BANK OF FINLAND DISCUSSION PAPERS

27 • 2004

Hanna Jyrkönen
Financial Markets Department

30.12.2004

Less cash on the counter – Forecasting Finnish payment preferences

Suomen Pankin keskustelualoitteita
Finlands Banks diskussionsunderlag

Suomen Pankki
Bank of Finland
P.O.Box 160
FIN-00101 HELSINKI
Finland
☎ + 358 10 8311

http://www.bof.fi

BANK OF FINLAND
DISCUSSION PAPERS

27 • 2004

Hanna Jyrkönen
Financial Markets Department
30.12.2004

Less cash on the counter – Forecasting Finnish payment preferences

The views expressed are those of the author and do not necessarily reflect the views of the Bank of Finland.

The author is grateful to Pekka Pere (University of Helsinki), Heikki Koskenkylä and Jarmo Pesola for their valuable comments.

Suomen Pankin keskustelualoitteita
Finlands Banks diskussionsunderlag

http://www.bof.fi

ISBN 952-462-178-9
ISSN 0785-3572
(print)

ISBN 952-462-179-7
ISSN 1456-6184
(online)

Multiprint Oy
Helsinki 2004

Less cash on the counter – Forecasting Finnish payment preferences

Bank of Finland Discussion Papers 27/2004

Hanna Jyrkönen
Financial Markets Department

Abstract

Finnish payment methods have changed rapidly as payment cards have gained increasing popularity and have, to an extent, replaced cash. This article examines this phenomenon and the trends in cash and electronic payment methods in Finland. It starts with an introduction to the statistical data on different payment methods used at points of sale and their electronification, after which learning curve and dynamic regression models are employed to analyse changes in the share of cash payments. Finally, forecasts are presented for the future path of the cash-share.

The data indicate that the use of cards, especially debit cards, has increased substantially. For example, in 1984 some 80% of total purchases (in value terms) were made with cash, whereas by 2002 the corresponding figure had dropped below 50%. Estimation results suggest that learning curve models are not suitable for explaining electronification of payment methods in Finland – at least at this stage – whereas the error correction model and its special-case partial adjustment model, coupled with independent explanatory variables, seem to do a better job. A forecast based on the latter indicates that electronification will continue in future and that by 2010 the cash-share of total value of point-of-sale payments will fall to less than 30%.

Key words: retail payments, payment instruments, electronification

JEL classification numbers: G20, G21, G28

Vähemmän käteistä kassalla – Suomalaisten maksutapojen kehityksen ennustaminen

Suomen Pankin keskustelualoitteita 27/2004

Hanna Jyrkönen
Rahoitusmarkkinaosasto

Tiivistelmä

Maksukortit ovat yleistyneet Suomessa nopeasti ja korvanneet osittain käteisen käyttöä. Tässä työssä tutkitaan tätä ilmiötä ja analysoidaan käteisen ja elektronisten maksutapojen kehitystä Suomessa. Aluksi esitellään tilastoaineistoa myyntipisteissä käytettävistä eri maksutavoista ja niiden elektronisoitumisesta. Tämän jälkeen käteisen korvautumista analysoidaan käyttäen ns. oppimiskäyrämallia sekä dynaamisia regressiomalleja. Lopuksi ennustetaan käteismaksujen osuuden tulevaa kehitystä.

Tulosten mukaan maksukorttien, etenkin pankkikortin, käyttö on lisääntynyt selvästi. Kun vuonna 1984 noin 80 % kaikkien ostosten arvosta maksettiin käteisellä, vuonna 2002 vastaava luku oli enää alle 50 %. Estimointitulosten perusteella oppimiskäyrämallit eivät sovellu ainakaan tässä vaiheessa käteisen korvautumisen selittämiseen. Sen sijaan paremmin toimivat virheenkorjausmalli ja sen erikoistapaus, osittaisen sopeutuksen malli, joihin on lisätty ulkoisia selittäviä muuttujia. Viimeksi mainittuihin malleihin pohjautuvan ennusteen perusteella käteisen korvautuminen näyttäisi jatkuvan samanlaisena myös tulevaisuudessa. Vuonna 2010 käteismaksujen osuus kaikkien myyntipistemaksujen arvosta olisi enää alle 30 %.

Avainsanat: vähittäismaksut, maksuvälineet ja käteisen korvautuminen

JEL-luokittelu: G20, G21, G28

Contents

1 Introduction

Finnish payment methods have changed dramatically during the last 20 years. Today's palette of payment cards in Finland has displaced not only cheques but also cash, to an extent. In fact, the value of card payments has increased 16-fold in the last 20 years, and new payment services – based eg on mobile phones and the Internet – are being developed all the time.

As electronification of payment methods moves ahead, the need for cash declines. In Europe as a whole, the ratio of cash in circulation to GDP has actually decreased. Nonetheless, since the changeover to euro banknotes and coins, the value of banknotes issued in Finland has increased substantially. Given that the amount of cash used to pay for purchases of goods and services is likely to continue to decline, the increased demand for cash could stem from the fact that banknotes nowadays move across the entire euro area and so it is possible that for Finland outflows have exceeded inflows. Moreover, euro banknotes have apparently found their way to countries beyond Europe to a greater extent than did the former national currencies of euro countries.

The last year for which there is Finland-only data on cash in circulation is 2001. At that time Finland's ratio of cash in circulation to GDP was 1.9% – one of the lowest of the EU countries. This is a positive thing for Finland in that handling costs for cash are high compared to those for electronic payment methods. On the other hand, a declining cash stock means less seigniorage for euro countries. Currently, euro area seigniorage is allocated among euro area countries according to the ECB's 'capital share mechanism', which favours countries with smaller cash stocks. For these and other reasons, it is useful to get an idea of how important cash will be in the future. In practice, cash is used mainly for paying for purchases. Hence it is essential to consider the outlook for Finnish payment preferences at points of sale[1] (POS). Besides making payments at POS, cash is used for payments between individuals and eg for payments related to the underground economy. The latter are not taken into account in this study.[2]

The aim of this study is to analyse and forecast Finnish consumers' use of payment instruments for POS purchases. Of particular interest is the electronification of POS payments, viz the use of payment cards instead of cash. First we describe the data, which enable us to summarise payment preferences in Finland in 1984–2002. This is followed by presentation of models that are capable of explaining electronification of POS payments from the data and hence of forecasting as well. The models of choice are the learning curve and error correction models, including the latter's partial adjustment version.

[1] Here, POS refers to a place where payments are made for goods or services.

[2] The different uses of cash are analysed in Paunonen and Jyrkönen (2002).

Section 2 reviews the literature on changing POS payment preferences and section 3 brings together the statistical data on Finnish consumers' use of payment instruments at POS in 1984–2002. Section 4 presents the learning curve models applied and the estimation results. Section 5 analyses the electronification of POS payment methods using error correction and partial adjustment models. Section 6 concludes with an evaluation of the findings, some implications, and suggestions for future research.

2 Literature on changing payment methods

Despite interest in the topic, very little research has focused on consumers' payment preferences. This stems mainly from a lack of data on cash payments. Because cash circulates freely, it is impossible to trace. However, one can estimate frequencies of different uses of cash. In this section several published works are cited, that deal with changes in POS payment methods with a focus on displacement of cash by electronic payment methods.

Snellman and Vesala (1999) examined the electronification of retail payments in Finland, using and an S-shaped learning curve to model the process of cash substitution (displacement) and generated forecasts by extrapolating such curves. The approach is based on the idea that an S-shaped curve is steep and readily reflects short periods of slow growth at both ends. Although S-shaped growth models were previously used mainly in the natural sciences, Snellman and Vesala show that they are also well suited for modelling payments electronification. The data are from the years 1988–1996, and the findings suggest that cash displacement was gradually reaching the saturation level and that cash usage was likely to remain at a high level in retail payments. It was forecasted that the cash-share of POS payments would stabilise at 65%.

Snellman, Vesala and Humphrey (2000) extended Snellmanin and Vesalan (1999) to include other European countries in the forecasts. Because equally detailed data were not available for the other countries, the latter study developed a cash demand equation for analysing cash payments and used it to estimate currency in circulation, using as independent variables cheque payments, interest rate, and number of terminals for electronic funds transfer at point of sale (EFTPOS terminals). The data were input into the learning curve framework of Snellman and Vesala (1999) and forecasts were made of the electronification-degree of cash payments. Panel date for ten European countries (1988–1996) were used in the estimation. The findings suggest that cash displacement is similar across the countries studied and that the extent of it depends critically on the extent of payment-card infrastructure. Increasing numbers of cash dispensers and EFTPOS terminals are found to have negative effects on currency in circulation.

Of the countries studied, Belgium, Denmark, Finland and France appear to have reached a more mature stage of cash displacement and so are nearer to their saturation level, which is estimated at about 60% (ratio of cash and other manual payments' value to total POS payments). The Netherlands and Switzerland have witnessed an acceleration in electronification. On the other hand, Germany, Italy and UK are moving at a more deliberate pace; it was estimated that at the end of the estimation period (1996) cash still accounted for 95% of POS payments in these countries.

Humphrey, Kaloudis and Øwre (2000) combined the same framework with Norwegian data to study cash usage in Norway. Their findings also suggest that the learning curve provides a useful framework for this type of analysis. According to their calculations, cash accounted for 50% of the value of Norwegians' POS payments in 1999. Their forecasts indicate further declines in the ratio: 30% in 2005, 18% in 2010 and only 10% in 2015. In a very recent article, Humphrey et al (2004) revised the forecasts to 38% in 2005 and 25% in 2010, implying a more gradual decline.

Other studies, in addition to Snellman et al (2000), have found that increasing numbers of cash dispensers and ETF-POS dampen the demand for cash. Rinaldi (2001) used a cash demand equation based on Snellman et al (2000) and others to test the extent to which cash demand can be met by other payment methods, especially debit cards. Rinaldi examined changes in how payments are made in Belgium and, like Snellman et al (2000), found that increasing numbers of cash dispensers and EFTPOS terminals negatively affect cash demand. Rinaldi went on to examine cash demand using an error correction model and found a long-run relationship between cash and payment cards. To be sure, the adjustment parameter was so small as to indicate that cash stock reacts very slowly to imbalances. Boeschoten (1992) did a micro-level study on changes in payment preferences in the Netherlands in 1990 and found that the use of cash dispensers, cheques, and EFTPOS terminals has substantial negative effects on consumers' cash holdings. Humphrey, Pulley and Vesala (1996) also came to the same conclusion based on a study of 14 industrial countries using panel data.

The prevailing level of interest rates has also been found to be an important factor. Attanasio, Guiso and Jappelli (2002) used a version of the Baumol-Tobin model to estimate cash demand. Using micro data, they found the interest rate to have a substantial effect on ownership of cash cards. Moreover, Attanasio et al (2002) found the interest-rate elasticity of demand for cash to be about -0.5 and that owners of cash cards are notably more sensitive than non-owners to changes in the interest rate. Markose and Loke (2000) used the Baumol-Tobin cash balance equation as a basis for their study and found that, given the aggregate supply of cash, an economy where cards are used will have lower interest rates than an economy that relies solely on cash.

Emprical studies have also found that mere ownership of payment cards reduces the demand for cash. Duca and Whitesell (1995) combined cross-sectional data on US households and found that credit-card ownership is related to less use of cheques and cash. Blanchflower, Evans and Oswald (1998) also found that credit cards enable an economy to function with a smaller amount of cash. Mantel's (2000) extensive study presents three important determining factors in what payment instruments or channels are used by households. Choice of such channels is affected by a household's living standard, personal preferences, and factors related to making payments.

The use and marketing of e-money[3] has also been studied. Bos (1993) estimated the possible effect of e-money on the amount of banknotes and coins in circulation in EU countries. His calculations are based on the assumption that all purchases valued below a given amount are paid for with e-money and that all consumers and sellers have access to equipment for using e-money. The findings showed wide differences between EU countries in the negative effect of e-money on cash usage. Shy and Tarkka (1998) also studied the use and marketing of e-money. They developed a theoretical model to explain e-money pricing and areas of usage, which they used to explain the pricing structure of cash cards and traditional payment cards in both competitive and monopoly situations. Shy and Tarkka also considered the possibilities for e-money and reasons why it has not really found a market. In fact, some years ago it was expected that e-money would fairly quickly displace cash; but this has not happened. Jyrkönen and Paunonen (2003) studied the factors behind e-money's lack of acceptance. One potential factor in the paucity of e-money usage is that consumers have become so accustomed to making payments with other payment cards, especially debit cards, which can also be used to pay for small-value purchases.

For Finland, the most recent evaluation of the importance of cash in POS payments is thus the forecast of Snellman et al (2000), which suggests a saturation level of 60%. This would mean that even in the future at least 60% of the total value of POS payments will be accounted for by cash or other manual methods. It had actually been estimated around the time of the changeover to euro cash that card payments (in value terms) would by this time be on a par with, or perhaps even have overtaken, cash payments. For this reason, a 60% saturation level seems surprisingly high. For the studies by Snellman and Vesala (1999) and Snellmanin et al (2000), the available data covered only nine years. Now we have similar data covering 19 years (1984–2002), and so it is interesting to see what kind of results we get with a learning curve model and the new data set. This study also presents an alternative forecasting method that takes makes use of the above-mentioned sources.

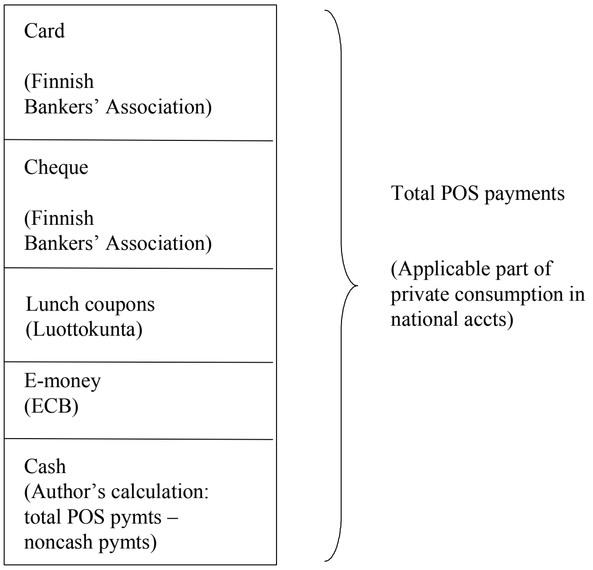
---

[3] E-money is electronic cash meant for making small-value payments, which is loaded on a chip eg in a debit card. In Finland the best known of such cards are the Avant cards.

3 Payment methods in Finland, 1984–2002

Payment methods used at Finnish POS include cash, payment cards, cheques, and various types of lunch and other coupons. The bulk of these payments are made with cash and different kinds of payment cards. Figure 1 graphically depicts the distribution of payment methods, with data sources in parentheses.

Figure 1. **Payment methods (data sources in parentheses)**



Data on *card payments* is available (for 1984–2003) from the Finnish Bankers' Association. Card payments are made with debit cards, credit cards, retailer cards, and online debit cards. Annex 1 contains a table of values of payment-card payments for 1984–2003.

Cheques are no longer used for POS payments but, because they were popular until the end of the 1980s, they are included in the calculations. The Finnish Bankers' Association has data on numbers and values of *cheque payments*. But because these data include bank bills, which are very large in value terms, one gets a highly distorted picture of the value of POS payments by cheque. In terms of numbers of payments, however, bank bills probably account for a small portion of cheque payments. For this reason, the assumption is made that cheque payments are of the same magnitude as debit card payments, so that cheque payments can be estimated by multiplying the number of cheques by the average value of a debit card payment. The same method was used by Humphrey et al (2000) and Paunonen and Jyrkönen (2002). The result indicated that the value of cheque payments has dropped sharply until it is now virtually zero (annex 1).

Because data on *lunch coupons* are available from Luottokunta, this payment method can be included in the analysis (annex 1). Data on *e-money* payments for purchases are published by the European Central Bank in its Blue Book (ECB 2002); so that, even though e-money usage has been fairly insignificant, it can be included in the analysis. Data are lacking for some of the latest payment methods, eg Internet- and mobile phone-based, but their usage is still minimal. Moreover, the more popular of these are based on credit cards and so are included in the Bankers' Association data on card payments.

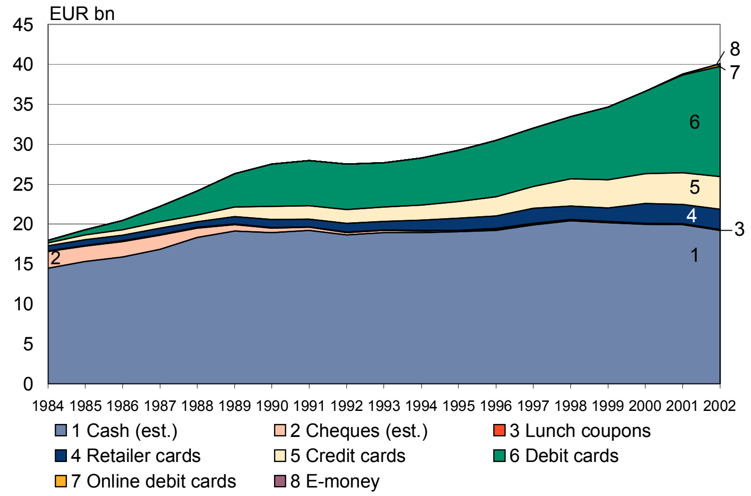
Analysis of *cash payments* is more problematic, because cash circulates freely and specific data are not available on cash payments. However, the value of POS cash purchases can be estimated by subtracting noncash purchases from total value of POS purchases. The total value of cash payments is thus a residual. To get the value of POS purchases, one can select those items in private consumption (national accounts) that are typically paid for with cash, card or cheque, as eg in Humphrey et al (2000). Car purchase payments and rental payments, for example, would be excluded, as these are usually paid by giro. Since national accounts data[4] can be obtained for as late as 2002, the period of study here is 1984–2002.

Figure 2 includes the values of all POS payments by method for the years 1984–2002. Corresponding time series are given in annex 1. From the figure, one sees that cash has been a very popular payment method, albeit cards, especially debit cards, have been rapidly gaining acceptance. The total value of card payments in 2002 was about 15 times the 1984 level. Lunch coupons and e-money are used so little that they cannot be distinguished in the figure. The value of cheque payments, on the other hand, has markedly declined, so that nowadays cheques are hardly used at all to pay for purchases. The uptrend in card payments during the period studied paused only in the early 1990s, at least partly due to a severe recession.

---

[4] One can also consider the value of retail sales (Statistics Finland) to reflect total POS purchases, so that another approach is to subtract from that figure the total of noncash POS payments. But data on retail stores' turnover are not available for as long a period as national accounts data. Alternatively, the value of POS cash payments can be estimated using cash dispenser withdrawals, as in Snellman and Vesala (1999). With this approach, one utilises the fact that currently about 90% of cash withdrawals are from dispensers and that over the years 1988–1996 the share rose from 30% to 80%. The problem with this approach is that precise data are not available on the share of cash withdrawals. Although estimates of POS cash payments via the different approaches are of like magnitudes, this study relies on the first-mentioned approach, in view of the problems cited above. The other approaches are presented in annex 1.

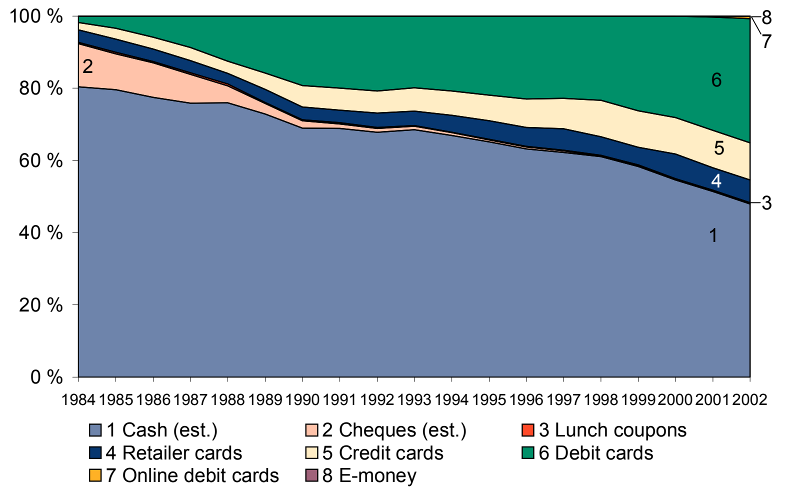
Figure 2. **Distribution of POS payments by method**



Sources: Finnish Bankers' Association, Statistics Finland, Luottokunta, ECB.

From figure 3, which gives the percentage breakdown of payment methods, one sees how card payments have become increasing widespread over the years. It is also apparent from figure 3 that, although the value of cash payments has increased over the period studied, cash has declined in relative importance as a payment method. If we compare the value of cash payments to total POS payment value, we see that cash has declined quite steadily during the period studied, in relative terms. Yet in 1984 some 80% of purchase value was accounted for by cash payments, whereas in 2002 the ratio was under 50%.

Figure 3. **Distribution of POS payments by method**



Sources: Finnish Bankers' Association, Statistics Finland, Luottokunta, ECB.

The lowest series in figure 3, ie cash payments as a percentage of total POS payments, is denoted as C. In the following sections, we explain how the chosen methodologies were used to model the time series that describe electronification of POS payments and hence to produce some forecasts.

4 Learning curve models

This section deals with the application of learning curve models to explaining the relative importance of cash payments. First, learning curves are introduced, with emphasis on the logistic and Gompertz curves used by Snellman and Vesala (1999). This is followed by an empirical analysis of the data discussed above.

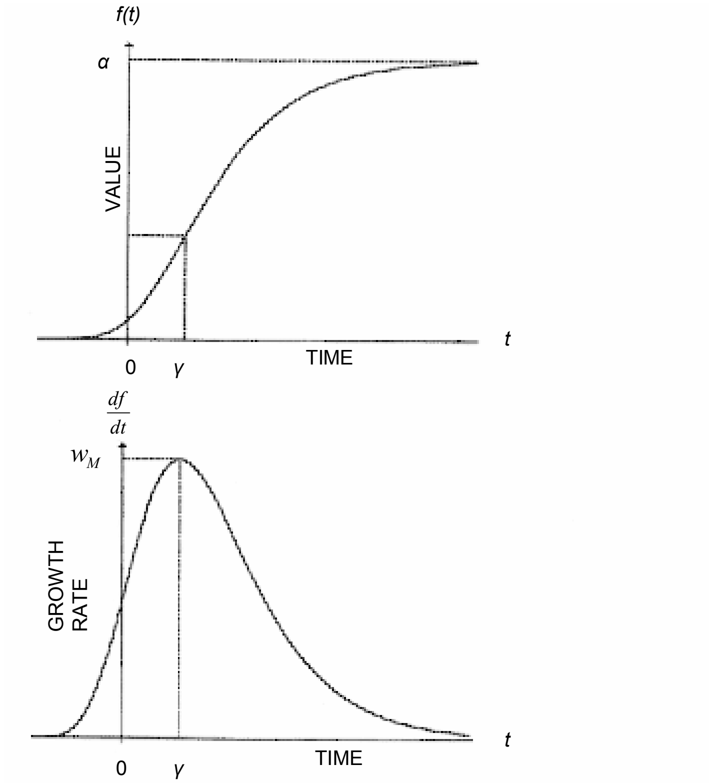
4.1 Theory

Learning curves are S-shaped growth models that are used for forecasting eg the speed at which an innovation becomes widely used. Growth that follows an S-curve is fairly slow at first, after which there is a phase of rapid growth followed by another phase of slow growth. The saturation level may be less than 100% if eg not all potential users adopt a new invention.

Learning curve models are used extensively in biological research, but the analysis of growth data is also important in research eg in chemistry and agriculture (Seber and Wild 1989, p. 326). Snellman and Vesala (1999) were the first to use learning curves to study payment methods.

Figure 4 illustrates a typical S-shaped learning curve. The inflection point is where the growth rate, w, is maximised. Since growth stops at the level $f(t) = \alpha$, the constant α is the saturation level.

Figure 4. **S-shaped learning curve model (upper curve shows the final magnitude, α, and inflection point, γ, the lower growth rate curve shows the maximum growth, w_M)**



Source: Seber and Wild (1989).

In the two models discussed below, S-shaped behaviour results from our modelling of the current value (observation) and remaining growth as a product of functions as follows:

$$\frac{df}{dt} \propto g(f)[h(\alpha) - h(f)] \tag{4.1}$$

where f is the value at time t, and g and h are increasing functions with g(0) = h(0) = 0.

4.1.1 Logistic model

The simplest form of equation (4.1) is where $g(f) = h(f) = f$ (Seber and Wild 1989). In this case

$$\frac{df}{dt} = \frac{\kappa}{\alpha} f(\alpha - f) \tag{4.2}$$

where constant $\kappa > 0$ and $0 < f < \alpha$. Equation (4.2) has the general solution

$$f(t) = \frac{\alpha}{1 + e^{-\kappa(t-\gamma)}} \qquad -\infty < x < \infty \tag{4.3}$$

This is known as the *logistic model*. The curve has asymptotes $f = 0$ for $t \to -\infty$ and $f = \alpha$ for $t \to \infty$. The growth rate is maximised at $f = \alpha/2$, where $t = \gamma$ (equations (4.2) and (4.3)). If $\gamma > 0$, the inflection point of the function f(t) appears as in figure 4. The maximum growth rate is $w_M = \kappa\alpha/4$; the growth rate here is symmetric with respect to $t = \gamma$ while the learning curve is symmetric with respect to its inflection point.

Letting $e^{\kappa\gamma} = \beta$, equation (4.3) becomes a logistic model of the form

$$f(t) = \frac{\alpha}{1 + \beta e^{-\kappa t}} \tag{4.4}$$

According to Seber and Wild (1989), this is probably the most common parameterisation of the logistic model. It is also used in Snellman and Vesala (1999) and this study.

For a logistic curve of the type in equation (4.4), α is the saturation level, β the curve's vertical position and κ its slope. The function f(t) gives the cash-share of POS payments at time t, ie C_t. Because f(t) is decreasing here, we have an inverse learning curve.

4.1.2 Gompertz model

The Gompertz growth curve is also S-shaped but, unlike the logistic curve, not symmetric with respect to its inflection point. It is often used in studying population growth for humans and animals, for which growth is not symmetric with respect to its inflection point. Actually, the learning curve of figure 4 is a Gompertz curve with growth rate

$$\frac{df}{dt} = \kappa f(\log\alpha - \log f) \qquad (\kappa > 0, \alpha > 0) \tag{4.5}$$

Equation (4.5) yields

$$f(t) = \alpha \exp\{-e^{-\kappa(t-\gamma)}\} \tag{4.6}$$

The inflection point is at $t = \gamma$, where $f = \alpha/e$ and the growth rate peaks at value of $w_M = \kappa\alpha/e$. The Gompertz model is based on a model that Gompertz developed in 1825 to explain death probabilities based on a table of length of life (Seber and Wild 1989, p. 330–331).

Letting 6 $e^{\kappa\gamma} = \beta$ in equation 4.6, we get the Gompertz curve applied by Snellman and Vesala (1999)

$$f(t) = \alpha \exp(-\beta e^{-\kappa t}) \tag{4.7}$$

where parameters α, β and κ are interpreted as in the logistic equation (4.4).

4.2 Empirical analysis

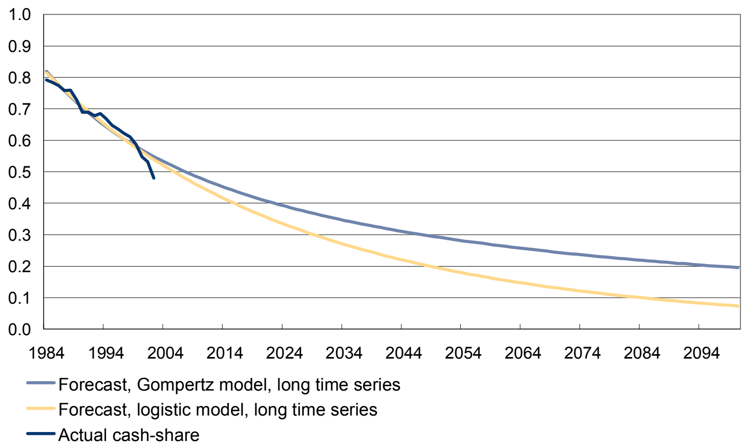
In the learning curve model, the dependent variable, as explained in section 3, is the cash-share of POS payments, shown in figure 3. Denote this variable as C. With our data we estimated the logistic curve of equation (4.4) and the Gompertz curve of equation (4.7) using nonlinear least squares estimation. The results given in table 1.

Table 1. **Estimation results for logistic and Gompertz models, 1984–2002**

	Logistic model $C_t = \frac{\alpha}{1+\beta e^{-\kappa t}}$		Gompertz model $C_t = \alpha \exp(-\beta e^{-\kappa t})$	
	Coefficient	t-value	Coefficient	t-value
α	0.00	0.00	0.00	0.01
β	-1.00	-1.27	-11.1	-0.09
κ	0.00	0.00	0.00	0.08
R^2	0.93		0.94	
Adj R^2	0.92		0.94	
DW	0.47		0.56	

The estimation results from the two models seem to be quite similar. The saturation level, α, appears to be very close to zero, suggesting that cash is destined to completely disappear at some point. This is also apparent when forecasts are obtained by extrapolating the estimation results (figure 5). The t-value, however, indicates that the regression coefficient, α, is not statistically significant, nor are the other coefficients, β (curve's vertical position) and κ (curve's slope). Also noteworthy is the high degree of autocorrelation, as indicated by both the Durbin-Watson statistic and the residuals shown in annex 2, figures 10 and 11 (solid lines). The coefficient of determination, R^2, is surprisingly high for both models.

Figure 5. **Model-based forecasts, estimation period 1984–2002**

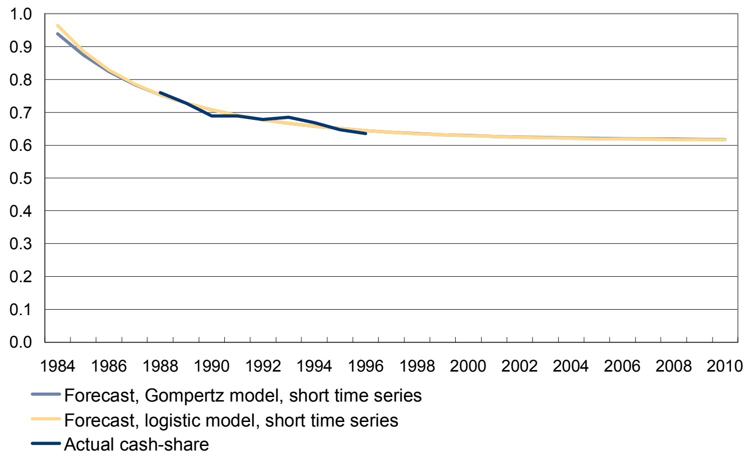


These results are from time series data for 1984–2002. If the same estimation methodology is applied to the 1988–1996 data used by Snellman and Vesala, the results are quite different (table 2). For the shorter period, the saturation level coefficient, α, is clearly significant and equal to 0.61. This means that the cash-share of POS payments would stabilise at 61%, as is also clear from figure 6. For the shorter time series, autocorrelation appears not to be quite as high as for the longer series. These results are much in line with those of Vesala and Snellman (1999), even though the time series is calculated in a slightly different way (see section 3).

Table 2. **Estimation results for logistic and Gompertz models, estimation period 1988–1996**

	Logistic model $C_t = \dfrac{\alpha}{1+\beta e^{-\kappa t}}$		Gompertz model $C_t = \alpha \exp(-\beta e^{-\kappa t})$	
	Coefficient	t-value	Coefficient	t-value
α	0.61	13.4	0.62	14.4
β	-0.22	-5.10	-1.07	-1.25
κ	0.17	1.42	0.19	1.54
R^2	0.91		0.91	
Adj R^2	0.89		0.88	
DW	1.29		1.28	

Figure 6. **Model-based forecasts, estimation period 1988–1996**



The results for the two estimation periods are similar as regards autocorrelation and the closely matching results for the two models – logistic and Gompertz. The biggest differences in estimation results are in the estimates and significance of the coefficients. Comparison of results indicates that the learning curve fits much better for the shorter estimation period. Why this is the case is an interesting question. Looking at the longer time series, one notices small waves, ie that electronification progresses in faster and slower phases. Focusing on the period 1988–1996, one sees just one definite regression phase, at the onset of the severe recession of the 1990s. That is, in the shorter time period one perceives an S-shaped path, which is not visible in the longer period. On the other hand, figure 6 shows that the fit for the shorter time period is not S-shaped either, and the same is true for the corresponding figure in Snellman and Vesala (1999, p. 18).

From the recent time series, one notices that the learning process for using payment cards has been undulating but that no S-shape is visible. It is possible that the path over a longer time period is S-shaped, ie slow at first, then accelerating and finally slowing down. However, this would not be visible until the start of the slowing phase, ie when the majority of consumers have already switched from cash to payment cards and the growth of card payments is definitely slowing – and we have not yet reached this phase.

Because electronification of payment methods is a one-time and long-lasting phenomenon, it is perhaps fair to say that the learning curve is not a suitable model for it. S-shaped growth models are typically used in the natural sciences, where phenomena of interest – eg animal growth rates – are often repetitive and shorter-lasting. Thus it may be that models that make use of empirical independent variables are better able to explain electronification of payment methods. In section 5 an attempt is made to find such an alternative model.

5 Dynamic regression models

It was shown in section 4 that the learning curve model does not provide a good fit for the currently available data. In this section we attempt to clarify whether electronification of payment methods can be forecasted with an econometric forecasting model in which cash-share behaviour is explained by exogenous variables. Because electronification occurs gradually, an *error correction model* and the special-case *partial adjustment model* are offered as alternatives. Both of these are dynamic regression models that include lagged values of the dependent variable as independent variables.

5.1 Error correction model

We start with the error correction model. This is a dynamic model in which, in long-run equilibrium, a given period's change in the value of a variable is related to the previous period's change. In fact, an error correction model is an autoregressive distributed lag model, ie an AD(p, q) model, written in error correction form. In AD(p, q), p denotes the number of lags of the dependent variable and q the number of lags of the independent variables. With just one independent variable, the linear dynamic regression model AD(1,1) takes the form

$$y_t = \beta_0 + \beta_1 z_t + \beta_2 y_{t-1} + \beta_3 z_{t-1} + \varepsilon_t \quad (5.1)$$

where y_t is the dependent and the z_t the independent variables, the β_i are parameters, and ε_t is the error term.

Subtracting y_{t-1} from each side yields

$$\begin{aligned}\Delta y_t &= \beta_0 + \beta_1 z_t + (\beta_2 - 1)y_{t-1} + \beta_3 z_{t-1} + \varepsilon_t \\ &= \beta_0 + \beta_1(z_t - z_{t-1}) + (\beta_2 - 1)y_{t-1} + (\beta_1 + \beta_3)z_{t-1} + \varepsilon_t \\ &= \beta_0 + \beta_1 \Delta z_t + (\beta_2 - 1)(y_{t-1} - \kappa z_{t-1}) + \varepsilon_t\end{aligned} \tag{5.2}$$

The last equality follows from the fact that $\kappa(1-\beta_2) = \beta_1 + \beta_3$ (Hendry 1995, p. 213–214). The final form of equation (5.2) is the error correction version of the AD(1,1) model. In an error correction model, the difference $y_{t-1} - \kappa z_{t-1}$ is the error correction term, which tells how far the relationship between y_t and z_t is from its long-run equilibrium. The negative of the parameter $\beta_2 - 1$, ie $1-\beta_2$, is called the adjustment parameter, and it tells how much of the divergence from equilibrium is typically corrected in one period (see eg Hendry 1995). Thus, in an error correction model, a change in the dependent variable, y_t, derives from a change in the variable z_t and in the error correction term, and adjustment speed per se is determined by the adjustment parameter, $1-\beta_2$. All the differenced variables must be (weakly) stationary, and their levels are determined by the long-run equilibrium relationship.

The variable y_t here corresponds to C_t in cash-share modelling. In the case of several independent variables, z_t corresponds to a $1 \times k$ vector, z_t, where k is the number of independent variables. Here, the independent variables were selected on the basis of the studies discussed in section 2. These showed that cash-share is influenced by numbers of cash dispensers and EFTPOS terminals. While an extensive network of cash dispensers facilitates the use of cash in paying for purchases, it also enables people to get by with smaller cash balances. With an EFTPOS terminal, card payments at a store's check-out counter can be processed electronically, so that the more there are in the stores, the easier and faster it is to use cards. The extent of EFTPOS terminals is also a good indicator of technological progress and hence the extent of the payment infrastructure. Another factor that influences cash-share is the level of interest rates, which is an opportunity cost. Examination of the bottom part of figure 3, which shows the dependent variable, raises a question: could overall economic conditions also have an impact on the speed of electronification? For example, during the recession of the early 1990s there was a surge in credit delinquencies and customers were obliged to return payment cards. This of course slowed the electronification of POS payments. One might conjecture that underground economic activity increases as unemployment increases. For these reasons, we chose the unemployment rate as the measure of overall economic conditions. Figures showing the dependent variables and their expected time paths are in annex 4.

The complete model thus takes the form

$$\begin{aligned}\Delta C_t &= \beta_0 + \beta_1 \Delta E_t + \beta_2 \Delta A_t + \beta_3 \Delta i_t + \beta_4 U_t \\ &\quad + (\beta_5 - 1)(C - \kappa_1 E - \kappa_2 A - \kappa_3 i)_{t-1} + \varepsilon_t\end{aligned} \tag{5.3}$$

where C is cash-share of POS payments; E is number of EFTPOS terminals; A is number of cash dispensers; i is avg rate on bank accoounts (nominal interest rate[5]); U is unemployment rate; β_0 is constant; $\beta_1,\ldots,\beta_4$ is short-run coefficients; β_5-1 is negative of adjustment parameter, $1-\beta_5$; $\kappa_1,\ldots,\kappa_3$ is long-run coefficients; ε is error term and t is time.

The unemployment rate, U, would seem to be stationary and so is not differenced. Nor is it added to the error correction term.

Coefficients β_1 and β_3 are assumed to be negative, since an increase in EFTPOS terminals or a rise in the interest rate should have a negative effect on cash-usage. In contrast, a rise in the unemployment rate is assumed to have a positive effect, so that β_4 should be positive. One might conjecture that an increase in the number of cash dispensers would facilitate, and hence increase, the use of cash (β_2 positive). However, because previous studies have found a negative effect on the demand for cash, the sign of this coefficient is left open. But the long-run effect is assumed, at least tentatively, to be of the same direction as the short-run effect, so that the coefficients κ_1 and κ_3 are assumed to be negative and κ_2 positive.

Besides the chosen variables, the pricing of different payment methods will have an important impact on consumers' payment preferences. But because time series data on pricing of payment methods are not available, it is left out of the model.

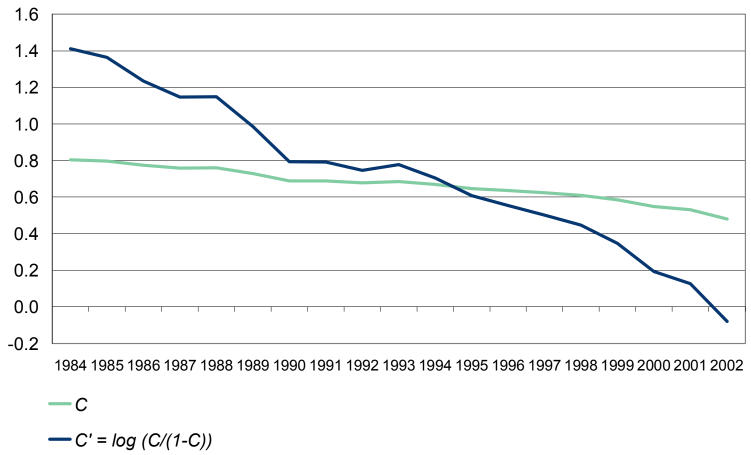
There is a fundamental problem with the model presented above. The cash-share of POS payments (C), ie the dependent variable, is restricted to values in the interval [0.1], while the independent variables are not. In order to have the dependent variable in an unrestricted form, we apply the log transformation

$$C' = \log\frac{C}{1-C}$$

which can take any value in $[-\infty,\infty]$. Both he transformed and the original time series are shown in figure 7.

[5] Consumers evaluate the nominal interest rate against the return they could obtain by keeping money in a bank account. For cash the nominal rate is 0%; for a bank account slighty higher. Because inflation has the same kind of effect on both assets, the advantage of keeping money in an account is equal to the nominal interest rate.

Figure 7. **Original and transformed versions of cash-share of POS payments**



The adjusted model is thus

$$\begin{aligned}\Delta C'_t &= \beta_0 + \beta_1 \Delta E_t + \beta_2 \Delta A_t + \beta_3 \Delta i_t + \beta_4 U_t \\ &\quad + (\beta_5 - 1)(C' - \kappa_1 E - \kappa_2 A - \kappa_3 i)_{t-1} + \varepsilon_t\end{aligned} \tag{5.4}$$

Estimation results are presented in table 3.

Table 3. **Estimation results for complete model (equation (5.4))**

	Coef	t-value
β_0 (constant)	1.44	2.48
β_1 (ΔEFTPOS term)	-0.02	-2.66
β_2 (Δcash dispensers)	0.39	1.95
β_3 (Δnom interest rate)	0.02	0.55
β_4 (unemployment rate)	0.04	4.06
$\beta_5 - 1$	-1.38	-3.62
κ_1 (EFTPOS terminals)	-0.02	-21.2
κ_2 (cash dispensers)	0.20	4.48
κ_3 (nominal interest rate)	-0.07	-5.67
R^2	0.84	
Adjusted R^2	0.65	
Akaike information criterion	-3.26	
Schwarz information criterion	-2.82	
Durbin-Watson	2.39	

The results indicate that an increase in the number of EFTPOS terminals has a negative effect on cash usage at POS. This is as expected, since the more terminals in the store, the easier and faster it is to use a card. Coefficient signs for the number of cash dispensers also accord with prior belief, according to which a decrease in the number of cash dispensers will reduce the use of cash in making purchases. With fewer cash dispensers, more customers will pay by card rather than withdrawing cash on the way to the store. Nonetheless, earlier studies have found that reducing the number of cash dispensers has a positive effect on the demand for cash. The reason offered is that the less dispensers there are, the larger the individual withdrawals. The difference in findings may stem from the fact that here we look solely at the use of cash at POS whereas the earlier studies examined the overall demand for cash. That is, according to earlier studies, the decline in the number of cash dispensers since the early 1990s has led to an increase in the overall demand for cash, while this study suggests that the use of cash to make purchases has decreased during the same period. Empirical results support these findings: cash in circulation has increased while the use of cash to make purchases has continuously declined.

Our results indicate that a rise in the unemployment rate increases the use of cash. Because the unemployment rate is assumed here to reflect overall economic conditions, this result appears reasonable in terms of the earlier argumentation. Coefficients of the nominal interest rate and changes therein get opposite signs. It was thought ex ante that a rise in the interest rate would reduce cash usage, as it would increase the advantage of keeping money in an account as long as possible. The coefficient sign for interest rate level supports this view, but the opposite is true for the difference form of the variable, albeit the latter coefficient was not statistically significant. While it is possible that the short- and long-run effects of the interest rate are different, it is more likely that the interest rate does not have a short-run impact on payment methods used by consumers.

The estimate of the parameter $\beta_5 - 1$ was –1.38, so that the adjustment parameter, $1 - \beta_5$, becomes 1.38. This hardly seems reasonable, since it implies that in one period (year) 138% of the imbalance would be corrected. However, Pere (2004) has shown that the adjustment parameter estimate can be outside of the interval [0.1]. This might be the result eg of a two-equation system, where the second (unknown) equation's dependent variable is corrected in the same direction but by more, so that there is an attempt to correct the whole deviation in the expected direction. Here, it is not known what such a second equation could be. The estimate of the parameter $\beta_5 - 1$ is statistically significant, which supports the idea that there is also a long-run relationship between cash-share, numbers of EFTPOS terminals and cash dispensers, and nominal interest rate.

Table 3 presents the Akaike information criterion,

$$\mathrm{AIC} = -2\frac{l}{T} + 2\frac{p}{T}$$

and the Schwarz Bayesian information criterion,

$$\mathrm{BIC} = -2\frac{l}{T} + \frac{p \log T}{T}$$

which can used to compare models for superiority. In both criteria, l denotes the value of the log-likelihood function, p the number of parameters, and T the number of observations. A model is normally considered the better, the smaller the value of AIC or BIC (see eg Verbeek 2000).

In considering a t-value, one should keep in mind that it is valid for an infinite number of observations. Here, the number of observations is very small, especially relative to the number of parameters, so that the t-values can only be indicative. Neither the t-values for testing the normality of the residuals distribution nor the figures are included in this article but, from the histogram of residuals from model (5.4), it is clear that the observed residuals are normally distributed. The Jarque–Bera normality test does not reject the null hypothesis of normally distributed residuals. The Durbin-Watson statistic indicates that the model has some (negative) autocorrelation, albeit in the context of a dynamic regression model the Durbin-Watson test must be considered merely indicative, since its distribution is not valid when the model contains lagged explanatory variables (Davidson and MacKinnon 1993, p. 363). Based on the graph of the residuals (annex 3, figure 13) and Ljung-Box Q-test[6], it seems the residuals are not autocorrelated.

Because the coefficient of the interest rate in the differenced version was not significant, Δi is dropped from the model. The equation becomes

$$\Delta C'_t = \beta_0 + \beta_1 \Delta E_t + \beta_2 \Delta A_t + \beta_3 U_t + (\beta_5 - 1)(C' - \kappa_1 E - \kappa_2 A - \kappa_3 i)_{t-1} + \varepsilon_t \qquad (5.5)$$

Estimation results for equation (5.5) are given in table 4.

[6] Brüggemann, Lütkepohl and Saikkonen (2004) examined autocorrelation testing for vector error correction models and found that the Portmanteau test p-values, used here with the EViews 4 program, are apparently based on an inappropriate approximating distribution. Because the Ljung-Box test is essentially a Portmanteau test, so that the same problem may arise in testing for autocorrelation in a one-dimensional model, one should contemplate the test results with extra caution.

Table 4. **Estimation results for equation (5.5)**

	Coef	t-value
β_0 (constant)	1.64	3.88
β_1 (ΔAFT-POS term)	-0.02	-3.95
β_2 (Δcash dispensers)	0.32	2.18
β_4 (unemployment rate)	0.04	5.09
$\beta_5 - 1$	-1.47	4.45
κ_1 (AFT-POS terminals)	-0.02	-26.0
κ_2 (cash dispensers)	0.20	4.98
κ_3 (nominal interest rate)	-0.07	-6.35
R^2	0.83	
Adjusted R^2	0.68	
Akaike information criterion	-3.34	
Schwarz information criterion	-2.96	
Durbin-Watson	2.39	

For this model all coefficients are statistically significant at the 95% confidence level and coefficient signs are as expected. the residuals are normally distributed and fairly free of autocorrelation (annex 3, figure 14). The Akaike and Schwarz information criteria indicate that model (5.5) is better than the complete model.

As for model (5.4), the estimate of the adjustment parameter for model (5.5), 1.47, is not between zero and one. Again, this is not an impossible result (Pere 2004).

In discussing the above models, the starting point has been the AD(1,1) model. We could also have started with the model AD(p, q), allowing for more lags of the dependent and independent variables. But because the time series to be analysed is very short, it is not a good idea to increase the number of parameters – ideally the number would be reduced. For this reason, some testing was done on models with still fewer independent variables than in model (5.5). One such model is

$$\Delta C'_t = \beta_0 + \beta_1 \Delta E_t + \beta_2 i_t + \beta_3 U_t + (\beta_5 - 1)(y - \kappa_1 E - \kappa_2 A)_{t-1} + \varepsilon_t \qquad (5.6)$$

for which estimation results are reported in table 5.

Table 5. **Estimation results for equation (5.6)**

	Coef	t-value
β_0 (constant)	1.16	1.87
β_1 (ΔEFTPOS term)	-0.02	-1.96
β_2 (Δnom interest rate)	-0.04	-1.13
β_3 (unemployment rate)	0.02	2.66
β_5–1	-0.91	-2.13
κ_1 (EFTPOS terminals)	-0.02	-11.4
κ_2 (cash dispensers)	0.13	1.73
R^2	0.62	
Adjusted R^2	0.37	
Akaike information criterion	-2.68	
Schwarz information criterion	-2.34	
Durbin-Watson	2.47	

Table 5 shows that the signs of the parameter estimates are as expected, but not all of the independent variables are significant. The adjustment parameter, $1-\beta_5$, becomes 0.91, so that in this respect model (5.6) seems to be the most typical error correction model introduced so far. However, the parameters' small t-values, the clearly lower explanatory power, the larger values of AIC and BIC, and the fairly high Durbin-Watson statistic all argue against this model. Moreover, from annex 3, figure 15, we see that the fit of the model is not very good. Results for other combinations of variables were not any better, so model (5.5) was chosen as the best error correction model.

Usually in connection with an error correction model one would perform unit root and cointegration tests, which are discussed eg in Davidson and MacKinnon (1993). These tests are not done here in order to keep the study within limits.

Next, the number of parameters is reduced by letting $\kappa = 0$ in the error correction term $y_{t-1} - z_{t-1}\kappa$ (where z_{t-1} is a 1 × k vector and κ a k × 1 vector) and the result is a partial adjustment model.

5.2 Partial adjustment model

In this section we deal with another – and frequently used – type of dynamic model, the partial adjustment model. We start with an AD(1,1) model (equation 4.8) and add the restriction $\beta_3 = 0$ (ie we drop the lagged value of independent variable z_t). The end result is an AD(1,0) model which, with one independent variable, takes the form

$$y_t = \beta_0 + \beta_1 z_t + \beta_2 y_{t-1} + \varepsilon_t \tag{5.7}$$

Equation (5.7) is thus an error correction model with fewer parameters than in the general case – viz a partial adjustment model. The model has a long history in economics, going back to 1950s. One can also arrive at a partial adjustment model without the AD(1,1) model. In this case, it is assumed that the desired level of an economic variable y_t, denoted y_t^*, is associated with a $1 \times k$ vector of explanatory variables, z_t:

$$y_t^* = z_t\beta^* + u_t \tag{5.8}$$

where β^* is a $k \times 1$ coefficient vector and u_t an error term. Variable y_t is assumed to adjust toward the desired level[7], y_t^*, according to the following equation

$$y_t - y_{t-1} = (1-\delta)(y_t^* - y_{t-1}) + v_t \tag{5.9}$$

where $(1-\delta)$ is the adjustment parameter and v_t the error term. Solving equations (5.8) and (5.9) for y_t yields

$$y_t = y_{t-1} - (1-\delta)y_{t-1} + (1-\delta)z_t\beta^* + (1-\delta)u_t + v_t \tag{5.10}$$

where $\beta \equiv (1-\delta)\beta^*$ and $\varepsilon_t \equiv (1-\delta)u_t + v_t$. Equation (5.10) now corresponds to equation (5.7). As with the general error correction model, the adjustment parameter, $1-\delta$, indicates the proportion of long-run divergence that can be corrected in one period. In principle, the partial adjustment model makes sense only if $0 < \delta < 1$ and δ is not too close to unity. If δ is too close to unity, $1-\delta$ will be too close to zero and adjustment will be unreasonably slow (see eg Davidson and MacKinnon 1993, p. 680).

As regards the modelling of cash-share, the dependent variable, y_t, becomes cash-share at time t, denoted C_t. Again, the independent variable, C_t, is restricted while the independent variables are not. Hence the log transformation applied in section 5.1 is also used here, and the dependent variable is now C_t'. The independent variables are the same as in the general error correction model, and equation (4.1) becomes

$$C_t'^* = \beta_0^* + \beta_1^* E_t + \beta_2^* A_t + \beta_3^* i_t + \beta_4^* U_t + u_t \tag{5.11}$$

where C′* is log of desired cash-share of POS payments; E is number of EFTPOS terminals; A is number of cash dispensers; i is average interest rate on stock of

[7] Desired level y* can also be interpreted as the long-run equilibrium level (Rowley and Trivedi 1975, p. 80).

bank deposits (nom interest rate); U is unemployment rate; $\beta_0^*,...,\beta_4^*$ is parameters; u is error term and t is time.

Equation (5.9) becomes

$$C'_t - C'_{t-1} = (1-\delta)(C'^*_t - C'_{t-1}) + v_t$$

where $(1-\delta)$ is adjustment parameter; C′ is log of cash-share of EFTPOS payments; C′* is log of desired cash-share of EFTPOS payments; v is error term and t is time.

Equation (5.10) becomes

$$C'_t = \beta_0 + \beta_1 E_t + \beta_2 A_t + \beta_3 i_t + \beta_4 U_t + \beta_5 C'_{t-1} + \varepsilon_t \tag{5.12}$$

Estimation results are given in table 6.

Table 6. **Estimation results for partial adjustment model (equation (5.12))**

	Coef	t-value
β_0 (constant)	0.78	2.11
β_1 (ΔEFTPOS terminals)	-0.01	-2.74
β_2 (cash dispensers)	0.08	1.49
β_3 (nominal interest rate)	-0.02	-1.15
β_4 (unemployment rate)	0.02	3.68
δ	0.30	1.11
R^2	0.99	
Adjusted R^2	0.98	
Akaike information criterion	-2.82	
Schwarz information criterion	-2.53	
Durbin-Watson	2.37	

The results indicate that an increase in the number of EFTPOS terminals or a rise in the interest rate will reduce the use of cash in POS payments. This finding agrees with expectations, since the more EFTPOS terminals there are in a store, the easier and faster it is to pay with a card. Moreover, a rise in the interest rate makes it more advantageous to leave money in an account rather than withdrawing it beforehand. Because the t-value for the estimate of the interest-rate coefficient is only -1.15, caution is advised regarding the interest rate effect.

Nor is the coefficient estimate for the number of EFTPOS terminals statistically significant at the 95% confidence level. The sign of the coefficient estimate for the number of cash dispensers, according to which a decrease in the number of dispensers reduces the use of cash for purchases, does however seem reasonable in light of prior argumentation. A rise in the unemployment rate increases cash usage, which again seems reasonable by prior argumentation.

Note that the dependent variable has been log-transformed, and so interpretation of the parameters – eg the elasticity – is not as straightforward as in the non-transformed case. Annex 5 contains the results for model (5.2), with the original-form dependent variable.

Because the estimate of δ is 0.30, the estimate of the adjustment parameter, $1-\delta$, is 0.70. This implies that in one period (year) 70% of the divergence from long-run equilibrium is corrected. The Durbin-Watson statistic indicates that the model is somewhat negatively autocorrelated, even though the residuals do not seem to be autocorrelated (solid line in appendix 13, figure (5.9)). The residuals are normally distributed.

Because of the large size of the adjustment parameter, we can perhaps also consider the electronification of cash payments to occur immediately with changes in independent variables. Thus equation (5.11) can be directly estimated (results in table 7).

Table 7. **Estimation results for logistic regression model (equation (5.11))**

	Coef	t-value
β_0 (constant)	1.18	17.43
β_1 (EFTPOS terminals)	-0.02	-15.30
β_2 (cash dispensers)	0.11	2.41
β_3 (nominal interest rate)	-0.03	-2.17
β_4 (unemployment rate)	0.02	5.24
R^2	0.98	
Adjusted R^2	0.98	
Akaike information criterion	-2.83	
Schwarz information criterion	-2.59	
Durbin-Watson	2.32	

All coefficient estimates were statistically significant at the 95% confidence level.[8] As with the immediately-preceding model, this one also indicates that an increase in the number of AFT-POS terminals or a rise in the interest rate reduces cash usage in POS payments. This model also agrees with the above one in that an increase in the number of cash dispensers or a rise in the unemployment rate increases cash usage in POS payments. According to the Akaike and Schwarz information criteria, this model is slightly better than the above model. The Durbin-Watson statistic again indicates the presence of slight negative autocorrelation, although the residuals do not seem to be autocorrelated (annex

[8] Here, to simplify, we ignore possible nonlinearity effects on the underlying distribution theory.

13, figure 17). The assumption of normally distributed residuals is accepted also for this model.

5.3 Forecasts

Because the best of the models presented above, according eg to the Akaike and Schwarz information criteria, are models (5.5), (5.11) and (5.10), these are used for forecasting purposes.

Using projected future values of independent variables, a model can be used to forecast future values of the dependent variable. It is assumed here that the number of EFTPOS terminals will increase from the current number at the current pace and that the number of cash dispensers will decrease at its current pace. Also assumed is that the unemployment rate will behave according to forecasts by the Bank of Finland (2004) and Ministry of Finance (2003). In estimating average interest rates on bank deposits, it is assumed that households and banks behave as currently, that the structure of deposits remains fixed, that 40% of any change in market interest rates passes through to deposit rates, and that the equilibrium average bank deposit rate in 1.5%. Figures 18-21 of annex 4 show the actual and projected paths of the independent variables.

Using models (5.5), (5.11) and (5.10), we obtain forecasts of the transformed dependent variable, C'. Because

$$C' = \log \frac{C}{1 - C}$$

it is necessary to revert to the original variable for forecasting; hence we apply the transformation

$$C = \frac{\exp(C')}{1 + \exp(C')}$$

to obtain cash-share of EFTPOS payments. Forecasts generated by models (5.5), (5.11) and (5.10) are presented in figure 8 and table 8.

Figure 8. **Model fitting and forecasts**

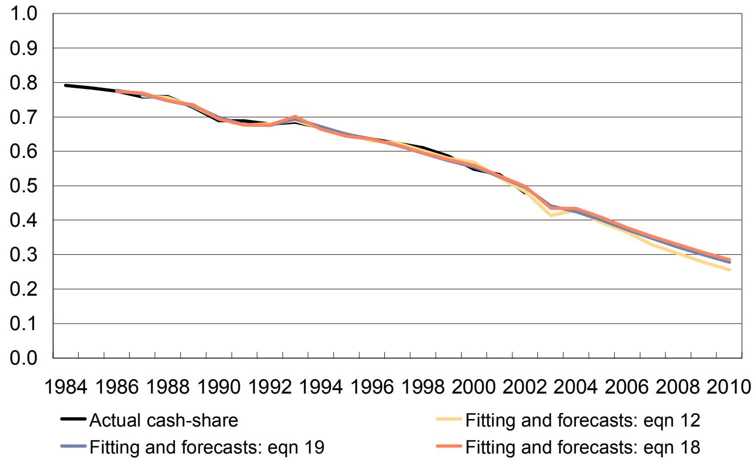


Table 8. **Data on model fitting and forecasts**

	Actual cash-share	Fitting and forecast: eqn 12	Fitting and forecast: eqn 19	Fitting and forecast: eqn 18
1984	0.792			
1985	0.783			
1986	0.775		0.776	0.774
1987	0.759	0.760	0.766	0.769
1988	0.759	0.756	0.747	0.747
1989	0.728	0.731	0.732	0.734
1990	0.689	0.695	0.698	0.694
1991	0.688	0.677	0.677	0.676
1992	0.678	0.680	0.675	0.677
1993	0.685	0.689	0.694	0.701
1994	0.669	0.667	0.672	0.665
1995	0.647	0.652	0.649	0.644
1996	0.635	0.630	0.635	0.635
1997	0.622	0.624	0.617	0.617
1998	0.610	0.602	0.595	0.596
1999	0.586	0.579	0.573	0.576
2000	0.548	0.568	0.555	0.560
2001	0.532	0.524	0.527	0.529
2002	0.480	0.483	0.496	0.498
2003		0.414	0.441	0.435
2004		0.429	0.424	0.434
2005		0.393	0.401	0.408
2006		0.365	0.373	0.379
2007		0.328	0.346	0.352
2008		0.303	0.322	0.329
2009		0.279	0.299	0.307
2010		0.256	0.277	0.285

As seen from figure 8 and table 8, the fittings and forecasts for the different models are quite similar. The forecasts indicate that the disappearance of cash will continue and that by 2010 cash will account for less than 30% of the value of EFTPOS purchases. According to the forecast, the saturation level is not yet in sight. Because the forecast is based on the above-mentioned assumptions about numbers of cash dispensers and EFTPOS terminals, interest rate level, and unemployment rate, any unexpected change in these could of course affect the accuracy of the forecasts.

The model provides evidence that the electronification of POS payments could be accelerated especially by increasing the number of EFTPOS terminals and reducing the number of cash dispensers. The number of EFTPOS terminals could in fact increase even faster than expected in the context of the ongoing EMV changeover[9]. On the other hand, many of the outlets that do not yet have EFTPOS terminals are small stores that may not acquire these terminals at all, even if they change over to EMV. It is also noteworthy that the direction of causation regarding cash dispensers and EFTPOS terminals is not crystal clear. At least part of the change occurring in numbers of cash dispensers and EFTPOS terminals could be caused by (rather than cause) changes in payment habits.

6 Conclusions

This study provides two major findings:

- The popularity of electronic payment methods as a substitute for cash has grown faster and the saturation level for cash-share is lower than could be foreseen in 2000.
- According to our new forecasts, the disappearance of cash continues at a steady pace and in five years the cash-share of POS payment value will be only about 30%.

Payment cards have gained rapid acceptance in Finland, and cash is needed less and less for making purchases. Moreover, new payment methods are being created all the time, which may further reduce the use of cash. This article has analysed the outlook for cash as a payment means. Section 3 presented statistical data on the use of different payment methods in Finland. It was found that the importance of cash in POS payment value has declined substantially. In 1984

[9] EMV is a joint project of Eurocard, MasterCard and Visa for changing over from magnetic stripe cards to more secure smart cards. It is motivated by increased fraudulant use of magnetic stripe cards. At the start of 2005 responsibility for card fraud will shift from credit card company to the store, if the latter does not have a functioning smart card reader.

about 80% of such value was accounted for by cash; by 2002 slightly less than 50%. This is less than forecasted by Snellman et al (2000), who reported that the cash-share of POS payments would eventually stabilise at 60%. Thus the popularity of payment cards used mainly in place of cash has already recorded faster growth than could be forecasted in 2000.

In section 4 an attempt was made to explain the new data by modelling cash-share using learning curve methodology, which has been used before eg by Snellman and Vesala (1999). Snellman and Vesala had access to annual data over nine years for their estimations, and the learning curve has been found to be quite suitable for forecasting electronification of POS payments. Now we have 19 years of data available, and our results suggest that their model is not suitable for explaining the currently available observations. The apparent reason for this is that the S-shape assumed in the learning curve context was observable in the shorter time series but not in the longer one. In examining the question ex post one notes that the S-shape was at least partly attributable to the recession of the early 1990s, at which time electronification of payment methods came to a halt because of an increase in payment disturbances and the resulting decline in the number of payment cards. Based on the results in section 4, it was found that forecasting the electronification of payment methods may be accomplished more successfully with models that incorporate empirical independent variables. Thus section 5 presented such an alternative approach to modelling cash-share.

Two alternative models were used: the error correction model and its special-case partial adjustment model. With the error correction model, there are so many parameters that caution is needed with respect to the results. While the partial adjustment model involves fewer parameters, they are still abundant relative to the number of observations. The small number of observations must be taken into account in interpreting the results.

Results for both general error correction model and partial adjustment model indicate that an increase in the number of EFTPOS terminals or a rise in the interest rate will have a negative effect on cash-usage in POS payments, whereas a rise in the unemployment rate or an increase in the number of cash dispensers will have a positive effect. As regards cash dispensers, the result is somewhat surprising, since earlier research indicates that a decrease in the number of cash dispensers will have a positive effect on the demand for cash. The differing results may be due to the restriction of the dependent variable here to cash used in POS purchases whereas the earlier research looked at cash demand as a whole. Thus the downward trend in the number of cash dispensers that began at the start of the 1990s has, according to the earlier research, increased the overall demand for cash whereas this study suggests that the trend has reduced cash-usage in purchases. This finding gets further support from the real world: the amount of cash in circulation has increased despite a continuous decline in cash-usage in purchases.

Forecasts generated by both the error correction and partial adjustment models indicate that the disappearance of cash will continue so that by 2010 cash will account for only 25–30% of the value of POS purchases. The forecasts are based on assumptions eg that the increase in the number of EFTPOS terminals and the decline in the number of cash dispensers will each continue at its current pace. If big changes occur in these developments, there would probably be a change in the use of cash.

Besides the variables used here in the models, the pricing of different payment methods clearly has a considerably influence on consumers' payment preferences. Even though nowadays no charge is made for using cash, it is clear that cash usage is not cost-free. For the banks, it is costly to transport cash to, and to maintain, cash dispensers. For the stores, cash usage causes extra work and costs, eg in connection with overnight transport to storage facilities. In the end, these costs are borne by customers. Van Hoven's (2002) calculations indicate that cash is very costly to society, and he suggests that customers should be induced to use more economical payment methods, eg by charging a transaction fee per cash withdrawal. This has in fact been done at least in Norway, where electronification of payment methods has been proceeding at a rapid pace (Humphrey et al 2000). Even if such fees are not charged, one should be able to use more efficient payment methods at reasonable cost. It might in fact be worth considering whether eg payment cards should be treated like cash as a public good, in order to ensure the efficiency of payment methods.

The Finnish banking sector is one of the most efficient in the world in the area of payment systems. One reason for this is that banks have worked within the Finnish Bankers' Association to develop more efficient electronic payment methods and have provided (mainly pricing) incentives for customers to use them. However, not all bank customers are able or want to change over to more efficient payment methods and such people do not benefit fully from banks' product development efforts.

Although generally speaking products developed by banks have ended up being used by customers, not all electronic payment methods have gained wide popularity. One example of such a failure is the e-money system Avant, which was expected to displace coins in small-value purchases. Sweden's comparable Cash system is reported to be slated for shut-down in autumn 2004. There are doubtlessly many reasons for e-money's lack of wide acceptance. For example, with the removal of the minimum purchase value also from debit and credit cards, one can use these cards to make such small-value purchases as had been planned for e-money.

It is of course possible that electronification of payment methods will not occur at the expected pace. For example, a change in the pricing of payment cards or a loss of customer confidence in new technologies could induce consumers to return to cash. On the other hand, consumers' confidence could be increased in connection with the ongoing changeover to the more secure EMV smart cards, and this could further accelerate the electronification of retail payment methods. New payment instruments and eg the growth of e-commerce would naturally increase the use of electronic payment methods.

6.1 Recommendations for future research

Because of a lack of time series data on pricing of different payment methods this factor had to be totally excluded from the present study. But because pricing is crucial for how consumers make payments it would be interesting to do cost-benefit analyses for different payment methods, from the perspectives of banks, stores and customers. Moreover, the error correction and partial adjustment models used here could be revised eg so as to be rooted in money demand theory.

It would also be interesting to work with an autoregressive model that makes use of the distribution of the error term to take account of the restriction of the dependent variable to the interval [0,1]. Such a model could take the form

$$\log C_t = \phi \log C_{t-1} + \log \varepsilon_t, \qquad \varepsilon_t \sim \text{Beta}(a,b), \qquad 0 < \phi < 1 \tag{6.1}$$

In equation (6.1), ε_t is thus Beta distributed and is in the interval [0,1]. In order to estimate the equation by the maximum likelihood method, we need to know the density function of the error term ε_t, which in this case is

$$\log\left(\frac{1}{\text{Beta}(\alpha,\beta)}\right) + (\alpha - 1)\log(C_t) + (\beta - 1)\log(1 - C)$$

where

$$\beta = \frac{\alpha - \left(\alpha\mu C_{t-1}^{\phi}\right)}{\mu C_{t-1}^{\phi}}$$

Consideration of a simultaneous equation model affords another interesting avenue of research. In connection with equation (5.4), one might well conjecture that cash-share (C), number of EFTPOS terminals (E), and number of cash dispensers (A) are simultaneously determined. The adjustment parameter estimates of section 5.1 that were outside of the interval [0,1] may also indicate that what is involved here is a system of several equations.

References

Attanasio, O P – Guiso, L – Jappelli, T (2002) **Demand for Money, Financial Innovation, and the Welfare Cost of Inflation: An Analysis with Household Data.** Journal of Political Economy, Vol. 110, No. 2.

Blanchflower, D G – Evans, D S – Oswald, A J (1998) **Credit Cards and Consumers.** NERA Working Papers, December.

Boeschoten, W (1992) **Currency Use and Payment Patterns.** Financial and Monetary Policy Studies, 23, Kluwer Academic Publishers, Norwell, MA, USA.

Bos, J W D (1993) **Effects of prepaid chipcards on note and coin circulation.** Research Memorandum WOE Nr. 9314, De Nederlandsche Bank, June.

Davidson, R – MacKinnon, J G (1993) **Estimation and inference in econometrics.** Oxford University Press.

Duca, J V – Whitesell, W C (1995) **Credit Cards and Money Demand: A Cross-sectional Study.** Journal of Money, Credit, and Banking, 27, 2. May, 604–623.

Hendry, D F (1995) **Dynamic econometrics.** Oxford University Press.

Van Hove, L (2002) **Electronic money and cost-based prising.** Wirtschaftpolitische Blätter (Economic Policy Papers, Austria), Nr. 2, April.

Humphrey, D – Pulley, L – Vesala, J (1996) **Cash, Paper and Electronic Payments: A Cross-Country Analysis.** Journal of Money, Credit, and Banking, 28, 4. November.

Humphrey, D – Kaloudis, A – Øwre, G (2000) **Forecasting Cash Use in Legal and Illegal Activities.** Norges Bank, Arbeidsnotat 2000/14.

Humphrey, D – Kaloudis, A – Øwre, G (2004) **The future of cash: falling legal use and implications for government policy.** Journal of International Financial Markets, Institutions and Money, 14, 221–233.

Jyrkönen, H. – Paunonen, H (2003) **Card, Internet and mobile payments in Finland.** Bank of Finland Discussion Papers 8/2003.

Mantel, B (2000) **Why Don't Consumers Use Electronic Banking Products? Towards a Theory of Obstacles, Incentives, and Opportunities.** Federal Reserve Bank of Chicago.

Markose, S – Loke, Y (2000) **Network effects on cash-card substitution in transactions and low interest rate regimes.** The Economic Journal, 113 (April), 456–476.

Paunonen, H – Jyrkönen, H (2002) **Cash usage in Finland – How much can be explained?** Bank of Finland Discussion Papers 10/2002.

Pere, P (2004) **Lecture notes on multivariate times-series.** University of Helsinki, spring 2004, exercise 10.1 vi) (in Finnish, unpublished).

Rinaldi, L (2001) **Payment Cards and Money Demand in Belgium.** University of Leuven, July.

Rowley, J C R – Trivedi, P K (1975) **Econometrics of Investment.** John Wiley & Sons.

Seber, G A F – Wild, C J (1989) **Nonlinear Regression.** Wiley, USA.

Shy, O – Tarkka, J (1998) **The market for electronic cash cards.** Bank of Finland Discussion Papers 21/1998.

Snellman, J – Vesala, J (1999) **Forecasting the Electronification of Payments with Learning Curves: The Case of Finland.** Bank of Finland Discussion Papers 8/1999.

Snellman, J – Vesala, J – Humphrey, D (2000) **Substitution of Noncash Payment Instruments for Cash in Europe.** Bank of Finland Discussion Papers 1/2000.

Verbeek, M (2000) **A guide to modern econometrics.** Wiley, Chichester, England.

Data sources

European Central Bank (2002) **Payment and securities settlement systems in the European Union** (Blue Book).

Luottokunta: **Annual reports**.

Bank of Finland (2004) **Economic outlook.** Bulletin 1/2004.

Bank of Finland: **databank**

Finnish Bankers' Association (1989) **Maksujärjestelmät ja pankkien jakeluverkot** (Payment systems and banks' distribution networks).

Finnish Bankers' Association (1992) **Maksujärjestelmät ja pankkien jakeluverkot vuosina 1987–1991** (Payment systems and banks' distribution networks, 1987–1991).

Finnish Bankers' Association (2003) **Tilastotietoja pankkien maksujärjestelmistä Suomessa 1993–2002** (Statistical data on the banks' payment systems in Finland 1993–2002).

Finnish Bankers' Association (2004) **Tilastotietoja pankkien maksujärjestelmistä Suomessa 1994–2003** (Statistical data on the banks' payment systems in Finland 1994–2003) (www.pankkiyhdistys.fi)

Statistics Finland: **national accounts 1984–2002**

Statistics Finland: **Vähittäiskaupan liikevaihto vuosilta 1993–2000** (Retail sales in 1993–2000).

Ministry of Finance (2003) **Työvoima 2020 -loppuraportti** (Labour force 2020 -final report).

Annex 1.

Data

Table 9. **Card payment values**

	Debit cards, EUR bn	Credit cards, EUR bn	Retailer cards, EUR bn	Online debit cards, EUR bn	E-money, EUR bn	Total, EUR bn
1984	0.3	0.4	0.6			1.3
1985	0.7	0.6	0.7			2.0
1986	1.2	0.7	0.7			2.6
1987	1.9	0.8	0.8			3.5
1988	3.0	0.8	0.7			4.6
1989	4.2	1.2	0.9			6.3
1990	5.3	1.6	1.0			7.9
1991	5.6	1.7	1.0			8.3
1992	5.7	1.7	1.1			8.5
1993	5.5	1.8	1.1			8.4
1994	5.9	1.9	1.3			9.1
1995	6.4	2.1	1.5			10.1
1996	7.0	2.4	1.6			10.9
1997	7.3	2.7	1.9		0.0002	11.9
1998	7.8	3.4	1.7		0.0003	12.9
1999	9.1	3.5	1.7		0.0009	14.2
2000	10.3	3.7	2.5	0.0	0.0012	16.4
2001	12.2	4.0	2.4	0.1	0.0015	18.6
2002	13.8	4.1	2.5	0.3		20.7
2003	14.8	4.2	2.5	0.7		22.3

Sources: Finnish Bankers' Association, ECB.

Table 10. **Cheque payments: value, number and estimated value**

	Value of cheque pymts (incl. bank bills), EUR bn	Number of cheque pymts, millions	Average value of debit card pymt, EUR	Estimated cheque pymts, EUR bn
1984	351	70.0	30.6	2.14
1985	407	64.0	29.8	1.91
1986	398	58.0	33.6	1.95
1987	457	50.8	34.5	1.75
1988	654	32.7	34.4	1.12
1989	696	23.2	33.8	0.78
1990	702	14.0	39.2	0.55
1991	820	9.9	38.1	0.38
1992	142	7.4	38.0	0.28
1993	182	6.7	38.5	0.26
1994	178	5.7	38.6	0.22
1995	180	4.0	39.3	0.16
1996	168	3.7	39.8	0.15
1997	123	2.8	41.0	0.11
1998	121	1.9	40.8	0.08
1999	110	1.4	41.9	0.06
2000	126	1.2	40.4	0.05
2001	108	1.0	41.9	0.04
2002	77	0.8	38.1	0.03
2003	60	0.8	35.7	0.03

Source: Finnish Bankers' Association.

Table 11. **Sales of lunch coupons, EUR bn**

	Lunch coupon sales, EUR bn
1984	0.06
1985	0.07
1986	0.09
1987	0.11
1988	0.13
1989	0.07
1990	0.08
1991	0.07
1992	0.06
1993	0.06
1994	0.05
1995	0.05
1996	0.06
1997	0.07
1998	0.07
1999	0.08
2000	0.09
2001	0.10
2002	0.11
2003	0.11

Source: Luottokunta.

Table 12. **Cash payments and private consumption (cash pymt = POS pymt – card pymt – cheque pymt – lunch coupons)**

	POS pymt, EUR bn	Card pymt, EUR bn	Cheque pymt (est.), EUR bn	Lunch coupons, EUR bn	**Cash pymt, EUR bn**
1984	18.0	1.3	2.14	0.06	**14.5**
1985	19.3	2.0	1.91	0.07	**15.4**
1986	20.5	2.6	1.95	0.09	**15.9**
1987	22.2	3.5	1.75	0.11	**16.9**
1988	24.1	4.6	1.12	0.13	**18.3**
1989	26.3	6.3	0.78	0.07	**19.2**
1990	27.5	7.9	0.55	0.08	**18.9**
1991	27.9	8.3	0.38	0.07	**19.2**
1992	27.5	8.5	0.28	0.06	**18.7**
1993	27.7	8.4	0.26	0.06	**18.9**
1994	28.3	9.1	0.22	0.05	**18.9**
1995	29.2	10.1	0.16	0.05	**18.9**
1996	30.4	10.9	0.15	0.06	**19.3**
1997	32.0	11.9	0.11	0.07	**19.9**
1998	33.5	12.9	0.08	0.07	**20.4**
1999	34.7	14.2	0.06	0.08	**20.3**
2000	36.6	16.4	0.05	0.09	**20.1**
2001	38.8	18.0	0.04	0.10	**20.6**
2002	40.1	20.7	0.02	0.11	**19.2**

Sources: Finnish Bankers' Association, Statistics Finland, Luottokunta, ECB.

Table 13. **Cash payments and retailers' turnover (cash payment = POS pymt – card pymt – cheque pymt – lunch coupons)**

	POS pymt, EUR bn	Card pymt, EUR bn	Cheque pymt (est.) EUR bn	Lunch coupons, EUR bn	**Cash pymt, EUR bn**
1984		1.3	2.14	0.06	
1985		2.0	1.91	0.07	
1986		2.6	1.95	0.09	
1987		3.5	1.75	0.11	
1988		4.6	1.12	0.13	
1989		6.3	0.78	0.07	
1990		7.9	0.55	0.08	
1991		8.3	0.38	0.07	
1992		8.5	0.28	0.06	
1993	26.1	8.4	0.26	0.06	**17.4**
1994	25.8	9.1	0.22	0.05	**16.5**
1995	27.2	10.1	0.16	0.05	**16.9**
1996	28.5	10.9	0.15	0.06	**17.4**
1997	30.4	11.9	0.11	0.07	**18.3**
1998	32.0	12.9	0.08	0.07	**19.0**
1999	33.0	14.2	0.06	0.08	**18.7**
2000	34.4	16.4	0.05	0.09	**17.8**
2001		18.0	0.04	0.10	
2002		20.7	0.02	0.11	

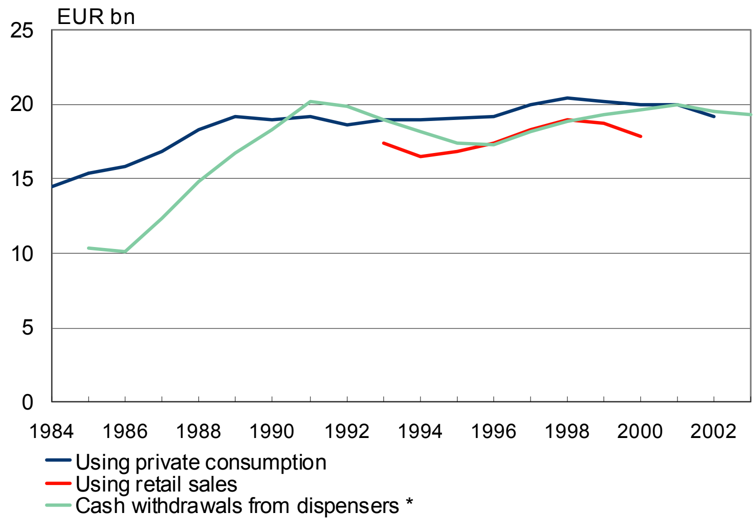
Sources: Finnish Bankers' Association, Statistics Finland, Luottokunta, ECB.

Table 14. **Cash payments and cash dispenser withdrawals**

	Cash dispenser withdrawal value, EUR bn	Dispenser share of cash withdrawals, Snellman–Vesala (1999) method	**Cash pymt, EUR bn**
1984			
1985	1.2	11 %	**10.3**
1986	1.8	18 %	**10.1**
1987	2.9	24 %	**12.3**
1988	4.5	30 %	**14.9**
1989	6.1	36 %	**16.7**
1990	7.8	43 %	**18.3**
1991	9.9	49 %	**20.2**
1992	10.9	55 %	**19.8**
1993	11.6	61 %	**18.9**
1994	12.3	68 %	**18.2**
1995	12.8	74 %	**17.4**
1996	13.8	80 %	**17.3**
1997	14.8	81 %	**18.2**
1998	15.6	83 %	**18.8**
1999	16.3	84 %	**19.3**
2000	16.8	86 %	**19.6**
2001	17.4	87 %	**20.0**
2002	17.3	89 %	**19.5**
2003	17.4	90 %	**19.3**

Sources: Finnish Bankers' Association, Bank of Finland.

Figure 9. **Value of cash payments: 3 calculation methods**



Sources: Finnish Bankers' Association, Luottokunta, ECB, Bank of Finland.

* As in Snellman and Vesala (1999), account is taken of the fact that cash dispenser popularity has grown gradually. Presently, about 90% of cash withdrawals are from dispensers; the rest from bank branches.

Annex 2

Learning curve model: analysis of residuals

Time series, fitting and residuals, estimation period 1984–2002

Figure 10. **Logistic model: time series, fitting and residuals**

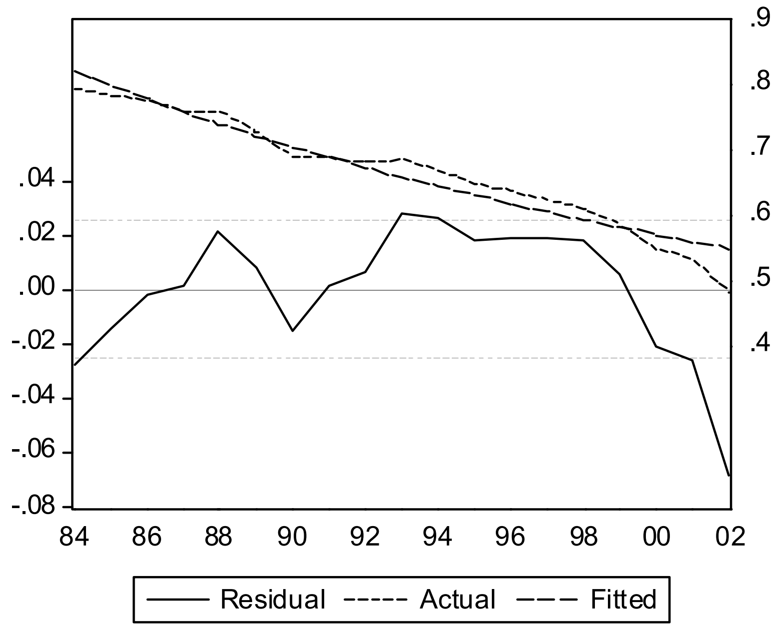
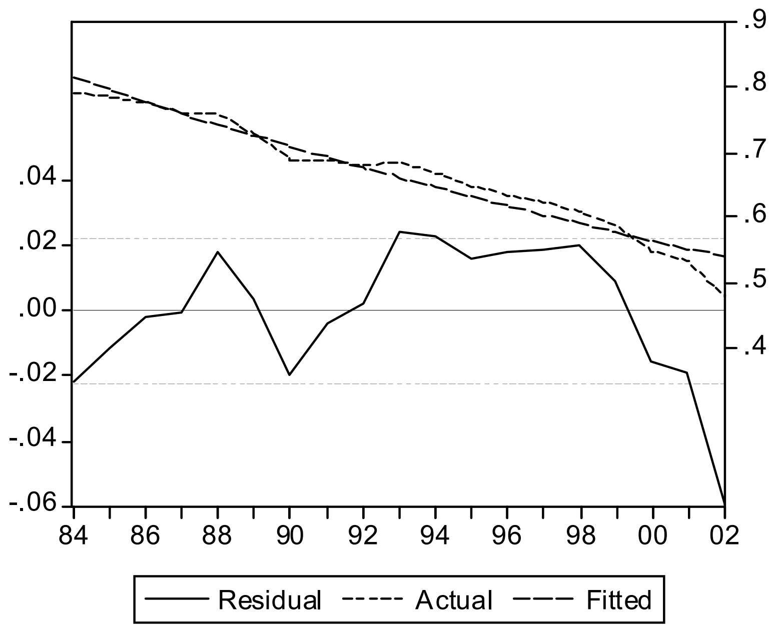


Figure 11. **Gompertz model: time series, fitting and residuals**



Annex 3

Dynamic regression model: analysis of residuals

Figure 13. **Model (5.4): time series, fitting and residuals**

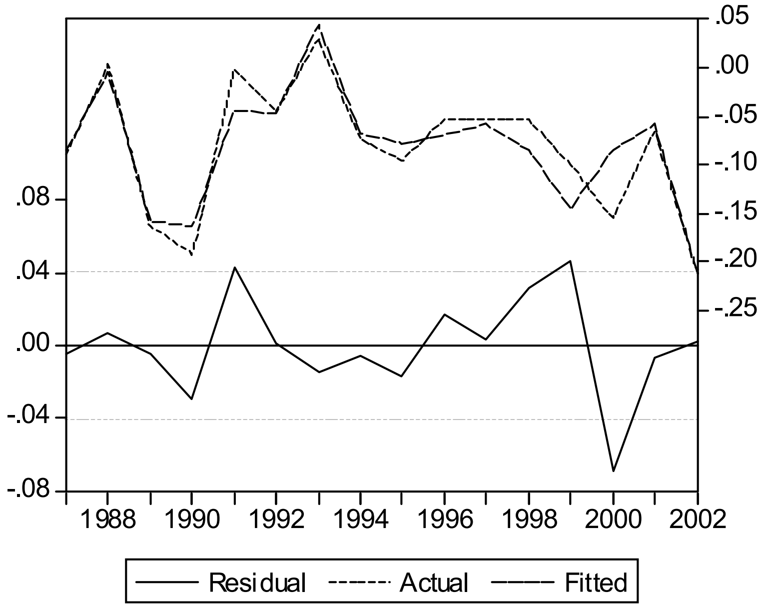


Figure 14. **Model (5.5): time series, fitting and residuals**

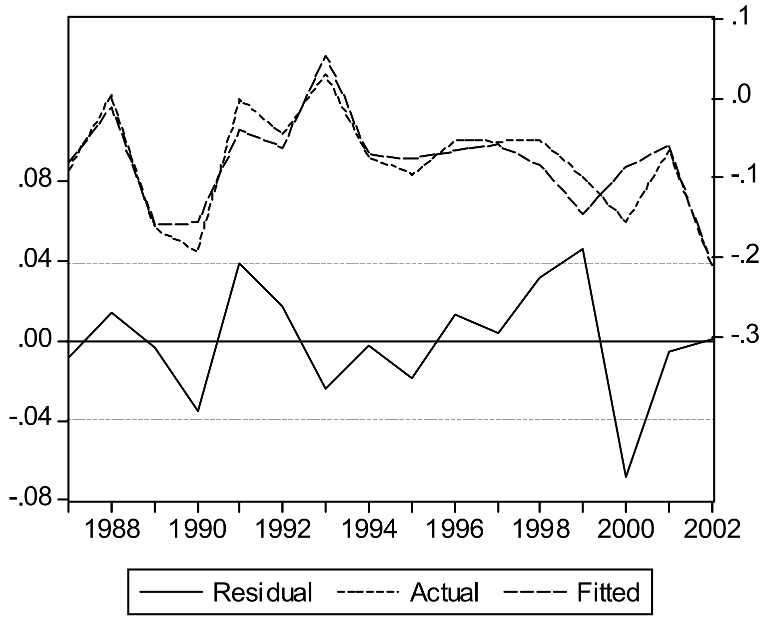


Figure 15. **Model (5.6): time series, fitting and residuals**

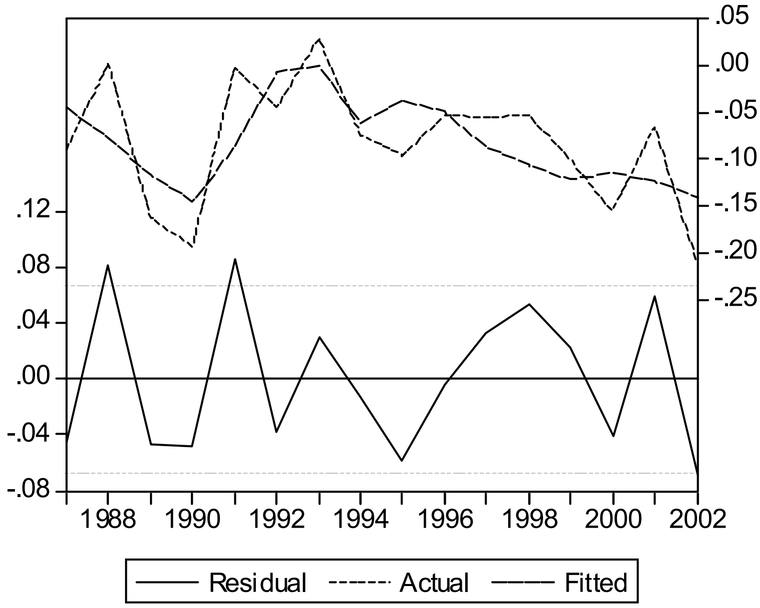


Figure 16. **Partial adjustment model: time series, fitting and residuals (equation (5.12))**

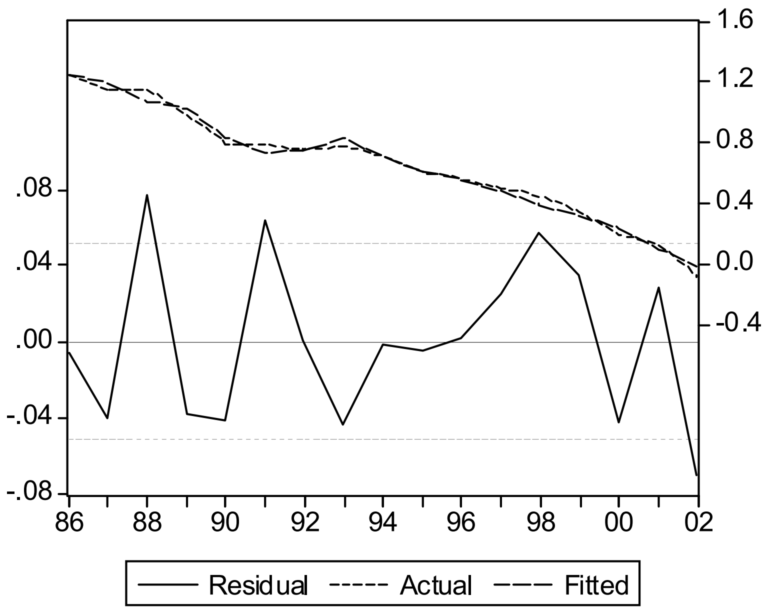
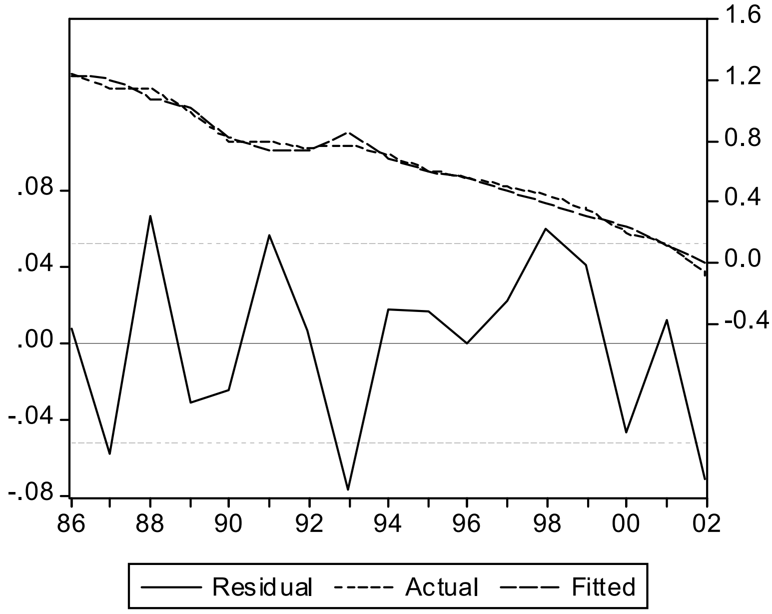


Figure 17. **Logistic regression analylsis: time series, fitting and residuals (equation (5.11))**



Annex 4

Forecast assumptions

Figure 18. **Actual and forecasted number of EFTPOS terminals**

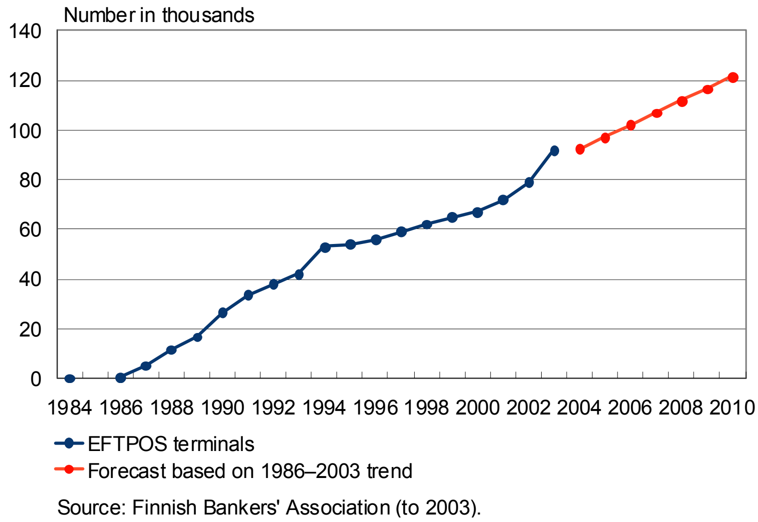


Figure 19. **Actual and forecasted number of cash dispensers**

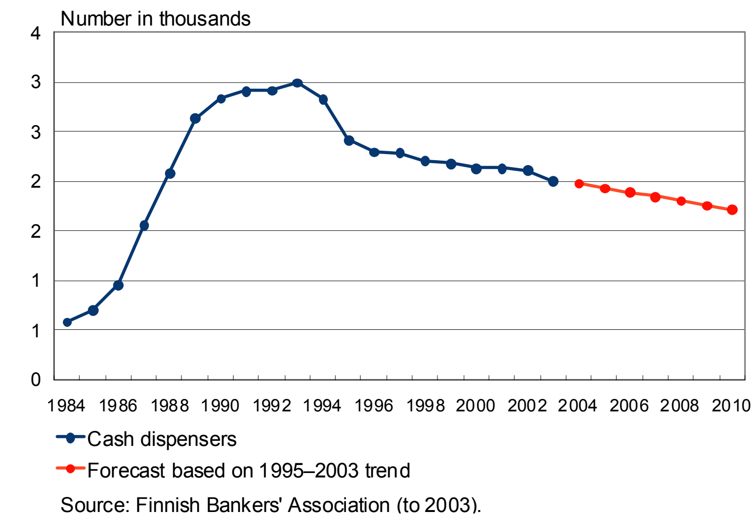
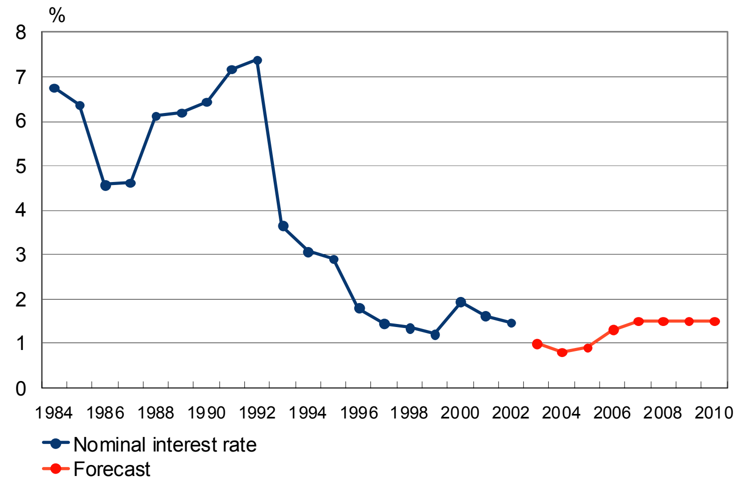


Figure 20. **Actual and forecasted nominal interest rate**



Source: Bank of Finland (to 2002).

Figure 21. **Actual and forecasted unemployment rate**

Sources: Bank of Finland (to 2006), Ministry of Finance (2007–2010).

Annex 5

Elasticities for partial adjustment model

If, instead of equation (5.12), one estimates

$$C_t = \beta_0 + \beta_1 E_t + \beta_2 A_t + \beta_3 i_t + \beta_4 U_t + \beta_5 C_{t-1} + \varepsilon_t \tag{A5.1}$$

where the dependent variable C is not log-transformed, the interpretation of parameters is much more straightforward than with the dependent variable log-transformed as in equation (5.12). Estimation results for equation (A5.1) are presented in table 15.

Table 15. **Estimation results for partial adjustment model (equation (A5.1))**

	Coef	t-value	Long-run coefficient	Average elasticity
β_0 (constant)	0.373	1.73	0.724	–
β_1 (AFT-POS terminals)	-0.003	-2.14	-0.006	-0.403
β_2 (cash dispensers)	0.018	1.32	0.035	0.112
β_3 (nominal interest rate)	-0.004	-0.87	-0.008	-0.047
β_4 (unemployment rate)	0.004	3.15	0.008	0.107
δ (= 1–adj parameter)	0.485	1.78	–	–
R^2		0.99		
Adj R^2		0.98		
Akaike information criterion		-5.71		
Schwarz information criterion		-5.41		
DW		2.22		

The results are very similar to those for model (5.11). In this model the adjustment parameter (0.52) is smaller than that for model (5.11).

According to Rowley and Trived (1975), the desired level C* can also be interpreted as the long-run equilibrium level. In this case, the parameters β_0 through β_4, obtained directly from equation (A5.1), are short-run parameters and those from equation (5.11), β_0^* through β_4^*, are long-run parameters. The connection between the short- and ling-run parameters is via the adjustment parameter, $1-\delta$. Writing equation (5.10) as

$$\beta \equiv (1-\delta)\beta^*$$

enables one to obtain the long-run parameters by dividing each short-run parameter by the adjustment parameter

$$\beta^* = \frac{\beta}{(1-\delta)}$$

The long-run parameters and respective average elasticities are given in table 15. The relationship between each independent variable's elasticity and the dependent variable is calculated by multiplying the independent variable's coefficient by the ratio of means of independent to dependent variable. Thus, for EFTPOS terminals, the elasticity is calculated as

$$\hat{\beta}_1\left(\frac{\overline{E}}{\overline{C}}\right) = -0.00582 * \frac{46{,}25}{0{,}668} = -0.403$$

where $\hat{\beta}_1$ is the coefficient estimate for EFTPOS terminals, $\overline{E}$ is the mean number of EFTPOS terminals, and $\overline{C}$ is the mean cash-share. The numerical result implies that a 1% increase in the number of AFT-POS terminals could reduce cash-share by 0.40%, and a 1% increase in the nominal interest rate would reduce cash-share by 0.05%. A 1% increase in cash dispensers or in the unemployment rate would increase cash-share by 0.11%. In evaluating the results, one should note that the coefficients for number of cash dispensers and nominal interest rate are not significant at the 95% confidence level.

As mentioned above, there is a fundamental problem with model (A5.1). Cash-share of POS payments (C) can take values only in [0,1], whereas the independent variables are not restricted to the interval. To get the dependent variable into unrestricted form, a log-transformation is performed. The transformed variable is used in all the dynamic regression models presented in this article, except in this annex. Despite the fundamental problem with model (A5.1), the results that it generated – and the forecast – are very close to those from all the other dynamic models. Therefore, one can perhaps have some confidence in the elasticity estimates presented in this annex as measures of the dependent variables' effects on the dependent variable.

BANK OF FINLAND DISCUSSION PAPERS

ISSN 0785-3572, print; ISSN 1456-6184, online

1/2004 Jukka Railavo **Stability consequences of fiscal policy rules.** 2004. 42 p. ISBN 952-462-114-2, print; ISBN 952-462-115-0, online. (TU)

2/2004 Lauri Kajanoja **Extracting growth and inflation expectations from financial market data.** 2004. 25 p. ISBN 952-462-116-9, print; ISBN 952-462-117-7, online. (TU)

3/2004 Martin Ellison – Lucio Sarno – Jouko Vilmunen **Monetary policy and learning in an open economy.** 2004. 24 p. ISBN 952-462-118-5, print; ISBN 952-462-119-3, online. (TU)

4/2004 David G. Mayes **An approach to bank insolvency in transition and emerging economies.** 2004. 54 p. ISBN 952-462-120-7, print; ISBN 952-462-121-5, online. (TU)

5/2004 Juha Kilponen **Robust expectations and uncertain models – A robust control approach with application to the New Keynesian economy.** 2004. 43 p. ISBN 952-462-122-3, print; ISBN 952-462-123-1, online. (TU)

6/2004 Erkki Koskela – Roope Uusitalo **Unintended convergence – how Finnish unemployment reached the European level.** 2004. 32 p. ISBN 952-462-124-X, print; ISBN 952-462-125-8, online. (TU)

7/2004 Berthold Herrendorf – Arilton Teixeira **Monopoly rights can reduce income big time.** 2004. 38 p. ISBN 952-462-126-6, print; ISBN 952-462-127-4, online. (TU)

8/2004 Allen N. Berger – Iftekhar Hasan – Leora F. Klapper **Further evidence on the link between finance and growth: An international analysis of community banking and economic performance.** 2004. 50 p. ISBN 952-462-128-2, print; ISBN 952-462-129-0, online. (TU)

9/2004 David G. Mayes – Matti Virén **Asymmetries in the Euro area economy.** 2004. 56 p. ISBN 952-462-130-4, print; ISBN 952-462-131-2, online. (TU)

10/2004 Ville Mälkönen **Capital adequacy regulation and financial conglomerates.** 2004. 29 p. ISBN 952-462-134-7, print; ISBN 952-462-135-5, online. (TU)

11/2004 Heikki Kauppi – Erkki Koskela – Rune Stenbacka **Equilibrium unemployment and investment under product and labour market imperfections.** 2004. 35 p. ISBN 952-462-136-3, print; ISBN 952-462-137-1, online. (TU)

12/2004 Nicolas Rautureau **Measuring the long-term perception of monetary policy and the term structure.** 2004. 44 p. ISBN 952-462-138-X, print; ISBN 952-462-139-8, online. (TU)

13/2004 Timo Iivarinen **Large value payment systems – principles and recent and future developments.** 2004. 57 p. ISBN 952-462-144-4, print, ISBN 952-462-145-2, online (RM)

14/2004 Timo Vesala **Asymmetric information in credit markets and entrepreneurial risk taking.** 2004. 31 p. 952-462-146-0, print, ISBN 952-462-147-9, online (TU)

15/2004 Michele Bagella – Leonardo Becchetti – Iftekhar Hasan **The anticipated and concurring effects of the EMU: exchange rate volatility, institutions and growth.** 2004. 38 p. 952-462-148-7, print, ISBN 952-462-149-5, online (TU)

16/2004 Maritta Paloviita – David G. Mayes **The use of real time information in Phillips curve relationships for the euro area.** 2004. 51 p. 952-462-150-9, print, ISBN 952-462-151-7, online (TU)

17/2004 Ville Mälkönen **The efficiency implications of financial conglomeration.** 2004. 30 p. 952-462-152-5, print, ISBN 952-462-153-3, online (TU)

18/2004 Kimmo Virolainen **Macro stress testing with a macroeconomic credit risk model for Finland.** 2004. 44 p. 952-462-154-1, print, ISBN 952-462-155-X, online (TU)

19/2004 Eran A. Guse **Expectational business cycles.** 2004. 34 p. 952-462-156-8, print, ISBN 952-462-157-6, online (TU)

20/2004 Jukka Railavo **Monetary consequences of alternative fiscal policy rules.** 2004. 29 p. 952-462-158-4, print, ISBN 952-462-159-2, online (TU)

21/2004 Maritta Paloviita **Inflation dynamics in the euro area and the role of expectations: further results.** 2004. 24 p. 952-462-160-6, print, ISBN 952-462-161-4, online (TU)

22/2004 Olli Castrén – Tuomas Takalo – Geoffrey Wood **Labour market reform and the sustainability of exchange rate pegs.** 2004. 35 p. 952-462-166-5, print, ISBN 952-462-167-3, online (TU)

23/2004 Eric Schaling – Sylvester Eijffinger – Mewael Tesfaselassie **Heterogeneous information about the term structure, least-squares learning and optimal rules for inflation targeting.** 2004. 47 p. 952-462-168-1, print, ISBN 952-462-169-X, online (TU)

24/2004 Helinä Laakkonen **The impact of macroeconomic news on exchange rate volatility.** 2004. 41 p. 952-462-170-3, print, ISBN 952-462-171-1, online (TU)

25/2004 Ari Hyytinen – Tuomas Takalo **Multihoming in the market for payment media: evidence from young Finnish consumers.** 2004. 38 p. 952-462-174-6, print, ISBN 952-462-175-4, online (TU)

26/2004 Esa Jokivuolle – Markku Lanne **Trading Nokia: The roles of the Helsinki vs the New York stock exchanges.** 2004. 22 p. 952-462-176-2, print, ISBN 952-462-177-0, online (RM)

27/2004 Hanna Jyrkönen **Less cash on the counter – Forecasting Finnish payment preferences.** 2004. 51 p. 952-462-178-9, print, ISBN 952-462-179-7, online (RM)