A STUDY OF THE DIFFUSION OF ASSET PRICES

The Determinants of Asset Price Diffusion and a Practical Model of Asset Price Diffusion for use in Portfolio Management

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ABSTRACT

Brownian motion and diffusion processes have found considerable application in modern finance theory. In this paper, the diffusion coefficients of stock prices for the S&P/ASX300 are computed and analysed. Reasoning by analogy (from theoretical physics), market capitalisation and liquidity are identified as two variables that may be expected to explain the variance of the diffusion coefficients of stock prices. The analysis presented herein reveals that the actual relationship between these variables is *not* in accordance with expectations of the directions of the relationships derived by reasoning from physics to finance. In addition, the utilisation of asset price diffusion coefficients in portfolio management is discussed. Diffusion coefficients may play an extremely useful role in practice as 'transition probabilities': the probability that a particular change in the asset's price will be observed in a particular period of time and may be used to compute the expected value of a price movement.

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1. Introduction

Is there more substance to the analogical application of Brownian motion processes to asset price analysis than a similarity between the irregular movement of physical particles and the irregular movement of asset prices? In the mathematical structure of modern finance, Brownian motion processes play an important role. Specifically, the state variable processes, production processes, the structure of information evolution and the price processes specified in asset pricing models form Brownian motion diffusion processes. Furthermore, Brownian motion processes lay at the heart of a large number of the various classes of processes that are applied in other branches of modern finance theory.

Whilst Brownian motion processes have found considerable important application in modern finance theory, the real substance of the analogy (between particles and prices) that underlies this application has never been carefully analysed empirically. Huang (1987) identifies the assumption that asset prices form a Brownian motion process as one of the main assumptions underlying general equilibrium asset pricing theory and the intertemporal capital asset pricing model (I-CAPM). Huang (1987, p.118) argues that the validity of this assumption 'has been speculated upon and is, in its own right, an interesting open problem.' Herein lays the motivation for the present investigation.

This paper has two objectives. The first, primary objective of this investigation is the empirical analysis of the substance of the analogy that exists between the behaviour of physical particles and asset prices. The second, subsidiary objective of this investigation is the derivation of a diffusion model of asset prices that explicitly incorporates empirically computable asset price diffusion coefficients. This model, which is fully consistent with modern finance theory, permits the computation of probabilities for asset price movements as well as the expected values of such movements.

This paper is organised as follows. In the second section, the utilisation of Brownian motion processes in modern finance theory is explored. This utilisation is more pervasive than it appears to be on the surface. The third section contains a statement of the rationale for the study, a discussion of the methodology and a presentation of the results of the analysis. In the fourth section, a discussion of the results and their implications is presented. In the fifth section, a diffusion model of asset prices that allows for the explicit utilisation of asset price diffusion coefficients in practical portfolio management is derived. Directions for future research and conclusions are contained in the final section.

2. Brownian Motion Processes and Modern Finance Theory

Formally, according to Rogers and Williams (1994, p.1), a real-valued stochastic process $\{B_t : t \in \Re^+\}$ is a Brownian motion if it has the properties:

1. $B_0(\omega) = 0, \forall \omega$;
2. The map $t \mapsto B_t(\omega)$ is a continuous function of $t \in \Re^+$ for all ω;
3. For every $t, h \geq 0, B_{t+h} - B_t$ is independent of $\{B_u : 0 \leq u \leq t\}$, and has a Gaussian distribution with mean 0 and variance *h*.

At a fundamental level, the application of a Brownian motion process to the analysis of asset prices yields a Wiener process that depicts the marginal movement of asset prices in a mathematically idealised form:

$$dP = \alpha P\, dt + \sigma P\, dw \tag{1}$$

Where *dP* is the instantaneous change in the asset price, *α* is the constant rate of change in the asset price over the interval *dt*, *σ* is the instantaneous standard deviation of asset price returns and *dw* is a normally distributed error term with the mean of zero and standard deviation of $\sqrt{dt}$ (see Merton (1991)).

More sophisticated (and interesting) applications of Brownian motion processes in finance emerge as a direct consequence of the different ‘classes’ of Brownian motion processes that have been identified in (relatively) recent mathematical analyses of stochastic processes. These three classes of Brownian motion processes are: (1) Brownian motion as a martingale; (2) Brownian motion as a Markov process; and (3) Brownian motion as a diffusion process. Martingales, diffusion processes and Markov processes are familiar to financial economists. Perhaps less familiar is the relationship between Brownian motion processes, martingales, diffusion and Markov processes. Martingales, Markov processes and diffusion processes all contain a Brownian motion.

It is well known that when asset prices follow a martingale process, asset prices are equal to the discounted value of expected future cash flows (see Samuelson (1973) and LeRoy (1989)). The simple present value formula implies the martingale process and *vice versa*. That martingales contain a Brownian motion can be confirmed formally. Specifically, if $\{B_t : t \geq 0\}$ is a Brownian motion and

$\mathscr{B}_t = \sigma(\{B_s : s \le t\})$ then $(B_t, \mathscr{B}_t)_{t \ge 0}$ is a martingale (Rogers and William, 1994, p.2). Martingales remain a component of modern asset pricing (see Cochrane (2001)) and martingale models have long been associated with the concept of market efficiency. The fact that martingales contain a Brownian motion highlights the significance of Brownian motion processes in financial economics.

Like martingales, Markov processes are an integral part of the theoretical structure of financial economics. Markov processes describe a stochastically evolving process whose probability in the present time period is a function of the immediate history of the system. A prime example of the application of Markov processes to asset pricing is the work of Lucas (1978). In his examination of the stochastic behaviour of asset prices in a pure exchange (no endogenous production) economy, Lucas treats the motion of various components of his theoretical exchange economy as Markov processes and constructs a situation in which the asset prices exhibit a random 'martingale' character.

Like martingales, Markov processes also contain a Brownian motion. Formally, Brownian motion is a Markov process (Williams and Rogers, 1994, p.5). For any bounded Borel $f : \Re \to \Re$, and $s, t \ge 0$, the Markov process is defined by the transition function (Williams and Rogers, 1994):

$$E[f(B_{t+s}) | B_s] = P_t f(B_s)$$

Where

$$P_t f(x) = \begin{cases} \int_{-\infty}^{\infty} p_t(x, y) f(y) dy & (t > 0) \\ f(x) & (t = 0) \end{cases} \quad (2)$$

and

$$p_t(x, y) := (2\pi t)^{-1/2} \exp\left[-\frac{(x-y)^2}{2t} \right]$$

The Markov property—$E[f(B_{t+s}) | B_s] = P_t f(B_s)$—follows from the definition of Brownian motion (Williams and Rogers, 1994, p.5). The class of processes known as Markov processes contain Brownian motion. Hence, Brownian motion processes lay at the core of Markov processes and, therefore, at the core of applications of Markov processes in financial economics. This further highlights the significance of Brownian motion processes in financial economics.

The third class of processes that shall be considered here are diffusion processes. Formally, the mathematics of Markov processes and the mathematics of diffusion processes are 'linked' by

Brownian motion. In continuous time, a diffusion process is a homogenous Markov process (Williams and Rogers, 1994). To appreciate this relationship, consider the diffusion equation from theoretical physics:

$$\frac{\partial}{\partial t} p_t(x,y) = \frac{1}{2}\frac{\partial^2}{\partial y^2} p_t(x,y) \tag{3}$$

This equation can be derived in not too many steps from the Brownian transition density function, $p_t(x,y) := (2\pi t)^{-1/2} \exp\left[-\frac{(x-y)^2}{2t}\right]$, for the Markov process described in the set of Equations (2) (see Williams and Rogers, 1994, pp.5–7). Like martingales and Markov processes, therefore, diffusion processes also contain Brownian motion. Also like martingales and Markov processes, diffusion processes figure prominently in finance.

Two prime examples of the utilisation of Brownian motion diffusion processes in intertemporal general equilibrium asset pricing are Cox, Ingersoll and Ross (1985) and Chi-Fu Huang (1987). These examples were produced during the 1980s, which can perhaps be referred to as the ‘classical’ period for general equilibrium asset pricing theory. Unlike Lucas’s (1978) pure exchange economy, these examples are constructed in a production economy setting. In these models, Brownian motion diffusion processes appear explicitly and directly in the theoretical structures. Specifically, Brownian motion diffusion processes are utilised to describe the probabilistic structures of the models.

In the settings constructed by Cox, Ingersoll and Ross and Huang, components of the systems are described as finite dimensional Brownian motion processes on the probability space $(\Omega, \mathcal{F}, P)$. As an example, consider the information structure described by Huang (1987). In Huang’s treatment, the exogenous uncertainty in the economy is described by a Brownian motion: $W = \{W(t); t \in T\}$. The fact that the information structure in Huang’s intertemporal general equilibrium asset pricing model follows a Brownian motion diffusion process is far from trivial. Importantly, when economic agents receive their information as a Brownian motion, asset prices themselves follow a Brownian motion process. Hence the application of Equation (1), $dP = \alpha P\,dt + \sigma P\,dw$, to the analysis of asset prices is entirely justified (also see Merton (1991)).

Brownian motion diffusion processes maintain a place of prominence within the theoretical structure of contemporary financial economics. The portfolio optimisation conditions derived by Merton (1969) in a continuous-time setting where rates of return form a Wiener process retain their validity. The

Black and Scholes (1973) option pricing model, in which a Brownian motion diffusion process similar to Equation (3) figures prominently, remains a key component of modern finance theory and practice. Finally, of course, the Brownian motion process remains an integral part of the formal structure of asset pricing theory—both implicitly (as a building block for martingales and Markov processes) and explicitly—as an indispensable component of the analysis of asset prices in both discrete and continuous time settings (see, for example, Cochrane (2001)).

The spirit of Huang's (1987) theoretical investigation is similar to that of this present investigation. Dissatisfied with the absence of a formal justification for the assumption that equilibrium asset prices form a diffusion process, Huang (1987) set out to construct a well-defined economic context in which it could be demonstrated that asset prices did indeed form a diffusion process. Whilst this represented a theoretical justification for the application of Brownian motion (Wiener) processes to the analysis of asset prices, the real substance of the analogy that first initiated the application remains unexplored empirically. In 1987, the validity of the assumption that asset prices form a diffusion process was 'an interesting open problem.' Huang (1987) took some steps towards closing it. However, the real substance of the analogy between the Brownian motion of particles and the motion of asset prices that exists *beyond* the irregularity of particle movements and the irregularity of marginal price changes still remains an open problem that has not been explored empirically. It is in this place in the literature that the present paper may be situated.

3. Research Design, Data and Analysis

In order to ascertain whether there is more substance to the analogy between the Brownian motion of particles and the motion of asset prices, it is necessary to explore the possibility of analogical extensions beyond the similarity between the irregularity of particle movements and the irregularity of marginal price changes. To accomplish this, a further step must be taken; away from visible movement of physical particles and towards the determinants of particle diffusion. In the theoretical physics, apart from some universal constants, the diffusion of a particle depends only on the size of the suspended particle and the viscosity of the liquid in which the particle is suspended (Einstein 1905, p.12)[2]. Specifically, the diffusion coefficient for a particle will be *larger* the *smaller* the particle and the *less* the viscosity of the surrounding medium.

Whilst the analogy that exists between the irregularity of particle movements and the irregularity of marginal asset price changes is clear, we now seek analogy at a deeper, more substantive, level. To be precise, we seek economic analogues for the determinants of physical particle diffusion. If it is

[2] Also see Einstein (1908). Einstein is the seminal reference here.

possible to find a plausible analogical extension of these properties of diffusion (particle size and viscosity) to the domain of modern finance theory, it will be possible to examine the determinants of the diffusion of stock prices and establish whether the analogy between particle movements and asset price movements extends to a deeper level and, in the process, determine whether there is empirical substance to the analogy beyond the similarity between the irregularity of particle movements and the irregularity of marginal price changes.

Fortunately, analogical extensions for particle size and viscosity to the domain of modern finance theory are readily apparent. The economic analogues for particle size and viscosity are the company size (market capitalisation) and the liquidity (measured by daily turnover) of the equity on issue. The analogy that exists between particle size and company size (market capitalisation) is clear. The analogy that exists between viscosity and liquidity is an inverse analogy. The less gelatinous or sticky the turnover of the stock's equity or, alternatively, the greater the liquidity of the equity on issue, the less difficult it is for the stock's price to move, to disperse, to diffuse. Reasoning by analogy, the finance theorist would expect the diffusion coefficient for a particular stock to be *larger* the *smaller* the size of the company and the *greater* the issue's liquidity. This expectation is subjected to analysis in this section.

In order to examine the determinants of asset price diffusion, an empirical value for asset price diffusion coefficients must be computed. The diffusion of a stock price may be defined as the tendency of the stock price to disperse from a given starting point (*i.e.* a given starting price). In experimental (*vis-à-vis* theoretical) physics, a method exists for the computation of an experimental value of a particle's diffusion coefficient. In keeping with the theme of this investigation, we derive an analogue of this method for application in financial economics. Specifically, a value for the diffusion coefficient for a stock may be obtained by observing and recording the stock price at particular intervals. The successive displacements are squared, averaged and divided by two in just the same manner that a particle's successive displacements are in the physical sciences (see Hersh (1978)). Formally, this may be expressed as the following equation for computation of the diffusion coefficient of asset prices:

$$D = \left[1/n \sum_{t=1}^{n} \left(P_t - P_{t-1} \right)^2 \right] 1/2 \qquad (4)$$

Hence, beginning with a series of prices for a particular stock, one takes and squares the differences between successive prices. One then averages the series of successive displacements computed in the first instance. Finally, the average is divided by two and the diffusion coefficient for the stock is revealed. This is the measure of the tendency for the stock's price to disperse or spread from a starting point. This method for obtaining an empirical value for the diffusion coefficient of an asset price has never been deployed in empirical finance before this time.

It is important to note that the tendency for an asset's price to disperse or spread from a starting point and our numerical measure of this tendency (the diffusion coefficient) is *not* the same thing as dispersion around a mean and its numerical measure (standard deviation). For example, two of the stocks (A and B) in our sample possessed diffusion coefficients computed utilising Equation (4) above of 0.00151 and 0.001014 respectively. The standard deviation of these particular stocks' price series was 0.961075 and 3.104199 respectively and the standard deviation of the returns series—$\left(p_t - p_{t-1}\right)/\, p_{t-1}$—was 1.27% and 1.92% respectively. Rather, our diffusion coefficients are very closely related to a measure of volatility called root mean square (RMS). This is quite appropriate and unsurprising because RMS has implications for the Brownian motion of securities.

The data utilised in this analysis are as follows. The data set consists of the 300 Australian shares that comprised the S&P/ASX300 in May 2006. For each of the 300 shares, the closing price, the number of shares on issue and the turnover (or volume) was gathered. The data were gathered at *daily* intervals for a *ten* year period (May 1996 to May 2006) from the Thomson DataStream database. During this period there were approximately 2,500 trading days. There are a total of approximately 7,800 data points for each stock that was trading as at May 1996 and a total of more than 2,000,000 data points across the 300 stocks.

The daily prices were utilised in the manner described by Equation (4) to compute the diffusion coefficients for each stock. The product of the each stock's number of shares on issue and the stock's daily closing price was computed and averaged to determine an average for each stock's market capitalisation over the ten year period. The series of daily volume numbers for each stock was averaged to determine an average for each stock's daily trading volume over the ten year period. The end product of this preliminary data preparation was three series of numbers—a diffusion coefficient, an average market capitalisation and an average daily turnover—for each of the 300 stocks in the S&P/ASX300. Summary descriptive statistics are provided in Table 1:

Table 1

Descriptive Statistics for the Variables

	Mean	Median	Standard Deviation
Diffusion Coeff.	0.009304811	0.0012355	0.04008
Avg. Capitalisation	$2,121,285,000	$517,475,000	5,971,221
Avg. Liquidity	1,227,000	504,000	1,983,000

Notes: This table reports the descriptive statistics for the variables. That is, the mean, median and standard deviation for the 300 diffusion coefficients, each of the 300 stocks' average capitalisation for the period and each of the 300 stocks' average daily turnover for the period.

Reasoning on the basis of analogy from the physical sciences to modern finance theory and asset pricing, the following function for the diffusion of stock prices is posited:

$$D = f\left(\overset{-}{\text{average market capitalisation}}, \overset{+}{\text{average daily volume}}\right) \quad (5)$$

This is the foundation for the regression equation analysed in this section. It is, of course, necessary to determine a specific functional form for the regression equation. Unfortunately, there is little in the way of theoretical reasoning to guide us on the exact specification of a functional form for a regression equation. Following standard econometric practice in the absence of specific guidance on functional form, a *log-linear* specification is adopted as a default specification.

Formally, the log-linear regression equation that is analysed herein (with the data transformed by natural logarithms) is presented below. Ordinary least squares is used to estimate the regression equation:

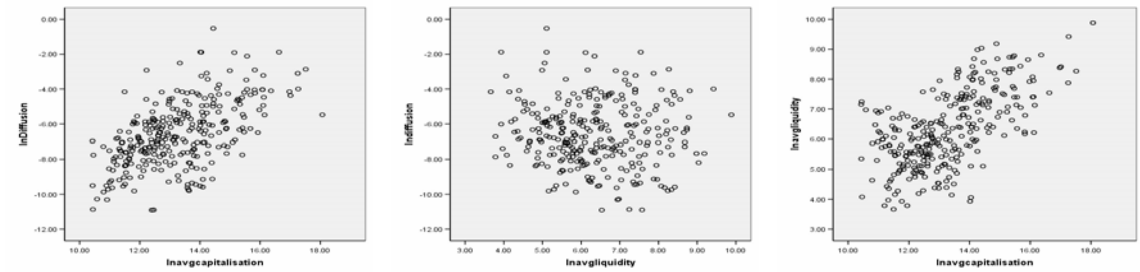
$$\ln Y_i = \beta_1 + \beta_2 \ln X_{1i} + \beta_3 \ln X_{2i} + u_i \quad (6)$$

Where the dependent variable Y_i is the diffusion coefficient for stock i, the first independent variable X_{1i} is average market capitalisation for the i^{th} stock and the second independent variable X_{2i} is average daily turnover or volume for the i^{th} stock. The expected signs of the coefficients are as follows: (1) the expected sign for the coefficient β_2 is negative; and (2) the expected sign for the coefficient β_3 is positive. Essentially, it is expected that the tendency for an asset price to disperse or spread from a starting point to be greater the smaller the asset's market capitalisation and the greater the asset's liquidity *if* the analogical application of diffusion from physics to finance proceeds in the manner that it is expected to.

Before the results of the regression estimation are presented, three scatter plot graphs are displayed representing the relationship between (1) the natural logarithm of the diffusion coefficients of the stocks in the sample and the natural logarithm of the average market capitalisation of the stocks in the sample; (2) the natural logarithm of the diffusion coefficients of the stocks in the sample and the natural logarithm of the average daily turnover (liquidity) of the stocks in the sample; and (3) the natural logarithm of the average market capitalisation of the stocks in the sample and the natural logarithm of the average daily turnover (liquidity) of the stocks in the sample. The scatter-plots are presented in the three parts of figure one:

Figure 1

Scatter Plots for Each Pair of Variables



Notes: The three diagrams depict (from left to right) scatter plots of the relationship between the natural logarithms of diffusion and average capitalisation, the natural logarithms of diffusion and average liquidity and the relationship between the two independent variables. The vertical axes in the first two diagrams correspond to the natural logarithm of diffusion. The vertical axis in the third diagram corresponds to average liquidity with the horizontal axis corresponding to average capitalisation.

The scatter plots reveal the following. First, there does appear to be a relationship between the natural logarithm of the diffusion of stock prices and the natural logarithm of average market capitalisation (size). Second, there also appears to be a relationship between the natural logarithm of the diffusion of stock prices and the natural logarithm of the average daily turnover (liquidity). Third, there appears to be a relationship between the natural logarithm of size and the natural logarithm of liquidity. This might reveal the presence of a possible collinearity problem. However, the majority of the observations appear to be clustered with no discernable positive or negative relationship (within the cluster). Finally, the scatter plots reveal the absence of any (far) outliers. Hence, the application of regression analysis to the data proceeds without removing any particular observations. The results of the regression estimation are presented below:

$$\begin{aligned} \ln \hat{Y}_i &= -16.326 + 1.222 \ln X_{1i} - 1.020 \ln X_{2i} \\ &\quad\ (0.601) \quad\ (0.057) \qquad\ (0.069) \\ t &= -27.175 \qquad 21.315 \qquad -14.718 \\ &\qquad \overline{\mathrm{R}}^2 = 0.609 \quad \mathrm{R}^2 = 0.611 \end{aligned} \tag{7}$$

The ratio of the explained sum of squares to the total sum of squares is a reasonably high 0.61 and the coefficients are highly significant at the 0.05 level. The numbers in the parentheses are the OLS standard errors. The ANOVA statistics reveal that the regression explains a significant amount of the variation in the dependent variable (the natural logarithm of the diffusion of stock prices) and that this explanation is not due to chance:

Table 2

ANOVA Statistics for the Regression

Model	Sum of Squares	F	Significance
Regression	608.624	228.890	.000
Residual	386.888		
Total	995.512		

Notes: The table shows the ANOVA statistics for the OLS regression. The F statistic and the associated significance value show that the OLS regression explains a significant amount of the variation in the diffusion of asset prices.

The various diagnostic checks reveal that the regression is sound. Importantly, the residuals for the regression are normally distributed. There is also very good ‘scatter’ in the plot of the residuals, revealing the absence of any tendency for the variance of the error terms to increase as the values of the independent variables increase. That is, there is no heteroskedasticity. The collinearity diagnostics revealed the absence of any serious multicollinearity. The variance inflation factors (VIF) for each of the independent variables, which were equal to 1.632, reveal the absence of any serious collinearity problem (a value greater than 2 indicating such a collinearity problem). The condition index values—12.425 and 24.496 for the independent variables—revealed a minor collinearity problem (a value greater than 15 is considered to indicate possible or minor collinearity and a value of greater than 30 is considered to indicate a major or serious collinearity problem). Finally, the Durbin-Watson d statistic, which was computed as 1.799, revealed an absence of serial correlation. It can be confirmed that the regression is sound and the assumptions of the classical linear regression model have not been violated.

4. A Discussion of the Findings

The purpose of the investigation is to explore empirically the substance of the analogy that exists between particle movements and asset price changes. In pursuit of this objective, it became necessary to examine the relationship between the diffusion coefficients of asset prices and market capitalisation (size) and liquidity. As explained above, reasoning on the basis of analogy from theoretical (and experimental) physics, there is reason to expect such a relationship, providing, of course, that the analogy between physical particles and asset prices is an appropriate analogy that is deeper than the obvious similarity between the irregularity of particle movements and the irregularity of marginal price changes. Also reasoning on the basis of analogy, there is *a priori* reason to expect the diffusion of stock prices to be negatively related to market capitalisation (size) and positively related to liquidity.

First, it may certainly be confirmed that there does indeed exist a statistically significant relationship between the diffusion of stock prices and market capitalisation (size). Also, it may certainly be confirmed that there does indeed exist a statistically significant relationship between the diffusion of stock prices and liquidity, which is our (inverse) analogue for viscosity or stickiness. The ANOVA statistics, coefficient of determination and the individual t-values confirm the existence of a statistically significant relationship between the dependent variable (diffusion) and the independent variables (size and liquidity). However, whilst a relationship between the diffusion of stock prices and size and liquidity was detected, the directions of these relationships is the *opposite* of that which was expected on the basis of analogically reasoning from physics to financial economics.

Market capitalisation or size is, according to the regression analysis, *positively* related to the tendency for a stock's price to disperse from a starting point. A *negative* relationship was expected. The second explanatory variable included in the regression analysis was the average liquidity over the sample period for each of the stocks in the sample. The results of the regression analysis revealed that there is a *negative* relationship between the diffusion of stock prices and liquidity, implying that the tendency for a stock's price to disperse from a starting point *diminishes* as the liquidity of the stock *increases*. Reasoning on the basis of analogy from physics to finance, the *opposite* relationship was expected to prevail.

The regression equation (7) may be interpreted as follows. The coefficient for the size variable, β_2, is interpreted as a constant elasticity equal to +1.222. This suggests that if market capitalisation (size) changes by one percent (holding the other independent variable constant) the diffusion coefficient is expected to change by 1.222 percent. As the size variable increases, there is a more than proportional increase in the tendency for a stock's price to spread or disperse from a starting point. The coefficient for the liquidity variable, β_3, is interpreted as a constant elasticity equal to –1.020. This suggests that if liquidity changes by one percent (holding the size variable constant) the diffusion coefficient is expected to change by 1.020 percent. As the liquidity variable increases, there is a more than proportional decrease in the tendency for a stock's price to disperse from a starting point.

The analogy that exists between the motion of physical particles and the motion of asset prices initiated the application of the physical-mathematical Brownian motion processes to the analysis of asset prices. If this analogy between the motion of physical particles and the motion of asset prices is substantive, it is reasonable to expect that the analogy may be deeper than the obvious (surface) similarity between the irregularity of particle movements and the irregularity of marginal price changes. At this deeper level, not only must the motion (diffusion) of physical particles and asset prices be considered but so too must the determinants of this diffusion. An empirical analysis of the determinants of asset price diffusion can therefore be expected to shed some light upon the real substance that underlies the analogy between the motion of particles and the motion of asset prices on modern financial markets.

The results of the empirical analysis of asset price diffusion may be interpreted in one of two ways. On the one hand, the presence of a statistically significant relationship between an asset price's tendency to disperse and size and liquidity may be interpreted as at least circumstantial evidence of more substantive analogy between physical particles and asset prices. On the other hand, the fact that the directions of the relationships between asset price diffusion and size and liquidity are the opposite to what might have been expected on the basis of analogy from physics to finance may be interpreted as contrary evidence. Perhaps the most sensible interpretation lays somewhere in the middle: like physical particles, size and liquidity (the inverse of viscosity) may be considered to be determinants of asset price diffusion. In this regard, the analogical reasoning from physics to financial economics does have more substance than the obvious similarity between the irregularity of particle movements and the irregularity of marginal price changes. However, one cannot be sure that such reasoning will always lead in the right direction and there remains 40 per cent of the variance of asset price diffusion to explain.

5. An Asset Price Diffusion Model

Before drawing this paper to a close, it remains to be demonstrated how the asset price diffusion coefficients computed empirically via Equation (4) may be utilised by practitioners in portfolio management. The coefficients of asset price diffusion have considerable application in the practice of managing a portfolio of assets. Whilst the asset price diffusion coefficients computed via Equation (4) are, on the one hand, interpreted as a measure of the tendency of an asset's price to disperse from a starting point, the asset price diffusion coefficients may also be interpreted as probabilities. In this guise they may be deployed to compute both the probability that an asset price will experience a particular change in a particular time period and the expected value of such a change. The objective of this section is to present, theoretically, an asset price diffusion model that explicitly includes the empirically computed diffusion coefficients.

Countless occasions arise both in theory and in practice where a value for the probability associated with a particular asset price change is required. The standard procedure is to assume a particular probability distribution for asset prices or returns and infer the desired probability value by reference to probability tables. Of course, this approach is always susceptible to the criticism that the particular series of prices or returns does not follow the particular probability distribution that has been chosen. There is, however, another way that a value can be obtained for the probability that an asset's price will change during a particular period of time. This value is the diffusion coefficient associated with the particular asset. Whilst a diffusion coefficient is usually interpreted as a measure of the tendency of an asset price to disperse from a starting point, one can also interpret the diffusion coefficient as the probability of a price change.

The diffusion processes utilised by modern finance theorists have not explicitly contained a place for the diffusion coefficient. This is primarily due to the fact that the diffusion processes deployed have been mathematical idealisations of physical models rather than analogical application of the physical models themselves. As an example, consider the mathematical idealisation of Brownian movement, the Wiener process, as applied to asset prices:

$$dP = \alpha P\, dt + \sigma P\, dw \tag{1}$$

This is the standard diffusion process that is applied to the analysis of asset prices by modern finance theorists and practitioners (see above). As can be easily seen, however, there is no explicit place in Equation (1) for an empirically computed asset price diffusion coefficient.

In order to derive a diffusion model of asset prices in which the empirically computed diffusion coefficient (the outcome of Equation (4)) is explicit, it is necessary to explore the application of diffusion models in the broader social sciences. Some of the more interesting applications of diffusion models in the social sciences (outside of finance) deal with the adoption of technologies or innovations over time. It has been discovered that this adoption of innovation follows a diffusion process. The adoption of new innovations diffuses until a 'ceiling' is reached. This is the total number of potential adopters in the social system (Mahajan and Peterson 1985). Unlike the Wiener processes that have been applied in modern finance theory, the diffusion models applied in other branches of the social sciences have maintained an explicit role for the diffusion coefficient. It is these models that are utilised as the foundation for the derivation of an operational diffusion model of asset prices.

In a discrete-time setting (where time is assumed to flow in discrete units), a basic prototype diffusion *model* of asset prices in which the diffusion coefficient is explicitly present may be formulated as follows:

$$\frac{dP_t}{dt} = D \cdot \left[P_t^* - P_t\right] \tag{8}$$

Where D is the asset price's diffusion coefficient, P_t^* is the (rational expectations) 'ceiling' price computed by a dividend discount model and P_t is the current market price. The model says that an asset's price will move until there is a correspondence between the rational expectations price and the market price. If there is no such correspondence at the beginning of the period, one can expect there to be a price movement during the time period of a magnitude equal to $D \cdot \left[P_t^* - P_t\right]$. Here D is interpreted as the probability of a movement in the asset's price at time *t*. This being the case, $D \cdot \left[P_t^* - P_t\right]$ is the expected value of such a movement. In an efficient market, where asset prices follow a martingale process, the expected value of a movement is zero because the martingale process implies that prices equal the discounted value of expected future dividends, P_t^* (see LeRoy (1989)). Assuming a probability space $(\Omega, \mathcal{F}, P)$ one can imagine a situation where the probability measure, *P*, is actually the diffusion coefficient itself.

In discrete time, the model describes the path followed by the difference between the price series modelled as a martingale process and the market price. Equation (8) represents a simple, prototype model of asset price diffusion that explicitly incorporates the asset's diffusion coefficient into a discrete-time model. The model is completely consistent with modern finance theory, permitting a scenario where the efficient market hypothesis holds. In a reasonably efficient market like the Australian Stock Exchange, one would expect very small coefficients of diffusion for the shares traded there. This 'prediction' is supported by the computations of the diffusion coefficients for the S&P/ASX300. However, the diffusion coefficients are not zero. One could say, therefore, that the ASX is quite efficient but not perfectly so.

The simple diffusion model of asset prices depicted by Equation (8) can be adapted to allow for the situation where the rational expectations price does not remain constant over the course of the diffusion but changes dynamically. When P_t^* is permitted to vary over time it is necessary to specify a vector Y_t of state variables (see Cox *et al.* 1985) that affect $P_t^* = f(Y_t)$. Substituting in Equation (8) yields the following diffusion model of asset prices:

$$\frac{dP_t}{dt} = D \cdot [f(Y_t) - P_t] \tag{9}$$

Completing the link between this simple model, orthodox financial economics and the intertemporal general equilibrium asset pricing model developed by Cox, Ingersoll and Ross (1985), we set the evolution through time of Y_t equal to their equation (2) (Cox *et al.* 1985, p.365) such that the movement of Y_t through time is described by the system of stochastic differential equations: $dY_t = \mu(Y,t)dt + S(Y,t)dw_t$. In this equation, $\mu(Y,t) = [\mu_i(Y,t)]$ and $S(Y,t) = [s_{ij}(Y,t)]$ are a *k*-dimensional vector and a $k \times (n+k)$ dimensional matrix respectively (see Cox *et al.* 1985, p.364–365). Appropriately, *Y* is Markov.

For practitioners, the diffusion models of asset prices developed here are fully operational and have useful properties. The parameters are easily estimated, as follows. *D*, of course, can be computed in the manner described above. The unobservable parameter P_t^* may be approximated by consensus of analyst estimates of the discounted value of expected future dividends or by the application of an asset pricing model. The current price P_t is directly observable. By interpreting *D* as the probability of a movement and $D \cdot [P_t^* - P_t]$ as the expected value of the movement, one obtains a very useful tool with practical implications for portfolio management.

In closing this section, the diffusion models of asset prices that have been developed here have their origins in the quantitative application of diffusion models in the broader social sciences. One finds analogous models for diffusion of innovations where the diffusion coefficient is interpreted as the probability of change in the number of innovation adopters in a particular period of time. One also finds an analogy for our rational expectations price ceiling. This analogous element is the total number of potential adopters N in a social system. In accordance with our suggestion that P_t^* be approximated by analyst opinions, N is estimated on the basis of expert opinions (see Mahajan and Peterson 1985, pp.13–14 and p.59). Hence, in addition to being consistent with modern finance theory and plausible within the domain of financial economics, the model is entirely in accordance with the application of diffusion models that has been undertaken in the broader social sciences.

6. Conclusions and Future Research

In this paper, we set out to compute and analyse the diffusion coefficients of stock prices in order to reach conclusions regarding the substance of the analogy between physical particles and asset prices that exists beyond the irregularity of particle movements and the irregularity of marginal price changes. Reasoning on the basis of analogy from physics to finance, it was expected that there would be a relationship between company size (market capitalisation) and liquidity and the diffusion of stock prices. A regression analysis revealed that there was indeed such a relationship but the directions of the relationships were the opposite of those which had been expected on the basis of analogical reasoning. This leads to the conclusion that, as with physical particles, size and liquidity (the inverse of viscosity) may be considered to be determinants of asset price diffusion. In this regard, the analogical reasoning from physics to financial economics does have more substance than the obvious similarity between the irregularity of particle movements and the irregularity of marginal price changes. However, one cannot be sure that such reasoning will always lead in the right direction and may not be relied upon to explain all of the motion of financial variables.

Some possible directions for future research can be identified. First, the sample analysed herein consisted of ten years of daily data on 300 Australian stocks. Despite the extensive nature of this investigation, there is certainly scope for further empirical investigations in other markets. A replication or extension of this research utilising an overseas index is one possible empirical investigation. Whilst the discrete-time diffusion model for asset prices that has been presented is theoretically sound and practically operational, it would be very interesting to empirically test its accuracy at predicting expected values for asset price movements. Specifically, how well do the model's predictions of expected values of asset price movements accord with the actual movements observed *ex post*? Additionally, how does this accuracy compare to the accuracy of other, more standard, models based upon fitting of probability distributions to asset prices or returns? Further work, both theoretical and empirical, on the construction and utilisation of diffusion models in financial economics is in order.

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APPENDIX A
DIFFUSION COEFFICIENTS

CODE	COMPANY NAME	DIFFUSION COEFFICIENT
AVV	AAV Limited	0.054004
ABS	ABC Learning Centres Limited	0.002507
ADB	Adelaide Bank Limited	0.004452
ABC	Adelaide Brighton Limited	0.000401
ADZ	Adsteam Marine Limited	0.000873
ALS	Alesco Corporation Limited	0.002811
ALN	Alinta Limited	0.004925
AWC	Alumina Limited	0.003632
AMU	Amadeus Energy Limited	0.0000744
AMC	Amcor Limited	0.004259
AMP	AMP Limited	0.016563
ANN	Ansell Limited	0.017505
APN	APN News & Media Limited	0.001644
AQP	Aquarius Platinum Limited	0.016848
ARP	ARB Corporation Limited	0.000618
ARQ	Arc Energy Limited	0.000234
ALL	Aristocrat Leisure Limited	0.007913
AHS	Atlas Group Holdings Limited	0.000157
ANE	Auspine Limited	0.001214
ASB	Austal Limited	0.000653
AUN	Austar United Communications Limited	0.002428
AEO	Austereo Group Limited	0.000494
ALZ	Australand Property Group	0.000277
ANZ	Australia And New Zealand Banking Group Limited	0.015796
AAC	Australian Agricultural Company Limited.	0.000305
AEU	Australian Education Trust	0.000304
AGL	Australian Gas Light Company (The)	0.009417
AIX	Australian Infrastructure Fund	0.000467
API	Australian Pharmaceutical Industries Limited	0.001164
APA	Australian Pipeline Trust	0.000905
ASX	Australian Stock Exchange Limited	0.032151
AUW	Australian Wealth Mgt	0.000704
AWE	Australian Worldwide Exploration Limited	0.00032
AVJ	Avjennings Limited	0.000245
AWB	AWB Limited	0.002854
AXA	AXA Asia Pacific Holdings Limited	0.001553
BBI	Babcock & Brown Infrastructure Group	0.000217
BNB	Babcock & Brown Limited	0.052454
BBW	Babcock & Brown Wind Partners Group	0.000273
BJT	Babcock&Brown Japan Property Trust	0.000273
BGF	Ballarat Goldfields NL	0.000103
BOQ	Bank Of Queensland Limited.	0.005711
BCA	Baycorp Advantage Limited	0.003095
BPT	Beach Petroleum Limited	0.000123
BMX	Bemax Resources NL	0.00005172
BEN	Bendigo Bank Limited	0.005061

BDG	Bendigo Mining Limited	0.001933
BHP	BHP Billiton Limited	0.018406
BBG	Billabong International Limited	0.012615
BTA	Biota Holdings Limited	0.010168
BSL	Bluescope Steel Limited	0.007668
BSG	Bolnisi Gold NL	0.000196
BOL	Boom Logistics Limited	0.000916
BLD	Boral Limited	0.002826
BKN	Bradken Limited	0.002892
BIL	Brambles Industries Limited	0.009708
BWP	Bunnings Warehouse Property Trust	0.000181
BPC	Burns Philp & Company Limited	0.000495
CAB	Cabcharge Australia Limited	0.0014954
CTX	Caltex Australia Limited	0.010757
CAA	Capral Aluminium Limited	0.001162
CST	Cellestis Limited	0.002876
CEY	Centennial Coal Company Limited	0.001285
CNP	Centro Properties Group	0.000736
CER	Centro Retail	0.00007892
GAN	CFS Gandel Retail Trust	0.000109
CGF	Challenger Financial Services Group Limited	0.006827
CIY	City Pacific Limited	0.003265
COA	Coates Hire Limited	0.00132
CCL	Coca-Cola Amatil Limited	0.018013
COH	Cochlear Limited	0.151631
COF	Coffey International Limited	0.000428
CML	Coles Myer Limited	0.005549
CLH	Collection House Limited	0.002234
CDO	Colorado Group Limited	0.001967
CDR	Commander Communications Limited	0.000487
CBA	Commonwealth Bank Of Australia	0.045109
CPA	Commonwealth Property Office Fund	0.00007257
CPU	Computershare Limited	0.006749
CEU	Connecteast Group	0.00006872
CSM	Consolidated Minerals Limited	0.000895
CXP	Corporate Express Australia Limited	0.002654
CRG	Crane Group Limited	0.00896434
CRS	Croesus Mining NL	0.000119
CSL	CSL Limited	0.14816
CSR	CSR Limited	0.000469
CUE	Cue Energy Resources Limited	0.00001902
DJS	David Jones Limited	0.000439
DRT	DB RREEF Trust	0.000107
DVC	DCA Group Limited	0.000542
DUE	Diversified Utility and Energy Trusts	0.000413
DOW	Downer Edi Limited	0.002802
ENE	Energy Developments Limited	0.010721
ENV	Envestra Limited	0.00009838
EQI	Equigold NL	0.00023
ERG	ERG Limited	0.045545

EXL	Excel Coal Limited	0.01278
FXJ	Fairfax (John) Holdings Limited	0.001952
FLX	Felix Resources Limited	0.015596
FKP	FKP Property Group	0.001014
FWD	Fleetwood Corporation Limited	0.002452
FLT	Flight Centre Limited	0.038615
FMG	Fortescue Metals Group Ltd	0.002556
FGL	Foster's Group Limited	0.00151
FUN	Funtastic Limited	0.00389
FCL	Futuris Corporation Limited	0.0006
GSA	Galileo Shopping America Trust	0.00006624
GAS	Gasnet Australia Group	0.000388
GTG	Genetic Technologies Limited	0.000179
GDY	Geodynamics Limited	0.000885
GCL	Gloucester Coal Limited	0.005893
GFF	Goodman Fielder Limited	0.00047
GPT	GPT Group	0.000433
GHG	Grand Hotel Group	0.000175
GRD	GRD Limited	0.000635
GTP	Great Southern Plantations Limited	0.002038
GUD	GUD. Holdings Limited	0.003454
GNS	Gunns Limited	0.000572
GWT	Gwa International Limited	0.00103
HDR	Hardman Resources Limited	0.000441
HVN	Harvey Norman Holdings Limited	0.001519
HST	Hastie Group Limited	0.000577
HDF	Hastings Diversified Utilities Fund	0.000295
HSP	Healthscope Limited	0.001452
HGI	Henderson Group PLC	0.000277
HIG	Highlands Pacific Limited	0.000117
HIL	Hills Industries Limited	0.001035
HWI	Housewares International Limited	0.000531
HPX	Hpal Limited	0.000502
IGD	Iamgold Corporation	0.000464
IBA	IBA Health Limited	0.000346
IIN	iiNET Limited	0.000999
ILU	Iluka Resources Limited	0.003301
IGO	Independence Group NL	0.00055
IFM	Infomedia Limited	0.000663
IIF	ING Industrial Fund	0.0002
IOF	ING Office Fund	0.00007992
IAG	Insurance Australia Group Limited	0.001906
IWF	Integrated Group Limited	0.000538
IPG	Investa Property Group	0.000193
IVC	Invocare Limited	0.001528
IFL	IOOF Holdings Limited	0.007608
IRE	Iress Market Technology Limited	0.001504
JHX	James Hardie Industries N.V.	0.004899
JBH	JB Hi-Fi Limited	0.001913
JUI	JF US Industrial Trust	0.00001832

JBM	Jubilee Mines NL	0.003035
JST	Just Group Limited	0.001177
KZL	Kagara Zinc Limited	0.000555
KIM	Kimberley Diamond Company NL	0.000507
KCN	Kingsgate Consolidated Limited	0.002667
LEI	Leighton Holdings Limited	0.013445
LLC	Lend Lease Corporation Limited	0.030889
LHG	Lihir Gold Limited	0.000883
LNN	Lion Nathan Limited	0.002665
LSG	Lion Selection Group Limited	0.000432
MCC	Macarthur Coal Limited	0.003692
MAH	Macmahon Holdings Limited	0.00007197
MAP	Macquarie Airports	0.000688
MBL	Macquarie Bank Limited	0.120997
MCG	Macquarie Communications Infrastructure Group	0.001858
MCW	Macquarie Countrywide Trust	0.000175
MDT	Macquarie DDR Trust	0.0000557
MGQ	Macquarie Goodman Group	0.000589
MIG	Macquarie Infrastructure Group	0.001
MLE	Macquarie Leisure Trust Group	0.000221
MOF	Macquarie Office Trust	0.00008679
MPR	Macquarie Prologis Trust	0.00005902
MXI	Maxitrans Industries Limited	0.00006006
MYP	Mayne Pharma Ltd	0.001261
MGW	McGuigan Simeon Wines Limited	0.0019
MCP	Mcpherson's Limited	0.001555
MBP	Metabolic Pharmaceuticals Limited	0.000731
MTS	Metcash Limited	0.00053
MFS	MFS Limited	0.000386
MRL	Miller's Retail Limited	0.000801
MRE	Minara Resources Limited	0.018764
MCR	Mincor Resources NL	0.00007429
MGR	Mirvac Group	0.000742
MND	Monadelphous Group Limited	0.000695
MOS	Mosaic Oil NL	0.0000332
MGX	Mount Gibson Iron	0.01538
MPF	Multiplex Acumen Property Fund	0.00005477
MXG	Multiplex Group	0.002923
MYO	Myob Limited	0.00218
NAB	National Australia Bank Limited	0.057074
NCM	Newcrest Mining Limited	0.023596
NRT	Novogen Limited	0.007872
NUF	Nufarm Limited	0.004536
NLX	Nylex Limited	0.000939
OMP	Oamps Limited	0.00036
OGD	Oceana Gold Limited	0.00019
OSH	Oil Search Limited	0.001389
OST	Onesteel Limited	0.000872
ORI	Orica Limited	0.014033
ORG	Origin Energy Limited	0.001855

OXR	Oxiana Limited	0.000239
PBG	Pacific Brands Limited	0.000863
PBB	Pacifica Group Limited	0.003183
PDN	Paladin Resources Limited	0.000658
PNA	Pan Australian Resources Limited	0.00003449
PPX	Paperlinx Limited	0.002378
PRK	Patrick Corporation Limited	0.002242
PTD	Peptech Limited	0.002349
PEM	Perilya Limited	0.00039
PPT	Perpetual Limited	0.152369
PSV	Perseverance Corporation Limited	0.00009101
PSA	Petsec Energy Limited	0.002817
PXS	Pharmaxis Ltd	0.001126
PMP	PMP Limited	0.000975
PLF	Primelife Corporation Limited	0.001117
PGL	Progen Industries	0.015661
PRG	Programmed Maintenance Services Limited	0.000941
PMN	Promina Group Limited	0.00178
PSD	Psivida Limited	0.001068
PBL	Publishing & Broadcasting Limited	0.013178
QAN	Qantas Airways Limited	0.001975
QBE	Qbe Insurance Group Limited	0.015033
QGC	Queensland Gas Company Limited	0.000099604
RHC	Ramsay Health Care Limited	0.003082
RCD	Record Investments Limited	0.00427
RDF	Redflex Holdings Limited	0.001626
RCL	Repco Corporation Limited	0.001
RMD	ResMed Inc.	0.003927
RSG	Resolute Mining Limited	0.009347
RSP	Resource Pacific Holdings Limited	0.000335
RIC	Ridley Corporation Limited	0.000261
RIN	Rinker Group Limited	0.017723
RIO	Rio Tinto Limited	0.152119
ROC	Roc Oil Company Limited	0.000683
RAT	Rubicon America Trust	0.0000813
REU	Rubicon Europe Trust Group	0.00001851
SAI	SAI Global Limited	0.000862
SMY	Sally Malay Mining Limited	0.000243
SLM	Salmat Limited	0.002621
STO	Santos Limited	0.00584
SEK	Seek Limited	0.001687
SEN	SENETAS CORPORATION	0.00055
SEV	Seven Network Limited	0.004659
SFE	Sfe Corporation Limited	0.015595
SIP	Sigma Pharmaceuticals Ltd	0.000823
SLX	Silex Systems Limited	0.004979
SGM	Sims Group Limited	0.014529
SGX	Sino Gold Limited	0.002768
SKE	Skilled Group Limited	0.001785
SSX	Smorgon Steel Group Limited.	0.000397

SMX	Sms Management & Technology Limited.	0.081466
SHL	Sonic Healthcare Limited	0.00717
SBC	Southern Cross Broadcasting (Australia) Limited	0.010311
SOT	SP Telemedia Limited	0.000445
SPT	Spotless Group Limited	0.003798
SBM	St Barbara Limited	0.00006568
SGB	St George Bank Limited	0.01463
SGP	Stockland	0.000879
SGN	Stw Communications Group Limited	0.001014
SUN	Suncorp-Metway Limited.	0.011213
SDG	Sunland Group Limited	0.000262
SUL	Super Cheap Auto Group Limited	0.001257
SGL	Sydney Gas Limited	0.000296
SYB	Symbion Health Limited	0.001715
TAH	Tabcorp Holdings Limited	0.010305
TAP	TAP OIL Limited	0.000648
TTS	Tattersalls Limited	0.000679
TNE	Technology One Limited	0.000315
TEL	Telecom Corporation Of New Zealand Limited	0.004151
TLS	Telstra Corporation Limited.	0.004185
TEN	Ten Network Holdings Limited	0.000768
TIM	Timbercorp Limited	0.000654
TSO	Tishman Speyer Office Fund	0.000132
TOL	Toll Holdings Limited	0.007012
TWR	Tower Limited	0.001204
TSE	Transfield Services Limited	0.003288
TPI	Transpacific Industries	0.011434
TCL	Transurban Group	0.002275
UTB	UniTAB Limited	0.007557
UGL	United Group Limited.	0.003611
UXC	UXC Limited	0.594752
VPG	Valad Property Group	0.00009274
VCR	Ventracor Limited	0.00065
VWD	Villa World Limited	0.000238
VLL	Village Life Limited	0.00107
VGH	Vision Group Holdings Limited	0.002682
VSL	Vision Systems Limited.	0.000747
VGL	Volante Group Limited	0.000489
WYL	Wattyl Limited	0.002083
WES	Wesfarmers Limited	0.054706
WAN	West Australian Newspapers Holdings Limited	0.002819
WSA	Western Areas NL	0.000846
WDC	Westfield Group	0.01773
WBC	Westpac Banking Corporation	0.012666
WPL	Woodside Petroleum Limited	0.039976
WOW	Woolworths Limited	0.007163
WOR	Worleyparsons Limited	0.01408
ZFX	Zinifex Limited	0.010098