ROBUSTNESS OF THE HEADQUARTERS-CITY EFFECT ON STOCK RETURNS

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Abstract

Recent studies report that U.S. firms headquartered near each other experience positive comovement in their stock returns, a finding suggestive of local biases in equity trading activity. We investigate the robustness of these findings and find that including additional pricing factors in models for monthly stock returns materially reduces the magnitude of the headquarters-city effect in stock returns. Additionally, we find that an implicit null hypothesis of zero local return comovement is inappropriate as there is positive comovement between a stock’s return and returns on portfolios of stocks from nonheadquarters cities, on average. Nevertheless, results benchmarked against estimates based on resampling methods indicate a significant and robust headquarters-city effect in stock returns.

JEL Classification: G11, G12, C15

I. Introduction

U.S. companies headquartered near each other or in the same city appear to experience positive comovement in their monthly stock returns (Pirinsky and Wang 2006; Barker and Loughran 2007). Comovement in stock returns among firms that share headquarters cities suggests that local biases in stock trading, as documented by Coval and Moskowitz (1999), Huberman (2001), and Zhu (2003), leave discernible traces on stock returns. Contrary to this finding, one might expect that local biases in stock trading would have negligible effects on security prices in the United States, a country home to the world’s most developed capital markets and in which institutional investors account for a large proportion of trading activity.

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We investigate the robustness of the apparent headquarters-city effect in stock returns to alternative pricing models and test methods based on resampling techniques. Specifically, we test for comovement in monthly returns for same-city stocks across 3 five-year periods spanning 1989 to 2004. We control not only for overall market movements in returns but also the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor. We are concerned that inevitable misspecification in empirical models for monthly returns may lead to spurious positive factor loadings on excess returns for even arbitrary city-based portfolios of small size. In addition, failure to adjust for similar factor sensitivities among same-city stocks may bias inferences on return comovement attributable to a headquarters-city effect. We are also concerned that a null hypothesis of zero same-city comovement is inappropriate. Consequently, for our tests based on resampling techniques we match sample stocks to portfolios of stocks from other nonheadquarters cities to generate a more appropriate null hypothesis empirically. For example, the common stock of a firm headquartered in Miami can be matched to a portfolio of stocks of firms headquartered in Kansas City, a Seattle stock can be paired with a portfolio of Atlanta stocks, and so forth. We estimate the degree of comovement between returns on sample stocks and returns on nonheadquarters-city portfolios. We then investigate whether same-city return comovement is significantly greater than comovement with other city portfolios.

We find that when the model for returns includes the size, value, and momentum factors the comovement between monthly returns on stocks and returns to their headquarters-city portfolios is materially lower than when the return model includes only returns to the market portfolio or matching industry portfolios. We show that standard test statistics on the cross-section of comovement coefficients are more than halved when we employ the multiple-factor model, but the tests still reject the null hypothesis of zero average comovement among returns of same-city stocks. These results suggest that a material portion of the previously documented local comovement effect can be attributed to incomplete specification of the model for stock returns. In particular, return sensitivities to these additional pricing factors appear to be correlated among firms headquartered in the same city. Consequently, controls for size, value, and momentum effects in equity pricing are important when attempting to isolate the headquarters-city effect from return patterns attributable to general pricing factors.

Resampling test methods reveal several additional findings regarding the robustness of local comovement. First, the appropriateness of the null hypothesis of zero local return comovement is strongly refuted by the results from resampling test methods. Specifically, we find that stock returns comove positively, on average, with returns on portfolios of nonheadquarters-city stocks, and this comovement is especially large when the models for returns include only market and industry factors. Nevertheless, same-city return comovement measures materially exceed comovement with most other city portfolios, on average. Furthermore, actual
return comovement with same-city portfolios is several times larger than the average comovement estimated for other city portfolios under the implicit null hypothesis in 1,000 randomized samples constructed for each of our 3 five-year periods. Similarly, actual standard test statistics are more than double the average test statistics generated by estimations for randomized samples. Most important, randomization tests reveal that the actual comovement measures and their test statistics fall beyond even the most extreme counterpart measures under the null hypothesis, with empirical $p$-values of less than 1 in a 1,000 (<0.1%) for each of the 3 five-year sample periods.

Finally, we investigate an explanation for our finding of positive average return comovement between stocks and portfolios of stocks from nonheadquarters cities. Specifically, Barker and Loughran (2007) find that correlations in monthly returns among pairs of S&P 500 stocks tend to vary inversely with distance between the firms’ headquarters cities. Consequently, we sort cities by distance from a sample firm’s headquarters city and find that return comovement with nonheadquarters-city portfolios of stocks diminishes with distance, and more distinctly so when we use a four-factor model for returns. In particular, return comovement with portfolios of stocks headquartered in other cities within 100 miles of the firm’s own headquarters city averages twice the comovement with portfolios of stocks from cities located more than 200 miles away. In short, returns on stocks tend to move not only with returns of same-city stocks but also to a lesser extent with returns on stocks headquartered in proximate cities. Hence, exclusion of proximate-city portfolios from our resampling tests only enhances the statistical robustness of the headquarters-city effect in stock returns. More important, investors’ local biases and their influence on stock returns appear to extend beyond home cities to nearby cities.

Our investigation reveals that the specification of models for returns and the design of test methods are critical in making appropriate inferences about comovement in stock returns. Nevertheless, even after prudent return modeling and application of powerful test methods based on resampling techniques we find a headquarters-city effect in stock returns. We also contribute to the literature by establishing that a firm’s return comovement with portfolios of stocks headquartered in other cities diminishes with distance from a firm’s own headquarters city. Our evidence supports the notion that the previously documented bias toward trading locally prominent stocks leaves observable traces on U.S. stock returns. This finding can be added to the growing evidence that investor habitats induce patterns in returns among securities that otherwise do not share common fundamentals.

II. Local Bias in Equity Investments and Return Comovement

The tendency of investors to deviate from global diversification and instead hold portfolios of financial assets that disproportionately overweight home-country
securities has been widely observed (French and Poterba 1991; Chan, Covrig, and Ng 2005). Differences in political and economic systems, tax implications, language, culture, and limited access to foreign markets explain at least some of this observed home-country bias.

Even within the United States, investors hold portfolios that are biased toward securities of local firms or otherwise familiar firms. Coval and Moskowitz (1999) find that U.S. money managers hold portfolios of companies that are located about 10% closer to their offices, on average, than randomly formed domestic portfolios. Huberman (2001) finds that U.S. investors invest disproportionately in their local former Regional Bell Operating Company compared to distant companies; he suggests investors prefer familiar companies in spite of portfolio theory-based rationales for broader diversification. Zhu (2003) observes local bias behavior among individual investors that attenuates with distant firms’ advertising expenditures, also consistent with the familiarity hypothesis.

The local bias in portfolio holdings within the United States appears to affect trading activity and stock pricing for firms that are headquartered near each other. For instance, Loughran and Schultz (2004) show that the time zone in which a firm is headquartered conditions intraday trading patterns in its common stock. Similarly, they show that religious holidays and blizzards influence stock trading volume of companies headquartered in affected cities. Hong, Kubik, and Stein (Forthcoming) show that local bias may have implications for stock prices in some regions via an “only game in town” effect. Specifically, companies located in areas with relatively few firms per capita appear to be valued more highly than companies from regions with many resident firms. This suggests that excess demand by local investors drives up share prices of proximate firms when there are few other local stocks in which to invest.

Two recent studies add to the local bias literature by showing that returns on stocks tend to comove when firms are headquartered near each other. Barker and Loughran (2007) find that correlations in monthly returns for pairs of stocks in the S&P 500 vary inversely with distance between the headquarters of the firms over 2000–2004. Similarly, Pirinsky and Wang (2006) report that stocks of firms headquartered in the same city experience residual comovement in monthly stock returns. Pirinsky and Wang measure the degree of local comovement as the sensitivity of a firm’s monthly stock returns to the returns on an index of other same-city stocks. Specifically, consider the following time series model for returns to stock $j$:

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + \lambda_j (R_{HQ_{city-j,t}} - R_{F,t}) + \varepsilon_{j,t},$$

(1)

where $R_{j,t}$ is the monthly return on stock $j$, $R_{F,t}$ is the monthly risk-free rate, $R_{M,t}$ is the monthly return on a diversified value-weighted market portfolio, and $R_{HQ_{city-j,t}}$ is the return on an equally weighted portfolio of stocks with headquarters in the
same city as firm $j$, excluding firm $j$. The coefficient $\lambda_j$ is the measure of firm $j$’s return comovement with same-city stocks.

Pirinsky and Wang (2006) show that estimates for $\lambda_j$ are strongly positive, on average, suggesting that returns on stocks tend to move together with returns on stocks of other firms headquartered in the same city. This local comovement persists after including pricing factors based on returns on industry-focused portfolios. The headquarters effect also appears robust to controls for company fundamentals and the economic condition of the geographic areas associated with the companies’ headquarters. Finally, when firms change headquarters city, return comovement with the old headquarters-city portfolio decreases and comovement with the new headquarters-city portfolio increases.

The proximity effect among U.S. stocks is an example of an investor habitat effect (Barberis, Shleifer, and Wurgler 2005). An investor habitat effect is manifest when groups of investors who share a literal or virtual common habitat concentrate their attention on certain classes of securities. Correlated trading by such investors may result in return comovement among securities that is not attributable to underlying fundamentals or exposure to common risk factors.1 Such correlated trading might be induced by privileged access to locally generated information or, alternatively, by rumors or noise trading among local traders who share social networks (Hong, Kubik, and Stein 2004, 2005; Ozsolyev 2005). An implicit habitat effect motivates much of the research on integration of international capital markets. Specifically, national securities markets that are segmented from global capital markets are largely the habitats of domestic investors. Integration is inferred to occur following stock market liberalizations when the influence of global investors increases, the relative influence of domestic investors declines, comovement among returns of formerly segmented domestic stocks decreases, and their comovement with global pricing factors increases (Bekaert, Harvey, and Lumsdaine 2002; Karolyi and Stulz 2003). The headquarters-city effect among U.S. stocks suggests that such habitat effects can occur within a country.

Similar to the investor habitat effect is an investment category effect attributable to patterns in investor demand that evolve in response to seemingly arbitrary categorizations of financial assets. For example, Kumar and Lee (2006) show that return comovement among so-called retail stocks (e.g., small-cap and lower priced stocks) appears to be driven by correlated trades of individual investors. Barberis, Shleifer, and Wurgler (2005) find that returns on stocks added into a

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1For example, prices of airline stocks can be expected to move together in response to new information about fuel prices or changes in consumer demand for travel services due to terrorist incidents. Likewise, prices of even seemingly dissimilar stocks can experience comovement if they are similarly exposed to underlying factors that have been shown to affect security returns. For example, two firms may be from seemingly dissimilar industries, but returns on their stocks may be similarly exposed to pricing factors such as the well-known Fama–French (1993) size and value factors.
stock index begin to comove more with returns on other stocks in the index and less with returns on stocks outside the index. Similarly, Ambrose, Lee, and Peek (2007) show that the inclusion of real estate investment trusts (REITs) into broader stock indexes results in stronger comovement between REIT returns and returns on non-REIT index components. The headquarters-city effect could be considered a category effect because many local newspapers provide tables of prices for stocks of local interest or otherwise highlight financial developments of local companies, effectively making these stocks a salient category for local investors.

The finding of a headquarters-city effect in stock returns also adds to the literature on costly behavioral biases by investors such as the lack of prudent diversification (e.g., excessive allocation of retirement savings to employer stocks as shown by Benartzi 2001). Locally biased portfolios are by construction underdiversified and expose investors to excessive idiosyncratic risk. Individuals within local communities face largely undiversified risks related to employment income and residential real estate holdings, and a skew toward local stocks with correlated returns would seem to add to the problem of underdiversification in asset portfolios.

**III. Questions, Data, and Methods**

We investigate two related issues in the measurement and testing of return comovement among stocks headquartered in the same city. First, any model of stock returns will be subject to some degree of misspecification, and equation (1) and its extension to incorporate returns on industry portfolios in addition to the market risk factor are not exceptions. Specifically, it is well established that stock returns are sensitive to pricing factors such as the differential returns on portfolios of small firms versus big firms, on portfolios of value firms versus growth firms, and on portfolios of stocks that have been recent winners versus recent losers (Fama and French 1993; Carhart 1997). Our objective is to investigate whether the headquarters-city effect persists after controlling for these known empirical pricing factors. To the extent that these additional factors proxy for economic risk factors, we reduce possible specification errors that may otherwise inflate or obscure the observed headquarters-city effect.

There is debate, however, as to whether empirical pricing factors based on firm size, value, and observed momentum effects in returns reflect not economic risk factors but rather persistent mispricing, investor sentiment, or other “animal spirits” and, hence, whether their inclusion in return models biases against rejecting market efficiency (e.g., see Loughran and Ritter 2000). In terms of this perspective, our investigation seeks to establish whether the headquarters-city effect is an independent anomaly as opposed to merely a manifestation of previously observed patterns in stock returns.

In particular, one potential problem is that Pirinsky and Wang (2006) use returns on a value-weighted market portfolio and returns on an equally weighted headquarters-city portfolio. Because much of their sample is small firms, at least
part of the comovement with returns on a city portfolio, itself comprising mostly small firms, might reflect comovement with any portfolio sensitive to returns on small firms in general. In addition, if the spatial distribution of firms across U.S. cities is related to characteristic factor sensitivities, failure to control for such pricing factors might bias estimates of return comovement among same-city stocks. For example, consider the geographic concentration of many small-growth firms in areas such as California’s Silicon Valley and North Carolina’s Research Triangle. After controlling only for market returns and industry returns, prices of stocks in such areas might move together because of similarly negative factor loadings on the Fama–French value factor derived by subtracting returns of growth firms from returns of value firms. Conversely, consider the location of many old-economy value firms in the industrial Midwest and the likely positive sensitivity of their stock returns to the value pricing factor. Consequently, we first consider extensions to equation (1) that include additional pricing factors. As discussed later, there appear to be systematic relations between pricing factor sensitivities of a sample stock and the pricing factor sensitivities of its headquarters-city portfolio, such that failure to control for these additional pricing factors in equation (1) results in excessive factor loading on the headquarters-city portfolio return factor.

Second, the explicit null hypothesis in equation (1) is that the $\lambda_j$ coefficient on returns for a sample firm’s headquarters-city portfolio should be zero after controlling for market returns. A positive estimate for $\lambda_j$ is assumed to be evidence for comovement suggestive of locally biased investment behavior. But is the assumption of a zero $\lambda_j$ an appropriate null hypothesis, even if we extend equation (1) to include additional pricing factors? What coefficient might we expect if an alternative portfolio were substituted for each firm’s headquarters-city portfolio? In particular, what result might we expect if we were to substitute a portfolio of securities unlikely to be included in local investors’ habitat, say stocks of firms headquartered in another city entirely? In such an experiment, what would we infer from a positive coefficient estimate for $\lambda_j$ for a sample firm and a nonheadquarters-city portfolio (e.g., a firm located in Atlanta and the portfolio of stocks headquartered in Milwaukee)? What should we infer from a large test statistic associated with the cross-sectional mean of such coefficients across a sample of returns on stocks and nonheadquarters-city portfolios? Rather than a headquarters-city effect attributable to local bias in stock trading we might instead infer some form of misspecification in the return equation or a bias in our test statistics. The scenario we describe forms the basis for our resampling test methods, which we describe next along with our data and methods.

*Headquarters Cities and Portfolios of Headquartered Companies*

We use the merged Compustat/CRSP (University of Chicago’s Center for Research in Securities Prices) databases available from Wharton Research Data Services to
TABLE 1. Attributes of Headquarters (HQ) City Stock Portfolios.

<table>
<thead>
<tr>
<th>Period</th>
<th>Stocks</th>
<th>HQ Cities</th>
<th>Mean</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
</tr>
</thead>
<tbody>
<tr>
<td>July 1989 to June 1994</td>
<td>1,927</td>
<td>85</td>
<td>22.7</td>
<td>9</td>
<td>15</td>
<td>34</td>
</tr>
<tr>
<td>July 1994 to June 1999</td>
<td>2,563</td>
<td>98</td>
<td>26.2</td>
<td>8</td>
<td>16</td>
<td>35</td>
</tr>
<tr>
<td>July 1999 to June 2004</td>
<td>3,058</td>
<td>100</td>
<td>30.6</td>
<td>8</td>
<td>16</td>
<td>41</td>
</tr>
</tbody>
</table>

Note: This table shows the number of common stocks for CRSP/Compustat-listed firms that are identified with their respective HQ cities (metropolitan statistical areas) for each of 3 five-year periods. We exclude financial firms, real estate investment trusts, and American Depositary Receipts, as well as stocks with fewer than 36 valid monthly returns within each five-year period. We also exclude cities with fewer than five HQ firms that meet these constraints.

identify all firms for which monthly returns and headquarters location are available. Following the local bias literature (Loughran and Schultz 2004; Hong, Kubik, and Stein 2004), each firm’s location is based on its official headquarters address. We refer to the Federal Information Processing Standards state/county codes and the metropolitan statistical area definitions from the Office of Management and Budget to assign each firm’s headquarters address to a specific metropolitan area. We exclude all American Depositary Receipts, REITs, and financial firms. We discard stocks without at least 36 months of data within three predetermined five-year periods spanning 1989 to 2004 and firms from cities that do not contain at least five headquartered firms. This procedure results in a sample of 85 cities and 1,927 stocks for July 1989–June 1994, 98 cities and 2,563 stocks for July 1994–June 1999, and 100 cities and 3,058 stocks for July 1999–June 2004. Table 1 summarizes the number of stocks and associated headquarters cities, as well as the distribution of the number of stocks per city, over each of our 3 five-year sample periods.

The database we construct allows us to create portfolios of firms headquartered in the same city and to calculate their monthly returns. We calculate the monthly return for each city portfolio using an equally weighted portfolio of local firms \((i = 1 \ldots, N)\) as follows:

\[
R_{HQ\text{city},t} = \frac{1}{N} \sum_{i=1}^{N} R_{i,t},
\]

where \(R_{HQ\text{city},t}\) is the return on the city index for month \(t\), \(R_{i,t}\) is the monthly return on the stock for headquartered firm \(i\), and \(N\) firms are headquartered in this city. We exclude the sample firm in question from its respective headquarters-city index to avoid spurious results when we explore the comovement between returns on a specific stock and its headquarters-city index. More formally, each firm \(j\) is paired to a unique headquarters-city index with a monthly return computed as follows:

\[
R_{HQ\text{city} - j, t} = \frac{1}{N - 1} \sum_{i=1}^{N} R_{i,t},
\]
where $R_{HQ\text{city} - j,t}$ is the monthly return for firm $j$’s headquarters-city portfolio, excluding firm $j$.

**Local Stock Return Comovement**

Following Pirinsky and Wang (2006), we define local return comovement as the estimated time-series sensitivity of a stock’s monthly returns to the returns on a same-city stock portfolio that we calculate with equation (3). We control for a market risk factor as in equation (1) but also extend the model to include the monthly return on an industry portfolio matched to the industry of firm $j$, as follows:

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + \varphi_j (R_{IND,t} - R_{F,t})$$
$$+ \lambda_j (R_{HQ\text{city} - j,t} - R_{F,t}) + \epsilon_{j,t},$$

(4)

where $R_{IND,t}$ is the monthly industry return for firm $j$’s industry. Firms within some industries tend to cluster geographically (Wheeler 2004); therefore, controlling for industry return is particularly important when examining the relation between the physical location of a firm and its stock return returns. We classify firms to industries according to Kenneth French’s 48-industry classification (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html), and we obtain returns on industry portfolios from his online data library.

We next extend the analysis by testing whether local comovement is robust to the Fama and French (1993) three-risk factor model extended to include the Carhart (1997) momentum risk factor. The resulting four-factor model plus the headquarters-city factor is specified in equation (5):

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t + m_j UMD_t$$
$$+ \lambda_j (R_{HQ\text{city} - j,t} - R_{F,t}) + \epsilon_{j,t},$$

(5)

where $SMB_t$, $HML_t$, and $UMD_t$ are, respectively, the returns on a portfolio of small stocks minus returns on a portfolio of big stocks (the size factor), returns on a portfolio of high book-to-market ratio firms minus returns on a portfolio of low book-to-market ratio firms (the value factor), and returns on a portfolio of stocks whose prices are recently up minus returns on a portfolio of stocks whose prices are recently down (the momentum factor). We obtain these pricing factors, along with market return, risk-free rate, and returns on industry portfolios, from Kenneth French’s online data library.

Within each of our 3 five-year sample periods we estimate versions of equations (1), (4), and (5) on monthly returns for all sample stocks that meet the minimum data requirements. Thus, for July 1989–June 1994 our estimations result in 1,927 sets of time-series equation coefficients for each of the alternative specifications. Similarly, for 1994–1999 we obtain 2,563 sets of coefficient estimates, and for 1999–2004 we obtain 3,058 sets of coefficient estimates. We are specifically
interested in the estimates for $\lambda_j$ under the alternative specifications and periods. We test whether the coefficient estimates for $\lambda_j$ appear to be drawn from a distribution with a zero mean by means of a $t$-statistic based on the cross-sectional distribution of the estimates within each sample period. The null hypothesis for this $t$-test is that the cross-sectional $\lambda_j$ estimates average to zero.$^2$

**Robust Tests Based on Resampling Methods**

We employ powerful test methods that are based on resampling and randomization to assess the statistical robustness of return comovement among same-city stocks. Randomization tests, sometimes referred to as permutation tests, have precedent dating to Fisher (1935).$^3$ The basic idea of resampling is to produce and benchmark estimates and test statistics against an empirical null derived by randomly permuting the sample at hand in a manner motivated by the implicit null hypothesis. In particular, we purposefully avoid the unverified assumption that a firm’s stock return covariance with nonheadquarters-city portfolios is negligible. In contrast, we test directly whether the return comovement between stocks and their headquarters-city portfolios differs meaningfully from the return comovement observed between stocks and other city portfolios. Only if same-city return comovement were to exceed return comovement with other city portfolios could we infer that local biases in stock trading activity affect returns.

In particular, for every sample stock in each of our five-year sample periods we estimate the comovement coefficient with respect to each potential nonheadquarters-city portfolio as in equations (6) and (7):

\[
R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + \theta_j (R_{IND,t} - R_{F,t})
+ \lambda_j (R_{NonHQcity,t} - R_{F,t}) + \epsilon_{j,t} \tag{6}
\]

\[
R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t + m_j UMD_t
+ \lambda_j (R_{NonHQcity,t} - R_{F,t}) + \epsilon_{j,t}. \tag{7}
\]

For example, for the 1999–2004 sample period there are 100 city portfolios. For every one of this period’s 3,058 sample stocks we estimate equation (6) for

$^2$This is the test method employed by Pirinsky and Wang (2006). Barker and Loughran (2007) note that such a $t$-statistic will be biased upward because of a violation of the independence assumption. Specifically, if firm $j$’s stock return moves positively with the return on its headquarters-city portfolio there will be a similar positive movement, on average, between returns on other firms in that city and the city portfolio when it is constructed with firm $j$ as a component. Our subsequent tests based on resampling techniques permit us to avoid exclusive reliance on these $t$-statistics.

$^3$Moore and McCabe (2005) provide an excellent primer on permutation tests and provide several examples. Additional references to the randomization method include Welch (1990), Edgington (1995), and Kennedy (1995). Because the original sample is used to assess test statistics, the randomization test method is closely related to the bootstrap method and other methods based on resampling.
each of the 99 nonheadquarters-city portfolios, resulting in 99 nonheadquarters-city-specific estimates of $\lambda_j$ in addition to the coefficient estimate for the firm’s headquarters-city portfolio. Thus, we produce an entire matrix of headquarters-city and nonheadquarters-city $\lambda_j$ coefficients with dimensions $3,058 \times 100$. Similarly, we estimate the entire matrix of possible stock-city portfolio coefficient estimates for 1989—1994 ($1,927 \times 85$) and 1994—1999 ($2,563 \times 98$). We then use these resampled comovement coefficient estimates in two kinds of tests.

First, for each sample stock in each of our three sample periods we compare the headquarters-city comovement measure to the distribution of comovement measures for all nonheadquarters cities. If a null hypothesis of zero comovement is appropriate, the distributions of firm-specific nonheadquarters-city $\lambda_j$s should have a central tendency of zero. Even if the central tendency is positive, a robustly positive headquarters-city effect should be rejected if the estimated $\lambda_j$ for the headquarters-city portfolios falls in the middle of the distribution of such coefficients across nonheadquarters-city portfolios, on average. At the very least, the fraction of sample firms whose same-city $\lambda_j$s exceed the median of coefficients among nonheadquarters-city portfolios must be large if the headquarters-city effect is robustly significant.

For a second test we construct randomized samples in which stocks are randomly paired with nonheadquarters-city portfolios. As mentioned earlier, a firm from Atlanta might be randomly matched with the portfolio constructed from all firms headquartered in Milwaukee. In constructing a randomized sample, all nonheadquarters-city portfolios within each sample period are equally likely to be randomly paired with any particular sample firm. The resulting permuted sample is equal in sample size—in terms of number of stocks—to the original sample. For example, a randomized sample for 1999—2004 pairs each of the 3,058 stocks with a randomly chosen nonheadquarters-city portfolio of stocks. We estimate the $\lambda_j$ for each stock’s returns relative to the returns on its randomly assigned nonheadquarters-city portfolio using equations (6) and (7). We then compute the average from the cross-section of resulting nonheadquarters-city $\lambda_j$s and the traditional cross-sectional $t$-statistic. We employ this process 1,000 times for each equation specification, independently assigning different nonheadquarters-city portfolios, estimating coefficients across all sample firms within each of the randomized samples, and computing mean nonheadquarters-city $\lambda_j$ and the $t$-statistic for each of the 1,000 permuted samples. This procedure is applied independently to each of the 3 five-year sample periods.

The randomization test method is useful in two respects. First, the validity of the presumed null hypothesis of zero comovement among returns of same-city stock can be assessed by examining the central tendencies and dispersions of the coefficient estimates for the randomized samples. If this null hypothesis is appropriate, the randomized coefficient estimates for $\lambda_j$ should have a central tendency of zero. However, if the central tendency of the comovement coefficients
for randomly assigned cities is reliably greater than zero, prediction of zero comovement between stock returns and returns on headquarters-city portfolios would appear to be an inappropriate null. Second, the true headquarters-city mean \( \lambda_j \) and its associated \( t \)-statistic can then be compared with the empirical distribution of 1,000 mean coefficients generated when sample stocks are randomly matched with other-city portfolios. If comovement between stock returns and same-city portfolios is unusually strong, the mean \( \lambda_j \) for headquarters-city portfolios should lie in or beyond the upper tails of the randomized empirical distributions. In particular, the empirical \( p \)-values for the mean headquarters-city \( \lambda_j \) are discernible as the frequencies at which figures drawn from the randomized distributions exceed actual statistics. Given our 1,000 randomized samples per sample period, our randomization test method allows us to assess empirical \( p \)-values to 0.1% precision.

**Comovement and Distance**

Barker and Loughran (2007) examine correlations in monthly stock returns among all possible pairs of 456 domestically headquartered firms in the S&P 500 for 2000–2004. They find that return correlation appears to vary inversely with the distance between the headquarters of these firms. Our sample includes many more firms of diverse size and industry mix across many more U.S. cities, and like Pirinsky and Wang (2006), we control for common factors that affect stock returns to focus on residual return comovement. Thus, for our sample we are also able to investigate whether a firm’s stock return comoves not only with same-city stocks but also with proximate-city stocks. Support for a proximate-city effect would complement the headquarters-city effect and provide additional evidence that investor habitat effects influence stock pricing.

To investigate this hypothesis, we calculate the distance from the city center of each headquarters city to the center of each of the other sample cities with resident firms. We obtain the longitude and latitude of each city center from the U.S. Census Bureau’s *US Gazetteer*. We then calculate the distance between any two city centers (city \( x \) and city \( y \)) according to the following equation, where longitude and latitude of respective city centers are measured in radians and 3,963 is the radius of the earth in miles:

\[
d_{xy} = 3963 \times \arccos \left[ \sin (\text{lat}_x) \sin (\text{lat}_y) + \cos (\text{lat}_x) \cos (\text{lat}_y) \cos (|\text{long}_x - \text{long}_y|) \right].
\]

For each sample firm, we sort the nonheadquarters-city portfolios by distance from the sample firm’s headquarters city. We then observe the return comovement coefficients associated with the nonheadquarters-city portfolios (as identified by \( \lambda_j \) in equations (6) and (7)) and see how these coefficients vary by distance from the sample firm’s headquarters city.
IV. Results

We first demonstrate that return comovement among stocks headquartered in the same city diminishes when models for monthly returns include size, value, and momentum pricing factors. We then use resampling test methods to establish that return comovement with nonheadquarters-city portfolios is positive, on average, but also that same-city return comovement significantly exceeds comovement with nonheadquarters-city stock portfolios. Finally, we document that stock return comovement with nonheadquarters-city portfolios is inversely related to distance from a firm’s headquarters city.

Measures of the Headquarters-City Effect Under Alternative Models of Stock Returns

Table 2 presents estimates of the headquarters-city effect on stock returns under alternative models for monthly returns. Specifically, we report the mean of the $\lambda_j$ estimates for each of our 3 five-year sample periods as well as the associated

<table>
<thead>
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<tbody>
<tr>
<td>Model for Returns</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Equation (1) Market and HQ-City Portfolio Returns $\tilde{\lambda}_j(t\text{-statistic})$</td>
</tr>
<tr>
<td>Period</td>
</tr>
<tr>
<td>July 1989 to June 1994</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>July 1994 to June 1999</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>July 1999 to June 2004</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Note: This table shows mean coefficient estimates and cross-sample $t$-statistics for $\lambda_j$, the comovement between monthly returns on common stock of firm $j$ and monthly returns on the portfolio of other stocks that share firm $j$’s HQ city. Mean estimates $\tilde{\lambda}_j$ and cross-sectional $t$-statistics differ according to the specification of the model for monthly returns. Specifically, the three models for monthly returns are as follows:

1. $R_{jt} - R_{F,t} = \alpha_j + \beta_j(R_{Mt} - R_{F,t}) + \lambda_j(R_{HQcity-j,t} - R_{F,t}) + \epsilon_{j,t}$
2. $R_{jt} - R_{F,t} = \alpha_j + \beta_j(R_{Mt} - R_{F,t}) + \psi_j(R_{IND,t} - R_{F,t}) + \lambda_j(R_{HQcity-j,t} - R_{F,t}) + \epsilon_{j,t}$
3. $R_{jt} - R_{F,t} = \alpha_j + \beta_j(R_{Mt} - R_{F,t}) + \sigma_jSMB_t + h_jHML_t + m_jUMD_t$
   $\quad + \lambda_j(R_{HQcity-j,t} - R_{F,t}) + \epsilon_{j,t}$

where $R_{Mt} - R_{F,t}$ is the excess return of the value-weighted market portfolio over the risk-free rate, $R_{HQcity-j,t} - R_{F,t}$ is the excess return on firm $j$’s HQ-city portfolio (excluding firm $j$), $R_{IND,t} - R_{F,t}$ is the excess return on firm $j$’s industry portfolio, $SMB_t$ and $HML_t$ are the Fama–French size and value factors, and $UMD_t$ is the Carhart factor for momentum. Average coefficients and test statistics for pricing factors other than the HQ-city portfolio are not reported. The sample sizes with respect to number of stocks and HQ cities are as follows: 1,927 stocks and 85 HQ cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.
cross-sectional $t$-statistics. For brevity we omit reporting any information on coefficients for other equity pricing factors included in the alternative models of stock returns. The first two columns in Table 2 report results for models of returns that contain only the market return factor (equation (1)) or also include each firm’s industry-matched portfolio (equation (4)), respectively. For the market-factor-only specification, the mean estimates for $\lambda_j$ are 0.661 for July 1989–June 1994, 0.670 for 1994–1999, and 0.843 for 1999–2004; corresponding cross-sectional $t$-statistics are 27.03, 33.13, and 41.95, respectively. When we add the excess return on industry-matched portfolios to the model (equation (4)), the mean estimates for $\lambda_j$ across the three sample periods are 0.618, 0.606, and 0.774, and $t$-statistics remain large. The mean coefficient estimates for returns on the same-city portfolio shown in these two columns are similar in magnitude to those reported by Pirinsky and Wang (2006, Table 2), as are the $t$-statistics on the cross-sectional means.

The third column of Table 2 shows measures of same-city comovement after controlling for the Fama–French (1993) size and value factors and the Carhart (1997) momentum factor as specified in equation (5). These results indicate that estimates of same-city return comovement decrease materiality when additional pricing factors are included in the model of monthly stock returns. Specifically, compared to the first two columns, mean $\lambda_j$ estimates conditioned on the four-factor model are lower in magnitude for each of the three sample periods, at 0.303, 0.361, and 0.586. In other words, the mean estimated comovement coefficients in the third column of Table 2 are lower than the market-factor model results in the first column by 54%, 46%, and 30% for the three respective periods. Compared to the two-factor model, $\lambda_j$ coefficient estimates are 51%, 40%, and 24% lower in the multifactor model. The $t$-statistics in the multifactor model results are approximately half those for the single-factor and two-factor models as reported in the first two columns of Table 2. Nevertheless, the $t$-statistics indicate that mean estimates of return comovement with headquarters-city stocks remain meaningfully positive even after controlling for additional equity pricing factors. The material reduction in mean $\lambda_j$ coefficients conditioned on the four-factor model of returns indicate that in addition to market portfolio returns it is important to control for size, book-to-market, and momentum effects to discern more accurately the magnitude of return comovement with headquarters-city portfolios. Failing to control for exposure to such common return factors appears to be a specification error likely to inflate estimates of sensitivity to returns on headquarters-city portfolios.

We confirm this inference by estimating four-factor pricing models for all sample firms in each period, but we exclude the excess return on the headquarters-city portfolio from the return model. We then estimate coefficients for a four-factor model of monthly returns for each sample firm’s unique headquarters-city portfolio. Thus, for each firm we obtain its own estimated factor pricing sensitivities as well as the factor pricing sensitivities for its uniquely matched headquarters-city portfolio, and then we investigate how these factor sensitivities are related. We
find that stock- and city-level factors tend to be related to each other, as shown in Figure I and Table 3. This relation is especially strong with respect to sensitivity to the size ($SMB$) factor, but there are also statistically significant associations for sensitivities to the value ($HML$) and momentum ($UMD$) factors. For example, Figure I shows that the sample stocks and their unique headquarters-city portfolios share the same sign on the $SMB$ coefficient for 78.9%, 80.6%, and 82.4% of the cases in the respective five-year sample periods. This strong association is in part due to using a value-weighted market portfolio factor but an equally weighted headquarters-city portfolio. In particular, returns to both small firms and equally weighted headquarters-city portfolios of largely small firms tend to vary positively with the $SMB$ factor; hence, absent an $SMB$ factor in the empirical return model, a small firm’s return tends to load on the returns of its city portfolio.\(^4\) The association between sensitivities to the size factor goes beyond this simple misspecification, however. Table 3 shows estimated slope coefficients from regressions of stock-specific factor sensitivities on the factor sensitivities for each stock’s unique headquarters-city portfolio. For example, the slope coefficients obtained from a simple regression of firm-specific $HML$ sensitivities on respective headquarters-city portfolio $HML$ sensitivities are 0.256, 0.752, and 1.029 for each respective sample period; $t$-statistics associated with these coefficients have $p$-values of less than 1%. Hence, even after controlling for market returns there are materially positive associations between sensitivities of a firm’s return to the size ($SMB$), value ($HML$), and momentum ($UMD$) factors and the corresponding sensitivities for portfolios of other firms that share the headquarters city. We infer that geographic patterns in firms’ headquarters locations are correlated with stock return sensitivity to such factors and that controlling for these additional factors is important in isolating the headquarters-city effect.\(^5\) Specifically, adding the excess return on the headquarters-city portfolio as a pricing factor in a model that otherwise excludes the $SMB$, $HML$, and $UMD$ factors is likely to lead to upwardly biased coefficient estimate for the headquarters-city pricing factor. Incorporating the $SMB$, $HML$, and $UMD$ factors reduces the upward bias in estimates of the headquarters-city effect.

\(\text{Tests of Headquarters-City Return Comovement Based on Resampling Techniques}\)

In addition to estimating return comovement between a stock and the portfolio of same-city stocks we estimate return comovement with all other nonheadquarters-city portfolios using equations (6) and (7). In the 1989–1994 sample period, these

\(^4\)This appears to be a general problem when failing to include a size-related factor in a model for returns that otherwise includes a factor derived from equally weighted portfolios of mostly small firms.

\(^5\)How the geographic distribution of firms across the United States is conditioned by underlying firm-specific characteristics such as size and value seems an intriguing question for additional research.
Panel A. July 1989 to June 1994

<table>
<thead>
<tr>
<th>β&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</th>
<th>+</th>
<th>3</th>
<th>1,753</th>
<th>0.2%</th>
<th>91.0%</th>
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<tbody>
<tr>
<td></td>
<td>-</td>
<td>0</td>
<td>171</td>
<td>0.0%</td>
<td>8.9%</td>
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</table>

<table>
<thead>
<tr>
<th>s&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</th>
<th>+</th>
<th>3</th>
<th>1,521</th>
<th>0.2%</th>
<th>78.9%</th>
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<tr>
<td>h&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</td>
<td>+</td>
<td>0</td>
<td>403</td>
<td>0.0%</td>
<td>20.9%</td>
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<table>
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<tr>
<th>m&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</th>
<th>+</th>
<th>97</th>
<th>1,088</th>
<th>5.0%</th>
<th>56.5%</th>
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<tr>
<td></td>
<td>+</td>
<td>53</td>
<td>689</td>
<td>2.8%</td>
<td>35.8%</td>
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Panel B. July 1994 to June 1999

<table>
<thead>
<tr>
<th>β&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</th>
<th>+</th>
<th>2</th>
<th>2,260</th>
<th>0.1%</th>
<th>88.2%</th>
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<tbody>
<tr>
<td></td>
<td>-</td>
<td>0</td>
<td>403</td>
<td>0.0%</td>
<td>15.7%</td>
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<table>
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<tr>
<th>s&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</th>
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<th>2,065</th>
<th>0.1%</th>
<th>80.6%</th>
</tr>
</thead>
<tbody>
<tr>
<td>h&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</td>
<td>+</td>
<td>0</td>
<td>496</td>
<td>0.0%</td>
<td>19.4%</td>
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<table>
<thead>
<tr>
<th>m&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</th>
<th>+</th>
<th>612</th>
<th>821</th>
<th>23.9%</th>
<th>32.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+</td>
<td>642</td>
<td>488</td>
<td>25.0%</td>
<td>19.0%</td>
</tr>
</tbody>
</table>

Panel C. July 1999 to June 2004

<table>
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<tr>
<th>β&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</th>
<th>+</th>
<th>1</th>
<th>2,763</th>
<th>0.0%</th>
<th>90.4%</th>
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<tbody>
<tr>
<td></td>
<td>-</td>
<td>0</td>
<td>294</td>
<td>0.0%</td>
<td>9.6%</td>
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<table>
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<tr>
<th>s&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</th>
<th>+</th>
<th>4</th>
<th>2,518</th>
<th>0.1%</th>
<th>82.3%</th>
</tr>
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<tbody>
<tr>
<td>h&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</td>
<td>+</td>
<td>2</td>
<td>534</td>
<td>0.1%</td>
<td>17.5%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>m&lt;sub&gt;HQ city portfolio&lt;/sub&gt;</th>
<th>+</th>
<th>387</th>
<th>1,582</th>
<th>12.7%</th>
<th>51.7%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+</td>
<td>482</td>
<td>607</td>
<td>15.8%</td>
<td>19.8%</td>
</tr>
</tbody>
</table>

| RHQcity<sub>j,t</sub> - RF<sub>_t</sub> = α<sub>j</sub> + β<sub>j</sub>(RM<sub>_t</sub> - RF<sub>_t</sub>) + s<sub>j</sub>SMB<sub>_t</sub> + h<sub>j</sub>HML<sub>_t</sub> + m<sub>j</sub>UMD<sub>_t</sub> + ε<sub>j,t</sub> |
|-----------------------------|---|---|------|------|-------|
| RHQcity<sub>j</sub> - RF<sub>_t</sub> = α<sub>HQ city</sub><sub>_j</sub> + β<sub>HQ city</sub><sub>_j</sub>(RM<sub>_t</sub> - RF<sub>_t</sub>) + s<sub>HQ city</sub><sub>_j</sub>SMB<sub>_t</sub> + h<sub>HQ city</sub><sub>_j</sub>HML<sub>_t</sub> + m<sub>HQ city</sub><sub>_j</sub>UMD<sub>_t</sub> + ε<sub>HQ city</sub><sub>_j</sub> |

Figure I. Associations Between Factor Sensitivities for Stocks and Headquarters (HQ) City Portfolios.

Note: This figure shows the association between estimates of coefficients for four-factor models of monthly returns estimated independently for returns on sample stocks and returns on each stock-specific portfolio of other stocks of firms headquartered in the same city. Specifically, for each stock and again for its unique HQ-city portfolio we estimate the following four-factor models of monthly returns:

\[ R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t + m_j UMD_t + \epsilon_{j,t} \]
\[ RHQcity_{j,t} - R_{F,t} = \alpha_{HQ city,j} + \beta_{HQ city,j} (R_{M,t} - R_{F,t}) + s_{HQ city,j} SMB_t + h_{HQ city,j} HML_t + m_{HQ city,j} UMD_t + \epsilon_{HQ city,j} \]

where \( R_{j,t} \) is the monthly return on sample stock \( j \), \( RHQcity_{j,t} \) is the return on the unique portfolio of securities of other firms that share HQ city with stock \( j \), \( R_{F,t} \) is the risk-free rate, \( R_{M,t} \) is the return of the value-weighted market portfolio, \( SMB_t \) and \( HML_t \) are the Fama–French size and value factors, and \( UMD_t \) is the Carhart factor for momentum. After obtaining estimates of factor sensitivities for stocks and their respective HQ-city portfolios, we assess the relations between them. The table entries report the associations between the signs of the coefficient estimates for stocks and their matched HQ-city portfolios. Binomial tests reject that the sum of the diagonal frequencies (++, +−, −+, and −−) versus (−+, ++, and +−) are equal at \( p \)-values of less than .1% for each comparison except for the \( m \) coefficients for the 1989–1994 sample period, where the \( p \)-value is 1.2%. The sample sizes with respect to number of stocks and HQ cities are as follows: 1,927 stocks and 85 HQ cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.
TABLE 3. Relations Between Factor Sensitivities for Stocks and Headquarters (HQ) City Portfolios.

<table>
<thead>
<tr>
<th>Period</th>
<th>$\beta$</th>
<th>$s$</th>
<th>$h$</th>
<th>$m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>July 1989 to June 1994</td>
<td>0.353</td>
<td>0.405</td>
<td>0.256</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(3.25)</td>
<td>(4.40)</td>
<td>(2.58)</td>
<td>(-0.18)</td>
</tr>
<tr>
<td>July 1994 to June 1999</td>
<td>0.077</td>
<td>0.367</td>
<td>0.752</td>
<td>0.218</td>
</tr>
<tr>
<td></td>
<td>(0.75)</td>
<td>(4.26)</td>
<td>(12.12)</td>
<td>(2.16)</td>
</tr>
<tr>
<td>July 1999 to June 2004</td>
<td>0.660</td>
<td>0.612</td>
<td>1.029</td>
<td>0.267</td>
</tr>
<tr>
<td></td>
<td>(10.57)</td>
<td>(8.51)</td>
<td>(18.37)</td>
<td>(2.55)</td>
</tr>
</tbody>
</table>

Note: This table shows the relation between estimates of coefficients for four-factor models of monthly returns estimated independently for returns on sample stocks and returns on each stock-specific portfolio of other stocks of firms headquartered in the same city. Specifically, for each stock and again for its unique HQ-city portfolio we estimate the following four-factor models of monthly returns:

$$ R_{j,t} = \alpha_j + \beta_j(R_{M,t} - R_{F,t}) + s_jSMB_t + h_jHML_t + m_jUMD_t + \epsilon_{j,t} $$

$$ RHQcity_{j,t} = \alpha_{HQcity_{j}} + \beta_{HQcity_{j}}(R_{M,t} - R_{F,t}) + s_{HQcity_{j}}SMB_t + h_{HQcity_{j}}HML_t + m_{HQcity_{j}}UMD_t + \epsilon_{HQcity_{j},t}, $$

where $R_{j,t}$ is the monthly return on sample stock $j$, $RHQcity_{j,t}$ is the return on the unique portfolio of securities of other firms that share HQ city with stock $j$, $R_{F,t}$ is the risk-free rate, $R_{M,t}$ is the return of the value-weighted market portfolio, $SMB_t$ and $HML_t$ are the Fama–French size and value factors, and $UMD_t$ is the Carhart factor for momentum. After obtaining independent estimates of factor sensitivities for both stocks and their respective HQ-city portfolios, we assess the relations between them. The table entries report results of regressions of firm-specific factor sensitivities on their respective HQ-city factor sensitivities. Specifically, we estimate ordinary least squares regressions of the following general form and report the estimated slope coefficients:

$$ \hat{\theta}_j = a_j + b_j\hat{\theta}_{HQcity_{j}} + \mu_j, $$

where $\theta$ is, alternatively, the estimated factor sensitivity $\beta, s, h, or m$ from the estimated return models. The numbers reported in parentheses below the estimated slope coefficients are $t$-statistics, which suggest a positive relation between stock-specific and HQ-city-specific factor sensitivities excepting $m$ for 1989–1994 and $\beta$ for 1994–1999. The sample sizes with respect to number of stocks and HQ cities are as follows: 1,927 stocks and 85 HQ cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.

estimations result in 84 nonheadquarters-city $\lambda_j$ coefficients for each of the 1,927 sample stocks, or 161,868 nonheadquarters-city coefficients in addition to the 1,927 coefficients estimated with the actual headquarters-city portfolio. Similarly, for the 1994–1999 period we estimate 97 nonheadquarters-city $\lambda_j$s for each of the 2,563 sample stocks (248,611 coefficients), and for 1999–2004 we estimate 99 nonheadquarters-city $\lambda_j$s for each of the 3,058 sample stocks (302,742 coefficients). We use these nonheadquarters-city $\lambda_j$s in two types of tests based on resampling techniques.

First, we use the same-city and nonheadquarters-city comovement measures in a test we refer to as a permutation test, as we compare the headquarters-city $\lambda_j$ for each stock with the entire distribution of $\lambda_j$s estimated using returns
on nonheadquarters-city portfolios. Specifically, for each sample stock in each sample period, we order the headquarters-city \( \lambda_j \) and other city coefficient estimates from lowest to highest and observe the percentile of each stock-specific empirical distribution at which the \( \lambda_j \) coefficient associated with the true headquarters city falls. Focusing on percentiles of each stock-specific distribution of coefficients allows us to compute and compare average percentile ranks and other measures of central tendencies across the entire sample of stocks and across the three sample periods. Detailed information from alternative summary measures associated with our permutation tests is displayed in Figures II and III. Figure II shows results when we use a two-factor model of returns (the market factor and an industry factor) in addition to the city portfolio factor. Figure III shows the results when we use the four-factor model of returns in addition to the city portfolio factor.

Both Figures II and III show a distinct skew to the upper percentiles for the location of the headquarters-city portfolio’s comovement measure relative to the distribution of measures estimated for portfolios for other cities for each of our five-year sample periods. For example, in Figure III mean (median) percentile ranks are 55.7% (60.6%) for 1989–1994, 56.3% (61.3%) for 1994–1999, and 60.9% (70.0%) for 1999–2004. Conversely, the summary measures in Figure III indicate that on average return comovement with many nonheadquarters-city portfolios exceeds comovement with the headquarters-city portfolio. Specifically, many nonheadquarters-city portfolios result in higher return comovement measures than the true headquarters-city portfolio—on average, 44.3% of nonheadquarters-city portfolios in 1989–1994, 43.7% in 1994–1999, and 39.1% in 1999–2004. Nevertheless, given the large sample sizes in each sample period, these mean and median percentile ranks of the true \( \lambda_j \) estimates all significantly exceed 50% at \( p \)-values considerably less than 1%. Naturally, the 50% threshold results from a naïve null hypothesis that comovement with the headquarters city does not differ from comovement with other cities, on average.

Figures II and III also report the number and percentage of stocks in each sample period for which the headquarters-city \( \lambda_j \) falls above or below the median of the empirical distribution of nonheadquarters-city coefficient estimates. As shown in Figure III, in each sample period many headquarters-city coefficients fall below the empirical medians for nonheadquarters cities—43.6% of stocks in 1989–1994, 42.1% of stocks in 1994–1999, and 35.7% of stocks in 1999–2004. Again, however, most headquarters-city coefficients fall in the upper half of their respective distributions. Finally, Figures II and III also show the distribution of headquarters-city coefficients across the vintiles of the respective empirical distributions. A naïve null hypothesis would be that a stock’s comovement with respect to its headquarters-city portfolio is equally likely to fall in any vintile of its distribution of comovement estimates associated with all city portfolios. The results in Figures II and III clearly show a significant skew to the upper tails of the distributions, with the highest
Figure II. Return Comovement with Headquarters (HQ) City Portfolio Versus All Other City Portfolios: Two-Factor Model of Returns Plus a City Portfolio Factor.

Note: We estimate measures of comovement between monthly stock returns of firm $j$ and returns on the portfolio of other firms headquartered in the same city as measured by $\lambda_j$ in equation (4):

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + \varphi_j (R_{IND,t} - R_{F,t}) + \lambda_j (R_{HQcity,j,t} - R_{F,t}) + \epsilon_{j,t}.$$  

For each firm $j$ we then estimate equation (5) multiple times, each time substituting for $R_{HQcity,j,t}$ in turn, returns on each of the other available non-HQ-city portfolios. We then observe at which percentile of the distribution of all possible city portfolio comovement coefficients the coefficient for firm $j$’s HQ-city portfolio lies. We repeat this exercise for each sample firm, its respective HQ-city portfolio, and the set of all other non-HQ-city portfolios, resulting in the entire distribution of comovement coefficients across all cities for all firms. The height of each column in the graphs shows the sample frequency with which same-city comovement coefficients fall within each vintile for each stock-specific distribution of all city comovement coefficients. The sample size with respect to number of stocks and total number of city portfolios are as follows: 1,927 stocks and 85 cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.
Figure III. Return Comovement with Headquarters (HQ) City Portfolio Versus All Other City Portfolios: Four-Factor Model of Returns Plus a City Portfolio Factor.

Note: We estimate measures of comovement between monthly stock returns of firm \( j \) and returns on the portfolio of other firms headquartered in the same city as measured by \( \lambda_j \) in equation (5):

\[
R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + \gamma_j \cdot \text{SMB}_t + \delta_j \cdot \text{HML}_t + \epsilon_j \cdot \text{UMD}_t + \lambda_j (R_{HQ_{city,j,t}} - R_{F,t}) + \epsilon_{j,t}.
\]

For each firm \( j \) we then estimate equation (5) multiple times, each time substituting for \( R_{HQ_{city,j,t}} \) in turn, returns on each of the other available non-HQ-city portfolios. We then observe at which percentile of the distribution of all possible city portfolio comovement coefficients the coefficient for firm \( j \)'s HQ-city portfolio lies. We repeat this exercise for each sample firm, its respective HQ-city portfolio, and the set of all other non-HQ-city portfolios, resulting in the entire distribution of comovement coefficients across all cities for all firms. The height of each column in the graphs shows the sample frequency with which same-city comovement coefficients fall within each vintile for each stock-specific distribution of all city comovement coefficients. The sample size with respect to number of stocks and total number of city portfolios are as follows: 1,927 stocks and 85 cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.
vintile (> 95%) more likely to be populated with headquarters-city \( \lambda_j \)'s than any other vintile in each sample period.

We next use the resulting city-specific coefficient estimates in an additional test that we call a randomization test. In this test we match each sample stock with a randomly chosen nonheadquarters-city portfolio and use the resulting distribution of randomized \( \lambda_j \)'s to compute mean coefficients and \( t \)-tests comparable to the way we did for headquarters-city portfolios in Table 2. We conduct 1,000 separate randomizations for each sample period, resulting in 1,000 estimates of mean nonheadquarters-city \( \lambda_j \) and 1,000 \( t \)-statistics based on the 1,000 distributions of these coefficient estimates. Table 4 reports summary measures for these

**TABLE 4. Randomization Tests of the Headquarters (HQ) City Effect in Stock Returns.**

<table>
<thead>
<tr>
<th>Period</th>
<th>Mean ( \bar{\lambda}_j ) (t-statistic) for 1,000 Randomized Samples with Non-HQ-City Portfolios</th>
<th>99.9 Percentile ( \bar{\lambda}_j ) (t-statistic) for 1,000 Randomized Samples with Non-HQ-City Portfolios</th>
<th>( \bar{\lambda}_j ) (t-statistic) for Actual Sample of HQ-City Portfolios</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A. Two-Factor Model of Returns Plus Random City Portfolio Return Factor</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>July 1989 to June 1994</td>
<td>0.250 (15.52)</td>
<td>0.292 (18.60)</td>
<td>0.618 (25.39)</td>
</tr>
<tr>
<td>July 1994 to June 1999</td>
<td>0.332 (21.76)</td>
<td>0.370 (23.98)</td>
<td>0.606 (30.03)</td>
</tr>
<tr>
<td>July 1999 to June 2004</td>
<td>0.394 (24.92)</td>
<td>0.431 (27.42)</td>
<td>0.774 (38.66)</td>
</tr>
<tr>
<td>Panel B. Four-Factor Model of Returns Plus Random City Portfolio Return Factor</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>July 1989 to June 1994</td>
<td>0.058 (3.30)</td>
<td>0.110 (5.94)</td>
<td>0.303 (11.78)</td>
</tr>
<tr>
<td>July 1994 to June 1999</td>
<td>0.109 (6.08)</td>
<td>0.178 (9.75)</td>
<td>0.361 (13.74)</td>
</tr>
<tr>
<td>July 1999 to June 2004</td>
<td>0.172 (9.32)</td>
<td>0.216 (11.76)</td>
<td>0.586 (22.46)</td>
</tr>
</tbody>
</table>

Note: This table shows mean coefficient estimates and \( t \)-statistics for \( \lambda_j \), the comovement between monthly returns on common stock of firm \( j \) and monthly returns on a portfolio of stocks headquartered in a city other than firm \( j \)'s HQ city. Panel A shows results from estimates of city portfolio return comovement (\( \lambda_j \)) conditional on a two-factor model of returns that incorporates a market factor and a matching industry portfolio, as per equation (6):

\[
R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + \varphi_j (R_{IND,t} - R_{F,t}) + \lambda_j (R_{RandomCity,j,t} - R_{F,t}) + \epsilon_{j,t}.
\]

Panel B shows estimates of city portfolio return comovement conditional on a four-factor model of returns that includes a market factor, size factor, value factor, and momentum factor, as per equation (7):

\[
R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + s_j \text{SMB}_t + h_j \text{HML}_t + m_j \text{UMD}_t + \lambda_j (R_{RandomCity,j,t} - R_{F,t}) + \epsilon_{j,t}.
\]

The first column of each respective panel shows the mean coefficient estimates and \( t \)-statistics across 1,000 such randomized samples. The second column shows the maximal values observed for mean \( \lambda_j \) and its cross-sample \( t \)-statistic across the 1,000 randomized samples. The final column shows the mean \( \lambda_j \) observed when stocks are matched with their true HQ-city portfolio of stocks. The sample sizes with respect to number of stocks and cities for each randomized (true) sample are as follows: 1,927 stocks and 85 HQ cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.
randomizations; Panel A shows the results for a two-factor model of returns, and Panel B shows results for a four-factor model of returns. Specifically, the first column in each panel shows the average mean coefficient estimate and t-statistics that result from 1,000 randomized resamplings in which stocks are matched with nonheadquarters-city portfolios. The second column reports the maximum mean coefficient estimates and t-statistics obtained for each of the 1,000 randomized samples in each five-year sample period. The maximum mean estimates and t-statistics indicate the 99.9 percentiles of their respective distributions derived for our 1,000 randomized samples for each five-year period. The final column of shows the mean headquarters-city $\lambda_j$s and associated t-statistics that result when sample stocks are paired with their actual headquarters-city portfolios.

The randomization test results shown in Table 4 have several implications. First, an implicit null hypothesis of negligible stock return comovement with the headquarters-city portfolio appears inappropriate because return comovement with any randomly chosen city portfolio can be expected to be positive on average. Specifically, the mean coefficients of stock return comovement with returns on portfolios of randomly paired nonheadquarters-city portfolios are positive and significantly greater than zero when tested by traditional t-statistics in both Panels A and B. This is especially so when a two-factor model of returns is employed; Panel A shows mean nonheadquarters-city $\lambda_j$ estimates (t-statistics) of 0.250 (15.52), 0.332 (21.76), and 0.394 (24.92) for each respective period. Panel B shows a similar but lesser effect when a four-factor model of returns is employed; mean nonheadquarters-city $\lambda_j$ estimates (t-statistics) are 0.058 (3.30), 0.109 (6.08), and 0.172 (9.32) for each period.

The positive estimates of stock return comovement with randomly chosen nonheadquarters-city portfolios could be due to omitted equity pricing factors or other kinds of misspecification in the model for stock returns. In the presence of such misspecification, extending the return model to include returns on some additional portfolio, especially a portfolio comprising a small number of securities, is likely to lead to some positive loadings on the added factor. Consequently, we should expect some positive comovement between returns on a stock and the portfolio of other firms headquartered in the same city because we empirically observe comovement with returns on portfolios from any city, on average.

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6 For brevity we omit randomization test results for return models that include only the market return factor. Inferences based on these results are similar to those based on the two-factor model shown in Table 4 and subsequent figures.

7 Again, each of the 1,000 randomized samples matches all sample stocks with nonheadquarters-city portfolios, with sample size in each randomized sample equal to the total number of stocks in each respective five-year period.

8 Our previous illustration of this with respect to sensitivity to the SMB factor is an example of this. Other inevitable misspecifications in the empirical pricing model could have similar effects.
Given the appropriate data-driven assumption of some likely positive same-city return comovement, the relevant question is whether observed local return comovement is materially larger than comovement with nonheadquarters-city portfolios. With respect to this question, the inferences based on Table 4 are unambiguous: observed stock return comovement with the headquarters-city portfolio is indeed materially larger than expected under the empirical (randomized) null hypothesis. The mean $\lambda_j$ coefficients on the headquarters-city portfolio shown in the third column of each panel of Table 4 are materially larger than the mean coefficients for randomized samples, as are the $t$-statistics. More important, the mean headquarters-city comovement coefficients exceed even the maximal (99.9 percentile) mean random city coefficients reported in the second column of Panels A and B of Table 4.

Figures IV and V illustrate more directly the inferences supported by the randomization test method. For two alternative models of returns, respectively, these figures show histograms representing the empirical distributions of mean $\lambda_j$ coefficients across the 1,000 randomized samples for each of our five-year sample periods. For each model of returns and for each of the three sample periods the distribution of the mean $\lambda_j$ coefficients generated for the 1,000 randomized samples lie entirely above zero. The randomized distribution results for the two-factor model in Figure IV are materially farther to the right than the results for the four-factor model shown in Figure V, emphasizing the finding of our previous section that extending the return model to include more factors is important in discerning comovement with headquarters-city portfolios. Nevertheless, for either return specification and for each sample period the actual within-sample mean comovement coefficient for headquarters-city portfolio returns lies well beyond the distribution of the mean coefficients estimated for the 1,000 randomized samples in which the city portfolio is not the headquarters-city portfolio. In summary, Figures IV and V illustrate the main inferences from Table 4. Specifically, positive estimates for return comovement can be expected even for random pairings of stocks and nonheadquarters-city portfolios, especially when a two-factor as opposed to a four-factor model of returns is employed. Nevertheless, the actual return comovement with headquarters-city portfolios is significantly larger than even the upper extreme of the distribution of randomized results. In short, the headquarters-city effect in stock returns appears to be a robust statistical phenomenon.

Return Comovement with Proximate-City Portfolios

Barker and Loughran (2007) show that the pairwise correlation in returns for stocks in the S&P 500 varies inversely with the distance between the respective firms’ U.S. headquarters. Consequently, we next explore how distance affects return comovement with nonheadquarters-city portfolios in our sample comprising many more firms of diverse size and greater location dispersion. We hypothesize that the
Figure IV. Randomization Tests for Headquarters (HQ) City Effect: Two-Factor Model.

Note: The extreme right “pinheaded” figures are the actual mean estimates of the comovement of monthly stock returns for sample firm \( j \) and the portfolios of other firms headquartered in the same city as measured by \( \lambda_j \) in equation (4):

\[
R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + \varphi_j (R_{IND,t} - R_{F,t}) + \lambda_j (R_{HQcity-j,t} - R_{F,t}) + \epsilon_{j,t}.
\]

Histograms represent the distribution of mean local return comovement coefficient \( \lambda_j \) across 1,000 permuted samples for each of the three indicated sample periods on which we estimate equation (6):

\[
R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + \varphi_j (R_{IND,t} - R_{F,t}) + \lambda_j (R_{Randomcity-j,t} - R_{F,t}) + \epsilon_{j,t},
\]

where \( R_{Randomcity,t} \) is the return on a randomly selected city portfolio other than firm \( j \)'s HQ city. The sample sizes with respect to number of stocks and associated HQ cities are as follows: 1,927 stocks and 85 HQ cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.

The phenomenon of local comovement applies not only to same-city stocks but also to proximate-city stocks. Such a finding would be consistent with return patterns associated with local biases in stock investments extending beyond an investor’s city to nearby cities.
Figure V. Randomization Tests for Headquarters (HQ) City Effect: Four-Factor Model.

Note: The extreme right “pinheaded” figures are the actual mean estimates of the comovement of monthly stock returns for sample firm \( j \) and the portfolios of other firms headquartered in the same city as measured by \( \lambda_j \) in equation (5):

\[
R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t \\
+ m_j UMD_t + \lambda_j (R_{HQcity} - R_{F,t}) + \varepsilon_{j,t},
\]

Histograms represent the distribution of mean local return comovement coefficient \( \lambda_j \) across 1,000 permuted samples for each of the three indicated sample periods on which we estimate equation (7):

\[
R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t \\
+ m_j UMD_t + \lambda_j (R_{Randomcity} - R_{F,t}) + \varepsilon_{j,t},
\]

where \( R_{Randomcity,t} \) is the return on a randomly selected city portfolio other than firm \( j \)’s HQ city. The sample sizes with respect to number of stocks and associated HQ cities are as follows: 1,927 stocks and 85 HQ cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.

Figures VI and VII show that comovement with portfolios of stocks headquartered in cities other than a sample firm’s headquarters city decreases with distance from the headquarters city. This finding is most apparent in Figure VII, in which a four-factor model of returns is used to condition the estimation of
Panel A. July 1989-June 1994

Panel B. July 1994-June 1999

Panel C. July 1999-June 2004

Figure VI. Return Comovement with City Portfolios and Distance from Headquarters (HQ) City: Two-Factor Model for Returns.

Note: This figure shows how return comovement with city-based stock portfolios varies with distance in miles from the sample stock’s HQ city. Comovement between returns on stock j and its HQ-city portfolio is measured as the estimate for $\lambda_j$ as per equation (4):

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_j(R_{M,t} - R_{F,t}) + \phi_j(R_{IND,t} - R_{F,t}) + \lambda_j(R_{HQcity,j,t} - R_{F,t}) + \epsilon_{j,t}.$$  

Comovement between returns on stock j and a non-HQ-city portfolio is measured via a similar equation (equation (6)) where the HQ-city return is replaced by the return on a portfolio of stocks headquartered in another city. The $\lambda_j$ coefficients associated with these other cities are sorted by distance in miles from the HQ city and then averaged across all sample stocks to produce the bar graphs. The sample sizes with respect to number of stocks and associated HQ cities are as follows: 1,927 stocks and 85 HQ cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.

return comovement with city stock portfolios. Specifically, Figure VII shows that return comovement with portfolios of stocks headquartered within 100 miles of

---

9Barker and Loughran (2007) suggest that there may be a bicoastal effect in return correlations among S&P 500 firms, perhaps because more high-tech growth firms are located on the East and West coasts. Including the HML factor in the empirical model for returns should reduce this effect and heighten the effect of distance per se.
Figure VII. Return Comovement with City Portfolios and Distance from Headquarters (HQ) City: Four-Factor Model for Returns.

Note: This figure shows how return comovement with city-based stock portfolios varies with distance in miles from the sample stock’s HQ city. Comovement between returns on stock $j$ and its HQ-city portfolio is measured as the estimate for $\lambda_j$ as per equation (5):

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_j(R_{M,t} - R_{F,t}) + s_jSMB_t + h_jHML_t + m_jUMD_t + \lambda_j(R_{HQ\text{-city,}j,t} - R_{F,t}) + \varepsilon_{j,t}.$$ 

Comovement between returns on stock $j$ and a non-HQ-city portfolio is measured via a similar equation (equation (6)) where the HQ-city return is replaced by the return on a portfolio of stocks headquartered in another city. The $\lambda_j$ coefficients associated with these other cities are sorted by distance in miles from the HQ city and then averaged across all sample stocks to produce the bar graphs. The sample sizes with respect to number of stocks and associated HQ cities are as follows: 1,927 stocks and 85 HQ cities for 1989–1994; 2,563 stocks and 98 cities for 1994–1999; and 3,058 stocks and 100 cities for 1999–2004.

The sample stock’s headquarters city averages 0.177, 0.264, and 0.304 across the three respective five-year sample periods. These average figures are 58%, 73%, and 52% as large as the return comovement with the headquarters-city portfolio in the three respective periods. Estimates of return comovement with portfolios of
stocks headquartered in cities more than 200 miles away from the sample firm’s headquarters city, in contrast, are all less than half as large as for portfolios of proximate cities, and average just 28%, 31%, and 26% of the comovement observed for the headquarters-city portfolio. In short, Figure VII indicates that stock returns for a locally headquartered firm will also tend to move with returns on stocks headquartered in proximate cities, although to a lesser degree than with returns on same-city stock portfolios. Finally, although we omit the reporting of alternative results for the sake of economy, eliminating proximate-city portfolios in our resampling test procedures only reinforces the inference that return comovement with headquarters-city portfolios is significantly greater than comovement with distant city portfolios.

V. Conclusions

We investigate the magnitude and the robustness of the headquarters-city effect in monthly stock returns, first observed by Pirinsky and Wang (2006). Specifically, monthly returns on stocks appear to display positive comovement with the returns on stock portfolios of other firms that share a sample firm’s headquarters city. The headquarters-city effect in stock returns appears to be a manifestation of a habitat effect attributable to locally biased stock investment and trading. We advance study of this phenomenon by demonstrating the importance of well-specified return models and the utility of powerful test methods in investigations of return comovement.

Specifically, we show that the inclusion of additional pricing factors, specifically the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor, materially reduces the magnitude of the local comovement effect. This result suggests that same-city stocks tend to have similar sensitivities to these additional pricing factors, which we indeed confirm for our sample. Nevertheless, even after including these additional pricing factors we find that stock return comovement with headquarters-city portfolios is positive according to standard tests.

We employ additional test methods based on resampling techniques to identify an appropriate empirical null hypothesis and to establish statistical robustness. In these resampling tests we estimate comovement between a firm’s stock returns and the returns on portfolios of stocks headquartered in cities other than the firm’s headquarters city. We find that for many sample stocks the estimate of return comovement with the headquarters-city portfolio is exceeded by estimates of return comovement with most other nonheadquarters-city portfolios, and this is especially true when we do not control for additional pricing factors. For most firms, however, return comovement with the headquarters-city portfolio exceeds comovement with other city portfolios, on average. Furthermore, positive comovement with a city
portfolio can be expected even when a headquarters-city portfolio is replaced by a randomly selected city portfolio. Nevertheless, observed comovement measures and associated test statistics for the actual sample of stocks and headquarters-city portfolios lie well beyond even the extreme tails of the distributions generated for samples in which stocks are randomly paired with city portfolios.

Finally, we show that a portion of the observed positive return comovement with stocks headquartered in other cities is attributable to portfolios of stocks from proximate cities. In other words, return comovement is displayed not only among stocks headquartered in the same city but also to a lesser degree among stocks headquartered in proximate cities. To the extent that comovement in returns results from an investor habitat effect, our findings suggest that such habitats extend beyond cities where investors reside to wider geographic areas.

References


