Asset Price Effects of Peer Benchmarking: Evidence from a Natural Experiment*

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Abstract

We estimate the effects of peer benchmarking by institutional investors on asset prices. In order to isolate the trades driven by peer benchmarking, we exploit a natural experiment involving a change in a government imposed under-performance penalty applicable to Colombian pension funds. We find that peer effects generate excess stock return volatility, with stocks exhibiting short-term abnormal returns followed by returns reversal in the subsequent quarter. Additionally, peer benchmarking produces an excess in comovement across stock returns beyond the correlation implied by fundamentals.

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1 Introduction

In financial markets, institutional investors manage a significant portion of the total assets and account for an even greater portion of the trading volume. Among these institutions, pension funds have often been thought of as behaving in a patient, counter-cyclical manner, making the most of cyclically low valuations to seek attractive investment opportunities. Consequently, they have traditionally been considered stabilizers of the financial system, providing liquidity and long-term financing. This belief has increasingly started to come under question [See for example Shin (2013)]. In particular, an emerging theoretical literature shows how reputational and relative performance concerns might distort the behavior of asset managers by introducing implicit short-term objectives.[1] Such concerns may arise due to market and regulatory monitoring, or even private benefits accruing to a manager from the desire to perform at least as well as her peers. In these cases, managers might have incentives to mimic each other or "*herd*" towards common assets, causing stock prices to move for reasons unrelated to fundamentals.

This paper quantifies the contribution of such herding behavior to financial market inefficiency. In particular, we ask the following question: To what extent do changes in the demand for a stock due to relative performance concerns drive the price of that stock? We concentrate on changes in demands which arise due to an asset manager's desire to track peer-group benchmarks and are independent of changes in fundamentals. We will refer to this as the demand due to peer-benchmarking from this point onwards.

Because we observe trades, and not the incentives driving them, identifying the demand for a stock based on peer-benchmarking (and not based on fundamentals) is an empirical challenge. In this paper, we exploit a natural experiment associated with a policy change in the Colombian pension fund industry which allows us to identify precisely such demand. In particular, we study trading behavior by Colombian pension fund managers in the presence of

[1]See Gromb and Vayanos (2013) for an excellent survey on the role of financial institutions and agency frictions for asset prices.

a peer-based under-performance penalty known as the Minimum Return Guarantee (MRG).[2] The MRG resembles a reputational risk, in that the manager is penalized financially if returns are below the maximum allowed shortfall relative to the peer-benchmark. The desire to avoid the penalty induces managers to herd towards the peer-portfolio. In June 2007, the Colombian government changed the MRG formula, increasing the maximum allowed shortfall and thereby loosening the MRG. This change is orthogonal to changes in stock fundamentals but reduces the propensity of pension fund managers to track the portfolio of their peers.

Exploiting the change in the MRG, first, we estimate demands for a particular stock by pension funds due to peer-benchmarking. Our empirical strategy follows a *difference-in-difference* approach by assessing whether there were any disproportional changes in (i) trading activity across stocks that are over- or under-weighted relative to the peer-portfolio, and (ii) among funds with more exposure to the penalty (i.e. poor performing funds). We show that prior to 2007, the tighter MRG raised the likelihood that pension fund managers traded in the direction of their peers, buying stocks where they were underexposed relative to the peer-portfolio. This behavior was particularly pronounced for under-performing managers. Managers minimize the risk of falling below the minimum return requirement by shifting their portfolio closer to their peers, with larger shifts when the MRG was more strict. Second, we use the estimated component of pension funds' demands which can be attributed to peer-group incentives (i.e. the part that responds to the MRG change) to test whether these trades affect stocks' contemporaneous returns, subsequent returns, and the level of comovement with other securities in the peer-portfolio.

Our results indicate that institutional investors' demands driven by peer-benchmarking have both statistically and economically significant effects on asset prices. In particular, we find that trades motivated by peer-benchmarking generate on average 3.93 percent contemporaneous-month abnormal returns. The estimated excess returns are fully reversed

[2] The MRG is also common in many countries that moved from defined benefit pension systems to defined contributions systems based on individual accounts. See for instance Turner and Rajnes (2001) for a review on these systems and Kritzer et al. (2011) for other Latin American countries with MRG requirements.

after six months, indicating that peer-effects among pension funds tend to generate excess volatility in stock prices. We also find that when the funds are buying a stock to track the peer-portfolio, the stock price comoves more with the prices of other stocks in the peer-portfolio. This increase in comovement is persistent over the next six months following the trades of pension funds and is not explained by economic fundamentals. The effect is economically significant, i.e. trades motivated by peer-benchmarking increase the correlation between daily stock returns by 0.35. Overall, our findings suggest that peer-effects and relative performance concerns among institutional traders reduce market efficiency.

There is a large literature which studies the asset price effects of herding by focusing on correlated trading behavior. A key distinction (and advantage) that our identification strategy has over this existing empirical literature is that we are able to directly isolate peer-benchmarking demands. This is important because correlated trading may arise due to reasons other than peer-benchmarking or reputational concerns. For example, managers may receive correlated private information, perhaps from analyzing the same indicator (Hirshleifer et al., 1994), or they might infer private information from the prior trades of better-informed managers and trade in the same direction (Bikhchandani et al., 1992). Additionally, managers might simply have correlated specific preferences over certain types of securities (Guercio, 1996; Bennett et al., 2003). Furthermore, these multiple reasons behind correlated trading are likely to affect asset prices in potentially opposing ways. For instance, if institutions herd due to informational motives, such behavior may promote price discovery and improve market efficiency. Conversely, if institutional investors systematically overlook their own private signals and trade with the crowd, prices may move away from fundamental values and display excess volatility.

Stemming from the concerns above, the literature has developed several approaches to identify reputational herding vis-à-vis informational herding. One such approach is to compare correlated trading among different institutional investors. For example, Sias (2004) and Choi and Sias (2009) compare the incidence of correlated trading between mutual funds and banks. They argue that the relatively higher incidence of correlated trades amongst mutual funds reflects greater reputational concerns which stems from higher redemption risk and greater short-term market monitoring faced by them. Alternatively, evidence of short-term momentum (Wermers, 1999; Sias, 2004) and long-term reversals (Gutierrez and Kelley, 2009; Dasgupta et al., 2011a; Brown et al., 2014) in stock returns following the trades of institutional investors has been linked indirectly to reputational concerns. However, these strategies cannot rule out for the presence of multiple motives to herd and consequently, cannot disentangle counteracting asset price effects arising from these different motives. In contrast, we can identify the asset price effects of such demands without confounding effects from other forces.

Our findings provide credence to the fast growing theoretical literature which studies how asset prices are affected by the compensation structure of money managers and other complementarities in asset management. For example, Malliaris and Yan (2011), Dasgupta et al. (2011b), Guerrieri and Kondor (2012) and Vayanos and Woolley (2013) introduce models with career-concerned money managers and examine the implications for asset prices. In addition, short-term market monitoring, by typically relying on past returns or returns of peers to gauge managerial ability, may encourage managers to imitate the behavior of better performing peers. These papers argue that such herding behavior could potentially explain short-term momentum and long-term reversal in asset returns. In the context of our paper, the MRG is an explicit penalty on under-performance and induces similar behavior in managers as the papers mentioned above. To the best of our knowledge, our results provide the first direct evidence on the impact of relative-performance-concerns driven trades on stock returns.

Our findings are also related to a broader literature that studies whether the relation between institutional trades and asset prices can be attributed to news about fundamental value or from frictions such as market power, limits to arbitrage, or sentiments which are delinked from fundamentals. In order to control for the role of new information, many studies have focused on events when stocks are added to or deleted from an index.[3] Chen et al. (2004) find that stocks added to the S&P 500 exhibit 6.4 percent abnormal returns during the month following the announcement. However, a crucial difference in our results is that we find a subsequent reversal in abnormal returns whereas they find these effects to be permanent, potentially because index additions do in fact contain relevant new information about the firm.[4]This literature has argued that these asset price effects arise in part from the behavior of passive traders such as index funds and exchange-traded funds who must buy the stock that was added to the index. In our setting, the incentives to benchmark to their peers induces pension funds to buy stocks to which they are under-exposed relative to their peers. Thus, similar to index funds who must buy a stock just by virtue of it being added to the index, the pension fund managers are induced to buy stocks just by virtue of the stock being in the peer portfoilo.

In addition to the effects on abnormal returns, recent studies have also found that stocks added to popular indexes experience increases in comovement with the rest of the stocks in the index, generally providing support for the friction- or sentiment-based view. For example, Barberis et al. (2005) find that stocks added to the S&P 500 experienced an average increase of 0.07 increase in R^2. Other papers have found stronger effects outside the U.S. For instance, Greenwood and Sosner (2007) find an increase of 0.3 in the correlation between daily returns of stocks added to the Nikkei 225, while Greenwood (2008) finds that the R^2 increases on average by 0.21 for stocks that are overweighted relative to the Nikkei 225. Our estimates on comovement are larger than those findings for developed countries, potentially because of the relative smaller size of the Colombian stock market.

The rest of the paper is organized as follows. In Section 2 we describe the data and provide some institutional features of the MRG and the Colombian stock market. Section 3.1 discusses the changes in trading behavior by Colombian pension following the change of the

[3] Harris and Gurel (1986) and Shleifer (2000) present evidence from index additions and deletions, while Greenwood (2005) and Hau (2011) present evidence from more general index redefinitions.

[4] The uninformativeness of stock addition and deletions has been questioned. For example, see work such as Denis et al. (2003) and Cai (2007).

MRG. In Section 4 we perform the main empirical exercises. Section 5 concludes.

2 Data and Institutional Setting

2.1 Data

The data in this paper was collected from three sources. Information on portfolio holdings by Colombian Pension Funds was provided by the Colombian Association of Pension Fund Administrators (ASOFONDOS). It includes monthly security allocations for all privately-managed pension funds between January 2004 and December 2010. We use Compustat Global for stock-specific information, i.e. price, trading volume, and firm size. However, Compustat Global has missing observations for several of the domestic stocks held in the pension fund portfolios. We collect missing information directly from the *Superfinanciera de Colombia* (SFC), a supervisory agency within Colombia's Finance and Public Credit Ministry which oversees all financial, insurance and pension services in the country.

Next, to facilitate an understanding of the data and the Colombian institutional environment, we provide a brief description of the Colombian private pension industry and the portfolio and stock data.

2.2 Pension Fund Administrators (PFAs)

In Colombia, Pension Fund Administrators (PFAs) are in charge of the mandatory contributions of the working population. The investment decision of a worker is restricted to the choice of the PFA, while the PFA is in charge of the portfolio allocation. Each PFA pools the contributions of all the workers into one fund. Consequently, any two workers associated with a particular PFA have the same asset allocation independent of their age or the size of their contributions.[5]

[5] Starting in 2011, PFAs were allowed to offer three different funds with different risk profiles but this period lies outside our sample period.

Between January 2004 and December 2010, there were six private PFAs. During this period the total assets managed by these six PFA's grew from \$13.8 billion to over \$50 billion. This increase in the assets reflects the fact that most of the workers contributing to these funds are still young (more than 70% were younger than 40 years old as of December, 2010). This increase in assets managed by these PFAs also coincided with their increased participation in the Colombian stock market. In fact, by June 2010, these PFA's had 32.4% of their \$51.7 billion invested in domestic stocks, which amounted to 7.1% of the total domestic market capitalization. Moreover, during 2010, conditional on trading, the average monthly change in the holding of a stock was 24.2% of the average trading volume on the same stock.[6] Furthermore, the average number of stocks held by the PFAs in their portfolio was 30. Hence, not only do these funds make up for a significant portion of the domestic stock market, but they also represent a large fraction of the trading volume. Thus, their trading behavior is likely to affect stock prices. Table 1 documents various characteristics of these PFAs.

The government regulates PFAs' portfolio strategies by imposing limits on specific asset classes and individual securities for these funds. For example, in June 2008 some of the limits on asset holdings were given by: (i) Maximum 50% on domestic government debt. (ii) Maximum 40% on equity securities. (iii) Maximum 40% on foreign securities. In addition to these restrictions, the PFAs are subject to a Minimum Return Guarantee (MRG). The MRG imposes a lower threshold on returns that each individual PFA needs to guarantee its investors. If a PFA fails to provide at least this return, the PFA must transfer part of its own net worth to the fund to make up the shortfall. These regulations are common in many developing countries and are motivated by the desire to curtail *excessive* risk taking by these institutional investors.[7]

Between January 2004 and June 2007, the minimum return guarantee was calculated as $70\%\Pi$, where $\Pi = (A + B)/2$ and A denotes returns on the portfolio held by the other

[6] Here trading refers to the change in holdings for a given stock during a month. Total volume trading for each stock is calculated as the average volume trading during the year.

[7] The MRG is also common in many other Latin American and Eastern European countries such as Chile, Peru, Uruguay, Poland and Hungary.

pension funds (the peer-portfolio). B denotes the returns of a benchmark portfolio calculated as the weighted sum of three components: (i) theindex of domestic fixed income, (ii) domestic equity index (IGBC) and (iii) foreign equity index (S&P500). Each component's returns is weighted by the share that pension funds invest in each particular asset class during the measurement period. Thus, for each pension fund, tracking the peer-portfolio matters for two reasons. First, the peer-portfolio determines component A directly and second, the share of the peer-portfolio in each of the components of the benchmark is used to calculated the relative weight of the returns of each component.

In June 2007, the formula for the threshold was changed from $70\%\Pi$ to $\min\{70\%\Pi, \Pi - 2,6\%\}$. Notice that $70\%\Pi > \Pi - 2.6\%$ for $\Pi < 8.66$ percent. Since, between October 31, 2005 and October 31, 2008 the average Π was 4.7%[8], it is reasonable to assume that the expected returns for the PFAs were in the region below 8.66%. Consequently, under the new formula, the minimum return that the PFAs were required to deliver was 2.11% which was 113 basis points lower than the value stipulated by the old formula. Thus, from the point of view of individual PFA, the change in formula implied an effective loosening of the MRG requirement after June 2007. As we discuss in the following sections, we use this change in regulation as an instrument to identify the demand for stocks which are independent of fundamentals and are driven from peer benchmarking motives.

In addition to managing mandatory pension contributions, PFAs also manage voluntary retirement funds in separate accounts. These voluntary accounts supplement the compulsory retirement savings in the pension funds. The bottom panel of Table 1 shows that these accounts are smaller than the compulsory accounts. Unlike mandatory pension funds, these accounts are subject to very few regulations. Most notably, they are not subject to the MRG. In the next section, we contrast the difference in strategies of the PFAs in managing the voluntary and non-voluntary funds.

We conclude this section by providing some details about the Colombian stock market.

[8] The industry annual average returns A were 4.71% and the returns on the benchmark portfolio B was 4.70%

To avoid stocks with small trading activity, we restrict our sample to stocks that trade at least 25% of the business days when the stock was active. We also limit our sample to stocks in which at least one PFA had any holdings during the period. Our final sample includes 47 different stocks, which represent 92% of total stock market capitalization and 94% of the trading volume. Table 2 presents monthly averages of stock-level information before and after the MRG change. The SFC reports a quarterly *Liquidity Score* on each stock which ranges from 0 to 10, based on the number of trades and average trading volume. With this measure each stock is classified into one of four categories of marketability. We also split our sample into stocks with *HIGH* marketability as reported by the SFC, and *LOW* marketability for all other stocks.

3 Empirical Strategy

The primary objective in this paper is to test the extent to which herding arising from the desire to benchmark to peers causes asset price effects. The change in the MRG in June 2007 provides a natural experiment which we exploit in order to identify the component of demand for each stock that is solely driven by peer effects. Our identification strategy relies on two key related elements: (1) the MRG induces pension fund managers to benchmark against their peer-group portfolio, and (2) the loosening of the MRG requirement in June 2007 affects the incentive for peer-benchmarking by individual PFAs but is unrelated to stocks' fundamentals. In this section we provide evidence for the above.

3.1 Portfolio decisions of PFAs under the MRG

Under the MRG, the returns of a PFA are partly evaluated relative to the average returns of all the PFAs. A PFA which is performing poorly relative to its peers has an incentive to mimic the portfolio of other managers in order to reduce the shortfall relative to the peer-portfolio returns. In other words, PFAs track their peer-group performance in order to avoid the penalty associated with failing to deliver the minimum allowable return.

The urgency of staying on the correct side of the MRG is driven by the penalty for falling too far behind the industry average returns, especially since this penalty may push the PFA to bankruptcy. For example, given the size of each PFA and the total value of assets under management, a typical Colombian PFA falling 50 bps below the MRG threshold would use up its entire net worth compensating its investors.

We start by summarizing aggregate trading strategies and PFAs' response to the MRG change by calculating the correlation between the direction of monthly trades on each stock and the relative exposure to the peer-portfolio. Let $w_{i,s,t}$ denote the weight of stock s in the portfolio of PFA i at the end of month t. The industry or peer-portfolio refers to the holdings of all six pension funds in each stock ($\pi_{s,t}$). We define *overexposure* as the weight of stock s in the portfolio of fund i relative to the weight in the peer-portfolio, i.e. $oexp_{i,s,t} = w_{i,s,t} - \pi_{s,t}$. For each stock, trading by pension funds is summarized by the variable $trade_{i,s,t}$, which is equal to 1 if the fund buys stock s during month t, and 0 otherwise. All calculations are based on the compulsory accounts (which are affected by the MRG) unless specified otherwise.

Figure 1 depicts the time series behavior of the correlation between trades and lagged overexposure, $corr(trade_{i,s,t}, oexp_{i,s,t-1})$ (solid line). The y-axis measures the correlation while the x-axis represents time at a monthly frequency. For each month, the correlation is calculated across all stocks and for all pension funds over a six month rolling window. Note that this correlation can be interpreted as a measure of herding behavior by PFAs. The average correlation between trades and overexposure before June 2007 was -6.8% which is significantly different from zero at the 99% confidence level. This negative correlation suggests that a PFA which was under-exposed ($oexp < 0$) to a particular stock relative to the peer-portfolio, was more likely to buy that stock during this period. In contrast, after June 2007, the average correlation was 9.0% suggesting a reduced incentive to mimic the peer-portfolio. In summary, the correlation between trades and overexposure over the two periods suggest that with a tighter MRG, PFAs were more likely to change their holdings in the direction of the peer-portfolio.[9]

In order to show that the measure of herding used above is closely related to conventionally used measures, we also calculate *active share* (Cremers and Petajisto, 2009). This portfolio-similarity measure is defined as (one-half of) the sum of the absolute distance between the portfolio weights of each fund and its benchmark index (the peer-portfolio in our case).[10] We calculate *active share* for each fund-month, and take the average before and after the MRG change. The equally-weighted active share among pension funds before June 2007 is 27% and 56% thereafter.[11] A lower active share before June 2007 implies higher similarity between the portfolios of PFAs and is consistent with a stronger incentive to closely track the peer-portfolio.

These measures of herding validate the first element of our identification strategy. However, a point of concern might be that the change in the trading behavior before and after June 2007 is driven by some change in fundamentals and not by the MRG. This is particularly worrisome since the change in the regulation is adjacent to the global financial crisis. Thus, the change in trading behavior in the second half of the sample might be driven by a deterioration in fundamentals caused by the crisis. If this was, in fact, the case, the increased uncertainty in fundamentals following the crisis should have induced PFAs to herd more so as to avoid the penalty. Thus, this hypothesis would not be able to explain the switch in the sign of the correlations between overexposure and the direction of trades. We also try to directly address this concern by looking at the trading behavior of voluntary funds before and after June 2007. Figure 1 plots the time series of the correlation between trades and overexposure for voluntary funds (dashed line). In contrast to the compulsory accounts, the relationship between demands and over-exposure for the voluntary accounts reveals a correlation of 13.4% before June 2007 and 14.1% after. There are two salient features to note from these

[9] Pedraza (2015) finds similar results using a fund-level measure of the similarity in trading among Colombian PFAs. The author focuses on the changes in correlated trading in response to the MRG, while we extend our analysis to estimate the asset price implications of such behavior.

[10] A fund's *active share* is the sum across assets of the absolute value of overexposure.

[11] The value-weighted *active share* before June 2007 was 30% and 55% after this date.

numbers. First, the correlation is on average higher for voluntary funds across the entire sample period. In other words, relative to the mandatory funds, voluntary funds seem to have weaker incentives to track their peers. Second, there is no change in the sign or magnitude of the correlation before and after June 2007 (the difference across the two sub-periods is not statistically different from zero) which further provides credence to the notion that differences in trading behavior among mandatory pension funds are driven by the change in the MRG and not by some other changes in fundamentals.

3.2 Trading strategies

The description above of how the MRG affected the trading behavior of PFAs was very parsimonious. To complement the analysis, we perform the following parametric exercise. We estimate a probit model:

$$Pr(trade_{i,s,t} = 1) = \Phi\left(\alpha_i + \delta MRG_{t-1} + \sum_m \beta_m V_{i,s,t-1} + \sum_m \gamma_m V_{i,s,t-1} \times MRG_{t-1}\right) \quad (1)$$

where Φ is the cumulative distribution function of the standard normal, and the vector of independent variables V are fund and stock specific characteristics and MRG_t is a time dummy equal to one for dates before June 2007 and zero thereafter, representing the policy change. The objective here is twofold, first to determine what fund-based characteristics determine PFA trading on individual stocks, and second to measure whether there was any change in the impact of these characteristics after the MRG formula was modified. When a fund buys shares in stocks in which it is already overexposed (underexposed) it moves away from (towards) the peer-benchmark.

We set $V_{i,s,t} = (W_{i,s,t}, Controls_{i,s,t})$, with the first set of explanatory variables defined as $W_{i,s,t} = (oexp_{i,s,t}, rel_{i,t}, oexp_{i,s,t} \times rel_{i,t}, Market_{i,s,t}, Market_{i,s,t} \times rel_{i,t})$. Peer-overexposure ($oexp_{i,s,t}$) was defined in the previous section and captures whether in period t, PFA i is over or underexposed in a stock s relative to its peers. Since managers with poor performance are more exposed to the penalty, these managers might buy stocks in which they are under-weighted relative to the industry portfolio in order to reduce the likelihood of future loses vis-à-vis their peers. To capture this dimension of trading behavior, we define $rel_{i,t} = R_{i,t} - R_{-i,t}$ as a measure of relative performance of PFA i at date t where $R_{i,t}$ denotes 36 month returns prior to t for fund i and $R_{-i,t}$ is the average 36 month returns prior to t for all funds other than i. We choose a period of 36 months to make the measure consistent with the measurement period of the MRG. We also include the interaction between $oexp_{i,s,t} \times rel_{i,t}$ to test whether PFAs who performed poorly relative to the peers move more strongly towards the peer-group, and the triple interaction when the MRG is more strict.

Similar to the peer-portfolio, the MRG also induces PFAs to closely track the IGBC index (see description of MRG in previous section). To control for changes in strategies relative to the market, we include stock-fund overexposure to the IGBC index, i.e. $Market_{i,s,t} = w_{i,s,t} - \Pi^{IGBC}_{i,s,t}$. However, if the peer-portfolio and the IGBC index have similar weights in their underlying stocks, trades to track the market might be wrongly interpreted as if managers are moving towards the peer-portfolio. For this reason, we calculate the component of $Market_{i,s,t}$ that is orthogonal to peer-overexposure by estimating $Market_{i,s,t} = \alpha_s + \alpha_i + \theta oexp_{i,s,t} + \varepsilon_{i,s,t}$ and use the estimated errors as our measure of market overexposure in equation. (1).[12]

In addition we also include a set of PFA and stocks specific variables which we refer to as $Controls_{i,s,t}$. For the PFA specific controls, we include fund size and monthly flows. For each stock, we include lagged returns at one, three and six months to account for momentum trading, defined as purchasing (selling) assets with positive (negative) past returns. We also include firm size and liquidity, as institutional investors may share an aversion to stocks with certain characteristics, as documented by Wermers (1999), who find evidence that US mutual funds tend to herd in small stocks.

Table 3 documents the estimation results. For mandatory funds, the estimated coefficient

[12] θ is 0.99 with a t-statistic of 74.9 and the adjusted R^2 is 0.44.

for $MRG \times oexp$ is -0.142 and statistically significant at the 1% level. Consistent with figure 1, PFAs were more likely to buy a stock in which they are underexposed relative to the peer-portfolio when the MRG was tighter. Furthermore, poor performing PFAs ($rel < 0$) move more strongly towards the peer-portfolio before June 2007 than after this date. The estimated coefficient for the triple interaction $MRG \times oexp \times rel$ is 0.158 and statistically significant. In contrast, voluntary funds (which are not subject to the MRG) did not exhibit any changes in trading behavior after June 2007, which further suggests that the MRG is independent to changes in fundamentals (exclusion restriction).

To summarize, a stricter MRG prior to June 2007 is associated with greater peer effects. PFAs trade more in the direction of peers, and in particular buy more stocks in which they were under-exposed relative to their peers. Furthermore, this incentive was stronger for under-performing managers who traded more actively towards the peer-portfolio prior to June 2007 than after this date.

4 Estimation Framework and Results

The previous section provided support for using the change in the MRG as a valid instrument. To identify the component of demand which is driven by the desire to track the peer-portfolio, we use a *difference-in-difference* approach that estimates any disproportional changes in trading activity across stocks that are over- or under-weighted relative to the peer-portfolio, and among funds with more exposure to the penalty. We then use these demands to study whether relative performance concerns and peer-benchmarking among pension funds affect stock prices. We measure asset price effects in two broad ways. First, we study whether pension fund trades affect contemporaneous and subsequent abnormal stock returns. Second, we measure the degree of excess comovement in stock prices (i.e. the extent to which comovement in prices is not explained by fundamentals) following the trades of pension funds.

4.1 The Effect on Stock Returns

We start by testing whether stocks' abnormal returns are related to PFA demands from peer-benchmarking motives. The following equation at the stock-month level summarizes the relationship to be estimated:

$$ar_{s,t} = \beta_0 + \beta_s + \beta_t + \beta_1 \hat{y}_{s,t} + \beta_2 liq_{s,t} + \beta_3 \hat{y}_{s,t} \times liq_{s,t} + \Upsilon assets_{s,t} + \varepsilon_{s,t} \qquad (2)$$

where $ar_{s,t}$ denotes stock abnormal returns, calculated as the residuals of a one-factor market model. Stock and market returns are calculated in excess to the 3-month Colombian government bond yield as well as relative to the 3-month US T-bill rate (in Colombian currency).[13] $\hat{y}_{s,t} = \sum_{i=1}^{6} \hat{y}_{i,s,t}$ denotes the total demand from all the PFAs for stock s driven by peer-benchmarking considerations. Stocks' liquidity is captured by $liq_{s,t}$ and is defined as the *marketability dummy* equal to 1 if the stock is reported as highly marketable according to the SFC and zero otherwise. To investigate the price effects from trades on stocks with different liquidity we include the interaction with pension funds demands ($\hat{y}_{s,t} \times liq_{s,t}$).[14] We also control for firm size during the observation month ($assets_{s,t}$), defined as the logarithm of firms' total book value of assets. We also account for time-invariant heterogeneity across stocks by including stock fixed effects (β_s) and time-specific effects by including year fixed effects (β_t).

To test whether peer-benchmarking demands are correlated with subsequent stock returns we estimate equation (2) using abnormal returns in the contemporaneous quarter $ar_{s,q}$ (i.e. including month t, $t+1$, and $t+2$), and the following two quarters, $ar_{s,q+1}$ and $ar_{s,q+2}$. The coefficient β_1 measures how pension funds demands are related to abnormal returns over time and across stocks. Given the potential persistence, we allow the error term ($\varepsilon_{s,t}$) to be correlated within stocks and correct the standard errors as in Petersen (2009). Finally, we

[13] The market index is the IGBC index. As a robustness test, we perform the empirical analysis using the residuals from a Carhart four factor model and find similar results.

[14] See for example, Brown et al. (2014) find that, return reversals following mutual funds trades are mostly concentrated for small and illiquid stocks.

standardize fund demands so that the estimated coefficients are directly informative about their economic significance.

In order to identify the total peer-benchmarking demand for stock s by PFAs, we use an instrumental variable (IV) approach. In particular, we use the dummy variable MRG $\in \{0, 1\}$ as one of the instruments. It represents the policy change and is equal to one for dates before June 2007 and zero thereafter. In addition, we include other instruments in the form of linear interactions with the MRG dummy, i.e. $MRG_t \times W_{i,s,t}$, where the vector $W_{i,s,t}$ was defined in Section 3.2, and includes funds relative performance, peer and market overexposure. More precisely, we estimate pension funds' demand and its interaction with liquidity as follows:

$$\hat{y}_{s,t} = \alpha_0 + \alpha_s + \alpha_t + \sum_{i=1}^{6} \gamma_i W_{i,s,t-1} + \delta_0 \text{MRG}_t + \sum_{i=1}^{6} \delta_i W_{i,s,t-1} \times \text{MRG}_t + e^1_{s,t} \tag{3}$$

$$\hat{y}_{s,t} \times liq_{s,t} = \bar{\alpha}_0 + \alpha_s + \bar{\alpha}_t + \sum_{i=1}^{6} \bar{\gamma}_i W_{i,s,t} + \bar{\delta}_0 \text{MRG}_t + \sum_{i=1}^{6} \bar{\delta}_i W_{i,s,t} \times \text{MRG}_t + e^2_{s,t} \tag{4}$$

Equations (3) and (4) are the *first-stage* of the IV estimation. These equations capture the behavior documented in Section 3.1. According to Table 4, the estimated coefficients for $MRG \times oexp$ are negative for under-performing funds (PFA_1 through PFA_4). That is, when the MRG was tighter, these managers tend to increase their demands for stocks in which they have a smaller relative weight than the peer-portfolio. Conversely, the demands from funds PFA_5 and PFA_6, which on average out performed their peers before June 2007, are positively correlated with overexposure, although not statistically significant at standard levels. According to a likelihood-ratio test, our instrumental variables, i.e. MRG and $MRG \times W$, are jointly significant for $\hat{y}_{s,t}$ and $\hat{y}_{s,t} \times liq_{s,t}$ with p-values below 0.01%.

We now turn to the estimation on abnormal returns. Note that $\hat{y}_{s,t}$, the fitted values from equations (3) and (4), represents the component of aggregate demand for stock s in month t which arises because of peer-benchmarking considerations and not due to a change in fundamentals. Using $\hat{y}_{s,t}$ as our measure of demand and controlling for $W_{i,s,t}$ in equation (2), we can estimate the effects of peer-benchmarking on abnormal returns. Columns (1) through

(4) in Table 5 present the results of estimating equation (2) using the instrumented aggregate demand for each stock.[15] In the top panel, excess returns are calculated relative to the 3-month domestic government yield. The results suggest that trades by these pension funds have strong effects on contemporaneous returns, with trades motivated by peer-benchmarking generating 3.93 percent of contemporaneous-month abnormal returns on the average stock. The estimated effect is slightly smaller at 3.46 percent when excess returns are calculated relative to the 3-month US T-bill rate (see bottom panel Table 5). These abnormal returns are fully reversed after six months.

Our results indicate that there is an overreaction in stock prices followed by a reversal. In related theoretical work, Dasgupta et al. (2011b) show that such behavior is consistent with the presence of investors with relative performance concerns. Dasgupta et al. (2011b) argue that a manager may be willing to overpay to buy an asset because of relative performance concerns and other market participants extract the surplus by overcharging. They also show that the degree of reversal in returns is higher with stronger relative performance concerns. Our estimation results provide support for these theoretical findings. We find that when the magnitude of trades motivated by peer-benchmarking is larger, there are higher abnormal returns during the contemporaneous month, and larger reversals in the subsequent quarter. In our setting, a manager may be willing to overpay for a stock when she needs to reduce the likelihood of under-performance, or at least to guarantee that her performance is not below the MRG. The results indicate that institutional investors' peer-benchmarking generates excess volatility in stock prices and these effects are stronger when the incentive to be closer to the peer-group is more pronounced.

Our findings also agree with other studies (e.g. Brown et al., 2014) that measure herding indirectly. In particular, evidence on overreaction in stock prices and stock return reversals following institutional trades is often interpreted as evidence of herding that is not related to information. However, without a direct measure of herding such measures might under or

[15] The Table also includes p-values of the "Differences-in-Sargan" test for endogeneity and the Hansen over-identification test.

over-estimate price effects. In order to appreciate this, consider the exercise of estimating equation 2 with total trades of stock s as opposed to demands that originated solely due to peer-benchmarking concerns. Trades are driven by multiple factors some of which not be observed. For example, a PFA might have some private information about the abnormal returns of a particular stock which may cause it to increase demand for that stock. In our specification, this private information would be captured in the error term which then violates the classical assumptions under which the OLS estimator is BLUE. Consequently, the OLS estimated effect on asset prices may be biased and inconsistent.

The last four columns of Table 5 present the estimation results of equation (2) using OLS. As can be seen from the results, demands for a stock by pension funds are positively correlated with contemporaneous abnormal returns and negatively correlated with abnormal returns in subsequent quarters. These results are consistent with our IV estimation result. However, note that the magnitude of the effects are considerably smaller for the OLS estimates. Under the IV estimates, trades motivated by peer-benchmarking generate 3.93 percent of contemporaneous-month abnormal returns on the average stock, while the corresponding OLS estimate is only 1.69 percent. Thus, the OLS estimates would tend to underestimate the effects of peer-benchmarking in our context.

4.2 Comovement

The traditional explanation for why a group of stocks move in tandem is that they have correlated *earnings news*. Consequently, covariation in returns simply reflects covariation in fundamentals. Alternatively, Barberis and Shleifer (2003) suggest that stock prices can covary in excess of fundamentals if investors allocate funds across security labels rather than on individual securities, a practice known as "*style investing*". The capital flows of such an investor in and out of specific assets are perfectly correlated across securities with the same label even though the fundamental values of these securities are only partially related. There is compelling evidence supporting the excess in covariance generated by index recompositions (Barberis et al., 2005; Boyer, 2011). In our context, if pension fund managers follow their peer-group closely to protect against under-performance, flows by these managers can generate excess comovement in the price of stocks belonging to the peer-portfolio. In this section we test whether peer-benchmarking incentives affect the level of comovement across domestic stocks.

We start by estimating equation (2) using the correlations between daily stock returns and the returns of the peer-portfolio as the dependent variable ($corr^n_{s,t}$). To avoid spurious correlations, we exclude stock s from the peer-portfolio to calculate daily returns. This correlation is measured over three ($corr^3_{s,t}$) and six months ($corr^6_{s,t}$) rolling windows, following the trades of pension funds. We include firm size as control as well as firm and year fixed effects. The relationship estimated is identical to equation (2) but with a different dependent variable.

As in the previous sub-section with abnormal returns, we use our IV approach to estimate the actual effects on comovement from peer-benchmarking and to test the hypothesis that all comovement can be explained by correlated fundamentals. Columns (1) through (4) of Table 6 (top panel) present these results while results from the OLS are presented in Table 6 (top panel), columns (5) through (8).

Using the IV strategy, we find that peer-benchmarking demand for a stock results in a higher comovement of that stock's returns with that of the peer-portfolio. The effect is stronger for less liquid stocks. The correlations across daily returns between a stock and the peer-portfolio increases in the following months after the trades of pension funds. For the average stock, peer-benchmarking increases the correlation of daily stock returns by 0.35 during six months. This is a sizable increase in comovement, since average stock return correlation over the sample period is 0.46. In contrast, OLS results suggest that there is only a marginal change in comovement across stocks following the trades by pension funds (0.02 over six months).

There are at least two reasons for which an OLS approach might underestimate the effects of peer benchmarking on comovement. First, the covariance of stock returns is affected in different and potentially opposite ways depending on the motivation of a trade. For instance, trading on private firm-specific information is expected to increase the fraction of total volatility due to idiosyncratic shocks and make stock returns less correlated in the cross section. Conversely, trading to track the peer-group might increase the covariance across stock returns given the correlated flows into or out of the stocks in the peer-portfolio. Since a combination of both these motives might be driving trades, the OLS estimation results in a downward biased estimate of the effects of peer-benchmarking on comovement. Second, pension funds flows might increase exactly when the covariance structure of fundamental values also changes. In this case, an increase in stock comovement following pension funds trades would reflect changes in fundamentals rather than the effects of institutional investors flows into these assets.

In addition to the measure of comovement above, we estimate univariate time series regressions of daily stock returns on the peer-portfolio returns:

$$r_{st} = \alpha_i + \beta_{peer,s} R^{-s}_{peer,t} \tag{5}$$

To compute $R^{-s}_{peer,t}$, the value-weighted peer-portfolio daily return, we exclude stock s to avoid spurious correlations. For each stock in the sample, we estimate equation (5) for three and six month rolling windows. Our measure of comovement is the R^2 from these regressions, which captures the correlation between a stock's return and the return of all other stocks in the peer-portfolio.

Results are documented in Table 6 (bottom panel). Consistent with our previous results on excess correlations, stocks with large flows from pension funds due to relative performance concerns tend to exhibit higher R^2. In other words, a large fraction of variation in stock returns is common to all stocks in the peer-group. In particular, peer-benchmarking increases the R^2 by 0.29 over the six months following the trades of pension funds. Thus, on average, peer-benchmarking explains close to thirty percent of the cross-sectional variation in daily comovement among stocks in the pension fund portfolios. In all our measures of comovement, OLS estimates are at least one order of magnitude smaller than those estimated with our IV approach.

5 Conclusions

Effective management of retirement savings is fast becoming an important agenda in many countries due to a rapidly aging population. In addition to fulfilling this critical function, pension funds have also been thought of as stabilizers of the financial system. However, a growing theoretical literature has pointed out that reputational concerns and monitoring may interfere with this function of pension funds by introducing short-term objectives. This paper provides direct empirical evidence of how relative performance concerns induces herding amongst pension funds. Furthermore, the paper shows that such complementarities in asset management can have large and persistent effects on outcomes in financial markets.

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Appendix

A Tables

Table 1
Pension Funds Summary Statistics

Key statistics are provided below (at two-year intervals) for Colombian pension funds. The database, made available by the Association of Pension Fund Administrators (ASOFONDOS), includes monthly portfolio holdings of each security in every pension fund from January 31, 2004 to December 31, 2010.

	Year			
	2004	2006	2008	2010
Panel A. Mandatory Pension Funds				
Number of funds	6	6	6	6
Total assets ($billions)	13.8	22.6	30.5	51.7
Percent invested in domestic stocks	6.3	14.7	20.2	32.4
Investment in Stocks/Market Capitalization	6.6	11.3	13.5	15.4
Net flows (contributions minus withdraws $billions)	1.2	2.0	2.4	1.7
Largest fund share (percentage over the pension industry)	27.1	26.6	27.2	27.5
Smallest fund share (percentage over the pension industry)	3.2	3.9	4.7	4.9
Average number of stocks held per fund	16.2	21.2	26.3	30.0
Number of distinct stocks held by all pension funds	41	50	44	47
PFA trades/Stock Trading Volume (percent)	19.7	14.9	16.5	24.2
Panel B. Voluntary Pension Funds				
Total assets ($billions)	1.9	3.2	3.3	5.1
Percent invested in domestic stocks	7.8	11.7	12.7	19.7
Investment in Stocks/Market Capitalization	1.1	1.3	0.9	0.9
Net flows (contributions minus withdraws $billions)	0.8	1.5	0.4	1.2
Largest fund share (percentage over the pension industry)	36.6	32.7	37.3	36.6
Smallest fund share (percentage over the pension industry)	2.0	3.3	5.6	4.4
Average number of stocks held per fund	5.2	13.8	17.8	20.3
Number of distinct stocks held by all pension funds	23	30	36	34
PFA trades/Stock Trading Volume (percent)	2.1	2.8	3.7	2.3

Table 2
Summary for stocks

This table presents monthly averages of stock-level information, classified by marketability *HIGH* and *LOW* as reported by the SFC, and split by period, before the MRG change and after. Numbers in December 2010 U.S. dollars. Standard deviation in parenthesis.

	Monthly average across stocks		
	All stocks N=47	High Marketability N=24	Low Marketability N=23
Firm Size ($Billions)			
Before June 2007	3.22	5.38	1.28
	(5.12)	(6.59)	(1.68)
After June 2007	6.25	9.60	2.58
	(12.14)	(12.14)	(3.06)
PFAs Trading Volume ($millions)			
Before June 2007	17.44	25.04	3.11
	(30.99)	(34.57)	(14.32)
After June 2007	25.41	42.43	1.56
	(63.66)	(78.93)	(5.72)

Table 3
Probit Regression

The dependent variable is $buy_{i,s,t}$, defined as 1 if fund i buys stock s during month t and zero otherwise. MRG is a dummy variable equal to one for dates prior to June 2007 and zero thereafter. Overexposure is the difference between the weight of stock s in fund i's portfolio and the weight in the peer portfolio. Relative performance is the 36 months returns of fund i minus the industry average returns. Market is a measure of overexposure relative to a domestic equity index. All specifications include fund fixed effects, fund monthly flows, and fund market share. Stock controls are liquidity, firm size, and past returns. Standard errors in parenthesis are adjusted for within-stock clustering. Note: ***/**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5%/10% level.

	Mandatory Funds	Voluntary Funds
MRG x Overexposure	-0.142***	-0.121
	(0.042)	(0.088)
MRG x Overexposure x Relative Performance	0.158***	0.107
	(0.037)	(0.077)
MRG x Relative Performance	0.060	0.070
	(0.056)	(0.077)
Overexposure	0.048**	0.008
	(0.019)	(0.020)
Relative Performance x Overexposure	-0.100***	-0.029**
	(0.036)	(0.014)
MRG x Market	-0.163	-0.087
	(0.128)	(0.067)
MRG x Market x Relative Performance	-0.071	-0.005
	(0.075)	(0.177)
Market x Relative Performance	-0.014	0.056**
	(0.020)	(0.024)
MRG	-1.487	1.136
	(1.036)	(1.086)
Number of Observations	14,271	8,173
Pseduo R^2	0.149	0.123

Table 4
First Stage

First stage results (equations (3) and (4)). The dependent variables are $y_{s,t}$ and $y_{s,t} \times liq_{s,t}$, where $y_{s,t}$ denotes total demands from all PFAs and $liq_{s,t}$ is the marketability dummy equals to 1 if the stock is reported as highly marketable according to the SFC and zero otherwise. MRG is a dummy variable equal to one for dates prior to June 2007 and zero thereafter. Overexposure is the difference between the weight of stock s in fund i's portfolio and the weight in the peer portfolio. Specifications include stock fixed effects, stock liquidity and firm size. Note: ***/**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5%/10% level. The last column reports funds' average relative performance ($\overline{rel}$) before June 2007 with t-statistics in parenthesis.

	First Stage				
Dependent variable: $y_{s,t}$	$MRG \times oexp$	$oexp$	$MRG \times rel$	rel	Relative returns before June 2007
PFA_1	-91.90*	142.0***	-91.50*	24.59	-0.14%***
	(-1.88)	(4.88)	(-2.08)	(0.71)	(-5.57)
PFA_2	-82.41*	-49.06	-0.654	15.32	-0.75%***
	(-1.65)	(-1.29)	(-0.02)	(0.69)	(-15.41)
PFA_3	-94.66**	-15.60	-2.518	3.798	-0.82%***
	(-2.23)	(-0.84)	(-0.19)	(0.32)	(-7.90)
PFA_4	-4.340	-74.64***	-38.82*	5.706	-0.59%***
	(-0.11)	(-4.09)	(-1.88)	(0.33)	(-7.07)
PFA_5	51.52	-61.80**	18.69	-19.14*	2.86%***
	(0.91)	(-2.89)	(1.47)	(-2.03)	(28.75)
PFA_6	43.32	-25.97	-1.829	-16.11	0.33%***
	(1.17)	(-1.23)	(-0.10)	(-1.12)	(3.13)
$R^2 = 0.138$					
p-value Likelihood-ratio test = 0.01%					

Dependent variable: $y_{s,t} \times liq_{s,t}$	$MRG \times oexp$	$oexp$	$MRG \times rel$	rel
PFA_1	-107.8***	150.7***	-35.11	11.01
	(-2.64)	(6.20)	(-0.96)	(0.38)
PFA_2	-66.89	-39.38	-16.80	10.06
	(-1.02)	(-1.24)	(-0.63)	(0.54)
PFA_3	-93.68***	-17.50	-14.94	11.88
	(-2.64)	(-1.12)	(-1.32)	(1.20)
PFA_4	14.41	-64.88***	-37.84**	14.44
	(0.45)	(-4.26)	(-2.20)	(1.00)
PFA_5	31.67	-55.82***	8.647	-14.67
	(0.67)	(-3.12)	(0.81)	(-1.86)
PFA_6	50.41	-23.47	-19.14	-5.452
	(1.64)	(-1.34)	(-1.22)	(-0.45)
$R^2 = 0.136$				
p-value Likelihood-ratio test = 0.00%				

Table 5
Peer Benchmarking and Abnormal Returns

The dependent variable is abnormal returns $ar_{s,t}$, calculated as the residuals of a one-factor market model. Stock and market returns are calculated in excess to the 3-month domestic government bond yield (top panel) as well as relative to the 3-month US T-bill rate (bottom panel). The market index is the IGBC index, a widely used value- and liquidity-based index for the Colombian stock market. Abnormal returns are calculated over the contemporaneous month and quarter, $ar_{s,t}$ and $ar_{s,q}$ respectively, and the following two quarters, $ar_{s,q+1}$ and $ar_{s,q+2}$. "Demands" is the total dollar value of purchases of stock s during month t by all pension funds normalized by the stock average monthly trading volume. "Marketability" is a dummy variable equal to one for stocks classified as highly marketable according to the Colombian financial supervisory agency (SFC), and zero for other stocks. "Size" is the logarithm of firm's total assets. The table compares the IV specification with the OLS. Estimators include stock and year fixed effects. Standard errors in parenthesis are adjusted for within-stock clustering. Note: ***/**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5%/10% level. Table reports p-values of the "Differences-in-Sargan" test for endogeneity and Hansen over-identification test.

	IV				OLS			
Variable	$ar_{s,t}$	$ar_{s,q}$	$ar_{s,q+1}$	$ar_{s,q+2}$	$ar_{s,t}$	$ar_{s,q}$	$ar_{s,q+1}$	$ar_{s,q+2}$
Demands	3.934***	1.343***	-0.872***	0.106	1.687***	0.208	-0.404***	-0.313***
	(0.961)	(0.186)	(0.202)	(0.257)	(0.367)	(0.179)	(0.106)	(0.084)
Marketability	-0.247	-1.388***	-2.178***	-1.903***	-0.377	-1.431***	-2.018***	-2.508***
	(1.131)	(0.450)	(0.530)	(0.521)	(0.816)	(0.419)	(0.706)	(0.923)
Demands X Marketability	-3.622***	-1.450***	0.319	-0.511	-1.708***	-0.221	0.385***	0.226*
	(1.204)	(0.460)	(0.371)	(0.402)	(0.373)	(0.185)	(0.121)	(0.113)
Size	0.402	0.252	-0.665	-0.141	0.627*	0.277*	-0.217	-0.124
	(0.522)	(0.192)	(0.484)	(0.268)	(0.323)	(0.163)	(0.231)	(0.297)
Constant	-8.860	-5.813	12.667	2.452	-17.110*	-7.073	7.158	4.831
	(13.192)	(4.858)	(10.121)	(6.565)	(8.997)	(4.601)	(6.561)	(8.652)
Observations	2002	1944	1760	1647	2073	2015	1824	1709
Adjusted R-squared	0.018	0.201	0.247	0.042	0.002	0.284	0.035	0.047
p-value hansen	0.122	0.004	0.122	0.017	.	.	.	.
p-value C	0.108	0.072	0.096	0.238	.	.	.	.
Demands	3.459**	1.616***	-1.105***	2.259	1.664***	0.184	-0.383***	-0.338***
	(1.687)	(0.530)	(0.159)	(16.372)	(0.361)	(0.166)	(0.120)	(0.088)
Marketability	-0.269	-1.249***	-1.758***	-1.623	-0.381	-1.396***	-2.034***	-2.498***
	(1.145)	(0.461)	(0.527)	(3.581)	(0.797)	(0.439)	(0.719)	(0.916)
Demands X Marketability	-3.074*	-1.487**	0.494	-8.203	-1.686***	-0.189	0.383***	0.237**
	(1.850)	(0.652)	(0.348)	(82.667)	(0.368)	(0.175)	(0.134)	(0.114)
Size	0.474	0.263	-0.009	0.758	0.699**	0.334*	-0.215	-0.118
	(0.534)	(0.199)	(0.473)	(10.642)	(0.324)	(0.166)	(0.226)	(0.298)
Constant	-10.836	-6.220	-0.076	-18.834	-19.120**	-8.706*	7.061	4.623
	(13.473)	(5.036)	(9.710)	(250.422)	(9.043)	(4.697)	(6.414)	(8.668)
Observations	2002	1944	1760	1647	2073	2015	1824	1709
Adjusted R-squared	.	.	0.018	-0.010	0.004	0.023	0.039	0.044
p-value Hansen	0.192	0.07	0.140	0.109	.	.	.	.
p-value C	0.179	0.011	0.150	0.127	.	.	.	.

Table 6
Peer Benchmarking and Changes in Return Comovement

The dependent variable in the top panel is the correlation between the daily returns of stock s and the returns of the peer portfolio measured over three and six months. In the bottom panel, the dependent variable is the R^2 from an univariate regression of firm i's daily returns and the peer portfolio returns during n-month rolling windows following t. "Demands" is the total dollar value of purchases of stock s during month t by all pension funds normalized by the stock average monthly trading volume. "Marketability" is a dummy variable equal to one for stocks classified as highly marketable according to the Colombian financial supervisory agency (SFC), and zero for other stocks. "Size" is the logarithm of firm's total assets. The table compares OLS estimation with IV specification. Estimators include stock and year fixed effects. Standard errors in parenthesis are adjusted for within-stock clustering. Note: ***/**/* indicate that the coefficient estimates are signicantly different from zero at the 1%/5%/10% level. Table reports p-values of the "Differences-in-Sargan" test for endogeneity and Hansen over-identification test.

	IV		OLS	
Variable	3 months	6 months	3 months	6 months
Demands	0.391***	0.354***	0.019*	0.021**
	(0.115)	(0.116)	(0.011)	(0.010)
Marketability	0.025	-0.008	0.043	0.052*
	(0.030)	(0.026)	(0.038)	(0.027)
Demands X Marketability	-0.367***	-0.339***	-0.020*	-0.015
	(0.118)	(0.116)	(0.012)	(0.011)
Size	0.013	0.018	0.001	0.005
	(0.015)	(0.013)	(0.019)	(0.023)
Constant	-0.109	-0.315	0.273	0.158
	(0.394)	(0.362)	(0.536)	(0.645)
Observations	1563	1463	1613	1511
Adjusted R-squared	0.095	0.138	0.525	0.635
p-value Hansen	0.14	0.196	.	.
p-value C	0.000	0.000	.	.
Demands	0.378***	0.288***	0.020***	0.014**
	(0.103)	(0.090)	(0.007)	(0.007)
Marketability	-0.010	-0.026	0.024	0.027*
	(0.028)	(0.021)	(0.017)	(0.015)
Demands X Marketability	-0.341***	-0.245***	-0.011	-0.010
	(0.104)	(0.092)	(0.008)	(0.008)
Size	0.009	0.011	-0.001	0.008
	(0.012)	(0.010)	(0.018)	(0.021)
Constant	-0.117	-0.242	0.275	-0.014
	(0.308)	(0.275)	(0.510)	(0.597)
Observations	1517	1404	1517	1404
Adjusted R-squared	0.158	0.146	0.52	0.631
p-value hansen	0.150	0.180	.	.
p-value C	0.000	0.000	.	.

B Figures

Figure 1. Trades before and after the MRG change. Correlation between fund buys and lagged overexposure, $corr(buy_{i,s,t}, oexp_{i,s,t-1})$ for pension funds (solid line) and voluntary funds (dashed line).