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Payday Effects: An Examination of Trader Behavior within Evaluation Periods

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Security firms typically link trader compensation to performance. We examine how this influences traders to allocate their trading activities over time. Traders employed at a U.S. broker-dealer trade more actively on their last day of trading in a monthly evaluation period. Self-employed traders, who trade on their own behalf, do not exhibit this behavior. Employed traders intensify their trading at the very last moment to increase their ensuing compensation payout. We label this behavior the payday effect. The payday effect is not driven by a change in market trading conditions, or due to traders possessing more information. Instead, we show that this behavior is highly dependent upon a trader's cumulative income within the performance evaluation period.

Keywords: Trading, Mental accounting, Loss aversion, Incentive compensation, Evaluation periods

Financial market participants, such as mutual fund managers, brokers, and traders, are often heavily, if not entirely, compensated on their performance. Performance is typically measured over a well-defined measurement interval. Such incentive compensation schemes are used to align the interests of employees with their firms. In this article, we examine how incentive compensation influences behavior. Specifically, we look at the effect of performance evaluation periods on professional equity trader behavior (i.e., trading activity). Understanding how incentive compensation impacts employee behavior has many useful applications. For example, it can help securities firms design optimal compensation schemes and provide insight into the implications incentive pay might have for security prices and/or market liquidity.

While there is widespread use of incentive compensation in the finance industry, there is little if any direct research examining the effects of incentive compensation on employee behavior. Data constraints have likely hindered research efforts in this area. Compensation contract data and corresponding worker output data are usually confidential and not easily obtainable. Because of this obstacle, many financial researchers have attempted to indirectly measure the link between incentive compensation and employee behavior. However, in such settings it is difficult to tell whether the observed underlying behavior is being driven by the compensation contract or some other factor. For example, researchers have examined the strategic behavior of fund managers around the end of the quarter (Carhart et al. [2002]) and end of the year (e.g., Chevalier and Ellison [1997], Brown et al. [1996]). The year-end/quarter-end closing date often has important implications for managerial incentive pay and or compliance requirements. The authors of these studies do not have any data (i.e., the compensation contract), though, on how fund managers are compensated. Our article fills this gap by including this data and directly examining how incentive compensation influences behavior.

Despite the paucity of direct research examining the effects of incentive compensation on employee behavior in financial settings, the economics literature has examined a variety of issues related to incentives in other settings.[1] In general, these studies provide evidence that employees respond to incentives (e.g., Paarsch and Shearer [1999], Lazear [2000]). However, an important finding in the incentive compensation literature is that not all responses induced by incentive compensation schemes are beneficial. For example, Asch [1990] and Oyer [1998] provide evidence on how

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incentive pay causes employees to engage in actions that are privately beneficial but publicly costly. For example, the employee's actions are costly in terms of overall efficiency. They show that incentive compensation causes recruiters and sales force employees to vary their productivity levels over time and to exert more effort just prior to the close of their evaluation period. Intertemporal effort reallocation in response to incentive compensation is not efficient, at least from the employer's perspective.

In this article, we examine the effects of incentive compensation in a financial market setting where traders can readily experience both gains and losses with their risky bets. In general, all incentive compensation contracts comprise two main components: (1) the monetary incentive and (2) the evaluation period over which performance is measured. The monetary incentive structure can vary considerably. For example, some employees are exposed to contracts that are nonlinear in performance measures (e.g., a bonus based on exceeding a sales quota), while others are exposed to contracts in which a linear or near-linear relation exists between performance and compensation. While monetary incentives can vary widely, all incentive contracts must have a discrete time interval over which an employee's performance is measured (i.e., the evaluation period or the pay cycle period). Our study focuses on the effects of this particular aspect of incentive compensation.

Trading settings provide an ideal setting for isolating the effect of a performance evaluation period. It is possible to examine the behavior of two traders who share a similar monetary incentive where one trader may be susceptible to a formal evaluation period for measuring their performance while another trader may not. For example, some traders earn their living trading for themselves while others trade on behalf of a firm. Many securities firms have proprietary trading programs where traders are hired to trade firm capital, but the trader's compensation contract is similar to that of a self-employed trader.[2] The key difference that arises between the two groups of traders is the evaluation period.

We obtain proprietary data on the transaction records of 361 employed traders, who traded the capital of a large U.S. broker-dealer over the four-year period ending August 2003. The traders were compensated entirely on their ability to generate intraday trading profits utilizing firm capital. The traders were exposed to an incentive compensation contract in which they absorbed their trading losses (100%) and shared their trading gains (typically 70–80%) with the firm. Performance was measured and payouts occurred on a month-to-month basis. We compare the trading activities of the employed traders with a matched sample of 595 self-employed traders. The self-employed traders are not subject to an evaluation period, and they keep 100% of their gains and absorb 100% of their losses. Both groups of traders have a clear incentive to trade profitably, yet the employed traders are subject to a well-defined evaluation period for measuring their performance while the self-employed traders are not.

An examination of the trading records of employed traders reveals that trader activity varies across the pay cycle period but consistently rises above average at the end of the pay cycle. We denote this behavior as the "payday effect." The payday effect is robust to alternative measures of trading activity and data outliers. We do not find any evidence of this behavior with the self-employed traders even though their incentive to trade profitably is similar to the employed traders. We consider alternative factors that might lead to an abnormal rise in trader activity at the end of the pay cycle. For example, the rise in trading activity could be the result of a rational response to certain market condition changes, the arrival of new information, or some other driving factor(s). We find the payday effect remains robust after controlling for changes in market returns, volume, volatility, and other factors that have been suggested to influence trade.

We test the possibility of private information as a rational motivator for trade by looking at the direction of future price changes after traders execute their orders. Private information does not appear to influence the payday effect. We test the possibility of whether trader's cumulative income within the pay cycle influences trading activity. Decision theorists have argued that decisions are rarely made in temporal isolation and that prior performance outcomes influence subsequent decision making. We find that a trader's cumulative income is correlated with trader activity at the end of the evaluation period. The magnitude of monthly cumulative gains and losses is important. Payday effects are strongest when traders exhibit a large cumulative gain or a large cumulative loss as the pay cycle period draws to a close. On the other hand, the payday effect weakens or vanishes when cumulative income is closer to the break-even point as the pay cycle period draws to a close.

We reconcile our findings with general theories on decision making. When firms set evaluation periods for measuring employee performance, we suspect this often causes employees to engage in mental accounting activities where they consider each pay cycle as a separate mental account and then frame concurrent decisions within the pay cycle together rather than evaluating them independently. Both rising cumulative gains and losses within the pay cycle may, in turn, stimulate an increasing desire to gamble. For example, Thaler and Johnson [1990] examine risky choice in a multi-period setting when, for example, a gain or loss has already occurred. They find people engage in risk-seeking behavior in *both* the presence of prior gains and losses. The effect of prior gains and losses is likely to be most pronounced at the end of the pay cycle because this is employees' last chance to alter their ensuing compensation payout.[3]

To see the effect of prior gains on risky choice, consider a trader who is up $2,500 within the pay cycle and is now evaluating the opportunity to engage in a trading opportunity. The trader evaluates the potential trade as a 50% chance of winning $500 and a 50% chance of losing $500. According to Thaler and Johnson, the trader would be more likely to engage in the trade (i.e., risky bet) because the trader will net the $500 potential loss against the prior pay cycle gain. As long as the absolute value of the potential loss is less than the prior gain, a majority of decision makers will take the risk-seeking choice.[4] Thus, traders who are further in the black will have an increasing desire to gamble. Thaler and Johnson refer to this behavior as the "house money effect." The house money effect is employed by Barberis et al. [2001], who incorporate the effect into a model to help explain stock market returns. Liu et al. [2006] provide empirical evidence of the house money effect. They find market makers at the Taiwan Futures Exchange take above average risks in afternoon trading after morning gains.

In the presence of prior losses, and a subsequent gamble that offers the opportunity to break even, a trader would also be more prone to take the risky bet (i.e., trade) because they have a strong desire to get even. Thaler and Johnson refer to this behavior as the "break even effect," which is consistent with the loss averse tendencies described in Kahneman and Tversky's [1979] prospect theory.[5] People who are loss averse are more sensitive to losses than to gains of equal magnitude. In financial market settings, several researchers have used loss aversion to help explain securities returns (see, e.g., studies by Bernatzi and Thaler [1995] and Barberis et al. [2001]). Kahneman and Tversky [1979] discuss the empirical finding that betting on long shots increases on the last race of a day when the average bettor is losing money on the day and is anxious to break even. Coval and Shumway [2005] provide empirical evidence consistent with this tendency. They find that market makers at the Chicago Board of Trade engage in above average afternoon risk-taking to recover from morning losses. This result is consistent with our findings. For example, we find trading activity rises as traders move deeper in the red and the pay cycle period winds down. After the pay cycle closes, trader activity precipitously drops. Presumably traders, on average, increase their trading activity (in the domain of loss) at the very last moment to recoup their prior losses. As traders move deeper in the red and the pay cycle end draws near, they will have an increasing desire to get even.

If the employed traders considered each of their trade decisions in a separate mental account, then prior trading outcomes across the pay cycle would have no effect on current trade decisions. However, when firms set an evaluation period for measuring performance as part of an overall incentive compensation plan, this gives employees a clear incentive to organize, evaluate, and keep track of their financial activities within each pay cycle period separately. Such mental accounting practices, in turn, affect how decisions are made within each pay cycle period.

DATA

The data for our study were 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 (employed) and retail (self-employed) 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 attract more sophisticated traders.[6] The firm also had internal proprietary trading operations.

Our analysis primarily focused 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 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 (100%). Each month the firm issued percentage payouts based on traders' prior month trading gains (typically 70–80%). After they were hired but before they began to trade, traders would initially put up capital with the firm. This protects the firm from any losses the traders might incur. The last day in a monthly pay cycle is three trading days before the last trading day of each month.[7] Shortly after this date, the firm issues compensation payouts accordingly. If the traders experience a loss, they are required to put up more capital with the firm to ensure that they will always meet their obligation to cover their losses. To control risk, the firm requires traders to close out their positions on a daily basis. In rare circumstances, traders are allowed to carry over a position from one day to the next (0.02% of the trades are carried overnight).

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, and so forth. The traders pay for these other benefits because they receive a percentage of their trading gains. Traders who do not generate profits are usually fired (or will quit) because they represent an opportunity cost to the firm. Novice traders are not likely to be hired by the firm in the first place. The firm seeks out experienced traders for positions on their trading desk, and they require incoming traders to hold their Series 7 licenses.

While our focus is on traders who worked on behalf of the firm, we also examined data on traders who traded through the firm's brokerage operation. Data on self-employed traders were of interest because self-employed 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. While self-employed traders are not subject to formal evaluation period, firm traders are governed by a compensation contract in which performance is assessed over a well-defined time horizon. The 361 employed traders all trade in at least 10 trading days in a month and close out more than 90% of their trades intraday. Therefore, to make a like comparison with the self-employed traders, we select self-employed traders with the same minimal criteria. There are 595 self-employed traders who trade through the firm's brokerage business that meet these two criteria.[8]

We include data on both groups of traders in a transaction database that spans the four-year period from October 7, 1999, to August 1, 2003. For every order request, we have the identity of the trader, the time of submission, the time of execution, the original volume submitted, the executed volume, the execution price(s), the stock symbol, the order type, and various other information concerning the trade execution and executing account.

Both the employed and self-employed traders only traded equities, and they mainly traded Nasdaq listed stocks (99% and 90% of employed and self-employed 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.[9] Execution speed is a crucial factor for traders engaging in short-term trading strategies. The traders concentrate their trading in certain stocks on certain days and they often account for a sizeable portion of trading volume on the stocks they choose to trade.

Table 1 provides trading activity information on the traders in our sample data. First, the firm traders are much more active than the self-employed traders. The 361 employed traders combine to execute 7.3 billion shares (4.3 million trades). The average employed trader executes 157,983 shares per day (92 trades). On the other hand, the 595 self-employed traders combine to execute 350 million shares (874 thousand trades). The average self-employed trader executes 10,660 shares per day (26 trades).

TABLE 1
Trader Activity.

	Employed Traders	Self-Employed Traders
Total trading activity		
Number of traders	361	595
Shares traded	7,306,271,452	350,274,863
Trades	4,266,326	873,891
Monthly trader averages		
Shares traded	2,870,833	173,403
Trades	1,676	432
Daily trader averages		
Shares traded	157,983	10,660
Trades	92	26

This table provides summary trading statistics for 956 stock traders. The traders traded over the near four-year period October 1999 to August 2003. Employed traders traded the capital of a U.S. broker dealer while self-employed traders traded on their own behalf through the firm's brokerage operation. Employed traders were compensated entirely on their monthly trading performance.

THE PAYDAY EFFECT

Both employed and self-employed traders closely monitor quoting and trading activity in the market and seek to profit from short-term price trends.[10] This article considers whether the performance evaluation period causes employed traders to deviate from their normal trading patterns. The main measure of trading activity is the daily shares traded by each trader. We also examine the number of trades traded by each trader. We focus on the 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.[11]

Casual observations of trader activity reveal there is a large heterogeneity in trader activity across traders. To account for the differences, we need to normalize trader activity on a trader-by-trader basis to derive economic meaning from any data analysis. For example, executing 20,000 shares one day means very different things to different traders. One trader might rarely trade more than 10,000 shares a day while another might have a daily trading average that exceeds more than 100,000 shares per day. We normalize the data on a month-by-month basis because trader behavior varies over time due to various factors including changes in market conditions (e.g., returns, volume, volatility), trading rules (e.g., the tick size), trading technology, trader experience, and so forth. A monthly interval for normalizing the data is in line with the firm's monthly compensation scheme and seems well suited to control for these time-varying occurrences.

To normalize the data and correct for differences across trader and time, we calculate the mean and standard deviation of daily shares traded for every trader (both employed and self-employed) using data for every day they traded in an actively traded month. We define an actively traded month as one in which trader's trade in at least 10 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.[12] 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 monthly standard deviation of each trader.

In Figure 1, we average abnormal trading activity across both groups of traders on a daily basis and then plot trader's cumulative abnormal trading activity leading up to the pay cycle close.[13] We consider 10 days prior to the last day of

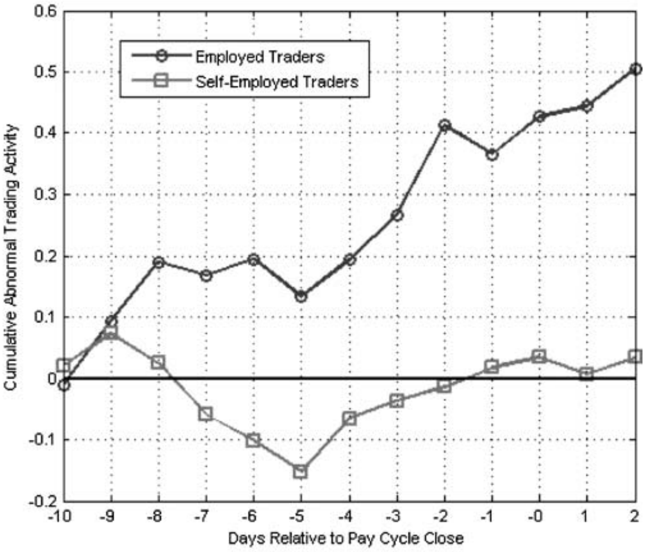

FIGURE 1 Cumulative abnormal trading activity leading up to a pay cycle close. Note: This figure depicts traders' cumulative abnormal trading activity leading up to a pay cycle close. The results are based on 361 employed and 595 self-employed traders during October 1999 to August 2003. Both groups of traders conducted their trading through a U.S. broker-dealer. Employed traders traded the capital of the firm while self-employed traders traded on their own behalf through the firm's brokerage operation. Employed traders were compensated entirely on their trading performance. The last trading day included in a monthly pay cycle (0) is three trading days prior to the last trading day of each month. Trading activity (shares traded) is normalized by trader and averaged across trader for trading days in relation to the pay cycle close.

trading in a monthly pay cycle, the last trading day in a pay cycle, and 2 trading days after a pay cycle close. The magnitude of abnormal trading activity in the days leading up to the pay cycle close is much greater with the employed traders than it is with the self-employed traders. As the pay cycle period winds down, employed traders deviate from their normal trading practices and increase their trading activity. There is also evidence of a spillover effect with the employed traders after the pay cycle closes. We theorize reasons why and when abnormal trading activity might persist into a new pay cycle period in later sections.

Our initial results indicate that traders who are exposed to an incentive-based compensation scheme deviate from their normal trading practices and trade more actively as their formal assessment period draws to a close. On the other hand, traders who are not bounded by any type of contractual timeframe for measuring their performance do not exhibit this behavior. While the monetary reward for profitable trading differs slightly between the two types of traders (employed traders keep 20–30% less of their trading gains), both employed and self-employed traders have a clear incentive to maximize their trading performance. A distinct difference between the two groups of traders is the employed trader's formal evaluation period. Employed traders seem to intensify their trading leading up to the end of the pay cycle to alter (increase) their ensuing compensation payout.

While employed traders engage in above average trading activity around the end of the pay cycle, there could be other factors contributing to or causing this rise in trading activity. Perhaps the most logical motivation for the rise in trader activity is changes in market conditions. Market conditions could simply require traders to trade more often at the end of the pay cycle. For example, the rise in employed trader activity could coincide with a rise in overall 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 the anticipation of price changes reflected through price volatility. The rise in trading activity could also be driven by a trading continuation effect (e.g., Coval and Shumway [2005]) or prior market returns including trend following or contrarian trading strategies. Finally, traders could trade differently at the end of the year for various incentives (e.g., Grinblatt and Keloharju [2001]).

Given that there are multiple factors that can influence a trader's decision to trade, it is important to control for these factors in a regression setting when analyzing changes in trader activity patterns over time. We focus on three trading periods within each monthly interval. Our main period of interest is the last day of trading in a monthly pay cycle. This is the employed trader's last chance to effectively alter performance prior to a payout. We also look at trading activity in the two days before and after the last day of trading in a pay cycle. We estimate a fixed-effect regression that takes the format:

$$\overline{Share}_{i,t} = \alpha_i + \beta_2 Before_{i,t} + \beta_3 Close_{i,t} + \beta_4 After_{i,t} + \sum \lambda X + \varepsilon_{i,t} \quad (1)$$

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;dummy variables take the value of 1 or 0 otherwise if a trading day is: (1) one or two days before the last trading day in a monthly pay cycle (*Before*), (2) the last trading day in a monthly pay cycle (*Close*), and (3) one or two days after the last trading day in a monthly pay cycle (*After*); the coefficients for these dummy variables measure the difference between the abnormal trading behavior around the end of the pay cycle and other periods in a month; Xcontains a vector of control variables including: (1) the lagged normalized shares traded for each trader i, (2) the log daily trading volume on the Nasdaq stock market at day t, (3) 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, (4) the daily (lagged) returns on the Nasdaq composite index at day t, and (5) a dummy variable that takes the value of 1, or 0 otherwise, if day t is in the month of December.

TABLE 2
Market Conditions and Abnormal Trading.

	Employed traders		Self-employed traders	
	Panel A Univariate results			
Other	−0.0160		−0.0046	
Before	0.0641		0.0299	
Close	0.0646		0.0169	
After	0.0166		0.0011	
Before vs. Other	0.0801		0.0345	
p-value	(0.000)		(0.063)	
Close vs. Other	0.0806		0.0216	
p-value	(0.000)		(0.399)	
After vs. Other	0.0326		0.0057	
p-value	(0.126)		(0.762)	
	Employed traders		Self-employed traders	
	Coefficients	p-values	Coefficients	p-values
	Panel B Multivariate results			
Before	0.0636	(0.000)	0.0441	(0.018)
Close	0.0935	(0.000)	0.0263	(0.303)
After	0.0642	(0.002)	0.0192	(0.309)
Trader activity (t-1)	0.1883	(0.000)	0.0996	(0.000)
Daily Nasdaq volume	0.8282	(0.000)	0.4983	(0.000)
Daily Nasdaq volatility	0.9130	(0.036)	0.9061	(0.038)
Daily Nasdaq return	1.9900	(0.000)	1.6429	(0.000)
Nasdaq return (t-1)	−0.3860	(0.081)	0.4547	(0.057)
Nasdaq return (t-2, t-20)	0.2338	(0.000)	0.1772	(0.020)
December dummy	0.0336	(0.045)	0.0052	(0.809)
Trader fixed effects	Yes		Yes	
Adj.R^2	4.70%		1.53%	
Obs.	46,247		32,859	

This table reports employed and self-employed traders' monthly trading activity in relation to employed trader's monthly evaluation period. The sample encompasses 361 employed traders and 595 self-employed traders who conducted their trading through a U.S. broker-dealer during October 1999 to August 2003. Employed traders traded the capital of the firm while self-employed traders traded on their own behalf through the firm's brokerage operation. The data are normalized by trader on a monthly basis. Panel A. reports univariate results. The average normalized shares traded are computed for 4 monthly trading periods. Before represents 1 or 2 days before the last trading day in a monthly pay cycle, Close represents the last trading day in a monthly pay cycle, After represents 1 or 2 days after the last trading day in a monthly pay cycle, and Other represents all other trading days in the monthly interval. The p-values test if the mean difference between the Before, Close, and After periods with the Other period is significantly different from 0. Regression results are reported in Panel B. The dependent variable is traders' daily normalized shares traded. Dummy variables take the value of 1, or 0 otherwise, if a trading day is 2 days before employed traders' pay cycle close (*Before*), the last day in a pay cycle (*Close*), or 2 days after a pay cycle close (*After*). Control factors also serve as independent variables including: traders normalized lagged trading activity (shares/trades), 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 daily (lagged) 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.

Table 2 reports the regression results for employed and self-employed traders. The results remain strong among employed traders after controlling for certain factors that could potentially cause their trading activity to rise. The coefficient representing the last day of trading in a monthly pay cycle is positive and highly significant. The rise in trading activity just prior to the close of a pay cycle is consistent with the notion that employed traders alter their trading activities in response to their performance evaluation period. There is very little evidence that self-employed traders engage in abnormal trading at the end of the pay cycle. If we conduct a simple means test of abnormal trading around the close of a pay cycle (Panel A), our main result does not change. For example, traders trade 0.0646 standard deviations more than normal (average) on their last day of trading in a monthly pay cycle. On the other hand, traders trade -0.0160 less than normal on other days within the month. The mean difference between the two periods is significantly different from zero at the 1% level.

We know from casual observations of the data that there is a large heterogeneity across traders in our sample. We can now also see from Equation 1 regression results that other factors influence trade or are correlated with abnormal trading. These two findings are expected in a financial market setting like ours and they highlight the complexities involved with developing a formal model of the payday effect. A given factor may increase or decrease a trader's activity depending on their individual preferences. Trader activity will (should) vary across pay cycles and these variations in trader activity will (should) exhibit different patterns across traders. However, the regression results in Table 2 indicate that when trader heterogeneity and common factors which influence trade are controlled for, abnormal trading among employed traders persists at the end of the pay cycle.

We conduct three robustness regression checks to ensure that these results are not being driven by any data outliers present in our sample. First, our results could be affected by a subgroup of the more active traders who generate a large portion of the regression observations. To control for this, we exclude the top 5% most active traders (number of days traded) in our overall sample and rerun Equation 1. Second, we exclude traders based on trading size rather than the number of days they trade. Trading size variations among traders may be smoothed out with our monthly normalization procedure. Nevertheless, we exclude the top 5% largest traders (average daily shares traded) in our overall sample and rerun Equation 1. Finally, the data normalization procedure is affected by traders' trading practices. For example, if a trader significantly varies their trading activity across the month, the standard deviation for normalizing this trader data will be quite high and could result in a larger variation in trader activity from normal on some days. If these traders account for a significant portion of the regression observations, this could potentially bias our results. We therefore exclude the top 5% of traders with the largest monthly trading activity variation (average monthly standard deviation from the normalization procedure) in the overall sample and rerun Equation 1. Under all three regressions, the results indicate that the self-employed traders do not significantly vary their trading activity, yet the employed traders systematically increase their trading activity at the end of the pay cycle. Hence, we label this behavior the payday effect.

The behavior underlying the payday effect may have some general similarities to the behavior behind the "turn of the year" or "January" effect. The January effect is the tendency for small capitalization stocks to realize unusually high returns in early January.[14] While the literature provides several hypotheses to explain this phenomenon, the tax-loss selling hypothesis is the most frequently cited explanation. The tax-loss selling hypothesis predicts that shortly before year end (i.e., December), investors will realize their losing positions to lower their annual taxable income. The increased selling demand at year end depresses market prices, yet prices subsequently rebound in January, resulting in large January returns. Consistent with this hypothesis, several researchers have found that stocks declining in price tend to exhibit abnormally high trading volume in December and abnormally high returns in January. The tax-loss selling hypothesis has also been supported through examinations of individual investor trades (e.g., Badrinath and Lewellen [1991], Dyl and Maberly [1992], Ritter [1998], Odean [1998], Grinblatt and Keloharju [2001], Ivkovic et al. [2005]). While the high frequency traders in our study clearly act with a different purpose than long-term investors (who seek to minimize their taxable income by year end), there may be similarities with the behavior exhibited by both market participants. Specifically, individuals show a strong tendency to act (trade) at the very last moment within a set trading horizon. It is not clear, though, if this behavior is optimal. For example, Constantinides (1984) provides evidence that delaying loss realization to December is not an optimal tax trading strategy. In our monthly pay cycle setting, we find little evidence (see subsequent analyses) that traders actions, or surge in trading activity at the very last moment, are benefiting them financially.

While the payday effect does not appear to be driven by changes in market conditions, other exogenous factors may help explain this behavior. For example, a change in the riskiness of the stocks traded by these traders may induce trade. Increases in a stocks risk lead to trade in which traders less tolerant of risk sell the stock to more risk tolerant traders. While changes in the riskiness of a stock may very well induce trade, it seems unlikely that this would systematically happen at the end of each pay cycle, which varies across months (the last day in a pay cycle is three trading days before the end of each month). Another logical explanation for the sharp rise in trader activity could be due to the arrival of new information. Perhaps the employed traders are quick to act after public news releases, or they have access to private information as the pay cycle close draws near. We are not aware of any macroeconomic news releases that systematically occur around the end of our pay cycle period. Also, it is difficult to measure if corporate news announcements were, on average, generally higher at the end of the pay cycle period in comparison to other times within the pay cycle period. If news announcements were more frequent at the end of the pay cycle, then presumably this would be reflected in higher trading volume. Thus, we examine overall daily Nasdaq trading volume for each day in our sample. Our intent is to see if trading volume is unusually high at the end of the pay cycle. This could be an indicator that news releases were more frequent and a possible driving factor behind the payday effect. On average, trading volume is slightly lower around the end of the pay cycle than it is during other times within the month.

WHAT DRIVES THE PAYDAY EFFECT?

Private Information as a Motivation for Trade

We have considered some exogenous factors as plausible explanations for an increase in trade. In this section, we consider some endogenous factors for why employed traders might systematically increase their trading activity at the end of each pay cycle period. First, traders might trade more actively at the end of the pay cycle in response to private information. If traders possess higher levels of information at the end of the pay cycle, this should be reflected in their trading activity. Because some of the orders in our data execute with multiple trades, we aggregate multiple trades into a single order and proxy for the information content behind each order by looking at the future price direction after traders execute their orders.[15] Measuring the direction of the stock price after traders execute their orders is one way to proxy for the information content behind an order (e.g., Odean [1999]). For example, if the future stock price rises (declines) after a trader buys (sells) a stock, then this could be an indicator that the trader possesses private information.

We classify traders orders as either marketable, which are market orders and marketable limit orders with a buy (sell) limit price set greater (less) than or equal to the national best offer (bid), or nonmarketable, which are limit orders priced away from the inside quotes and not immediately executable. There are 1.2 million marketable orders and 1.8 million nonmarketable orders executed on 1,565 stocks in our data. For each order type, we then measure the change in the national best bid and offer (NBBO) quote midpoint five minutes after each order is executed. Our proprietary data are matched to the intraday NBBO quotes using Reuters tick history database.[16] For both marketable and non-marketable orders, we further segregate orders by size and the bid-ask spread at the time of order submission. Table 3 reports the results.

When traders submit marketable orders the price generally rises in the future and when they submit limit orders the price generally declines in the future. This is consistent with the standard assumption in the microstructure literature that informed traders are more likely to submit marketable

TABLE 3
Private Information and Abnormal Trading.

Panel A Marketable orders

Spread =	1 cent or less			> 1 cent to 5 cents			More than 5 cents		
Order Size =	<=500	501–1999	>=2000	<=500	501–1999	>=2000	<=500	501–1999	>=2000
Other	0.0082	0.0072	0.0031	0.0102	0.0102	0.0041	0.0450	0.0361	0.0356
Before	0.0066	0.0067	0.0029	0.0105	0.0114	0.0045	0.0442	0.0365	0.0283
Close	0.0084	0.0079	0.0029	0.0089	0.0104	0.0039	0.0335	0.0315	0.0433
After	0.0081	0.0064	0.0026	0.0097	0.0097	0.0039	0.0427	0.0368	0.0399
Before vs. Other	−0.0016	−0.0005	−0.0002	0.0003	0.0012	0.0004	−0.0008	0.0003	−0.0073
p-value	(0.115)	(0.377)	(0.351)	(0.723)	(0.040)	(0.035)	(0.789)	(0.823)	(0.181)
Close vs. Other	0.0002	0.0007	−0.0002	−0.0013	0.0002	−0.0002	−0.0114	−0.0046	0.0077
p-value	(0.854)	(0.362)	(0.486)	(0.269)	(0.843)	(0.486)	(0.006)	(0.029)	(0.364)
After vs. Other	−0.0001	−0.0008	−0.0005	−0.0005	−0.0005	−0.0002	−0.0023	0.0006	0.0043
p-value	(0.907)	(0.187)	(0.033)	(0.571)	(0.417)	(0.322)	(0.475)	(0.691)	(0.580)

Panel B Nonmarketable (limit) orders

Spread =	1 cent or less			> 1 cent to 5 cents			More than 5 cents		
Order Size =	<=500	501–1999	>=2000	<=500	501–1999	>=2000	<=500	501–1999	>=2000
Other	−0.0058	−0.0058	−0.0053	−0.0048	−0.0052	−0.0049	−0.0200	−0.0230	−0.0233
Before	−0.0061	−0.0054	−0.0049	−0.0048	−0.0058	−0.0051	−0.0168	−0.0216	−0.0251
Close	−0.0062	−0.0052	−0.0054	−0.0036	−0.0056	−0.0045	−0.0195	−0.0234	−0.0221
After	−0.0064	−0.0051	−0.0051	−0.0046	−0.0052	−0.0047	−0.0160	−0.0239	−0.0224
Before vs. Other	−0.0003	0.0005	0.0004	0.0000	−0.0006	−0.0002	0.0033	0.0014	−0.0018
p-value	(0.701)	(0.348)	(0.033)	(0.953)	(0.122)	(0.027)	(0.126)	(0.277)	(0.569)
Close vs. Other	−0.0004	0.0006	−0.0001	0.0012	−0.0005	0.0004	0.0005	−0.0004	0.0011
p-value	(0.692)	(0.324)	(0.795)	(0.122)	(0.370)	(0.016)	(0.867)	(0.831)	(0.805)
After vs. Other	−0.0006	0.0008	0.0002	0.0003	0.0000	0.0002	0.0040	−0.0009	0.0009
p-value	(0.424)	(0.100)	(0.229)	(0.647)	(0.968)	(0.055)	(0.082)	(0.524)	(0.810)

This table presents the change in the National Best Bid and Offer (NBBO) quote midpoint five minutes after a traders order is executed. The 361 employed traders conducted their trading through a U.S. broker-dealer during October 1999 to August 2003. The traders were compensated entirely on their trading performance. The last trading day included in a monthly pay cycle period is 3 trading days prior to the last trading day of each month. Traders orders are either classified as marketable (1.2 million), which are market orders and marketable limit orders with a buy (sell) limit price set greater (less) than or equal to the national best offer (bid), or nonmarketable (1.9 million), which are limit orders priced away from the inside quotes and not immediately executable. Marketable and nonmarketable orders are executed on 1,565 stocks. The results are segregated based on the size of an order (shares) and the bid/ask spread at the time of order submission. The average price change across traders' orders is computed for 4 monthly trading periods. Before represents 1 or 2 days before the last trading day in a monthly pay cycle, Close represents the last trading day in a monthly pay cycle, After represents 1 or 2 days after the last trading day in a monthly pay cycle, and Other represents all other trading days in the monthly interval. The p-values test if the mean difference between the Before, Close and After periods with the Other period is significantly different from 0.

orders to profit from private information. On the other hand, limit orders (if executed) are susceptible to adverse selection costs. There is little evidence indicating that trading is more informative around the close of a pay cycle. Most of the quote midpoint change differences between the Before, Close, and After periods, with the Other period, are not statistically significant. Our selection of a five-minute window is standard in the microstructure literature for measuring the information content behind an order, and it also seems well-suited for analyzing the short-term trading nature of our data. In any case, we use other intervals (e.g., 1 and 3 minutes) to check the robustness of our results. The results with these alternative time horizons are qualitatively similar to those reported and are omitted for brevity.

Cumulative Income as a Motivation for Trade

Traders might decide to trade more often at the end of the pay cycle in response to their cumulative income (profits) to date. Decision theory posits that prior outcomes influence subject decision making and empirical studies have shown that prior performance outcomes influence financial market participant decisions. For example, Brown et al. [1996] find that managers of poorly performing mutual funds in the first half of the year increase their risk taking in the second half of the year. Coval and Shumway [2005] find commodity traders trade more actively (i.e., increased risk taking) in the afternoon trading session when they have experienced a morning trading loss. The authors of these two studies argue that prior performance outcomes influence subsequent trade decisions in their respective settings.[17]

In a pay cycle setting such as ours, monthly performance evaluations could reasonably lead traders to engage in mental accounting activities where they consider each pay cycle as a separate mental account (see Thaler [1999]). Consequently, concurrent trade decisions within the pay cycle (or each mental account) are framed together rather than separately. If traders systematically integrate their prior gains and losses across the pay cycle with their subsequent trade decisions, this could lead to an increasing desire to gamble in both the presence of prior gains and losses (see Thaler and Johnson [1990]). For example, in the presence of prior trading gains, traders may have a tendency to integrate their prior gains with the future loss prospect associated with an ensuing risky bet (i.e., the house money effect). Thus, on average, rising cumulative gains would lead to higher levels of trading activity. In the presence of prior losses traders may have, on average, a strong desire to recoup their prior losses and "break even." The more traders are down, the more they will want to trade to try and recover from their prior losses. A trader's desire to engage in risky bets will be lowest around the pay cycle break-even point.

The behaviors underlying the house money effect and break even effect are somewhat puzzling to financial economists. One would expect a trader to be solely focused on his future gain-loss prospects when evaluating a risky bet. However, there is ample evidence to suggest that traders are influenced by their outcomes on prior bets, too. Some of the greatest trading losses of all time have shed light on this reality. For example, Jerome Kerviel, the Société Générale trader who lost $7.2 billion in early 2008, experienced the largest single trading loss ever and alleged that his large losses were the result of prior trading gains. Kerviel described himself as "both proud and surprised by the results" of his earlier trading gains and this made him want to continue making high risk bets. He asserted that "there's a snowball effect" with trading.[18] Nicholas Leeson, the Barings trader who lost more than $1.4 billion through trading, confessed that his large losses were driven by his prior trading losses. Leeson alleged that he "gambled on the stock market to reverse his mistakes and save the bank." While disturbing, the actions of Messrs. Kerviel, and Leeson are consistent with the notion that prior outcomes can influence subsequent decision making.[19]

To measure the effects of cumulative gains and losses on trader decisions, we match up 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. To do this, we searched forward in time each day until the opening position was closed out, and we kept track of accumulated intraday inventory and the corresponding prices paid or received. We were able to match up a high percentage of trading activity over the four years using our matching algorithm. For example, 99.8% of

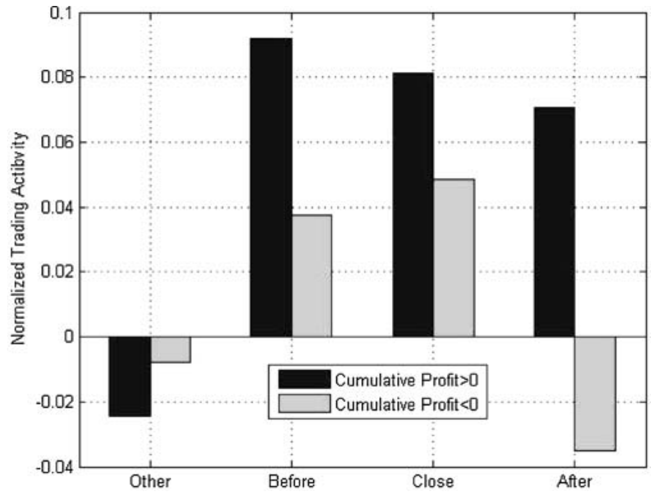

FIGURE 2 Cumulative gains and losses and abnormal trading. Note: This figure displays the relationship between employed traders' cumulative monthly profits to date and their subsequent trading activity around the end of the monthly pay cycle. The results are based on 361 traders who traded the capital of a U.S. broker-dealer during October 1999 to August 2003. The traders were compensated entirely on their trading performance. The last trading day included in a monthly pay cycle is three trading days prior to the last trading day of each month. Before represents one or two days before the last trading day in a monthly pay cycle, Close represents the last trading day in a monthly pay cycle, After represents one or two days after the last trading day in a monthly pay cycle, and Other represents all other trading days in the monthly interval. Cumulative monthly trading profits (*CP*) up to two trading days prior to the last trading day of each pay cycle are classified as either a cumulative profit above (gain) or below (loss) zero. Cumulative trader gains and losses are plotted against corresponding trader's average normalized daily shares traded in each period.

trader's trades can be matched intraday and 96.7% of all trader-day observations have a 100% match rate. We define cumulative income to date as traders' monthly cumulative income up to three days before the end of the pay cycle (i.e., just prior to our Before classification).

We first examine trader activity at the end of the pay cycle with respect to if a trader is experiencing a prior cumulative trading gain or loss. There are 23,560 pay cycle gains and 22,687 pay cycle losses leading up to the close of the pay cycle.[20] Figure 2 shows the common pattern of abnormal trading activity at the end of the pay cycle in relation to both cumulative trading gains and cumulative trading losses. Trader activity dramatically declines after the close of the pay cycle when traders are below the break-even point, but it remains high when traders are above the break-even point. One possible explanation for continued abnormal trading in the presence of prior gains is that traders become increasingly overconfident about their abilities after closing their mental account at a gain and receiving an ensuing payout. Theoretical models indicate that trading activity rises after prior trading gains if traders learn from their prior trading experiences. Gervais and Odean [2001] develop a model in which traders take too much credit for their past

TABLE 4
The Magnitude of Prior Performance and Abnormal Trading.

	Large gain	Small gain	Small loss	Large loss
Before	0.1426 (0.000)	0.0710 (0.025)	−0.0528 (0.091)	0.1050 (0.001)
Close	0.1543 (0.000)	0.0871 (0.006)	0.0352 (0.249)	0.1102 (0.000)
After	0.2263 (0.000)	0.0188 (0.658)	−0.0361 (0.388)	0.0649 (0.125)
Trader activity (t-1)	0.1865 (0.000)	0.1917 (0.000)	0.1722 (0.000)	0.2045 (0.000)
Daily Nasdaq volume	0.8974 (0.000)	1.1715 (0.000)	0.8995 (0.000)	0.7206 (0.000)
Daily Nasdaq volatility	−0.9519 (0.314)	0.7026 (0.381)	1.8572 (0.045)	1.8410 (0.056)
Daily Nasdaq return	2.4967 (0.000)	2.3601 (0.000)	1.4543 (0.001)	1.6797 (0.000)
Nasdaq return (t-1)	−1.3752 (0.003)	−0.1421 (0.736)	−0.1962 (0.670)	0.1792 (0.691)
Nasdaq return (t-2, t-20)	0.4001 (0.002)	0.1462 (0.213)	0.2493 (0.059)	0.1916 (0.149)
December dummy	−0.0032 (0.941)	0.0537 (0.136)	0.0285 (0.395)	0.0572 (0.190)
Trader fixed effects	Yes	Yes	Yes	Yes
Adj.R^2	5.00%	5.67%	4.00%	5.09%
Obs.	11,113	11,574	11,996	11,564

This table reports results for four fixed effects regressions which measure the relationship between employed traders' cumulative monthly profits to date and their subsequent trading activity around the end of a monthly pay cycle. The results are based on 361 traders who traded the capital of a U.S. broker-dealer during October 1999 to August 2003. The traders were compensated entirely on their trading performance. The last trading day included in a monthly pay cycle is 3 trading days prior to the last trading day of each month. Monthly cumulative trading profits are computed across the pay cycle and classified into 4 cumulative profit (*CP*) categories: large gain, small gain, small loss, and large loss. There are 23,560 pay cycle gains and 22,687 pay cycle losses. The dependent variable in each (4) regression is traders' daily normalized shares traded for each *CP* category. Dummy variables take the value of 1, or 0 otherwise, if a trading day is 2 days before employed traders' pay cycle close (*Before*), the last day in a pay cycle (*Close*), or 2 days after a pay cycle close (*After*). Market control factors serve as independent variables and include: traders' lagged daily normalized shares traded, traders' lagged daily normalized trading profit, 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 daily (lag) 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. The coefficients and their respective p-values in parentheses are listed below.

success, which leads them to become increasingly overconfident. As traders become increasingly overconfident, they engage in higher levels of trading activity. Empirical support for overconfidence theory and the lead-lag relationship between returns and trading activity is provided by Thorley et al. [2006].

We examine the interaction between the payday effect and the magnitude of cumulative profits leading up to the end of the pay cycle. To do this, we define traders' cumulative income into four cumulative profit (*CP*) categories: (1) large gains, (2) small gains, (3) small losses, and (4) large losses. We conduct four separate regressions for each *CP* category using the regression specification reported in Equation 1. The results are reported in Table 4. When traders experience a larger gain or a larger loss, the payday effect is quite strong. However, for smaller gains the payday effect is much weaker and in the case of smaller losses there is no payday effect at all. While prior gains and losses are correlated with trading activity, the results are much more pronounced when traders experience larger gains or losses.

Trader activity declines when trader profits get closer to the break-even point because this also registers psychologically as a break-even or near break-even performance. Traders do not possess a strong desire to get even, and traders are also less likely to feel like they are playing with house money. Consequently, payday effects are less likely to occur in these situations. When cumulative losses move further away from the break-even point, traders have an increasing desire to get even. Payday effects increase with surmounting losses because traders have an even greater desire to get back to the break-even point. Of course, the chance to alter a compensation payout and get even ends with the close of the pay cycle. This is why the payday effect immediately dissipates (or is not statistically significant) after the pay cycle closes.

Losing traders' desire to place more risky bets at the close of the pay cycle is consistent with loss aversion, which is an important implication of Kahneman and Tversky's [1979] prospect theory. Decision makers who are loss averse are more likely to engage in risk-seeking behavior when confronted with the prospect of realizing a loss. Kahneman and Tversky note that "a person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise" (p. 287). Consistent with loss aversion, numerous studies in the financial literature document evidence of the disposition effect, which states that traders are more likely to realize their winning investments at a faster rate than their losing investments (see Shefrin and Statman [1985], Odean [1998]). Empirical support for loss aversion is also provided by Coval and Shumway [2005], Garvey et al. [2007], and Locke and Mann [2004], who find professional traders have a tendency to increase their afternoon risk taking following morning trading losses. In our setting, loss-averse traders who are losing money within a pay cycle period have a tendency to increase their risk taking (i.e., engage in more risky bets) just prior to a pay cycle close.

When cumulative gains move further away from the break-even point, payday effects occur but for a very different reason than they do in the presence of trading losses. If traders experience abnormal trading gains, they may have a sense of playing with the house money. This will lead them to integrate prior gains against subsequent trading losses and they will end up trading more often. On average, greater levels of success will lead to greater levels of trading activity. Hence, payday effects become more pronounced when cumulative gains move further away from the break-even point. The evaluation timeframe appears less relevant in the domain of gains. When traders close a pay cycle (mental account) at a gain and receive an ensuing payout, they may learn to be overconfident about their abilities (especially in the case of a large payout), and overconfidence does not quickly subside like loss-averse tendencies do after an evaluation period is closed. This is why the rise in trader activity might persist in the presence of large gains after the pay cycle is closed. Our results reveal that abnormal trading activity only carries over from one pay cycle period to the next if traders are experiencing their largest trading gains. In all other situations (small cumulative gains or cumulative losses), the *After* dummy coefficient is not statistically significant.[21]

TABLE 5
Overall Performance and Abnormal Trading.

	Coefficient	p-value
Before	0.0144	(0.3754)
Close	−0.0363	(0.0222)
After	0.0514	(0.0181)
Trader performance (t-1)	0.0707	(0.0000)
Daily Nasdaq volume	0.2061	(0.0000)
Daily Nasdaq volatility	1.1017	(0.0140)
Daily Nasdaq return	8.4844	(0.0000)
Nasdaq return (t-1)	0.5254	(0.0209)
Nasdaq return (t-2, t-20)	0.1710	(0.0057)
December dummy	−0.0469	(0.0066)
Trader fixed effects	Yes	
Adj.R^2	3.77%	
Obs.	46,247	

This table presents performance results for 361 employed traders who traded the capital of U.S. broker-dealer during October 1999 to August 2003. The traders were compensated entirely on their trading performance. The last trading day included in a monthly pay cycle period is 3 trading days prior to the last trading day of each month. 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. The table reports results of a fixed effect regression. The dependent variable is traders' normalized daily profit. The independent variables include dummy variables representing traders lagged daily performance and some market controls (see Table 2).

IMPLICATIONS OF THE PAYDAY EFFECT

While our results provide strong evidence that trader activity systematically rises at the end of the pay cycle period, a natural question that arises is: what are the implications that flow from this behavior? From an employer or employee perspective, the payday effect is likely to have important implications for performance. A surge in trader activity will impact performance either positively or negatively. We investigate how employed trader performance varies across the pay cycle period. First, we compute the normalized trading profits for each trader i at day t(same manner as the normalized shares traded computation). The daily trading profit is determined by matching up the intraday round-trip trades. While trading activity rises at the close of the 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 deviation rise in trading activity on this day. The decline in performance on the last day of trading is significantly different from zero at the 1% level.

We estimate a regression similar to Equation 1 in that the dependent variable is trader's normalized trading profit. The vector of control variables includes: (1) the lagged normalized profit for each trader i; (2) the log daily trading volume on the Nasdaq stock market at day t; (3) 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; (4) the daily (lagged) return on the Nasdaq index at day t; and (5) a dummy variable that takes the value of 1, or 0 otherwise, if day t is in the month of December. The results are reported in Table 5. Our initial finding that traders experience below average performance at the close of the pay cycle does not change when controlling for factors that could influence trader performance. Trading profits subsequently increase after the pay cycle is closed. Note, the coefficients representing a trader's prior trading performance, Nasdaq volume, Nasdaq volatility, the Nasdaq market return, and the end-of-calendar year dummy are all positively correlated with trader performance at time t.

The payday effect may have broader implications for the marketplace, too. If, in the aggregate, institutional traders systematically increase their trading activity at the end of each pay cycle period, then this could have a significant impact on market prices and or market liquidity. Understanding the true impact of the payday effect from this perspective requires further data on the compensation structure and trading decisions of other financial market participants. While most market participants are exposed to some type of incentive pay scheme, other financial market participants may respond differently. Moreover, there is likely to be considerable variations with respect to the time horizons used for evaluating performance across financial market participants (e.g., day, week, month, year).

TABLE 6
Order Selection and Abnormal Trading.

Panel A Distribution of order types and comparison between days around the end of a pay cycle and monthly normal

	Marketable	*p*-values	Quote improving	*p*-values	At the quote	*p*-values	Away from the quote	*p*-values
% of entire sample	36.54%		13.49%		44.75%		5.21%	
Before vs. Other	−0.2794%	(0.273)	0.2649%	(0.213)	0.0845%	(0.740)	−0.4592%	(0.004)
Close vs. Other	1.1558%	(0.000)	0.0556%	(0.816)	−1.7436%	(0.000)	0.5596%	(0.011)
After vs. Other	−0.6116%	(0.025)	0.4574%	(0.038)	−0.1305%	(0.627)	−0.5364%	(0.001)

Panel B Marketable order usage around the end of a pay cycle period in relation to monthly cumulative performance

	Large gain	*p*-values	Small gain	*p*-values	Small loss	*p*-values	Large loss	*p*-values
Before vs. Other	0.1618%	(0.768)	−0.2560%	(0.601)	−1.0496%	(0.032)	0.0523%	(0.912)
Close vs. Other	1.8446%	(0.006)	−0.1839%	(0.770)	1.1410%	(0.082)	1.8336%	(0.004)
After vs. Other	0.6834%	(0.265)	−1.4150%	(0.006)	−0.9368%	(0.066)	−0.7769%	(0.150)

This table measures traders order selection decision (Panel A) around the end of the pay cycle and traders order selection decision in relation to traders' monthly cumulative performance (Panel B). Orders are classified generally as either marketable, which are market orders and marketable limit orders with a buy (sell) limit price set greater (less) than or equal to the national best offer (bid), or nonmarketable, which are limit orders priced away from the inside quotes and not immediately executable. There are 1.2 million marketable orders and 1.8 million nonmarketable orders executed on 1,565 stocks. The daily percentage of marketable orders is computed on a monthly basis (share basis) for each trader. The average percentage of marketable orders is computed for four monthly trading periods. Before represents 1 or 2 days before the last trading day in a monthly pay cycle, Close represents the last trading day in a monthly pay cycle, After represents 1 or 2 days after the last trading day in a monthly pay cycle, and Other represents all other trading days in the monthly interval. In Panel A, nonmarketable orders are further classified based on whether the limit price improves the best price in the market, matches the best price in the market, or is inferior to the best price in the market at the time a trader submits an order. The trader data is matched with tick data from Reuters in order to properly classify orders relation to the National Best Bid and Offer. In Panel B, monthly cumulative trading profits are computed across the pay cycle and classified into 4 cumulative profit (*CP*) categories. In both panels, the *p*-values in parentheses test if the reported mean difference between the Before, Close and After periods with the Other period is significantly different from 0 across the various classifications.

An important issue regarding the payday effect and its potential impact in the marketplace is whether or not the rise in trader activity coincides with a change in how traders submit their orders. Our sample traders have direct access to the marketplace and they continually either trade against existing quotes and orders in the marketplace (i.e., marketable orders) or they set prices in the marketplace (i.e., nonmarketable orders). Traders order selection decision can alter security prices and or liquidity in the marketplace. Thus, we examine if traders order selection decision is altered at the end of the pay cycle period.

We compute a daily percentage of marketable orders for each trader on a monthly basis. The average percentage of marketable orders across traders for our Before, Close, and After periods are compared to Other (normal) days within the monthly interval. We also compare the percentage of limit orders that improve the best price in the market, match the best price in the market, or are inferior to the best price in the market around the end of the pay cycle to other days within the month. The trader data is matched with tick data from Reuters to properly classify orders relation to the National Best Bid and Offer. We use the NBBO quotes at the time of order submission (in relation to traders limit price) to properly classify orders.

Table 6 Panel A reports traders order type decision around the close of a pay cycle. At the close of the pay cycle, traders become more aggressive with their order selection decision and submit more marketable orders. We examine this decision in relation to our four cumulative performance measures, too. The results are reported in Table 6 Panel B. When traders experience a large gain or a large loss, the results are most significant for submitting marketable orders. If submitting more marketable orders is considered a proxy for increased risk taking, these results seem consistent with the relation between cumulative performance and abnormal trading activity at the close of a pay cycle. Traders increase their appetite for risk when their pay cycle account (i.e., mental account) moves further into the black or deeper into the red as the pay cycle end draws near.

CONCLUSION

Despite the widespread use of incentive pay in finance-related jobs, there is little, if any, direct research examining how these compensation schemes influence decision making. In this article, we address this issue by examining how professional traders vary their trading activities in response to their incentive compensation contract. Our study focuses on how employer-imposed evaluation periods, which are used with incentive compensation to measure performance and determine existing compensation payouts, influence trader behavior.

Understanding the effects of compensation structure on employee behavior is beneficial to firms for designing compensation schemes. Moreover, the effect of evaluation periods on decision making has broad appeal. Many financial theories are built around important assumptions pertaining to when financial market participants evaluate their performance and how they respond. Due to data constraints, financial researchers have always been forced to estimate performance evaluation periods.[22] The inability of prior researchers to know when performance evaluation occurs naturally complicates any empirical measurement or purported link between performance evaluation and subsequent behavior change. We know precisely when performance evaluation occurs and we directly measure the link between performance evaluation and subsequent behavior. Our study is unique in this respect.

Our primary results are based on a sample of 361 employed traders who traded the capital of a U.S. broker-dealer intraday. The traders combined to execute 7.3 billion U.S. equity shares over the near four-year period ending August 2003. The traders set market prices on approximately 73% of the shares executed. Trader compensation was entirely based on performance. Performance was formally assessed and payouts occurred on a month-to-month basis.

Trader activity varies over time but consistently rises above average at the end of the pay cycle period. The unusual rise in trading activity at the end of the pay cycle is not driven by external market factors which could cause their trading activity to rise. Controlled matched samples of 595 self-employed traders, who trade in a similar manner and are not governed by an employee compensation contract, do not exhibit signs of this behavior. The employed traders' behavior appears driven by a desire to alter their performance or compensation payout just prior to the close of an evaluation period. We label this behavior the payday effect.

Traders systematically increase their trading activity at the end of each pay cycle, but there is no sign that this behavior is driven by a trader's possession of new information. Instead, we show the payday effect is highly correlated with traders' monthly cumulative trading profits to date. When traders are close to breaking even as the pay cycle draws to a close, the payday effect is less pronounced. However, payday effects become more pronounced when traders move further into the black or deeper into the red as the pay cycle end draws near. We explain why this result might occur using some common theories on decision making.

While the payday effect is likely to have implications for both employee and firm performance, its greatest appeal may be whether it has any sort of impact on market prices and or market liquidity. To adequately address this issue, future research is needed on how prevalent this behavior is among other financial market participants, as well as research into the compensation structure of other financial market participants.

NOTES

1. See Prendergast [1999] for a review of the incentive literature.
2. For example, Knight Trading Group compensates their proprietary traders solely on trading performance (Ip [2000]). Knight has one of the largest institutional trading operations in Nasdaq stocks.
3. As noted by Prendergast [1999], "people simply prefer to wait to exert effort" (p. 25). And this general human tendency is independent of how the monetary incentive component of the contract is structured (e.g., linear, nonlinear). If traders exert more effort at the end of the pay cycle, then presumably they will come to evaluate more trade decisions around this time and the patterns we observe should be most pronounced at or around this time, too.
4. In our empirical results, we equate an abnormal rise in trading activity with an increased appetite for risk taking or an increased desire to take on risky bets. This proxy for risk taking is used in prior studies (see, e.g., Coval and Shumway [2005]).
5. A prior loss does not always induce subsequent risk-seeking behavior. Thaler and Johnson [1990] note that an initial loss may cause a subsequent increase in risk aversion, particularly when the second choice does not offer the opportunity to break even. In Kahneman and Tversky's [1979] prospect theory, all of the examples of risk seeking in the domain of loss were accompanied by an opportunity to break even. This is quite important. Kahneman and Tversky note that cancellation (breaking even) enables people to reduce problem complexity.
6. 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.
7. 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 is settled and end-of-month pay checks are issued.
8. We are able to match 99.8% (99.7%) of the employed (self-employed) trader's trades intraday.
9. Approximately 80% of NYSE-listed volume was executed at the NYSE during our sample periods. Source: www.nyse.com/pdfs/NYSEMarketQualityFeb2003.pdf.
10. We spent some time at the firm observing traders trade and talking with traders and management at the broker-dealer.
11. We conduct all of our empirical results using the number of trades as a measure of trading activity. The

results are qualitatively similar to those reported and are available upon request.

12. More than 97% of the shares traded occurred in actively traded months. We estimated our empirical results using all trader months and found qualitatively similar results.
13. The number of trading days in a pay cycle period ranges from 15 to 24. Monthly calendar days and exchange holidays impact the number of trading days in each pay cycle.
14. The January effect was first documented by Rozeff and Kinney [1976], who found stock returns were unusually high in January relative to other months. Later, Banz [1981] showed smaller firms drive the January effect.
15. Our data have a unique order transaction identifier with each trade which enables us to assign trades to a single order.
16. For information on Reuters tick history database, see http://about.reuters.com/productinfo/tickhistory/.
17. There is evidence of cumulative income effects in nonfinancial settings as well. For example, Camerer et al. [1997] find evidence that taxi cab drivers keep track of their cumulative income for the day and quit when they reach a target income level for the day.
18. Kerviel was up more than $2 billion at the end of 2007. On January 23, 2008, his total cumulative losses were $7.2 billion (see Gauthier-Villars and Mollenkamp [2008]).
19. Leeson's demise, due to his strong desire to get even, is highlighted in Shefrin [2002]).
20. Trader (pay cycle) profitability considerably varies. Overall, the group managed to generate $2,960,993 in a "challenging" market trading environment. For example, the revenues of broker-dealers with a Nasdaq market making operation fell more than 70% during 2000–2004 (General Accounting Office [2005]), and our sample firm had an active Nasdaq market-making operation. The GAO cited the sharp decline in stock prices, heightened competition, the switch to a smaller tick size, etc., for the sharp decline in dealer revenues during our sample period.
21. Barber and Odean [2001] note overconfidence thrives in financial market settings. They cite the overconfidence literature which indicates overconfidence is greatest for difficult tasks, for forecasts with low predictability, and for undertakings lacking fast, clear feedback. Trading stocks profitability is a difficult task. Predictability is low and feedback is noisy. Therefore, traders are highly susceptible to be overconfident.
22. For example, Bernatzi and Thaler [1995] assume individual investors evaluate their portfolios annually. This annual performance evaluation assumption has been used in other studies. As noted by Barberis and Thaler [2003], identifying the appropriate investment horizon is critical for behavioral studies.

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