Payday Matters: A Look at Trader Behavior within Pay Cycles

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Abstract

Security firms typically link trader compensation to performance. We examine how this influences trader behavior within a pay-for-performance measurement interval. Institutional traders employed at a U.S. broker-dealer trade more actively on their last day of trading in a monthly pay cycle. Retail traders, who trade on their own behalf, do not exhibit this behavior. Institutional traders intensify their trading at the very last moment in order to increase their ensuing compensation payout. We label this behavior the payday effect. While trading activity rises at the end of a pay cycle, trading performance declines.

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1 Introduction

In this paper, we examine how professional stock traders respond to incentive compensation. Professional traders, who work on U.S. institutional trading desks, are often heavily, if not entirely, compensated on their trading performance and trader payouts are determined over defined measurement intervals.[1] Such compensation schemes, which are meant to align the interests of traders with the security firms they work for, may also cause both parties' interests to diverge at certain points in time. Our paper explores how and why this may occur. Our primary results are based on 361 professional traders, who traded the capital of a U.S. broker dealer intraday. The traders were compensated entirely on their ability to generate intraday trading profits utilizing firm capital.

Previous studies have found that incentive compensation can lead to behavioral distortions among investment managers. For example, Carhart et al. (2002) find high performing mutual fund managers "lean-for-the-tape," or inflate quarter-end portfolio prices with last minute purchases of stocks already held. Chevalier and Ellison (1997) and Brown et al. (1996) find mutual fund managers increase their risk-taking as the end of the year approaches. And Lakonishok et al. (1991) find pension fund managers alter their portfolio holdings just prior to quarter and year-ends, or they engage in behavior consistent with "window dressing."

There are very few studies which directly observe how people respond to incentive compensation contracts.[2] The lack of direct research in this area is most likely due to confidentiality issues, which commonly arise with personnel data. In our study, we know the precise terms of employee compensation including how their compensation is determined and over what time interval their performance is measured. We also have detailed data on every decision employees make within their performance measurement period. Such information provides a robust setting

[1]For example, Knight Trading Group compensates their proprietary traders solely on trading performance (Ip 2000).

[2]We are not aware of any financial studies that directly observe compensation contracts and employee behavior (note, the studies mentioned above do not examine investment manager compensation). There have been some direct analyses of compensation contracts and behavior in other settings, though, including auto glass workers (Lazear 2000), tree farm workers (Paarsch and Shearer 1999), and Navy recruiters (Asch 1990).

for directly measuring behavioral responses to incentive compensation.

The traders were exposed to a symmetrical, rather than an asymmetrical, compensation contract in which they absorbed their trading losses (100%) and shared their trading gains (typically 70-80%) with the firm.[3] Performance was measured and payouts occurred on a month-to-month basis. Our assumption is that incentive contracts like these will cause institutional traders to engage in unusual trading behavior just prior to being evaluated or paid. We denote this as the "payday effect" hypothesis. The payday effect is most closely related to the seasonal behavioral distortions of mutual fund managers who try and raise their performance just prior to a quarter-end close by purchasing stocks already held (Carhart et al. 2002) or fund managers who alter their risk-taking as the end of the year approaches in response to the incentives created by both the flow-performance relationship (Chevalier and Ellison 1997) and the funds overall standing among a peer group of funds (Brown et al. 1996). In a non-financial setting, the payday effect is similar to the behavior of recruiters and sales professionals who exert more effort at the end of their evaluation period in order to meet a quota (e.g., Asch 1990 and Oyer 1998).

Our empirical results support the payday effect hypothesis. Institutional traders engage in higher than normal trading just prior to being evaluated or paid. This behavior holds when controlling for certain factors that may cause their trading activity to rise. We do not find signs of this behavior when we analyze the trading behavior of a matched sample of 595 retail traders who manage their own accounts and trade through the firms' brokerage operation. Presumably institutional traders trade more actively just prior to being evaluated in order to increase their monthly payout. Our findings are thus consistent with an incentive to "gamble" at the end of an assessment period, which has been found in both financial and non-financial settings (e.g., Carhart et al. 2002, Chevalier and Ellison 1997, Brown et al. 1996, Asch 1990, and Oyer 1998). While trader activity rises at the end of a pay cycle, we also find below average performance at the end of a pay cycle. This suggests that the payday effect can reduce the efficiency of incentive contracts resulting in an agency cost. Incentive compensation schemes may not always

[3]Incentive compensation schemes can considerably differ among traders at other firms or among other types of market participants (investment managers, hedge fund managers, etc.).

be desirable if employees engage in heightened risk-taking in response to their incentive pay.

While our study improves the understanding of professional traders employed in U.S. equity markets, our primary focus is to examine if incentive compensation directly causes variations in institutional trader behavior. In this respect, our study is related to a large literature that studies the effect of performance evaluation schemes on employee behavior. [4] The systematic deviations in behavior we observe are not only of interest to the traders themselves. The traders' actions can have far-reaching implications. For example, market prices can be influenced due to institutional traders' trading frequency and close proximity to the price-setting process. Our sample traders continually provide and consume liquidity in U.S. equity markets. In total, they execute 7.3 billion shares in just under four years. The traders' actions also have likely implications for the firm's stakeholders. The inverse relationship between aggressive trading and below-average performance at pay-cycle end imposes a cost to the firm since they receive a percentage of the traders' trading profits.

Agency relationships cause institutional traders to increase their trading activities at the end of their monthly pay cycle, but behavioral theories are useful in understanding what extent traders will deviate from their normal trading activities. For example, Coval and Shumway (2005) and Garvey et al. (2007) find that when professional traders experience prior trading losses in the morning, they subsequently trade more actively or increase their risk taking in the afternoon. We find similar evidence of this behavior when applied to our setting. When traders experience a cumulative trading loss leading up to the close of their monthly pay cycle, they become much more active on their last day of trading. Trading activity increases with the magnitude of the loss. This result is likely driven by an inner desire to recover from a loss, just prior to the close of trading books and the formal assessment of trader compensation. When traders experience a cumulative trading performance closer to zero, this registers psychologically as a break-even or near break-even performance and the payday effect is much less likely to occur. Traders' decisions to trade more actively in the presence of loss is consistent with both

[4] See Prendergast (1999) for a review of the literature on incentives.

the decision-making framework of Kahneman and Tversky's (1979) prospect theory and also with the way people tend to frame their choices in a multi-period setting (Thaler and Johnson 1990). In our case, traders are likely focusing on their cumulative performance as a reference point. In order to avoid taking a loss, traders become more risk-seeking in an attempt to, at the very least, break-even. This leads to a rise in trading just before performance is assessed and compensation payouts occur. After an evaluation period is closed, trader activity resorts back to normal levels.

In the presence of a prior trading gain, traders may become risk averse just prior to a pay cycle close which would be consistent with prospect theory. On the other hand, traders may feel like they are playing with "house money" (Thaler and Johnson 1990) or they may become increasingly overconfident about their recent success (Gervais and Odean 2001). Both of these latter theories indicate that trading activity will rise just prior to performance being assessed. We find that when traders experience a cumulative trading gain, trading is higher than normal leading up to, on, and immediately after the close of an evaluation period. Trading activity increases with the magnitude of the gain. We suspect this rise in trading activity is the result of traders framing their decisions in a manner consistent with the house-money effect and or traders becoming increasingly overconfident as they attribute their ongoing success to skill, which leads to excessive trading. This excessive trading results in a problem for both the firm and the trader.

The remainder of our paper proceeds as follows. In the subsequent section we discuss our data. Next, we lay out our empirical results which test the payday effect hypothesis and its' implications on performance. Lastly, we provide concluding remarks.

2 Data

The data for our study are obtained from a U.S. broker-dealer. The firm had several trading operations. In their brokerage operation, they provided direct access trading and support to both institutional and retail clients. Direct access brokers differ from more traditional brokers in that they allow their users to control where and how their orders are routed for execution.

Consequently, direct access brokers mainly attract institutional or professional type traders. [5] The firm also had internal proprietary trading operations. Our analysis primarily focuses on the firms' 361 traders who were employed on the short-term proprietary trading desk. These traders were not executing orders on behalf of a client. Instead, they traded the firm's capital in order to generate intraday trading profits. The traders were compensated entirely on their short-term trading performance, which was measured on a month-to-month basis. The traders were responsible for their trading losses. Each month, the firm issued percentage payouts based on traders' prior month trading profits. The last day in a monthly pay cycle is three trading days before the last trading day of each month. [6] Why would traders choose to work under a system in which they absorb their trading losses and receive only a percentage of their trading gains? There are various reasons for this. Traders, who work on behalf of a firm typically have access to more trading capital, better trading technology, benefit packages, training, camaraderie with other like traders, etc.

While our focus is on institutional traders, we also examine data on independent or retail traders who traded through the firm's brokerage operation. Data on retail traders is of interest because retail traders trade their own account and can make withdrawals from their brokerage account at any time. Thus, their trading activity serves as a useful comparison to the firm traders who were governed by a compensation contract. The 361 firm traders all trade in at least ten trading days in a month and close out more than 90% of their trades intraday. Therefore, in order to make a like comparison with the retail traders, we select retail traders with the same minimal criteria. There are 595 retail traders who trade through the firm's brokerage business that meet these two criteria. [7]

Data on both groups of traders are in the form of a transaction database and spans the

[5] A considerable amount of trading activity in U.S. equity markets flows through Direct Access brokerage firms. For example, Bear Stearns (Goldberg and Lupercio 2004) notes that approximately 40% of Nasdaq and NYSE trading volume is executed by active traders (25+ trades per day) who use Direct Access brokers.

[6] The firm uses this system due to trade date + 3 settlement procedures. This ensures that by the last calendar trading day of each month all trading will have been settled and end-of-month pay checks are issued.

[7] If trading more actively is considered a sign of financial sophistication, one could argue that our retail trader selection criteria is somewhat biased because sophisticated traders may be more disciplined and less likely to deviate from their normal trading patterns. However, behavioral studies have shown that market professionals, or more sophisticated traders, often suffer from behavioral biases in their decision-making.

near four-year period October 7, 1999 to August 1, 2003. For every order request, we have the identity of the trader, the time of execution, the market where the order was sent, the original volume submitted, the executed volume, the execution price(s), the stock symbol, the order type, the contra party, the location of the trader in the U.S., and various other information concerning the trade execution and executing account.

Both the institutional and retail traders only traded equities and they mainly traded Nasdaq listed stocks (99% and 90% of institutional and retail trader activity respectively). However, neither group was under any obligation to do so. Professional traders who engage in short-term trading strategies are attracted to Nasdaq stocks because of their fully electronic trading environment. In contrast, most NYSE-listed trading occurs through the NYSE specialist, which can considerably slow down the execution process. [8] Execution speed is a crucial factor for professional traders engaging in short-term trading strategies.

While nearly all of the traders' trades are closed out intraday, we do not have the trading profits on these intraday round-trip trades, which are needed for subsequent analysis. In order to measure trader performance, we match up the intraday trades using a first-in first-out (FIFO) matching algorithm. For every stock, and for all traders, we matched opening trades with the subsequent closing trade(s) in the same day. In order to do this, we searched forward in time each day until the opening position was closed out, keeping track of accumulated intraday inventory and the corresponding prices paid or received. We were able to match up a high percentage of trading activity using our matching algorithm. For example, 99.8% of trader's trades can be matched intraday and 96.7% of all trader-day observations have a 100% match rate.

[8] Approximately 80% of NYSE-listed volume was executed at the NYSE during our sample periods. Source: *www.nyse.com/pdfs/NYSEMarketQualityFeb2003.pdf.*

3 Empirical Results

3.1 Empirical Design and Data Summary

Our main objective is to test whether or not performance-based compensation schemes influence institutional trader behavior. Specifically, we examine if traders deviate from their normal trading patterns at certain times within their monthly evaluation period. The data is first normalized on a trader-by-trader and month-by-month basis in order to derive economic meaning from the data analysis. We normalize the data on a trader-by-trader basis because trader behavior varies across trader. For example, executing 20 thousand shares one day means very different things to a trader who rarely trades more than 10 thousand shares a day than to one who's daily trading average exceeds more than 100 thousand shares per day. We normalize the data on a month-by-month basis because trader behavior varies over time due to changing market conditions, trader experience, etc. A monthly interval captures the time-varying property of trader behavior within a pay cycle.

In order to normalize the data and correct for differences across trader and time, similar to Coval and Shumway (2005), we calculate the mean and standard deviation of daily shares traded for every trader (both institutional and retail) using data for every day they traded in an actively traded month. We define an actively traded month as one in which traders trade in at least ten trading days in a respective month (or approximately one-half of the month). Recall, all of our traders meet this criteria in at least one month, but not all traders meet this criteria in every month throughout our entire sample. The actively traded month restriction is necessary because traders enter and exit our firm in a dynamic fashion and some months have too few observations to make meaningful intra-month comparisons (see below). [9] Our second step is to use the trader specific means for each month to demean the trader's daily shares traded. Then we divide the demeaned data by the trader specific standard deviation of each trader.

Table 1 provides some summary information on the traders and our data. First, the firm

[9] Over 97% of the shares traded occurred in actively traded months. We estimated our empirical results using all trader months and found qualitatively similar results.

traders are much more active than the retail traders. The 361 firm traders combine to execute 7.3 billion shares (4.3 million trades). The average institutional trader executes 157,983 trades per day (92 trades). On the other hand, the 595 retail traders combine to execute 350 million shares (874 thousand trades). The average retail trader executes 10,660 shares per day (26 trades). While the institutional traders trade much more often, they do not seem to generate a significant amount more in trading revenues. The firm traders generate \$2.96 million in gross trading profits and the retail traders generate \$1.80 million. Overall, the U.S. equity markets experienced a bearish trend during our approximate four-year sample period.

3.2 The Payday Effect

The payday effect hypothesis predicts that agency relationships will cause institutional traders, whose compensation is linked to their performance, to engage in unusual trading behavior at the end of their respective evaluation period. Retail traders, who trade on their own behalf, should not exhibit signs of this unusual behavior because they can make withdrawals from their brokerage account at any time. In order to test the payday effect hypothesis, we test for abnormal trading activity around the close of a pay cycle. Our main period of interest is the last day of trading in a monthly pay cycle. This is the trader's last chance to effectively alter their month-to-date performance. We also look at trading activity in the two days before and after the last day of trading. Finally, trading activity in all other trading days in a monthly pay cycle is measured too.

To measure trader abnormal trading activity over a trading month, we estimate the following regression using Generalized Method of Moments (GMM):

$$\overline{Share}_{i,t} = \beta_1 Other_{i,t} + \beta_2 Before_{i,t} + \beta_3 Close_{i,t} + \beta_4 After_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $\overline{Share}_{i,t}$ is the normalized shares traded for each trader i on day t; dummy variables take the value of 1, or 0 otherwise, if a trading day is not one of the last three trading days in a monthly pay cycle (*Other*), one or two days before the last trading day in a monthly pay cycle (*Before*), the last trading day in a monthly pay cycle (*Close*), and one or two days after the last trading day in a monthly pay cycle (*After*); the random error term is $\varepsilon_{i,t}$. Table 1 Panel A reports GMM estimation of Eq. (1) that pools together all traders. The coefficients represent the mean trading activity across the four selected time periods and the p-values reported either test the coefficients from zero or test whether the difference between the coefficients is equal to zero.

The parameter estimates of the regression support the payday effect. For example, traders trade 0.0646 standard deviations more than normal (average) on their last day of trading in a monthly pay cycle. This rise in trading activity is significantly different from zero and also from other monthly observation periods of note. There is also evidence of a rise in trading activity leading up to the close of a pay cycle. In the two days prior to the last day of trading, traders trade 0.0641 standard deviations more than normal. This increase in trading activity is significantly different from zero. While the institutional traders exhibit payday effects, the retail traders do not. There is little evidence of a rise in retail trading activity at the end of the month. In Table 2 Panel B, we run Eq. (1) on a trader-by-trader basis and report the mean and median coefficients. The p-values test the mean and median from zero. On a trader-by-trader basis, the results show even stronger support for the payday effect. For example, the mean (median) trader trades 0.0849 (0.0369) standard deviations more than normal on their last day of trading in a monthly pay cycle. Both mean (median) measures are significantly different from zero at the 1% level.

While institutional traders clearly increase their trading activity at the end of a pay cycle, there may be other factors driving this result. For example, the rise in trading activity may be the result of a trading continuation effect (Coval and Shumway 2005) or perhaps changes in market conditions, such as market volume and volatility. Volume and volatility are quite important for short-term traders, who often derive their trading profits from the bid-ask spread or anticipating price changes which is reflected through price volatility (Garvey and Murphy 2005). The rise in trading activity may also be driven by prior returns, i.e. trend following or contrarian trading. Finally, traders may trade differently at the end of the year for various incentives (Grinblatt and Keloharju 2001). Therefore, we estimate the following fixed effects regression in order to control for some of these factors:

$$\overline{Share}_{i,t} = \alpha_i + \beta_1 Before_{i,t} + \beta_2 Close_{i,t} + \beta_3 After_{i,t} + \sum \lambda \boldsymbol{X} + \varepsilon_{i,t} \qquad (2)$$

where $\overline{Share}_{i,t}$ is the normalized shares traded for each trader i at day t, α_i is a trader-specific constant term; $Before_{i,t}$, $Close_{i,t}$, and $After_{i,t}$ are dummy variables assigned for our three monthly time periods, the coefficients for these dummy variables measure the difference between the abnormal trading behavior around the pay-cycle and other periods in a month; $\boldsymbol{X}$ contains a vector of control variables including: the lagged normalized shares traded for each trader i, the log daily trading volume on the Nasdaq stock market at day t, the daily volatility on the Nasdaq stock market at day t, which is measured by dividing the difference in the Nasdaq composite high and low by the Nasdaq composite index opening level, the one-month lagged cumulative return on the Nasdaq composite index prior to time t, and a dummy variable that takes the value of 1, or 0 otherwise, if day t is in the month of December.

Table 3 reports the regression results for both institutional and retail traders. The payday effect remains strong among institutional traders after controlling for certain factors that may potentially cause their trading activity to rise.[10] The coefficient representing the last day of trading (and before and after this day) in a monthly pay cycle is positive and highly significant. The control factor coefficients are all positive and statistically significant too. The rise in trading activity just prior to the close of a pay cycle is consistent with the hypothesis that professional traders alter their regular behavior in response to their compensation scheme. These traders varied their effort over time, which is inline with the economic literature on how employees reallocate their efforts in response to performance evaluation dates. For example, Asch (1990) examines Navy recruiters who receive compensation based on the number of recruits they are able to enlist. The recruiter's performance gradually increases up until the end of their evaluation

[10] We estimated Eq. (2) using trader's number of trades per day rather than trader's daily shares traded. Eq. (2) yields qualitatively similar results with the alternative dependent variable. We focus on daily shares traded because traders may engage in strategies to split up their orders or market conditions may cause their orders to be split up. Thus, daily shares traded will give a more precise measure of trading activity.

period. After performance is assessed at a given evaluation date, productivity precipitously declines. Similar evidence of this behavior has been found among sales force employees. Oyer (1998) finds that sales force employees influence business seasonality by adjusting their effort levels over time. The salespeople are motivated to exert more effort at the end of the fiscal year in order in order to try and reach annual profit or revenue goals. The intertemporal effort reallocation observed in these studies seems consistent with how the institutional traders varied their trading activity over their evaluation period.

3.3 Prior Performance and the Payday Effect

The findings above show that traders engage in higher than usual trading just prior to the close of their monthly pay cycle. While principal-agent relationships are a necessary condition for payday effects to exist, behavioral theories are useful in understanding what extent traders will deviate from their normal trading behavior. For example, behavioral research indicates that people act differently when confronted with risky choices involving gains and losses. If traders experience a trading loss, they may trade more aggressively in order to erase their loss and, at the very least, break-even or get back to their original reference point. The notion that decision-makers engage in risk-seeking behavior when confronted with a loss is a central feature of Kahneman and Tversky's (1979) prospect theory, and the way decision-makers frame their choices over multi-period settings is further examined in Thaler and Johnson (1990). Some recent empirical research has found evidence that prior trading losses influence subsequent trader behavior. For example, both commodity and stock traders trade more actively, or they become more risk-seeking, in the afternoon trading session when they have experienced a prior morning loss (see Coval and Shumway 2005 and Garvey et al. 2007).

In our case, we believe traders' cumulative monthly trading profit serves a good estimate of the reference point. Trader payouts are based on this rolling profit number and so it seems highly unlikely that traders are not focused on this measure. Our assumption is that when traders experience a cumulative trading loss leading up to the end of a monthly pay cycle, their desire to recover from a loss will lead them to trade more aggressively.

While we expect a rise in trading activity when traders experience a cumulative trading loss, traders may trade more or less actively when they experience a cumulative trading gain. For example, prospect theory predicts that decision-makers will become risk averse in the domain of gains. An increase in risk aversion means that traders will trade more conservatively at the end of a monthly pay cycle in order to try and preserve their trading gains.

On the other hand, trading may rise in the presence of prior gains. Thaler and Johnson (1990) develop a quasi-hedonic editing hypothesis, which describes the way decision-makers frame their choices in a multi-period setting. In our case, this means that if traders experience a cumulative trading gain leading up to the end of an evaluation period, subsequent losses that traders perceive to be smaller than their cumulative trading gain will be integrated with traders' month-to-date cumulative trading gain. This integration process will facilitate a risk-seeking behavior (i.e. trading will increase) at the end of a pay cycle. Traders will psychologically see themselves as above their break-even point for the month, even if they incur subsequent losses just prior to a pay cycle close. Thaler and Johnson (1990) label their framing theory as the "house money effect."

Trading activity may also rise in the presence of trading gains if traders become increasingly overconfident about their past gains. Gervais and Odean (2001) develop a model in which traders take too much credit for their past successes, which leads them to become increasingly overconfident. As traders become increasingly overconfident, they engage in excessive trading. And higher amounts of trading activity result in lower trading profits.

To see how prior gains and losses interact with traders trading activity at the end of a monthly pay cycle, we estimate the following regression:

$$\begin{aligned} \overline{Share}_{i,t} &= \alpha_i + \beta_1 Before_{i,t} \times G + \beta_2 Close_{i,t} \times G + \beta_3 After_{i,t} \times G \\ &\quad + \beta_4 Before_{i,t} \times L + \beta_5 Close_{i,t} \times L + \beta_6 After_{i,t} \times L + \sum \lambda \boldsymbol{X} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where *G (L)* is an indicator that takes the value 1 if trader i is experiencing a cumulative trading gain (loss) prior to the pay-cycle measure in a particular month, and 0 if otherwise; cumulative trading gains and losses are determined by matching up the intraday round-trip trades. Recall that we are able to match up 99.8% of the 4.3 million trades. The control variables are discussed in Eq. (2).

The regression results are reported in Table 4. Prior trading performance is correlated with subsequent trading activity. When traders experience a prior trading loss they significantly increase their trading activity on the last day of trading in their evaluation period. The dummy variable, which represents trading on the last trading day, is positive and significant at the 1% level. There is weaker evidence that trading activity rises in the days leading up to the close of a pay cycle. The coefficient representing a cumulative loss two days prior to a pay cycle's close is positive and significant at the 10% level. After the pay cycle is closed and performance is assessed, trading activity reverts back to normal. The coefficient representing a cumulative loss two days after a pay cycle's close is not significant.

When traders experience a prior trading gain they significantly increase their trading activity on the last day of trading in their evaluation period. The dummy variable which represents trading on the last trading day is positive and significant at the 1% level. There is also strong evidence that in the presence of prior gains, trading activity is higher than normal leading up to the close of a pay cycle and after the close of a pay cycle. We interpret this result to mean that traders, who experience trading gains, either frame their choices consistent with the house money effect and or they become increasingly overconfident with their prior trading success. This is what leads them to engage in higher than usual trading in the days leading up to a pay cycle close, the last day in a pay cycle, and the days after a pay cycle closes.

Our results linking prior performance to the payday effect provide a possible explanation to potential agency conflicts arising between professional traders and the security firms they work for. This explanation is consistent with that proposed in the mutual fund industry. Mutual fund managers (companies) are often given compensated-based rewards based on the flow of investments into their funds (management fees are calculated based on a percentage of the funds' assets) and their performance relative to a comparison group of funds. Chevalier and Ellison (1997) attribute the incentive of flow-performance to an increase in mutual fund risk-taking, while Brown et al. (1996) attribute the incentive of peer performance to an increase in mutual fund risk-taking. Both studies find mutual fund managers have incentives to gamble late in the year, in order to improve performance. In our case, institutional traders have an incentive to gamble at the end of their pay cycle in order to increase their compensation payout.

While the regression above provides a straightforward test of the hypothesis that a relationship exists between the payday effect and traders' prior cumulative performance, we would like to measure the robustness of this relationship. In order to do so, we use an alternative method to provide a more detailed picture of the interaction between prior performance and the payday effect. We segregate the gains and losses into four profit categories and rerun our Eq. (2) regression. The cumulative profits (CP) are sorted into profit categories of $CP \geq \$500$, $\$0 < CP < \$500$, $\$0 > CP > -\$500$, and $CP \leq -\$500$. [11] The regression results are reported in Table 5.

When traders experience a large gain ($CP \geq \$500$) or a large loss ($CP \leq -\$500$), the regression results are similar to our prior performance regression results. The payday effect is strong in both the presence of prior trading gains and losses. However, for small gains ($\$0 < CP < \$500$) the results are much weaker. And in the case of a small prior loss ($\$0 > CP > -\$500$), the results are no longer significant for abnormal trading at the end of a pay cycle. While prior gains and losses are correlated with trading activity, the results are much more pronounced when traders experience large gains or losses. When traders experience prior gains or losses closer to zero, this also registers psychologically as a break-even or near break-even performance. Consequently, traders to do not posses a strong desire to get-even, integration is less likely to occur, and traders are less likely to be overconfident.

[11] The unreported CP distribution shows that the number of observations is almost evenly distributed across our four CP categories.

3.4 Does the payday effect carry costs?

The analysis above demonstrates that institutional traders who are exposed to a linear compensation scheme systematically deviate from their normal trading behavior at the close of a pay cycle. The extent to which this occurs is largely dependent on a trader's prior outcomes. Institutional traders appear to intensify their trading at the very last moment in order to increase their ensuring compensation payout. Thus, a naturally related question arises: is this induced effort positively correlated with performance? If not, does it imply a dynamic phenomenon of the agency problem, hence an agency cost, in which symmetric incentive compensation schemes are unable to eliminate entirely?

To help address these questions, we first investigate whether trader performance varies across a trading month. Specifically, we estimate a regression similar to Eq. (1). The dependent variable is the normalized trading profit (rather than the normalized shares traded) for each trader i at day t ($\overline{Profit}_{i,t}$). The daily trading profit is determined by matching up the intraday round-trip trades. The regression results are reported in Table 6 Panel A.

While trading activity rises at the end of a pay cycle, trading performance declines. For example, traders trading profits are -0.0514 standard deviations less than normal on their last day of trading in a monthly pay cycle. Recall, this corresponds with a 0.0646 standard deviations rise in trading activity on this day. The decline in performance on the last day of trading is highly significant. Trading profits subsequently increase after the pay cycle is closed.

Trader performance, similar to trader activity, can be affected by various external market factors and so our next step is to control for potentially performance-altering factors in a regression setting. Our regression takes a similar form to Eq. (2). The dependent variable is the normalized trading profit for each trader i at day t ($\overline{Profit}_{i,t}$). The vector of control variables include: the lagged normalized profit for each trader i, the log daily trading volume on the Nasdaq stock market at day t, the volatility of the Nasdaq composite index at day t, which is measured by dividing the difference in the Nasdaq composite high and low by the opening level, and the return on the Nasdaq index at day t.

The results are reported in Table 6 Panel B. Our initial finding that traders experience below-average performance at the end of a pay cycle does not change when controlling for factors that may influence trader performance. Trading performance declines on the last day of trading in a pay cycle and then rises in the days immediately following a pay cycle close. The coefficients representing trader's prior trading performance, Nasdaq volume, and the Nasdaq market return are all positively correlated with trader performance at time t.

Our finding that trading activity rises and trading performance declines at the end of a pay cycle provides some interesting implications for the existing literature in both behavioral finance and agency theory. From a behavioral perspective, our results support the key prediction of the "overconfidence" model developed by Gervais and Odean (2001). Gervais and Odean model the process by which traders learn about their ability and how a bias in this learning creates overconfident traders. Their model predicts that overconfident traders will increase their trading volume and thereby lower their expected profits. From an agency perspective, our results indicate agency problems can arise with symmetric compensation contracts between security firms and the traders who work on their behalf. The payday effect is not cost-free and it clearly has the potential to reduce the efficiency of incentive compensation. This supports the argument that symmetric compensation incentives are not sufficient for compatibility of principal and agent interests in financial markets. For example, Modigliani and Pogue (1975) contend that symmetric performance contracts may instill incentives for portfolio managers to choose risk levels that exceed owners' optimal risk levels.

Our findings also have some interesting practical implications. If the payday effect is costly, firms would naturally like to implement control measures to prevent it. How can they do so? One option is to change trader compensation to base pay or asymmetric pay. While this approach would eliminate the payday effect, it is probably not optimal under a cost-benefit consideration. Empirical research has found that incentive compensation schemes are effective in increasing employee productivity (e.g., see Lazear 2000 and Paarsch and Shearer 1999) and Starks (1987) shows symmetric contracts, while not necessarily eliminating agency costs, are preferable to asymmetric contracts in aligning principal and agent interests. An alternative option is to examine the payday effect from a behavioral standpoint. For example, a firm could alter trader evaluation dates without giving prior knowledge to their traders. Thus, traders would be kept off guard and unable to anchor their performance to a specific deadline. Traders seemingly view the last day of trading in a monthly pay cycle as their last chance to alter their monthly payout. Simply moving this last day of trading around could be an effective way for a firm to reduce or eliminate the payday effect.

4 Conclusion

The compensation of professional traders who work on U.S. institutional trading desks is in large part driven by their trading performance. Our paper directly examines how pay-for-performance compensation schemes influence trader behavior. In particular, we focus on how traders react just prior to the close of their evaluation or pay cycle period.

Our primary results are based on 361 institutional traders who traded the capital of a U.S. broker-dealer intraday. The traders combined to execute 7.3 billion U.S. equity shares (4.3 million trades) on behalf of the firm over the near four-year period October 1999 to August 2003. Trader compensation was entirely based on performance. Performance was formally assessed and payouts occurred on a month-to-month basis.

We find that traders engage in higher than usual trading just prior to the close of their monthly pay cycle. This unusual rise in trading is not driven by external market factors which may cause their trading activity to rise. Matched samples of 595 retail traders, who trade in a similar manner and are not governed by an institutional compensation contract, do not exhibit this behavior. The institutional traders' behavior appears driven by a desire to alter their performance or compensation just prior to a payout. We label this behavior the payday effect. Although traders try and improve their performance just prior to being evaluated, their actions actually cause the opposite effect to occur. When traders increase their trading activity on the last day of a pay cycle, their trading performance declines on this day and their monthly payout is subsequently lower.

Our paper takes an initial step forward in examining how institutional compensation schemes influence professional trader behavior. What implications, if any, the payday effect has on market-wide prices is dependent on the trading behavior of market professionals employed at other financial institutions. Future studies which directly examine institutional compensation structure along with employee behavior would be insightful in helping to further develop research in this area.

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Table 1
Data

This Table provides summary statistics for 956 short-term (intraday) stock traders. The traders traded over the near four-year period October 1999 to August 2003. Institutional traders traded the capital of a U.S. broker dealer while retail traders traded on their own behalf through the firm's brokerage operation. Institutional traders were compensated entirely on their monthly trading performance.

	Institutional Traders	Retail Traders
Total		
Number of traders	361	595
Shares traded	7,306,271,452	350,274,863
Trades	4,266,326	873,891
Percentage of trades matched intraday	99.8%	97.3%
Gross profits	$2,960,993	$1,795,762
Monthly trader averages		
Shares traded	2,870,833	173,403
Trades	1,676	432
Gross profits	$1,163	$889
Daily trader averages		
Shares traded	157,983	10,660
Trades	92	26
Gross profits	$64	$55

Table 2
Abnormal Trading

This table presents monthly trading activity for 361 institutional and 595 retail traders during October 1999 to August 2003. Both groups of traders conducted their trading through a U.S. broker dealer. Institutional traders traded the capital of the firm while retail traders traded on their own behalf through the firm's brokerage operation. Institutional traders were compensated entirely on their monthly trading performance. The last trading day included in a monthly evaluation period is three trading days prior to the last trading day of each month. The data are normalized by trader on a monthly basis. Panel A. reports results of a generalized method of moments (GMM) regression model with dummies for four monthly trading periods and no intercept. The dependent variable is traders' daily normalized shares traded. Dummy variables take the value of 1, or 0 otherwise, if a trading day is not one of the last three trading days in a monthly pay cycle (*Other*), one or two days before the last trading day in a monthly pay cycle (*Before*), the last trading day in a monthly pay cycle (*Close*), and one or two days after the last trading day in a monthly pay cycle (*After*). The coefficients represent traders' average normalized shares traded. The p-values test for differences between the four monthly periods. Panel B. reports results of the mean/median normalized shares traded across traders for each monthly period. The p-values test if the mean and median are significantly different from zero.

Panel A. Aggregate traders

	Institutional Traders Abnormal Trading Changes		Retail Traders Abnormal Trading Changes	
	Coefficient	p-values	Coefficient	p-values
Other (β_1)	-0.0160	(0.0003)	-0.0046	(0.3037)
Before (β_2)	0.0641	(0.0002)	0.0299	(0.0980)
Close (β_3)	0.0646	(0.0001)	0.0169	(0.4913)
After (β_4)	0.0166	(0.4377)	0.0011	(0.9566)
$\beta_1 = \beta_2$		(0.0000)		(0.0874)
$\beta_1 = \beta_3$		(0.0000)		(0.4089)
$\beta_1 = \beta_4$		(0.1604)		(0.7886)
$\beta_3 = \beta_4$		(0.0435)		(0.5905)

Panel B. Mean/median measured trader-by-trader

	Mean	p-values	Mean	p-values
Other	-0.0236	(0.0001)	-0.0048	(0.3884)
Before	0.0915	(0.0024)	0.0156	(0.5352)
Close	0.0849	(0.0017)	0.0101	(0.7604)
After	0.0529	(0.1240)	0.0001	(0.9963)
	Median	**p-values**	**Median**	**p-values**
Other	-0.0143	(0.0000)	0.0000	(0.8107)
Before	0.0515	(0.0097)	-0.0237	(0.7280)
Close	0.0369	(0.0052)	-0.0730	(0.1896)
After	-0.0010	(0.6999)	-0.0711	(0.0800)

Table 3
Market Control Factors and Abnormal Trading

This table reports results for two fixed effects regressions which measure institutional and retail traders trading activity while controlling for certain market factors. The sample encompasses 361 institutional and 595 retail traders who conducted their trading through a U.S. broker-dealer during October 1999 to August 2003. Institutional traders traded the capital of the firm while retail traders traded on their own behalf through the firm's brokerage operation. The data are normalized by trader on a monthly basis. The dependent variable is traders' daily normalized shares traded ($\overline{Share}$). Dummy variables take the value of 1, or 0 otherwise, if a trading day is two days before institutional traders' pay cycle close (*Before*), the last day in a pay cycle (*Close*), or two days after a pay cycle close (*After*). Market control factors also serve as independent variables including: the log daily trading volume on Nasdaq, the daily volatility of Nasdaq, which is measured by the difference in the Nasdaq composite index daily high/low divided by the opening level, the previous month's return on the Nasdaq composite index, and a dummy variable that takes the value of 1, or 0 otherwise, if trading occurs in the month of December.

	Institutional Traders		Retail Traders	
	Coefficient	p-values	Coefficient	p-values
Before	0.0651	(0.0000)	0.0364	(0.0503)
Close	0.0917	(0.0000)	0.0276	(0.2808)
After	0.0645	(0.0023)	0.0143	(0.4468)
Lagged $\overline{Share}$	0.1880	(0.0000)	0.0996	(0.0000)
Daily Nasdaq Volume	0.8354	(0.0000)	0.5468	(0.0000)
Daily Nasdaq Volatility	1.4860	(0.0005)	0.5322	(0.1982)
Previous Month Nasdaq Return	0.2005	(0.0007)	0.1284	(0.0889)
December Dummy	0.0347	(0.0387)	0.0063	(0.7673)
R^2	4.51%		1.30%	
Obs.	46,247		32,859	

Table 4
Prior Performance, Market Control Factors and Abnormal Trading

This table reports results of a fixed effects regression which measures the relation between institutional traders trading activity and their prior trading performance. The sample period is October 1999 to August 2003. The 361 traders worked on behalf of a U.S. broker dealer and they were compensated entirely on their monthly trading performance. The daily share amount traded is normalized by trader on a monthly basis. The dependent variable is traders daily normalized shares traded ($\overline{Share}$). Dummy variables take the value of 1, or 0 otherwise, if a trading day is two days before institutional traders' pay cycle close (*Before*), the last day in a pay cycle (*Close*), or two days after a pay cycle close (*After*). $G(L)$ is an indicator that takes the value 1 if trader i is experiencing a cumulative trading gain (loss) prior to the pay-cycle measure in a particular month, and 0 if otherwise. Cumulative trading gains and losses are determined by matching up the intraday round-trip trades. Market control factors also serve as independent variables including: the log daily trading volume on Nasdaq, the daily volatility of Nasdaq, which is measured by the difference in the Nasdaq composite index daily high/low divided by the opening level, the previous month's return on the Nasdaq composite index, and a dummy variable that takes the value of 1, or 0 otherwise, if trading occurs in the month of December.

	Coefficient	p-value
$Before \times G$	0.0951	(0.0000)
$Close \times G$	0.1034	(0.0000)
$After \times G$	0.1068	(0.0003)
$Before \times L$	0.0363	(0.0925)
$Close \times L$	0.0804	(0.0001)
$After \times L$	0.0239	(0.4133)
$Lagged\ \overline{Share}$	0.1879	(0.0000)
$Daily\ Nasdaq\ Volume$	0.8348	(0.0000)
$Daily\ Nasdaq\ Volatility$	1.4831	(0.0006)
$Previous\ Month\ Nasdaq\ Return$	0.1921	(0.0012)
$December\ Dummy$	0.0350	(0.0368)
R^2	4.52%	
Obs.	46,247	

Table 5
The Magnitude of Prior Performance and Abnormal Trading

This table reports results of four fixed effects regressions which measure the relation between institutional traders' trading activity and the magnitude of their prior performance. For each month, the cumulative trading profits (CP) two days before a pay cycle's close are used to segregate the trader observations into four profit categories. The coefficients and their respective p-values in parentheses are listed below. See Table 3 for a discussion of the regression variables.

	Prior Performance			
	$CP \geq \$500$	$\$0 < CP < \$500$	$\$0 > CP >$ -\$500	$CP \leq -\$500$
Before	0.1216	0.0517	-0.0464	0.0890
	(0.0001)	(0.0857)	(0.1308)	(0.0027)
Close	0.1222	0.0655	0.0337	0.1005
	(0.0001)	(0.0281)	(0.2588)	(0.0006)
After	0.2049	-0.0041	-0.0280	0.0488
	(0.0000)	(0.9205)	(0.4998)	(0.2306)
Lagged $\overline{Share}$	0.1880	0.1888	0.1890	0.1885
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Daily Nasdaq Volume	0.8165	0.8057	0.7996	0.8101
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Daily Nasdaq Volatility	1.5471	1.6214	1.6468	1.5669
	(0.0003)	(0.0002)	(0.0001)	(0.0003)
Previous Month Nasdaq Return	0.1930	0.1952	0.1995	0.2048
	(0.0011)	(0.0010)	(0.0008)	(0.0006)
December Dummy	0.0343	0.0324	0.0317	0.0328
	(0.0408)	(0.0533)	(0.0591)	(0.0507)
R^2	4.51%	4.42%	4.41%	4.45%
Obs.	10,591	12,098	11,529	12,029

Table 6
Overall Performance and the Payday Effect

This table presents performance results for 361 institutional traders who traded the capital of U.S. broker-dealer during October 1999 to August 2003. The traders were compensated entirely on their monthly trading performance. For each trader, the daily trading profit is calculated by matching up the intraday round-trip trades. The daily gross profits are then normalized by trader on a monthly basis. Panel A reports results of a generalized method of moments (GMM) regression model with dummies for four monthly trading periods and no intercept. The coefficients represent traders' average normalized gross trading profit for four monthly periods. The p-values test for differences between the four monthly periods. Panel B. reports results of a fixed effect regression. The dependent variable is trader's normalized daily profit ($\overline{Profit}$). The independent variables include dummy variables representing the monthly trading periods and some market control factors.

Panel A. GMM estimation

	Coefficient	p-value
Other (β_1)	0.0009	(0.9101)
Before (β_2)	0.0160	(0.3310)
Close (β_3)	-0.0514	(0.0006)
After (β_4)	0.0572	(0.0053)
$\beta_1 = \beta_2$		(0.3710)
$\beta_1 = \beta_3$		(0.0008)
$\beta_1 = \beta_4$		(0.0058)
$\beta_3 = \beta_4$		(0.0000)

Panel B. Fixed effects regression with market control factors

	Coefficient	p-value
Before	0.0154	(0.3430)
Close	-0.0365	(0.0214)
After	0.0534	(0.0141)
Lagged $\overline{Profit}$	0.0715	(0.0000)
Nasdaq Volume	0.2207	(0.0000)
Nasdaq Volatility	0.6434	(0.1268)
Nasdaq Return	8.4678	(0.0000)
R^2	3.73%	
Obs.	46,247	