Dividends and Stock Prices:
A Fresh Look at the Relationship

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Abstract

The relationship between dividends and stock prices can be traced back to the Bernoulli's paradox (1738). Later Williams (1938) independently re-established the link. Finally, in a series of works, Walter (1956), Gordon (1959), and Miller-Modigliani (1961) examined the relationship. However, Miller-Modigliani's result received the most attention in the literature. In this paper, we first present the Bernoulli's paradox, and then take a fresh look at other studies, and finally we show that Miller-Modigliani claim of dividend irrelevance does not seems to hold as it has been mostly recognized in the existing literature. It should be noted that the existing literature in corporate finance has unequivocally established that stock price is the discounted value of the expected dividends and the expected future price of the asset at the time of disposal. Based on this basic notion of valuation, there exist three major strands of thought that have resulted in three distinct relationships between stock prices and dividends: 1. Gordon result, 2. Walter result, and 3. Miller-Modigliani result, – all derived with no taxes or market distortions in the

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picture. Later, under tax environment and other environments, more results or relationships have been noted. In this work, we examine the adequacy and/or legitimacy of these results and make an attempt to shed more light on the existing knowledge and reestablish the link between dividends and stock prices with and without taxes. Most important part of this fresh look is the disagreement with Miller-Modigliani stand that dividends do not affect stock price.

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JEL Classification: G30, G35.

1 – Introduction

The existing literature in corporate finance waxes eloquently on the relationship between dividends and stock prices, as developed by Gordon (1959, 1962, 1963), and Miller and Modigliani (1961), and Walter (1956, 1963), (although his, that is, Walter‘s papers are hardly cited in the literature); all of these studies are derived in the environment, marked by the absence of taxes. Black and Scholes (1974) re-examine the effects of dividend yields and dividend policy on common stock prices and returns. We have major works since then where taxes are factored in, and the pre-existing results are re-evaluated. Miller and Scholes (1978), and Litzenberger and Ramaswamy (1979), and a few others listed later are the most-cited papers in this area of research.

2 – Tax-Free Environment

2.1 Bernoulli-Williams-Gordon

It is well- recognized now that stock price is the discounted value of dividends, and no one has disputed this valuation concept. This notion of valuation came from Williams (1938), who remarked, "…the old man knew where milk and honey came from, but he made no such mistake as to tell his son to buy a cow for her cud or bees for their buzz." He expressed further in the words of an old farmer to his son:

A cow for her milk,
A hen for her eggs,
A stock by heck,
For her dividends.

An orchard for fruit,
Bees for their honey,
And stocks, besides
For their dividends.

Ever since we are used to ascertaining the intrinsic value of any stock as the discounted value of income stream the stock is expected to generate in years to come. Formally, given the dividend stream as $D_1, D_2, D_3,$ and so on, price of stock today (P_0) is computed as follows:

$$P_0 = \frac{D_1}{(1+y)} + \frac{D_2}{(1+y)^2} \frac{D_3}{(1+y)^3} + ... + \frac{D_n}{(1+y)^n} + \frac{P_n}{(1+y)^n} \quad (1)$$

Or, in more general terms,

$$P_j = \sum_{i=1}^{n} \frac{D_{j+i}}{(1+y)^i} + \frac{P_{j+n}}{(1+y)^{j+n}} \quad \text{for } j = 0, 1, 2, ... \quad (2)$$

Here y is the rate of return required by the stockholders. For $j = 0, n \to \infty,$ and $D_{j+i} = D \quad \forall\, i$, obviously, equation (2) reduces to $P_0 = \frac{D}{y}$. If there is a growth in the dividend stream such as $D_2 = D_1(1+g), D_3 = D_1(1+g)^2, ..., D_n = D_1(1+g)^{n-1}, ...,$ and this growth rate (g) continues *ad infinitum*, current stock price ((P_0) is easily derived as follows:

$$P_0 = \frac{D_1}{(y-g)} \quad \text{for y > g, and}$$
$$= \infty, \text{ otherwise} \quad (3)$$

Equation (3) is the so-called Gordon result in basic textbooks and in the formal literature. However, two more scholars should be associated with Myron J. Gordon, and these scholars are John B. Williams (1938) and Daniel Bernoulli (1738). In 1738, Bernoulli, in his classic paper on probability, "Petersburg Paradox," presented in the *Imperial Academy of Sciences* brought out the following issue:

"Peter tosses a coin and continues to do so until it should land 'heads' when it comes to the ground. He agrees to give Paul one ducat if he gets "heads' on the very first throw, two ducats if he gets it on the second, four if on the third, eight on the fourth, and so on, so that with each additional throw the number of ducats he must pay is doubled. Suppose we seek to determine the value of Paul's expectation."

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Consider Table 1 now on the calculation of the expectation.

Table 1

Sequence of Tosses	Probability (= p_i)	Payment (= r_i)
H	1/2 (= p_1)	1 (= r_i)
TH	1/4 (= p_2)	2 (= r_2)
TTH	1/8 (= p_3)	4 (= r_3)
TTTH	1/16 (= p_4)	8 (= r_4)
TTTTH	1/32 (= p_5)	16 (= r_5)

The calculation from the data in Table 1 is as follows:
the expected value of the payoff (P_0) is:

$$P_0 = p_1r_1 + p_2r_2 + p_3r_3 + p_4r_4 + p_5r_5 = (1/2)\times 1 + (1/4)\times 2 + (1/8)\times 4 + (1/16)\times 8 + (1/32)\times 16 = 5/2$$

It is obvious that if there are n throws, the expected value of the payoff is ***n*/2**, and that means that if $n \to \infty$, Paul will earn infinite amount of ducats.

Now, Durand (1957), and later Ghosh (2010) picked up, and put the Bernoulli work in the framework of William's notion of stock pricing. Let $p_i = 1/(1 + y)^i$, $r_i = D_i(1 + g)^{i-1}$, i = 1, 2, 3, ……., n, Then we can have the following payoff value(P_0) as

$$P = \frac{D_1}{(1+y)} + \frac{D_1(1+g)}{(1+y)^2} + \frac{D_1(1+g)^2}{(1+y)^3} + \ldots\ldots\ldots\ldots + \frac{D_1(1+g)^{n-1}}{(1+y)^n}$$

$$= D_1 \left(\frac{1}{y-g} \left[1 - \left\{ \frac{1+g}{1+y} \right\}^n \right] \right) \qquad (4)$$

Expression (4) is the same as expression (3) for $n \to \infty$, expression (4) is reduced to:

$$P = \frac{D_1}{y-g} \qquad \text{for y > g} \qquad (5)$$

This is exactly the duplication of expression (3). It is the result of the Petersburg Paradox modified, as already explained. However, it should be noted that the so-called Gordon result expressed by (3) and (5) can be derived under the following assumptions: earnings per share of a corporation at time t, say**,** E_t is a fraction of the book value of a share V_t **.** That is,

$$E_t = \alpha V_t \qquad 0 < \alpha < 1, \qquad (6)$$

and dividend per share (D_t) is a constant fraction of (E_t). That is,

$$D_t = \beta . E_t = \alpha . \beta . V_t \qquad 0 < \beta < 1 \qquad (7)$$

From (6) and (7), one can see that $E_t(1-\beta)$ is the retained earnings to get

$$V_{t+1} = V_t + E_t(1-\beta) = V_t\{1+\alpha(1-\beta)\} \qquad (8)$$

If the book value, dividends, and earnings grow at the same rate *g*, where $g = \alpha(1-\beta)$, expression (5) can be re-written as:

$$P = D_1 \frac{1}{y-g} = E_1 \frac{\beta}{y-g} = V_1 \frac{\alpha\beta}{y-g} \qquad (9)$$

This expression (9) was derived by Williams (1938) long before Myron Gordon established (3).

We call this result the ***Bernoulli-Williams-Gordon*** proposition because the analytical structure embedded in Bernoulli's Petersburg Paradox and William's relationships between value, earnings, and dividend growth manifest themselves in the Gordon model.

Having made the point, the Gordon result should be properly recognized as ***Bernoulli-Williams-Gordon*** result, and we should interpret it to explain the relationship between dividends and stock price. There one can note the following:

(i) P_0 varies directly with D_1 (that is, $\frac{\partial P_0}{\partial D_1} > 0$), which means the higher the dividend, the higher the value of the stock (Gordon's prescription on dividend pay-out policy) and *vice versa*;

(ii) P_0 varies *inversely* with the discount rate y (that is, $\frac{\partial P_0}{\partial y} < 0$), which means the lower the interest rate +that is, the rate of return, the higher the value of the stock and *vice versa*;

(iii) P_0 varies directly with g (that is, $\frac{\partial P_0}{\partial g} > 0$), which means the higher the growth rate of dividend, the higher the value of the stock and *vice versa*

Seemingly, these results are correct, and these relationships have been recorded in academic journals as well as in textbooks. Yet these claims have been questioned and/or invalidated in the literature which will be posited soon in this paper.

2.2 Walter (1956)

Walter (1956) brought out the relation between dividends and stock price and made the relation clear and crispier. To the dismay of some of us, that relation has not been on focus in the literature. Walter (1956) derived that price of a share of common stock (P_0) as follows:

$$P_0 = \frac{D + \frac{y_C}{y_S}(E - D)}{y_S}, \qquad (10)$$

where D = dividend per share, E = earnings per share, y_C = rate of return the corporation generates, and y_S = rate of return the stockholder can generate (his/her required rate of return). From (10) it is obvious that

$$\frac{\partial P_0}{\partial D} = \frac{y_S - y_C}{y_S^2} \underset{<}{\overset{\geq}{=}} 0 .$$

So, if $y_C > y_S$, then lowering dividend payments increases the value of the stock as $\frac{\partial P_0}{\partial D} < 0$, and, if $y_C < y_S$, then increasing dividend payout increases the value of the stock as $\frac{\partial P_0}{\partial D} > 0$. When $y_C = y_S$, then it does not matter if the dividend is increased, decreased, or held unchanged because $\frac{\partial P_0}{\partial D} = 0$, and stock price will remain unaffected by any of those dividend payments. The *Dividend Irrelevance Proposition* was born with this condition. Walter thus provided more substantive statements on stock price, conditioned by the differential between the rate of return investors required and the rate of return corporations could generate. In his later work (1963), he further states, "the impact of a change in dividend upon operating cash flows will be *exactly* offset (or negated) by a corresponding and opposite change in supplemental (or external) financing" which is what Miller and Modigliani (1961) advocates as well. Walter further states that "to the degree that the anticipated level of operating cash flows, that is, the growth rate, is connected with the dividend payout for one reason or another, the market value of the firm may be conditioned by variation in dividend payout. The policy changes must, of course, be unexpected, and their price effect hinges at least partly upon the relation between the *internal* and *external* rates of return. If the former exceeds the latter, the present value of a dollar employed by the firm (other things being equal) will be greater than a dollar of dividends distributed and invested elsewhere." Lintner (1962) made the point that "generalized uncertainty" could suffice to make stockholder *not indifferent* as to whether cash dividends are increased or decreased by substituting new equity issues for retained earnings to finance given capital budgets. This position directly challenges Miller-Modigliani claim that has reigned supreme since the debut of their *dividend irrelevance* proposition.

2.3 Miller-Modigliani

Miller and Modigliani (1961) astounded academic scholars and corporate executives by their bold statement that the price of a share of common stock is independent of the dividend payout. In simple terms, they established that $\frac{\partial P_0}{\partial D} = 0$ always. Dividend payout, they asserted, was *irrelevant* as far as the dividend payout's impact on the price of the stock was concerned. This has been recognized as the *Dividend Irrelevance Proposition* in the existing literature on financial economics. The question for all of us has been since that publication: How is it true that Miller-Modigliani's dividend irrelevance proposition discards the Bernoulli-Williams-Gordon, and Walter's propositions when $y_C \neq y_S$?

Here we re-examine Miller-Modigliani's work (1961). Note that they took the following facts and analytical structure:

$D_j(t)$ = dividend per share of stock *j* at the start of time *t*[1],
$P_j(t)$ = price (ex-dividend) of a share of stock *j* at the start of time *t*, and
then it is obvious that

$$y(t) = \frac{D_j(t+1) + P_j(t+1) - P_j(t)}{P_j(t)} \tag{11}$$

or

$$P_j(t) = \frac{D_j(t+1) + P_j(t+1)}{1 + y(t)} \qquad \forall\ t \text{ and for each } j \tag{12}$$

Now, use the following:

$N(t)$ = the number of shares of record at the beginning of time *t*,

$M(t+1)$ = the number of *new* shares sold during *t* at the ex-dividend closing price

$P_j(t+1)$ so that we have $N(t+1) = N(t) + M(t+1)$,

$d_j(t) = N(t)D_j(t)$, which is total dividends, and

$v_j(t) = N(t)P_j(t)$, which is total equity value.

With these notations on hand, multiply both sides of (12) by $N(t)$ to get:

$$N(t)P_j(t) = \frac{N(t)D_j(t+1) + N(t)P_j(t+1)}{1 + y(t)} \tag{13}$$

Since $N(t)P_j(t) \equiv v_j(t)$, $N(t)D_j(t) \equiv d_j(t)$, and

$N(t) = N(t+1) - M(t+1)$, expression (13) can be re-written as:

$$v_j(t) = \frac{N(t)D_j(t+1) + N(t)P_j(t+1)}{1+y(t)}$$

$$= \frac{[(N(t+1) - M(t+1)]D_j(t+1) + [(N(t+1) - M(t+1)]P_j(t+1)}{1+y(t)}$$

$$= \frac{N(t+1)D_j(t+1) + N(t+1)P_j(t+1) - M(t+1)[D_j(t+1) + P_j(t+1)]}{1+y(t)} \qquad (14)$$

At this point in time we find that Miller and Modigliani ‘s exposition runs into a serious problem. After paying dividend out, $N(t+1)(D(1+1)) \equiv d_j(t+1)$, if the firm refills its coffer by issuing new securities to the tune of $I_j(t+1) - (X_j(1+t) - d_j(1+1))$ where $I_j(t+1)$ is the target investment outlay, $X_j(t+1)$ is the net earnings before dividend payout, expression (14) above will be as follows:

$$v_j(t) = \frac{N(t+1)D_j(t+1) + N(t+1)P_j(t+1) - \{N(t+1) - N(t)\}[D_j(t+1) + P_j(t+1)]}{1+y(t)}$$

$$= \frac{N(t+1)[(D_j(t+1) + P_j(t+1)]}{1+y(t)} \qquad (15)$$

Expression (15) demonstrably states that the value of the firm depends on the dividend – a statement that directly contradicts the dividend irrelevance proposition espoused and firmly asserted by Miller and Modigliani (1961).

One may wonder how could the celebrated result of Miller and Modigliani go astray. Let us go to the basic construction of their proof. First, their notations are non-standard. Note the following expression and notations:[2]

$$P_j(t) = \frac{D_j(t) + P_j(t+1)}{1+y(t)} \qquad (16)$$

where

$D_j(t)$ = dividends per share paid by firm *j* during period *t*,

$P_j(t)$ = price (ex any dividend in t-1) of a share in firm *j* at the start of time *t*.

First see the expressions (12) and (16), side by side. Next note the fuzziness that was created by using time index, *t*, in their notations. The notation *t* refers to the *start of period t* for $P_j(t)$ and *t* refers to *during the period* for $D_j(t)$. Does $D_j(t)$ refer to the end of period? In the literature, we write:

$P_0 = \frac{D_1 + P_1}{(1+y)}$ or, in general expression, $P_t = \frac{D_{t+1} + P_{1t+1}}{(1+y)} \equiv \frac{D(t+1) + P(t+1)}{(1+y)}$. It is different from Miller-Modigliani's expression (7). Non-uniform notations have created confusions and derivation of ***their equation*** (5) (which here in this paper is equation (16)), where they have shown that value of the firm is independent of the current dividend decision. In our expression (12), it is clear that value of the firm is dependent on dividend.

On a much deeper reflection, one should re-think that Miller-Modigliani work started with *their* expression (2):

$$P_j(t) = \frac{D_j(t) + P_j(t+1)}{1 + y(t)}, \qquad \text{(that is, } P_j(0) = \frac{D_j(0) + P_j(1)}{1 + y(1)}\text{)}$$

where $P_j(t)$ depended on $D_j(t)$ in their expression (and on $D_j(t+1)$ in our expression), and ended up with dividend as a disappeared argument. It has to be inconsistent. Miller-Modigliani's work arrived at, and showed that their value of the firm, $(V(t))$, did not have $D(t)$ as the explanatory variable, but depended on $V(t+1)$. Then they argued, "having established that $V(t)$ is unaffected by the current dividend decision it is easy to go on to show that $V(t)$ must also be unaffected by any future dividend decision as well. Such future decisions can influence $V(t)$ only via their effect on $V(t+1)$. But we can repeat the reasoning above and show that $V(t+1)$ - and hence $V(t)$ - is unaffected by dividend policy in $t+1$; that $V(t+2)$ - and hence $V(t+1)$ and $V(t)$ - is unaffected by dividend policy in $t+2$; and so on for as far into future as we care to look. Thus, we may conclude that given a firm's investment policy, the dividend payout policy it chooses to follow will neither affect the current price of its shares nor the total return to its stockholders."

In his response to Miller-Modigliani, Gordon (1963) showed quite brilliantly that the price of a stock could remain unaffected by dividends if by postponing dividend payment can generate the rate of return required by stock holders. Consider the following three scenarios to make the point with the assumption that dividends at the end of current year and at the end of subsequent years ad infinitum are as follows:

Scenario 1: Constant dividend amount of $50

0	1	2	3	4	………………..	∞
	$50	$50	$50	$50		$50

Assume that the rate of discount is 12 percent (that is, y = 12 percent). Here then, $P_0 = \dfrac{\$50}{0.12} = \$416.67.$

Scenario 2: Constant dividend amount of $56

0	1	2	3	4	………………..	∞
	$0	$56	$56	$56		$56

Here you can see that dividend payment is deferred by one period. Under this situation of constant payment stream of dividends, $P_1 = \dfrac{\$56}{0.12} = \$466.67,$ and hence $P_0 = \dfrac{\$466.67}{(1+0.12)} = \$416.67.$

Scenario 3: Constant dividend amount of $62.72

0	1	2	3	4	………………..	∞
	$0	$0	$62.72	$62.72		$62.72

In this scenario of dividend payment being further deferred, $P_2 = \dfrac{\$62,.72}{0.12} = \$522.67,$ and then $P_0 = \dfrac{\$522.67}{(1+0.12)^2} = \$416.67.$ There is no magic in having the **same** current price $P_0 = \$416.67.$ In these three scenarios deferment comes with growth of dividends by 12 percent (56 = 50(1 + 0.12) and (62.72 = 56(1 +0.12) = 50(1+0.12)^2) and the rate of discount (which is the rate of return required by stockholders) is 12 percent. In general case, if the constant amount of dividends (D) is deferred by *one* period and in the next period onward the annuity in the amount of $D(1+g)$ is given perpetually, or

$D(1+g)^2$ is given perpetually if D is deferred by 2 period, the current stock price will be

$P_0 = \dfrac{D}{y}$ if there is no deferment (scenario 1);

$P_0 = \dfrac{D(1+g)}{y(1+y)}$ if there is deferment of dividend payment by 1 period (scenario 2);

$P_0 = \dfrac{D(1+g)^2}{y(1+y)^2}$ if there is deferment of dividend payment by 2 periods (scenario 3), and so on.

One can realize now immediately that if $g = y$, stock price remains unchanged. This is Gordon's result. It is reminiscent of Walter scenario as well under the condition: $y_C = y_S$. Recently, even at the textbook level (see Ross *et al* (2008), Brealey *et al* (2009)), we can see the measure of net present value growth opportunity (λ), say in the scenario 2 above as follows:

$$\lambda = \left\{ \frac{D(1+g)}{y(1+y)} - \frac{D}{y} \right\}.$$

If $g = y$, $\lambda = 0$, and in that case, stock price remains invariant. If $g > r$, stock price will go up, and if $g < r$, stock price will drop. So the proposition advanced by Miller and Modigliani that stock price is independent of dividend distribution is appropriately being questioned. At this point, we bring out the statement made by Lintner that "generalized uncertainty" could suffice to make stockholder **not indifferent** as to whether cash dividends are increased or decreased by substituting new equity issues for retained earnings to finance given capital budgets. It should be pointed out that at early part of their paper, Miller and Modigliani postulated "perfect certainty" to develop their result, and hence the generalized uncertainty of Lintner should not be posited against Miller-Modigliani. Having noted that, it must be further noted that Miller and

Modigliani brings out uncertainty in the later part of the paper and maintained irrelevance of dividend policy despite uncertainty.

3 – Tax-Laden Environment

In the previous section, we have stayed away from tax consideration. Here we bring it out, and in view of taxes we reconsider the value of the firm. Miller and Scholes (1978) correctly noted
a historical reality (by quoting the estimate of Kaufman *et al* (1977)) that "in 1976 corporations paid the Treasury 43 percent of their earnings of $111 billion in corporation income taxes. From the after-tax remainder, they then paid out $31 billion in dividends, thereby subjecting a substantial fraction of their stockholders to still another tax bite under the personal income tax." This observation opens the door for further examination of dividend payout in the context of taxes on dividends. It should be noted that many scholars have examined various aspects of dividends with taxes. The works of Litzenberger and Ramaswamy (1979), Long (1978), West (1988), Palmon and Yaari (1981), Arditti and Levy (1977), DeAngelo and Masulis (1980), Feldstein and Green (1983), Levy and Sarnat (1994), Bierman and Smidt (1986), and many others must be noted in this context.

To discuss dividends subject to taxes, consider the following scenario. Assume that the firm gives dividend (D), which is subject to the tax rate of T_D applicable to dividend income. Obviously, the stockholder gets $D(1-T_D)$, and it is then invested by the stockholder at the rate of return, y_S , to end up with

$$D(1-T_D)+y_S D(1-T_D)(1-T_P) \tag{17}$$

where T_P is the personal income tax rate. Note that personal income tax rate is the same as the tax rate on dividend income tax rate in the United States (that is, $T_D = T_P$). So if this equality holds in any economy the expression (17) is reduced to:

$$D(1-T_D)\{1+y_S(1-T_P)\} \tag{18}$$

Instead of paying dividend, if the corporation retains D dollars and invests the amount at y_C, D dollars becomes $D(1+y_C)$, and if this amount is paid as dividend, stock holder will get then after-tax dollar amount of

$$D(1+y_C)(1-T_P) \tag{19}$$

Obviously, if (19) exceeds (18) deferment of dividend is better than immediate dividend payout. That is, if

$D(1+y_C)(1-T_P) \quad > \quad D(1-T_P)\{1+y_S(1-T_P)\}$: deferment is desirable; (20A)

$D(1+y_C)(1-T_P) \quad = \quad D(1-T_P)\{1+y_S(1-T_P)\}$: stockholder is indifferent; (20B)

$D(1+y_C)(1-T_P) \; < \; D(1-T_P)\{1+y_S(1-T_P)\}$: payout is desirable. (20C)

A closer look at these expressions (20A) through (20C) yields that if $y_C \geq y_S$, deferment of dividend payment is better for the stockholder. It changes one claim of Walter, noted earlier in the absence of taxes. For $y_C = y_S(1-T_P)$ the stockholder should be indifferent. However, in case of $y_C < y_S(1-T_P)$, non-deferral and immediate payout is definitely preferable.
One more scenario is worth exploring. It is a situation that involves tax rate on capital gains, T_G, which is usually less than T_D (that is , $T_G < T_D$). If the money is taken after one year, income is subjected to tax rate on capital gains. So, if the corporation reinvests D dollars and the invested amount after one year is taxed at T_G, then the stockholder gets $D(1+y_C)(1-T_G)$. Here one can see that

$$D(1+y_C)(1-T_G) \; > \; D(1-T_P)\{1+y_S(1-T_P)\} \tag{21}$$

If $y_C \geq y_S$. Under some condition still the inequality of (21) can be reversed or equality can be restored.
Along with these observations, we may bring out clientele effect and signaling effects. In one case (former one) the tug war between stockholders in low or zero-income tax bracket and stockholders with high-income tax bracket decides the dividend payout or postponement. In the other case, immediate

payout has the signaling effect in the market, and it creates a climate in which corporations can have easy access to more capital, and it can thus lend support for un-delayed dividend disbursement.

4 – Conclusion

In this paper, we have taken a fresh look at the age-old results on dividend policy with and without taxes. It is shown that Gordon model is realistically or heuristically should be called or renamed as *Bernoulli-Williams-Gordon* model. The policy implications are then brought to light. Then, the almost-forgotten results of James Walter's policy prescriptions are heighted, and shown the conditions under which dividend irrelevance is a meaningful and intuitively a clear proposition, presented seven years before Miller-Modigliani conclusion to that effect. The conditions under which an increase and/or a decrease in dividends increase the stock price are fully spelled out. Miller-Modigliani's derivations are re-examined, and their proof and claim of dividend irrelevance is questioned. Gordon's later paper gives a condition which is in agreement with Walter's, and that provides the situation for dividend irrelevance and non-irrelevance. All of these works are structures in no-tax regime. When taxes are introduced, once again the impact of dividend on stock price is examined. Dividend income tax and capital gains tax are brought into the analytical framework, and a series of policy statements are made.

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Transitory and Permanent Volatility Components in the Main US ETF Markets: An Empirical Analysis

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Abstract

This paper examines the impact of both unexpected and expected trading volumes on permanent and transitory components of variance of 5 selected Exchange Traded Funds (ETFs). To develop the broadest spectrum of assets possible, we selected five ETFs involving stocks, bonds and selected commodities. Clearly, since the chosen ETFs all have different underlying fundamentals that influence returns, we can investigate whether the postulated relationships are different for assets driven by different fundamentals. Using daily returns data over the October 2007 – May 2012 period, our findings suggest that expected and unexpected volumes both impact permanent volatilities for longer duration than they do transitory volatilities for all ETFs. The impact on transitory volatilities is most ephemeral for the stock ETF, followed (in order) by the agricultural, the oil, the gold, and the bond ETFs. On the other hand, the permanent volatility component tends to show strongest persistence (in order) for the commodity (the gold, the oil, and the agricultural) ETFs. Using appropriate trading strategies from information available in the permanent and transitory volatility components, we find that investors can make profits ranging from 0.5% and 18.64% using sample ETFs.

Key words: Exchange Traded Funds, unexpected and expected trading volumes, permanent and transitory components.
JEL Classification: G11, G12, G14

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1 - **Introduction**

In recent times, researchers have examined the links between volatility and trading volume of assets such as stocks, futures, and options. However, there are few academic papers investigating these relationships for Exchange Traded Funds (ETFs). Existing ETF literature has examined the links between volatility and return spillovers (Krause and Tse, 2013), nonlinear price dynamics related to ETF returns (Caginalp, DeSantis, and Sayrak, 2014), and the effects of ETFs on the liquidity of the underlying assets (De Winne, Gresse, and Platten, 2014). Still others have examined the links between total trading volume (surrogate for available market information) and ETF returns in the literature (Lin, 2013). However, a subpart of this stream argues that unexpected trading volume (appropriately defined and captured) is a better proxy for capturing market information than expected trading volume (Wagner and Marsh, 2005; Aragó and Nieto, 2005; and Girard and Biswas, 2007). Expected trading volume is generally assumed as the "normal" trading volume based on available information, and unexpected trading volume is deemed to represent unanticipated information flowing to the market (Aragó and Nieto, 2005).

Despite the extensive empirical research in this area, to the best of our knowledge, a surprising observation is that there is a paucity of papers that deal with the impact of *expected* and *unexpected* trading volume on the permanent and transitory volatility of ETF returns. While many papers distinguish between expected and unexpected volatility when examining links between ETF volatility and returns, few distinguish between expected trading volume and unexpected trading volume[4] when examining volatility persistence of ETF returns. Can splitting up total trading volume into its expected and unexpected components prove valuable in ETF investment strategies? What are the impacts of expected and unexpected trading volumes on the transitory and permanent volatilities for ETFs? In this paper, both permanent volatility (the long term trend) and transitory volatility (volatility above or below the trend) components are introduced while selectively controlling for expected and unexpected trading volumes. Depending on the significance of each factor, there may be a superior basis for predicting ETF returns with obvious implications for asset management strategies.

To conduct this research, appropriate methodology is required. At first glance, it may seem that a GARCH model with a long run and a short run

[4] Those that do only use total trading volume.

components (introduced originally by Engle and Lee (1999)) may be appropriate for this study. The traditional GARCH model relies on a one factor model generating returns. However, extant empirical studies have shown (Chernov et al, 2003; Colacito, Engle, and Ghysels, 2011) that the one factor model does not fit the data well, and at the least two factors models are required to capture the volatility dynamics more accurately. Since volatility flows are examined in the paper, a two factor model is appropriate. Hence, and following extant literature, we adopt the generalized autoregressive conditional heteroscedasticity (CGARCH) model (also developed by Engle and Lee (1999)) to examine the dynamic impact of expected/unexpected volume on ETF volatility components. Using daily data over the October 2007 – May 2012 period, this paper reexamines the link between ETF return volatility and *expected* and *unexpected* trading volume. Does the ETF permanent/ transitory returns volatility - trading volume relationship get impacted if trading volume is broken up into expected and unexpected components? Specifically, what are the links between the permanent (transitory) component of volatility and expected (unexpected) trading volume? Since there are potentially four relationships examined, our findings can therefore provide a more precise understanding of what drives ETF volatility with obvious consequences for ETF asset management and hedging strategies.

Hence, this paper studies the relationships of Exchange Trade Fund (ETF) trading volume (both expected volume and unexpected volume), and volatility (both transitory volatility and permanent volatility) for selected ETFs.

The paper is organized as follows. In Section 2, we provide a brief introduction into the nature and characteristics of ETFs, followed by a literature review in Section 3. Data and methodology are provided in Section 4 and the results discussed in Section 5. Possible abnormal profit opportunities from using information on volatility components from sample ETF time series are explored in Section 6. Concluding comments, suggestions for further research and policy implications follow in Section 7.

2 - What are Exchange Traded Funds?

An ETF is traded like a stock in the stock market. Normally an ETF attempts to closely mimic a preselected stock index, a commodity, bonds, or a basket of assets. A key feature of ETFs is that while they loosely track the benchmark index, they do not fully replicate the index. The popularity of ETFs is primarily due to the fact that investors have the luxury of trading in selected sectors of the economy at costs lower than what they would have to pay if they bought/sold these assets individually (Gutierrez, Martinez and Tse, 2009). Since ETFs generally follow the underlying assets that make up the index, their prices are obviously driven by the fundamentals related to the underlying assets (Lauricella and Gullapalli, 2007). The final benefit is that packaged ETFs are routinely traded on major exchanges. In 2014, the global ETF market accommodates over $2.7 trillion in assets, of which the US ETF market accounts for approximately 74% in volume.[5]

3 - ETFs: Literature review and rationale for this study

The contemporaneous relationship between trading volume and volatility of stocks were examined by Karpoff (1987). While he used a contemporaneous *linear* model to examine these relationships, other researchers have argued for a lead/lag type of relationship as a better characterization of the links between the two variables. Unfortunately, the results of these subsequent runs are mixed. While some document a positive link between volume and lagged returns (Saatcioglu and Starks, 1998; Statman, Thorley, and Vorkink, 2006), others suggest no linkages between volume and returns[6] (Lee and Rui, 2002).

Next, Lamoureux and Lastrapes (1990) document that the persistence in volatility (ARCH effects) disappears when trading volume is introduced as an explanatory variable in the variance equation. Subsequent researchers, building on Lamoureux and Lastrapes work, have further distinguished between expected (or normal) volume and unexpected (or abnormal) volume, in influencing the stated relationship. They suggest that unexpected volume represents new information (or is the surprise component of information) in the market place (Wagner and Marsh, 2005; Aragó and Nieto, 2005). Given this distinction, the focus then became on examining the relationship between volatility and unexpected trading volume. Using the asymmetric GARCH in-mean model, Wagner and Marsh (2005) show that unexpected trading volume shocks lead to *increased* volatility, whereas unexpected trading volume breakdowns lead to *decreased* volatility. In contrast, Aragó and Nieto (2005)

[5] Investment Company Institute at http://www.icifactbook.org/fb_ch3.html.
[6] In a Granger causality sense.

examine the relationship between unexpected volume and volatility, and unlike the results reported earlier by Lamoureux and Lastrapes (1990), they report that volatility persistence does *not* disappear when both expected and unexpected trading volumes are included in the model. In another twist, Girard and Biswas (2007) report that volatility persists even with the inclusion of total volume, but this persistence decreases when expected and unexpected volumes are also introduced. Chuang, Liu, and Susmel (2012) find evidence of a positive contemporaneous relationship between volume and volatility for stocks from Singapore, China, and Thailand, but a negative relationship for those from Taiwan and Japan.[7]

In terms of research methodology, researchers have used some sophisticated tools. For instance, much of the existing literature generally uses a two-step procedure to study the relationships between volume and volatility (for instance, Chuang, Liu, and Susmel, 2012). In the first step, the causal relation between current stock returns and lagged trading volume, between current trading volume and lagged stock returns, and between current trading volume and lagged return volatility, are examined. Using consistent and efficient parameter generated from the first step (Pagan, 1984), the statistical relationships second moments of stock returns and trading volume and between current volatility and lagged trading volume are examined (Chuang, Liu, and Susmel, 2012), and appropriate conclusions made.

Researchers have also preferred the Component generalized autoregressive conditional heteroscedasticity (CGARCH) model to examine the links between volume and volatility. Later modifications include the decomposition of conditional volatility into transitory and permanent components (for instance by Guo and Neely (2008)) in analyzing stock market volatility, and by Ahmed, Bashar, and Wadud (2012) to examine oil price volatility.

There is no study that examines the influences of expected and unexpected volumes on the volatility *components* of ETFs. Doing so will allow us to provide insights into whether opportunities for superior trading strategies using these instruments are available. Hence in this paper, we adopt the CGARCH model to examine the relationship between returns, volume, and volatility for selected ETF markets in the US using daily data spanning from April 10, 2007 through May 31, 2012.

[7] Using the bivariate GARCH model to examine the simultaneous volume/volatility relationship.

4 - Data and methodology

4.1 Data

We use daily closing prices collected from *Datastream,* for each of five ETFs traded on NYSE's ACRA market, over the April 10, 2007 through May 31, 2012 period.[8] The selected ETFs are respectively:

1) Standard and Poor's Depositary Receipt and Standard and Poor's 500 ETF Trust (SPY),
2) Standard and Poor's Depositary Receipt Gold Shares (GLD),
3) Standard and Poor's Depositary Receipt Standard and Poor's Oil and Gas Exploration and Production ETF (XOP),
4) Powershares DB Agriculture Fund (DBA), and
5) Vanguard Long-Term Bond ETF (BLV).

The data starting points of each sample ETF depend on when they were established. The SPY was launched on 1993/1/29; GLD on 2004/11/18; DBA on 2007/1/15; XOP on 2006/6/22; and BLV on 2007/4/10. The first part of the empirical analysis involves estimating expected volume proxies[9] for each time series for subsequent examination in the second step. April 10, 2007 is chosen as the starting day for all ETFs used in the study. The procedure for generating the proxies is illustrated for the time series BLV. Similar procedures are utilized for the other time series. For BLV, data for 132 days after its initiation by the exchange are used to estimate expected volume parameters as follows: To forecast the first value, we used 132 days of total volume data prior to the estimation date to compute the initial forecast. For the second and subsequent estimations, ARMA model estimates generated as a moving average (dropping the first observation in the series and adding the next realization) was used. This procedure generates expected volume estimates using an ARMA model using information from the previous 132 trading days. Once expected volume estimates are generated, the second step regressions are run. The starting date for the second step regressions is for all sample time series is October 16, 2007.

These five ETFs have different underlying fundamentals. For instance, the SPY index follows the stock market whereas GLD follows gold

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[8] Please note that the study final date is determined by data availability and on the need to conduct out-of-sample trading strategy tests. Since we need enough data beyond the parameter estimation period to measure any profits from adopted trading strategies, our data period for parameter estimation ends on May 31, 2012.

[9] The specific definition of trading volume and the equations identifying expected and unexpected trading volume are described below.

prices. Similarly, the others follow S&P Oil & Gas Exploration and Production Select Industry Index (XOP), DBIQ Diversified Agriculture Index Excess Return (DBA) and the Barclays U.S. Long Government/Credit Float Adjusted Index (BLV). Basically, all five series follow different fundamentals and hence a priori, one would expect the relationship between returns, volume, and volatility to be quite different for all series. Does this contention materialize when data are formally examined? This is the subject matter of the paper. As an added feature, it will also be interesting to compare any different impacts of unexpected/expected trading volumes on the transitory and permanent volatilities of the ETFs as they influence returns. ETF returns are computed as difference in the log daily closing prices over successive trading days:

$$\mathrm{r_t}(\%) = \ln\left(\frac{\text{closing price}_\mathrm{t}}{\text{closing price}_{\mathrm{t-1}}}\right) \times 100 \tag{1}$$

Next, trading volume is calculated as follows:

$$\mathrm{vo_t} = \ln\left(\frac{\text{total volume}_\mathrm{t}}{\text{total volume}_{\mathrm{t-1}}}\right) \tag{2}$$

Finally, following Wagner and Marsh, (2005), Aragó and Nieto, (2005), and Girard and Biswas, (2007), unexpected volume, calculated as the difference between actual volume and expected volume, is used as a surrogate for the unexpected information flow:

$$\text{unexpected value}_\mathrm{t} = \text{value}_\mathrm{t} - \mathrm{E}\left(\text{value}_\mathrm{t} | \text{value}_{\mathrm{t-j}},\ \ \mathrm{j} = 1{,}2, \dots\right) \tag{3}$$

$\mathrm{E}(\text{value}_\mathrm{t}|\text{value}_{\mathrm{t-j}})$ is defined as the expected volume and is calculated as the forecasted values from ARMA (p, q) models which best fit the sample time series. In particular, expected volume was computed as:

$$\mathrm{vo_t} = \sum_{\mathrm{j=1}}^{\mathrm{p}} \mathrm{b_j vo_{t-j}} + \sum_{\mathrm{k=i}}^{\mathrm{q}} \mathrm{c_k} \varepsilon_{\mathrm{t-k}} + \mathrm{DW_t} + \varepsilon_\mathrm{t} \tag{4}$$

Where $\mathrm{vo_t}$ is the total trading volume on day t.

Since average returns (trading volumes) for Monday have been shown to be lower (higher) than the average returns (trading volumes) for other days of the week (French, 1980); Lakonishok and Maberly, 1990), DW is used as a dummy variable (DW = 1 on Mondays, 0 on other days) to control for possible difference due to these factors.

Unexpected volume is then calculated as the difference between the total traded volume and the expected volume, as defined in equation (3). Since available data for computing unexpected volume spans the October 16, 2007 through May 31, 2012 period, both actual and unexpected volumes are computed over the same time period.

Table 1 provides sample descriptive statistics for all data time series. The mean returns for sample EFTs are quite different. The mean returns are positive for the gold ETF (GLD) and bond ETF (BLV), and negative for the others. Gold ETF has the highest mean return (6%) and the stock ETF (SPY) has the lowest mean return (-1.3%) over the sample period. The volatilities for sample EFTs are also very different. All series exhibit high degrees of volatility: daily standard deviation of returns ranges from 0.81% for the bond ETF (BLV) to 2.99% for the oil ETF (XOP), implying annualized volatilities of 12.85% to 47.46%.

The unexpected volume for SPY is 2.4 times the total volume, whereas the unexpected volume and total volume for GLD are almost the same. The SPY ETF exhibits significantly higher total volume and unexpected volume relative to the other sample ETFs and needs to be rationalized. First, since SPY tracks the S&P 500 index, investors use the SPY as an inexpensive way to generate intraday liquidity. Second, the high trading volumes associated with SPY may be induced in part by the arbitrage links between SPY and the underlying S&P securities that make up the index. Finally, it is possible that trading volatility for both the SPY and the S&P 500 securities are increased because of simultaneous activity in both markets. Indeed, the low transaction costs for trading SPYs can also provide increased demand shocks to the market. Since the SPY transactions and arbitrage trading can occur many times during the day, SPY are affected to a greater extent by demand shocks than the other sample ETFs.

With one exception (the stock ETF), all return series exhibit negative skewness. All five sample ETFs show positive excess kurtosis over the sample time period. Finally, the Jacque-Berra test for normality is rejected for all sample series, implying that the series are not normal over the study time period.

Table 1 : Descriptive statistics

	Mean	Max.	Min.	Std.	Skew	Kurt.	JB	Obs.
SPY								
Returns(%)	-0.013	13.56	-10.36	1.71	0.01	11.57	3566.80 ***	1165
Total vol	0.014	112.90	-127.22	29.83	0.02	4.07	55.50 ***	1165
Unexp. vol	0.033	1.20	-1.23	0.33	-0.02	3.50	12.31 ***	1165

GLD								
Returns(%)	0.060	10.69	-7.72	1.45	-0.09	7.68	1063.25 ***	1165
Total vol	0.036	177.80	-112.28	43.40	0.32	3.19	21.85 ***	1165
Unexp. vol	0.038	2.01	-1.23	0.48	0.22	2.97	9.03 ***	1165
XOP								
Returns(%)	-0.006	19.82	-19.80	2.99	-0.53	9.72	2248.78 ***	1165
Total vol	0.297	308.61	-347.62	54.07	-0.11	7.43	953.03 ***	1165
Unexp. vol	0.024	3.59	-4.07	0.64	-0.42	7.52	1025.11 ***	1165
DBA								
Returns(%)	-0.009	6.46	-9.00	1.56	-0.34	6.32	555.90 ***	1165
Total vol	0.016	188.44	-183.79	48.42	0.16	3.66	25.91 ***	1165
Unexp. vol	-0.001	2.13	-2.03	0.56	0.14	3.62	22.45 ***	1165
BLV								
Returns(%)	0.021	2.93	-4.78	0.81	-0.28	4.82	175.62 ***	1165
Total vol	0.071	326.63	-380.40	87.16	-0.04	4.40	95.35 ***	1165
Unexp. vol	0.012	4.32	-4.16	1.01	0.07	4.04	53.02 ***	1165

*** Significant at 1%; JB represents the Jacques-Berra Test for normality. Return is measured by equation 1:$r_t(\%) = \ln\left(\frac{\text{closing price}_t}{\text{closing price}_{t-1}}\right) \times 100$. Total volume is = $vo_t = \ln\left(\frac{\text{total volume}_t}{\text{total volume}_{t-1}}\right)$. Unexpected volume is $= \text{value}_t - E\left(\text{value}_t | \text{value}_{t-j},\ j = 1,2,\ldots\right)$. Volumes are expressed as ratios.

Legend: Standard and Poor's Depositary Receipt and Standard and Poor's 500 ETF Trust (SPY); Standard and Poor's Depositary Receipt Gold Shares (GLD); Standard and Poor's Depositary Receipt Standard and Poor's Oil and Gas Exploration and Production ETF (XOP); Power shares DB Agriculture Fund (DBA), and Vanguard Long-Term Bond ETF (BLV).

4.2 The Component GARCH (CGARCH) Model

The component GARCH model (CGARCH) developed by Engle and Lee (1999) is utilized in this study. The conditional variance in the GARCH(1, 1) model can be described as follows:

$$\sigma_t^2 = \overline{\omega} + \alpha(\varepsilon_{t-1}^2 - \overline{\omega}) + \beta(\sigma_{t-1}^2 - \overline{\omega}) \quad (5)$$

This form shows that the series exhibits mean reversion to a constant, $\overline{\omega}$. In contrast, the component model allows mean reversion to a varying level m_t, as shown below:

$$\sigma_t^2 - m_t = \alpha(\varepsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1}) \tag{6}$$

$$m_t = \omega + \rho(m_{t-1} - \omega) + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{7}$$

Where σ_t^2 is the volatility at time t and m_t is the time varying long-run volatility. In equation (6), the transitory volatility component, $\sigma_t^2 - m_t$ converges to zero with powers of $(\alpha + \beta)$. The long run (or permanent) component of volatility m_t (in equation 7) converges to ω with the power ρ, which typically assumes a value between 0.99 and 1 implying that m_t converges to ω rather slowly. We can combine the transitory and permanent volatility equations into one equation as follows:

$$\begin{aligned}\sigma_t^2 = (1-\alpha-\beta)(1-\rho)\omega + (\alpha+\varphi)\varepsilon_{t-1}^2 - (\alpha\rho + (\alpha+\beta)\varphi)\varepsilon_{t-2}^2 \\ + (\beta-\varphi)\sigma_{t-1}^2 - (\beta\rho - (\alpha+\beta)\varphi)\sigma_{t-2}^2\end{aligned} \tag{8}$$

Clearly, the component model is a (nonlinear) restricted GARCH (2, 2) model. Given that sample descriptive statistics suggest excess kurtosis in all of the selected time series, our methodology must accommodate this feature. We capture the excess conditional kurtosis in the error term, which is a Student's *t*-distribution. The log-likelihood function is in the form

$$\begin{aligned}l_t = -\frac{1}{2}\log\left[\frac{\pi(\nu-2)\Gamma(\nu/2)^2}{\Gamma\big((\upsilon+1)/2\big)^2}\right] - \frac{1}{2}\log\sigma_t^2 \\ - \frac{(\nu+1)}{2}\log\left[1 + \frac{(y_t - X_t'\theta)^2}{\sigma_t^2(\nu-2)}\right]\end{aligned} \tag{9}$$

This distribution following a Student *t*-distribution when the degrees of freedom $\nu > 2$, and approaches the normal distribution as $\upsilon \to \infty$. Following Engle and Lee (1999), we denote r_t as the daily log returns on the asset (as defined in equation (1)), with expected returns captured by m_t. The Conditional variance of returns is now $\sigma_t \equiv \mathrm{Var}(r_t|\Omega_{t-1}) = E[(r_t -$ mt2|Ωt−1 where Ωt−1 denotes the set of all information available at time t-1. The GARCH specification of Bollerslev (1986) is used to capture the conditional variance in future returns.

As indicated earlier, model parameters are estimated using the CGARCH specification as outlined in Engle and Lee (1999). First, we place total trading volume in the conditional variance equation while dividing the variance into transitory and permanent components:

$$\sigma_t^2 - m_t = \alpha(\varepsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1}) + o_1 VO_{t-1} \tag{10}$$

$$m_t = \omega + \rho(m_{t-1} - \omega) + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + o_2 VO_{t-1} \tag{11}$$

Next, since prior literature has documented that unexpected trading volume represents a better proxy for information flow affecting market prices, we also split up volume into its expected and unexpected components as follows:

$$\sigma_t^2 - m_t = \alpha(\varepsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1}) + \delta_1 \mathrm{EXVO}_{t-1} + \delta_2 \mathrm{UNEXVO}_{t-1} \tag{12}$$

$$m_t = \omega + \rho(m_{t-1} - \omega) + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + \eta_1 \mathrm{EXVO}_{t-1} + \eta_2 \mathrm{UNEXVO}_{t-1} \tag{13}$$

These models are now tested using sample data and presented in the next section.

5. Results

Table 2 shows the results of the first model (as depicted in equations 6 and 7) representing transitory and permanent volatility persistence without volume. The permanent persistence volatility as measured by ρ is large and statistically significant (over 0.99 for all ETFs except for the bond series), which implies that the time series slowly revert to mean values. The transitory persistence volatility measured by the sum $(\alpha + \beta)$ suggests significance *only* for the stock series. Since the sum is less than 1, it suggests that transitory shocks decay with time (Chou, 1988). In contrast, permanent shocks as measured by φ remains significant for all time-series with the exception of those for the bond series. Finally, for three series, namely stock, oil, and agricultural ETFs, short term shocks (as measured by α) are negative and significant at the 5% level. These results suggest that the returns/volatility relationship remains noisy for the selected time series.[10]

[10] Panel B in Tables 2 through 6 present diagnostic tests for the various CGARCH models used in the paper. Based on these results, all models are well specified. The insignificant statistics of Q(5), Q(10), $Q^2(5)$, $Q^2(10)$, ARCH (5) and ARCH (10) are observed for all model, and suggest that the component- GARCH models capturing typical serial correlations present in sample time series. Finally, there seems to be little evidence in support of ARCH effects for any series.

Table 2 : Volatility persistence without volume

	SPY	**GLD**	**XOP**	**DBA**	**BLV**
Panel A: $\boldsymbol{\sigma_t^2 - m_t = \alpha(\varepsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1})}$					
$\boldsymbol{m_t = \omega + \rho(m_{t-1} - \omega) + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)}$					
ω	6.9622	2.3104 *	9.5586	2.1257 **	0.6549 ***
	(19.47)	(1.27)	(8.69)	(1.05)	(0.13)
ρ	0.9952 ***	0.9904 ***	0.9942 ***	0.9939 ***	0.9838 ***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
φ	0.1468 ***	0.0659 ***	0.0853 ***	0.0478 ***	0.0477
	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)
α	-0.1885 ***	-0.0545	-0.0716 **	-0.0660 **	0.0548
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
β	0.4466 ***	0.5321	-0.4777	-0.3503	0.7417 ***
	(0.17)	(0.46)	(0.30)	(0.37)	(0.28)
Panel B: diagnosis tests					
Q(5)	5.138	3.661	0.752	5.304	7.059
	(0.40)	(0.60)	(0.98)	(0.38)	(0.22)
Q(10)	10.597	13.377	2.737	7.889	15.248
	(0.39)	(0.20)	(0.99)	(0.64)	(0.12)
$Q^2(5)$	5.455	1.528	3.687	8.672	0.716
	(0.36)	(0.91)	(0.60)	(0.12)	(0.98)
$Q^2(10)$	8.718	6.797	5.633	11.066	7.534
	(0.56)	(0.74)	(0.85)	(0.35)	(0.67)
LM(5)	1.146	0.305	0.821	1.706	0.141
	(0.33)	(0.91)	(0.53)	(0.13)	(0.98)
LM(10)	0.898	0.630	0.612	1.091	0.745
	(0.53)	(0.79)	(0.80)	(0.37)	(0.68)

*** Significant at 1%; ** Significant at 5%; * Significant at 10%. Standard errors (probability values) are shown in parentheses in Panel A (Panel B). ETF definitions are provided in Table 1.

Next, in Table 3, volume is used as a proxy variable for information flow. In contrast to the models examined in the previous section, we use total trading volume as an explanatory variable to account for heteroscedasticity in returns. We find that the coefficient associated with permanent persistence is positive and significant at the 1% level for all time-series. On the other hand, the transitory persistence,$(\alpha + \beta)$, is significant only for the stock market and the oil series. The volume difference proxy is significant at the 1% level for all series (but one), implying the presence of a long term component in influencing returns. In contrast, when the results involving the short term components are examined, only the coefficients associated with stock, gold, and agricultural ETFs, are significant at the 5% level. Moreover, after the addition of the proxy for information flow (volume), only the bond series ETF seems immune to volume both in the short and long terms. When compared to the results presented in table 2, it is clear that when trading volumes are introduced into the model, both ARCH and GARCH effects get attenuated in both the permanent and transitory variance regressions only for the stock and the oil ETF.

Table 3 : Effect of total trading volume on volatility persistence

	SPY	**GLD**	**XOP**	**DBA**	**BLV**
Panel A : $\boldsymbol{\sigma_t^2 - m_t = \alpha(\varepsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1}) + o_1 VO_{t-1}}$					
$\boldsymbol{m_t = \omega + \rho(m_{t-1} - \omega) + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + o_2 VO_{t-1}}$					
ω	2.5138 ***	1.6561 ***	6.9506 *	1.8799 ***	0.5572 ***
	(0.94)	(0.55)	(3.99)	(0.62)	(0.09)
ρ	0.9880 ***	0.9950 ***	0.9931 ***	0.9922 ***	0.9809 ***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.08)
φ	0.1149 ***	0.0192 **	0.0705 ***	0.0406 ***	0.0236
	(0.02)	(0.01)	(0.01)	(0.01)	(0.23)
o_2	0.5531 ***	2.4473 ***	0.9671 ***	0.5950 ***	5.3035
	(0.09)	(0.88)	(0.29)	(0.22)	(281.97)
α	-0.1612 ***	0.0156	-0.0617 **	-0.0217	0.0208
	(0.03)	(0.01)	(0.03)	(0.03)	(0.24)
β	0.3396 *	0.9402 ***	-0.5448 **	0.5126 **	0.9569 ***
	(0.18)	(0.02)	(0.26)	(0.25)	(0.30)
o_1	-0.3233 **	-2.5843 ***	-0.3002	-0.6560 ***	-5.2366
	(0.16)	(0.88)	(0.25)	(0.23)	(281.97)
Panel B: diagnosis tests					
Q(5)	4.997	3.083	0.747	5.146	8.033
	(0.42)	(0.69)	(0.98)	(0.40)	(0.15)
Q(10)	10.281	11.677	2.839	7.402	15.797
	(0.42)	(0.31)	(0.99)	(0.69)	(0.11)

$Q^2(5)$	4.017	2.197	3.233	10.885	4.256
	(0.55)	(0.82)	(0.66)	(0.05)	(0.51)
$Q^2(10)$	9.962	7.011	4.680	13.726	10.034
	(0.44)	(0.72)	(0.91)	(0.19)	(0.44)
LM(5)	0.831	0.425	0.701	2.156	0.806
	(0.53)	(0.83)	(0.62)	(0.06)	(0.55)
LM(10)	1.003	0.615	0.519	1.335	0.955
	(0.44)	(0.80)	(0.88)	(0.21)	(0.48)

*** Significant at 1%; ** Significant at 5% ; * Significant at 10%. Standard errors (probability values) are shown in parentheses in Panel A (Panel B). ETF definitions are provided in Table 1.

Based on the results presented so far, it appears that unexpected volume could be a better proxy to capture the surprise information component. In Table 4, we document the results of the model where volume are replaced by the expected and unexpected volumes in the conditional variance model. The shock impacts on the long-run (or permanent) volatility component (captured by the ρ parameters) are positive and significant for all sample ETFs and are above 0.98. These results suggest the persistence of the permanent volatility component for all sample series, and indicate slow steady state convergence to the mean. Next, in Table 5, we present the permanent and transitory shock responses of each series ETF. From these results, it appears that the half-lives of the permanent responses to shocks are 207, 108, 84, 51, and 37 days for the gold, the oil, the agricultural, the stock, and the bond ETFs, respectively. From these results, it is clear that the permanent volatility component declines very slowly for the sample commodity (the gold, the oil, and the agricultural) ETFs[11], and relatively fast for the financial ETFs. These results have not been reported in the literature. The commodity ETFs with a permanent volatility that decays over a longer time period provides speculation opportunities for investors either by using a long-short strategy or a short-long strategy. A long-short strategy is to take a long position in an ETF that is expected to increase in price until the half-life period of the permanent volatility component. If the ETF really increases in price, the speculation strategy will generate a profit. On the other hand, a short-long strategy will require the assumption of a short position in an ETF that is expected to decrease in price until the half-life period of the permanent volatility

[11] Henceforth, when we refer to the commodity ETFs, we are implicitly referring to the gold, the oil, and the agricultural ETFs. Similarly, the sample financial ETFs are respectively the stock and the bond ETFs.

component. The speculation strategy makes money only if the ETF actually decreases in price.

Next, using the stock and the bond ETFs to hedge against stock and bond price volatility would obviously be of limited value in view of their relatively shorter half-lives. One implication of these findings is that investors would be better off using long half-life ETF assets for hedging the underlying asset price volatilities. Finally, in view of the strong persistence of permanent volatilities for the commodity ETFs, investors will benefit in terms of better asset management strategies if they can generate more accurate volatility predictions for these three ETF markets than for the remaining two financial ETFs.

In contrast, the transitory components exhibit much weaker persistence, as captured by the sum$(\alpha + \beta)$. The magnitude of the sum $(\alpha + \beta)$ is much smaller than the corresponding ρ values for all sample markets. In addition, transitory shocks seem to last for much shorter durations than they do for permanent shocks. The half-lives of the transitory responses to shocks are 30.96, 14.55, 1.73, 0.39, and 0.31 days for the bond, the gold, the oil, the agricultural, and the stock ETFs, respectively. The transitory volatility components decline considerably faster for the oil, the agricultural, and the stock ETFs, implying that there will be fewer short term investment strategies using this information for these three ETF markets. On the other hand, the relatively longer transitory volatilities will provide exploitable investment opportunities using the bond and the gold ETFs.

Clearly, permanent shocks are more persistent than transitory shocks for all markets. These results are consistent with those reported for stock markets (Wagner and Marsh, 2005; Aragó and Nieto, 2005) where permanent effects are more pronounced and last for a longer duration than transitory effects. Interestingly, among these five ETFs, the bond ETF has the longest half-life of transitory response and shortest half-life of permanent response. The expected and unexpected volumes have the longest impact time on the transitory volatility of bond ETF and the shortest impact time on the permanent volatility of bond ETF. The expected and unexpected volumes have the second shortest impact time on the permanent volatility of stock ETF.

How do the relative magnitudes of the permanent components compare with each other? Examining the values of α (the transitory volatility component) with those of φ (the permanent volatility component) for each sample series provides a clue. The α's are much smaller than the φ's for all sample series, indicating that the impact of the shocks on the transitory volatility component is weaker than those on the permanent volatility component. In addition, the ratio (φ/α) is 1.11 on average, for sample time series. Finally, the persistence factor proportionality, $\rho/(\alpha+\beta)$ is 6.69, and can be attributed to the presence of noise traders and speculators in the ETF markets selected for analysis, since transactions made by this group are relatively sensitive to the impact of shocks.

Another major finding is that surprise information flows through the unexpected volume variable, and is more severe on the permanent volatility component than on the transitory component. In fact, the coefficients of unexpected volumes on the permanent volatility components are positive and significant at the 1% level for all sample time series. In contrast, with one exception (for the oil ETF), all sample ETFs the coefficients of both unexpected and expected volumes on the transitory volatility components are negative and significant, implying a negative volume volatility relationship for sample series. These findings show the existence of a *negative* impact of unexpected volume on the transitory volatility component and a *positive* impact of unexpected volume on the permanent volatility component. There results have not been reported in the literature.

Table 4 : Effect of expected and unexpected trading volume on volatility persistence

	SPY	**GLD**	**XOP**	**DBA**	**BLV**
Panel A: $\boldsymbol{\sigma_t^2 - m_t = \alpha(\varepsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1}) + \delta_1 EXVO_{t-1} + \delta_2 UNEXVO_{t-1}}$; $\boldsymbol{m_t = \omega + \rho(m_{t-1} - \omega) + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + \eta_1 EXVO_{t-1} + \eta_2 UNEXVO_{t-1}}$					
ω	1.4174 *	-0.5154	8.5417	1.8513 ***	0.5633 ***
	(0.73)	(2.17)	(5.46)	(0.56)	(0.10)
ρ	0.9865 ***	0.9967 ***	0.9937 ***	0.9918 ***	0.9813 ***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
φ	0.1027 ***	0.0126 **	0.0664 ***	0.0385 ***	0.0299
	(0.02)	(0.01)	(0.01)	(0.01)	(0.16)
η_1	0.2478	2.0082 ***	1.4855 ***	0.4563 *	4.8010 ***
	(0.29)	(0.71)	(0.43)	(0.25)	(0.88)
η_2	0.5629 ***	2.1800 ***	0.9905 ***	0.4697 ***	4.8243 ***
	(0.14)	(0.66)	(0.28)	(0.18)	(0.93)
α	-0.1443 ***	0.0244	-0.0598 **	-0.0444	0.0126
	(0.02)	(0.02)	(0.03)	(0.03)	(0.17)

β	0.2535	0.9291 ***	-0.6100 ***	0.2172	0.9652 ***
	(0.19)	(0.02)	(0.17)	(0.25)	(0.16)
δ_1	-0.6524 **	-2.4052 ***	0.6694	-0.9798 ***	-4.719 ***
	(0.31)	(0.69)	(0.49)	(0.36)	(0.88)
δ_2	-0.4385 ***	-2.3362 ***	-0.2110	-0.5611 ***	-4.764 ***
	(0.16)	(0.66)	(0.17)	(0.17)	(0.94)
Panel B: diagnosis tests					
Q(5)	5.512	3.174	0.596	5.010	8.104
	(0.36)	(0.67)	(0.99)	(0.42)	(0.15)
Q(10)	10.469	11.433	2.480	7.361	15.749
	(0.40)	(0.33)	(0.99)	(0.69)	(0.11)
$Q^2(5)$	3.018	2.268	3.324	8.460	4.423
	(0.70)	(0.81)	(0.65)	(0.13)	(0.49)
$Q^2(10)$	11.521	6.438	5.183	11.491	10.220
	(0.32)	(0.78)	(0.88)	(0.32)	(0.42)
LM(5)	0.634	0.436	0.704	1.684	0.837
	(0.67)	(0.82)	(0.62)	(0.14)	(0.52)
LM(10)	1.159	0.562	0.570	1.105	0.975
	(0.31)	(0.85)	(0.84)	(0.35)	(0.46)

*** Significant at 1%; ** Significant at 5% ; * Significant at 10%. Standard errors (probability values) are shown in parentheses in Panel A (Panel B). ETF definitions are provided in Table 1.

Table 5 : Response to permanent and transitory components for each ETF

Half-life	SPY	GLD	XOP	DBA	BLV
Permanent $\ln(0.5)/\ln(\rho)$	51	207	108	84	37
Transitory $\ln(0.5)/\ln(\alpha+\beta)$	0.31	14.55	1.73	0.39	30.96

ETF definitions are provided in Table 1. The definitions of permanent and transitory volatilities have been provided earlier.

6 - Possible superior trading strategies from information in volatility components

If we believe that both expected and unexpected trading volumes are surrogates for new information, can a superior trading strategy (based on persistence in the permanent component of trading volume) be developed and exploited?

Since the three commodity ETFs (gold, oil, and agriculture) exhibit relatively longer persistence in the permanent volatility component as opposed to the transitory component, it seems clear that a possible trading strategy for the gold and oil ETFs is to sell the ETFs short at the first permanent volatility shock and then cover the short sell by buying it back later at the half-life of the permanent volatility component. A trading strategy for the agriculture EFT is to have a long position at the first permanent volatility shock and then short sell it at the half-life day. To examine this contention, we use the parameter estimates developed in the previous sections and investigate profit making opportunities from superior investment strategies from an out-of-sample data for each of three commodity ETFs. For each series, for the June 2012 – Jan 2016 period, we develop a trading strategy as follows: We initially locate the first volume shock (defined as volume 4 times the average in the permanent component of volume for the first time) to each sample time series. Once we detect a volume shock, we sell the underlying ETF short. At the half-life of the permanent response component, we then buy back the underlying ETF and compute the profits from this trading strategy.

First, for GLD (the gold ETF), the shock is generated on 2013/4/15. Selling the ETF short the next day (2013/4/16) at 132.8 and buying it back after 207 days (the half-life of the permanent response volatility component to shocks of GLD), at a price of 122.47 results in a 8.43% abnormal profit. Similarly, for the DBA (the agricultural ETF), the shocks occur on 2014/3/3. Starting with a long position of the ETF on 2014/3/4 at 27.96 and selling it after 84 days (the half-life of permanent volatility component) at 29.32 generates a profit of 4.86%. For XOP (the oil ETF), since the shock occurs on 2014/10/16, we short sell at 57.79 on 2014/10/17 and buy it back after 108 days at 47.02 resulting in a 18.64% profit.

For SPY (the stock ETF), the shock is generated on 2015/8/24. The correct profit making strategy here is to buy the stock ETF the next day (2015/8/25) at 187.27 and *selling* it after 51 days (the half-life of the permanent response volatility component to shocks), at a price of 211, thereby generating a 12.67% abnormal profit. Similarly, for the bond ETF (BLV), the shocks occur on 2014/8/27. Buying the ETF long on 2014/8/28 at 92.63 and selling it after 37 days (the half-life of the permanent volatility component) at 93.07 generates a profit of 0.5%.

Given the relatively short half-life of the *transitory* components of sample ETFs (relative to the half-life for permanent components), there seems to be little trading value from this information. However, from among the sample ETFs, the bond ETF and the Gold ETF have relatively longer transitory half-lives than the other sample ETFs. Can trading profits exist for the bond and the gold ETFs using the transitory components?

First, for GLD (the gold ETF), the shock is generated on 2013/4/15. *Buying* the gold ETF long the next day (2013/4/16) at 132.8 and *selling* it after 15 days (the half-life of the transitory response volatility component to shocks of GLD) at a price of 142.15 results in a 7.04% abnormal profit. Similarly, for the bond ETF (BLV), *selling* the ETF short on 2014/8/28 at 92.63 and *buying* it back after 31 days (the half-life of transitory volatility component) at 91.93 generates a profit of 0.76%.

These results suggest that profits are forthcoming if information in the volatility components are exploited.

7 - Conclusions, policy implications, and suggestions for further research

In this paper we further contribute to the growing body of literature that discusses the complex relationship between ETF returns and volatility for 5 major US traded ETFs over the October 16, 2007 through May 31, 2012 period. While extant literature primarily documents a positive volume/volatility link, we use the component CGARCH model to show that while the long run links are positive, the short run (or transitory) link is negative for the sample time series examined in this study. We find the “unexpected” volume is a better proxy than total volume to capture the surprise information influencing the volume/volatility relationship. This has not been reported in the literature.

The permanent volatility component represents the expected fluctuation of ETF price (trend) volatility while the transitory volatility component captures deviations from long run equilibrium price volatility. The expected and unexpected volumes have the longest (shortest) impact times on the transitory (permanent) volatility of the sample bond ETF. Next in line, the sample stock ETF records the second shortest impact time to expected and unexpected volumes on permanent volatility. Our results also indicate that the transitory volatility components decline relatively fast for the oil, the agriculture, and the stock ETFs, implying fewer short term investment strategies available using this information for these ETF markets. In contrast, the relatively longer transitory volatilities captured for the bond and gold ETFs imply available exploitable long term investment opportunities using these ETFs. From a hedging perspective, investors may be better off using long half-life ETF assets for hedging the underlying asset price volatilities. Finally, in view of the strong persistence of permanent volatilities for gold, oil, and agricultural ETFs, investors' benefits critically depend on their ability to accurately predict permanent volatility in these three markets.

Overall, more precise strategic portfolio allocation strategies in the ETFs should use information present in both the permanent and transitory volatility components for better performance results. Future research may expand the research to include more ETFs from US and foreign markets to see if our conclusions are robust. In addition, trading strategies involving information available from volatility components have been shown to provide profits to investors for select sample ETFs. More systematic investigation of these issues can be the subject matter for future papers.

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