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Momentum Strategies with Home Price Indices and Stocks

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We investigate the profitability of momentum strategies in the market for single-family homes by using 10 city-level Case-Shiller home price indices (HPIs). Compared with the momentum strategies based on the Fama-French 10-industry portfolios of stocks, the profits from the single-family HPIs are more statistically significant, less sensitive to the construction methods of the momentum strategies and more correlated across different strategies. The momentum profits from the HPIs tend to be counter-cyclical, unlike the pro-cyclical behaviors of the momentum profits from stock portfolios. The differences in the momentum profits with HPIs and stocks indicate that a momentum strategy with the former can help diversify the risk in the asset portfolio of investors.

Keywords

Real Estate Portfolio, Momentum Strategy, Risk Diversification

1. Introduction

A decade after the housing bust upended the lives of millions of Americans, more U.S. households are headed by renters than at any point since at least 1965, according to a Pew Research Center analysis of the U.S. Census Bureau housing data. More interestingly, hedge funds and institutional investors have amassed colossal portfolios of single-family rentals in the aftermath of the financial crisis and housing crash. At least three new companies like the HomeUnion of Irvine, CA, Investability of Westminster, CO, and Roofstock of Oakland, CA have started to help investors buy rental houses in far-flung markets – from Chicago to Charlotte, and from Birmingham to Baton Rouge – with high rents and low prices. With a click of mouse, investors can shop for properties, buy them, fix them up, hire a property manager, then start collecting the rents as home values rise.

While a great deal of research has documented momentum profits from winner-minus-loser portfolios of stocks and other asset classes, to the best of our knowledge, there are fewer studies on the momentum profits from similar portfolios of real estate assets, especially residential single-family homes. Chui et al. (2003) find that momentum can predict real estate investment trust (REIT) returns, together with other predicting factors such as size and turnover, especially after 1990 when momentum profits are the strongest, and momentum is the dominating predictor of REIT returns. REIT returns, however, are found to poorly reflect the returns of the underlying properties (Mühlhofer, 2013), which are commercial properties. Instead, Hoesli and Reka (2015) find strong evidence of comovement between REITs and stocks in the U.S. to an extent that is beyond the expectations of economic fundamentals, so investing in REITs can hardly diversify the risk of stock market investors. Similar comovements are also observed in several other countries, as shown in Liow and Lee (2013), Liow and Schindler (2014), and Liow et al. (2015). In contrast, our study focuses on the momentum profits on contracts that are directly related to the prices in the residential home markets, and we show later that these momentum profits are noticeably different from those in the stock markets. Hence, they can help to diversify the risk in the asset portfolio of investors.[1]

Earlier studies of the momentum behaviors of house prices focus on serial correlations of the price changes rather than returns on winner-minus-loser portfolios (Case and Shiller, 1988, 1989; Capozza et al., 2004; Gao et al., 2009; Titman et al., 2014; Li, 2015). Beracha and Skiba (2011) construct long-short zero-cost investment portfolios of HPIs from more than 380 metropolitan areas. They find that the momentum portfolio returns in the residential housing market are statistically significant during the 1983-2008 sample period. Beracha and

[1] Residential property prices and stock prices are also found to behave differently in other countries, as reported in Bahmani-Oskooee and Ghodsi (2018), Fleischmann et al. (2019), and so on and so forth.

Skiba (2013) propose a multifactor asset pricing model for housing returns that includes a momentum factor. Unlike the stock market, there is considerable friction, such as high transactions costs, low liquidity and inability to buy (ownership and rental restrictions) in the housing market that make it quite impossible, or at least very difficult and costly, to take advantage of the momentum strategies in the housing market. To mitigate the problem, our housing market analysis focuses on 10 city-level Case-Shiller HPIs, which have been indirectly traded via the future and future options markets at the Chicago Mercantile Exchange (CME) since 2006.

One of the original motivations to set up these derivative markets to indirectly trade HPIs is to provide housing market investors with an alternative investment facility that can overcome the high transaction costs and low liquidity in the real home markets. Our housing market momentum strategy takes a long position in the futures contract on the city index with the highest prior return and a short position in the futures contract on the city index with the lowest prior return.[2] Since we form our winner-minus-loser momentum portfolios by using only 10 large metro area HPIs, our portfolios incur significantly less transaction costs and portfolio management expenses than the portfolios formed by Beracha and Skiba (2011) who use more than 300 metro area HPIs. Another reason that we choose the 10 city-level Case-Shiller HPIs is that they are literally available for indirect trading as futures and futures options in the CME. Trading derivatives like futures and futures options tend to experience far less market friction than the underlying single-family homes. Note that one possible reason that these indices are not yet directly traded but only indirectly traded in the derivatives markets is that the monthly indices are published with a 2-month delay, therefore it is more convenient and meaningful to trade the futures of these indices than trading the indices themselves. This also makes this futures market different from other futures markets, in the sense that the futures contracts are set based on the existing home market transactions, so the price prediction function of the futures price is less important than in the other markets. Therefore, the futures price movement should be more in line with the movement of the spot price (that is, the home price index) than in the other futures markets. We develop a home price futures trading strategy that essentially resembles a trading strategy on the HPIs directly.

As a comparison, we conduct a similar analysis for the Fama-French 10-industry portfolios of stock, to explore the similarities, differences and correlations among the momentum strategies with HPIs and those with stocks. A reason that we choose this comparable sample is that, in the asset pricing literature, several studies find that the profits of the stock momentum are largely driven by the profits of the industry momentum (see, for instance, Moskowitz and Grinblatt, 1999). Another reason is that, compared to the stock portfolios

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[2] Even in the real home market where short-selling is prohibited, the manager of single-family home portfolios can exchange homes between two different cities.

based on stock-level data, those based on sector aggregate data are more comparable to our housing portfolios based on city aggregate data.

We study the Case-Shiller HPIs and the stock market for the period of 1987:Q1 to 2014:Q4. We design four momentum strategies based on the appreciation rates of the HPIs, in the prior 1 to 2 quarters, prior 3 to 4 quarters, prior 2 to 4 quarters, or prior 1 to 4 quarters. We examine the performance of each momentum strategy during three different post-ranking periods: 1 quarter, 2 quarters, or 4 quarters. Compared with evidence from the winner-minus-loser industry portfolios of stocks, the profits from single-family HPIs are more pervasive and less sensitive to the ways in which the portfolios are constructed.

We find that in the stock market, momentum strategies based on the 10 industry portfolios produce a significant performance in only a few cases, especially for the strategies based on the prior 2-quarters and the post-ranking returns over 4 quarters. However, with the HPIs, we document that momentum strategies based on recent or distant historical performances all generate statistically significant profits as measured by the post-ranking returns over 1, 2 or 4 quarters. We also find that the profits to momentum strategies based on past performance over different periods tend to be much more consistent for HPIs than stocks.

Unlike the results from the stock portfolios that we study, the profits from the momentum portfolios of the different HPIs become more correlated as the post-ranking returns are measured over a longer period of time; that is, 4 quarters rather than 1 or 2 quarters. This "horizon effect" might be associated with the measurement errors which tend to diminish with the holding period and heterogeneity of houses traded in different periods. Given the significance of the momentum profits from various strategies based on past performances and post-ranking periods, the profits from HPIs are pervasive and likely to be exploitable in practice. This finding is valuable, given the prevailing view that it is difficult to diversify the geographical risks in the U.S. housing markets, largely due to the increasing integration or synchronization across markets, as argued in Hirata et al. (2013), Cotter et al. (2015), and Zhu et al. (2013).[3] Our finding provides different insights into the possibility and value of geographical risk diversification in the housing markets.

Lastly, we find that the profits in the housing and stock markets are weakly or negatively correlated, thus suggesting that a momentum strategy with HPIs can help to diversify the risk in the stock portfolio of an investor. The diversification seems more effective when the momentum strategy is based on a more distant past performance or when the momentum portfolio performance is measured

[3] Some studies find it valuable to diversify the real estate geographic risk across countries, such as Ciochetti et al. (2015), Al-Abduljader (2018), and Deng et al. (2018). In addition, Leung et al. (2013) find that in Hong Kong, housing sub-market comovements tend to decline after a financial crisis.

over a longer time horizon. Similar to Chordia and Shivakumar (2002), we find momentum profits from stocks and single-family HPIs to be related to macroeconomic variables. However, the momentum profits from single-family homes tend to be counter-cyclical, unlike the pro-cyclical behaviors of the momentum profits from stock portfolios. The results suggest that different forces, rational or behavioral, may be responsible for the momentum profits in different markets. The results contradict the findings of previous studies, which suggest that common factors explain for the momentum profitability in all asset classes (Asness et al., 2013). The evidence of the difference in the behaviors of the momentum strategies between the HPIs and stocks offers new insights into the fundamental causes of the momentum profitability.

The rest of the paper proceeds as follows: The next section discusses our research data and methodologies. We then present our empirical results in the third section. The last section concludes.

2. Data and Methodologies

One of the most studied capital market phenomena is the relation between the return of an asset and its recent historical performance. Jegadeesh and Titman (1993) find that buying winning stocks and selling losers generate significantly positive returns over a three- to twelve-month period. Since their study, researchers have documented many intriguing facts about the momentum behaviors of stock returns and other asset classes. For example, Moskowitz and Grinblatt (1999) find that stock momentum profits are largely driven by the industry momentum profits. Chordia and Shivakumar (2002) document that profits from momentum strategies are related to business cycles. Novy-Marx (2012) finds that in the stock market, a momentum strategy based on a more recent historical performance is less profitable than a comparable momentum strategy based on a more distant historical performance. Asness et al. (2013) find consistent momentum return premia across diverse markets and asset classes, and a strong common factor structure among their returns.

We study the HPIs and stock markets for the period of 1987:Q1 to 2014:Q4. Our home price index analysis focuses on 10 city-level Case-Shiller HPIs that are currently available for trading as futures and futures options in the CME. Their ticker names are LAX (Los Angeles), SDG (San Diego), SFR (San Francisco), DEN (Denver-Aurora), WDC (Washington D.C.), MIA (South Florida), CHI (Chicago), BOS (Boston), LAV (Las Vegas) and NYM (New York).

Since the Case-Shiller HPIs are quarterly data, we consider a trading strategy in their futures market that rebalances the futures portfolio quarterly, and each futures contract that we choose has cash settlement after one quarter. For each quarter, we rank the 10 cities based on the appreciation rates of the Case-Shiller

HPIs, which we name as prior returns (excluding implicit rental incomes). Data for the HPIs are available from the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis. Let r_t denote the return on an index for quarter *t*. We use four methods to measure the previous returns for each index: (1) the cumulative returns of the prior 1 to 2 quarters, $R_{12} = (1+r_{t-1})(1+r_{t-2}) - 1$; (2) cumulative returns of the prior 3 to 4 quarters, $R_{34} = (1+r_{t-3})(1+r_{t-4}) - 1$; (3) cumulative returns of the prior 2 to 4 quarters, $R_{24} = (1+r_{t-2})(1+r_{t-3})(1+r_{t-4}) - 1$; and (4) cumulative returns of the prior 1 to 4 quarters, $R_{14} = (1+r_{t-1})\cdots(1+r_{t-4}) - 1$. For each quarter, our housing market momentum strategy takes a long position in the futures contract on the home price index of the city with the highest prior return, and a short position in the futures contract on the home price index of the city with the lowest prior return.

For instance, on May 1st, the last-quarter (from January to March) Case-Shiller HPIs are released (with a two-month delay). Using Strategy (1) above, we take a long position on futures on the home price index of the "winner" city that experienced the highest cumulative returns in the previous two quarters (last July to last December), and take a short position on futures on the home price index of the "loser" city that experienced the lowest cumulative returns also in the previous two quarters, with both contracts to be settled on August 1st. Then, on August 1st, the two contracts are settled, and we receive a return from the momentum trading in May that equals the gain from the long position (that is, the settlement price of the winner city - its contract price) and gain from the short position (that is, the contract price of the loser city - its settlement price). Meanwhile, we re-rank the 10 cities based on their prior return of the last two quarters (last October to this March), take a long position in the futures contract on the home price index of the new winner city, and a short position in the futures contract on the home price index of the new loser city, with both contracts settled on November 1st. Subsequently, on November 1st, the two August futures contracts are settled, and we receive a return from the August momentum trading, and make a new momentum trading for this quarter, etc. The process will recur quarter by quarter, thus generating time-series quarterly returns for this quarterly momentum trading strategy.

Note that the futures contract prices of the CME housing index are set based on the most recent Case-Shiller HPIs, with the contract size per unit being $250 times the most recently released HPIs at the contract time, and the final settlement prices are equal to the most recently released HPIs at the settlement time. [4] That means, in May for the example above, the futures are priced based on the HPIs of selected cities in the quarter of January to March; at the time of

[4] See futures contract specifications of CME metro area housing index at https://www.cmegroup.com/trading/real-estate/residential/SandP-case-shiller-price-index_contract_specifications.html

the settlement in August, the settlement prices are based on the indices of the quarter of April to June. In other words, an investor who takes a long (or short) position in a futures contract in May and settles the contract in August can realize a profit (loss) that is reflected by the change in the underlying home price index. When we conduct this trading strategy every quarter, the prior returns of HPIs can also reflect the prior returns of home price futures, and then the profits from the momentum strategies of the home price index futures can be reflected by the profits from the momentum strategies on the underlying HPIs. In fact, most investors and speculators trade home price futures mainly to capture the opportunities of home price changes. As a result, to simplify the story, we discuss momentum strategies below as if HPIs are traded directly. These momentum strategies are similar to studies of stock market momentum trading (e.g., Chordia and Shivakumar, 2002), and for every quarter, our housing market momentum strategy takes a long position in the city with the highest prior return and a short position in the city with the lowest prior return.

We examine the performances of this momentum strategy during three different post-ranking holding periods: (1) 1 quarter (q=1), r_{t+1}; (2) 2 quarters (q=2), $(1+r_{t+1})(1+r_{t+2})-1$; and (3) 4 quarters (q=4), $(1+r_{t+1})\cdots(1+r_{t+4})-1$. Note that a longer holding period results in lower transaction costs associated with portfolio rebalancing. Here, we skip return r_t for quarter *t* to avoid micro-structure problems. We conduct momentum analyses by using two sets of Case-Shiller indices: the seasonally- and the non-seasonally adjusted indices. As investors in the HPI futures market and the single-family real home markets face non-seasonally adjusted home prices in reality, we use both HPI sets to study the effect of seasonality adjustments on momentum profitability. Thus, with three post-ranking periods for each of the four ranking methods, and using two sets of data (with or without seasonal adjustment), we have a total of $3\times4\times2=24$ time-series datasets of momentum profits for HPIs. The calculations of the prior and post-ranking returns result in a sample of 103 overlapping post-ranking quarterly returns from 1988:Q2 to 2013:Q4.[5]

The Fama-French 10-industry portfolios of stock are available from the web site of Kenneth French. [6] For the stock market analysis, we examine two sets of

[5] The portfolio formation here differs from that used by Beracha and Skiba (2011), who consider the prior price appreciation (return) of 1, 2, 3, and 4 quarters. Note that the calculated home price index returns do not include rental returns, as the indices are based on home price changes only. In Section 3.6, we discuss the implications of the HPI momentum strategies to the real home market, by addressing the influences of rental returns and other factors.

[6] This website provides the data of various industry portfolios. We chose the 10-industry portfolios of stocks to match the number of cities with Case-Shiller HPIs tradable as futures and futures options in the CME. Using stock portfolios with an alternative number of industries may generate less comparable results. For instance, when we long the best performer and short the worst performer from varied number of candidates, the consistency (or the rebalancing frequency) of the winners and losers will be varied (see

data: value-weighted and equal-weighted industry portfolios. As a result, with three post-ranking periods (q=1, 2, and 4), each of which corresponds to the four ranking methods as used for the housing market data, and using two sets of industry portfolio data, we also derive 24 time-series datasets of the momentum strategy profits in the stock market. Descriptions of the momentum portfolios of the HPIs and stocks are presented in Table 1. For example, for each post-ranking period, HLN12 represents the difference in the post-ranking period returns between the city with the highest returns of the prior 1 to 2 quarters and the city with the lowest returns of the prior 1 to 2 quarters calculated from non-seasonally adjusted HPIs. HLS12 represents the difference in returns in a similar way, except that returns are calculated from seasonally adjusted HPIs. HLV12 represents the difference in the post-ranking period returns between the value-weighted industry portfolio with the highest returns of the prior 1 to 2 quarters and the value-weighted industry portfolio with the lowest returns of the prior 1 to 2 quarters . HLE12 is defined in a similar way, except that equal-weighted industry portfolios are used.

Table 1 Definition of Momentum Portfolio Returns

Panels A and B provide definitions of the momentum portfolio returns in the housing and stock markets, respectively.

Panel A: Housing Market

HLN12	Difference in returns between the metro areas with the highest and lowest non-seasonally adjusted house returns in the prior 1 to 2 quarters
HLN34	Difference in returns between the metro areas with the highest and lowest non-seasonally adjusted house returns in the prior 3 to 4 quarters
HLN24	Difference in returns between the metro areas with the highest and lowest non-seasonally adjusted house returns in the prior 2 to 4 quarters
HLN14	Difference in returns between the metro areas with the highest and lowest non-seasonally adjusted house returns in the prior 1 to 4 quarters
HLS12	Difference in returns between the metro areas with the highest and lowest seasonally adjusted house returns in the prior 1 to 2 quarters
HLS34	Difference in returns between the metro areas with the highest and lowest seasonally adjusted house returns in the prior 3 to 4 quarters
HLS24	Difference in returns between the metro areas with the highest and lowest seasonally adjusted house returns in the prior 2 to 4 quarters
HLS14	Difference in returns between the metro areas with the highest and lowest seasonally adjusted house returns in the prior 1 to 4 quarters

Section 3.5 City Effects for discussion on the consistency issue.). In addition, the portfolio management costs (which are omitted in our study for simplification purposes) will also be less comparable across portfolios when different numbers of underlying assets are included.

Panel B: Stock Market

HLV12	Difference in returns between the value-weighted industry stock portfolios with the highest and lowest returns in the prior 1 to 2 quarters
HLV34	Difference in returns between the value-weighted industry stock portfolios with the highest and lowest returns in the prior 3 to 4 quarters
HLV24	Difference in returns between the value-weighted industry stock portfolios with the highest and lowest returns in the prior 2 to 4 quarters
HLV14	Difference in returns between the value-weighted industry stock portfolios with the highest and lowest returns in the prior 1 to 4 quarters
HLE12	Difference in returns between the equal-weighted industry stock portfolios with the highest and lowest returns in the prior 1 to 2 quarters
HLE34	Difference in returns between the equal-weighted industry stock portfolios with the highest and lowest returns in the prior 3 to 4 quarters
HLE24	Difference in returns between the equal-weighted industry stock portfolios with the highest and lowest returns in the prior 2 to 4 quarters
HLE14	Difference in returns between the equal-weighted industry stock portfolios with the highest and lowest returns in the prior 1 to 4 quarters

To study the time series properties of the momentum portfolio profits, we include three macroeconomic variables that previous studies have shown to predict stock returns. The first is the three-month constant maturity Treasury rate (TB3), available from the FRED database. The second is the term spread (TEM), calculated as the difference between the yield on the Moody's Aaa-rated long-term bonds and the TB3. The third is the default spread (DEF), calculated as the difference between the yield on the Moody's Aaa- and Baa-rated long-term bonds. Data on these two bonds are also taken from the FRED database. Fama and Schwert (1977) report that the short-term interest rate is inversely related to future stock returns. Keim and Stambaugh (1986) document that information from long-term bond yields predict future stock returns. Fama and French (1989) find that the predictability of stock returns is related to business cycles. TEM is an indicator of a short-term business cycle, while DEF acts as an indicator of a long-term business cycle. Chordia and Shivakumar (2002) find that the profits to stock market momentum strategies are explained by similar macroeconomic variables.

3. Empirical Findings

3.1 Momentum Portfolio Performance

Overall, our empirical analyses demonstrate substantial differences in the momentum profits in the two markets, as elaborated below. Table 2 reports the performance results of the HPI momentum strategies, and Table 3 compares them to the stock market momentum strategies. The *t*-statistics are based on standard errors adjusted for heteroskedasticity and residual autocorrelations up to q-1 lags for q-quarter cumulative returns. In these two tables and the subsequent tables, Panels A, B and C report the results for post-ranking portfolio returns that are 1-, 2- and 4-quarters ahead (q=1, 2 and 4), respectively.[7]

For the HPIs, all of the 24 shown time-series performance data exhibit momentum profits significant at the 1% level, with *t*-statistics of profits consistently above 5, and profit size consistently above 1.7%. The results are in striking contrast to the similar momentum strategies in the stock market, which exhibit profits significant at the 10% level in only three cases, and significant at the 5% level in only one case (HLV12, q=4), out of the 24 shown performance data.

Compared to those in the stock market, the momentum strategies with HPIs generate profits with far less variation. With HPIs, the 1-quarter-ahead (q=1) returns range from -7% to 13% (versus -52% to 58% in the stock market), the 2-quarter-ahead (q=2) returns range from -10% to 23% (versus -80% to 89% in the stock market), and the 4-quarter-ahead returns (q=4) range from -15% to 38% (versus -105% to 127% in the stock market). These suggest that momentum strategies seem less risky for HPIs than for stocks.

According to the literature (see, for instance, Novy-Marx, 2012), a momentum strategy based on a more recent historical performance in the stock market is less profitable than a comparable momentum strategy based on a more distant historical performance. Additionally, similar patterns are found in the momentum strategies for trading other assets such as commodities, currencies and international equity indices. Consistent with these findings, the performance of the momentum strategy in the stock market based on our data shows that when the value-weighted industry portfolios are ranked based on the cumulative returns of the prior 1 to 2 quarters, R_{12}, (the only case with positive momentum profits), the short-run post performances are less profitable than the long-run post performances. The 1-quarter-ahead return (q=1) does not have a significant profit, the 2-quarter-ahead return (q=2) is 4.3% with a *t*-statistic of 1.978, and the 4-quarter-ahead return (q=4) is 9.1% with a *t*-statistic of 2.550.

[7] The *t*-statistic for the sample average is closely related to the Sharpe ratio, which measures the risk-adjusted performance, since the former is the sample average divided by its standard error, while the latter is the sample average divided by the sample standard deviation.

Considering that the measured performance of the 4-quarter-ahead return is over a longer period of time than that of the 2-quarter-ahead return, we can compare their average quarterly returns, which are 2.3% and 2.1%, respectively. Thus, the average quarterly return in the post 4-quarter period is 0.2% higher than that in the post 2-quarter period, with a *t*-statistic that is also higher by 0.572.

Table 2 Summary Statistics of Momentum Portfolio Returns in the Housing Market

This table presents the summary statistics of momentum portfolio returns in the housing market. Definitions of the momentum portfolio returns in the housing market are provided in Panel A of Table 1. Panels A, B, and C of this table report the results of post ranking portfolio returns 1-, 2-, and 4-quarters-ahead (q=1, 2, and 4). The *t*-statistics are based on standard errors adjusted for heteroskedasticity and residual autocorrelations of up to lags q-1 due to quarterly overlapping returns. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample includes 103 overlapping post-ranking quarterly returns from 1988:Q2 to 2013:Q4.

Portfolio	Mean Return	*t*-stat.	Minimum	Maximum
Panel A: 1 Quarter Ahead (q=1)				
HLN12	0.023***	6.130	-0.070	0.125
HLN34	0.020***	6.369	-0.060	0.121
HLN24	0.025***	6.943	-0.060	0.122
HLN14	0.025***	6.449	-0.060	0.122
HLS12	0.029***	9.313	-0.050	0.123
HLS34	0.017***	5.061	-0.050	0.100
HLS24	0.022***	6.605	-0.050	0.100
HLS14	0.025***	7.147	-0.050	0.100
Panel B: 2 Quarters Ahead (q=2)				
HLN12	0.045***	6.555	-0.091	0.226
HLN34	0.041***	7.262	-0.088	0.179
HLN24	0.050***	7.674	-0.094	0.185
HLN14	0.050***	6.987	-0.093	0.198
HLS12	0.059***	9.906	-0.088	0.217
HLS34	0.034***	5.570	-0.093	0.170
HLS24	0.044***	7.090	-0.087	0.170
HLS14	0.050***	7.562	-0.087	0.168
Panel C: 4 Quarters Ahead (q=4)				
HLN12	0.092***	5.906	-0.092	0.371
HLN34	0.083***	7.199	-0.116	0.259
HLN24	0.102***	7.473	-0.134	0.270
HLN14	0.099***	6.338	-0.147	0.280
HLS12	0.118***	8.694	-0.061	0.370
HLS34	0.070***	5.367	-0.125	0.281
HLS24	0.088***	6.446	-0.116	0.281
HLS14	0.099***	6.696	-0.116	0.279

Table 3 Summary Statistics of Momentum Portfolio Returns in the Stock Market

This table presents the summary statistics of momentum portfolio returns in the stock market. Definitions of the momentum portfolio returns in the stock market are provided in Panel B of Table 1. Panels A, B, and C of this table report the results for post ranking portfolio returns 1-, 2-, and 4-quarters-ahead (q=1, 2, and 4), respectively. The *t*-statistics are based on standard errors adjusted for heteroskedasticity and residual autocorrelations of up to lags q-1 due to quarterly overlapping returns. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample includes 103 overlapping post-ranking quarterly returns from 1988:Q2 to 2013:Q4.

Portfolio	Mean Return	*t*-stat.	Minimum	Maximum
Panel A: 1 Quarter Ahead (q=1)				
HLV12	0.021*	1.670	-0.372	0.383
HLV34	-0.005	-0.412	-0.420	0.379
HLV24	-0.001	-0.043	-0.513	0.383
HLV14	0.015	1.125	-0.347	0.383
HLE12	0.017	1.216	-0.333	0.520
HLE34	-0.013	-0.982	-0.352	0.319
HLE24	-0.010	-0.648	-0.348	0.571
HLE14	0.001	0.072	-0.422	0.571
Panel B: 2 Quarters Ahead (q=2)				
HLV12	0.043*	1.978	-0.598	0.575
HLV34	-0.010	-0.457	-0.577	0.582
HLV24	0.001	0.025	-0.777	0.585
HLV14	0.031	1.321	-0.598	0.585
HLE12	0.036	1.396	-0.494	0.773
HLE34	-0.027	-1.127	-0.627	0.473
HLE24	-0.019	-0.710	-0.507	0.633
HLE14	0.004	0.137	-0.794	0.889
Panel C: 4 Quarters Ahead (q=4)				
HLV12	0.091**	2.550	-0.439	0.800
HLV34	-0.021	-0.542	-1.042	0.523
HLV24	0.004	0.079	-0.998	0.532
HLV14	0.066	1.483	-0.760	0.916
HLE12	0.076*	1.675	-0.729	0.835
HLE34	-0.058	-1.161	-0.869	1.059
HLE24	-0.043	-0.872	-0.977	1.127
HLE14	0.011	0.210	-0.963	1.267

The results for the HPIs are quite different. Using non-seasonally adjusted data, when the city HPIs are ranked based on the cumulative returns of the prior 1 to 2 quarters, the post 1-quarter, 2-quarter and 4-quarter returns are 2.3%, 4.5% and 9.2%, respectively. These indicate corresponding average quarterly returns of 2.3%, 2.2% and 2.3%. The *t*-statistics are 6.130, 6.555 and 5.906, respectively. Both the magnitudes and the significances of the returns are not very different from each other. Similar results hold when we analyze other momentum strategies or use different datasets (with or without seasonal adjustment).

When we compare different cases, we see that with or without seasonal adjustment, the amount of momentum profit is the lowest for either q=1, 2, or 4, when the portfolios are constructed based on the cumulative returns of the prior 3 to 4 quarters, R_{34}, as compared to portfolios constructed based on other three methods. For instance, using the non-seasonally adjusted data, the momentum strategy returns based on the ranking of R_{34} are 2.0% (q=1), 4.1% (q=2) and 8.3% (q=4), while those based on the ranking of R_{12} are 2.3%, 4.5% and 9.2%, respectively. This implies that a momentum portfolio based on the more distant historical returns is about 10-12% less profitable than that based on the more recent historical returns. Using the seasonally adjusted data, this tendency is even more prominent. The returns of the momentum strategy based on the ranking of R_{34} (versus those based on the ranking of R_{12}) for q=1, 2,and 4 are 1.7% (versus 2.9%), 3.4% (versus 5.9%) and 7.0% (versus 11.8%), respectively. Thus a momentum strategy based on more recent historical returns is much more profitable than that based on more distant historical returns. The result is opposite in the stock market.

3.2 Consistency of Momentum Portfolio Performance

We now explore the consistency of the momentum performance by analyzing the correlations among the returns from different momentum strategies or with different datasets. A higher correlation indicates a more consistent momentum performance. The results are reported in Tables 4 to 6. Table 4 reports the correlations between the pairs of HPI returns. Table 5 reports the correlations between the pairs of stock returns. Table 6 reports the correlations between the two markets. The coefficient of correlation between the returns from any two HPI momentum strategies ranges from 0.382 to 0.987, with only 2 out of the 84 shown coefficients below 0.5, averaging 0.794. In comparison, the coefficient of correlation between the returns from any two stock-market momentum strategies range from 0.126 to 0.883, with 23 out of the 84 coefficients below 0.5, averaging 0.613. In general, the momentum strategy performances are more persistent with HPIs than stocks.

With HPIs, the momentum portfolio returns are in general more correlated with each other for the seasonally-adjusted data than for the non-seasonally adjusted data. The average of the correlation coefficients is 0.807 for the former and

0.727 for the latter. As a comparison, the momentum performances in the stock market are in general more correlated with each other for the value-weighted industry portfolios than for the equal-weighted industry portfolios. The average of the correlation coefficients is 0.660 for the former, and 0.582 for the latter. Note that for the HPIs, a seasonally-adjusted momentum portfolio is usually less volatile than its non-seasonally adjusted counterpart. Similarly, a value-weighted portfolio in the stock market is generally less volatile than its equal-weighted counterpart. Furthermore, by comparing the performance of the HPIs to that of the stock market (which is usually more volatile), we find that the former shows higher correlations than the latter.

Table 4 Correlations of Momentum Portfolio Returns in the Housing Market

This table presents the correlation coefficients between returns from different housing market momentum strategies. Definitions of the momentum portfolio returns in the housing market are provided in Panel A of Table 1. Panels A, B, and C of this table report the correlation coefficients for the post ranking portfolio returns 1-, 2-, and 4-quarters-ahead (q=1, 2, and 4), respectively.

	HLN34	HLN24	HLN14	HLS12	HLS34	HLS24	HLS14
Panel A: 1 Quarter Ahead (q=1)							
HLN12	0.382	0.661	0.650	0.768	0.525	0.698	0.627
HLN34		0.704	0.632	0.466	0.736	0.675	0.630
HLN24			0.796	0.605	0.705	0.851	0.760
HLN14				0.725	0.590	0.803	0.947
HLS12					0.504	0.661	0.779
HLS34						0.811	0.665
HLS24							0.865
Panel B: 2 Quarters Ahead (q=2)							
HLN12	0.546	0.750	0.721	0.855	0.651	0.772	0.713
HLN34		0.783	0.747	0.595	0.843	0.773	0.739
HLN24			0.842	0.737	0.801	0.874	0.803
HLN14				0.825	0.732	0.885	0.966
HLS12					0.626	0.789	0.855
HLS34						0.888	0.774
HLS24							0.923
Panel C: 4 Quarters Ahead (q=4)							
HLN12	0.640	0.776	0.811	0.903	0.725	0.822	0.792
HLN34		0.825	0.788	0.736	0.914	0.862	0.812
HLN24			0.855	0.829	0.826	0.895	0.838
HLN14				0.910	0.793	0.936	0.987
HLS12					0.750	0.866	0.903
HLS34						0.914	0.823
HLS24							0.953

Table 5 Correlations of Momentum Portfolio Returns in the Stock Market

This table presents the correlation coefficients between returns from different stock market momentum strategies. Definitions of the momentum portfolio returns in the stock market are provided in Panel B of Table 1. Panels A, B, and C of this table report the correlation coefficients for the post ranking portfolio returns 1-, 2-, and 4-quarters-ahead (q=1, 2, and 4), respectively.

	HLN34	HLN24	HLN14	HLS12	HLS34	HLS24	HLS14
Panel A: 1 Quarter Ahead (q=1)							
HLV12	0.444	0.561	0.703	0.687	0.218	0.482	0.609
HLV34		0.842	0.817	0.443	0.548	0.639	0.659
HLV24			0.865	0.511	0.460	0.667	0.679
HLV14				0.624	0.380	0.625	0.705
HLE12					0.126	0.554	0.695
HLE34						0.574	0.488
HLE24							0.838
Panel B: 2 Quarter Ahead (q=2)							
HLV12	0.459	0.563	0.690	0.706	0.298	0.565	0.665
HLV34		0.846	0.800	0.462	0.541	0.690	0.692
HLV24			0.883	0.556	0.428	0.703	0.705
HLV14				0.624	0.370	0.672	0.728
HLE12					0.188	0.606	0.724
HLE34						0.576	0.495
HLE24							0.864
Panel C: 4 Quarter Ahead (q=4)							
HLV12	0.326	0.474	0.569	0.688	0.343	0.636	0.658
HLV34		0.810	0.728	0.294	0.550	0.646	0.617
HLV24			0.872	0.473	0.417	0.675	0.672
HLV14				0.539	0.303	0.632	0.703
HLE12					0.192	0.581	0.652
HLE34						0.703	0.500
HLE24							0.866

The housing market results also generally show increasing consistency in the momentum performance when the post-momentum period is longer in time. The correlation coefficients range from 0.382 to 0.947 for q=1, 0.546 to 0.966 for q=2, and 0.640 to 0.987 for q=4. The average correlation coefficients are 0.717, 0.805 and 0.860, respectively, for q=1,2 and 4. In fact, each pairwise correlation between the returns from two momentum strategies increases with the return horizons. For instance, for non-seasonally adjusted returns data (which are relatively low), the correlation between HLN12 and HLN34 is 0.382 for q=1, 0.546 for q=2, and 0.640 for q=4. The correlation between HLS24 and HLS14 using seasonally adjusted return data (which are relatively high) is 0.865 for q=1, 0.923 for q=2 and 0.953 for q=4. Finally, the correlation between HLN12 with the non-seasonally adjusted data and HLS12 with the seasonally adjusted data is 0.768 for q=1, 0.855 for q=2, and 0.903 for q=4. Similar patterns, however, do not appear with the stock market data. The results further suggest that momentum profits with HPIs are more persistent with a longer post-momentum performance period, an effect that we label as the "horizon effect", which is absent in the stock market.

One possible justification for the "horizon effect" is related to the measurement errors with the HPIs. As we discussed earlier, there is considerably more friction in the housing market than in the stock market. The effect of market friction should cause more measurement errors in the HPIs at a higher frequency (e.g., 1 or 2 quarters) than at a lower frequency (4 quarters). In addition, measurement errors may also arise from the heterogeneity of houses in the transactions, which is not an issue for the stock transactions. Although the Case-Shiller HPIs are based on repeat sales data so the transactions compared are based on the same houses, the heterogeneity problem cannot be completely eliminated because some houses are resold after they have been purchased for a long time as such that there might be noticeable changes in the properties of the house (such as house age, conditions, remodeling effects, etc.).[8] The influence of this type of measurement error, however, also generally becomes smaller as the return horizon increases. As a result, these measurement errors may help to explain why the momentum strategy profits show a "horizon effect" with HPIs (that is, with higher correlations between momentum strategies for a longer post-ranking period).

3.3 Relations to the Stock Market

We next examine the results in Table 6 for the correlations of the momentum strategy performances between the HPIs and the stock market. Among the 192 correlation coefficients shown, only 13 have an absolute value over 0.3, which indicates that the correlations between the momentum strategy performances in the two markets are generally low. In addition, only 15 out of the 192 correlation coefficients are positive, and none are greater than 0.25 in absolute value. A positive but low correlation occurs only when at least one momentum strategy in the pair of the correlation is based on the returns of the previous 1 to 2 quarters. The prevalent low or negative correlations are consistent with the differences (in terms of the magnitude and the consistency of the momentum profits) that we find earlier between the two markets.

[8] Repeat-sales HPIs have been found to incur more revisions than those based on the hedonic methods, see, for instance, Clapham et al. (2006) and Silverstein (2014).

Table 6 Correlations of Momentum Portfolio Returns between Housing and Stock Markets

This table presents the correlation coefficients between returns from housing market and stock market momentum strategies. Definitions of the momentum portfolio returns in housing and stock markets are provided in Panels A and B of Table 1. Panels A, B, and C of this table report the correlation coefficients for the post ranking portfolio returns 1-, 2-, and 4-quarters-ahead (q=1, 2, and 4), respectively.

	HLV12	HLV34	HLV24	HLV14	HLE12	HLE34	HLE24	HLE14
Panel A: 1 Quarter Ahead (q=1)								
HLN12	0.111	-0.036	0.001	0.046	0.021	-0.132	-0.066	-0.036
HLN34	-0.196	-0.110	-0.207	-0.154	-0.189	-0.111	-0.160	-0.205
HLN24	-0.128	-0.146	-0.163	-0.159	-0.172	-0.110	-0.161	-0.235
HLN14	-0.067	-0.141	-0.131	-0.098	-0.109	-0.256	-0.200	-0.225
HLS12	0.023	-0.208	-0.148	-0.121	-0.073	-0.253	-0.269	-0.186
HLS34	-0.098	-0.088	-0.151	-0.077	-0.092	-0.096	-0.104	-0.117
HLS24	-0.020	-0.114	-0.108	-0.070	-0.118	-0.138	-0.143	-0.185
HLS14	-0.040	-0.154	-0.157	-0.103	-0.129	-0.263	-0.214	-0.220
Panel B: 2 Quarter Ahead (q=2)								
HLN12	0.087	-0.069	-0.018	0.027	0.055	-0.213	-0.120	-0.018
HLN34	-0.284	-0.121	-0.235	-0.192	-0.257	-0.257	-0.254	-0.273
HLN24	-0.170	-0.159	-0.171	-0.169	-0.175	-0.206	-0.270	-0.268
HLN14	-0.146	-0.227	-0.218	-0.166	-0.162	-0.359	-0.321	-0.301
HLS12	-0.051	-0.241	-0.194	-0.184	-0.114	-0.283	-0.269	-0.205
HLS34	-0.124	-0.058	-0.136	-0.064	-0.088	-0.205	-0.211	-0.178
HLS24	-0.089	-0.144	-0.159	-0.103	-0.119	-0.295	-0.293	-0.243
HLS14	-0.122	-0.220	-0.230	-0.164	-0.176	-0.361	-0.318	-0.283
Panel C: 4 Quarter Ahead (q=4)								
HLN12	0.165	-0.047	0.009	0.096	0.213	-0.180	-0.024	0.083
HLN34	-0.237	-0.164	-0.273	-0.185	-0.170	-0.269	-0.324	-0.275
HLN24	-0.068	-0.157	-0.170	-0.128	-0.020	-0.151	-0.235	-0.158
HLN14	-0.030	-0.282	-0.242	-0.130	-0.020	-0.352	-0.327	-0.230
HLS12	0.037	-0.203	-0.168	-0.119	0.030	-0.207	-0.186	-0.124
HLS34	-0.191	-0.132	-0.177	-0.094	-0.042	-0.264	-0.323	-0.233
HLS24	-0.089	-0.204	-0.197	-0.095	-0.035	-0.334	-0.346	-0.236
HLS14	-0.059	-0.261	-0.253	-0.133	-0.075	-0.358	-0.349	-0.247

The findings of low or negative correlations between the portfolio returns in the two markets indicate that a momentum strategy with HPIs can be a valuable complement to that in the stock market, so it can help to diversify the risk in the portfolio of an investor. The diversification seems to be more effective when the momentum strategy is based on more distant returns or the post-momentum performance is measured for a longer horizon time.

3.4 Relations to the Business Cycle

Next, we run regressions of momentum portfolio returns on the macroeconomic variables that are possible determinants for the stock market momentum performance. These selected macroeconomic variables include the TB3, term spread (TEM), and DEF, all measured at the beginning of each quarter. The TEM is the difference between the Moody's Aaa-rated corporate bond yields and TB3. The DEF is the difference between the Moody's Aaa-rated and Baa-rated bond yields. Among these variables, the DEF reflects a long-term business cycle, and increases during recessions but decreases during booms. These variables have been widely used in the finance literature (Fama and Schwert, 1977; Keim and Stambaugh, 1986; Fama and French, 1989; Chordia and Shivakumar, 2002).[9]

The regression results for the HPIs and stock market are reported in Tables 7 and 8. For the stock market, the most influential macroeconomic variable on the momentum strategy performance is the DEF. In all of the 24 regressions shown, the coefficient of the DEF is consistently negative, and significant at the 1% or 5% level for three out of the four equal-weighted portfolios for q=1, and at least half of the value-weighted and all of the equal-weighted portfolios for q=2 and 4. These confirm that the momentum performance of the stock market is generally in line with the long-term business cycle, which implies that the strategies are more profitable when the DEF is smaller (or, the economy is growing). When the post-momentum performance is measured over a longer horizon, the magnitude of the significantly negative coefficients is generally larger. These coefficients range from -9.050 to -5.011 for q=1, -21.546 to -10.619 for q=2, and -32.646 to -10.477 for q=4. These suggest that the procyclical characteristic of a stock market momentum strategy is more prominent when the performance is measured for a longer term in the future.

For the HPIs, the results are substantially different from those for the stock market although the DEF is also the most influential variable among the three macroeconomic variables. The coefficients of the DEF are positive (rather than negative) in 19 out of the 24 regressions. Among the 19 regressions with positive coefficients, the DEF is significant at the 1% or 5% level in 2 regressions for q=1, 2 regressions for q=2, and 2 regressions for q=4. Among the 5 regressions with negative coefficients, the DEF is only weakly significant (at the 10% level) in 1 regression (for q=4). At the 1% or 5% level, the DEF is significant when the momentum portfolios are based on the prior 1 to 4 quarters for each post-ranking period q=1,2, and 4. This is true for both seasonally and non-seasonally adjusted data. More specifically, the coefficients of the DEF are 2.466 and 2.326 for q=1 (both significant at the 1% level); 4.133 (significant at the 5% level) and 3.749 (significant at the 1% level) for q=2; and 4.752 and

[9] Other variables like long-term interest rates are not included since these variables tend to be non-stationary (unit root) and variables like TEM tend to be stationary and have better predictability of the asset returns.

4.477 for q=4 (both significant at the 5% level). These indicate that unlike in the stock market, the momentum strategy performance with HPIs is generally countercyclical. In other words, if the performance of these strategies responds to business cycles, they are more profitable when the DEF is larger (or, when the economy is weaker).

Table 7 Regressions of Momentum Portfolio Returns in Housing

This table reports the regression results on the determinants of returns from different housing market momentum strategies. Definitions of the momentum portfolio returns in the housing market are provided in Panel A of Table 1. TB3 is the 3-month T-bill rate. TEM is the spread between the AAA-rated bond yield and the TB3. DEF is the spread between the AAA-rated and BAA-rated bond yields. Panels A, B, and C of this table report the regression results for the post ranking portfolio returns 1-, 2-, and 4-quarters-ahead (q=1, 2, and 4), respectively. The *t*-statistics, reported in parentheses, are based on standard errors adjusted for heteroskedasticity and residual autocorrelations of up to lags q-1 due to quarterly overlapping returns. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Constant	TB3	TEM	DEF	$\overline{R^2}$
Panel A: 1 Quarter Ahead (q=1)					
HLN12	0.009	0.210	0.205	-0.051	-0.018
	(0.50)	(1.11)	(0.56)	(-0.06)	
HLN34	-0.015	0.149	0.421	1.745*	0.059
	(-0.84)	(0.85)	(1.30)	(1.83)	
HLN24	0.013	-0.045	-0.056	1.578*	0.018
	(0.64)	(-0.23)	(-0.14)	(1.70)	
HLN14	-0.020	0.307	0.331	2.466***	0.063
	(-0.85)	(1.28)	(0.75)	(2.78)	
HLS12	0.016	0.048	0.192	0.548	-0.013
	(1.05)	(0.28)	(0.66)	(0.94)	
HLS34	-0.018	0.212	0.479	1.354	0.040
	(-0.94)	(1.13)	(1.35)	(1.25)	
HLS24	-0.014	0.254	0.339	1.684*	0.039
	(-0.77)	(1.48)	(0.95)	(1.82)	
HLS14	-0.024	0.362*	0.446	2.326***	0.095
	(-1.26)	(1.75)	(1.19)	(3.23)	

(***Continued…***)

(Table 7 Continued)

Dependent Variable	Constant	TB3	TEM	DEF	$\overline{R^2}$
Panel B: 2 Quarters Ahead (q=2)					
HLN12	0.035	0.336	0.472	-1.633	0.000
	(0.96)	(0.92)	(0.71)	(-0.97)	
HLN34	-0.021	0.240	0.930*	2.569	0.093
	(-0.76)	(0.83)	(1.87)	(1.58)	
HLN24	0.048	-0.233	-0.108	1.381	-0.001
	(1.33)	(-0.68)	(-0.15)	(0.75)	
HLN14	-0.025	0.489	0.581	4.133**	0.063
	(-0.63)	(1.16)	(0.74)	(2.55)	
HLS12	0.035	0.082	0.446	0.733	-0.009
	(1.18)	(0.25)	(0.84)	(0.73)	
HLS34	-0.026	0.397	1.179*	1.063	0.040
	(-0.76)	(1.22)	(1.84)	(0.52)	
HLS24	-0.012	0.429	0.773	1.729	0.013
	(-0.37)	(1.36)	(1.17)	(0.99)	
HLS14	-0.034	0.611	0.854	3.749***	0.080
	(-0.99)	(1.62)	(1.24)	(2.66)	
Panel C: 4 Quarters Ahead (q=4)					
HLN12	0.058	0.752	1.422	-3.726*	0.022
	(0.90)	(1.01)	(1.20)	(-1.75)	
HLN34	-0.003	0.313	2.387***	0.096	0.146
	(-0.08)	(0.64)	(3.17)	(0.05)	
HLN24	0.131**	-0.593	0.298	-1.853	0.015
	(2.34)	(-0.93)	(0.23)	(-0.98)	
HLN14	-0.015	0.766	1.311	4.752**	0.032
	(-0.22)	(0.97)	(0.96)	(2.15)	
HLS12	0.063	0.177	1.040	1.701	0.010
	(1.11)	(0.26)	(0.99)	(1.05)	
HLS34	-0.022	0.700	2.884***	-2.262	0.112
	(-0.46)	(1.24)	(2.84)	(-1.15)	
HLS24	0.004	0.719	1.783	0.339	0.011
	(0.09)	(1.19)	(1.52)	(0.17)	
HLS14	-0.031	0.948	1.715	4.477**	0.048
	(-0.48)	(1.24)	(1.32)	(2.03)	

Table 8 Regressions of Momentum Portfolio Returns in Stocks

This table reports the regression results on the determinants of returns from different stock market momentum strategies. Definitions of the momentum portfolio returns in the stock market are provided in Panel B of Table 1. TB3 is the 3-month T-bill rate. TEM is the spread between the AAA-rated bond yield and the TB3. DEF is the spread between the AAA-rated and BAA-rated bond yields. Panels A, B, and C of this table report the regression results for post ranking portfolio returns 1-, 2-, and 4-quarter-ahead (q=1, 2, and 4), respectively. The *t*-statistics, reported in parentheses, are based on standard errors adjusted for heteroskedasticity and residual autocorrelations of up to lags q-1 due to quarterly overlapping returns. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Constant	TB3	TEM	DEF	$\overline{R^2}$
Panel A: 1 Quarter Ahead (q=1)					
HLV12	0.091	-0.231	-1.051	-3.068	-0.010
	(1.20)	(-0.32)	(-0.87)	(-0.71)	
HLV34	-0.017	0.250	1.111	-3.240	-0.016
	(-0.23)	(0.36)	(0.97)	(-0.80)	
HLV24	0.011	0.193	0.938	-4.930	-0.011
	(0.14)	(0.27)	(0.68)	(-1.19)	
HLV14	-0.029	1.017	1.253	-3.118	0.000
	(-0.36)	(1.32)	(0.92)	(-0.70)	
HLE12	0.156**	-0.570	-1.078	-8.821***	0.043
	(2.06)	(-0.69)	(-0.79)	(-3.00)	
HLE34	0.135*	-1.843**	-1.121	-5.011**	0.039
	(1.83)	(-2.51)	(-0.82)	(-2.13)	
HLE24	0.086	-0.700	-0.956	-4.340	-0.014
	(1.01)	(-0.85)	(-0.64)	(-1.46)	
HLE14	0.117	-0.227	-0.639	-9.050**	0.034
	(1.34)	(-0.26)	(-0.43)	(-2.40)	

(***Continued…***)

(Table 8 Continued)

Dependent Variable	Constant	TB3	TEM	DEF	$\overline{R^2}$
Panel B: 2 Quarters Ahead (q=2)					
HLV12	0.246**	-0.764	-2.163	-11.295*	0.053
	(2.07)	(-0.61)	(-1.13)	(-1.93)	
HLV34	0.023	0.326	1.905	-10.619*	0.025
	(0.20)	(0.28)	(1.08)	(-1.76)	
HLV24	0.065	0.459	1.604	-13.369**	0.033
	(0.52)	(0.37)	(0.74)	(-2.33)	
HLV14	0.006	1.875	2.420	-11.894**	0.074
	(0.05)	(1.51)	(1.10)	(-2.05)	
HLE12	0.316***	-0.942	-1.400	-21.026***	0.135
	(2.63)	(-0.68)	(-0.62)	(-5.55)	
HLE34	0.366***	-4.192***	-3.584*	-13.887**	0.115
	(2.70)	(-3.30)	(-1.73)	(-2.18)	
HLE24	0.213	-1.471	-1.868	-12.571***	0.025
	(1.50)	(-1.02)	(-0.80)	(-2.68)	
HLE14	0.249*	-0.297	-0.847	-21.546***	0.123
	(1.70)	(-0.19)	(-0.36)	(-3.71)	
Panel C: 4 Quarters Ahead (q=4)					
HLV12	0.395**	-1.355	-5.010*	-10.477*	0.064
	(2.18)	(-0.64)	(-1.65)	(-1.73)	
HLV34	0.074	0.550	3.834	-24.026**	0.112
	(0.41)	(0.30)	(1.42)	(-2.42)	
HLV24	0.115	1.469	2.622	-25.141***	0.106
	(0.56)	(0.71)	(0.72)	(-2.80)	
HLV14	-0.011	4.093**	4.104	-20.011***	0.165
	(-0.06)	(2.26)	(1.16)	(-2.98)	
HLE12	0.402*	-0.353	-1.530	-27.430***	0.158
	(1.82)	(-0.15)	(-0.41)	(-3.86)	
HLE34	0.727***	-8.570***	-7.448**	-26.149***	0.203
	(3.31)	(-3.77)	(-2.53)	(-2.92)	
HLE24	0.480**	-3.476	-4.517	-26.965***	0.124
	(2.14)	(-1.44)	(-1.31)	(-3.62)	
HLE14	0.403	-0.330	-2.056	-32.646***	0.156
	(1.57)	(-0.13)	(-0.49)	(-3.98)	

We next examine the sensitivity of the momentum performance to the indicator of a short-term business cycle, TEM. At the 1% or 5% significance level, TEM is influential in only 1 (HLE34 with q=4) of the 24 regressions for the stock market, and 2 (HLN34 and HLS34, also with q=4) of the 24 regressions for the HPIs. This demonstrates that, the momentum strategies in the two markets are less influenced by a short-term business cycle than a long-term business cycle. A possible reason is that in the short-run, it is possible for the two markets to temporarily deviate from their fundamentals, but in the long-run, they will move towards the fundamentals. Another similarity between the two markets is, the short-term business cycle is more influential when the post-momentum performance is measured in longer time horizons, and the significant influences are mostly concentrated in regressions when the momentum strategy is based on the cumulative returns of the prior 3 to 4 quarters, R_{34}. Despite these similarities, TEM tends to have opposite influence on the two markets. The significant coefficient in the stock market is negative: -7.448 (HLE34), whereas the significant coefficients with HPIs are consistently positive: 2.387 (HLN34) and 2.884 (HLS34). These results suggest that, a few momentum strategies (based on distant historical returns) may generate performances consistent with short-run business cycles when they are used for the HPIs, but against short-run business cycles when they are used in the stock market. These are in contrast to our findings on the relations of momentum strategies with a long-run business cycle (which we discussed earlier).

Finally, we explore the sensitivity of the momentum performance towards another important economic indicator, the TB3. At the 1% or 5% significance level, TB3 is influential in none of the regressions for the HPIs, but influential in 4 regressions for the stock market. Three of the four significant coefficients are negative, and consistently related to the momentum strategies (HLE34) based on the ranking of the cumulative returns of the 3 to 4 quarters, R_{34}, on the equal-weighted industry portfolios. These coefficients are -1.843 (q=1), -4.192 (q=2) and -8.570 (q=4). Interestingly, another significant coefficient is positive for the momentum portfolio HLV14, based on R_{14}, on the value-weighted industry portfolio. The coefficient is 4.093, and significant at the 5% level. The results of the TB3, along with those for the TEM and DEF, show that the cyclical properties of the momentum strategies for the housing market are quite different from those for the stock market.

In summary, we find that macroeconomic variables affect the two markets in substantially different ways, and in most situations, the influences are the opposite. The momentum strategy is often procyclical for the stock market, while mostly countercyclical for the HPIs.[10]

[10] The results here should be viewed with caution, as the few significant estimates with opposite signs could just be a coincidence in the many regressions with a large number of estimated coefficients.

3.5 City Effects

It is interesting to examine if the profitability in the momentum strategies with HPIs is associated with some city fixed effects, such as the investment of cities in public infrastructure, topographical and climatic conditions, which might increase the propensity of these cities to create jobs, agglomerate economics, and so on and so forth. We explore this by analyzing if the winners and losers in our HPI portfolios are relatively consistent across the quarters. The results are shown in Tables 9 and 10.

Recall that for each quarter, we take a long position in the futures contract on the home price index of the winner city, that is, the city with the highest prior return; and a short position in the futures contract on the home price index of the loser city, that is, the city with the lowest prior return. We then compare the winner of each quarter with the winners of the previous 1, 2 or 3 quarters, to see if the winners are consistent, and conduct a similar analysis on the losers as well. Table 9 reports the percentages of quarters in our sample with persistent winners or losers, with the persistency lasting for 2, 3 or 4 quarters. For instance, we find that in 55.7% of the quarters of our sample, the winner city is persistent for at least 2 quarters, if the winner is chosen based on the non-seasonally adjusted return in the previous 1 to 2 quarters. Intuitively, the persistency is declining with the time horizon. For instance, winner cities are persistent for 4 quarters for only 23.3% of the quarters based on the same method. Also intuitively, if the winner is chosen based on the historical return of a longer horizon, the persistency increases. For instance, the method based on the non-seasonally adjusted return in the prior 1 to 4 quarters generates 72.6% of the quarters with winner cities persistent for 2 quarters. Furthermore, when the data are seasonally adjusted, the persistency in most cases is higher, which is again intuitive. Interestingly, the losers seem to be a little bit more persistent than the winners.

The next question is: who are the winners and who are the losers? Table 10 shows the results. For a total of 107 quarters, the most frequent winner is Denver (29-31 quarters), regardless of the winner selection method and whether the data are seasonally adjusted, followed by San Francisco (16-20 quarters). Las Vegas, Miami, Los Angeles and San Diego are also frequent winners. New York, however, is the least likely to be the winner, and Boston, Washington DC and Chicago are similar. This seems to indicate that house prices in areas with a warmer climate tend to increase faster than those in areas with a colder climate. Interestingly, Las Vegas, Denver and Los Angeles also lead on the loser list, thus demonstrating that these areas are more volatile than other areas. For instance, regardless of the method and data, Denver was the winner continuously for about 14 quarters from 1993 to 1996, and the loser continuously for about 14 quarters from 2002 to 2005. In comparison, other areas with a warmer climate such as Miami, San Diego and San Francisco seem to be more stable with less frequency as the losers. Among the areas with a colder climate, Chicago and Boston are generally more frequent as losers than

Table 9 Persistence of Winner or Loser Portfolios

The winner (loser) is the metro area with the highest (lowest) house return in the previous 1 to 2, 3 to 4, 2 to 4 or 1 to 4 quarters.

% of quarters persistent for at least the following quarters	Non-seasonally adjusted for following prior quarters				Seasonally adjusted for following prior quarters			
	1-2	3-4	2-4	1-4	1-2	3-4	2-4	1-4
Panel A: Winner								
2 quarters	55.7%	55.7%	64.2%	72.6%	66.0%	65.1%	69.8%	71.7%
3 quarters	32.4%	32.4%	42.9%	53.3%	44.8%	44.8%	48.6%	52.4%
4 quarters	23.3%	23.3%	32.0%	38.8%	31.1%	31.1%	34.0%	37.9%
Panel B: Loser								
2 quarters	56.6%	57.5%	70.8%	83.0%	68.9%	68.9%	80.2%	83.0%
3 quarters	33.3%	33.3%	50.5%	69.5%	48.6%	47.6%	63.8%	69.5%
4 quarters	24.3%	25.2%	37.9%	55.3%	36.9%	36.9%	51.5%	55.3%

Table 10 Winner and Loser Frequencies

The winner (loser) is the metro area with the highest (lowest) house return in the previous 1 to 2, 3 to 4, 2 to 4 or 1 to 4 quarters.

Panel A: Winner frequency

	Non-seasonally adjusted for following prior quarters				Seasonally adjusted for following prior quarters			
Metro area	1-2	3-4	2-4	1-4	1-2	3-4	2-4	1-4
CA-Los Angeles	9	10	9	12	12	12	10	12
CA-San Diego	10	10	8	8	7	7	9	8
CA-San Francisco	19	18	19	19	20	19	16	19
CO-Denver	30	30	29	31	30	30	30	31
DC-Washington	3	3	3	4	3	4	5	4
FL-Miami	12	12	13	13	12	12	13	14
IL-Chicago	6	5	4	2	5	5	4	2
MA-Boston	3	3	6	4	4	4	6	4
NV-Las Vegas	13	13	13	14	13	12	14	13
NY-New York	2	3	3	0	1	2	0	0
Total quarters	107	107	107	107	107	107	107	107

(***Continued…***)

(Table 10 Continued)

Panel B. Loser frequency

	Non-seasonally adjusted for following prior quarters				Seasonally adjusted for following prior quarters			
Metro area	1-2	3-4	2-4	1-4	1-2	3-4	2-4	1-4
CA-Los Angeles	14	14	17	17	16	16	16	17
CA-San Diego	5	5	5	5	5	5	5	5
CA-San Francisco	7	7	5	3	6	6	4	3
CO-Denver	19	19	19	20	19	19	20	20
DC-Washington	9	8	6	8	7	6	7	8
FL-Miami	6	6	4	1	3	3	2	1
IL-Chicago	12	12	6	3	9	9	6	3
MA-Boston	10	10	11	11	11	11	13	11
NV-Las Vegas	18	20	24	28	21	23	24	28
NY-New York	7	6	10	11	10	9	10	11
Total quarters	107	107	107	107	107	107	107	107

New York and Washington DC. In comparing the winner and loser lists, we can see that New York and Washington DC have relatively less extreme returns and hence have a more stable housing market than the other areas. These two tables do not provide strong and consistent evidence for the hypothesis that the momentum profitability that we have found for the housing price indices are largely driven by the city fixed effects.

3.6 Implications for the Real Home Market

An immediate follow-up question is whether the findings on the momentum strategies for the HPIs and their derivatives also apply to the real home markets. We think that one should be very cautious in making this link for the following reasons.

First, as mentioned earlier, unlike the trading of HPI derivatives or the hypothetical direct trading of HPIs, trading real homes will have significantly more friction, such as high transactions costs, low liquidity and inability to buy (ownership and rental restrictions). These make it very hard and costly to take advantage of the momentum strategies with the HPIs.

In addition, the calculated home price index returns do not include rental returns nor tax benefits from mortgage interest and depreciation, as the indices are based on home price changes only. However, the rental returns and tax benefits are important for real home investments, and may bring about complications to evaluations on the real momentum performance of the home market. For instance, rental returns could reduce the momentum profits, since the rental yield (at least in theory) tends to be higher in areas with lower expectations of price growth. Related to rental returns, another friction in the direct housing market is caused by the need to find a reliable tenant.

Furthermore, the Case-Shiller HPIs, as well as many other HPIs, are based on repeat sales only, so their changes do not reflect the performance of all of the transactions in the real home markets. All these issues remind us to be cautious in applying the momentum strategies with the HPIs to real home investments.

4 Conclusion

In this study, we explore the performance from momentum strategies with the Case-Shiller HPIs of 10 cities (which are currently traded as futures and future options on the CME) by using various momentum strategies and performance measurement periods. We compare the results to those from a comparable stock market sample, and find momentum strategies to generally perform better and more persistently with HPIs than with stocks. We also document a 'horizon effect' on correlations of momentum profits with HPIs but not with stocks. In addition, we find that, if the performance of a momentum strategy responds to the business cycle, it is usually procyclical in the stock market, while countercyclical with HPIs. Our study shows that the momentum performance in the two markets is either uncorrelated or slightly negatively correlated. These findings suggest that a momentum strategy with HPIs can be a profitable investment, or a good risk-diversification vehicle for the portfolio of an investor. It also shows the value of further developing the home price index trading markets such as the CME metro area home price futures and futures options markets, which have so far captured surprisingly little attention even from real estate investors, not to mention investors of other markets. Our results provide valuable insights for investors, practitioners, and policy makers into the real estate markets and other financial markets. Further studies could explore the reasons that the momentum strategies for the HPIs outperform those for the stocks, and how our findings are related to the efficiency of the real estate market.

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