003	0.080+++
Medium Hold	4,260	-0.001**	-0.001	0.016	2,130	-0.003	-0.000	0.026+++
Long Hold	8,141	-0.001***	0.000^^^	0.011	3,177	-0.002	-0.001	0.016+++
In Separate Account	7,714	-0.001	-0.000^^^	0.022	3,090	0.000	-0.002	0.054+++
Never in Separate	13,207	-0.000	-0.001	0.026	6,599	0.002**	-0.001	0.057+++

Table 7: Distribution of IRRs

Panel A

Property IRR	N	mean	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
Core	20921	0.0209	-0.6345	-0.0505	-0.0126	-0.0008	0.0117	0.0207	0.0297	0.0416	0.0534	0.1023	0.7605
Noncore	9689	0.0190	-0.8476	-0.1156	-0.0429	-0.0203	0.0024	0.0175	0.0323	0.0544	0.0783	0.1959	1.2229

Panel B

IRR Index	N	mean	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
Core	20921	0.0215	-0.0921	-0.0154	0.0014	0.0078	0.0154	0.0214	0.0288	0.0354	0.0386	0.0470	0.0810
Noncore	9689	0.0179	-0.1374	-0.0692	-0.0110	-0.0001	0.0127	0.0205	0.0280	0.0352	0.0376	0.0472	0.0757

Panel C

Excess IRR	N	mean	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
Core	20921	-0.0005	-0.6517	-0.0625	-0.0292	-0.0205	-0.0092	-0.0005	0.0073	0.0176	0.0277	0.0722	0.7016
Noncore	9689	0.0011	-0.8913	-0.1275	-0.0523	-0.0342	-0.0157	-0.0012	0.0117	0.0326	0.0573	0.1797	1.1920

Table 8: Property level IRRs: HARD SALES

We calculate the IRR using quarterly cash flows calculated as net operating income – Capital expenditures + partial sales of the property. In the final quarter of the property, we also add on the net sales price. The initial cost is assumed to be the market value of the property at the beginning of the quarter it enters the sample. The table shows the mean, median, and standard deviation of property IRRs split by core and noncore. *, **, *** indicate that the mean between core and non-core IRRs is different at the 10%, 5%, and 1% level, respectively. For ease of comparison, the stars are placed on the larger mean. Subsample groups are shaded together. Property types are based on the last quarter (i.e. the sale quarter) for each property.

	Core Properties	Mean Core IRR	Median Core IRR	Std Dev Core IRR	Noncore Properties	Mean Noncore IRR	Median Noncore IRR	Std Dev Noncore IRR
Full Sample	2,410	0.023***	0.020^^^	0.041	1,050	0.007	0.011	0.068+++
Nongateway	1,945	0.023***	0.020^^^	0.042	889	0.005	0.010	0.071+++
Gateway	465	0.023	0.020	0.039	161	0.017	0.018	0.045++
East	556	0.023	0.020	0.037	153	0.016	0.017	0.080+++
Midwest	556	0.023	0.020	0.037	153	0.016	0.017	0.080+++
South	624	0.024***	0.021^^^	0.047	348	0.008	0.011	0.062+++
West	817	0.026***	0.021^^^	0.042	333	0.006	0.010	0.074+++
Apartment	547	0.029**	0.026^	0.023	79	0.022	0.021	0.022
Industrial	806	0.020***	0.017^^^	0.038	370	0.006	0.010	0.050+++
Office	611	0.024***	0.018^^^	0.059	374	0.000	0.002	0.084+++
Retail	446	0.019	0.018	0.033	227	0.015	0.019	0.072+++
In Separate Account	520	0.030	0.027	0.039	233	0.031	0.027	0.068+++
Never in Separate	1,890	0.021***	0.018^^^	0.042	817	0.000	0.005	0.066+++
Not in Open End Fund	2,036	0.023***	0.020^^^	0.043	738	0.009	0.011	0.070+++
In Open End Fund	374	0.021***	0.020^^^	0.029	312	0.003	0.012	0.064+++
Bottom 25% Size	556	0.019***	0.018^^^	0.054	453	0.007	0.012	0.073+++
Middle 50% Size	1,466	0.025***	0.022^^^	0.037	481	0.007	0.011	0.067+++
Top 25% Size	388	0.021***	0.018^^^	0.032	116	0.004	0.008	0.048+++
Short Hold	1,023	0.034***	0.031^^^	0.057	432	0.005	0.007	0.101+++
Medium Hold	507	0.017***	0.022^^	0.025	208	0.010	0.016	0.032+++
Long Hold	880	0.013***	0.014^^	0.016	410	0.008	0.011	0.023+++

Table 9: Property level excess IRRs: HARD SALES

We calculate the excess IRR as the IRR less the IRR of the relevant index. Separate indices are computed in our sample for each group of geographic region and property type at every possible time combination. For a property which is of type i in region j bought in quarter t and sold in quarter T, the excess IRR is calculated as $IRR_{i,j,t,T} - IndexIRR_{i,j,t,T}$. IRR using quarterly cash flows is calculated as net operating income – Capital expenditures + partial sales of the property. In the final quarter of the property, we also add on the net sales price. The initial cost is assumed to be the market value of the property at the beginning of the quarter it enters the sample. The table shows the mean, median, and standard deviation of property IRRs split by core and non-core. *, **, *** indicate that the mean between core and non-core IRRs is different at the 10%, 5%, and 1% level, respectively. For ease of comparison, the stars are placed on the larger mean. Subsample groups are shaded together. Property types are based on the last quarter (i.e. the sale quarter) for each property.

	Core Properties	Mean Core IRR	Median Core IRR	Std Dev Core IRR	Noncore Properties	Mean Noncore IRR	Median Noncore IRR	Std Dev Noncore IRR
Full Sample	2,410	0.003***	0.002^^^	0.037	1,050	-0.007	-0.003	0.065+++
Nongateway	1,945	0.003***	0.001^^^	0.038	889	-0.008	-0.004	0.068+++
Gateway	465	0.003	0.002	0.034	161	0.000	0.001	0.041+++
East	556	0.003	0.001	0.033	153	-0.003	-0.000	0.077+++
Midwest	556	0.003	0.001	0.033	153	-0.003	-0.000	0.077+++
South	624	0.005**	0.002^^	0.044	348	-0.003	-0.002	0.059+++
West	817	0.004***	0.002^^^	0.036	333	-0.009	-0.007	0.069+++
Apartment	547	0.004**	0.002^	0.021	79	-0.002	0.000	0.021
Industrial	806	0.001***	-0.000^^^	0.035	370	-0.011	-0.005	0.050+++
Office	611	0.006***	0.002^^^	0.053	374	-0.009	-0.007	0.077+++
Retail	446	0.003	0.004	0.031	227	0.001	0.005	0.073+++
In Separate Account	520	0.004	0.003	0.038	233	0.010	0.008^^^	0.069+++
Never in Separate	1,890	0.003***	0.001^^^	0.037	817	-0.012	-0.006	0.063+++
Not in Open End Fund	2,036	0.004***	0.002^^^	0.039	738	-0.005	-0.004	0.066+++
In Open End Fund	374	0.000***	0.000	0.026	312	-0.011	-0.002	0.062+++
Bottom 25% Size	556	0.002**	0.001	0.051	453	-0.006	-0.002	0.072+++
Middle 50% Size	1,466	0.004***	0.001^^^	0.034	481	-0.008	-0.003	0.062+++
Top 25% Size	388	0.003***	0.002^^^	0.027	116	-0.009	-0.005	0.044+++
Short Hold	1,023	0.009***	0.005^^^	0.054	432	-0.013	-0.015	0.097+++
Medium Hold	507	-0.002	-0.000	0.020	208	-0.004	-0.001	0.025+++
Long Hold	880	-0.000**	0.001	0.013	410	-0.002	-0.000	0.018+++

Figure 1: Property value by state (2019 mm dollars)

The graph shows the combined value of all properties in a state in millions of 2019 dollars. The market value of each property is measured in the first quarter it enters the database and then is converted to 2019 dollars using the CPI.

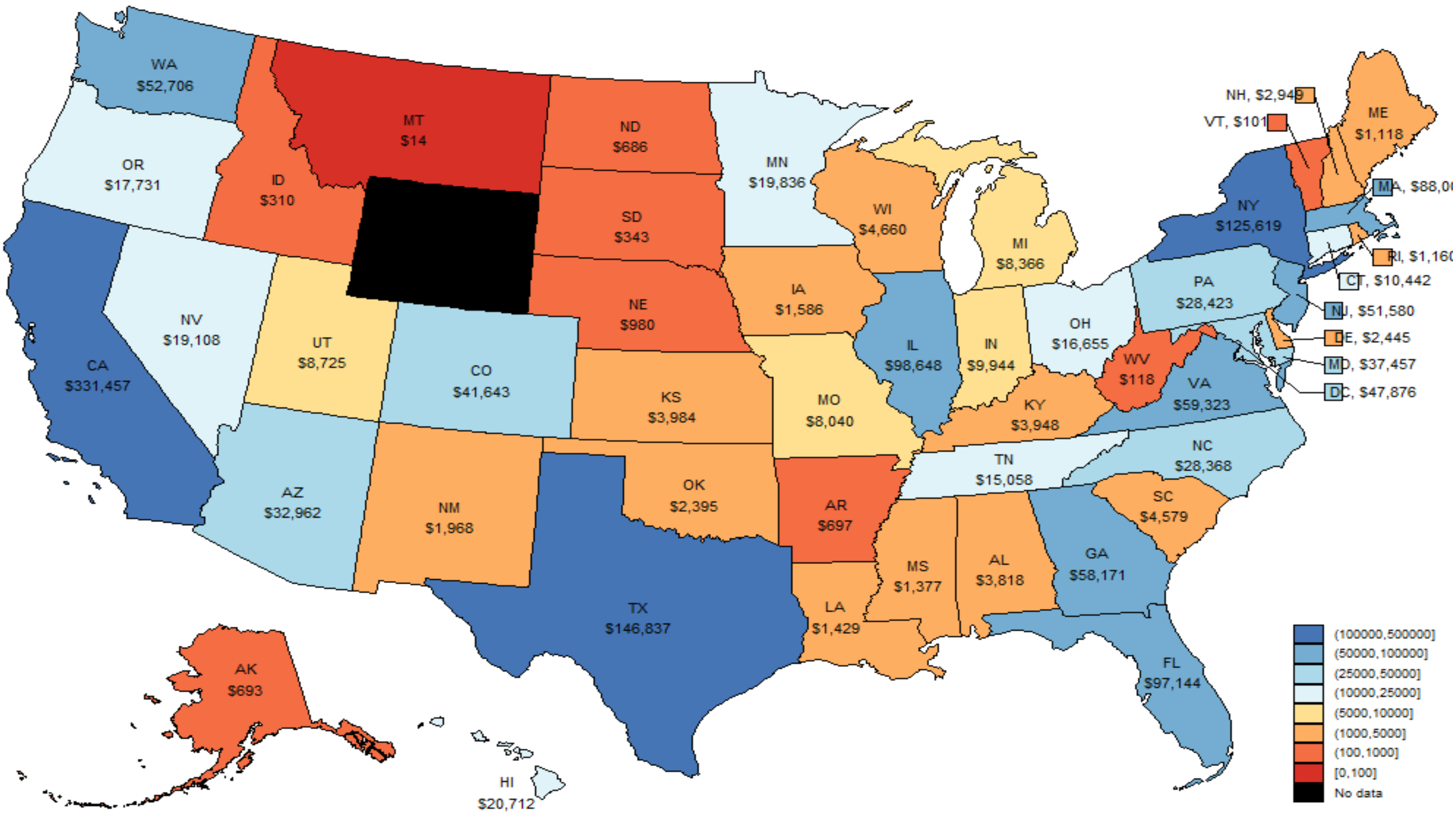

Figure 2: Percentage of properties classified as core, by state

The graph shows the percentage of all properties which are classified as core, by state. A property can be considered core if it satisfies ALL of the following criteria: it is leased at 85% or better at any point within the first four quarters it appears in the dataset; it has a lifecycle listed as operating sometime within the first four quarters it appears in our dataset. It has a property type of either Apartment, Industrial, Office, or Retail sometime within the first four quarters it appears in the dataset; and it has capital expenditures in its first four quarters in the dataset totaling less than 5% of the market value of the property as it was reported in the first quarter the property is in the dataset.

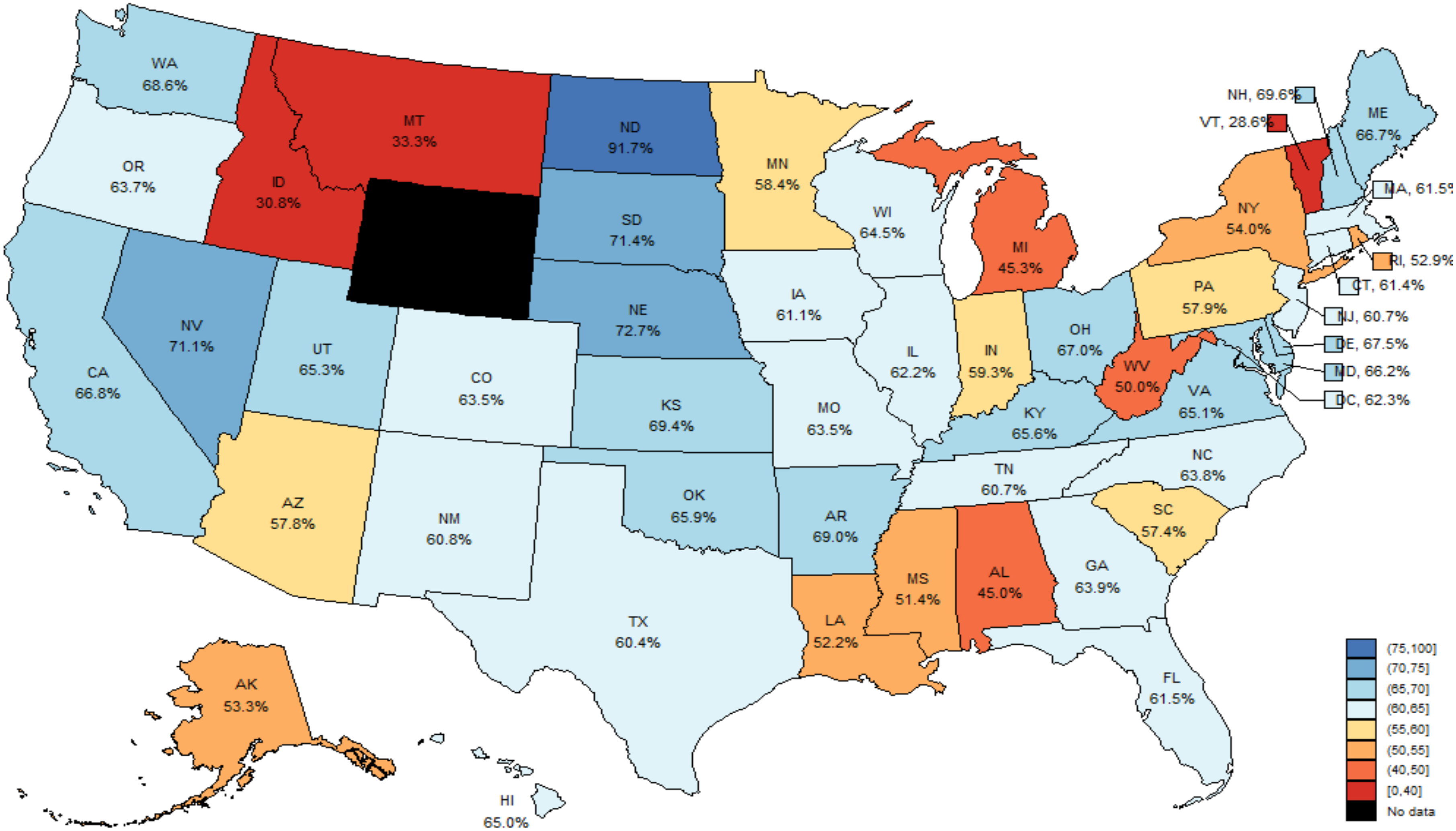

Figure 3: Time series of portfolio returns core vs non-core

All graphs show quarterly portfolio returns for 1988q1-2019q1. Each quarter we take the RAW return for the core portfolio and subtract the raw return for the non-core portfolio. VW indicates that the portfolio is value weighted based on dollar size of property. EW indicates that the portfolio is equally weighted by property.

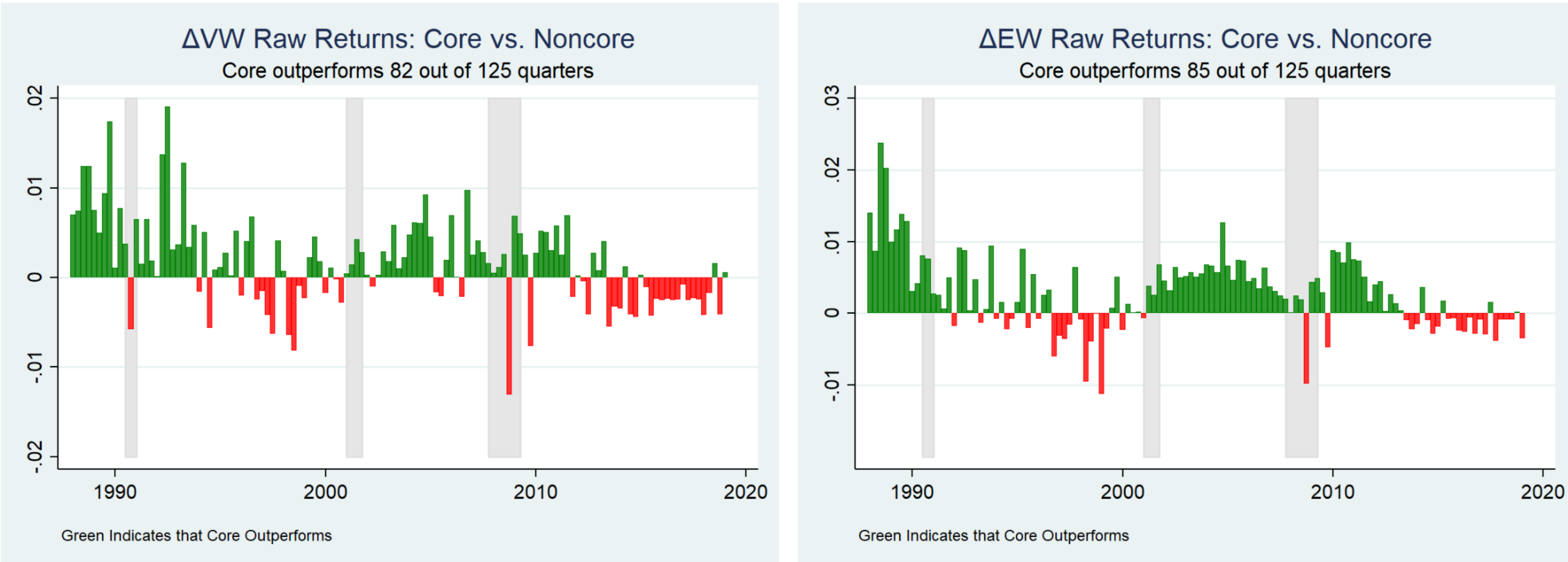

Figure 4: Estimates and confidence intervals of core coefficient

Each quarter t, regression (11) from Table 2 estimated: $return_{i,j,c} = \alpha + \lambda_j Manager_{i,j,c} + \gamma_c county_{i,j,c} + \delta_i Core_{i,j,c} + \Gamma X_{i,j,c} + \varepsilon_{i,j,c}$. The figure shows the estimates and 95% confidence intervals for the coefficient on Core. Blue (Red) indicates that the quarterly coefficient is significantly positive (negative) at the 5% level. Grey indicates that the quarterly coefficient is insignificantly different from zero at the 5% level.