

Forecasting Broadband Demand in Australia

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The analysis and opinions in this paper are those of the author and do not necessarily reflect those of the Department of Communications, Information Technology and the Arts or of the Australian Government.

Contents

Introduction.....	3
1 Characteristics of internet services in Australia.....	4
2 Test for a structural change in broadband data.....	5
3 Testing for unit roots and cointegration.....	6
4 Augmented Bass Model techniques.....	7
4.1 Diffusion modelling.....	7
4.2 Description of the ABM.....	10
5 Statistical accuracy of the ABM model compared with other models.....	13
5.1 Linear model (log transformed).....	17
5.2 Bass model.....	18
5.3 Autoregressive distributed lag model.....	18
5.4 Simple logistic model.....	19
5.5 Gompertz model.....	20
5.6 Holt's exponential smoothing.....	20
6 Forecast accuracy comparisons.....	21
7 ABM forecast for broadband demand in Australia (national demand and assumptions).....	23
8 Conclusion.....	25
Acronyms.....	26
References.....	27

Figures

Figure 1: Broadband subscribers in Australia.....	4
Figure 2: Adoption of an innovation (symmetric adoption).....	9
Figure 3: Model forecast comparisons from June 2005 to March 2006.....	23
Figure 4: Dynamic model forecast comparison from June 2006 to September 2011.....	23

Tables

Table 1: ABM estimates and forecasts to March quarter 2006 (in thousands of subscribers).....	14
Table 2: RMSE of the ABM estimates and forecast.....	14
Table 3: Significance level of the price coefficient in the ABM.....	15
Table 4: RMSE of various log-linear estimates and forecasts.....	17
Table 5: RMSE of the Bass model estimates and forecast.....	18
Table 6: RMSE Autoregressive model estimates and forecast.....	19
Table 7: RMSE of the simple logistic model estimates and forecast.....	20
Table 8: RMSE of the Gompertz model estimates and forecast.....	20
Table 9: RMSE of Holts exponential smoothing model estimates and forecast.....	21
Table 10: RMSE Model estimation from Sept 1999 to March 2005 (in-sample forecast).....	21
Table 11: Model forecast – RMSE four periods ahead from June 2005 to March 2006 (out-of-sample forecast).....	22

Introduction

As the number of broadband subscribers in Australia increases beyond 3 million, the full benefits of broadband are only just being realised. Government and business are increasingly interested in determining the extent of future broadband demand and the likely cost of new investment needed to meet this expected growing demand. The dynamics and history of broadband deployment in Australia makes forecasting broadband adoption particularly difficult, especially when the type and availability of broadband choices are not uniform. This paper looks at the issue of forecasting future broadband demand based on a comparison of the Augmented Bass Model (ABM) and a number of other commonly used forecast models.

In Australia, where there has been significant broadband infrastructure development over the past 10 years, accurate forecasting of broadband adoption is critical for business and government. For business, accurate demand forecasting provides an indication of the economic viability of broadband infrastructure investment given estimated market demand size. For the government, the issue is to develop policies where subsidies and incentives are provided to ensure that areas that don't have access to broadband due to insufficient demand are not disadvantaged.

When forecasting demand, the consequences for business in underestimating demand are lost business opportunities, opportunities that are becoming increasingly lucrative. When demand is over estimated, the investing company can suffer a loss from their investment, and that loss could continue for a period of time. For government policy decisions, accurate demand forecasting provides information to better target high cost areas with incentives to facilitate broadband provision. Investment in broadband based on the criterion of economic viability may not occur in these areas within a reasonable time frame without such incentives.

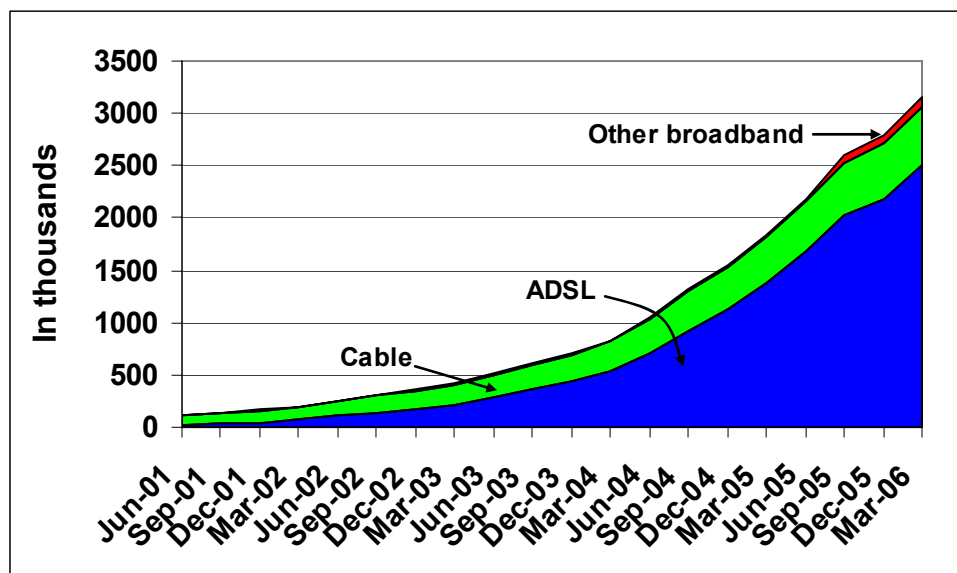
In choosing a forecasting model, the best model would clearly be the model that produced the lowest error for out-of-sample forecasts, given the state of infrastructure deployment, prices and competition. This paper seeks to demonstrate the superiority of the ABM in forecasting Australian broadband adoption over a number of more commonly used general forecasting models.

1 Characteristics of internet services in Australia

Australians have taken up internet services, particularly broadband with considerable enthusiasm over the last few years resulting in one of the highest growth rates of internet connectivity and broadband adoption in the OECD (OECD 2006). Increasingly this broadband adoption has taken the form of Digital Subscriber Line (DSL) technology utilising existing copper based telephone infrastructure to deliver fast broadband services to Australians. The benefit of this technology is principally its relatively low cost and reliability, as extensive copper telephone line infrastructure is already connected to the majority of household and businesses in Australia.

The adoption of broadband by technology in Australia is illustrated in figure 1. The growth story of broadband has been the rapid acceleration of Asymmetric DSL (ADSL) technology. Many factors have influence the adoption of broadband, but from the Australian experience, the price of the service appears to have had a significant influence on peoples desire to *adopt* the technology, when retail prices for broadband fell considerably in February 2004.

FIGURE 1: BROADBAND SUBSCRIBERS IN AUSTRALIA



Source: ACCC (2006)

There are a number of other factors that have influenced the adoption of broadband in Australia. The difficulty with testing these factors rests with obtaining reliable data at the national level with sufficient observations to be useful in quantitative analysis. A common decision variable in the adoption of technology such as broadband is the price of the technology. This is one of the variables that is more readily available and nationally consistent for estimation and forecasting.

The law of demand and supply in relation to price changes apply to broadband adoption as it does for other services. These price effects are expected to be different for different people based on the utility of the technology and other socioeconomic factors which affects the price elasticity of the consumer. For example, those who have not experienced any internet usage may have very elastic demand compared with

those who access internet via dial-up, those people who have had the ‘internet experience’.

It is expected that the demand for broadband is price inelastic based on the utility derived from this service compared to a dial-up service or not having any service at all.¹ Based on the Broadband Choice (Whirlpool 2004) surveys in 2003², 93.8 per cent of respondents would not go back to dial-up (based on either price or service) while only 4.6 per cent would consider price as a reason for going back to dial-up.³ This suggests that for those who *have* access to broadband, price is not a significant variable in their desire to keep the service.

In February 2004, Telstra had significantly reduced the price of their basic broadband service offer (by around 60 per cent) to \$29.95 per month for a 256 kbps connection. This price reduction was followed by most of Telstra’s competitors. The subscriber base increased in the March quarter by 15.6 per cent and by 20.5 per cent in the June quarter of 2004 (ACCC 2006). In developing a model which would account for price changes affecting the trajectory of broadband diffusion, the question is, did the price fall result in a structural change in demand take-up for broadband in Australia? Based on the significant growth in broadband adoption after the price of the service fell, price would be justified as a choice variable in any model.

2 Test for a structural change in broadband data

One of the difficulties in modelling the impact of decision variables that influence the adoption of broadband is data availability. Data for decision variables at the national level is difficult to obtain for the most part because it usually involves peoples tastes, preferences, and utility from use which are highly subjective. The best decision variables are highly objective, nationally consistent and widely advertised to provide homogeneous knowledge of the variable which directly influences people’s decision to adopt broadband technology. Thus, the price variable is appropriately chosen as the principal decision variable. We would expect that price would be the principal driver of adoption as it would be for almost any technology or innovation.

To determine if the price of broadband is a significant driver of broadband adoption for modelling purposes, analysis of any structural change in the data or stability of a series should be undertaken. The Chow test for structural change in the data did indicate that there was a structural break in the data in the second and third quarters of 2004, after the February 2004 price fall (occurring in the first quarter of 2004) in residential broadband prices by Telstra and followed by its competitors. For small business, a structural break is significant for the first and second quarters of 2004 but not the third quarter.

Government policy makers and broadband providers are increasingly interested in the level of demand and what is driving the level of demand for broadband services in Australia. For government, the interest lies in supporting the provision of broadband

¹ Based on the Australian Broadband Survey 2003, 2004 and 2005 (whirlpool.2004, 2005 and 2006), the utility derived from broadband adoption would suggest this is the case, but this issue is beyond the scope of this paper.

² Unfortunately, the question was not repeated in the 2004 and 2005 survey’s.

³ It must be noted that the price for an “average” 256 kbps service from Telstra (as the largest broadband provider) was \$76.45 for an ‘average’ 256 kbps plan during the period of the survey.

services in broadband blackspot areas (where currently there are no terrestrial services), where the level of demand is deemed to not be sufficient to support commercial provision of broadband services (based on a particular broadband technology).

For broadband providers, the level of demand in an area is a critical determinant for a provider's business case to invest in new broadband infrastructure or enhance existing infrastructure. The level of demand will determine the potential profitability of any new investment in broadband infrastructure.

3 Testing for unit roots and cointegration

When using decision variables in forecasting, it is important to know if the variables have a real rather than an incidental relationship to the dependant variable. One way to do this is through the econometric technique of cointegration and testing for the long term relationship of the data. This involves testing the time series for stationarity in broadband and the independent variable (price) data using the augmented Dickey-Fuller test and then testing for long run relationships or cointegration test between these variables using the test developed by Engle and Granger (Engle and Granger 1987).

The Augmented Dickey-Fuller test indicated that at the 5 per cent level of significance the household take-up and household price (both in log form) time series were both I(1). This means that both data series are non-stationary which is not surprising for broadband take-up considering the shape of the take-up curve shown in figure 1. To determine any long run relationship, the two variables were tested to see if they were cointegrated (based on the Engle-Granger cointegration test). The null hypothesis could not be rejected at the 5 per cent asymptotic level of significance, which suggests there is no long-run relationship between household broadband adoption and household price.

For small business take-up and small business price, the Augmented Dickey-Fuller test indicated that series was also integrated of order 1 at the 5 per cent level of significance. Based on the Engle-Granger test of Cointegration, the null hypothesis could not be rejected at the 5 per cent asymptotic level of significance, suggesting that both series do not have a long run relationship.⁴

As stated earlier, there are many factors that influence the adoption of broadband technology with price being the most obvious. The impact of the price change in broadband from February 2004 has limited the observations needed to determine a long-run relationship. There are simply not enough data points or variation in the data points to effectively utilise the cointegration asymptotic critical values. In addition, the price of most broadband services in Australia prior to the price change were set by Telstra, which did not change its prices or the prices it changed at the wholesale level to any great extent.⁵

⁴ Asymptotic properties of the Engle-Granger cointegration test are based on a large sample of data. The data available was not sufficient to accurately reflect the asymptotic critical values of the test.

⁵ These was based on price data collected on a quarterly basis form varies ISP websites.

However, the Chow test demonstrates that price changes did have an effect in the adoption of broadband in Australia as it indicated a structural change in the data at that point in time. In any event, the best model for the purposes of demand forecasting is the model with the lowest out-of-sample forecast error.

4 Augmented Bass Model techniques⁶

4.1 Diffusion modelling

Because technology innovation tends to follow a non-linear S shaped or sigmoid adoption pattern reaching a particular saturation level for a particular population, there has been a general trend to use various forms of diffusion modelling to accurately forecast the likely adoption of an innovation.

There are many decision variables that affect the shape of the diffusion curve for adoption. One of the most important decision variables is expected to be price of the innovation. In the product cycle that best demonstrates this process, when a technology innovation is first introduced to the market, the cost of the technology is high. Over time as the product matures and peoples preferences change and the cost of production falls with scale economies, the cost of the technology innovation falls, changing the demand profile of the innovation to one of increasing adoption.

The interactions of decision variables influence the trajectory of diffusion through a change in the demand profile of the innovation. Shocks in these variables may affect the trajectory of the innovation in the future. When modelling these effects, other considerations should be considered. These include:

- Models must be non-linear to take into account the process of innovator and imitator take-up of the innovation;
- The long term forecast must reach an asymptote for the particular population; and
- The ability to test the effects or shocks in decision variables on the adoption of an innovation.

Meade and Islam (1995) had undertaken an empirical comparison of various forecasting and diffusion models. Of the 14 different models identified, none include a decision variable in the model equation, failing the third key condition for technology modelling, the ability to model future shocks in decision variables. Thus, the data generating process of the models presented in their study was dependant on historic data for the technology. However, the historic data for the adoption of the technology has an underlying relationship with a variety of independent variables that influence the adoption of the technology at each point in time.

If these variables change in any point in time and they have a significant effect on the adoption of the technology, then these variables may change the diffusion trajectory of adoption of the technology at that point in time. There has been little public research done on demand modelling for broadband in an Australian context (most work has been done by private consultants). One model that was specifically

⁶ This section is based on Fainstein (2005) in describing the development of the ABM.

developed to forecast the growth of broadband in Australia and can be applied to other technologies is the Augmented Bass Model (ABM) (Fainstein 2005).

The ABM is a diffusion model that permits the incorporation of decision variables which can be shocked to model a change in the trajectory of diffusion. Most diffusion models do not include decision variables so they are invariant to shocks in decision variables and so forecasts based on these models do not change except if they are re-estimated with new data. However, it is clear that changes in decision variables do influence the diffusion trajectory of a diffusion curve. A price shock, such as the fall in broadband subscription prices as illustrated in the previous section appears to have changed the trajectory take-up of broadband services in Australia after that period.

The ABM utilises the existing Bass model (Bass 1969) as its key component. The Bass model component of the ABM is a simple recursive model represented in equation 1. The model is made up of two elements, the first is an auto regressive component representing the previous periods' adoption of the innovation and the second is a growth component or the additional adoption of the innovation. Both components dependant on the parameter estimates of p, q and m, representing external factors influencing growth, internal factors influencing growth and the population potential.

$$N_t = \underbrace{N_{t-1}}_{Autoregressive} + \underbrace{p(m - N_{t-1}) + q \frac{N_{t-1}}{m} (m - N_{t-1})}_{Growth} \quad (1)$$

This model is of interest as the decision variables such as price, tastes and preferences and expectations are contained in the model parameter estimates from the historic data but are *unobservable*.

The Bass model was chosen to develop the ABM because the p and q parameters represented implicitly all the internal and external decision variables that determined the trajectory of diffusion, contained in the historic data. For example, the variable price is expected to influence the demand for an innovation, which will affect the diffusion trajectory of the innovation over time. However, this and other variables are implicitly contained in both the p and q parameters in the Bass model in some unknown ratio. The Bass model does not provide a way of separating out the effects of these variables from the estimated p and q parameters.

The Bass model is based on a number of underlying assumptions, two important ones are:

- m will be the total potential purchases of the product, where there are *no replacement sales*; and
- the likelihood that the innovation will be purchased by both an innovator and an imitator is represented by the parameter estimates of p and q respectively.

Note that the term $(m - N_{t-1})$ in equation 1 represents the proportion of the population whose demand for the innovation has not yet been satisfied.

The non-linear estimation of the Bass model for deriving the parameter estimates of p and q is represented in equation 2. The optimal choice of p and q are based on minimising the quadratic loss function between the actual and the estimated

cumulative change for the innovation represented by N_t (equation 3), subject to the diffusion constraints of the Bass model.

$$\hat{N}_t = \frac{m(1 - e^{-(p+q)t})}{1 + \frac{q}{p}e^{-(p+q)t}} \quad (2)$$

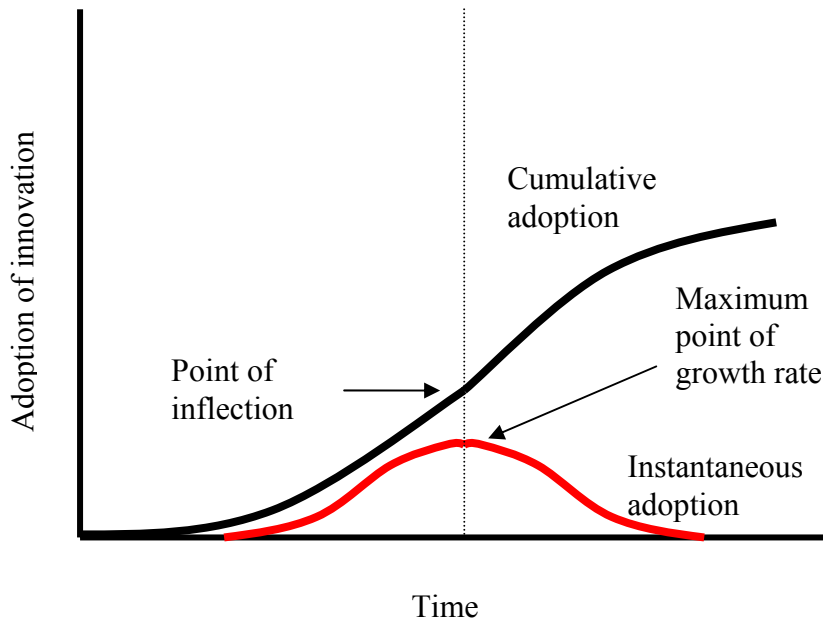
$$\text{Minimise } \sum_{t=1}^n (N_t - \hat{N}_t)^2 \quad (3)$$

Subject to the constraints: $0 < p, q < 1$

The estimates for the parameters in the model are totally dependent on the historic adoption data for the innovation. Forecasting future adoption of the innovation using the Bass parameter estimates must be based on *ceteris paribus* assumptions of “no change”, where the factors that determine p and q estimated from historic data are assumed to remain the same over the forecast period.

Figure 2 is a representation of a typical Bass diffusion pattern for an innovation following a typical S-shaped curve (the cumulative adoption curve).⁷ Adoption in the initial period is slow, however over time adoption of the innovation continues to increase at an increasing rate until it reaches the point of inflection. After the point of inflection is reached, adoption increases at a decreasing rate, until a saturation point is reached at an asymptote of the potential population.

FIGURE 2: ADOPTION OF AN INNOVATION (SYMMETRIC ADOPTION)



⁷ There is no reason to believe that either curve will be symmetric for an innovation, unlike a LOGIT curve formulation which is symmetric.

The instantaneous adoption (or growth curve) is the change in adoption in each period. The shape of the curve is concave, with the number of adoptors increasing until reaching the interior maximum point, after which, the rate of growth decreases. At any particular point in time, the maximum point of the instantaneous adoption curve is also the point of inflection of the cumulative adoption curve.

The Bass model tends to generate a pro-innovation bias (it is a non-decreasing function). The reason for this is that the forecast values generated by the Bass model are based on the conditions existing in the historic data that was used to estimate the p and q parameters. This data shows adoption of an innovation in the initial period. As there are no decision variables to change the trajectory of diffusion, the model generates a pro-innovation bias for adoption over a forecast period, regardless of what happens in the future.

A case in point where the Bass diffusion model is likely to be unsatisfactory is with a future shock to decision variables, such as price contained in the estimated Bass p and q parameters. If for example we assumed that the price for a particular technology fell from \$100 to \$1 in one year's time, as an *a priori* expectation (the law of demand and supply), the trajectory of adoption of the technology will increase dramatically when the saturation take-up point of the innovation is reached very quickly (assuming no supply constraints and the technology is not matured). Conversely, if the price of an innovation increased from \$100 to \$10,000 in one year's time, there would be an *a priori* expectation that there would be an almost total discontinuance of the innovation.

As the Bass model forecast is based on parameter estimates of p and q from historic data, any change in the future variables that influenced the estimation of the p and q parameters would be expected to lead to a change in the diffusion trajectory of the innovation (from higher demand due to a lower price). Since the Bass model includes only unobservable decision variables (in the p and q parameters) and there is no way to separate the individual influence on the p and q parameters, the Bass model as identified in equation 1 can not reflect the expected change in the diffusion trajectory of the innovation due to changes in factors such as price.⁸

The problem faced with forecasting diffusion of technology is the difficulty in identifying the wide variety of candidate decision variables that influences the take-up of the technology, which is why the Bass model is useful as it does not have any decision variables.

4.2 Description of the ABM

How can the problem of the Bass model discussed in the previous section be overcome when there are no decision variables in the model? One solution is to produce a combined forecast model which includes the trajectory of the Bass "no change" model with one that incorporated decision variables that influence the level shift of the diffusion trajectory.

⁸ Mahajan et. al. (1990) identifies a number of rigid assumptions that underpin the Bass model. These assumptions will impact on the forecasting accuracy for the adoption of an innovation over time.

The ABM is a combination of the Bass model and the difference between the actual and Bass model first difference and a non-linear model estimating the actual and Bass model first difference, which includes decision variables. The formulation of this model results in all the variables that affect the diffusion rate (that are available) from the historic data being augmented with the effects of changes in decision variables. The non-linear generalised Cobb-Douglas function component was designed to include decision variables, whose influence could be “stripped” out of the Bass parameter estimates.

Consider the Bass model in equation 1. The driving force of the change is not the whole equation, but only part of it. If we rearrange equation 1 to look at the instantaneous change between periods, the result is represented in equation 4, where the difference between the previous period adoption and the current period adoption is equal to the growth rate of the Bass model.⁹

$$(N_t - N_{t-1}) = p(m_t - N_{t-1}) + q \frac{N_{t-1}}{m_t} (m_t - N_{t-1}) \quad (4)$$

For Broadband, m_t is the potential market of premises with access to computers in period t , N_t is the number of premises who have connected to or adopted broadband in period t . The ‘no change’ Bass model difference component $N_t - N_{t-1}$ in equation 4 is incorporated (as a lag) into a generalised type Cobb-Douglas function as the principal decision variable to be estimated for the growth function and a decision variable for price. This function is represented by equation 5.

$$N_t = N_{t-1} + \left[A (N_t - N_{t-1})_{t-1}^{\alpha_1} \bullet Price_t^{\alpha_2} \right] + u_t \quad (5)$$

The lagged difference component (detrended data) represents all the factors (which have not been individually defined) that influence the growth of broadband subscribers, apart from price. The estimated value and significance of α_1 for the lagged difference term is expected to decline as additional decision variables are added to equation 5.¹⁰

In comparing equation 1 and equation 5 both have a lagged dependant variable and a growth component. If we apply the same transformation to the generalised type Cobb-Douglas function as equation 5, we get equation 6, which is the instantaneous difference between the current and past period’s adoption of the innovation and the growth function which is equal to the generalised type Cobb-Douglas (the broadband data is detrended).

⁹ In the ABM, the innovation population limit parameter m is no longer fixed but changes over time to account for things like population growth or in the case of broadband demand the level of the population (business and household) with computer.

¹⁰ The model can be used to test the impact and significance of other decision variables in addition to price such as advertising expenditure (ADD) and download volumes (DOWN) as a proxy for peoples’ desire to access a faster internet service. Including these decision variables in an ABM framework is represented by the example equation below.

$$N_t = N_{t-1} + \left[A (N_t - N_{t-1})_{t-1}^{\alpha_1} \bullet Price_t^{\alpha_2} \bullet ADD_{t-1}^{\alpha_3} \bullet DOWN_{t-1}^{\alpha_4} \right] + u_t$$

The limitation of testing decision variables in this modelling framework is data consistency and availability.

$$(N_t - N_{t-1}) = \left[A(N_t - N_{t-1})_{t-1}^{\alpha_1} \text{Price}_t^{\alpha_2} \right] + u_t \quad (6)$$

Equation 4 and equation 6 represents a re-arrangement of equations 1 and 5 respectively, so as to obtain the growth component on the right hand side. As a result, the growth components in either case are the same as the Bass first difference components for each model ($N_t - N_{t-1}$). By definition, the right hand component of equation 6 must be equal to the right hand component of equation 4.

In equation 6, the growth in broadband adoption is based on the ‘market price’ of broadband and the lag in the difference of broadband adoption. Equation 6 states that the growth in broadband adoption is equal to the generalised type Cobb-Douglas model based on the lagged difference in adoption and a price component with estimates for the α_1 and α_2 parameters (which are also the elasticities parameters).

In the general case the estimation of the elasticity parameters determine the significance of the decision variables. If the elasticity parameters are insignificant, any change in the decision variable will not significantly change the trajectory of the diffusion for the innovation (estimates are close to zero). It is expected that as additional variables are added to the ABM, the value and significance of the lagged difference component of the model is expected to decrease.

Rearranging equation 6 gives equation 7.

$$\Psi_t = 0 + u_t = \left[A(N_t - N_{t-1})_{t-1}^{\alpha_1} \text{Price}_t^{\alpha_2} \right] + u_t - (N_t - N_{t-1}) \quad (7)$$

Equation 7 is defined by the value Ψ_t (Psi), which states that if there is no change in historic prices over the forecast period, then the growth trajectory of broadband adoption in the generalised type Cobb-Douglas model would equal the first difference in broadband adoption of the Bass model (and as such equal to the growth component of the Bass model) and an error term over the forecast period. This is shown in equation 8, which represents the equality of the Bass and the generalised non-linear model.

$$\begin{aligned} \left[A(N_t - N_{t-1})_{t-1}^{\alpha_1} \text{Price}_t^{\alpha_2} \right] + u_t &= (N_t - N_{t-1}) \\ &= p(m - N_{t-1}) + q \frac{N_{t-1}}{m} (m - N_{t-1}) \end{aligned} \quad (8)$$

The Bass model estimates the growth of innovation adoption using historic data. The generalised type Cobb-Douglas model estimates the growth component of the Bass model based on the lag of the Bass model difference in adoption of the innovation and other decision variables. The ABM takes advantage of the auto-regressive and growth components of the Bass and generalised type Cobb-Douglas model and combines them through the first difference as equation 8 illustrates.

The impact of prices (and all the other variables) is already incorporated in the estimated parameters p and q in the Bass model. The ABM simply seeks to *extract or strip out* the influence of these decision variables and quantify them through the

generalised type Cobb-Douglas component of the model. The parameter estimates for price (if significant) will result in a change in the growth trajectory of the ‘no change’ Bass model for broadband demand given by the value Ψ_t .¹¹

Because of the auto regressive nature of the Bass and the derived ABM, no additional data is required. In many cases, there is a general paucity of variables expected to affect the diffusion of a technology or if variables are found, there may be insufficient observations to estimate any meaningful relationships. The ABM process avoids the need to utilise variables for forecasting, except variables that the user wishes to test for significant effects. The ABM may not be useful for models which are stationary or have a long-run trend, as the Bass model is non-linear and designed to reach an asymptote, so its primary use is for adoption forecasting.

5 Statistical accuracy of the ABM model compared with other models

The ABMs usefulness in making investment decisions in the development and marketing of new technologies where innovation adoption is a critical element must be based on the accuracy of the forecasting model. The first use of the ABM was to predict the adoption of broadband in Australia using Australian Competition and Consumer Commission (ACCC) data (Fainstein 2005).¹²

The models purpose was to determine the likely trajectory of the diffusion of broadband in Australia as accurately as possible, given broadband price changes. This was used to develop demand forecasting for the government to provide various forecasting scenarios to the Metro Broadband Connect and Broadband Connect programs.

In comparing likely model choice, the criteria used for model selection is that the lowest root mean squared error (RMSE) of the in-sample parameter estimates and out-of-sample forecast error must be less than 5 per cent. A RMSE of less than 5 per cent is acceptable for a 4 period ahead forecast, but the preference is for choosing the set of forecasting models with the lowest RMSE. The choice of a static forecast model means that the error is likely to be larger than in a recursive, dynamic forecast model.

Table 1 illustrates the different ABM model estimates over time and the forecast results as data became available. Table 2 identifies the statistical accuracy of these ABM models based on the RMSE. The accuracy range for the models (with and without forecast values) over the whole period is a RMSE of less than 3 per cent for the in-sample data and less than 4 per cent for the out-of-sample data.¹³

¹¹ If price is significant and the estimated coefficient is negative (normal good/service), then a fall in the price means that the value for $\psi > 0$

¹² The ACCC broadband adoption data is based on a survey of the 8-10 largest ISPs. The survey by its nature underestimates the actual number of broadband subscribers. However, the ACCC data will be used as a benchmark for comparison of the statistical accuracy of the modelling. The data is subject to historical and periodic revision.

¹³ Shaded cells in tables 2 to 9 represent the out-of-sample forecast accuracy of the model. This is the forecast error expected for subsequent forecasts.

**TABLE 1: ABM ESTAIMATES AND FORECASTS TO MARCH QUARTER 2006
(IN THOUSANDS OF SUBSCRIBERS)**

Quarter	ABM March 2005	ABM June 2005	ABM September 2005	ABM December 2005	ABM March 2006	ACCC Broadband Data ¹⁴
Sep-99	15.9	16.2	16.2	16.2	16.2	46.2
Dec-99	22.3	22.7	22.8	22.8	22.8	51.2
Mar-00	30.1	33.2	33.3	33.3	33.3	56.8
Jun-00	42.1	41.5	41.7	41.7	41.7	63.0
Sep-00	50.9	50.9	51.2	51.3	51.3	73.9
Dec-00	65.6	66.7	67.2	67.4	67.4	87.9
Mar-01	82.2	80.6	81.4	81.6	81.6	105.2
Jun-01	105.7	104.1	105.3	105.6	105.6	122.8
Sep-01	133.4	135.4	137.1	137.5	137.5	138.5
Dec-01	153.6	153.4	155.8	156.5	156.5	165.5
Mar-02	200.2	199.7	203.1	203.9	203.9	199.7
Jun-02	244.6	263.0	267.8	269.0	269.0	258.1
Sep-02	323.6	293.1	299.5	301.1	301.1	312.2
Dec-02	388.9	389.5	397.9	400.1	400.1	363.5
Mar-03	466.4	478.0	489.0	491.8	491.8	423.6
Jun-03	529.4	532.8	547.0	550.6	550.6	516.8
Sep-03	667.5	689.6	707.6	712.3	712.3	610.8
Dec-03	800.9	840.7	863.4	869.2	869.2	698.7
Mar-04	915.7	943.4	971.6	978.8	978.8	829.3
Jun-04	1049.4	1116.2	1150.6	1159.4	1159.4	1047.8
Sep-04	1279.1	1339.4	1381.0	1391.6	1391.6	1310.3
Dec-04	1530.2	1591.9	1641.4	1653.9	1653.9	1548.3
Mar-05	1698.9	1781.3	1839.3	1853.9	1853.9	1839.7
Jun-05	2125.3	2184.9	2109.8	2126.8	2126.8	2183.1
Sep-05	2395.4	2634.4	2455.1	2354.4	2354.4	2593.6
Dec-05	2663.3	2868.6	2943.4	2783.0	2951.3	2785.0
Mar-06	2942.8	3115.8	3197.8	3015.2	3107.4	3161.6

Source: ACCC 2006 and internal estimates.

Note: Bold values are forecast values.

TABLE 2: RMSE OF THE ABM ESTIMATES AND FORECAST

	ABM Mar 2005	ABM Jun 2005	ABM Sept 2005	ABM Dec 2005	ABM Mar 2006
RMSE Sept 1999 to Mar 2006	2.40%	1.61%	2.30%	2.62%	2.69%
RMSE Mar 2002 to Mar 2006	3.07%	2.02%	2.94%	3.37%	3.45%
RMSE Mar 2003 to Mar 2006	3.51%	2.26%	3.33%	3.82%	3.92%
RMSE Mar 2004 to Mar 2006	3.98%	1.64%	3.07%	3.75%	3.90%
RMSE June 2005 to Mar 2006	5.13%	1.64%	3.57%	4.52%	4.77%

¹⁴ This is the quarterly data published by the ACCC. It does not include corrections to historic data which the ACCC undertakes periodically.

Most of the errors in the differently timed ABM models are less than 3 per cent, suggesting the ABM is a very accurate representation of broadband adoption data. The ABM includes *weighted average price*¹⁵ data in the augmentation component. In the case of broadband in Australia, the only significant price change in published broadband plans was in February 2004, where there was a significant reduction in the price of broadband services across the three principal ADSL plans and cable.

The effect of price on the ABM estimates and forecasts is made clear in table 3. As indicated earlier, the price of broadband in Australia as provided by Telstra did not change to any great extent prior to February 2004. The ABM was run for the March, June, September and December quarters of 2004, with the result for price showed that the March quarter 2004 began having a significant effect on the adoption of broadband in Australia in the June and subsequent quarters of 2004.

TABLE 3: SIGNIFICANCE LEVEL OF THE PRICE COEFFICIENT IN THE ABM

Significance level	Household		Small Business	
	5%	10%	5%	10%
Mar-04	No	No	No	No
Jun-04	No	Yes	No	No
Sept-04	Yes	Yes	No	No
Dec-04	Yes	Yes	No	No
Mar-05	Yes	Yes	No	No
Jun-05	Yes	Yes	No	No
Sept-05	Yes	Yes	No	No
Dec-05	Yes	Yes	No	No
Mar-06	Yes	Yes	No	No

However, price did not have any significant effect on small business adoption. It is expected that other factors apart from price are driving the adoption of broadband in this market.¹⁶

Clearly, the ABM is accurate in predicting short term changes in broadband adoption, but how accurate would a number of other models be using the same ACCC data? There are many econometric and non-econometric models that can be used as a comparison to the ABM, however this paper permits only a limited number of models to be considered. A wide range of different forecasting models used in business and government have been chosen, although this selection is far from exhaustive. These models fit into two broad categories, models *with* decision variables and models *without* decision variables.

¹⁵ This is a calculation based on the relative adoption of various ADSL and cable plans and the price prevailing in that period of time. Telstra plan distribution data was used as a proxy for the national distribution to derive a price series for broadband in Australia.

¹⁶ For small business, the utility of internet access and email communication outweighs the monthly maintenance cost of the technology. In addition, the cost of broadband to a business would be tax deductible. A priori, this suggests that the price decision variable would not be significant, but other variables related to utility of the service would be.

Models with decision variables:

- Linear model
- Autoregressive distributed lag model

Models without decision variables

- Bass model
- Simple logistic model
- Gomperts model
- Holts exponential smoothing

Models without decision variables depend on the historic variability of the data to determine their future trajectory. Because of the non-linear nature of technology diffusion, it is expected that the linear models would be the most inferior in terms of a higher forecast errors as they do not have a point of inflection (a turning point), which is expected when forecasting technology diffusion such as broadband. The forecasting superiority expected from the ABM over other models is because future shocks can be modelled in the augmentation from the steady state component - the Bass model.

Broadband adoption data that was available for the ABM will be used to estimate the alternative forecasting models. This data includes ACCC broadband take-up data broken down into household and small business. In addition there is population data for these two sectors¹⁷. Because of the different dynamics of the household and business sector, the model estimates and forecasts presented below will be based on a combined forecast for these two sectors (in addition to the medium business, large business and government adoption of broadband). Where the price variable was insignificant, as in the case of the ABM sub-forecast for the small business sector, is equivalent to the 'no change' Bass model or there will not be an estimated coefficient in other models with this decision variable.¹⁸

To test the accuracy of the various models, a one year forecast will be made by all models and tested. Historic broadband adoption data for model estimation is from September 1999 to March 2005, which will allow for a testing of the models 'goodness to fit' of the data and for determining the models forecast accuracy.¹⁹ The forecast for each model will be based on a *static forecast*²⁰, four periods (one year) ahead from June 2005 to March 2006, with statistical accuracy based on actual ACCC broadband adoption data over that period.

All forecasts are based on the sum of the individual forecasts of household take-up, small business take-up and adding medium business, large business and government

¹⁷ Business population data is based on those with computers. Household populations are also defined by the proportion with computers. Growth rates for these variables are based on ABS long-term growth assumptions.

¹⁸ The ABM modelling looks only at the adoption of broadband by small business defined as non-employing, those employing 1-4 and 5-19 employees. It is assumed that virtually all business employing 20 or more employees have a broadband connection.

¹⁹ It is assumed that medium and large business and government exhibit 100% take-up of broadband. For modelling purposes, these populations are added to the forecast in each period in each model.

²⁰ Unlike a dynamic forecast, the models are not updated after each forecast period.

take-up which are assumed to be 100 per cent broadband enabled over the forecast period.²¹

5.1 Linear model (log transformed)

For the linear model of households and small business take-up, four different types of models are to be considered.

- Trend based estimation;
- Price estimation;
- Household population estimation; and
- Trend, price and household population.

This set of models is based on a double log transformation of the linear function to reduce the effects of outlier observations. Only significant parameters are reported and used in forecasts. Individually, all the variables are significant, however for the joint models (ie those with a price variable), price was insignificant. The models are estimated using ordinary least squares (OLS).

TABLE 4: RMSE OF VARIOUS LOG-LINEAR ESTIMATES AND FORECASTS

Sum of two separate forecasts for households and small business	Log-linear with time trend	Log-linear with price	Log-linear with population	Log-linear with trend, price and population
				RMSE by percentage
RMSE Sept 1999 to Mar 2006	13.71%	24.63%	15.74%	2.46%
RMSE Mar 2002 to Mar 2006	17.81%	31.90%	20.39%	3.19%
RMSE Mar 2003 to Mar 2006	20.56%	36.80%	23.49%	3.65%
RMSE Mar 2004 to Mar 2006	25.18%	44.78%	28.51%	4.40%
RMSE June 2005 to Mar 2006	35.52%	57.55%	33.10%	6.11%

Of the models used, the best model is the log-linear with trend, price and population. For the whole period (historic data and forecast) the RMSE value is 2.46 per cent. Some of the effects of the price change is reflected in the estimate. Price was not significant in any of the household models, but was significant in the business models.

Although the linear model has produced a good forecast in terms of a low error rate, it has an inherited flaw in modelling diffusion. It has a linear trend which does not reach an asymptote, something that is expected with technology diffusion. This means that its longer term forecast will become increasingly inaccurate over time as it will not reach a population asymptote, that is final penetration value. This is especially true if the adoption data which was used in the estimation has not reached the diffusion turning point (inflection point), where the growth rate for the series is expected to

²¹ Based on the 2006 Sensis survey (Sensis 2006), 92 per cent of medium businesses (20+ employees) have access to broadband (Sensis 2006). Because medium and large business represents such a small proportion of users, it is assumed in the modelling that there is 100% adoption of broadband in these two business sectors. This is reasonable as the same survey indicates that over 99 per cent of small businesses have internet access, which suggests that full broadband adoption by these business is inevitable based on the benefits that the survey indicated broadband brought to these business users.

decrease at an increasing rate. The out-of-sample forecast error is high for all the models in this class of forecast model.

5.2 Bass model

The Bass model represents the ‘no change’ component of the ABM, which is represented by equation 1. The Bass model maps the trajectory of broadband adoption based on historic data. As a result, this model does not provide any ability to model shocks in decision variables in the future, as the model contains no decision variables.

The Bass model sample estimation is expected to show a good fit, but the lack of decision variables means that the forecast accuracy of this model is expected to be inferior to the ABM model. Table 5 represents the forecast accuracy of the Bass model. Although the overall model accuracy is good at 3.6 per cent RMSE, for the out-of sample forecast period, the error is high at 8.74 per over the four period forecast. This model would not be useful for medium or long term forecasting of broadband adoption, especially when there are changes to decision variables over that period. The out-of-sample forecast error is high which can be explained by the small number of observations since the change in decision variables, such as the price fall in broadband plans in February 2004.

TABLE 5: RMSE OF THE BASS MODEL ESTIMATES AND FORECAST

	RMSE by percentage
RMSE Sept 1999 to Mar 2006	3.63%
RMSE Mar 2002 to Mar 2006	4.53%
RMSE Mar 2003 to Mar 2006	5.18%
RMSE Mar 2004 to Mar 2006	6.12%
RMSE June 2005 to Mar 2006	8.74%

5.3 Autoregressive distributed lag model

In this model, the weighted average price of broadband and a number of lagged dependant variables were incorporated in the model. Only those variables that were statistically significant at the 5 per cent level were included in the forecast for each autoregressive model. The forecast is made up of a composite result of a combined household and small business forecast.

The model estimation was based on a top down approach where significant variables were removed from the equation until no more insignificant variables remained. The variables that were available were price, household and small business populations *with* computers, all log transformed.

The estimated household model is represented by equation 9, where household broadband take-up is a function of a one period lag of take-up and an autoregressive process of order 1 and 2. These were the only variables that were significant in the estimated model. The measure of ‘goodness to fit’ (R-squared) was 0.999, suggesting these three variables contributed to most of the variation in the data. The estimated coefficient for the lagged dependant variable was 1.017 and was significant. As expected with a lagged dependant variable, there was no evidence of autocorrelation.

$$\begin{aligned} \ln X_t &= \beta_1 \ln X_{t-1} + \beta_2 AR(1) + \beta_3 AR(2) + \varepsilon_t \\ AR(1) &= \rho \varepsilon_{t-1} + u_t \\ AR(2) &= \rho \varepsilon_{t-2} + u_t \end{aligned} \tag{9}$$

The model estimation for the small business sector is represented by equation 10, where only the significant variables were modelled. Broadband take-up lagged two periods, the price lagged two periods, the population lagged one period and an autoregressive term of order 2 were the significant variables in this business model, which resulted in an R-squared of 0.996. The estimated coefficient for the twice lagged dependant variable was 1.66 and was significant. There was no evidence of autocorrelation.

$$\begin{aligned} \ln X_t &= \beta_0 + \beta_1 \ln X_{t-2} + \beta_2 \ln Price_{t-2} + \beta_3 \ln Pop_{t-1} + \beta_4 AR(2) + \varepsilon_t \\ AR(2) &= \rho \varepsilon_{t-2} + u_t \end{aligned} \tag{10}$$

The autoregressive model is useful in identifying the dynamics of broadband adoption. The autoregressive model provided very good forecast accuracy of the in-sample estimate, but more importantly, the forecast error of 5.47 per cent in the out-of-sample forecast indicates that this is a good forecasting model.

TABLE 6: RMSE AUTOREGRESSIVE MODEL ESTIMATES AND FORECAST

	RMSE by percentage
RMSE Sept 1999 to Mar 2006	2.37%
RMSE Mar 2002 to Mar 2006	2.76%
RMSE Mar 2003 to Mar 2006	3.15%
RMSE Mar 2004 to Mar 2006	3.78%
RMSE June 2005 to Mar 2006	5.48%

5.4 Simple logistic model

The simple logistic model is a sigmoid type model reaching an asymptotic in some future period. The model used in this paper is represented by equation 11:

$$X_t = \frac{a}{1 + ce^{(-bt)}} \tag{11}$$

The model was transformed into a linear function for estimation of the parameters c and b. The non-linear parameterisation of the simple logistic model is expected to fit Australian broadband take-up well. This is demonstrated by the low RMSE values from the estimated model in table 7. However, because there are no decision variables in the model, this model, like as with the Bass model can not accurately predict the effects of future shocks in adoption of broadband. Past shocks would take time to affect the adoption data and predict a new trajectory. There were insufficient observations in the sample to significantly change the trajectory of the diffusion.

The in-sample forecast estimate was very good with an in-sample estimation error over the whole period of 1.63 per cent, almost identical to the error result of the

ABM. The out-of-sample forecast error was also low at 2.63 per cent indicating a good forecasting model for future broadband adoption.

TABLE 7: RMSE OF THE SIMPLE LOGISTIC MODEL ESTIMATES AND FORECAST

	RMSE by percentage
RMSE Sept 1999 to Mar 2006	1.63%
RMSE Mar 2002 to Mar 2006	1.94%
RMSE Mar 2003 to Mar 2006	2.11%
RMSE Mar 2004 to Mar 2006	2.44%
RMSE June 2005 to Mar 2006	2.63%

5.5 Gompertz model

The Gompertz curve is represented by equation 12 below.

$$X_t = a * \exp(-1 * \exp(-bt)) + \varepsilon_t \quad (12)$$

The Gompertz curve is a non-linear function based on the population asymptote and a time trend. As with the simple logistic and Bass models, this model is expected to fit the in-sample data well as illustrated in table 8. However, as with the simple logistic and Bass models, this model can not forecast the effects of shocks based on these two parameter estimates. The Gompertz model is similar to the logistic model, but the forecast performance of the Gompertz was relatively poor by comparison especially for the out-of-sample forecast, with an RMSE of 11.18 per cent.

TABLE 8: RMSE OF THE GOMPERTZ MODEL ESTIMATES AND FORECAST

	RMSE by percentage
RMSE Sept 1999 to Mar 2006	4.77%
RMSE Mar 2002 to Mar 2006	5.78%
RMSE Mar 2003 to Mar 2006	6.42%
RMSE Mar 2004 to Mar 2006	7.66%
RMSE June 2005 to Mar 2006	11.18%

5.6 Holt's exponential smoothing²²

Only a small number of smoothing forecasting models can be used for predicting broadband adoption. Moving average or exponential smoothing can not be used as these two models do not incorporate a deterministic trend, and are used for stationary data (see section 3) which is not characteristic of broadband adoption data. Holt's exponential smoothing model is one model which can be used where the data exhibits a deterministic trend and a stochastic component. This level and trend component of the model is represented by equations 13 and 14.

$$F_{t+1} = \alpha X_t + (1 - \alpha)(F_t + T_t) \quad (13)$$

$$T_{t+1} = \beta(F_{t+1} - F_t) + (1 - \beta)T_t \quad (14)$$

²² Based on Wilson and Keating (1994)

F is the fitted value of the dependant variable X (broadband) and T is the trend in the dependant variable X. So the forecast fitted value of broadband adoption is based on a linear combination of the actual past value of broadband adoption and the sum of the fitted value and the trend component of broadband adoption in the previous period. The forecast of the trend is based on a linear combination of the current and forecast fitted value of broadband adoption and the trend in the current period.

Holt's forecast value for period t+m is represented by equation 15, which is the sum of equation 13 and 14, where the forecast trend component is multiplied by the length of the forecast period.

$$H_{t+m} = F_{t+1} + mT_{t+1} \tag{15}$$

The estimation of Holt's model for the in-sample case was good, as shown in table 9, however the forecast accuracy for a four step ahead forecast of this model was poor, with an error of 10.02 per cent. This is not surprising as the broadband data exhibits a non-linear trajectory which can not be very accurately estimated using a linear model such as this one.

TABLE 9: RMSE OF HOLT'S EXPONENTIAL SMOOTHING MODEL ESTIMATES AND FORECAST

	RMSE by percentage
RMSE Sept 1999 to Mar 2006	4.39%
RMSE Mar 2002 to Mar 2006	5.50%
RMSE Mar 2003 to Mar 2006	6.25%
RMSE Mar 2004 to Mar 2006	7.42%
RMSE Mar 2005 to Mar 2006	10.02%

6 Forecast accuracy comparisons

The purpose of this section is to identify the forecast accuracy of the ABM and to compare this to a number of other forecasting models used generally in business and government. In terms of overall 'goodness to fit', the ABM was superior to all the other models in the *in-sample* case. Almost all the model estimated exhibited a RMSE of less than 5 per cent which is shown in table 10. The difference in the best and worst case result in this table is when there are several permutations of the model in terms of variables used or the sample period chosen for parameter estimation.

TABLE 10: RMSE MODEL ESTIMATION FROM SEPT 1999 TO MARCH 2005 (IN-SAMPLE FORECAST)

	Best case	Worst case
ABM	1.61%	2.69%
Simple logistic	1.63%	
Auto regressive	2.37%	
Linear	2.46%	24.63%
Bass	3.63%	
Holts exponential smoothing	4.39%	
Gompertz	4.77%	

However, a better comparison of the forecasting ability is how accurately future adoption of broadband is predicted by these models, which is a comparison of the models *out-of-sample* RMSE. Table 11 represents this comparison of the forecast accuracy of the various models based on a static forecast. The ABM had the lowest RMSE of all the models predicting four periods ahead. It is interesting to note that of all the models in the out-of sample forecast, the ABM and the simple logistic models are the only models with a forecast RMSE of less than 5 per cent.

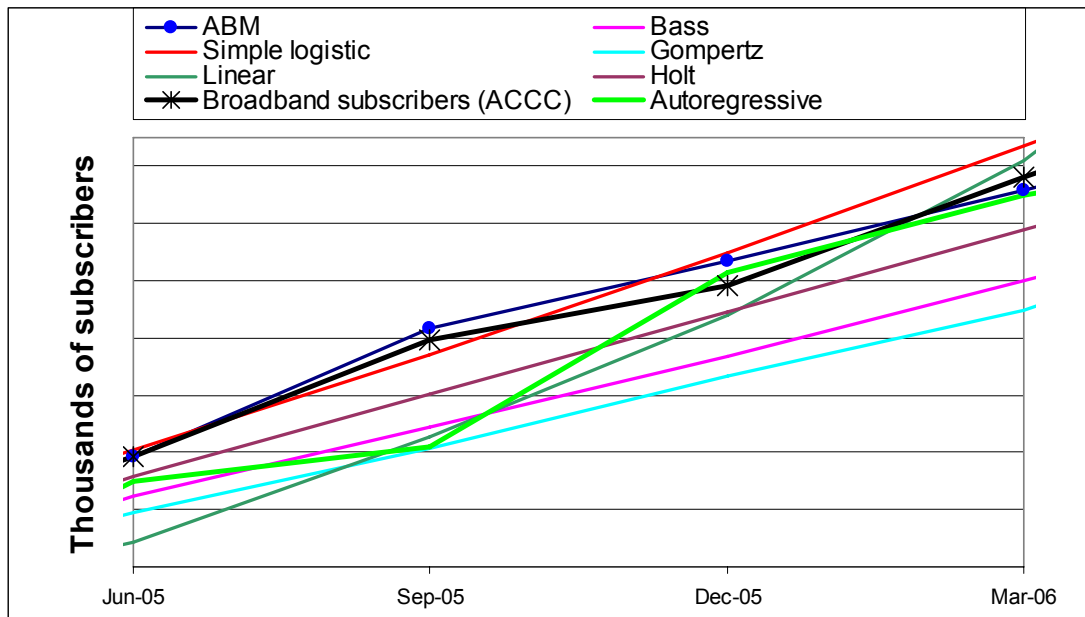
TABLE 11: MODEL FORECAST – RMSE FOUR PERIODS AHEAD FROM JUNE 2005 TO MARCH 2006 (OUT-OF-SAMPLE FORECAST)

	Best case	Worst case
ABM	1.64%	5.13%
Simple logistic	2.63%	
Auto regressive	5.48%	
Linear	6.11%	57.55%
Bass	8.74%	
Holts exponential smoothing	10.02%	
Gompertz	11.18%	

The main explanation for the superiority of the ABM over the next best model (simple logistic) is that the effects of lower prices felt in the last few periods of the sample are reflected in the ABM model estimate. This is not the case with either the Gompertz, simple logistic or Bass model, which contain no decision variables to account for the expected change in price over time (assuming price is significant). However, this can not account for the very small RMSE of the simple logistic model. From a Government policy perspective, the ABM also provides the ability to test policy responses on the adoption of broadband, such as those that may affect price

Because of the non-linear shape of the broadband diffusion curve, it is not surprising that the linear type models (linear, Holt and autoregressive) performed poorly in the forecast period (forecast RMSE greater than 5 per cent). This was expected as the diffusion trajectory of broadband has not reached an inflection point, making longer term forecasts using linear models unreliable. Graphically, forecasts are shown in figure 3.

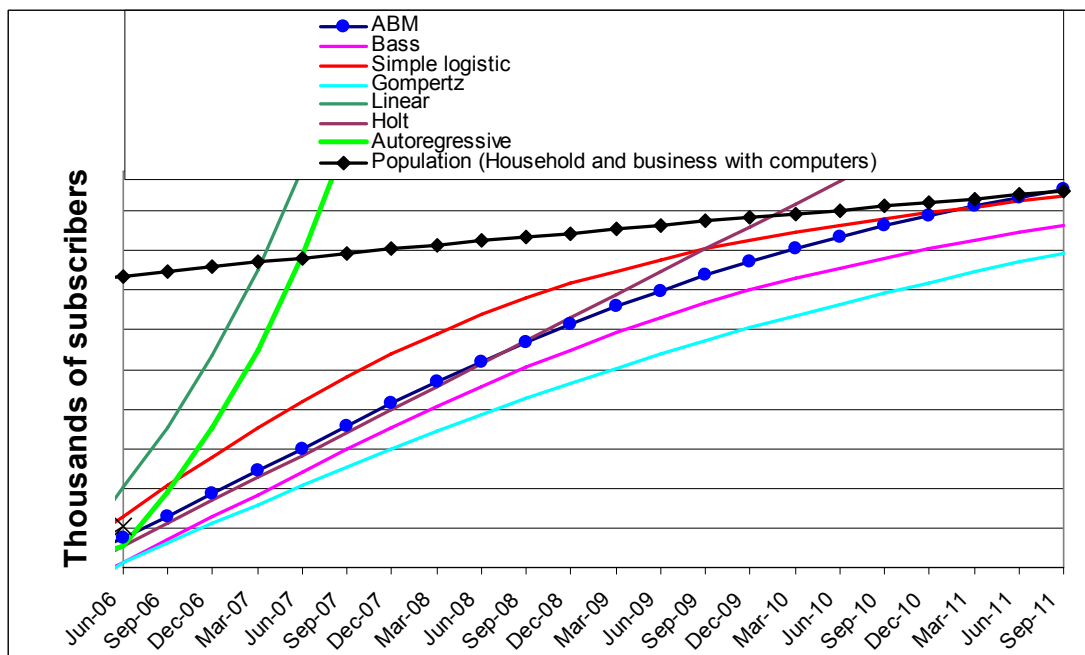
FIGURE 3: MODEL FORECAST COMPARISONS FROM JUNE 2005 TO MARCH 2006



7 ABM forecast for broadband demand in Australia (national demand and assumptions)

The main purpose of this paper is to identify which model, from a selection of common forecasting models and the ABM, would provide the best forecast for broadband adoption in Australia based on the lowest forecast accuracy from an out-of-sample comparison. Using the models presented in section 5, longer term forecasts can be estimated to September of 2011. These projections are presented in figure 4.

FIGURE 4: DYNAMIC MODEL FORECAST COMPARISON FROM JUNE 2006 TO SEPTEMBER 2011



Clearly, the linear, autoregressive and the Holt models greatly exceed the population level (that is the population *with* computers) which is generally regarded as the expected limitation of the adoption of broadband technology. This result is consistent with the poor forecasting errors shown in the out-of-sample period in table 11. The long term forecast presented in figure 4 illustrates that the ABM and the simple logistic model converges to the population limit in the longer term, which is expected as broadband is increasingly becoming an essential component of computer usage. Thus, in the longer term, the more likely forecast model for broadband adoption is the model that converges to the population level over the next 6 years.

The reason for the poor performance by the linear models is because the forecast estimates are based on a diffusion trajectory that has not reached its inflection point based on the historic data. The data for these estimates exhibits a function increasing at an increasing rate, and as linear functions don't have turning points, linear models can not adjust their trajectory for declining adoption when the diffusion of broadband reaches its saturation point.

The forecasts presented in this paper focus on the demand side of broadband adoption with the underlying assumption that there are no supply or coverage constraints.

8 Conclusion

Developing a model which provides the highest level of forecast accuracy for broadband demand is of critical importance for business investment and government policy making. This paper has provided a clear distinction between the linear and the non-linear trend models and their relative forecast accuracy.

Clearly those models which did not have turning points performed poorly compared to non-linear models because they did not have an inflection point. The non-linear models provided equally stark comparisons. Many of the non-linear models did not incorporate decision variables, making them poor forecasting models when shocks in the data, such as the price shock exhibited in early 2004 occur. Apart from the ABM and the simple logistic model, the out-of-sample four period forecast for all the models was poor.

What the ABM provides is the best of both worlds, a model that estimates the trajectory of the data based on a 'no change' assumption of historic data variation and an additional component that adjusts the trajectory for shocks. This combination is what has provided the superior forecast ability of the ABM from March 2005 data where the price decrease for ADSL and cable broadband access is yet to have an impact on the longer term trajectory of the data.

Acronyms

ABM	Augmented Bass Model
OECD	Organisation for Economic Co-operation and Development
DSL	Digital Subscriber Line
ADSL	Asymmetric Digital Subscriber Line
ACCC	Australian Competition and Consumer Commission
RMSE	Root Mean Squared Error

References

- Australian Competition and Consumer Commission (ACCC) (2006), "Snapshot of broadband deployment as at 31 March 2006", www.accc.gov.au, viewed on the 23 April 2006 – Various issues for historic data.
- Bass, F. M. (1969) "New Product Growth Model for Consumer Durables", *Management Science*, pp 215-227.
- Chow, G.C. (1967), "Technology change and the demand for computers", *American Economic Review*, Vol 57, pp1117-1130.
- Engle, R.F. and Granger, C.W.J. Granger (1987), "Coinetegration and error correction: representation, estimation and testing", *Econometrica* 55, p251-76.
- Fainstein, M. (2005), "Projecting technology diffusion: Broadband demand in Australia", paper presented at the Africa –Asia Australasia Regional Conference – ICT Networks –Building blocks for economic development, Perth.
- Mahajan, V., Muller, E. And Bass, F.M (1990), "New Product Diffusion Models in Marketing: A review and directions for research", *Journal of Marketing*, Vol. 54, pp 1-26.
- Mead, N. and Islam, T. (1995), "Forecasting the diffusion of innovations: implications for time-series extrapolation", *Principles of Forecasting*, pp577-595.
- OECD (2006), "Broadband Statistics 2005", http://www.oecd.org/document/16/0,2340,en_2649_34225_35526608_1_1_1_1,00.html#data2004, viewed on the 1 September 2006.
- Sensis (2006), "Sensis e-Business Report – The Online Experience of Small and Medium Enterprise", http://about.sensis.com.au/media/pdf/SBA-Archive/sba/tae/2006_eBusiness_Report.pdf, viewed on the 29 August 2006.
- Whirlpool (2004), "Australian Broadband survey 2003", www.whirlpool.net.au, viewed on the 16 June 2004.
- Whirlpool (2005), "Australian Broadband Survey 2004", www.whirlpool.net.au, viewed on the 20 June 2005.
- Whirlpool (2006), "Australian Broadband Survey 2005", www.whirlpool.net.au, viewed on the 28 June 2006.
- Wilson, J.H. and Keating, B. (1994), "Business Forecasting", Irwin Second edition.