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Positive Mean Currency Returns

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In this paper, we report evidence that mean currency returns are positive for both a domestic investor in a foreign currency and a foreign investor in a domestic currency. A shared currency gain creates a positive volatility factor for both. Volatility dominates other return determinants that have opposite impacts on an exchange rate and its inverse to produce positive average returns we find in excess of one percent per annum. Positive mean currency returns impact the global asset allocation of investors to accumulate to a large fraction of wealth creation over time. Currency returns are also large given the a priori *expectation of investors that they average to zero.*

Keywords: Currency Returns, Siegel Hypothesis

JEL Classification: G11, G15

I. Introduction

In this paper, we report evidence that mean currency returns are positive for both a domestic investor in a foreign currency and a foreign investor in a domestic currency despite the fact that changes in an exchange rate and its inverse relate negatively so that a gain to one is a loss to the other. In testing this provocative hypothesis, we find currency returns have a positive volatility-factor from a shared gain in opposing currencies (Siegel, 1972; Black, 1989 and 1990). Volatility dominates other return determinants that have opposite impacts on an exchange rate and its inverse to produce positive average returns that we find in excess of one percent per annum. The shared currency gain arises from convexity of the inverse exchange rate that converts a foreign back to a domestic currency and gives investors downside protection from adverse deviations. Since both have this "put" feature, we also report evidence of positive return skewness for both domestic and foreign investors.

Whether one percent is high or low depends upon one's perspective. It is unlikely high for speculative currency strategies not often profitable after transactions costs (Burnside *et al.*, 2007; Bacchetta and van Wincoop, 2010). On the other hand, most investors earn a currency return passively in conjunction with an unhedged foreign financial or business investment. The foreign return on the primary investment compensates investors for the time value of money, asset risk, and local inflation. For investors willing to bear the transactions costs of currency exchange in any

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event for business reasons, one percent per annum beyond the primary investment influences international business decisions, global asset allocation, and currency hedging. Currency returns are also large given the *a priori* expectation of investors that they equal zero. Frankel (1993) argues that Siegel's hypothesis (Siegel, 1972) is a mathematical inconvenience that is neither economically nor empirically significant. Others argue that the paradox remains outstanding (Kritzman, 2000; Gandolfo, 2001). With the exchange rates of thirty-five major currencies, we find evidence of positive mean currency returns, positive return skewness, and a positive relation between returns and exchange rate volatility as predicted by the Siegel hypothesis.

The number of positive and negative signs in a time-series of currency returns is roughly equal. Downside protection makes negative returns less negative than positive returns when positive. To detect a small positive mean return, we test with many exchange rates over long periods to average the randomness. Results from averaging should not be confused with a certainty that does not exist for currency returns. Even with positive mean returns, there are long periods when realized returns have a negative impact on investor wealth (Engel and Hamilton, 1990).

Currency returns and exchange rates require distinct modeling. In international business investment, global asset allocation, and currency hedging, downside protection gives currency returns a positive mean for domestic and foreign investors. On the other hand, without downside protection, exchange rate modeling and forecasting require equal mean changes of opposite sign.

We organize the remainder of our paper as follows. Section II reviews the existing literature and discusses our contribution to it. Section III develops hypotheses. Section IV describes the data and research methods. Section V reports evidence of positive mean currency returns, positive return skewness, and a positive relation between returns and volatility for domestic and foreign investors. Section VI concludes with summary comments and suggestions for future research.

II. Literature Review

Our paper contributes to the literature on exchange rate determinants and predictability, which begins with Meese and Rogoff (1983) who argue that macro exchange rate models forecast no better than a random walk. On the other hand, uncovered interest parity (UIP) predicts that the exchange rate of a high interest rate currency depreciates relative to a low interest rate currency (Siegel, 1972; Solnik, 1987). Contrary to UIP and contrary to a random walk, Fama (1984) and Bacchetta and van Wincoop (2010) find that high interest rate currencies appreciate. Rather than a random walk, recent evidence documents positive persistence in currency returns. Engel and Hamilton (1990) reject the random walk model in favor of one with long predictable swings. Caporale and Gil-Alana (2012) find long memories in the $US/Euro and $US/Yen exchange rates. Booth *et al*. (1982) find positive memory during the flexible exchange period of 1973-1979. Gençay (1999) finds currency return improvements beyond a random walk with several technical trading rules.

Persistence is consistent with the argument of Bacchetta and van Wincoop (2010) that investors adjust their global financial asset portfolios slowly. There is little evidence of abnormal returns from speculative currency strategies based on UIP (Burnside *et al*., 2007; Bacchetta and van Wincoop, 2010), but return persistence suggests the possibility of profitable "momentum" investment strategies of the type weakly effective for common equities (Jegadeesh and Titman, 1993). In addition, there is evidence of abnormal profits from currency strategies based on filter rules and trend-following in long-run currency movements (Levich and Thomas, 1993a and 1993b; Engel and Hamilton, 1990). Taylor (1995) surveys the results of several inefficiency studies for currency markets. Our results indicate that rebalancing global portfolios for currency volatility improves the global asset allocation of investors.

In a panel analysis of daily exchange rates, we find that interest rate differences impact exchange rates as predicted by UIP, that currency returns are weakly persistent, and that volatility positively impacts currency returns as predicted by the Siegel hypothesis. The UIP result is contrary to Fama (1984) and Bacchetta and van Wincoop (2010) and indicates that even long trends in exchange rates may not be permanent. Only with many exchange rates over long periods can we average trends away for analysis. The volatility effect is sufficiently strong to dominate other return determinants that have opposite impacts on an exchange rate and its inverse to produce positive average returns.

In the international finance literature, we are the first to jointly test the hypotheses of positive currency returns, a volatility component to returns, and positive return skewness for both domestic investors in a foreign currency and foreign investors in a domestic currency.

III. Hypotheses

Consider the US dollar as the "domestic" and the UK pound as the "foreign" currency. Of course, one can switch these roles or use any other two currencies. Let ω_t be the pound cost of a dollar at time *t*, so that ω pounds buys one dollar: $\omega = \mathcal{L}/\$$. Today's $\mathcal{L}/\$$ exchange rate is ω_0. If $\omega_t > \omega_0$, then the pound depreciates relative to the dollar so that a pound buys fewer dollars at *t* than 0.

A U.S. investor exchanges ω_0 pounds that cost a dollar today for $\omega_0/\widetilde{\omega}_t$ dollars at $t > 0$. Thus, the "dollar return" for a pound investment is,

$$\tilde{r}_{\mathcal{L}/\$} = \omega_0/\widetilde{\omega}_t - 1, \tag{1}$$

which is positive or negative as the pound appreciates ($\omega_t < \omega_0$) or depreciates ($\omega_t > \omega_0$) and is before the pound return on a U.K. financial or business investment that the U.S. investor also earns.

The dollar cost of a pound, $1/\omega$, in Equation (1) converts a pound back to a dollar and gives the U.S. pound investor downside protection from adverse currency deviations. Convexity of the inverse exchange rate (that is, $1/\omega$ is a convex function of ω) means that a one percent increase in the pound cost of a dollar (a pound depreciation) decreases the dollar cost of a pound by less than one percent. For example, suppose that the pound cost of a dollar is ω_0=0.65 and that it depreciates by 1%, so that, ω_t=0.65*1.01 = 0.6565. Substitute these amounts into Equation (1) to find that the U.S. investor's loss is less than 1%. A similar example shows that a U.K. investor in dollars has downside protection from a dollar depreciation. Equations (8) and (9) formalize this phenomenon below.

A. The Null Hypothesis: The Cost of Carry Model

The cost of carry model says that if the pound interest rate exceeds the dollar interest rate ($r_{\mathcal{L}}$>$r_{\$}$.), then we expect the pound to depreciate ($d\omega/\omega$>0). If real interest rates are the same in the two interest rates, so that pound inflation is greater, then UIP says that the pound depreciates so that goods and service costs between the two currency jurisdictions remains the same. With risk-neutrality (at least with respect to exchange rates), we expected the exchange rate change to equal the difference in the interest rates,

$$d\omega/\omega = (r_{\mathcal{L}} - r_{\$})dt + \sigma d\tilde{z}, \tag{2}$$

where $d\tilde{z}$ is a normally-distributed Gauss-Weiner increment with mean zero and variance dt so that the instantaneous variance of percentage changes in the exchange rate is $\sigma^2 dt$. Equation (2) is the pound return for dollars.

Similarly, we expect the dollar cost of a pound, $1/\omega_t$, to increase, $\frac{d(1/\omega)}{(1/\omega)}>0$, and the dollar to depreciate when the dollar interest rate exceeds the pound interest rate ($r_\$ > r_£$),

$$\frac{d(1/\omega)}{(1/\omega)} = (r_\$ - r_£)dt - \sigma d\tilde{z} \quad (3)$$

Equation (3) is the dollar return for pounds. Both the interest rate difference and the perturbation, $d\tilde{z}$, have opposite impacts on the pound cost of a dollar (ω) and the dollar cost of a pound (1/ω).

There are several empirical implications of the cost of carry model. First, if mean currency return is positive for a domestic investor in a foreign currency (Equation 3), then it is negative for the foreign investor in the domestic currency (Equation 2). Second, because the perturbation $d\tilde{z}$ has a normal distribution and is, thus, symmetric, neither the foreign return in a domestic currency nor the domestic return in the foreign currency is skewed. Further, even if the foreign return on the domestic currency has a positive skew due to $d\tilde{z}$, then the domestic return in the foreign currency has a negative skew due to $-d\tilde{z}$ and vice versa. Finally, there is no association between mean return and either the foreign return in a domestic currency or the domestic return in the foreign currency ($r_£ - r_\$$ and $r_\$ - r_£$, respectively) and currency volatility, σ^2dt.

We statistically reject all of these hypotheses in testing.

B. The Alternative Siegel Hypothesis

Presume that the exchange process ω_t follows a geometric Brownian motion,

$$\frac{d\omega}{\omega} = \mu dt + \sigma d\tilde{z} \quad (4)$$

Equation (4) is the pound return for dollars from the perspective of the U.K. investor. If there is a risk-premium for exchange rate risk, then it is contained within the parameter μ.

The inverse exchange rate, that is, the dollar cost of a pound, $1/\omega_t$, also follows a geometric Brownian motion. With Ito's lemma and Equation (4),

$$\frac{d(1/\omega)}{(1/\omega)} = -\mu dt + \sigma^2 dt - \sigma d\tilde{z} \quad (5)$$

Equation (5) is the dollar return for pounds from the perspective of the U.S. investor.

The pound return for dollars and the dollar return for pounds relate to one another in equations (4) and (5) because of stochastic calculus and not because of any pricing differences between U.S. and U.K. investors. Rather, the exchange rate between pounds and dollars is priced in a single currency market and highlights the fact that at this stage we do not presume risk-neutrality. If a risk premium has a positive impact on the expected return for a U.K. investor in dollars (μ is greater than otherwise), then it has a negative impact on the expected return for a U.S. investor in pounds (-μ is more negative than otherwise).

Add equations (4) and (5) to find that the sum of percentage changes in the pound cost of a dollar, ω, and the dollar cost of a pound, 1/ω, calculates volatility,

$$\frac{d\omega}{\omega} + \frac{d(1/\omega)}{(1/\omega)} = \sigma^2 dt > 0 \quad (6)$$

The sum of the foreign investor's return in the domestic currency and the domestic investor's return in the foreign currency is positive and riskless. Every instant, there is positive riskless currency gain that depends solely on volatility, σ^2, which is the Siegel (1972) paradox that Kritzman (2000) identifies as a prominent finance puzzle. The reason that the currency gain is positive and riskless is that any exchange deviation, $\sigma d\tilde{z}$, is to the detriment of the domestic investor in the foreign currency or vice versa. Convexity of the inverse exchange rate gives the injured investor downside protection, which is equal for the opposite party in the vice versa case. Because one or the other gets the same protection, the gain in aggregate is riskless and, thus, we can *calculate* realized currency volatility, σ^2, on the right of Equation (6).

Because the currency gain in Equation (6) is non-stochastic (it depends upon *dt* only), it is a component of the drift μdt in equations (4) and (5), which means that it is shared between the domestic investor in the foreign currency and the foreign investor in the domestic currency. The perturbation $\sigma d\tilde{z}$ is normally distributed (symmetric, in particular) and, thus, downside protection accrues half the time to the U.S. pound investor and half the time to the U.K. dollar investor. This sharing is consistent with the observation that the number of positive and negative signs in a time-series of currency returns is roughly equal. It is also within the arbitrage bounds of McCulloch (1975) and Roper (1975).

With risk-neutrality (at least with respect to exchange rates) and UIP, the drift μ is the difference in interest rates plus half the currency gain,

$$\mu = r_{£} - r_{\$} + ½\,\sigma^2 \tag{7}$$

Substitute Equation (7) into equations (4) and (5) to find the percentage changes in the pound cost of a dollar, ω, and the dollar cost of a pound, 1/ω,

$$\frac{d\omega}{\omega} = (r_{£} - r_{\$})dt + ½\,\sigma^2 dt + \sigma d\tilde{z}, \tag{8}$$

$$\frac{d(1/\omega)}{(1/\omega)} = (r_{\$} - r_{£})dt + ½\,\sigma^2 dt - \sigma d\tilde{z} \tag{9}$$

The interest-rate differential, $(r_{\$} - r_{£})$, and the random increment, $d\tilde{z}$, have opposite impacts on the pound cost of a dollar, ω and the dollar cost of a pound, $1/\omega$, but volatility, σ^2, impacts both positively and by the same amount: $½\,\sigma^2 dt$. Equation (9) is the domestic investor's return on a foreign currency and Equation (8) is the foreign investor's return on a domestic currency. The only distinction in pricing between the foreign cost of a domestic currency (ω) and the domestic cost of a foreign currency (1/ω) is that both the foreign and the domestic investor expect downside protection from adverse currency deviations in the amount $½\,\sigma^2 dt$, which is common in the drifts of equations (8) and (9). Downside protection increases with volatility, $\sigma^2 dt$.

C. Empirical Predictions of the Siegel Hypothesis

We investigate three empirical implications of the Siegel hypothesis. First, one of the interest rate differences in equation (8) or (9) is positive and the other negative. However, if volatility, σ^2, is sufficiently great, it offsets the negative differential and, in this case, mean currency return is positive for both for a domestic investor in a foreign currency (Equation 9) and a foreign investor in a domestic currency (Equation 8).

Second, over a *dt* holding-period, volatility, σ^2, is constant so that currency returns in equations (8) and (9) are normally distributed and, thus, without skewness. However, if volatility varies over time (that is, 0 to *t*), then a time-series of measured returns each with a *dt* holding period is positively skewed. When volatility is temporally low, not only is expected return low but, also, the likelihood of especially negative returns is low because low volatility does not allow them (or high positive returns either but we are concerned with negative returns in this instance). On the other hand, when volatility is high, not only is expected return high but, also, the likelihood of exceptionally high positive returns is high because high volatility promotes them (with high expected return, we are interested in positive returns). Muted negative returns when expected return is low and accentuated positive returns when expected return is high represents downside protection from adverse currency deviations and imparts a positive skewness to a time-series of currency returns. Thus, we expect positive return skewness both for a domestic investor in a foreign currency (Equation 9) and a foreign investor in a domestic currency (Equation 8).

Third, downside protection from adverse currency deviations takes form in equations (8) and (9) as a positive relation with volatility. Thus, we expect a positive relation between currency returns and volatility, $\sigma^2 dt$, for both a foreign investor in a domestic currency and a domestic investor in a foreign currency.

D. Cost of Carry Versus the Siegel Hypothesis

The cost of carry model does not incorporate the shared currency gain and, thus, without downside protection and with homogeneous expectations, exchange rate forecasting with equations (2) and (3) is alike for a foreign and a domestic investor. On the other hand, the currency return processes in equations (8) and (9) are distinct (even inversely) because both a domestic and a foreign investor have downside protection. This protection manifests itself as drift terms that are not the negative of one another. We present mutually supporting and consistent empirical results that strongly favor the Siegel hypothesis over the cost of carry model (the null hypothesis), which supports our contention that currency returns contain downside protection. The shared currency gain in Equation (6) is the source of this better empirical support.

Our results are important even if one is interested in an exchange rate process for forecasting rather than a currency return process for investing. The exchange rate drift parameters in equations (2) and (3) are a subset of the currency return drift parameters in equations (8) and (9). Estimating the impact of interest rate differences in equations (2) and (3) on percentage exchange rate changes has a missing variable bias without the volatility factor in equations (8) and (9). Only a currency return process permits unbiased tests of UIP and other asset-pricing hypotheses.

IV. Data and Research Methods

Our tests use thirty-four daily exchange rates listed in Table 1 for widely traded currencies versus the US dollar between January 4, 1971 and December 31, 2014 from the U.S. Federal Reserve's release H.10 available from Wharton's Research Data Service (WRDS) for noon New York buying rates for cable transfers in foreign currencies. We construct a set of 584 exchange rate time-series and a second set of 584 inverse exchange rate time-series. There are 35*34/2-11=584 exchange rate pairs (an exchange rate and its inverse). The "11" in this calculation is the number of former European currencies that stopped trading at year-end 1998 with the introduction of the euro.[1] We calculate the bulk of these 584 exchange rate pairs as cross-rates from Table 1. Using the currencies in Table 1, we match the first currency ($US as domestic) with each subsequent currency down to the euro (as foreign). Then, with the second currency (AUD as domestic) we match with each subsequent currency down to the euro again. We continue in a like manner until complete.

The purpose of this exchange rate and inverse exchange rate construction is to give no preference to any currency in our study. We report all results for both domestic investors in a foreign currency and foreign investors in a domestic currency. Essentially identical results in

[1] The Greek drachma traded until 2000 when Greece joined the euro-zone but the drachma/euro series is too short to be useful for testing.

paired testing is strong evidence for the Siegel hypothesis when the cost of carry model suggests that exchange rate determinants have opposite impacts for domestic and foreign investor returns. We recognize cross-sectional residual dependence across exchange rates with methodologies we discuss below. Equation (1) calculates daily currency returns (with the identity of currencies appropriately adjusted).

Table 1: Exchange Rates

	Country and Currency	Data Beginning	Data Ending
1	Australia (AUD/US$)	01-04-1971	12-31-2014
2	Brazil (Real/US$)	01-02-1995	12-31-2014
3	Canada (Can$/US$)	01-04-1971	12-31-2014
4	People's Republic of China (Yuan/US$)	01-02-1981	12-31-2014
5	Denmark (Krone/US$)	01-04-1971	12-31-2014
6	Hong Kong (Dollar/US$)	01-02-1981	12-31-2014
7	India (Rupee/US$)	01-02-1973	12-31-2014
8	Japan (Yen/US$)	01-04-1971	12-31-2014
9	South Korea (Won/US$)	04-13-1981	12-31-2014
10	Malaysia (Ringgit/US$)	01-04-1971	12-31-2014
11	Mexico (New Peso/US$)	11-08-1993	12-31-2014
12	New Zealand (NZ Dollar/US$)	01-04-1971	12-31-2014
13	Norway (Krone/US$)	01-04-1971	12-31-2014
14	Singapore (Dollar/US$)	01-02-1981	12-31-2014
15	South Africa (Rand/US$)	01-04-1971	12-31-2014
16	Sri Lanka (Rupee/US$)	01-02-1973	12-31-2014
17	Sweden (Krona/US$)	01-04-1971	12-31-2014
18	Switzerland (Franc/US$)	01-04-1971	12-31-2014
19	Taiwan (Dollar/US$)	10-03-1983	12-31-2014
20	Thailand (Baht/US$)	01-02-1981	12-31-2014
21	United Kingdom (Pound/US$)	01-04-1971	12-31-2014
22	Venezuela (Bolivar/US$)	01-02-1995	12-31-2014
23	Austria (Schilling/US$)	01-04-1971	12-31-1998
24	Belgium (Franc/US$)	01-04-1971	12-31-1998
25	Finland (Markka/US$)	01-04-1971	12-31-1998
26	France (Franc/US$)	01-04-1971	12-31-1998
27	Germany (D Mark/US$)	01-04-1971	12-31-1998
28	Greece (Drachma/US$)	04-13-1981	12-29-2000
29	Ireland (Pound/US$)	01-04-1971	12-31-1998
30	Italy (Lira/US$)	01-04-1971	12-31-1998
31	Netherlands (Guilder/US$)	01-04-1971	12-31-1998
32	Portugal (Escudo/US$)	01-02-1973	12-31-1998
33	Spain (Pesata/US$)	01-02-1973	12-31-1998
34	European Monetary Union (Euro/US$)	01-04-1999	12-31-2014

V. Results

A. Positive Mean Currency Returns

We describe the first set of 584 exchange rates for reporting in the first column of Table 2 as the domestic (D) return on a foreign currency (F), $\tilde{r}_{(F|D)_{k,t}}$, and the set of 584 inverse exchange rates for the second column as the foreign return on a domestic currency, $\tilde{r}_{(D|F)_{k,t}}$. The subscripts $(F|D)_{k,t}$ and $(D|F)_{k,t}$ represent the k'th of 584 exchange rates (and inverse rates) at trading day t for the domestic investor in the foreign currency$(F|D)$ and the foreign investor in the domestic currency $(D|F)$. There are 11,081 daily returns between January 1971 and December 2014. The total number of currency returns over all days and over all exchange rates is 3,908,487, which is less than 11,081×584 because not all exchange rates have a full time-series.

The upper panel of Table 2 reports pooled averages of currency returns $\tilde{r}_{(F|D)_{k,t}}$ and $\tilde{r}_{(D|F)_{k,t}}$ over all 3,908,487 days, the time-series average of the 11,081 cross-sectional average daily currency returns, and the cross-sectional average of the 584 time-series average daily currency returns. Consistent with the hypothesis that mean currency returns are positive, all six average currency returns are positive and all but one is statistically significant.

The cost of carry model says that if the currency return of a domestic investor in a foreign currency is positive, then the foreign investor return in the domestic currency is negative, which means currency returns are *always* of opposite sign. Thus, even though one of the mean returns in Table 2 is insignificant statistically, it still supports the Siegel hypothesis beyond its *t*-statistics because it is positive when the inverse mean return is also positive (and significant). Further, if an exchange rate trends greatly over a time series (from perturbations in equations 8 and 9), then the temporal average return for the domestic investor in the foreign currency and the foreign investor in the domestic currency are of opposite sign. Thus, to assess the impact of downside protection on currency returns we average away long trends with many exchange rates over long periods. In so doing, we find 95 of 584 exchange rates for which the temporal mean daily return for a domestic investor in a foreign currency and its inverse pair are both positive.

Since our choice of a currency return for the Foreign/Domestic rather than the Domestic/Foreign column is arbitrary (and vice versa), a reasonable interpretation of the paired results in Table 2 is that an investor is equally likely to have a currency return from either column. While we cannot combine tests because the columns are not statistically independent, we can combine columns to better gauge average currency returns. The annualized average of the 3,908,487 pooled foreign/domestic and domestic/foreign currency returns ($\tilde{r}_{(F|D)_{k,t}}$ and $\tilde{r}_{(D|F)_{k,t}}$) is 251.8*(0.000042+0.000047)/2 = 1.12% per annum (251.8 is the average number of trading days per annum from 1971 to 2014). The temporal average of 11,081 cross-sectional average currency returns is 251.8*(0.000035+0.000058)/2 = 1.17% per annum. The cross-sectional average of 584 temporal average currency returns is 251.8*(0.000085+0.000027)/2 = 1.4% per annum. In each case, the average currency return is more than one percent per annum.

Table 2: Daily Currency Returns for Thirty Five Currencies

	Foreign/Domestic			Domestic/Foreign		
	Pooled	Cross-Sectional	Time Series	Pooled	Cross-Sectional	Time Series
Average	0.000042	0.000035	0.000085	0.000047	0.000058	0.000027
Standard Error	0.000005	0.000025	0.000013	0.000005	0.000026	0.000014
t-statistics for average	8.08	1.37	6.73	8.87	2.21	1.98
% Positive	48.8%	49.8%	59.9%	49.2%	51.0%	53.8%
Minimum	-0.7024	-0.0466	-0.0005	-0.7049	-0.0464	-0.0009
Maximum	2.3892	0.1833	0.0016	2.3604	0.1825	0.0013
Observations	3,908,487	11,081	584	3,908,487	11,081	584
Skewness	72.915	0.027	4.319	73.661	0.033	1.740
Standard Error		0.005381	0.509281		0.005381	0.473787
t-statistics for skewness		5.03	8.48		6.06	3.67
% Positive		52.3%	64.0%		52.8%	56.7%
Minimum		-5.8303	-53.1896		-15.2823	-35.8860
Maximum		15.4629	49.4461		6.4468	67.0005

Notes: The left panel reports returns for 584 exchange rates as the domestic (D) return on the foreign currency (F), $\tilde{r}_{(F|D)_{k,t}}$. The right column reports returns for the second set of 584 exchange rates as the foreign (F) currency return on the domestic (D) currency, $\tilde{r}_{(D|F)_{k,t}}$. There are 11,081 daily currency returns between January 1971 and December 2014. The total number of currency returns over all days and over all exchange rates is 3,908,487. The cross-sectional average of currency returns are $\bar{r}_{(F|D)_t} = \sum_{k=1}^{N_t} \tilde{r}_{(F|D)_{k,t}}/N_t$ and $\bar{r}_{(D|F)_t} = \sum_{k=1}^{N_t} \tilde{r}_{(D|F)_{k,t}}/N_t$, t=1,2,…,11,081. The upper and lower panel report, respectively, the temporal average and the temporal skewness of these cross-sectional averages (skewness is the sum of cubed deviations from the mean over the time-series divided by the cube of the standard deviation times one minus the number of days 11,081-1). The time-series average of currency returns for exchange rate k=1,2,…,584 are $\bar{r}_{(F|D)_k} = \sum_{k=1}^{T_k} \tilde{r}_{(F|D)_{k,t}}/T_k$ and $\bar{r}_{(D|F)_k} = \sum_{k=1}^{T_k} \tilde{r}_{(D|F)_{k,t}}/T_k$. The upper and lower panel report, respectively, the cross-sectional average and the cross-sectional skewness of these temporal averages.

B. Positively Skewed Currency Returns

Our second hypothesis is that currency returns are positively skewed because of downside protection for both a domestic investor in a foreign currency and a foreign investor in a domestic currency.

The lower panel of Table 2 reports skewness[2] of $\tilde{r}_{(F|D)_{k,t}}$ and $\tilde{r}_{(D|F)_{k,t}}$ over all 3,908,487 daily currency returns, skewness of the 11,081 cross-sectional average daily currency returns, and skewness of the 584 time-series average currency returns.

Each skewness measure is positive and statistically significant. Averaging over exchange rates and over time removes the negative relation in equations (4) and (5) between the domestic return on a foreign currency, $\tilde{r}_{(F|D)_{k,t}}$, and the foreign return on a domestic currency, $\tilde{r}_{(D|F)_{k,t}}$ that arises from the drift μ and the random increment $\sigma d\tilde{z}$ that otherwise induce skewness of opposite sign. Since volatility is the only positive determinant of both returns, our interpretation of positive skewness is that it arises from volatility. Evidence of positive return skewness is supporting evidence also for positive average currency returns because the source of both is downside protection from adverse currency deviations.

C. A Positive Relation Between Currency Returns and Volatility

Our third hypothesis is that the relation between currency returns and return volatility is positive for domestic investors in a foreign currency and foreign investors in a domestic currency. The panel analysis below accounts for cross-sectional correlation in exchange rates.

Table 3: One Month Maturity Riskless Interest Rates

	Data Beginning	**Data Ending**
US Dollar 1Month Deposit (FT/TR) - Middle Rate	01-02-1975	12-31-2014
TR Australian Dollar 1 Month Deposit - Middle Rate	09-27-1988	12-31-2014
BRL Cash Deposit 1 Month (TP) - Middle Rate	06-30-2006	12-31-2014
Canadian Dollar 1 Month Deposit (FT/TR) - Middle Rate	01-02-1975	12-31-2014
Chi Interbank 1 Month - Offered Rate	01-09-2002	12-31-2014
Danish Krone 1 Month Deposit (FT/TR) - Middle Rate	06-14-1985	12-31-2014
Hong Kong Interbank 1 Month - Offered Rate	06-04-1990	12-31-2014
Inr 1 Month Mibor Avg Fix-Fbil - Middle Rate	12-01-1998	12-31-2014
Japanese Yen 1 Month Deposit (FT/TR) - Middle Rate	08-01-1978	12-31-2014
South Korea Ibk. 1 Month Seoul - Offered Rate	07-26-2004	12-31-2014
Malaysia Deposit 1 Month - Middle Rate	07-15-1982	12-31-2014
Tr Mx (Mxd) 1 Month Irs 130M - Middle Rate	07-17-2003	12-31-2014
Tr New Zealand $ 1 Month Deposit - Middle Rate	09-27-1988	12-31-2014

[2] Skewness is the sum of cubed current return deviations from the mean divided by the product of the sample size less one times the cube of the sample standard deviation. For example, for $\tilde{r}_{(F|D)_{k,t}}$, skewness is $sk_{(F|D)} =$

$\left(\sum_j^{3,908,487}\left(\tilde{r}_{(F|D)_j} - \bar{r}_{(F|D)}\right)^3 / (3,908,487 - 1) * \sigma^3_{(F|D)}\right)$, where, $\sigma_{(F|D)} = \sqrt{\left(\sum_j^{3,908,487}\left(\tilde{r}_{(F|D)_j} - \bar{r}_{(F|D)}\right)^2 / (3,908,487 - 1)\right)}$

Table 3: One Month Maturity Riskless Interest Rates: Continues

	Data Beginning	**Data Ending**
TR Norwegian Krone 1 Month Deposit - Middle Rate	01-09-1995	12-31-2014
Singapore Dollar 1 Month Deposit (TR/TP) - Middle Rate	01-04-1988	12-31-2014
S African Rand 1 Month Deposit (TR/TP) - Middle Rate	04-01-1997	12-31-2014
Sri Lanka Interbank 1 Month - Middle Rate	01-03-2000	12-31-2014
Tr Swedish Kro 1 Month Deposit - Middle Rate	01-09-1995	12-31-2014
Swiss Franc 1 Month Deposit (FT/TR) - Middle Rate	01-02-1975	12-31-2014
Taiwan Deposit 1 Month - Middle Rate	08-08-1989	12-31-2014
Thailand Interbank 1 Month (Bb) - Offered Rate	01-07-1992	12-31-2014
U.K. Sterling 1 Month Deposit (FT/TR) - Middle Rate	01-02-1975	12-31-2014
Venezuela 30-Day Deposit Rate - Middle Rate	01-02-1997	12-31-2014
Oe 1 Month Vibor Delayed See Eibor 1 Month - Offered	06-10-1991	12-31-1998
Bg Eu- Franc 1 Month Deposit (FT/TR) - Middle Rate	06-05-1978	12-31-1998
Fn 1 Month Intbk Delayed See Eibor1 Month - Offered	01-02-1987	12-31-1998
Fr Eu-Franc 1 Month Deposit (FT/TR) - Middle Rate	01-02-1975	12-31-1998
Bd Eu-Mark 1 Month Deposit (FT/TR) - Middle Rate	01-02-1975	12-31-1998
Greece Deposit 1 Month - Middle Rate	01-25-1994	12-29-2000
Ir 1 Month Intbk Delayed See Eibor 1 Month - Offered	01-20-1984	12-31-1998
It Eu-Lira 1 Month Deposit (FT/TR) - Middle Rate	06-09-1978	12-31-1998
Netherland Euro-Gldr 1 Month (Icap/TR) - Middle Rate	01-09-1995	12-31-1998
Pt Eu-Escudo 1 Month Deposit (FT/TR) - Middle Rate	11-16-1992	12-31-1998
Es Eu-Peseta 1 Month Deposit (FT/TR) - Middle Rate	04-02-1992	12-31-1998
Euro 1 Month Deposit (FT/TR) - Middle Rate	01-04-1999	12-31-2014

We investigate three primary currency return determinants: interest rate differences between currencies of an exchange rate, lagged currency returns, and currency-volatility. For all currencies in Table 1, we retrieve local one-month maturity interest rates from Datastream (Thomson Financial). Table 3 gives a short description of each rate and the beginning and end-dates for each. Because even the longest interest-rate time-series is shorter than for the exchange rates in Table 1, the panel regression for currency returns in Table 4 has fewer daily observations than in Table 2.

Table 4: Panel Analysis of Daily Currency Returns with Two-Way Clustered SE

Explanatory Variable	Domestic Return on a Foreign Currency, $\tilde{r}_{F\|D}$		Foreign Return on a Domestic Currency, $\tilde{r}_{D\|F}$	
Lagged Currency Return	-0.4285 (-1.70)	-0.4286 (-1.70)	-0.1153 (-2.29)	-0.1153 (-2.29)
Dummy Variate for First Sub-Period times Lagged Currency Return	0.4310 (1.71)	0.4312 (1.71)	0.1182 (2.23)	0.1182 (2.23)
Interest Rate Differential	-0.0442 (-2.86)	-0.0493 (-2.87)	-0.0347 (-3.46)	-0.0387 (-3.48)
Dummy Variate for First Sub-Period times Interest Rate Differential		0.0505 (2.59)		0.0399 (2.76)
Currency Volatility	0.7072 (2.75)	0.7073 (2.75)	0.5479 (5.65)	0.5479 (5.65)
Dummy Variate for First Sub-Period times Currency Volatility		-1.1604 (-0.54)		0.9046 (0.42)
R^2	24%	24%	18%	18%
Pooled Daily Observations	1,774,013			

Notes: Coefficient *t*-statistics in parentheses use robust two-way clustered standard-errors. The lagged currency return adjusts for autocorrelation. Currency volatility adjusts for heteroscedasticity. $\tilde{r}_{(F|D)_{k,t}}$ is the return on foreign currency F in a domestic-currency D. $\tilde{r}_{(D|F)_{k,t}}$ is the return on a domestic currency in foreign currency. The interest rate differential, $\Delta i_{(F|D)_{k,t}}$ is the difference in riskless interest rates (foreign minus domestic, i_F-i_D, in the F/D case and i_D-i_F in the D/F case). Currency-volatility for day *t* is from Equation (6). The panel of data is k=1,2,..,584 exchange rates and up to t=1,2,…,10,051 trading-days from January 1975 to December 2014. The first sub-period is January 1975 to December 1991.

To test for return persistence, we use lagged currency return as an explanatory variable. In addition, to test for a differential in return persistence between earlier and later sub-periods (January 1975-December 1991 and January 1992-December 2014) and the Pukthuanthong-Le *et al*. (2007) hypothesis that the efficiency of currency markets has improved over time, we include a dummy variable for the first sub-period times lagged currency return as an explanatory variable. As a test of UIP, we include the contemporaneous interest rate differential as a third explanatory variable. When the domestic (D) return on a foreign currency (F), $\tilde{r}_{(F|D)_{k,t}}$, is the dependent variable, the interest rate differential is the foreign less the domestic interest rate and, thus, UIP predicts that the coefficient on the interest rate differential should be negative. When the foreign interest rate is high, the foreign currency depreciates to generate a negative return for a domestic investor. Alternatively, when the dependent variable is the foreign currency return on a domestic currency, $\tilde{r}_{(D|F)_{k,t}}$, the interest rate differential is the domestic less the foreign interest rate and, again, the test of UIP is that the coefficient on the interest rate differential is negative. Currency volatility (daily return variance) calculated with Equation (6) is the final explanatory variable. Equations (8) and (9) indicate that a volatility factor prevents a missing-variable mis-specification in our test of the economic determinants of currency returns.

We regress currency returns on lagged currency return, the interest rate differential, and currency-volatility. For the domestic return on a foreign currency, the regression is,

$$\tilde{r}_{(F|D)_{k,t}} = \alpha_1 \cdot \tilde{r}_{(F|D)_{k,t-1}} + \alpha_2 \cdot \left(d \cdot \tilde{r}_{(F|D)_{k,t-1}}\right) + \alpha_3 \cdot \Delta i_{(F|D)_{k,t}} + \alpha_4 \cdot \sigma^2_{(F|D)_{k,t}} + \varepsilon_{k,t}, \quad (10)$$

where $\tilde{r}_{(F|D)_{k,t}}$ is the return on foreign currency F in units of a domestic currency D for the k'th exchange rate, k=1,2,…,584, $\tilde{r}_{(F|D)_{k,t-1}}$ is the lagged currency return, d is a dummy variable that takes a value of one if the return is in the first sub-period January 1975 to December 1991, $\Delta i_{(F|D)_{k,t}}$ is the difference in riskless interest rates (foreign minus domestic) associated with the k'th exchange rate, $\sigma^2_{(F|D)_{k,t}}$ is currency-volatility for period t.

The coefficient α_1 measures return-persistence in the sub-period January 1992 to December 2014. The sum of coefficients $\alpha_1+\alpha_2$ measures return-persistence for January 1975 to December 1991. Equivalently, the parameter α_2 measures the differential in return-persistence between the first and second sub-periods. The regression for the foreign return on a domestic currency is equivalent to Equation (10) but with *F/D* rather than *D/F*.

Because the null hypothesis is that currency markets are informationally efficient, our expectation is that both α_1 and α_2 are zero: the return for currencies that have recently appreciated or depreciated is the same and this is true regardless of the sub-period. UIP predicts that α_3 should be negative: currency returns for high interest rate currencies should be negative. Equations (8) and (9) predict that α_4 should be positive because volatility increases currency returns.

D. Panel Regression Results for the Relation Between Currency Returns and Volatility

Table 4 reports panel regression estimates of the model in Equation (10). Petersen (2009) shows that t-statistics calculated with two-way clustered standard-errors account for times-series residual dependence and are robust to heteroscedasticity.

The estimate of α_1 is negative and weakly statistically significant (at 10%) for both the foreign return on a domestic currency, $\tilde{r}_{(D|F)}$ and the domestic return on a foreign currency, $\tilde{r}_{(F|D)}$. Rather than positive persistence, this is evidence of a daily reversal in currency returns for the second sub-period (January 1992-December 2014). The estimate of α_2 is positive and weakly statistically significant (at 10%) for the foreign return on a domestic currency, $\tilde{r}_{(D|F)}$ and the domestic return on a foreign currency, $\tilde{r}_{(F|D)}$. Since, $\alpha_1+\alpha_2$ is close to zero, this is evidence that daily return reversals did not exist in the first sub-period (January 1975-December 1991).

The estimate of α_3 is negative for both the domestic return on a foreign currency, $\tilde{r}_{(F|D)}$, and the foreign return on a domestic currency, $\tilde{r}_{(D|F)}$, and in both cases the estimate is statistically significant. Consistent with UIP, higher interest rates in one currency jurisdiction relative to another is associated with a depreciation in the exchange rate of the former relative to the latter.

The estimate of α_4 is positive and statistically significant for the domestic return on a foreign currency, $\tilde{r}_{(F|D)}$, and the foreign return on a domestic currency, $\tilde{r}_{(D|F)}$, which is consistent with the hypothesis that there is a positive relation between currency returns and currency volatility. This result is consistent with our argument that a positive volatility-factor is the source of positive returns and positive return skewness we report in Table 2.

Beyond relations in Equation (10), the second set of panel regressions in Table 4 test for differential relations between the two sub-periods (January 1975-December 1991 and January 1992-December 2014) for currency returns versus interest rate differences and return volatility.

The evidence is that in the second sub-period (January 1992-December 2014), the interest rate difference has the impact predicted by UIP, whereas, in the first sub-period (January 1975-December 1991), there is no relation. This set of results is consistent with the hypothesis of Pukthuanthong-Le *et al*. (2007) that the informational efficiency of exchange rate markets has improved in recent years.

There is no evidence of a sub-period difference in the relation between currency returns and volatility, which is supporting evidence for the Siegel hypothesis. Relations between currency returns and lagged currency returns and currency returns and interest rate differences depend upon exchange rate pricing by individuals in currency markets that possibly change over time with their skill and understanding. On the other hand, the Siegel hypothesis arises from downside protection from adverse currency deviations due to convexity of the inverse exchange rate. Since this is a mechanistic rather than a pricing phenomenon, we do not expect the relation between currency returns and volatility to change over time.

VI. Conclusion

In this paper, we report evidence that currency returns are positive for both a domestic investor in a foreign currency and a foreign investor in a domestic currency. A positive relation between currency returns and volatility generates positive average returns in excess of one percent per annum. Volatility as a return factor arises from downside protection from adverse deviations that global investors in opposing currencies share from convexity of the inverse exchange rate.

Frankel (1993) argues that the Siegel paradox is a mathematical inconvenience that is neither economically nor empirically significant. We present mutually supporting and consistent empirical results that strongly favor the Siegel hypothesis over the cost of carry model for exchange rates. Sharing the currency gain between a domestic and a foreign investor captures downside protection from adverse currency deviations and is the source of better empirical support.

Is the Siegel hypothesis economically significant? We believe that a one percent currency return beyond a primary foreign investment is enough to influence international business decisions, global asset allocation, and currency hedging. If the performance of a globally diversified financial-asset portfolio improves using currency volatility as a predictor of future unhedged currency returns, then the Siegel hypothesis is economically significant.

The analysis and methods of our paper have application beyond currencies when the holding period rate return on an asset requires an inverse function. Examples including a barrel of oil/$US or an ounce of gold/$US. Because the value of a bond is the discounted value of fixed future coupons and par-value at the yield to maturity, bond owners have downside protection from interest rate deviations that adversely impact the yield.

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The Impact of Loyalty on Satisfaction: Reverse Logic and Unintended Consequences

By ARIFIN ANGRIAWAN*

Predictors of online satisfaction include website usability, performance, privacy, and security. Researchers have examined the effects of mediating and moderating variables on the relationship between online satisfaction and loyalty. The present study examines the reverse logic and feedback effects of loyalty on the relationship between satisfaction and its predictors. It is an important topic because satisfied customers may not be loyal. The idea of reverse logic is to emphasize satisfaction investments that focus on loyal customers, who are usually more profitable. The results of this study may indicate that it is more difficult to satisfy than to create loyal customers.

Keywords: Website Usability, Performance, Privacy, Security, Loyalty

JEL Classification: O14

I. Introduction

Online commerce has provided enormous business opportunities for millions of people in the world. It improves business efficiency and effectiveness by reducing the constraints of space, distance, and time. An important aspect of e-commerce is the website, where the merchants and customers meet and conduct transactions.

With the advantages and opportunities enabled by e-commerce, competition has increased exponentially. Consequently, customer relationship development in terms of attracting, developing, and maintaining successful relational exchanges (Morgan and Hunt, 1994) has experienced escalating costs and time requirements and has captured the attention and time allocation of business managers. This is especially true with the rise of social media. For example, social media have greatly changed how consumers strategize and interact with online businesses. Customers nowadays can rely on many social media sources to share and generate information about online businesses. The information changes their expectations and how they evaluate business experiences. Thus, attracting and maintaining customers have definitely become more difficult.

Researchers have found that one of the main predictors of online loyalty is satisfaction (Anderson and Srinivasan, 2003; Evanschitzky *et al.*, 2004; Flavián *et al.*, 2006; Picón *et al.*, 2014; Toufaily *et al.*, 2013; Valvi and West, 2013). A meta analysis concluded that satisfaction accounts for 25 percent of the variance of loyalty (Szymanski and Henard, 2001). Hundreds of studies have catalogued various antecedents, moderators, mediators, and outcomes of satisfaction.

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The extant literature and recent research results have indicated the feedback effect of loyalty on satisfaction. Furthermore, the rise of the customer lifetime value (CLV) metric has called for the reverse logic approach in studying satisfaction and loyalty (Homburg *et al.*, 2005; Kumar *et al.*, 2013; Kumar *et al.*, 2009). In the era of social media, instead of focusing on how satisfaction creates loyalty, the idea of reverse logic is to focus on satisfaction investment directed at loyal customers who are usually more profitable and more difficult to retain. In other words, instead of asking how to create loyal customers, we ask, if loyalty is so important, how do we satisfy these clients? Thus, creating loyal customers is not the same as satisfying loyal customers.

I believe that pursuing research from both causal logics is complementary and very important. This study follows the call for reverse logic and extends the literature by examining the moderating impacts of loyalty on the relationship between satisfaction and its predictors. The results of this study may indicate that it is more difficult to satisfy than to create loyal customers.

This paper begins by summarizing the current literature. I then propose a research model and several hypotheses. I explain the research methods and report on the data analysis and results. I describe and discuss the theoretical and practical implications. I propose Study 2 to test the hypotheses by solely focusing on social media. I conclude the paper by discussing some limitations and future research.

II. Literature Review and Hypotheses Development

Research results have provided ample empirical support for the importance of online satisfaction. It is a very significant predictor of loyalty. Loyal customers are very important because they are very difficult and costly to attract and maintain but bring various benefits and contribute significantly to a firm's profitability (Reichheld and Schefter, 2000). They found that increases in retention rates by 5 percent improve profits by 25 to 95 percent. Indeed, researchers have found that online satisfaction creates more loyalty than its offline counterpart (Shankar *et al.*, 2003). With the rise of social media, we might expect to see the stronger impact of retention on the bottom line.

Some important predictors of online satisfaction are website usability, perceived performance, privacy, and security (Angriawan and Pearson, 2009; Belanger *et al.*, 2002; Evanschitzky *et al.*, 2004; Muylle *et al.*, 2004; Palmer, 2002; Toufaily *et al*., 2013; Valvi and West, 2013). In an online context, websites can be seen as the merchants of offline businesses. The overall experience with the merchants is reflected by the experience of the consumers with the websites in terms of their navigation, content, interactivity, and responsiveness (Palmer, 2002).

Perceived performance relates to the reliability and integrity of the merchants and their products. In offline businesses, dealings with reliable managers and products provide better customer experience and higher satisfaction. As in offline businesses, satisfaction increases with good experiences of website usability, perceived performance, privacy, and security. However, the rise of social media makes these relationships more challenging and difficult to achieve.

Without the physical presence of the merchants and stores and in the absence of face-to-face communication, the presence of privacy statements can enhance customer experience and satisfaction. Customers become more confident and less concerned with how their data will be used. Similarly, the ability to protect consumer, transaction, and financial data will increase experience and satisfaction with the websites. This is especially true in the era of social media.

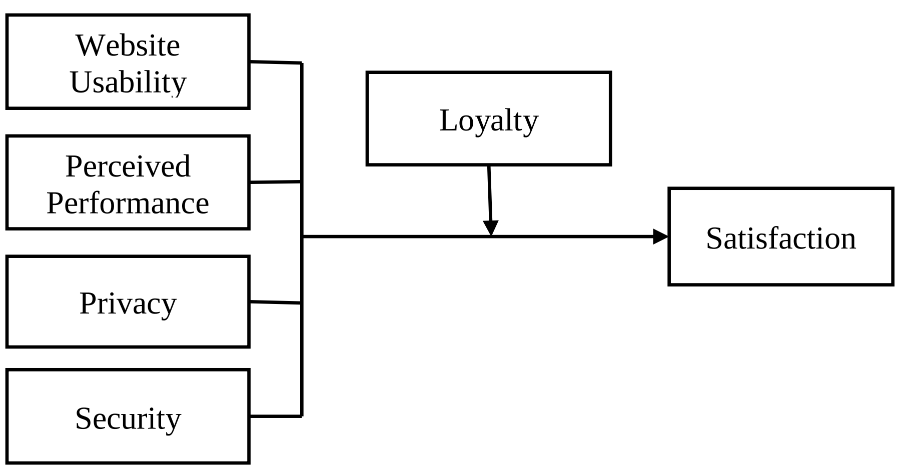
Researchers have also examined the effect of various mediating and moderating variables on the relationship between online satisfaction and loyalty. These mediating factors include switching costs and attractive alternatives (Picón *et al.*, 2014). Moderating variables include purchase size (Anderson and Srinivasan, 2003), switching costs (Yang and Peterson, 2004), industry and customer segments (Szymanski and Henard, 2001), gender, age, and income (Homburg and Giering, 2001).

Picón *et al.* (2014) noted the mediating roles played by perceived switching costs and attractiveness of alternatives. They found positive and significant effects of perceived switching costs on loyalty. They also found negative and significant effects of attractiveness of alternatives on loyalty. Homburg and Giering (2001) found that product satisfaction rather than sales process satisfaction has a stronger impact on loyalty for men and vice versa for women. They found that older people are more loyal if they are satisfied with the products they bought, while younger people tend to associate loyalty more with the sales process experience and satisfaction. They also found that the relationship between satisfaction and loyalty is stronger for higher income groups of people.

Recent research suggests that the satisfaction and loyalty relationship changes over time. For example, researchers found that as satisfaction increases, its impact on loyalty decreases (Agustin and Singh, 2005). Similarly, other researchers found that the satisfaction effect on loyalty decreases at the later stage of a relationship cycle (Lin and Kuo, 2013). This indirectly might suggest that satisfied and consequently loyal customers are more difficult to continuously satisfy. This indicates the feedback effect of loyalty on satisfaction (Melcher and Melcher, 1980). This might also indicate the presence of a systemic effect such as the increasing impacts of social media on relationship development.

Previous researchers on relationship marketing have observed that the impact of satisfaction on loyalty depends on the customers' relationship orientation. Some customers are more transactional while others are more relational (Jackson, 1985). In order to test the feedback impacts of loyalty, I specifically choose to focus on the moderating impact of loyalty on satisfaction, because previous research found that satisfaction is the main driver of loyalty for low relational customers, while trust and commitment are the main drivers of loyalty for high relational customer (Agustin and Singh, 2005; Garbarino and Johnson, 1999). Thus, the relationship between satisfaction and its predictors provides an appropriate context to examine the feedback effect of loyalty.

Below is the research model.



Following Flavián *et al.* (2006), I define satisfaction as "an affective consumer condition that results from a global evaluation of all the aspects that make up the consumer relationship" (p. 4). Thus, the definition refers to the relationship-specific rather than a service encounter satisfaction (Shankar *et al*., 2003). Based on the literature, some of the aspects that affect the online satisfaction include website usability, performance, privacy, and security.

I define website usability as the perceived ease of use of a website, such as site navigation and transaction execution (Flavián *et al*., 2006). Research shows that a positive perceived experience has a positive association with online satisfaction.

Perceived performance is defined as the integrity and reliability of the merchants and their products. This includes perceptions about price competitiveness, quality, on-time delivery, and after-sales service. These basic aspects of commerce eventually contribute to the customers' satisfaction with the website. In general, customers who have a positive perception will have higher satisfaction.

Privacy refers to customer information management. It includes usage tracking and customer data sharing (Belanger *et al*., 2002). Privacy policy is important because e-commerce usually requires the sharing of important personal and financial information. Security refers to website ability and reliability to protect the transaction system. Security issues include destruction, disclosure, and denial of survive (Kalakota and Winston, 1999). Previous researchers have found that privacy and security issues are important parts of customers' experience with a website. Customers who have positive experiences with a firm's privacy policies and security practices will have higher satisfaction.

Most of the existing literature on the relationship between satisfaction and loyalty assumes unidirectional causality. This contrasts with the dynamic system approach which takes into consideration the interdependence among variables and introduces two-way relationships or feedback effects into the relationships being investigated (Melcher and Melcher, 1980).

Consistent with the dynamic system approach, the expectation disconfirmation theory would predict that website satisfaction depends on the intensity and direction between the gap of expectations and perceived performance of the website by their customers (Cardozo, 1965; Oliver, 1980). Since loyal customers have good experiences with the website, they naturally increase their comparison baseline or even increase their expectations. Furthermore, with experience and learning, loyal customers become experts in evaluating the website usability and perceived performance. Collectively, loyal customers have a tendency toward higher expectations and lower perceived performance.

The explanation above suggests that online loyalty has a negative moderating effect on the relationships between satisfaction and website usability, as well as with perceived performance. I contend that the strength of the relationships decreases as loyalty increases. Based on the discussion above, I hypothesize:

H1: Online loyalty has a negative moderating effect on the relationship between website usability and satisfaction.

H2: Online loyalty has a negative moderating effect on the relationship between perceived performance and satisfaction.

Loyal customers share more data. Consequently, firms accumulate more data about them. Thus, loyal customers will be more concerned and expect higher levels of privacy and security. Furthermore, with experience and learning, loyal customers become experts in evaluating privacy policies and security issues. Collectively, loyal customers have the tendency toward lower perceived performance and higher expectations. The expectation disconfirmation theory would predict less satisfaction (Cardozo, 1965; Oliver, 1980).

The explanation above suggests that online loyalty has a negative moderating effect on the relationship between satisfaction, privacy, and security. I contend that the strength of the relationships decreases as loyalty increases. Based on the discussion above, I hypothesize:

H3: Online loyalty has a negative moderating effect on the relationship between privacy and satisfaction.

H4: Online loyalty has a negative moderating effect on the relationship between security and satisfaction.

III. Research Methods

A. Data Collection

Survey data were collected from students of a major university in the midwestern United States. The sample size was 400 students. The sample consisted of roughly 60 percent female students and 40 percent male students. Half of the sample had less than 5 years of work experience while the other half had more than 5 years.

The operationalizations of the variables of the study were adapted from previous studies (Anderson and Srinivasan, 2003; Flavián *et al*., 2006; Koufaris and Hampton-Sosa, 2004; Ranganathan and Ganapathy, 2002; Suh and Han, 2003). The constructs have 36 items. Summated scale was created for each construct. The items were measured using the Likert scale of 1 (strongly agree) to 5 (strongly disagree).

B. Analysis

Table 1 shows the descriptive statistics of the data. It shows the means, standard deviations, and correlation matrix of the predictors, moderator, and dependent variable. The SPSS (Statistical Package for the Social Sciences) results show that the assumptions of linearity, multicollinearity, and homoscedasticity are met.

Table 1: Means, Standard Deviations, and Correlations of All Variables

	Means	**Std Dev**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Website Usability (1)	3.95	.59					
Perceived Performance (2)	3.61	.68	.55				
Privacy (3)	3.65	.76	.38	.41			
Security (4)	3.92	.67	.57	.61	.52		
Loyalty (5)	3.68	.75	.55	.52	.37	.51	
Satisfaction (6)	4.06	.68	.64	.61	.45	.66	.62

All correlations are significant at .01 level.

Table 2 shows the hierarchical regression analysis results. Model 1 shows that, in order of strength, the four positive and significant predictors of loyalty are website usability, security, perceived performance, and privacy. They collectively explain 58 percent of the variance explained of loyalty. Hypothesis 1 predicts the negative moderating effect of the relationship between website usability and satisfaction. Model 2 of Table 2 shows that the moderating variable is significant and negative. It means that the relationship between website usability and satisfaction is less strong as loyalty increases. With the inclusion of the moderating variable, the variance explained slightly increases. It is also statistically significant.

Table 2: Results of Multiple Regression Models Predicting Satisfaction

Predictors	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Website Usability	.32***	.53***	.25***	.23***	.24***
Perceived Performance	.22***	.17***	.44***	.17***	.16***
Privacy	.07*	.06	.06	.41***	.06
Security	.31***	.25***	.25***	.26***	.58***
Loyalty		.66***	.53***	.57***	.64***
Loyalty X Website Usability		-.62**			
Loyalty X Perceived Performance			-.49**		
Loyalty X Privacy				-.56**	
Loyalty X Security					-.62***
Multiple R	.76	.78	.78	.79	.79
R2	.58	.61	.61	.62	.62
Adjusted R2	.58	.60	.61	.61	.61
Incremental R2 from Model 1		.01**	.01**	.01**	.01***

*** p< .01; ** p< .05; * p<.1.

Hypothesis 2 predicts the negative moderating effect of the relationship between perceived performance and satisfaction. Model 3 of Table 2 shows that the moderating variable is significant and negative. It means that the relationship between perceived performance and satisfaction is less strong as loyalty increases. With the inclusion of the moderating variable, the variance explained slightly increases. It is also statistically significant.

Hypothesis 3 predicts the negative moderating effect of the relationship between privacy and satisfaction. Model 4 of Table 2 shows that the moderating variable is significant and negative. It means that the relationship between privacy and satisfaction is less strong as loyalty increases. With the inclusion of the moderating variable, the variance explained slightly increases. It is also statistically significant.

Hypothesis 4 predicts the negative moderating effect of the relationship between security and satisfaction. Model 5 of Table 2 shows that the moderating variable is significant and negative. It means that the relationship between security and satisfaction is less strong as loyalty increases. With the inclusion of the moderating variable, the variance explained slightly increases. It is also statistically significant.

IV. Theoretical Implication

In the era of social media, customer relationship development is more complex and the study of satisfaction and loyalty becomes more important. Researchers have examined the predictors, mediators, moderators, and outcomes of online satisfaction. It is one of the most important predictors of online loyalty. Collectively, the extant literature has significantly improved our understanding of online satisfaction.

Current literature suggests that some important predictors of online satisfaction are website usability, perceived performance, privacy, and security. These relationships might be mediated or moderated by other variables. Mediating variables include trust, commitment, switching costs, and attractive alternatives. Moderating variables include purchase size, customer segment, industry, age, and income.

This study shows that the four predictors of satisfaction accounts for 58 percent of the variance explained of satisfaction. In general, satisfaction accounts for 25 percent of the variance explained of loyalty (Szymanski and Henard, 2001). However, the relationship does not hold for all contexts; in some contexts, the relationships are stronger and in others they are less strong. For example, for high relational customers, trust and commitment are better predictors of loyalty. Satisfaction might not lead to loyalty if attractive alternatives are easily available. However, unsatisfied customers are loyal if the switching costs are high. We might speculate that the study of trust and commitment would become more important in the future.

The current study extends the literature by examining the feedback effect of loyalty. Instead of treating loyalty as a dependent variable, it is treated as a moderating variable. This is consistent with the dynamic system approach and more specifically the expectation disconfirmation theory. Dynamic system analysis includes the feedback loop of the dependent variable. Similarly, the expectation disconfirmation theory would predict the increasing gap between the comparison baseline and the expectations of loyal customers. This study shows how the feedback effect of loyalty changes the relationships between online satisfaction and its predictors.

Furthermore, examining the feedback effect of loyalty is consistent with the call for the reverse logic approach to studying satisfaction. With the rise of the customer lifetime value approach, managers shifted their attention and resources to focus on satisfaction investment that aims at loyal customers who are usually more profitable. Given empirical studies that show the complexity of loyalty and how satisfied customers are not loyal for many reasons that are out of managers' control, I believe that studying the feedback effect of loyalty is complementary and equally important. It is even more important for firms that embrace the concept of customer lifetime value.

More specifically, the empirical results of this study support the feedback loop hypotheses. I found the negative moderating effects of loyalty on the relationship between satisfaction and its predictors. The results might suggest that loyal customers have better knowledge about site navigation and transactions. This knowledge increases their expectations. Similarly, loyal customers have better knowledge about price competitiveness, quality, on time delivery, and after sales service. This knowledge helps them identify subpar performance.

Furthermore, loyal customers have higher stakes and are even more concerned about privacy and security issues. As customers develop relationships and loyalty with e-commerce firms, the firms accumulate more data and information about their loyal customers. The data not only include usage tracking and customer data sharing, but also data breaches and disclosure. Thus, customers would be more concerned and expect higher levels of privacy and security.

In conclusion, this study enhances the current literature and our understanding of online satisfaction by examining the feedback effect of loyalty. This complements the previous unidirectional and contextual approach. This is also consistent with the customer lifetime value approach.

V. Managerial Implications

The literature shows that there are many predictors of online loyalty. One of the core variables is satisfaction. Thus, it is important for managers to achieve high level of satisfaction. However, it is not the only consideration. Other relational mechanisms include trust and commitment. For some customers, satisfaction is important, but they are loyal to the websites because of trust and commitment. These are the main drivers of loyalty for high relational customers. Thus, managers need to pursue different approaches to relationship development for different types of customers.

There are four predictors of satisfaction. They are website usability, perceived performance, privacy, and security. They account for 58 percent of the variance explained of satisfaction. Satisfaction itself accounts for 25 percent of variance explained of loyalty. In the era of social media, we might see the decreasing effects of these factors.

Research shows that the relationship between satisfaction and loyalty is not straightforward. For example, the relationship might have varying forms and strength given different contexts. Some of these contextual variables include age, income, customer segment, industry, life cycle, switching costs, attractive alternatives, and purchase size. For example, older men will be more loyal if they are satisfied with the products they bought. However, for younger buyers and especially women, sales process satisfaction is an important predictor of loyalty (Homburg and Giering, 2001). In this case, managers need to utilize social media as a relationship development tool with their young and female customers.

Research consistently shows that perceived switching costs are positively associated with loyalty. Thus, managers should utilize programs that increase the perceived switching costs such as loyalty programs.

In this study I examined the feedback effect of loyalty. It might suggest that satisfying loyal customers is more difficult than creating them. Maintaining loyal customers is not free. The implication is that managers must continuously improve what they do. Managers must find better ways to facilitate their website navigation and transactions, improve product performance, enhance privacy policies, and secure transaction systems and data management.

Furthermore, given the rise of social media and customer lifetime value, managers might want to reverse their logic of satisfaction practices. Instead of focusing on satisfying all of their customers, they are better off focusing on the right customers to satisfy and divert some the time and resources to satisfy these loyal customers. Research shows that satisfied customers might not be loyal for many reasons.

VI. Study Two

We have seen how social media transform the whole process of attracting, engaging, and retaining customers. We have seen viral videos of new products or excellent services. We have also seen what went wrong when a firm's products or services went viral and shook their loyal customers. Many of us have made buying decisions based on social media referrals from friends and families. In the era of social media, satisfying loyal customers is a very important research topic. Instead of focusing on how satisfaction creates loyalty, the idea of reverse logic is to focus on a satisfaction investment that concentrates on loyal customers who are usually more profitable and more difficult to retain.

Social media have transformed customer relationship management. But how do social media change the customer relationship management of the social media themselves? Previous research found that social media improved brand loyalty of a product (Erdoğmuş and Çiçek, 2012). Incite Group (2014), based on the results of the UK Customer Satisfaction Index from the Institute of Customer Service, reports that social media have decreased the level of satisfaction. A previous study has found that attitude is an important predictor of satisfaction and loyalty of social media (Currás-Pérez *et al.*, 2013).

I suspect that reverse logic applies for the social media as well. For example, the rise of social media may be responsible for the failure of MySpace. The current literature may indicate that loyal customers have the tendency to increase their expectations and decrease their perceived performance. Loyal customers are satisfied customers. Satisfied customers might not be loyal. Satisfied customers increase their expectations. With increased experience, they decrease their perceived performance. These relationships are especially true for social media. Based on the discussion above, I propose:

P1: Online loyalty has a negative moderating effect on the relationship between social media usability and satisfaction.

P2: Online loyalty has a negative moderating effect on the relationship between perceived performance and satisfaction.

Loyal customers of social media are more sensitive to privacy and security issues. Loyal customers are also better at evaluating privacy policies and security issues. This explanation suggests that online loyalty has a negative moderating effects on the relationships among satisfaction, privacy, and security. I propose:

P3: Online loyalty has a negative moderating effect on the relationship between privacy policy of social media and satisfaction.

P4: Online loyalty has a negative moderating effect on the relationship between social media security and satisfaction.

VII. Limitations and Future Research

Satisfaction is just one predictor of loyalty. There are many mediators and moderators. There are also other relational mechanisms such as trust and commitment. Future researchers may want to study the feedback effect of loyalty on trust and commitment or in the presence of other mediating and/or moderators. The presence of these variables may change the feedback impact of loyalty.

Future researchers may want to use longitudinal data to examine the relationship across time. Furthermore, even though college students are appropriate subjects for this study, future researchers may want to examine whether the findings hold for the general public. One issue is that students may be more familiar with technology. This could affect their expectations and create an evaluation gap of website experience.

Future researchers may want to test the social media propositions above. Or they may have to switch and focus on the feedback loop of loyalty on trust and commitment.

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Managerial Commitment to Open-Market Repurchases and Announcement Returns

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Open-market repurchase (OMR) announcements are non-committal because the percentage and timing of actual share repurchases are uncertain. Based on these observations, this study postulates that market participants can infer managerial commitment based on a firm's record of executing prior programs and will respond to the subsequent announcements accordingly. Using simple average and time-weighted methods to measure a firm's record, this study shows that the larger the percentage of shares repurchased and the shorter the time to complete prior programs, the greater the announcement returns for a firm's subsequent OMR announcements. In addition, market participants consider share and time records simultaneously when inferring managerial commitment to subsequent OMRs. We provide several directions for future studies to conclude this paper.

Keywords: Managerial Commitment, Share Repurchase; Open Market, Announcement Return

JEL Classification: G00, G32, G35, M20

I. Introduction

This study explores whether market participants can infer managerial commitment to open market share repurchase (OMR) announcements based on a firm's actual repurchase records in prior programs. Specifically, we postulate that firms establishing strong records of executing prior OMR programs will enjoy positive market reactions to subsequent announcements. This study makes theoretical and practical contributions to the literature. From the theoretical perspective, this study adopts the cognitive psychology literature to the field of finance by considering individuals' ability to retrieve relevant events from memory (Kahneman and Tversky, 1972; Tversky and Kahneman, 1973). Following this theory, this study develops measures according to the recency of OMR announcements, conducts empirical examinations, and finds market participants may assign more weight to the share repurchase records of recent programs than those of earlier ones. From a practical viewpoint, this study shows that both share and time records of prior OMR programs are valuable to market participants in assessing managerial commitment to the subsequent announcements. Particularly, market participants may consider share and time records simultaneously when inferring managerial commitment and respond to the subsequent OMR announcements accordingly.

We are motivated to conduct this study because the OMR has become one of the most common forms of corporate payout over the past several decades (Grullon and Michaely,

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2004).[1] As many researchers have pointed out, corporate executives have various reasons to buy back their company's own shares on the open market.[2] Some companies use OMRs to return free cash to shareholders to avoid overinvestments, while others announce programs to signal their financial prospects to market participants. A firm's management also may make OMR announcements to reveal share undervaluation, boost earnings per share, or deter hostile takeovers. Because of these perceived benefits, market participants have viewed OMRs as good news about the announcing firms. As a result, they tend to react positively to OMR announcements (Stephens and Weisbach, 1998; Jagannathan and Stephens, 2003; Grullon and Michaely, 2004).

Differing from fixed-price and Dutch auction tender offers, firms making OMR announcements are not obligated to buy back shares from the open market or to provide timetables as to when they plan to deliver on their promises. Given the non-committal nature of OMRs, firm executives making such announcements have considerable flexibility regarding the amount and timing of actual share repurchases (Guay and Harford, 2000; Jagannathan *et al*., 2000). As documented in the literature, some companies have acquired several times the number of shares announced, while others only bought back a small fraction thereof (Stephens and Weisbach, 1998). Moreover, some firms complete programs immediately after making announcements, whereas others take months, or even years, to reacquire shares from the open market (Cook *et al*., 2004). Despite these uncertainties, the empirical evidence reported in the literature has shown the average abnormal returns around announcements range between 2% and 3% (Stephens and Weisbach, 1998; Jagannathan and Stephens, 2003; Grullon and Michaely, 2004). This magnitude of market reactions to announcements supports the signaling value of OMR programs. Consequently, this perception leads to significant wealth transfer in capital markets. To avoid overly reacting to this corporate news, it is imperative for market participants to assess managerial commitment to OMRs in order to protect their financial interests.

This study argues that market participants can infer managerial commitments to the subsequent announcements based on managerial actions in the past. When a firm makes multiple announcements, its prior share repurchase records provide a trajectory of managerial actions. By tracking the records of executing previously announced programs, market participants can infer what management may do with regard to subsequent programs. If a firm bought back its shares as announced and completed prior programs promptly, it should strengthen market participants' confidence in the firm's commitment to subsequent announcements. On the other hand, if the firm failed to execute prior OMRs, it would weaken market participants' confidence in managerial promises. If prior records of share buybacks matter, we would expect market participants to react to the subsequent announcements according to a firm's records of executing previously announced programs. Moreover, market participants may take share and time records of all prior programs into account simultaneously

[1] As suggested by Ikenberry *et al.*, 1995, the adoption of U.S. Securities and Exchange Commission Rule 10b-18—the safe harbor provision—is the main driver of the increasing popularity of OMR programs. Under this provision, firms cannot be accused of manipulating stock prices using share repurchase programs as long as they have complied with the Securities and Exchange Commission regulations. Because of Rule 10b-18, most litigation risks have been removed for firms that decide to make OMR announcements.

[2] The literature suggests that firms buy back their own shares to adjust their capital structures (Dittmar, 2000; Grullon and Ikenberry, 2000; Brav *et al*., 2005). They can also use OMRs to boost earnings per share (Grullon and Ikenberry, 2000; Brav *et al*., 2005), substitute dividend payments (Ikenberry *et al*., 1995; Brav *et al*., 2005), deter hostile takeovers (Bagwell, 1991; Dittmar, 2000), and reveal share undervaluation (Vermaelen, 1981; Comment and Jarrell, 1991; Ikenberry *et al*., 1995; Stephens and Weisbach, 1998; Ikenberry *et al*., 2000; Jagannathan *et al*,, 2000; Cook *et al*., 2004; Oded, 2005). Moreover, firms can use these programs to return excess cash on hand to shareholders (Stephens and Weisbach, 1998; Dittmar, 2000; Jagannathan *et al*., 2000; Grullon and Michaely, 2004; Skinner, 2008; Oded, 2009).

to form their beliefs regarding the managerial actions on OMRs when firms have made multiple announcements.

To examine these questions empirically, we calculate a firm's records of prior OMR programs using two measures: the percentage of shares repurchased and the time to complete prior programs. To obtain the values for both records, we take the following steps. First, we calculate (1) the number of shares repurchased relative to the number of shares authorized to buy back (referred as "shares repurchased"), and (2) the time taken to complete each announcement (referred as "time to complete"). We then compute a firm's record of shares repurchased and time to complete of all previously announced programs. To calculate this record, we use the simple average and time-weighted average (TWA) methods. Differing from the simple average method which weighs all prior programs equally, the TWA method assigns more weight to the more recent OMR announcements. We implement the TWA method in this study because the cognitive psychology literature has pointed out that it is easier for individuals to recall a recent event than earlier ones when making decisions (Kahneman and Tversky, 1972; Tversky and Kahneman, 1973).

Using 2,644 non–first-time announcements made by the publicly listed firms in the United States and calculating the firms' records of shares repurchased and time to complete prior OMRs using the simple average and TWA methods, our analyses show that market participants are able to infer managerial commitment to OMRs. More importantly, their reactions to subsequent OMR announcements reflect a firm's record of executing all prior programs. Specifically, the larger the percentage of shares repurchased and the shorter the time to complete prior OMR programs, the greater the announcement returns to a firm's subsequent OMR announcements. To ensure the empirical results reported in this study are robust, we conduct several tests. These robustness tests yield results that are consistent with the main findings reported in the study.

The findings of this study have the following implications for corporate management and market participants. For firm management, this study indicates that it is beneficial for firms to have executed prior OMR programs. With good records on prior repurchases, OMR announcements can be one of the effective avenues for management to communicate with market participants. For market participants, reacting to OMR programs leads to wealth transfers. Therefore, they should infer managerial commitment to subsequent OMRs according to actions taken by the corporate executives in the past. In particular, a firm's record of executing prior programs over time can be a valid indicator to assess managerial commitment to subsequent OMR announcements.

This paper proceeds as follows. Section II reviews the literature and develops the research hypotheses. Section III outlines the data sources and measurements of OMR records over time. Section IV discusses the research methodology and outlines the regression models. Section V presents the empirical results. Section VI shows the results of robustness tests. Section VII summarizes the study, discusses the implications of empirical findings of the study to corporate management and market participants, and highlights directions for future studies.

II. Literature Review and Hypotheses Development

A. Literature Review

Firms making OMR announcements not only have flexibility in determining the percentage but also in the timing of share repurchases. As for the percentage of share repurchases, Stephens and Weisbach (1998) find the actual percentage of OMRs varies across U.S. firms. Ikenberry *et al*. (2000) also report that the percentage of shares repurchased in Canada differs among firms and the extent of repurchases could be contingent upon the degree of mispricing of equity shares. In addition, Rau and Vermaelen (2002) show that the percentage of shares repurchased in OMR programs among U.K. firms appears to be much smaller than those of companies in the U.S. Regarding the timing of share repurchases, the literature indicates that managerial assessments of market timing and trading strategy are major determinants of share repurchase decisions. Focusing on market timing, Ikenberry *et al*. (2000) report that executives in Canada buy more shares back from the open market when stock prices fall. Brockman and Chung (2001) and Zhang (2005) demonstrate that the managers of Hong Kong firms focus on the timing of share repurchases and buy more shares back after their stock prices drop. With regard to the trading strategy, Ginglinger and Hamon (2007) show that OMR activities in the French market largely reflect a contrarian trading strategy.

Since many firms make multiple share repurchase announcements, it is imperative to find out whether firm characteristics influence managerial decisions on executing OMRs. To explore this insight, Jagannathan and Stephens (2003) emphasize the relation between managerial incentives and the frequency of OMR announcements. Dividing the studied firms into two subgroups, the authors find that companies making less frequent announcements are more likely to have information asymmetry between corporate executives and market participants.[3] Moreover, companies making more frequent announcements tend to have a higher propensity for buying back shares from open markets and using this program in lieu of dividend payments. Overall, this result indicates that the frequency of announcements could be an important factor to consider when examining issues relate to OMRs.

To infer managerial actions, Weigelt and Camerer (1988) argue that individuals can gather historical data and form beliefs according to management's actions in the past to gauge how managers will act in the future. Applying this logic to OMRs, we argue that market participants probably can gauge managerial commitment to subsequent programs based on the percentage and timing of the execution of all prior OMRs. Since managers can establish a reputation based on their prior actions on OMRs, their records of shares repurchased and time to complete prior programs over time can be valid indicators for market participants to infer managerial commitment to subsequent announcements. If a firm reacquires shares from the open market as promised and completes programs promptly, these actions speak loudly about corporate executives' commitments to subsequent OMRs. On the other hand, if firms fail to deliver what they promise in prior programs, this lack of action will diminish market participants' confidence in managerial commitment to carry out the subsequent programs. Because the nature of OMRs is non-committal and managerial action is highly uncertain, this study provides an empirical link between a firm's records of executing prior programs over time, managerial commitment, and market reactions to subsequent OMR announcements.

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[3] Moreover, Jagannathan and Stephens (2003) show that larger firms with less volatile operating income and higher dividend payout ratios tend to make repurchase announcements more frequently. In contrast, smaller firms with more volatile operating incomes, lower institutional ownership, lower market-to-book ratios, and high degrees of information asymmetry tend to make repurchase announcements less frequently.

B. Effect of Prior Repurchases on Announcement Returns

Since market participants probably can infer managerial commitment to subsequent OMRs based on their actions in the past, corporate executives probably should build records of executing prior OMRs to ensure the effectiveness of communications made in subsequent announcements. If management fails to execute prior OMRs, a lack of managerial action will send a signal to market participants that the announcing firm does not have a strong commitment to their subsequent OMRs. Consequently, it would weaken the quality of the communication between firm management and market participants.

Following up on Weigelt and Camerer (1988), we also argue that market participants probably will consider all historical repurchasing records to form their beliefs on whether, and to what extent, the announcing firms will carry out the subsequent OMRs. To demonstrate their commitments to subsequent OMRs, corporate executives can repurchase a high percentage of shares in their previously announced programs and establish their reputation over time. Therefore, market participants should be able to infer managerial commitment to OMRs according to the prior records of actual shares repurchased and decide how to react to the subsequent announcements. Measuring market participants' reactions to OMR announcements based on the amount of cumulative abnormal returns (CARs), we predict the following:

Hypothesis 1: Firms repurchasing higher percentages of shares in prior OMRs will experience higher CARs on the subsequent announcements.

In addition to the percentages of shares repurchased in prior programs, the time taken to complete prior OMRs also may influence the announcement returns for the subsequent programs. If a firm buys back shares from the open market promptly following announcements, these actions indicate that corporate executives are not only confident about the repurchasing decisions they make but also have sufficient resources to fulfill their promises. Therefore, the timely completion of prior OMRs will enhance a firm's credibility for the promises made in subsequent announcements. Following this logic, we postulate that market participants may use the time to complete prior OMR programs to discern managerial commitment and determine how to react to subsequent announcements. Measuring market participants' reactions to OMR announcements using CARs, we predict the following:

Hypothesis 2: Firms taking shorter times to complete prior OMRs will experience higher CARs on the subsequent announcements.

III. Data

A. Sample Selection Processes and Data Collection

We obtained announcement data from the Security Data Company's (SDC) *Mergers and Acquisitions* database (Jagannathan and Stephens, 2003; Grullon and Michaely, 2004; Lie, 2005). To select samples for the study, we took the following steps. First, we identified 7,673 OMR programs, as completed by publicly listed firms in the U.S., from 1985 to 2012. Since the purpose of the study is to explore whether the records of executing previously announced OMRs over time would affect market reactions to the subsequent announcements, we excluded

3,116 first-time announcements from the study because these do not have prior programs.[4] We then removed 624 announcements from the pool of observations because the percentage of actual shares repurchased and the details of the repurchase timing were missing from the SDC database. We also eliminated 937 programs from the analyses since the data used to calculate CARs were incomplete in the Center for Research in Security Prices (CRSP) files. Finally, we took 352 more programs out of the sample pool because data for the control variables was not available in the database. This left us with 2,644 non–first-time OMR programs. Table 1 presents the sample selection procedures.

Table 1: Sample Selection Procedures

Sample Selection Procedures		**Number of Observations**
Total number of observations obtained from SDC during the studied period, from 1985 to 2012		7,673
Less: The first-time announcement	3,116	
Percentage of shares repurchased and elapsed time of programs missing from the SDC database	624	
No cumulated abnormal returns or excess return data available	937	
Data on control variables missing	<u>352</u>	<u>5,029</u>
Final samples included in this study		2,644

Note: This table presents the criteria used to select observations for the study. Since the purpose of this study is to determine whether the records of executing prior programs affect market reactions to subsequent OMR announcements, we exclude 3,116 *first-time* OMR announcements from the study.

As for the data source, prior OMR studies collected data from CRSP and/or Compustat (Stephens and Weisbach, 1998; Jagannathan *et al*., 2000; Lie, 2005). Instead, we retrieved the number of shares repurchased, authorization date, completion date, and other program-related data from the SDC *Mergers and Acquisitions* database.[5] We made this choice because companies included in the study may make multiple OMR announcements within a relatively short time (e.g., within a year). Therefore, estimating the records of shares repurchased and the time to complete prior OMRs using the CRSP database and/or Compustat files may lead to inaccurate measurements of variables for each OMR program.

Table 2 presents the sample distribution by year. The period of study is from 1985 to 2012. However, no OMR announcements made between 1985 and 1989 are included in the pool of observations for two reasons. One is that many programs announced during the late 1980s were first-time announcements. Therefore, there are no prior share and time records. In addition, we excluded some non–first-time programs announced during this period from the study because the SDC *Mergers and Acquisitions* database does not have the complete data required for the statistical analysis.

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[4] To form a record of executing previously announced OMRs, firms must make multiple OMR announcements. In this study, we argue that market participants will probably examine what firms have done in the past before determining what to do in relation to subsequent announcements. Therefore, first-time OMR announcements are not included in the study.

[5] To verify the source of the data, we contacted the SDC. The database representative informed us that they obtained the shares repurchased data from the announcing firms' press releases, regulatory filings, and other sources.

Table 2: Distribution of Sample by Year

Year	Frequency	Percentage	Cumulated percentage
1990	1	0.04	0.04
1993	1	0.04	0.08
1994	37	1.40	1.48
1995	96	3.63	5.11
1996	167	6.32	11.43
1997	120	4.54	15.97
1998	211	7.98	23.95
1999	205	7.75	31.70
2000	232	8.77	40.47
2001	191	7.22	47.69
2002	164	6.20	53.89
2003	155	5.86	59.75
2004	158	5.98	65.73
2005	191	7.22	72.95
2006	196	7.41	80.36
2007	191	7.22	87.58
2008	106	4.01	91.59
2009	48	1.82	93.41
2010	76	2.87	96.28
2011	85	3.22	99.50
2012	13	0.50	100.00
Total	2,644	100.00	

B. Share Record and Time Record

There are two test variables in the analyses: *Share Record* and *Time Record* of OMR programs. We calculate these records using the simple average method and the TWA method. To obtain the value of *Share Record* using the simple average method, we apply the following equation for the *n*th announcement of firm *i*:

$$\text{Share Record (Simple Average)} = \sum_{s=1}^{n-1}\left(\frac{actual\ shares\ repurchased_{i,s}}{shares\ authorized_{i,s}}\cdot\frac{1}{n-1}\right),\ n>1 \qquad (1)$$

To derive the value of *Share Record* using Equation (1), we first calculate the percentage of shares repurchased for each prior program. For a firm that made *n* announcements, there are *n - 1* prior OMRs. For every prior OMR announcement (denoted as *s*), we divide the number of actual shares repurchased (*actual shares repurchased*) by the number of shares authorized to repurchase (*shares authorized*). This computation yields the percentage of shares repurchased for every prior OMR program. We then take a simple average of the percentage of shares repurchased across *n - 1* announcements to obtain the *Share Record*.

We also follow the simple average method to calculate time to complete the *n*th announcement made by firm *i* by employing the following equation:[6]

$$\text{Time Record (Simple Average)} = \sum_{s=1}^{n-1}\left[ln\left(1 + day\ elapsed_{i,s}\right)\cdot\frac{1}{n-1}\right], n > 1 \qquad (2)$$

To obtain the value of *Time Record* using Equation (2), we first count the number of days elapsed from the date of announcement to the date of program completion for every prior OMR program (*days elapsed*). We then take the natural logarithm of (1 + *days elapsed*) to measure the time to complete each OMR announcement. Finally, we calculate a simple average of the time to complete across *n - 1* announcements to obtain *Time Record*.

As discussed earlier, the cognitive psychology literature suggests that decision-makers may assign more weight to more salient or easily remembered information (Kahneman and Tversky, 1972; Tversky and Kahneman, 1973). In particular, Kahneman and Tversky (1972) note that it is easier for individuals to access familiar pieces of information from memory than unfamiliar ones. Therefore, accessibility and familiarity could serve as essential cues of the relevance and accuracy of information for decision-making purposes. To consider this factor, we compute *Share Record* and *Time Record* using the TWA method by assigning more weight to the recent OMRs than those of the earlier ones. As shown below, we employ equations (3) and (4) to calculate *Share Record* and *Time Record* using the TWA method:

$$\text{Share Record (Time Weighted)} = \sum_{s=1}^{n-1}\left(\frac{actual\ shares\ repurchased_{i,s}}{shares\ authorized_{i,s}}\cdot\frac{s}{(n-1)\cdot n/_2}\right),\ n > 1 \qquad (3)$$

$$\text{Time Record (Time Weighted)} = \sum_{s=1}^{n-1}\left[ln\left(1 + day\ elapsed_{i,s}\right)\cdot\frac{s}{(n-1)\cdot n/_2}\right],\ n > 1 \qquad (4)$$

The definitions of equations (3) and (4) are the same as those of equations (1) and (2), except for the weights assigned to each prior OMR announcement. The weights of each prior announcement in equations (1) and (2) under the simple average method are the same across *n - 1* programs (i.e., equally weighted). In equations (3) and (4) used for the TWA method, however, we assign weights to the prior announcements using the time digits method. Therefore, the weights in equations (3) and (4) are fractions. To derive the weight for each program, we take the digit assigned to each prior announcement and divide it by the sum of the digits of all the preceding repurchase programs ($(n-1)\cdot n/2$). Therefore, the more recent the OMR announcement, the larger the weight assigned to the program.[7] Table 3 shows how *Share Record* and *Time Record* of prior OMRs are calculated using the simple average method and the TWA method.

[6] We take the natural log of the time to complete to reduce the effect of extreme values. This procedure is commonly-used in the literature (e.g., Fama and French, 1992 and 1995; Doidge *et al*., 2004). For programs completed on the day of announcements, the number of days elapsed equals zero. In order to include these programs in the study, we add one day to the number of elapsed days before calculating the natural logarithm of this variable.

[7] Let us assume that a company has announced three OMR programs in the past. The simple average method assumes that each repurchase record (both shares repurchased and the time to complete) of these three programs is equally important to market participants. On the other hand, the TWA method assumes that the repurchase record of the third announcement (3/6 of the weight) is more important to market participants than that of the second (2/6 of the weight) or the first (1/6 of the weight) announcement.

Table 3: Illustration of Computing Prior OMR Records

Announcement Date	Completed Date	Percentage of Shares Authorized to be Repurchased	Percentage of Shares Repurchased	In Prior OMR Programs: Time to Complete		Track Record of Shares Repurchased		Track Record of Time to Complete		Track Record of Execution Strength	
				In days	In log	Simple average	TWA	Simple average	TWA	Simple average	TWA
Sep. 17, 2001	Apr. 2, 2005	7.21	74.70	1294	3.11						
May 11, 2005	May 9 2006	2.31	87.30	364	2.56	74.70	74.70	3.11	3.11	24.00	24.00
May 09, 2006	Sep. 2, 2006	4.07	105.00	117	2.07	81.00	83.10	2.84	2.74	28.56	30.28
Oct. 24, 2006	Nov. 9, 2006	3.49	106.65	17	1.23	89.00	94.05	2.58	2.41	34.49	39.08

Note: This table demonstrates how this study measures repurchase records. The percentage of shares authorized to repurchase is the number of shares authorized to be repurchased divided by the number of shares outstanding at the repurchase authorization date. The percentage of shares repurchased is the number of shares actually repurchased scaled by the number of shares authorized. The time to complete in days is the difference between the completion and announcement dates. The log of the time to complete is the natural log of the difference between the completion and announcement dates. We calculate the record of shares repurchased in prior OMRs using the simple average and TWA methods. In the simple average method, we compute the record of shares repurchased in prior OMR programs by calculating the simple average of actual shares repurchased as a percentage of shares authorized in prior programs. In the TWA method, we compute the record of shares repurchased in prior OMR programs by taking the TWA of actual shares repurchased as a percentage of shares authorized in prior programs. We compute the record of the time to complete prior OMRs using both the simple average and TWA methods. In the simple average method, we compute the track record of the time to complete prior OMR programs by calculating the simple average of the length of time (as a natural log) to complete prior programs. In the TWA method, we compute the track record of time to complete prior OMR programs by calculating the weighted average length of time (as a natural log) to complete prior programs. Similarly, we compute the record of execution strength in prior OMR programs using the simple average and TWA methods. In the simple average method, we divide the simple average of the record of shares repurchased in prior OMR programs by the simple average of the record of time to complete prior OMR programs. In the TWA method, we divide the record of shares repurchased in prior OMR programs by the record of the time to complete prior OMR programs.

IV. Methodology

We develop regression models to explore whether market participants could infer managerial commitment to subsequent OMRs. We also examine whether firms that established strong records in the prior programs would enjoy higher and positive reactions to the subsequent announcements than those that have not. Using *Share Record* and *Time Record* to gauge managerial commitment, we predict that there is a positive (negative) effect of *Share Record* (*Time Record*) on the market reactions to subsequent OMRs. To measure market reactions to subsequent OMR announcements, we use a three-day CAR (CAR *(-1,1)*), centered on the announcement date, as the dependent variable.[8] To mitigate potential confounding effects on announcement returns, we control for both firm- and program-specific variables in the regression models (Vermaelen, 1981; Comment and Jarrell, 1991; Stephens and Weisbach, 1998; Dittmar, 2000). As shown in Equation (5), we present the regression model used for the analyses:

$$\begin{aligned}\text{CAR} = \beta_0 &+ \beta_1 Target\ Shares + \beta_2 Excess\ Returns + \beta_3 Assets + \beta_4 MTB \\ &+ \beta_5 Net\ Leverage + \beta_6 Dividend\ Payout + \beta_7 Excess\ OCF + \beta_8 Excess\ ICF \\ &+ \beta_9 Excess\ Cash + \beta_{10} Share\ Record + \beta_{11} Time\ Record + \varepsilon \qquad (5)\end{aligned}$$

[8] We calculate abnormal returns by taking actual returns minus the CRSP equally weighted returns.

To identify control variables for the regression model, we follow the findings reported in the literature. First, larger percentages of shares authorized to repurchase (*Target Shares*) reveal more information content about underlying OMR announcements. Thus, this factor may affect the announcement returns on subsequent OMR programs. Moreover, a series of negative abnormal returns prior to an OMR announcement (*Excess Returns*) may indicate the potential undervaluation of equity shares, which would also influence the amount of CAR. Furthermore, the literature shows that information asymmetry between firm management and their shareholders increases as firm size decreases. As such, firm size (*Assets*) may affect market reactions to OMRs as well. We also include the market-to-book ratios prior to OMR announcements (*MTB*) in the regression model to control for possible mispricing of shares and the potential impact of investment opportunities.[9] In addition, we follow Opler *et al*. (1999) and Oswald and Young (2008) by incorporating several variables in the regression model. These control variables are net leverage (*Net Leverage*), dividends (*Dividend Payout*), excess operating cash flows (*Excess OCF*), excess investing cash flows (*Excess ICF*), and excess cash on hand (*Excess Cash*). We incorporate these variables in the regression models to control their effects on market reactions to OMR announcements. Specifically, *Net Leverage* is included to control for the firm's motivation to use OMRs to adjust its capital structure. We also consider *Dividend Payout* to control for firm incentives to use stock repurchases as a substitute for dividend payments. Furthermore, firms with surplus cash but limited opportunities to invest could use share repurchases to mitigate the risk of overinvestment. Therefore, these firms are more likely to fulfill the promises made in OMR announcements. Referring to the extant literature, it documents a positive relation between share repurchase activities and surplus cash measures using *Excess OCF*, *Excess ICF*, and *Excess Cash*. By including these variables in the regression model, we control the effects of surplus cash on market reactions to subsequent OMR announcements.

V. Empirical Results

A. Descriptive Statistics

Table 4 presents the descriptive statistics for the dependent, independent, and control variables in the regression models. The dependent variable of the regression model is *CAR (-1,1)*, the announcement returns to OMRs during a three-day window centered on the announcement date. As shown in Table 4, the average *CAR (-1,1)* for non–first-time OMR programs is 1.72% (standard deviation = 5.33%), which is smaller than the announcement returns reported in prior studies with an average *CAR (-1,1)* for all OMR programs between 2% and 3%. For example, Jagannathan and Stephens (2003) show that the abnormal announcement returns of the first-time announcements are approximately 3%. However, *CAR (-1,1)* of the second and the third announcements are approximately 2% and 1%, respectively. These results suggest that the market reaction to non–first-time announcement returns reported in this study is comparable to those documented in the literature.[10]

[9] Dittmar (2000) includes the market-to-book ratio to control for a firm's investment opportunities, because this may indicate potential share undervaluation.

[10] This study argues that there is an effect of a firm's records on the returns of subsequent OMR announcements. Since there is no prior OMR before the first announcement, we cannot apply this predicted effect to the first-time announcements. To avoid possible confusion, the average market reactions, *CAR (-1,1),* as reported in Table 4, do not include the market reactions to the first-time announcements.

Table 4: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Median	P25	P75
CAR(-1, 1) (%)	2,644	1.72	5.33	1.29	-0.74	3.88
Target Shares (%)	2,644	8.22	22.88	5.33	3.87	9.52
Excess Returns (%)	2,644	-2.17	13.49	-1.65	-9.25	5.35
Assets	2,644	7.08	1.88	6.91	5.82	8.30
MTB	2,644	1.61	1.06	1.13	1.02	1.77
Net Leverage	2,644	61.64	42.79	73.97	40.37	91.20
Payout	2,644	13.83	67.95	0.00	0.00	14.27
Excess OCF	2,644	0.51	0.50	1	0	1
Excess ICF	2,644	0.10	0.30	0	0	0
Excess Cash	2,644	0.21	0.41	0	0	0
Share Record (Simple Average)	2,644	87.49	33.21	97.43	78.44	100.00
Time Record (Simple Average)	2,644	5.48	1.00	5.61	4.91	6.11
Share Record (TWA)	2,644	87.58	33.71	97.49	78.06	100.00
Time Record (TWA)	2,644	5.50	1.00	5.62	4.97	6.12

Referring to Table 4, the average percentage of shares authorized to be repurchased relative to shares outstanding is 8.22% (standard deviation = 22.88%). The average percentage of shares repurchased is 87.49% (standard deviation = 33.21%) of the shares authorized in the repurchase announcement. Although the average percentage of shares repurchased is similar to those documented in the literature (Stephens and Weisbach, 1998), there is a wide range of variation in the percentage of shares repurchased across announcements and firms. In addition, we find a sizable range in the average length of time to complete OMR programs. To simplify our presentation, in this study, we do not tabulate the ranges of time to complete OMRs.

B. Univariate Analysis

To conduct a univariate analysis, we first divide the pool of samples into two groups according to the medians of the shares repurchased in prior programs (high versus low) and of the time to complete prior programs (short versus long). We then compare the means and medians of *CAR (-1,1)* of these groups (high versus low records of the shares repurchased; short versus long records of the time to complete). These analyses provide preliminary evidence as to whether the market participants react to subsequent OMR announcements based on a firm's records in prior programs.

Table 5: Univariate Test of Market Reactions to Repurchasing Records

Classify Open-Market Repurchase Records According to	In Prior OMR Programs	
	Share Record (High vs. Low)	Time Record (Short vs. Long)
Mean of *CAR(-1, 1)*		
High or Short	1.86	1.97
Low or Long	1.58	1.47
Difference (*t*-Test)	0.28 **	0.50 ***
	(1.32)	(2.39)
Median of *CAR(-1, 1)*		
High or Short	1.34	1.62
Low or Long	1.24	0.98
Difference (Wilcoxon Rank Sum Test)	0.10 *	0.64 ***
	(1.32)	(3.55)

Note: The superscripts *, **, and *** indicate the 10%, 5%, and 1% one-tailed test significance levels in the statistical analysis, respectively. We present both *t*- and *z*-values in parentheses.

Table 5 reveals that the average *CAR (-1,1)* of the high *Share Record* group (1.86%) is larger than that of the low *Share Record* group (1.58%). The difference in *CAR*s between these two groups of observations (0.28%) is significant at the 5% level (t-test: t-value = 1.32; p-value < 0.05). The median of the *CAR (-1,1)* of the high *Share Record* group (1.34%) is also larger than that of the low *Share Record* group (1.24%). The difference in *CAR*s between the two groups of samples (0.10%) is significant at the 10% level (Wilcoxon rank sum test: z-value = 1.32; p-value < 0.10).

As for the records of the time to complete prior programs over time, the result from the analysis shows that the average *CAR (-1,1)* of the short *Time Record* group (1.97%) is higher than that of the long *Time Record* group (1.47%). The difference in average *CAR*s between the two groups (0.50%) is significant at the 1% level (t-test: t-value = 2.39; p-value < 0.01). Moreover, the median of the *CAR (-1,1)* of the short *Time Record* group (1.62%) is larger than that of the long *Time Record* group (0.98%). The difference in median *CAR*s between the two groups of observations (0.64%) is significant at the 1% level (Wilcoxon rank sum test: z-value = 3.55; p-value < 0.01). Based on the evidence obtained from univariate analysis, both *Share Record* and *Time Record* affect the announcement returns of the subsequent OMR programs.

C. Regression Analysis

To further examine the hypotheses stated above, we control the firm- and program-specific variables and regress *CAR (-1, 1)* on the records of executing prior OMRs. First, we include the variables of *Share Record* in Model 1 and *Time Record* in Model 2 separately to explore the individual effects of these records on announcement returns. We then include both records in Model 3 to investigate the joint effect of these two records on announcement returns. Table 6 presents the regression results using the simple average method to measure the prior repurchasing records. Table 7 shows the regression results using the TWA method to gauge a firm's records of executing prior OMR programs. For the purpose of the following discussions, we focus on Model 3 of Table 6 and Model 3 of Table 7 as these models consider both *Share Record* and *Time Record* simultaneously in the regression analyses. For these analyses, we calculate standard errors corrected for firm- and year-level clustering and present *t*-statistics in parentheses for the following models. We also remove observations with absolute standardized residuals larger than 3.0 before running the regression.

Table 6: Abnormal Returns and the Records of Prior OMR Programs Calculated Using the Simple Average Method

Variable	Pred. Sign	Model 1	Model 2	Model 3
Intercept		3.2352 ***	4.3801 ***	3.9727 ***
		(7.05)	(9.77)	(8.96)
Target Shares	+	0.0149 ***	0.0147 ***	0.0151 ***
		(4.92)	(4.86)	(4.94)
Excess Returns	-	-0.0267 ***	-0.0264 ***	-0.0265 ***
		(-2.41)	(-2.36)	(-2.38)
Assets	-	-0.2213 ***	-0.1991 ***	-0.2006 ***
		(-3.62)	(-2.85)	(-2.88)
MTB	-	-0.2262 ***	-0.2146 ***	-0.2147 ***
		(-2.67)	(-2.61)	(-2.59)
Net Leverage	-	-0.0041 *	-0.0046 *	-0.0049 **
		(-1.50)	(-1.64)	(-1.81)
Dividend Payout	?	-0.0006	-0.0006	-0.0005
		(-0.38)	(-0.38)	(-0.34)
Excess OCF	+	0.0849	0.0943	0.1015
		(0.73)	(0.78)	(0.84)
Excess ICF	+	-0.2792	-0.2406	-0.2466

Table 6: Abnormal Returns and the Records of Prior OMR Programs Calculated Using the Simple Average Method: Continues

Variable	Pred. Sign	Model 1	Model 2	Model 3
		(-0.85)	(-0.72)	(-0.75)
Excess Cash	+	0.0637	0.0618	0.0670
		(0.21)	(0.20)	(0.22)
Share Record (Simple Average)	+	0.0047**		0.0045**
		(1.96)		(1.83)
Time Record (Simple Average)	-		-0.1619**	-0.1555**
			(-1.77)	(-1.71)
N		2,595	2,595	2,595
F-Value		7.45	7.54	7.33
R^2		0.0268	0.0268	0.0280

Note: The superscripts *, **, and *** indicate the 10%, 5%, and 1% one-tailed test significance levels for a variable with a predicted sign and two-tailed test significance levels for a variable without a predicted sign in the statistical analysis, respectively. We delete observations with absolute studentized residuals greater than 3.0. We present all *t*-statistics in parentheses according to the estimated standard errors clustered by firms and years.

Table 7: Abnormal Returns and the Records of Prior OMR Programs Calculated Using the TWA Method

Variable	Pred. Sign	Model 1	Model 2	Model 3
Intercept		3.3051 ***	4.4442 ***	4.1084 ***
		(7.19)	(9.30)	(8.61)
Target Shares	+	0.0148 ***	0.0147 ***	0.0150 ***
		(4.90)	(4.86)	(4.92)
Excess Returns	-	-0.0265 ***	-0.0263 ***	-0.0263 ***
		(-2.40)	(-2.35)	(-2.36)
Assets	-	-0.2216 ***	-0.1991 ***	-0.2004 ***
		(-3.62)	(-2.87)	(-2.89)
MTB	-	-0.2270 ***	-0.2139 ***	-0.2146 ***
		(-2.67)	(-2.59)	(-2.57)
Net Leverage	-	-0.0040 *	-0.0045 *	-0.0048 **
		(-1.47)	(-1.63)	(-1.77)
Dividend Payout	?	-0.0006	-0.0006	-0.0005
		(-0.38)	(-0.38)	(-0.34)
Excess OCF	+	0.0809	0.0939	0.0989

Table 7: Abnormal Returns and the Records of Prior OMR Programs Calculated Using the TWA Method: Continues

Variable	Pred. Sign	Model 1	Model 2	Model 3
		(0.69)	(0.77)	(0.81)
Excess ICF	+	-0.2785	-0.2376	-0.2422
		(-0.85)	(-0.71)	(-0.73)
Excess Cash	+	0.0616	0.0607	0.0641
		(0.20)	(0.20)	(0.21)
Share Record (TWA)	+	0.0039 **		0.0037 *
		(1.70)		(1.55)
Time Record (TWA)	-		-0.1733 **	-0.1680 **
			(-1.84)	(-1.79)
N		2,594	2,594	2,594
F-Value		7.27	7.56	7.19
R^2		0.0264	0.0270	0.0278

Note: The superscripts *, **, and *** indicate the 10%, 5%, and 1% one-tailed test significance levels for a variable with a predicted sign and two-tailed test significance levels for a variable without a predicted sign in the statistical analysis, respectively. We delete observations with absolute studentized residuals greater than 3.0. We present all *t*-statistics in parentheses according to the estimated standard errors clustered by firms and years.

As illustrated in Model 3 of Table 6 and Model 3 of Table 7, *Share Record* has a significant and positive effect on the *CAR (-1,1)* of the subsequent announcements (the simple average method in Table 6: *t*-value = 1.83 and *p*-value < 0.05, and the TWA method in Table 7: *t*-value = 1.55 and *p*-value < 0.05). These results suggest that firms enjoy higher announcement returns to the subsequent programs when they bought back more shares in previously announced OMRs. As anticipated, the *Time Record* has a significant and negative effect on the *CAR (-1,1)* of the subsequent OMR announcements. (The simple average method in Table 6: *t*-value = -1.71 and *p*-value < 0.05, and the TWA method in Table 7: *t*-value = -1.79 and *p*-value < 0.05). These results confirm our expectations that firms experience higher announcement returns for subsequent programs when they took a shorter time to complete prior OMRs. Therefore, the empirical findings reported in this study support Hypothesis 1 and Hypothesis 2. Furthermore, we find the statistics for the control variables also are consistent with those documented in the literature (Dittmar, 2000; Oswald and Young, 2008). In particular, firms that authorized higher percentages of shares to buy back (*Target Shares*), experienced smaller excess returns (*Excess Returns*), and had smaller firm size (*Assets*) tend to enjoy stronger announcement returns to subsequent OMRs.

VI. Robustness Tests

We conduct three robustness tests in this study. First, we combine *Share Record* and *Time Record* to form an execution strength variable and use it as an alternative measure of a firm's records on prior OMR programs. Second, we use changes in *CAR (-1,1)* between announcements as the dependent variable to analyze the effects of *Share Record* and *Time Record* on market reaction to OMRs. Finally, we remove observations with concurrent OMR announcement date and quarterly earnings reporting date from the pool of observations and rerun regression analyses. Overall, the results obtained from these analyses are consistent with those documented in Section V.

A. Execution Strength of Prior OMR Programs

It is plausible that market participants may consider both records simultaneously to infer managerial commitment to subsequent OMRs. By buying back more shares (i.e., repurchasing a higher percentage of shares in relation to the number of shares authorized to be repurchased) and acquiring shares promptly (i.e., taking a shorter time to complete OMRs), firms send strong signals to market participants that they have made credible repurchase announcements. More importantly, reacquiring more shares at a rapid pace provides an opportunity for firm management to convert the promises made in the OMR announcements into action. In this study, we refer to this combined variable as *Execution Strength*. If market participants view the *Execution Strength* of prior announcements as a valid indicator of managerial commitment to the subsequent OMRs, one would expect that there is a significant and positive effect of a firm's records of execution strength on the announcement returns to the subsequent OMRs.

Similar to equations (1) to (4), we calculate the execution strength in prior OMRs over time using the simple average and TWA methods. To obtain values of *Execution Strength*, we employ equations (5) and (6), as shown below:[11]

$$\text{Execution Strength (Simple Average)}_{i,n} = \sum_{s=1}^{n-1}\left[\frac{\text{percentage repurchased}_{i,s}}{\ln(\text{days elapsed}_{i,s})}\cdot\frac{1}{n-1}\right],\ n > 1. \quad (6)$$

$$\text{Execution Strength (Time Weighted)}_{i,n} = \sum_{s=1}^{t-1}\left[\frac{\text{percentage repurchased}_{i,s}}{\ln(1+\text{days elapsed}_{i,s})}\cdot\frac{s}{(n-1)\cdot n/2}\right],\ n > 1. \quad (7)$$

Employing the records of execution strength over time, obtained from the above equations, we then rerun the regressions and report the results of our analyses in Table 8. In Model 1, we calculate the records of execution strength using the simple average method. In Model 2, we compute the records of execution strength using the TWA method. As shown in Table 8, the records of execution strength have significant and positive effects on the *CAR (-1,1)* of the subsequent OMR announcements (the simple average method: t-value = 2.07 and p-value < 0.05, and the TWA method: t-value = 2.13 and p-value < 0.05).

[11] The definitions of the variables in equations (6) and (7) are the same as those for equations (1) and (2).

Table 8: Abnormal Returns and the Strength of Executing Prior OMR Programs

Variable	**Pred. Sign**	**Model 1**	**Model 2**
Intercept		3.2606 ***	3.2847 ***
		(6.04)	(6.21)
Target Shares	+	0.0148 ***	0.0148 ***
		(4.95)	(4.95)
Excess Returns	-	-0.0265 ***	-0.0264 ***
		(-2.40)	(-2.39)
Assets	-	-0.2100 ***	-0.2115 ***
		(-3.38)	(-3.41)
MTB	-	-0.2217 ***	-0.2229 ***
		(-2.65)	(-2.64)
Net Leverage	-	-0.0045 **	-0.0044 **
		(-1.70)	(-1.66)
Dividend Payout	?	-0.0006	-0.0006
		(-0.37)	(-0.36)
Excess OCF	+	0.0947	0.0907
		(0.79)	(0.75)
Excess ICF	+	-0.2632	-0.2623
		(-0.79)	(-0.79)
Excess Cash	+	0.0687	0.0663
		(0.22)	(0.22)
Execution Strength (Simple Average)	+	0.0182 **	
		(2.07)	
Execution Strength (TWA)	+		0.0176 **
			(2.13)
N		2,595	2,594
F-Value		7.65	7.59
R^2		0.0269	0.0268

Note: The superscripts *, **, and *** indicate the 10%, 5%, and 1% one-tailed test significance levels for a variable with a predicted sign and two-tailed test significance levels for a variable without a predicted sign in the statistical analysis, respectively. We delete observations with absolute studentized residuals greater than 3.0. We present all *t*-statistics in parentheses according to the estimated standard errors clustered by firms and years.

B. Changes in CARs between Announcements

It is possible that the magnitude of announcement returns could depend on firm-specific properties omitted from the regression models presented in the study. To mitigate possible confounding effects of these properties on announcement returns, we use changes in *CAR (-1,1)* between announcements, instead of the *CAR (-1,1)* of individual announcements, as the dependent variable. To rerun the regression analysis, we calculate the changes in *CAR*s between OMR programs using the following equation:

$$\Delta CAR_{i,n} = CAR_{i,n} - CAR_{i,n-1} \quad (8)$$

In Equation (8), $CAR_{i,n}$ is the announcement return for firm *i* at the *n*th announcement during a three-day window. All control variables included in the regression model are those discussed earlier in the study.[12, 13] In Model 1 of Table 9, we present the results of the share and time records calculated using the simple average method. Model 2 of Table 9 shows the results of the share and time records calculated using the TWA method. We also rerun the regressions using the *Execution Strength* as the independent variable. In Table 10, we present the results of these analyses.

Overall, the results shown in Table 9 are similar to those presented in tables 6 and 7. However, the R^2 of the regression models in Table 9 are smaller than those reported in tables 6 and 7. Referring to Model 1 of Table 9, *Share Record* has a significant and positive effect on the changes in *CAR (-1,1)* (Model 1 of Table 9: *t*-value = 2.19 and *p*-value < 0.05, calculated using the simple average method, and Model 2 of Table 9: *t*-value = 2.03 and *p*-value < 0.05, calculated using the TWA method). Moreover, *Time Record* has a significant and negative effect on the changes in *CAR (-1,1)* (Model 1 of Table 9: *t*-value = -1.37 and *p*-value < 0.10, calculated using the simple average method, and Model 2 of Table 9: *t*-value = -1.75 and *p*-value < 0.05, calculated using the TWA method).

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[12] In the regression analysis presented in this section, we measure changes in *Target Shares*, *Excess Returns*, *Assets*, *MTB*, *Net Leverage*, and *Dividend Payout* between announcements and use them as control variables.
[13] In this study, we code *Excess OCF*, *Excess ICF* and *Excess Cash* as dummy variables. To examine the effects on changes in *CAR* between announcements, however, we measure the changes in *OCF* and *Cash* instead of coding them as dummies. We do not include changes in *ICF* as a control variable in this additional analysis, because these figures (sales of fixed assets, intangible assets, associates and other investments and subsidiaries) change dramatically from one period to another.

Table 9: Relative Changes in Abnormal Returns Between Announcements and Records of Share Repurchases and Time to Complete Prior OMR Programs

Variable	Pred. Sign	Model 1	Model 2
Intercept		0.3599	0.5955
		(0.35)	(0.59)
ΔTarget Shares	?	-0.0077 **	-0.0078 **
		(-2.36)	(-2.42)
ΔExcess Returns	?	-0.0159 *	-0.0159 *
		(-1.77)	(-1.76)
ΔAssets	?	-0.7891	-0.7566
		(-1.62)	(-1.58)
ΔMTB	?	-0.3491	-0.3506
		(-1.34)	(-1.35)
ΔNet Leverage	?	0.0129 **	0.0127 **
		(2.14)	(2.10)
ΔDividend Payout	?	-0.0003	-0.0003
		(-0.54)	(-0.53)
ΔCash	?	-2.7866	-2.7439
		(-1.35)	(-1.34)
ΔOCF	?	1.0876	1.0784
		(0.74)	(0.74)
Share Record (Simple Average)	+	0.0090 **	
		(2.19)	
Time Record (Simple Average)	-	-0.1919 *	
		(-1.37)	
Share Record (TWA)	+		0.0090 **
			(2.03)
Time Record (TWA)	-		-0.2355 **
			(-1.75)
N		2,403	2,403
F-Value		2.71	2.94
R^2		0.0142	0.0147

Note: The superscripts *, **, and *** indicate the 10%, 5%, and 1% one-tailed test significance levels for a variable with a predicted sign and two-tailed test significance levels for a variable without a predicted sign in the statistical analysis, respectively. We delete observations with absolute studentized residuals greater than 3.0. We present all *t*-statistics in parentheses according to the estimated standard errors clustered by firms and years.

In Table 10, we present the regression results obtained using the *Execution Strength* as the independent variable. Referring to Model 1 of Table 10, the *Execution Strength* has a significant and positive effect on the changes in *CAR (-1,1)*, calculated using the simple average method (*t*-value = 3.14 and *p*-value < 0.01). As shown in Model 2 of Table 10, the *Execution Strength* also has a significant and positive effect on the changes in *CAR (-1,1)*, calculated using the TWA method (Model 2 of Table 10: *t*-value = 3.44 and *p*-value < 0.01). These results demonstrate that the records of *Execution Strength* in previously announced programs over time have significant and positive effects on the changes in returns between the subsequent OMRs.

Table 10: Relative Changes in Abnormal Returns Between Announcements and Records of Execution Strength of Prior OMR Programs

Variable	Pred. Sign	Model 1	Model 2
Intercept		-0.5123 *	-0.5624 **
		(-1.91)	(-2.17)
ΔTarget Shares	?	-0.0077 **	-0.0077 **
		(-2.26)	(-2.29)
ΔExcess Returns	?	-0.0156 *	-0.0155 *
		(-1.74)	(-1.73)
ΔAssets	?	-0.8304 *	-0.8169 *
		(-1.71)	(-1.69)
ΔMTB	?	-0.3455	-0.3464
		(-1.31)	(-1.32)
ΔNet Leverage	?	0.0130 **	0.0129 **
		(2.15)	(2.12)
ΔDividend Payout	?	-0.0003	-0.0003
		(-0.51)	(-0.51)
ΔCash	?	-2.7950	-2.7857
		(-1.37)	(-1.37)
ΔOCF	?	1.1046	1.1081
		(0.75)	(0.76)
Execution Strength (Simple Average)		0.0345 ***	
		(3.14)	
Execution Strength (TWA)			0.0375 ***
			(3.44)
N		2,404	2,404
F-Value		2.66	2.78
R^2		0.0137	0.0141

Notes: The superscripts *, **, and *** indicate the 10%, 5%, and 1% one-tailed test significance levels for a variable with a predicted sign and two-tailed test significance levels for a variable without a predicted sign in the statistical analysis, respectively. We delete observations with absolute studentized residuals greater than 3.0. We present all *t*-statistics in parentheses according to the estimated standard errors clustered by firms and years.

C. OMR Programs Announcements Concurrently with Earnings Announcements

To mitigate the possible effect of events announced concurrently with OMR programs on the results reported in this study, we identify whether there are other major events announced concurrently with OMR programs. By carrying out this procedure, we find that numerous firms announced their OMRs concurrently with quarterly earnings announcements. To mitigate the effect of quarterly earnings announcements on the returns of OMR programs, we remove 407 OMR programs because these announcements were made at the same date when quarterly earnings were released. After these removals, we then rerun the regression analyses according to the models specified in tables 6, 7, and 8.

To simplify our presentations, we report the results of the *Share Record* and *Time Record* calculated using the simple average method. Referring to Table 11, we find the results obtained from these analyses are similar to those reported in Section V. According to these findings, we conclude that the results presented in this study are robust and are not sensitive to the concurrency of OMR announcements and quarterly earnings releases.

Table 11: Abnormal Returns and the Track Records of Prior OMR Programs Calculated Using the Simple Average Method (Excluding Concurrent Quarterly Earnings Announcements)

Variable	Pred. Sign	Model 1	Model 2	Model 3
Intercept		3.1630 ***	4.3270 ***	3.9992 ***
		(6.71)	(7.73)	(6.69)
Target Shares	+	0.0128 ***	0.0127 ***	0.0130 ***
		(6.43)	(6.25)	(6.31)
Excess Returns	-	-0.0236 ***	-0.0239 ***	-0.0237 ***
		(-2.78)	(-2.81)	(-2.79)
Assets	-	-0.1983 ***	-0.1757 ***	-0.1761 ***
		(-3.97)	(-3.37)	(-3.37)
MTB	-	-0.2513 **	-0.2415 **	-0.2416 **
		(-2.06)	(-1.99)	(-1.99)
Net Leverage	-	-0.0029	-0.0035 *	-0.0038 *
		(-1.10)	(-1.35)	(-1.46)
Dividend Payout	?	0.0005	0.0005	0.0005
		(0.59)	(0.59)	(0.67)
Excess OCF	+	0.0173	0.0336	0.0393
		(0.11)	(0.20)	(0.24)
Excess ICF	+	-0.3326	-0.2815	-0.2920
		(-0.92)	(-0.78)	(-0.81)
Excess Cash	+	0.0912	0.0868	0.0880
		(0.29)	(0.27)	(0.28)

Table 11: Abnormal Returns and the Track Records of Prior OMR Programs Calculated Using the Simple Average Method (Excluding Concurrent Quarterly Earnings Announcements): Continues

Variable	Pred. Sign	Model 1	Model 2	Model 3
Shares Record (Simple Average)	+	0.0038 *		0.0036 *
		(1.41)		(1.29)
Time Record (Simple Average)	-		-0.1777 **	-0.1722 **
			(-1.94)	(-1.88)
N		2,187	2,187	2,187
F-Value		8.89	9.33	8.56
R^2		0.0252	0.0259	0.0268

Note: The superscripts *, **, and *** indicate the 10%, 5%, and 1% one-tailed test significance levels for a variable with a predicted sign and two-tailed test significance levels for a variable without a predicted sign in the statistical analysis, respectively. Observations with absolute studentized residuals greater than 3 are deleted. All *t*-statistics are presented in parentheses and based on estimated standard errors clustered by firms and years.

VII. Summary and Conclusions

Over the past few decades, OMRs have become one of the important avenues for firms to return excess cash to shareholders, substitute for dividend payments, signal the undervaluation of equity shares, boost earnings per share, or fend off hostile takeovers. Although a rich body of literature has argued that share repurchases often provide positive signals about the announcing firms, the inherent nature of OMRs is highly uncertain since corporate executives are not obligated to deliver what they promise when making announcements. To mitigate the negative effects from overreacting to subsequent OMR announcements, this study contributes to the literature by exploring whether market participants can infer managerial commitment to OMRs. In particular, this study examines whether firms that established strong records of share repurchases and time to complete prior programs enjoy positive market reactions to their subsequent announcements.

In this study, we argue that corporate executives can establish records based on their execution of prior OMR programs over time. By demonstrating their commitment to subsequent programs, it would enhance a firm’s announcement returns. Examining companies that have made multiple OMRs, this study shows that the records of the shares repurchased and of the time to complete prior programs are important indicators for market participants to infer a firm’s commitment to subsequent announcements. More importantly, these indicators affect market reactions to subsequent OMRs. Given the non-committal nature of OMR announcements, these findings imply that records of OMR execution can be plausible indicators as to how firm management will behave with regard to the subsequent programs. In addition, market participants can use share repurchase records to mitigate the uncertainty associated with OMRs, and thus avoid over-reacting to a firm’s subsequent announcements.

Our findings have the following implications for corporate management and market participants. For corporate management, the results show that market participants react less favorably to subsequent OMRs when the announcing firms have failed to deliver what they promised in prior announcements. Thus, corporate executives who choose not follow through on OMR announcements may put themselves at risk of not being able to use open market share repurchase announcements as an effective tool to communicate with market participants in the future. To avoid this drawback, it is imperative for announcing firms to establish credible records on OMR programs over time. For market participants, the results of this study indicate that they should examine a firm's records of executing previously announced programs, use these to infer managerial commitment to the subsequent OMRs, and determine their own course of action, so they can avoid over-reacting to subsequent programs.

Several issues deserve researchers' attention in future studies. First, it is desirable to extend the findings reported in this study and to continue exploring possible additional factors and investigating their influences on the market reactions to OMR announcements. To conduct these examinations, it is imperative for researchers to develop a theoretical framework and use it to select factors and make predictions as to why certain firms choose to make OMR announcements while others decide not to. Second, as documented in the literature, it is difficult to completely rule out the endogeneity issue of OMR decisions. To mitigate this concern, researchers also should develop a research framework and conduct analyses so they can fully address endogeneity in OMR decisions. Finally, market participants may investigate firm performance following the announcement before reacting to the current announcements. In other words, if market participants observe that firms perform better following OMR programs, they are more likely to react to the subsequent announcements. Although this study has addressed this issue by incorporating control variables in regression models, it would be beneficial for researchers to build theoretical arguments and conduct investigations, so we can gain additional insights on the possible links between firm performance and market participants' reactions to subsequent OMR announcements.

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Does the Stock Market React Differently to Intangible Asset Investments than to Tangible Asset Investments?

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Using a large sample, we show that customer acquisition and customer service spending create intangible customer assets, much as research and development (R&D) spending creates intangible technology assets. We find that stock prices react positively to significant investments in these activities, similar to the positive reaction earlier studies find for investments in R&D. Conversely, we show that investments in physical assets produce negative stock price reactions. These results suggest that policies to encourage investment in intangible, rather than in physical, assets may be more valuable, at least in terms of stock market value.

Keywords: Intangibles, Valuation, Investments, Budgeting

JEL Classification: G12, G14, G31, M37

I. Introduction

The U.S. economy has shifted heavily toward service industries. Service industries accounted for 81.8 percent of non-farm employment at the end of 2002 compared to 57.8 percent in 1955, with a commensurate decline for manufacturing employment.[1] Service firms typically invest more in intangible assets such as research and development, brand, and customer loyalty (attraction and retention), but these assets do not usually appear on their balance sheets.[2] Akhigbe and Madura (2008) and Daniel and Titman (2006) suggest that firms with more intangible assets are more difficult to value, hence, the market response to intangible asset investments could differ from the response to tangible asset investments.

Consistent with Nelson (2006), who shows that intangibles are an important asset pricing factor, we find firms investing in intangible assets significantly outperform those investing in tangible assets. The two largest forms of intangible asset investment are research and development (R&D) and customer acquisition and service (A&S). Some studies such as Eberhart *et al*. (2004) and Hall *et al*. (2005) have examined the value effects of R&D investment, but few studies (including Chan *et al.* (2001) and Chauvin and Hirschey (1993)) have studied the effects of A&S. We separate A&S spending into two components: advertising

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[1] Strauss and Walster (2003) base their calculations on data from the U.S. Department of Labor, Bureau of Labor Statistics.

[2] Goodwill on the corporate balance sheet usually reflects only a small portion of the intangible assets created by a service firm. Goodwill measures the unimpaired capitalized value of the difference in market value and book value arising from a merger or acquisition that has not been assigned to specific assets or liabilities or from an intangible or tangible asset purchase. Goodwill does not represent the values of intangible assets created in-house from normal operating activities.

and marketing expense (A&M) used mostly to attract customers, and customer service spending (CS) used mostly to retain them. Our study isolates the contemporaneous and future firm value impacts of A&S investments, and compares them to the impacts of investments in R&D and tangible capital expenditures (CAPEX).

Eberhart *et al.* (2004) examine long-term abnormal returns following significant increases in R&D expenditure. They find that R&D improves firm value in the long term, but is not immediately reflected in stock prices. Chauvin and Hirschey (1993) find a positive relationship between firms' contemporaneous R&D or A&M spending and their market values. Chan *et al.* (2001) find that stock price accurately reflects the level of a firm's investment in R&D and A&M, that is, investors cannot earn positive abnormal returns after buying stocks with current high levels of either.

Other studies find that output measures of R&D investments, such as patents or Food and Drug Administration (FDA) drug approvals, are positively related to firm value. Hall *et al.* (2005) and Hirschey *et al.* (2001) show that "knowledge stock" or innovation output, measured by patent counts or patent citations, are significantly related to firms' market values.[3] Bosch and Lee (1994), Ahmed *et al.* (2002), and Alefantis *et al.* (2004) find that FDA decisions concerning new drugs undergoing R&D significantly affect firms' stock prices.

For firms with few physical assets, a substantial portion of their equity market value is the expected future cash-flows that accrue from their repeat customers. We posit that, analogous to the findings of Eberhart *et al.* (2004) for R&D expenditures, significant unexpected increases in A&M and CS expenditures should increase firms' stock price performance. We use cutoffs of at least 5 percent annual increase in A&M spending and a 10 percent increase or more for the much large CS spending.

Our study contributes to the extant finance literature in several ways. We compare the stock price performance of firms that significantly increase investments in A&M or CS against those that significantly increase R&D or CAPEX. Earlier studies do not consider CS spending, and studies like Chan *et al.* (2001) consider A&M in less detail with different methods.

We also use the actual fiscal year end month as the annual event date. Other studies establish annual event dates by assuming that all firms have a December fiscal year end and a four-month report lag, or they use the true fiscal year end and a three-month lag. We believe that it is more accurate to use a firm's true fiscal year end without lags because firms have already released investment information in quarterly reports and press releases by their fiscal year-end date.

Overall, our results show that firms that significantly increase their investments in intangible assets (A&M, CS, and R&D) earn positive abnormal returns following those investments. Firms investing in tangible assets (CAPEX) earn negative abnormal returns. The results from the Carhart four-factor event-time model find an economically and statistically significant positive 60-month cumulative return of around 20 percent, 10 percent, and 26 percent from significant increases in A&M, CA, and R&D spending respectively; the same model produces significant negative returns of approximately -6 percent for large increases in CAPEX spending. The monthly abnormal returns findings from a calendar-time study are similar is scope. Our results imply that policies designed to encourage investments in intangible assets have more value than tangible investments in manufacturing assets.

The rest of this paper proceeds as follows. Section II describes the data and the sample. Section III explains the empirical models, and Section IV presents their results. Section V is a conclusion.

[3] Hall *et al.* (2005) define "knowledge stock" as the intangible asset obtained as the output from investment in R&D.

II. Data Collection and Sample

A. Measures of A&M and CS Intensity

Previous studies in the finance literature define various measures of R&D intensity, a standardized measure of R&D. Chan *et al.* (2001) primarily measure R&D intensity as the ratio of R&D expenditures to market value of equity, and Eberhart *et al.* (2004) use R&D expenditure relative to total assets.

We use similar measures of A&M intensity and CS intensity. The data to calculate these measures are obtained from the COMPUSTAT Active and Research files and the Center for Research in Security Prices (CRSP) database. A&M intensity and CS intensity are measured as the ratio of expenditures to market value of equity. Market value of equity is measured as the product of closing price at calendar year end (COMPUSTAT annual data item 24) and common shares outstanding (COMPUSTAT annual data item 25). A&M expenditure is advertising expense (COMPUSTAT annual data item 45). No direct measures of customer service expenditure are available in the COMPUSTAT database. Our study focuses on firms whose primary assets are its customers, so our measure of CS expenditure is selling, general, and administrative spending (COMPUSTAT annual data item 189) less advertising spending (COMPUSTAT annual data item 45).[4] Our measure of R&D intensity is defined as the ratio of R&D expenditures (COMPUSTAT annual data item 46) to market value of equity, and CAPEX intensity is measured as the ratio of capital expenditures (COMPUSTAT annual data item 128) to market value of equity.

B. Sample Construction

Sample selection criteria are analogous to that of Eberhart *et al.* (2004). Our samples include all firm-year observations from 1951 to 2005 that have sufficient data available in the COMPUSTAT and CRSP databases, subject to the following requirements. First, our findings would be better revealed for firms that have economically significant levels of spending. Hence, firms in our samples have A&M, R&D, or CAPEX intensity measures of at least 5 percent. Since CS spending is a much larger component of spending, we use a cut-off of 25 percent – close to the median CS intensity measure of firms in our initial sample. Second, dollar A&M, R&D or CAPEX spending must increase by at least 5 percent (given the high level of CS spending relative to market value of equity, the CS sample only includes firms that increase spending by at least 10 percent).

Applying the first selection criterion of high investment intensity produces 17,783 A&M, 15,805 CS, 7,143 R&D, and 18,412 CAPEX firm-year observations. The second selection criterion of significant changes in investments reduces firm-year observations to 10,422 for the A&M sample, 12,369 for the CS sample, 5,790 for the R&D sample, and 14,310 for the CAPEX sample.

We use the last day of the fiscal year-end month as the event date. To obtain the event date, we use a fiscal year variable (COMPUSTAT annual data item YEAR A) and a fiscal year-

[4] All of the expenses in the COMPUSTAT database definition of SG&A may not clearly fit within our two variables i.e. advertising and marketing (A&M) and customer service (CS), but we believe that the majority do. During sample selection we select firms with relatively larger SG&A and examine when they make relatively larger changes in SG&A. For these firms, we believe that our definitions are especially good proxies, because sample selection identifies firms whose main business is customer service. Furthermore, the focus of our study is to compare effects between service firms' intangible asset investments and mostly manufacturers' tangible asset investment. Note that CAPEX or R&D measures face the same measurement problems because some of the expenditures do not fit into a pure definition of those terms (e.g., they can include transportation and installation costs).

end month (COMPUSTAT annual data item FYR). In line with COMPUSTAT data assignment, for firms with a fiscal year-end month between January and May, the actual calendar year corresponds to the year after the fiscal year variable YEAR A. For the other months (June to December), the actual calendar year is the same as the fiscal year variable YEAR A.

We examine in detail the characteristics of the firm-year observations in our samples. The statistics of interest are sales (COMPUSTAT annual data item 12), total assets (COMPUSTAT annual data item 6), book value of equity (COMPUSTAT annual data item 60), market value of equity, and A&M, CS, R&D and CAPEX intensity measures. We also study whether these characteristics differ over the various investment types.[5]

III. Empirical Models

We study abnormal returns around the event dates for various time windows. These abnormal returns may reflect premiums for risk differentials, rather than long-term abnormal stock returns. Consequently, we test for long-term abnormal stock returns using the market model and the Fama and French (1993) multifactor model. In additional tests, we include the momentum factor suggested by Carhart (1997).

There is considerable debate in the finance literature regarding the use of event-time or calendar-time and buy-and-hold returns or cumulative returns for long-run studies. Fama (1998) suggests that long-run studies suffer from the bad model problem, and that abnormal returns depend on the approach (event-time or calendar-time), the risk-adjustment model, the method used to aggregate returns, and the power of the statistic used to test for significance.[6] To check for the robustness of our findings, we specify our empirical models using various approaches.

A. Event-Time Approach

A.1 Cumulative Average Abnormal Return (CAAR)

In this traditional event-study approach, we calculate the cumulative average abnormal returns for various time windows around the sample events. We examine CAARs generated using various risk-adjustment models.

The traditional market model,[7] our first risk-adjustment model, takes the form:

$$\boldsymbol{R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt}}.$$

The empirical specification to obtain abnormal return is defined as:

$$\boldsymbol{AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{mt})},$$

where, for stock j in period t after an event,

AR_{jt} = abnormal return on stock,

R_{jt} = return on stock,

R_{mt} = return on the market index,

$\hat{\alpha}_j, \hat{\beta}_j$ = market model parameter estimates in estimation period using OLS.

[5] The various intensity measures come from the models in the paper. The other variables (sales, total assets, book value of equity, and market value of equity) are widely-followed descriptors of company characteristics, and are used extensively in the finance and accounting research literature.

[6] See Eberhart *et al.* (2004) for a detailed exposition of the debate.

[7] While Fama (1998) and others have criticized this model specification as particularly sensitive to the bad model problem for long-term studies, we present the results for the sake of completeness and to demonstrate the consistency of our overall findings using various model specifications.

The average of abnormal returns (AAR_t) in period t after an event is measured as:

$$AAR_t = \frac{1}{N}\sum_{j=1}^{N} AR_{jt} ,$$

where N = number of stocks in the sample.

The cumulative average abnormal returns ($CAAR_T$) during event-time window T is calculated as:

$$CAAR_T = \sum_{t=1}^{T} AAR_t .$$

In additional tests, we use the risk-adjustment models of Fama-French (1993):

$$R_{jt} = \alpha_j + \beta_j R_{mt} + s_j SMB_t + h_j HML_t + \varepsilon_{jt} ,$$

and Carhart (1997):

$$R_{jt} = \alpha_j + \beta_j R_{mt} + s_j SMB_t + h_j HML_t + u_j UMD_t + \varepsilon_{jt} ,$$

where

SMB_t = the return on a portfolio of small stocks minus the return on a portfolio of big stocks,

HML_t = the return on a portfolio of high book-to-market ratios minus the return on a portfolio of low book-to-market ratios,

UMD_t = the return on a portfolio of high momentum stocks minus the return on a portfolio of low momentum stocks,

α_j = monthly abnormal stock returns measure,

β_j, s_j, h_j, u_j = factor loadings on the systematic risk factors R_m, SMB, HML, UMD respectively.

Similar to the market model defined above, abnormal returns (AR_{jt}) using the Fama-French three-factor model and the Carhart four-factor model are defined respectively as:

$$AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{mt} + \hat{s}_j SMB_t + \hat{h}_j HML_t)$$

$$AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{mt} + \hat{s}_j SMB_t + \hat{h}_j HML_t + \hat{u}_j UMD_t),$$

where $\hat{\alpha}_j, \hat{\beta}_j, \hat{s}_j, \hat{h}_j, \hat{u}_j$ = model parameter estimates in estimation period using OLS.

The average abnormal return (AAR_t) and cumulative average abnormal returns ($CAAR_T$) using the Fama-French or Carhart models are calculated similarly to that for the market model defined above.

A.2. Buy-and-Hold Abnormal Return (BHAR)

We also test for the significance of long-term abnormal returns using a traditional buy-and-hold abnormal return model. The approach is defined as:

$$BHAR_{jt} = \prod_{t=1}^{T}(1 + R_{jt}) - \prod_{t=1}^{T}(1 + R_{mt}) ,$$

where, for stock j in event time window T,

BHAR = buy-and-hold abnormal return measure,

R_{jt} = return on stock in month t,

R_{mt} = return on market index in month t.

B. Calendar-Time Approach

Our study also tests for significance of long-term abnormal returns using the Fama-French (1993) three-factor model in calendar-time. The empirical model takes the form:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + \varepsilon_{pt},$$

where, for portfolio p in calendar period t,

R_{pt} = the average portfolio return,

R_{ft} = the one-month Treasury-bill rate,

R_{mt} = the return on the market index,

SMB_t = the return on a portfolio of small stocks minus the return on a portfolio of big stocks,

HML_t = the return on a portfolio of high book-to-market ratios minus the return on a portfolio of low book-to-market ratios,

α_p = monthly abnormal stock returns measure,

β_p, s_p, h_p = factor loadings on the systematic risk factors R_m, SMB, HML respectively.

Portfolios are created each calendar month during our sample period. A firm's stock return is part of the monthly portfolio return if the month is part of the firm's event window.

IV. Results of Study

A. Descriptive Statistics

In Table 1, we present key characteristics of the firm-year observations in our samples. The median values of sales, total assets, and book value of equity are statistically indistinguishable from that of the average firm in the COMPUSTAT North America database. Although the median values of market value of equity and the market-to-book ratio are consistently lower than that of the average COMPUSTAT firm, the differences are not statistically significant. In any case, we use the Fama-French (1993) three-factor model in additional tests to control for size and value effects.

The increase in investment expenditure for a typical firm in the COMPUSTAT database is between 8.3 percent and 10.7 percent, depending on the type of investment. Since we study firms that significantly increase investments, the firms in our samples have much higher increases in investments, ranging from 21.4 percent to 60.1 percent. The change is particularly striking for firms that increase capital expenditure investments.

Intensity measures vary depending on the type of investments. The typical firm only spends between 2.5 percent and 3.0 percent on A&M and R&D. However, capital expenditure spending is higher at 6.2 percent. CS expenditure is much higher at 37.6 percent for the median firm, because it includes all selling, general, and administrative expenses as defined in the COMPUSTAT database. Since our study requires high levels of investments relative to market value of equity, firms in our samples have significantly higher intensity measures for each investment category compared to the typical firm.

Table 1: Summary Statistics

Variable	A&M	CS	R&D	CAPEX
SALES ($MM)	86.1 (57.6)	79.4 (57.6)	53.0 (57.6)	109.6 (57.6)
ASSETS ($MM)	57.3 (70.5)	54.4 (70.5)	49.0 (70.5)	82.3 (70.5)
BVE ($MM)	18.6 (26.4)	22.6 (26.4)	25.6 (26.4)	32.4 (26.4)
MVE ($MM)	28.9 (55.6)	26.3 (55.6)	37.3 (55.6)	42.3 (55.6)
MTB	1.40 (1.46)	1.15 (1.46)	1.34 (1.46)	1.22 (1.46)
A&M change in percent	25.9 (9.1)			
CS change in percent		21.4 (10.7)		
R&D change in percent			25.2 (9.9)	
CAPEX change in percent				60.1 (8.3)
A&M Intensity in percent	12.0 (2.8)			
CS Intensity in percent		61.5 (37.6)		
R&D Intensity in percent			10.1 (2.5)	
CAPEX Intensity in percent				14.3 (6.2)

Notes: The variables are defined as sales SALES (COMPUSTAT annual data item 12), total assets ASSETS (COMPUSTAT annual data item 6), book value of equity BVE (COMPUSTAT annual item 60), market value of equity MVE, market-to-book value of equity MTB, and various investment intensity measures. MVE is calculated as the product of closing price at calendar year end (COMPUSTAT annual data item 24) and common shares outstanding (COMPUSTAT annual data item 25). MTB is calculated as the ratio of MVE to BVE. The investment categories are A&M, CS, R&D, and CAPEX. A&M is advertising and marketing expense (COMPUSTAT annual data item 45). CS is customer service expense, measured as the difference between selling, general, and administrative expenses (COMPUSTAT annual data item 189) and A&M. R&D is research and development expense (COMPUSTAT annual data item 46). CAPEX is capital expenditure (COMPUSTAT annual data item 128). The investment intensity measures are calculated as the ratio of the expenditure to market value of equity MVE. Reported statistics are median values of all variables. Comparative median values of all firms in the COMPUSTAT North America database are in parentheses.

B. Event-Time Approach

We report CAARs for portfolios of events of the four investment categories A&M, CS, R&D, and CAPEX. CAARs are reported for monthly windows (-6, 0), (+1, +6), (+1, +12), (+1, +36), (+1, +60) around the event dates. [8]

In Table 2, we present empirical results where abnormal returns are calculated as market-adjusted returns, that is:

$$\boldsymbol{AR_{jt} = R_{jt} - R_{mt}} \ .$$

Our sample of firms that have high A&M intensity, and that also significantly increase A&M spending, have poor short-run past returns. These firms under-perform the market by 7.06 percent over the six months before the event.[9] In the period after portfolio formation, however, these firms consistently outperform the market. The short-run CAARs are 6.68 percent over six months and 7.32 percent over one year. These firms continue to out-perform in the long run with cumulative abnormal returns of 24.79 percent over three years, and 35.05 percent over a five-year period. The empirical findings are similar for the other investment categories, although CAPEX has smaller magnitude returns.

[8] We also performed tests using CRSP daily returns. Since the results are qualitatively similar, and for the sake of brevity, we do not report them in the paper.

[9] In reported results, our proxy for the market index is the CRSP value-weighted market index. However, empirical results using the CRSP equal-weighted index, not reported here, are qualitatively similar.

Table 2: Cumulative Average Abnormal Returns (CAAR) Using Market–Adjusted Returns

CAAR	A&M	CS	R&D	CAPEX
(-6, 0)	-7.06	-6.78	-9.17	-4.09
	(-17.48**, -8.78**)	(-17.23**, -7.66**)	(-15.78**, -9.27**)	(-11.89**, -5.57**)
(+1, +6)	6.68	6.91	5.73	5.98
	(19.87**, 22.03**)	(21.80**, 23.35**)	(11.43**, 13.02**)	(21.18**, 20.61**)
(+1, +12)	7.32	8.16	8.83	6.35
	(15.23**, 21.09**)	(17.86**, 21.82**)	(12.32**, 14.44**)	(15.00**, 17.75**)
(+1, +36)	24.79	25.17	28.45	19.84
	(34.89**, 35.88**)	(36.89**, 37.37**)	(25.90**, 25.30**)	(32.66**, 33.46**)
(+1, +60)	35.05	37.48	39.02	30.31
	(43.18**, 41.08**)	(46.98**, 44.31**)	(31.14**, 29.58**)	(43.03**, 42.05**)
Sample Size	10422	12369	5790	14310

*, ** indicate significance at the 5 percent and 1 percent level respectively.

Notes: $AR_{jt} = R_{jt} - R_{mt}$, where, for stock j over the period t before or after a significant investment event, AR_{jt} is the abnormal return on stock, R_{jt} is the return on stock, and R_{mt} is the return on the market index. CAAR represents the cumulative average abnormal monthly percent return, around the event date for portfolios of firms' stocks formed for each investment category – A&M, CS, R&D, and CAPEX. A&M is advertising and marketing expense. CS is customer service expense, measured as the difference between selling, general, and administrative expenses (SG&A) and A&M. R&D is research and development expense. CAPEX is capital expenditure. CAARs are reported for monthly windows (-6, 0), (+1, +6), (+1, +12), (+1, +36), (+1, +60) around the event date. The data are collected from the COMPUSTAT Active and Research files and the Center for Research in Security Prices (CRSP) database for the period from 1951 to 2005. Patell z statistics and non-parametric generalized sign z test statistics are in parentheses.

Barber and Lyon (1997) and Kothari and Warner (1997) recommend using buy and hold returns (BHARs) because they more accurately reflect the wealth creation of a buy-and-hold investor. They also argue that the statistical tests used in generating long-run event CAARs are biased. Table 3 presents results for BHARs computed as follows:

$$BHAR_{jt} = \prod_{t=1}^{T}(1 + R_{jt}) - \prod_{t=1}^{T}(1 + R_{mt}).$$

BHAR and CAAR results are generally similar; however, the long-run abnormal returns using BHARs are larger in magnitude.[10] Over the six months before the event, firms in all categories underperform. Underperformance varies; -7.33 percent for firms investing in A&M, -7.09 percent for those investing in CS, -9.91 percent for those investing in R&D, and -4.25 percent for those investing in CAPEX.

Post-event, firms in all investment categories consistently outperform. Six-month future returns range between 4.92 percent for firms that invest in R&D to 6.75 percent for firms that invest in CS. Long-run abnormal returns are considerably larger and statistically significant. After five years (three years) stocks in the A&M portfolio earn abnormal returns of 68.23 percent (35.49 percent), those in the CS portfolio earn 62.09 percent (31.59 percent), those in the R&D portfolio earn 56.25 percent (30.50 percent), and those in the CAPEX portfolio earn 47.94 percent (26.69 percent).

[10] Due to monthly compounding of returns in the BHAR approach, rather than the monthly accumulation in the CAAR approach.

Table 3: Buy-and-Hold Average Abnormal Returns (BHAR)

BHAR	A&M	CS	R&D	CAPEX
(-6, 0)	-7.33	-7.09	-9.91	-4.25
	(-17.52**, -19.64**)	(-17.27**, -21.67**)	(-15.80**, -19.11**)	(-11.92**, -18.66**)
(+1, +6)	6.44	6.75	4.92	5.79
	(19.81**, 11.54**)	(21.77**, 10.71**)	(11.37**, 3.17**)	(21.13**, 8.33**)
(+1, +12)	7.32	8.32	7.57	6.73
	(15.15**, 5.35**)	(17.81**, 3.00**)	(12.25**, -0.68)	(14.91**, 0.18)
(+1, +36)	35.49	31.59	30.50	26.69
	(34.16**, 10.05**)	(36.77**, 5.98**)	(25.72**, 1.11)	(32.44**, 3.18**)
(+1, +60)	68.23	62.09	56.25	47.94
	(42.70**, 9.16**)	(46.73**, 5.90**)	(30.91**, -0.10)	(42.70**, 4.88**)
Sample Size	10422	12369	5790	14310

*, ** indicate significance at the 5 percent and 1 percent level respectively.

Notes: $BHAR_{jt} = \prod_{t=1}^{T}(1+R_{jt}) - \prod_{t=1}^{T}(1+R_{mt})$, where, for stock j over the period t before or after a significant investment event, R_{jt} is the return on stock, and R_{mt} is the return on the market index. BHAR represents the buy-and-hold abnormal monthly percent return around the event date for portfolios of firms' stocks formed for each investment category – A&M, CS, R&D, and CAPEX. A&M is advertising and marketing expense. CS is customer service expense, measured as the difference between selling, general, and administrative expenses (SG&A) and A&M. R&D is research and development expense. CAPEX is capital expenditure. BHARs are reported for monthly windows (-6, 0), (+1, +6), (+1, +12), (+1, +36), (+1, +60) around the event date. The data are collected from the COMPUSTAT Active and Research files and the Center for Research in Security Prices (CRSP) database for the period from 1951 to 2005. Patell z statistics and non-parametric generalized sign z test statistics are in parentheses.

However, our results may be driven by significant differences in risk between our sample firms and the market. Hence, we calculate risk-adjusted abnormal returns using other approaches.

First, consider a risk adjustment using the market model. Table 4 shows that the market model adjustment confirms that short-run (six months) pre-event performance is poor for all investment categories, with CAARS in the range -7.35 percent to -9.68 percent.

In the short run (six months), post-event abnormal returns for investments in intangible assets, A&M, CS, and R&D are positive at 5.43 percent, 4.40 percent, and 3.61 percent, respectively. This trend continues into the long-run with future five-year (three-year) CAARs at 22.09 percent (17.14 percent) for A&M, 14.37 percent (10.39 percent) for CS, and 22.20 percent (16.35 percent) for R&D. Our empirical results for A&M and R&D are in line with those of Chan *et al.* (2001).[11]

The post-event stock returns of the CAPEX sample differ significantly from our intangible asset investment samples. Future cumulative abnormal returns for such firms are 2.01 percent in six months, -1.81 percent in one year, -3.54 percent in three years, and -5.59 percent over a five-year period. Therefore, while firms that increase investments in capital expenditure may have small short-term positive stock price performance, their risk adjusted long-run performance is negative. These findings are in line with Daniel and Titman (2006)

[11] In their study, the average high-investment firm (one in Portfolio 4) that invests in A&M (R&D) has an annual return of 17.69 percent (16.87 percent) against 19.81 percent (20.25 percent) for the control sample. They also find that, in the long-run, Portfolio 4 firms do significantly better than the market; over the three-year period after portfolio formation, A&M (R&D) firms have an average annual return of 21.62 percent (21.03 percent) versus 18.92 percent (19.50 percent) for control firms. We do not compare our results to the highest investment firms (Portfolio 5 firms) in the Chan *et al.* (2001) study because our portfolio selection method yields a sample more comparable to their second highest investment group (our sample only includes the upper half of firms that invest in each category, and they need to increase investments significantly).

who hypothesize that stock markets may have differing reactions to investments in tangible and intangible assets. They are also consistent with Nelson (2006) who suggests that firms with intangible assets should earn larger returns.

Table 4: Cumulative Average Abnormal Returns (CAAR) Using the Market Model

CAAR	A&M	CS	R&D	CAPEX
(-6, 0)	-7.35	-8.15	-9.68	-7.97
	(-14.27**, -10.16**)	(-15.11**, -10.52**)	(-4.61**, -7.84**)	(-23.00**, -11.42**)
(+1, +6)	5.43	4.40	3.61	2.01
	(20.15**, 15.55**)	(19.94**, 13.88**)	(-84.51**, 7.05**)	(11.61**, 10.20**)
(+1, +12)	4.78	3.16	4.75	-1.81
	(15.51**, 12.22**)	(16.21**, 10.63**)	(-55.64**, 8.31**)	(1.61, 4.57**)
(+1, +36)	17.14	10.39	16.35	-3.54
	(33.69**, 18.29**)	(30.04**, 14.14**)	(-19.59**, 13.59**)	(4.44**, 7.94**)
(+1, +60)	22.09	14.37	22.20	-5.59
	(42.08**, 19.16**)	(38.66**, 13.94**)	(-7.58**, 13.73**)	(10.85**, 9.09**)
Sample Size	10422	12369	5790	14310

*, ** indicate significance at the 5 percent and 1 percent level respectively.

Notes: $AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{mt})$, where, for stock j over the period t before or after a significant investment event, AR_{jt} is the abnormal return on stock, R_{jt} is the return on stock, R_{mt} is the return on the market index, and $\hat{\alpha}_j, \hat{\beta}_j$ are the market model parameter estimates in estimation period using OLS. CAAR represents the cumulative average abnormal monthly percent return, around the event date for portfolios of firms' stocks formed for each investment category – A&M, CS, R&D, and CAPEX. A&M is advertising and marketing expense. CS is customer service expense, measured as the difference between selling, general, and administrative expenses (SG&A) and A&M. R&D is research and development expense. CAPEX is capital expenditure. CAARs are reported for monthly windows (-6, 0), (+1, +6), (+1, +12), (+1, +36), (+1, +60) around the event date. The data are collected from the COMPUSTAT Active and Research files and the Center for Research in Security Prices (CRSP) database for the period from 1951 to 2005. Patell z statistics and non-parametric generalized sign z test statistics are in parentheses.

The single factor market model may not properly adjust for risk, consequently, tables 5 and 6 present abnormal returns using the multifactor models of Fama and French (1993) and Carhart (1997), respectively.

Table 5 shows that the abnormal returns obtained using the Fama-French three-factor model are similar to those obtained using the market model in Table 4. In the pre-event short run (six months), the average firm in each investment category underperforms by approximately -7.50 percent.

Post-event, as in Table 4, firms outperform after investing in intangible assets (A&M, CS, R&D) by about 3 percent over six months, by between 5.77 and 15.76 percent over three years, and by between 6.93 and 22.68 percent over five years post-event. And again, firms investing in tangible assets underperform post-event by between -8.82 percent (three years) and -13.48 percent (five years). There is a significant performance difference between firms investing in intangibles and those investing in CAPEX.

Table 5: Cumulative Average Abnormal Returns (CAAR) Using the Fama-French Three-Factor Model

CAAR	A&M	CS	R&D	CAPEX
(-6, 0)	-7.40	-7.63	-7.38	-7.18
	(-4.83***, -10.33***)	(-4.84***, -10.82***)	(-3.96***, -8.72***)	(-4.84***, -11.02***)
(+1, +6)	2.97	2.48	3.81	-0.22
	(2.10**, 9.55***)	(1.70**, 7.65***)	(2.21**, 5.05***)	(-0.16, 4.80***)
(+1, +12)	2.69	2.27	5.87	-3.57
	(1.34*, 8.97***)	(1.10, 6.08***)	(2.41***, 6.08***)	(-1.84**, 1.41*)
(+1, +36)	10.11	5.77	15.76	-8.62
	(2.91***, 14.15***)	(1.62*, 10.25***)	(3.73***, 10.96***)	(-2.57***, 4.47***)
(+1, +60)	11.16	6.93	22.68	-13.48
	(2.49***, 15.66***)	(1.50*, 11.19***)	(4.16***, 12.63***)	(-3.11***, 6.85***)
Sample Size	10422	12369	5790	14310

*, **, *** indicate significance at the 10 percent, 5 percent and 1 percent level respectively.

Notes: $AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{mt} + \hat{s}_j SMB_t + \hat{h}_j HML_t)$, where, for stock j over the period t before or after a significant investment event, AR_{jt} is the abnormal return on stock, R_{jt} is the return on stock, R_{mt} is the return on the market index, SMB_t is the return on a portfolio of small stocks minus the return on a portfolio of big stocks, HML_t is the return on a portfolio of high book-to-market ratios minus the return on a portfolio of low book-to-market ratios, and $\hat{\alpha}_j, \hat{\beta}_j, \hat{s}_j, \hat{h}_j$ are the Fama-French three-factor model parameter estimates using OLS. CAAR represents the cumulative average abnormal monthly percent return, around the event date for portfolios of firms' stocks formed for each investment category – A&M, CS, R&D and CAPEX. A&M is advertising and marketing expense. CS is customer service expense, measured as the difference between selling, general, and administrative expenses (SG&A) and A&M. R&D is research and development expense. CAPEX is capital expenditure. CAARs are reported for monthly windows (-6, 0), (+1, +6), (+1, +12), (+1, +36), (+1, +60) around the event date. The data are collected from the COMPUSTAT Active and Research files and the Center for Research in Security Prices (CRSP) database for the period from 1951 to 2005. Portfolio time-series *t*-statistics and non-parametric generalized sign z test statistics are in parentheses.

Table 6 reports CAARs based on the Carhart four-factor model. Again, firms investing in each of the four investment categories have negative pre-event six-month CAARs ranging between -5.89 percent and -7.39 percent.

Firms that invest in intangible assets outperform after the event. In the short run (six months), their CAARs range from 2.53 to 4.19 percent and over longer periods their CAARs range from 7.81 to 26.22 percent.[12] But firms that invest in CAPEX underperform by -4.41 percent over three years, and -5.86 percent over five years.

[12] It is possible that the lower magnitude of returns for firms that invest in CS is due to the measure used in our study. We believe that CS is measured with more noise A&M and R&D; however, in the absence of any other direct measure of CS, this is the closest proxy.

Table 6: Cumulative Average Abnormal Returns (CAAR) Using the Carhart Four-Factor Model

CAAR	A&M	CS	R&D	CAPEX
(-6, 0)	-5.89	-6.72	-7.39	-6.41
	(-4.22***, -7.32***)	(-4.74***, -8.51***)	(-4.79***, -8.54***)	(-4.69***, -9.75***)
(+1, +6)	4.19	2.53	3.92	0.64
	(3.25***, 10.90***)	(1.93**, 8.30***)	(2.74***, 4.54***)	(0.51, 4.26***)
(+1, +12)	4.84	3.21	7.10	-1.43
	(2.65***, 10.85***)	(1.73**, 6.87***)	(3.52***, 6.40***)	(-0.80, 2.47***)
(+1, +36)	14.48	7.81	18.76	-4.41
	(4.58***, 15.89***)	(2.43***, 11.08***)	(5.36***, 11.06***)	(-1.42*, 6.04***)
(+1, +60)	20.27	10.49	26.22	-5.86
	(4.96***, 17.78***)	(2.53***, 11.58***)	(5.80***, 13.19***)	(-1.46*, 7.34***)
Sample Size	10422	12369	5790	14310

*, **, *** indicate significance at the 10 percent, 5 percent and 1 percent level respectively.

Notes: $AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{mt} + \hat{s}_j SMB_t + \hat{h}_j HML_t + \hat{u}_j UMD_t)$, where, for stock j over the period t before or after a significant investment event, AR_{jt} is the abnormal return on stock, R_{jt} is the return on stock, R_{mt} is the return on the market index, SMB_t is the return on a portfolio of small stocks minus the return on a portfolio of big stocks, HML_t is the return on a portfolio of high book-to-market ratios minus the return on a portfolio of low book-to-market ratios, UMD_t is the return on a portfolio of high momentum stocks minus the return on a portfolio of low momentum stocks, and $\hat{\alpha}_j, \hat{\beta}_j, \hat{s}_j, \hat{h}_j, \hat{u}_j$ are the Carhart four-factor model parameter estimates using OLS. CAAR represents the cumulative average abnormal monthly percent return, around the event date for portfolios of firms' stocks formed for each investment category – A&M, CS, R&D, and CAPEX. A&M is advertising and marketing expense. CS is customer service expense, measured as the difference between selling, general, and administrative expenses (SG&A) and A&M. R&D is research and development expense. CAPEX is capital expenditure. CAARs are reported for monthly windows (-6, 0), (+1, +6), (+1, +12), (+1, +36), (+1, +60) around the event date. The data are collected from the COMPUSTAT Active and Research files and the Center for Research in Security Prices (CRSP) database for the period from 1951 to 2005. Portfolio time-series *t*-statistics and non-parametric generalized sign z test statistics are in parentheses.

C. Calendar-Time Approach

Fama (1998) argues against buy and hold abnormal returns (BHAR) because systematic model errors get compounded over the long run. Moreover, the BHAR approach does not account for cross-sectional dependence among event firms. Fama (1998) and Mitchell and Stafford (2000) suggest that the calendar-time approach overcomes the cross-sectional dependence problem in the BHAR. They show that the calendar-time approach retains sufficient power to detect abnormal returns, particularly in comparison to the BHAR approach. Eberhart *et al.* (2004) suggest that the calendar-time approach is, in fact, biased in favor of the EMH. Consequently, detection of significant abnormal returns using this approach is stronger evidence than that provided by the BHAR approach.

Table 7 shows the abnormal returns using the calendar-time approach with the Fama-French three-factor model used for risk-adjustment. In Panels A, B, C, and D we present results of tests for investments in A&M, CS, R&D, and CAPEX, respectively. For all categories, in the six months before the event, average monthly abnormal returns range between -1.31 percent for CS investments and -0.61 percent for CAPEX investments. This confirms our earlier findings that firms in our portfolios are past losers (have low pre-event returns).

Post-event, A&M portfolio firms earn positive average long-run abnormal returns. Average monthly abnormal returns are highest (0.31 percent) when measured over the thirty months after the event. Over the same period, the R&D portfolio earns average abnormal monthly returns of 0.75 percent. The statistically significant abnormal return of 0.60 percent in the 60-month period is similar to that found by Eberhart *et al.* (2004). The CS and CAPEX portfolios do not exhibit statistically significant abnormal returns. The CAPEX results are in line with our previous findings that firms do not earn abnormal returns on tangible capital investments.

Table 7: Abnormal Returns Using the Calendar-Time Fama-French Three-Factor Model

Panel A: A&M	α	β	s	h	R-squared
(-6, 0)	-1.04	1.0070	1.0229	0.2942	0.7086
	(-6.27***)	(24.60***)	(18.97***)	(4.73***)	
(0, +6)	-0.02	1.0100	1.0333	0.3555	0.6114
	(-0.09)	(19.94***)	(15.55***)	(4.63***)	
(0, +12)	0.04	0.9958	1.0134	0.3789	0.6573
	(0.24)	(23.09***)	(17.65***)	(5.73***)	
(0, +36)	0.26	1.0006	1.0362	0.3743	0.6437
	(1.55)	(23.86***)	(18.17***)	(5.78***)	
(0, +60)	0.09	1.0299	1.0350	0.4172	0.6765
	(0.59)	(26.40***)	(19.29***)	(6.85***)	
Panel B: CS	**α**	**β**	**s**	**h**	**R-squared**
(-6, 0)	-1.31	1.0855	1.1770	0.2522	0.6396
	(-5.51***)	(18.77***)	(15.65***)	(2.90***)	
(0, +6)	0.05	1.0792	1.1273	0.2960	0.6006
	(0.20)	(17.69***)	(14.40***)	(3.23***)	
(0, +12)	0.06	1.0073	1.0764	0.3118	0.6293
	(0.29)	(19.14***)	(15.94***)	(3.94***)	
(0, +36)	0.20	1.0501	1.1822	0.3620	0.6896
	(1.05)	(21.84***)	(19.03***)	(5.01***)	
(0, +60)	0.18	1.0779	1.1502	0.3654	0.7423
	(1.08)	(25.44***)	(21.01***)	(5.75***)	
Panel C: R&D	**α**	**B**	**s**	**h**	**R-squared**
(-6, 0)	-1.17	1.1237	1.1657	-0.0861	0.7291
	(-5.31***)	(21.23***)	(16.91***)	(-1.09)	
(0, +6)	0.12	1.2066	1.2461	-0.0875	0.7111
	(0.49)	(20.10***)	(16.05***)	(-0.97)	
(0, +12)	0.31	1.2332	1.1340	-0.0086	0.7046
	(1.29)	(21.45***)	(15.28***)	(-0.10)	
(0, +36)	0.55	1.2182	1.1961	0.0545	0.6239
	(1.99**)	(17.97***)	(13.65***)	(0.54)	
(0, +60)	0.56	1.2024	1.1819	0.0485	0.6504
	(2.17**)	(19.00***)	(14.45***)	(0.51)	
Panel D: APEX	**α**	**B**	**s**	**h**	**R-squared**
(-6, 0)	-0.61	0.9801	0.9603	0.2283	0.6833
	(-3.50***)	(22.81***)	(17.06***)	(3.49***)	
(0, +6)	0.12	1.0244	0.9029	0.2234	0.5754
	(0.56)	(18.79***)	(12.72***)	(2.70***)	
(0, +12)	0.09	1.0358	0.8753	0.2248	0.6848
	(0.54)	(25.31***)	(16.14***)	(3.59***)	
(0, +36)	0.11	1.0171	0.8837	0.2761	0.7442
	(0.84)	(30.94***)	(19.92***)	(5.45***)	
(0, +60)	0.05	0.9915	0.8956	0.2926	0.7122
	(0.34)	(28.92***)	(19.26***)	(5.54***)	

*, **, *** indicate significance at the 10 percent, 5 percent and 1 percent level respectively.

Notes: $R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + \varepsilon_{pt}$ α_p represents the average abnormal monthly return, using the calendar-time Fama-French three-factor model, in percent for each investment category – A&M, CS, R&D, and CAPEX. A&M is advertising and marketing expense. CS is customer service expense, measured as the difference between selling, general, and administrative expenses (SG&A) and A&M. R&D is research and development expense. CAPEX is capital expenditure. R_{pt} is the average portfolio return, R_{ft} is the one-month Treasury bill rate, R_{mt} is the return on the market index, SMB_t is the return on a portfolio of small stocks minus the return on a portfolio of big stocks, HML_t is the return on a portfolio of high book-to-market ratios minus the return on a portfolio of low book-to-market ratios. β_p, s_p, h_p are the factor loadings on the systematic risk factors R_m, SMB, HML, respectively. Abnormal returns are reported for monthly windows (-6, 0), (0, +6), (0, +12), (0, +36), (0, +60) around the event date. The data are collected from the COMPUSTAT Active and Research files and the Center for Research in Security Prices (CRSP) database for the period from 1951 to 2005. *t*-statistics are reported in parentheses.

V. Conclusions

This paper analyzes whether firms' stocks earn abnormal returns after significant increases in investments in intangible and tangible assets. Earlier studies consider A&M in less detail with different methods, and do not consider CS at all. Also, unlike most previous studies, we use the actual fiscal year-end month as the annual event date.

We focus on firms that have high levels of investments in A&M, CS, R&D, and CAPEX, and study abnormal returns over various windows, before and after the investment event. Abnormal performance is measured with various methods including CAAR, BHAR, and calendar-time approaches. Although the CAAR approach may be less reliable for long-run studies, it is acceptable for detecting short-run abnormal performance. In any case, the methods produce similar results except that the calendar time results are somewhat weaker.

First, CAAR and BHAR results show positive short-run abnormal returns for large portfolios of firms that significantly increase their investments in intangible assets (A&M, CS, and R&D). Firms investing in tangible assets (CAPEX) earn no abnormal returns.

Second, we find consistent evidence of positive long-run abnormal performance for firms investing in A&M, CS, and R&D, although the results for CS are not as strong. Conversely, firms that significantly increase their CAPEX earn negative long-run abnormal returns.

Finally, we find that all of the portfolios underperform during the six-months before the investment events, by approximately – 5 percent to -7 percent. These results are consistent across a variety of empirical approaches.

Overall, our results show that stock prices respond favorably when firms invest in intangible assets and unfavorably when they invest in tangible assets. If stock investors have it right, our study suggests that policies designed to encourage intangible asset investment could be more valuable.

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