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Disposition in the Carbon Market and Institutional Constraints

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Abstract

This paper investigates the impact of banking and submission constraints, set by the EU Emission Trading Scheme, on the efficiency of the carbon permits spot market using intra-daily data. My aim is to identify whether there is a Disposition effect in the spot market. I will examine a data set that includes spot prices for the First and Second Phases of the Scheme from 24 June 2005 to 07 August 2009. I find that the Disposition effect is significantly high at the beginning of each Phase and decreases close to the first compliance event. In the light of these results I propose a lifting of the ban on banking between Phases and an increased emissions information disclosure in order to increase the efficiency of the Scheme.

JEL Classification: G11, G18, D84, Q48

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1 Introduction

The aim of the European Union Emission Trading Scheme (ETS) is to set up a platform for achieving a target reduction of CO₂ emissions in the most efficient way. In order to achieve

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the emissions target, each installation receives carbon permits on a yearly basis, which can be traded at one of the existing environmental trading platforms. The permits are valid only within the allocated Phase, and banking of permits between phases is not allowed.¹ By the end of March installations are required to submit enough permits to cover their yearly emissions. These institutional constraints allow installations to plan their investments and to also neutralise the irregularities of CO2 emission levels within each Phase.

However, such institutional constraints have also a negative effect on the efficiency of the market. Daskalakis *et al.* (2008) suggest that the behaviour of the carbon market is not consistent with weak-form efficiency according to which all the information contained in past prices is reflected in the current price. The authors demonstrate that permit returns are serially predictable and that simple trading strategies can be employed in order to produce substantial profits. The authors argued that one of the reasons that the carbon market is not efficient could be due to the restrictions imposed on permits banking. Spot prices for carbon permits also exhibit high volatility, where the highest decline followed the release of verified emissions in April 2006. Betz *et al.* (2006) suggest that spot price volatility has a profound impact on long-term investment risk and in turn can also affect the efficiency of the carbon market.

These institutional constraints can, therefore, have a potential negative effect on carbon market efficiency. Despite the importance of the topic, there is a scarcity of literature that analyses the role of institutional constraints in price dynamics and carbon market efficiency. Borak *et al.* (2006) find an overall increasing price volatility with an increase in maturity. These surprising results contradict the time to maturity effect that suggests a decline of price volatility as maturity increases. According to the authors these findings suggest that there is a high uncertainty in the market, which can result from the uncertainty with regard to the future allocation of the permits. Daskalakis *et al.* (2009) suggest, without providing empirical evidence, that the prohibition of banking permits between phases can have significant implications on the pricing of permits derivatives. The authors propose to lift the ban on banking in order to decrease the uncertainty in the market. Unrestricted

¹The First Phase covers the period from 2005 to 2007; the Second Phase covers the period from 2008 to 2012.

banking, in their opinion, increases efficiency in the market and leads to emissions reduction at the least possible cost. Chevallier *et al.* (2008) show that in the carbon market there is a relation between the institutional constraints and the modification of investors' subjective beliefs. The authors found a significant change in the risk aversion of traders in April 2006, when the actual figures on emissions were first published. However, the above studies do not provide an explanation for how those institutional constraints affect the evolution of the carbon permits price.

It is worth mentioning, however, those few studies that investigate the evolution of the carbon permits price. Bunn and Fezzi (2007) show that the price of permits and the price of energy in the UK have a major role in formulating each others' equilibrium price. The authors indicate that the permits price reacts quickly to shocks in gas prices; however, the pass through of shock in permits price to the electricity market is much slower. Extreme weather conditions are identified as one of the fundamental factors that determine permits price (Mansanet-Bataller *et al.*, 2007). Indeed, extreme temperatures affect the demand for energy. For instance, in cold winters there is an increased demand for heating. As a result, power generators increase their emissions and in turn the demand for permits increases as well. The significant effect of industrial indices on the determination of permits price is demonstrated by Alberola *et al.* (2007). The authors show that the price of permits reacts to the economic activity of the main sectors that are covered by the ETS. They point out that the announcement of the European Commission on verified emissions in 2006 revealed that prior to the announcement, trading had been based more on anticipation rather than the fundamental price mechanism. Benz *et al.* (2009) propose that due to different regimes in carbon price and volatility behaviour of returns, the AR-GARCH model outperforms constant volatility models.

Although the carbon permit is not a pure financial commodity in the usual sense as it expires at the end of each Phase, there seems to be a general consensus that it should be studied as such (among others see Kosobud *et al.*, 2002, Daskalakis *et al.*, 2009, Benz *et al.*, 2009). Explanations of the anomalies in the financial market can, therefore, assist in clarifying the role of the financial institutions' constraints in the context of the carbon market. One of the extensive fields of empirical finance incorporates psychological biases into the

analysis of investment decision making. One of the most documented psychological anomalies in financial literature is that of the Disposition effect. Disposition-prone investors tend to hold on to their losing assets, and realise their winning assets (Shefrin *et al.*, 1985). This tendency contradicts the rational behaviour of the market, where investors hold their winning assets and get rid of their losing assets. Another documented anomaly is the tendency of investors not to react to news, which creates a drift in price and return predictability. The risk aversion of the Prospect Theory type (Kahneman and Tversky, 1979) together with mental accounting explains both the Disposition effect (Grinblatt and Han, 2005) and the delayed reaction to news in the market (Frazzini, 2006).

In the light of the existing literature it seems that there is a place to analyse the effect of the Prospect type risk aversion, specifically the Disposition effect, on the pricing mechanism of carbon permits. I will contribute to the existing literature by evaluating the link between institutional constraints and the Disposition effect in the carbon market. I will investigate whether there is a change in the Disposition effect around compliance events of the First and Second Phases and towards the end of the First Phase. To perform my analysis I use a data set of intraday data from the BlueNext exchange platform (BlueNext Spot EUA 05-07, BlueNext Spot EUA 08-12, BlueNext Spot CER) a historical transactions data set recorded since 24 June 2005. Unlike Benz *et al.* (2009) and Chevallier *et al.* (2008) who use the GARCH process, I will use the ARMA process, which delivers estimations without remaining autocorrelation in the residuals. I will also use an additional dummy variable of capital gains that captures the Disposition effect in the market. To construct a capital gains variable I will follow a methodology proposed by Grinblatt and Han (2005). The authors show that disposition behaviour, where investors tend to hold their losing assets, has a predictive power on future returns. The use of high frequency data is necessary for a reasonable approximation of capital gains (Grinblatt and Han, 2005). High frequency data allows me to trace changes in Disposition that occur during the daily trade.

My findings suggest that the Disposition effect holds throughout the two sample periods. I have find that the Disposition effect significantly decreases after April 2006 and 2007, after the publication of verified emissions by the European Commissioner. These findings suggest that the compliance event that occurs between March and April has a significant effect on

shaping the behaviour of market participants. Specifically, the availability of information on total emissions contributes to the rational behaviour of the carbon market participants. My findings also show that after the first compliance event of the Second Phase the Disposition effect stabilises and remains constant throughout the rest of the period. These findings strengthen the argument that the first compliance event has a significant effect on the evolution of the carbon spot price and in turn the efficiency of the carbon market. Opposed to the proposition of Daskalakis *et al.* (2009), however, my finding shows no evidence of the effect of banking constraints on the risk perception in the market.

The remainder of the paper is organised as follows: Section 2 outlines the EU ETS structure, the BlueNext exchange platform and the data. Section 3 specifies the econometric model and discusses the results. I will also perform a robustness analysis of the results where various specifications of model and independent variables yield similar qualitative results. In section 4, I will test the relevance of institutional constraints in the context of the carbon market and provide policy recommendations. In Section 5 I present my conclusions.

2 EU ETS and BlueNext

The EU has introduced the Emission Trading Scheme to comply with the international emissions target commitment set by the Kyoto Protocol. The ETS is the first trading scheme to operate on the international scale so as to tackle global warming concerns. Each member state in the EU can achieve its obligations of reducing the total national emissions by using one of the flexible mechanisms set by the Protocol. Permits trading is one among the three mechanisms.² The first trade in carbon permits took place in 2005, three years prior to the protocol commitment period. The first three years of the scheme operation, which are usually referred to as First Phase (2005-2007), were aimed at adjusting the market to the emissions trade and smoothing the transactions of the market to the Protocol commitment period. This corresponds to the Second Phase (2008-2012) of the ETS. Each member state submits, prior to each Phase, its National Allocation Plan for approval by the European

²Clean Development Mechanism and Joint Implementation are additional mechanisms that aim to reduce emissions through projects that reduce emissions in foreign countries.

High Commissioner. The purpose of a NAP is to describe the allocation rules that govern the initial allocation of permits to installations, and the total of CO₂ that member states are to extract during each Phase. The total of emissions is referred to as a cap.

Most of the states chose to allocate their cap according to a relative historical benchmark, a method often labelled as grandfathering. For instance, according to the UK NAP for the Second Phase, allocation to installations is based on their relative production prior to the Phase, specifically during the period 2003-2005.³ Each permit allows extracting one tonne of CO₂ during the allocated Phase. An allocated permit expires at the end of each Phase, and the owner of the permit cannot bank it to cover emissions that are generated in a different Phase.⁴ The member states allocate permits to installations on a yearly basis, and the latter must submit enough permits to cover their yearly emissions. In April, when the submission process is over, the European High Commissioner publishes the verified figures of emissions for the previous year.⁵ The trade of the permits is open to the public. However, only a few sectors are covered by the NAPs. Only those installations whose historic production/emissions are above a predetermined threshold have to submit permits to cover their emissions.

There are currently a few trading platforms that allow the trade of emissions permits. Futures, options and Certified Emission Reduction (CER)⁶ are among the possible trading opportunities, in addition to the spot market available to traders. BlueNext Spot EUA is one of the leading spot exchanges for EU carbon permits with over 60 per cent of the market share in the spot exchange. It was founded by NYSE Euronext and Caisse des Depots, in December 2007. It consists of 101 members and has a 95 per cent market share. Futures and spots on EU permits as well as CER are traded on BlueNext. Cash held on account earns an interest rate of the Euro Overnight Index Average minus an eighth. The price tick is 0.01

³For a detailed description of NAP of the member states please visit the EU website: http://ec.europa.eu/environment/climat/emission_plans.htm.htm

⁴However, banking within the Phase is permitted.

⁵It is evident that the allocation of allowances for the First Phase of EU ETS has been too generous, as it is argued by environmental groups. This argument is debated by Ellerman and Buchner (2008). The authors argue that installations that abate for profit purposes would be considered as being in excess of permits.

⁶For more information on CER please see: <http://unfccc.int/2860.php>.

€/t, and the minimum price is 0.01 €/t. The volume tick is 1,000 tons and the minimum volume tick is 1,000 tons. Its trading hours are between 8:00 AM to 5:30 PM (UTC+1), from Monday to Friday. The delivery and settlement operated by BlueNext is in real time. Delivery consists of the transfer of the underlying permits from the seller's account to the buyer's account via a BlueNext transit account in the French registry for the EUA.⁷

2.1 Data description and regression

My data consists of a data set provided by BlueNext. The data set contains data of the spot prices and traded volumes of permits, including information about the date, time of trade and traded volume. The data is an irregular spread in time intra daily closing spot price from 24 June 2005 to 07 August 2009 amounting to total of 40,339 observations. The data set include data on permits for the First (BlueNext Spot EUA 05-07) and Second Phases (BlueNext Spot EUA 08-12), as well as some observations on CERs. I have divided the data set into two sets with observations related to the First and Second Phases. I do so in order to identify the effect of psychological biases on the price of permits for the First in contrast to the Second Phases. After excluding from the data set observations related to trade of CERs, in order to concentrate only on the price evolution of permits, the total number of observations is 37,924.

I denote P_t to be the spot price of carbon permit observation at time t . The log returns of carbon spot prices at time t is $r_t = \log \frac{P_{t+2}}{P_t}$. In order to account for high trading activity during the opening and closure of the market, I consider volatility adjusted returns $\tilde{r}_t = \frac{r_t}{s_T}$ where s_T denotes standard deviation of returns on the day r_t is observed. This way I construct a time series of standardised returns for the First and Second Phases, where the former consists of 4,927 and the latter of 32,997 observations. Figures 1 and 2 display the series of standardised log returns for both the First and Second Phases, respectively.

⁷The complete description of BlueNext is available at <http://www.bluenext.eu/>.

3 Disposition effect

In this section I will test whether in the market for carbon permits there exists a significant Disposition effect on the dynamics of carbon log returns.⁸ In what follows, I describe the capital gain specification of Grinblatt and Han (2005) and the statistical model. I conclude this section by performing a robust analysis which shows that my findings are robust to a different sampling, model and variable specification.

Table 1 documents the sample mean, standard deviation, minimum, maximum, median, skewness and kurtosis of the standardised log returns variable \tilde{r}_t . In the First Phase the log returns variable exhibits a slight deviation from the normal distribution by displaying a slight positive excess kurtosis, due to the high concentration of log returns around zero. In addition, log returns in the First Phase exhibit a slight positive skew. In contrast, in the Second Phase the standardised log returns exhibit a very high positive skew as well as a high kurtosis in comparison to the First phase. This may be due to a higher concentration of positive log returns in the Second Phase. Table 1 also reports a significantly high positive autocorrelation in the first lag for both First and Second Phases. There is no evidence for volatility clustering in the standardised log returns (Figures 1 and 2) in contrast to normal log returns (Figure 3 and 4). The latter suggests that volatility clustering in the log returns is mainly due to different regimes in daily trading activity.

I employ an ARMA specification to account for the autocorrelation in the log returns and unobserved shocks in the market. I will also consider a dummy variable for capital gains, which I will construct using a method similar to the one used by Grinblatt and Han (2005). As in Grinblatt and Han, I will construct a costs basis R_t as a proxy for the reference price of the permits portfolio. However, I lack the information on the real identity of the permit holders. To overcome this obstacle, Grinblatt and Han suggest that R_t can be approximated by $R_t = \sum_{n=1}^{\infty} \left(V_{t-n} \prod_{\tau=1}^{n-1} [1 - V_{t-n+\tau}] \right) P_{t-n}$, where $V_{t-n} \prod_{\tau=1}^{n-1} [1 - V_{t-n+\tau}]$ is a probability that a permit has been purchased at date $t-n$ and V_t is a turnover ratio. However, unlike Grinblatt and Han, I propose an alternative proxy for the turnover variable V_t at each point of time

⁸For evidence of the effect of psychological bias on the dynamics of prices in emerging markets see, among others, Tan *et al.*, 2008 and Chen *et al.*, 2007.

t . The proxy that I will use consists of the total number of traded permits the day the observation t is taken and the total number of traded permits at each observation point t . V_t is the proxy for turnover ratio, which represents the probability of buying an additional asset and is expressed in the following manner:

$$V_t = \frac{\text{Total of traded permits at each observation point } t}{\text{Total of traded permits the day observation } t \text{ is taken}}$$

I define capital gains g_t at time t as the log of the spot price of carbon permit P_t and the reference price R_t , which is $g_t = \log \frac{P_t}{R_t}$. Similar to Grinblatt and Han (2005) I employ g_{t-1} instead of g_t in the regression so as to avoid market microstructure effect, such as bid-ask bounce. To evaluate the Disposition effect in the carbon market, I have employed an ARMA(1,1) specification where I include the capital gain proxy variable g_t . This gives way to

$$r_t = +\alpha g_{t-1} + \phi r_{t-1} + \varepsilon_t + \varphi \varepsilon_{t-1} \quad (1)$$

where ε_t is iid. The capital gains coefficient α represents the Disposition effect on the log-returns. According to the theoretical framework of Grinblatt and Han (2005), the Disposition effect prevails in the market if the coefficient $\alpha > 0$.

3.1 Estimation results

I estimate by least-squares Equations (1) for the series of log returns for the First and Second Phases. I report the results in Table 3. I have employed the ARMA(1,1) process, as the latter copes better with autocorrelation in the residuals than the AR(1) process. The Q-statistics of the Ljung-Box test (1978) show that an MA(1) component is necessary to cope with the first order autoregressive structure in the log returns for two Phases. The results of the Ljung-Box test (1978) show no evidence of a remaining autocorrelation in the residuals up to the 13th order. I proceed, therefore, to the analysis of the estimates. All of the coefficients reported in Table 3 are significant.

Table 3 also reports that there is a significant momentum which arises from the strategies that form portfolios from the first autoregressive and moving average components ϕ and φ ,

respectively. However, the most important result comes from the variable of capital gains. The significant coefficient of α suggests that there is a significant positive effect on the returns coming from the capital gains variable. This is consistent with the Disposition effect reported by Grinblatt and Han (2005). Altogether, my findings indicate that during the First and Second Phases of ETS the price of carbon permits is affected by the Disposition tendency of traders in the market.

3.2 Robustness analysis

To evaluate the sensitivity of my findings I will perform a robustness analysis of the predicted coefficient on capital gains. In particular, I will test whether there are qualitative changes in the coefficient due to variations in the sample period, capital gains variable and model specifications. First, I will divide the data set into five subsamples: 2005, 2006, 2007, 2008 and 2009. The main goal is to show that during all the sub-periods of First and Second Phases of the Scheme capital gains have a significant positive effect on the log returns. Results of the Ljung-Box test (1978) in Table 4 show no evidence for the remaining autocorrelation in the residuals. The capital gains variable is still positive and significant. This suggests that my findings are robust to the sampling of the data. Another interesting feature of the subsample results is that there is a significantly high effect coming from the capital gains at the beginning of the each Phase. These latter findings may suggest that during the first year of each Phase market participants, on average, are more Disposition-prone than during the rest of the Phase. This may be due to the novelty of the market and/or commodity during the First Phase and the lack of information on the commodity price fundamentals during the Second Phase. As the market becomes more mature, the Disposition effect diminishes.

Secondly, I will consider an alternative capital gains variable that tests the sensitivity of my results to a different specification of the capital gains variable. To construct a new reference, instead of using reference R_t , I will set my reference to be a maximum past price (Heath *et al.*, 1999). I will take a maximum of the past 30 observations to be my alternative reference $\widetilde{R}_t = \max(P_{t-30}; P_{t-1})$. The new capital gains variable is, therefore, $\widetilde{g}_t = \log \frac{P_t}{\widetilde{R}_t}$. Table 4 shows that the alternative specification of the capital gains does not affect the

qualitative result which suggests that the capital gains variable is positive and significant in both Phases. I, therefore, conclude that the significant predictive power of the capital gains is not an artefact of the way I have constructed it.

Thirdly, I will test whether my results are due to the standardisation of log returns. Table 2 documents the sample mean, standard deviation, minimum, maximum, median, skewness and kurtosis of the log returns variable r_t . The log returns variable exhibits a positive excess kurtosis both in the First and Second Phases, due to the high concentration of log returns around zero. In addition, log returns in the First Phase exhibit negative skew, due to a larger concentration of negative log returns. However, in the Second Phase the log returns exhibit positive skew, due to a larger concentration of positive log returns. Table 2 also reports significantly high positive autocorrelation in the first two lags for First and Second Phases (in addition to the volatility clustering which is evident from Figure 3 and 4). I will, therefore, employ an ARMA(1,1)-GARCH specification to estimate the evolution of carbon spot log returns similar to Benz *et al.*, (2009) who consider AR-GARCH and Borak *et al.*, (2006) who consider MA-GARCH specifications. I will employ an ARMA(1,1)-GARCH(1,1) specification to account for the autoregressive component in addition to volatility clustering in the log returns. As before, I will include the capital gain variable g_t . This gives way to

$$r_t = \alpha_0 + \alpha_1 g_t + \phi_1 r_{t-1} + \varepsilon_t + \varphi_1 \varepsilon_{t-1} \quad (2)$$

$$\varepsilon_t = u_t \sigma_t \quad (3)$$

$$\sigma_t^2 = \beta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \sigma_{t-1}^2 \quad (4)$$

where $\varepsilon_t \sim iid(0, 1)$. Table 5 reports the estimated coefficients of Equation (2). Although the ARMA-GARCH specification cannot cope with autocorrelation in the residuals, the overall results indicate that there is a significant Disposition effect in the market both in the First and the Second Phases.

To conclude, my results provide robust evidence of the Disposition effect in the carbon market during the First and Second Phases. It is my next task to provide an explanation as to the cause of such an effect and how to diminish it. In the next section I suggest that

the institutional constraints of the Scheme are the main cause for increasing the Disposition effect in the market.

4 Institutional Constraints

In this section I will estimate Equation (1) for changes in the capital gains variable due to institutional constraints. The most important institutional features of the ETS are twofold: firstly, there is a statutory obligation for installations to submit their verified emissions by the end of March each year. The installations are obliged to submit enough permits to cover their yearly emissions. By the end of April, actual emissions figures are revealed to the market. The market, however, learns of the actual emissions prior to the publication of the actual emissions when the market is updated with the actual emissions figures. From the demand for permits in the carbon market, the traders can learn whether the market has a surplus or deficit of permits. If there is, therefore, a strong signal in the market of the real value of the permits, it can diminish the effect of psychological biases on the carbon price during and/or after the publication of official figures for the total emissions levels.

Secondly, there is a ban on permits banking between First and Second Phases.⁹ There is an argument in the literature that the banking prohibition has an effect on the efficiency of the carbon market (Daskalakis et al., 2008). This effect, however, has not been tested so far and no direct evidence points to that. The argument in favour of abandoning the ban is that during the transition period between Phases, there is a loss of installations' flexibility to adhere to the emissions limitation and the ban on banking can increase inefficiency towards the end of each Phase. This constraint, in turn, affects the efficiency of the trade (Schleich et al., 2006). In addition, at the beginning of each Phase market participants have to re-establish their expectations and learn the new commodity mechanism. This in turn creates uncertainty and may increase psychological biases at the beginning of each Phase.

In order to detect how these institutional constraints affect the price evolution in the market, I will conduct a two-step analysis. Firstly, I will trace the evolution of estimates for the capital gains coefficient throughout the First and Second Phases. Figures 5 and 6 provide

⁹Banking is suggested for the Third Phase of ETS.

a plot of α for the capital gains estimator for both First and Second Phases, respectively. Figure 5 shows a dramatic jump downwards which indicates a structural break in the data during the first compliance event in April 2006. This coincides with the release of official figures for total emissions. These results are in line with findings reported by Chevallier *et al.* (2008) who detected a dramatic change in the market perception of risk during the 2006 compliance event. After the first compliance event the coefficient slightly increased up until the second compliance event in April 2007, and decreased toward the end of the First Phase. Figure 6 shows no dramatic changes occurred in the Second Phase. The plot of α coefficient, however, stabilised after the first compliance event in April 2008. In addition, Figure 5 and 6 indicate that at the beginning of each Phase the α coefficients were significantly higher than during the rest of the Phase and decreasing toward the first compliance event.

Secondly, I will divide the data set into three subsamples categories: Jan-Feb, Mar-Apr and the rest of the year. The first two subsamples detect changes in the Disposition effect before and during the submission of verified emissions, respectively. Whereas the latter subsample distinguishes the magnitude of Disposition during the rest of the year from the two submission periods, Tables 6 and 7 report the results. It is evident from the results that during the Mar-Apr subsamples for the First and Second Phases capital gains variables are significantly lower than during the preceding year subsamples. This coincides with the results of the two plots of α coefficient.

These findings suggest that, whereas banking prohibition increases Disposition in the market at the beginning of each phase, the first compliance events significantly diminish it and contribute to the stabilisation of market expectations. Such behaviour of the capital gains coefficient can be attributed to the degree of information uncertainty in the market. The literature recognises that psychological biases are increasing under conditions of higher information uncertainty (Hirshleifer, 2001; Daniel *et al.*, 2001 and Zhang, 2006). When the market learns its real position, fewer participants are subject to psychological biases. This explanation is also in line with the framework proposed by Grinblatt and Han (2005). According to the authors, the smaller the number of investors who are subject to Disposition, the smaller their effect on the market price.

These results validate the proposition that institutional structure has an effect on the

efficiency of the carbon market, which is transformed to a high Disposition effect, as I have reported above. The results point out that Disposition in the carbon market is a factor of information uncertainty, especially during the first year of each Phase. In addition, the above results indicate that the first compliance event has a vital role in shaping the expectations in the market, by stabilising and/or diminishing the Disposition in the market. The question that arises is how to eliminate, or at the very least diminish, the Disposition in the market. The purpose of the next section is to address these questions.

4.1 Discussion and analysis

In previous sections I have demonstrated that the price trend in the market for carbon permits can be explained by assuming psychological biases, specifically, the Disposition effect. It is not surprising to find the Disposition effect in the market of carbon permits in light of extensive evidence, which tracks this phenomenon in financial markets. In the context of the carbon market, however, these results should receive major attention. The policy designer should seek and eliminate the Disposition that affects trade of carbon permits. Identifying the source of the Disposition effect in the institutional structure of the Scheme should allow the policy maker to diminish its effect and increase the efficiency of the carbon market.

As I have pointed out in the previous section, institutional constraints on the installation during the First and Second Phases of the Scheme operation, such as yearly submission and a ban on banking of permits, are the main drivers of the Disposition effect. Policy makers who wish to achieve emissions abatement in the most efficient manner should, therefore, not disregard these findings. These results point out that the carbon market, which should create an efficient environment for trade of carbon permits, is not efficient due to those constraints. Similar results have already been pointed out by Daskalakis *et al.* (2008) and Chevallier *et al.* (2008).

The above results indicate that before the first compliance event the Disposition effect is higher than during the rest of the year. As I suggested above, this could be due to information uncertainty. One suggestion that may reduce the Disposition in the market is to make the information on the emissions level public. Installations that trade carbon permits

should reveal their emissions intensity and make it publicly accessible throughout the year rather than once a year. A similar method is already practiced in the stock exchange market where publicly traded companies are required to make their information public on a regular basis. It seems reasonable to make emissions levels publicly known as the benefit would be in the highly efficient carbon trading platform, which would benefit both the installations, for having an efficient trading platform, and the public, in the way of an efficient abatement system.

Another way of reducing the information uncertainty as to the market position with respect to the carbon permits would be by engaging installations to submit permits to cover their emissions more frequently than once a year (a frequency that is suggested by current practice). This way the information gets to the market more frequently. This may eliminate such dramatic changes in the market expectations as were evident during the First Phase. It may also reduce the uncertainty in the market and in turn reduce the effect of psychological biases on the carbon price in a more consistent way, without creating unnecessary shocks to the system. The information uncertainty is to be diminished to make way for the efficient market of carbon permits. Reducing the uncertainty by revealing the information may reduce the psychological biases of the traders and create a more efficient market. These suggestions are in line with a proposition made by Seifert *et al.* (2008). The authors argue that in immature markets, such as the carbon market, expectation building is not working well. In such conditions frequent publication of emissions would improve expectation building in the market.

The results of the previous section also point to another flaw of the Scheme, which is the ban on banking between Phases. The results show that this constraint increases the Disposition effect at the beginning of each Phase. This flaw is addressed by the literature (among others see, Schleich *et al.*, 2006 and Alberola *et al.*, 2009). Indeed, in the proposal for the Third Phase of ETS, the banking ban is dropped. This proposition could contribute to the efficiency of the carbon market. The installations would not have to face the lack of information during the beginning of each Phase, and would be rewarded for carbon intensity, which could be planned for the future and not limited to only one Phase.

5 Conclusions

There is a scarcity of literature dealing with the fundamentals of the carbon price. My contribution to this literature is in presenting the first evidence of the Disposition effect in the carbon market, based on the spot price of carbon permits on the BlueNext trading platform from 24 June 2005 to 07 August 2009. The sample covers for the First and Second Phases of the EU Emissions Trading Scheme.

In the paper I presented evidence for the Disposition effect, which increases as a result of the institutional constraints, specifically the ban on banking and the yearly submission of the verified emissions. The estimated results indicate that the carbon price evolution is affected by the Disposition effect during the first year of each Phase. I assert that the main factor that drives the Disposition effect in the carbon market is information uncertainty. I have found that these results are robust by using an alternative method of tracing the Disposition effect. My results are in line with the previous evidence of the efficiency of the carbon market and findings that the Disposition has a positive effect on the evolution of price in the market.

I have suggested possible alternatives to resolve uncertainty in the market. Specifically, I have suggested revealing the information on the actual emissions level throughout the year and not only once a year. In addition, I suggest that more frequent submission of the verified emissions could reduce the Disposition effect in the market and make it more efficient. My finding also point out that the banking ban increases the psychological effect during the first year of each Phase.

It is worth mentioning, however, besides the possible policy implications outlined above that these new results have an important implication for portfolio construction and risk management. For further research it would be interesting to follow the evolution of the carbon price during the rest of the Second Phase and see whether there are changes in the market due to the alternations of institutional constraints in the Third Phase of the Scheme. Although I present evidence on one of the well-documented behavioural anomalies in the financial markets, there is place to extend current research and analyse the market for another source of inefficiency in the market. Detailed information on the identity of traders

could potentially contribute to more accurate analysis and policy recommendations.

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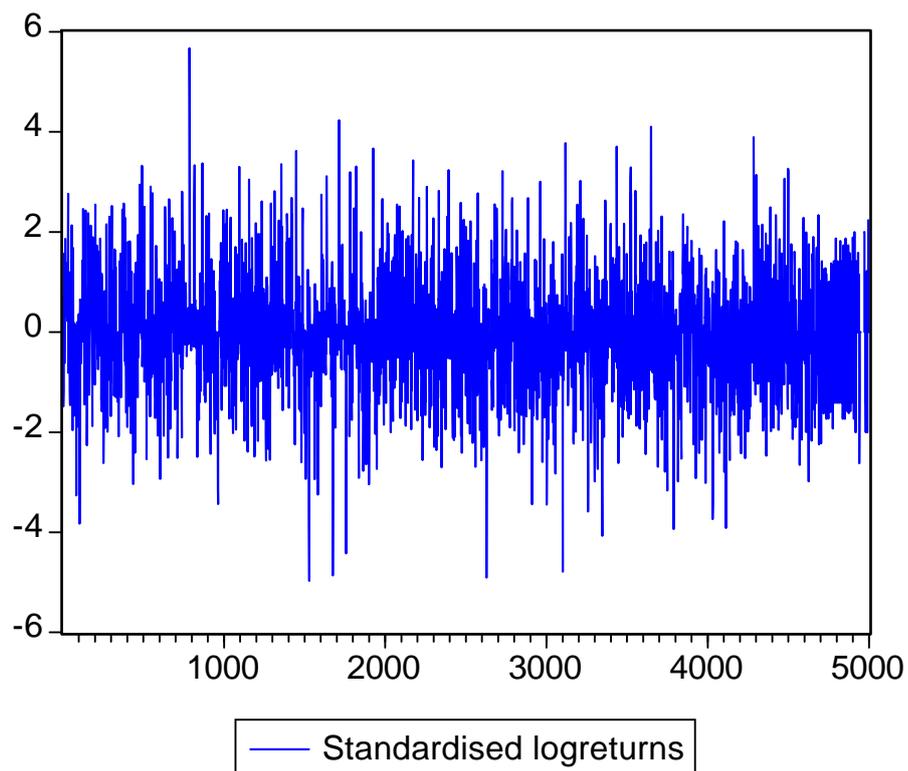


Figure 1: The figure shows the standardised log returns of carbon permit prices from 24 June 2005 to 27 February 2008, including all together 4,927 observations.

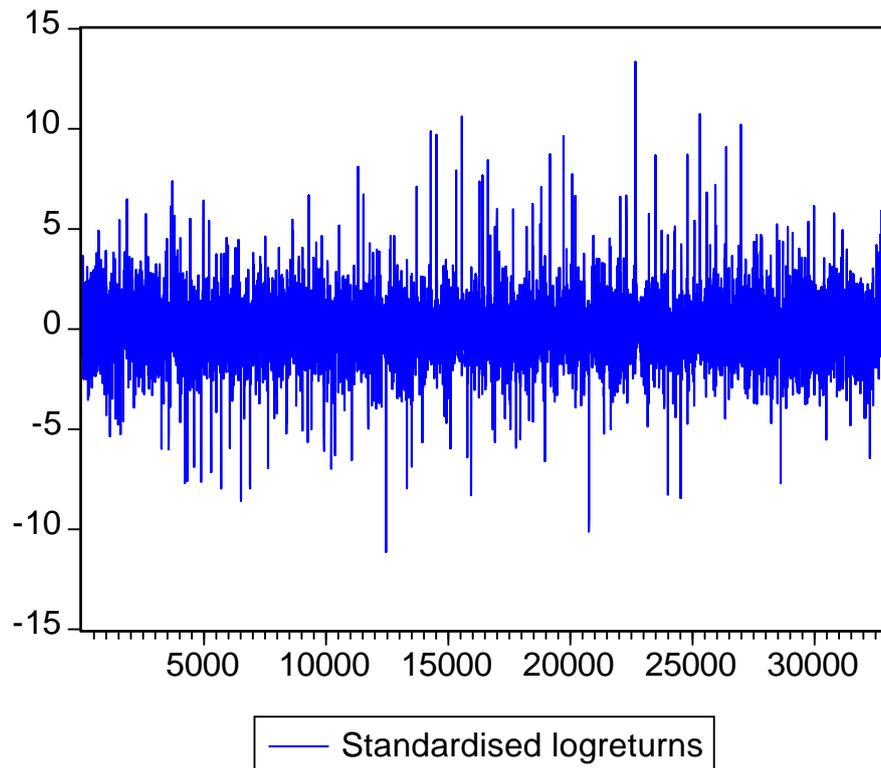


Figure 2: The figure shows the standardised log returns of carbon permit prices from 29 February 2008 to 07 August 2009, including all together 32,997 observations.

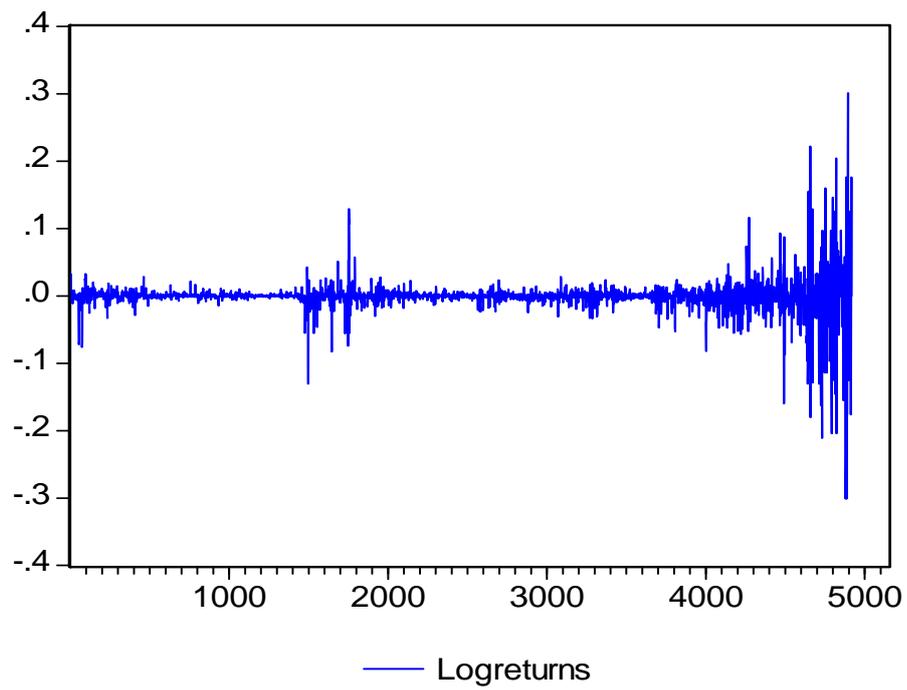


Figure 3: The figure shows the log returns of carbon permit prices from 24 June 2005 to 27 February 2008, including all together 4,927 observations.

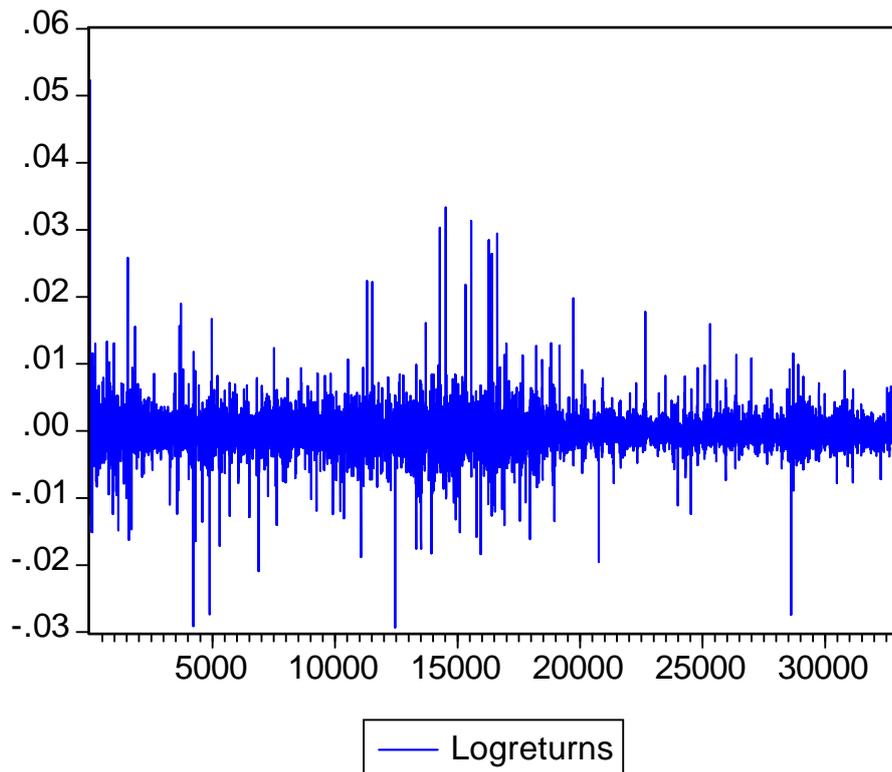


Figure 4: The figure shows the log returns of carbon permit prices from 29 February 2008 to 07 August 2009, including all together 32,997 observations.

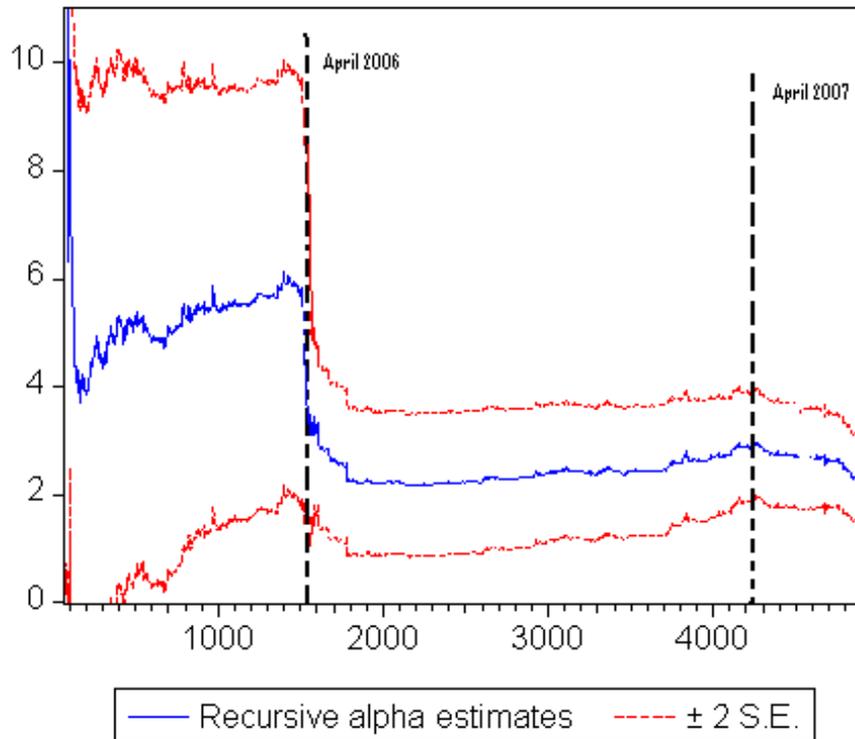


Figure 5: The figure shows the evolution of alpha coefficient for the First Phase of the Scheme from 24 June 2005 to 27 February 2008, including all together 4,927 observations. The dotted vertical lines point to the first and second compliance events, respectively.

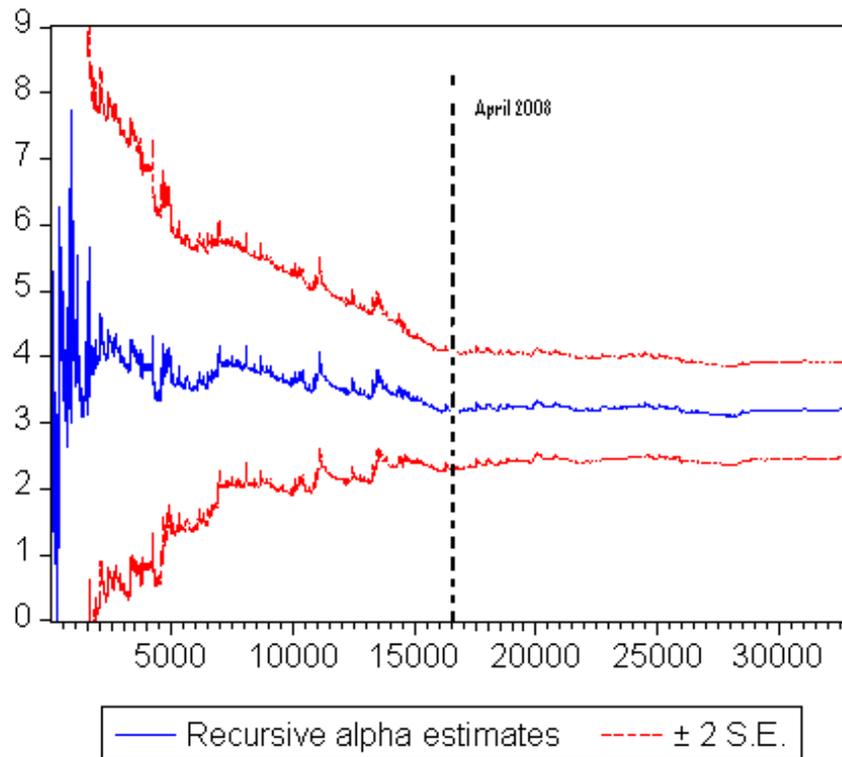


Figure 6: The figure shows the evolution of alpha coefficient for the Second Phase of the Scheme from 29 February 2008 to 07 August 2009, including all together 32,997 observations. The dotted vertical line points to the first compliance event.

Table 1: Descriptive statistics for the series of standardised log returns

The two sample period run from 24 June 2005 to 13 August 2009. I excluding from the data set observations related to trade of CERs, in order to concentrate only on the price evolution of EUAs. I compute the log returns and standardise them by the standard deviation for the day the log returns are computed. The total of observations is 37,924.

	First Phase	Second Phase
sample mean	-0.031	-0.004
sample median	0.000	0.000
sample maximum	5.671	13.341
sample minimum	-4.968	-11.127
sample standard deviation	0.999	1.000
sample skewness	0.036	0.389
sample kurtosis	5.001	18.017
number of observations	4,927	32,997
<i>n</i> th order autocorrelation		
<i>n</i> =1	0.456	0.472
<i>n</i> =2	-0.002	-0.011
<i>n</i> =3	0.021	0.022
<i>n</i> =4	0.012	0.018
<i>n</i> =5	0.011	0.009
<i>n</i> =6	0.018	0.010
<i>n</i> =8	0.020	0.011
<i>n</i> =10	0.016	0.010
<i>n</i> =11	0.009	0.011
<i>n</i> =13	-0.006	0.027

Table 2: Descriptive statistics for the series of logreturns

The two sample period run from 24 June 2005 to 13 August 2009. I exclude from the data set observations related to trade of CERs, in order to concentrate only on the price evolution of EUAs. The total of observations is 37,924.

	First Phase	Second Phase
sample mean	-0.001	0.000
sample median	0.000	0.000
sample maximum	0.301	0.043
sample minimum	-0.301	-0.029
sample standard deviation	0.022	0.001
sample skewness	-1.558	0.781
sample kurtosis	52.502	51.274
number of observations	4,927	32,997
<i>n</i> th order autocorrelation		
<i>n</i> =1	0.433	-0.015
<i>n</i> =2	-0.099	-0.489
<i>n</i> =3	-0.089	0.021
<i>n</i> =4	-0.078	0.000
<i>n</i> =5	-0.019	-0.006
<i>n</i> =6	-0.017	-0.001
<i>n</i> =8	-0.009	-0.005
<i>n</i> =10	0.012	0.007
<i>n</i> =11	0.043	0.010
<i>n</i> =13	0.012	-0.002

Table 3: Estimation results

I estimate by least squares the AR(1) and ARMA(1,1) models in Equation (1) for the First and Second Phases, with period that runs from 24 June 2005 to 07 August 2009, including all together 37,914 observations. For each parameter estimate, the figures within parenthesis refer to the White's (1980) robust t-statistics. The row Q-stat. reports Q-statistics of Ljung-Box's test (1979) for autocorrelation in the residuals up to order 13. The row sample size reports the number of observations.

	First Phase		Second Phase	
	ARMA(1,1)	AR(1)	ARMA(1,1)	AR(1)
α	2.036 (5.922)	0.465 (1.397)	3.220 (9.493)	0.305 (0.807)
ϕ	-0.037 (-1.706)	0.457 (43.867)	-0.046 (-4.384)	0.472 (39.173)
φ	0.730 (24.229)		0.869 (58.932)	
R^2_{Adj}	0.322	0.208	0.401	0.222
Q-stat.	0.367	0.000	0.367	0.000
sample size	4,914	4,915	32,997	32,997

Table 4: Robustness analysis: Sub-sampling and specification

I estimate by least squares ARMA(1,1) model in Equation (1) for the period that runs from 24 June 2005 to 07 August 2009, including all together 37,914 observations. The columns of 'subsample estimations' consider yearly subsamples and columns of 'alternative specification' consider capital gains variable with alternative reference. For each parameter estimate, the figures within parenthesis refer to the White's (1980) t-statistics. The row Q-stat. reports Q-statistics of Ljung-Box's test (1979) for autocorrelation in the residuals up to order 13. The row sample size reports the number of observations.

	sub-sample estimations					altrenative specification	
	2005	2006	2007	2008	2009	First Phase	Second Phase
α	11.192 (4.355)	3.969 (4.662)	1.774 (3.045)	9.499 (6.693)	4.710 (6.775)	1.926 (5.125)	17.566 (14.098)
ϕ	0.021 (0.333)	-0.040 (-1.476)	-0.006 (-1.522)	-0.072 (-3.829)	-0.043 (-3.410)	-0.041 (-2.064)	-0.045 (-4.244)
φ	0.669 (15.883)	0.747 (49.503)	0.726 (25.091)	0.847 (102.828)	0.881 (184.344)	0.734 (53.251)	0.868 (203.151)
R^2_{Adj}	0.324	0.335	0.288	0.376	0.412	0.326	0.404
Q-stat.	0.933	0.691	0.187	0.920	0.673	0.978	0.367
sample size	628	3,055	1,240	9,543	23,454	4,697	32,970

Table 5: Robustness analysis: ARMA-GARCH

I estimate by maximum likelihood the ARMA(1,1)-GARCH(1,1) models in Equations (3) and (5) for the First and Second Phases, with period that runs from 24 June 2005 to 07 August 2009 , including all together 37,914 observations. For each parameter estimate, the figures within parenthesis refer to the t-statistics. The row Q-stat. reports Q-statistics of Ljung-Box's test (1979). The row ARCH LM reports the p-value of Engle's (1982) LM test for autoregressive conditional heteroskedasticity up to order 13. The row sample size reports the number of observations.

	First Phase	Second Phase
α_1	0.074 (11.304)	0.005 (5.745)
ϕ_1	-0.011 (-0.687)	-0.085 (-6.262)
φ_1	0.963 (277.728)	0.997 (837324.2)
β_0	0.000 (33.231)	0.000 (5.103)
θ_1	0.094 (52.991)	0.262 (7.501)
θ_2	0.927 (772.548)	0.640 (19.781)
R_{Adj}^2	0.444	0.482
Q-stat.	0.023	0.000
ARCH LM	0.999	0.999
sample size	4,915	32,984

Table 6: Estimation results for Disposition effect in the First Phase

I estimate by least squares the ARMA(1,1) model in Equation (1) for the First Phase, with data for the period that runs from 24 June 2005 to 27 February 2008, including all together 4,925 observations. For each parameter estimate, the figures within parenthesis refer to the White's (1980) robust t-statistics. The row Q-stat. reports Q-statistics of Ljung-Box's test (1979) for autocorrelation in the residuals up to order 13. The row sample size reports the number of observations.

	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
	Jul-Dec '05	Jan-Feb '06	Mar-Apr '06	May-Dec '06	Jan-Feb '07	Mar-Apr '07	May-Dec '07
α	11.192 (4.252)	20.931 (3.098)	3.640 (4.072)	3.657 (3.875)	5.523 (4.916)	0.834 (0.474)	0.523 (0.734)
ϕ	0.021 (0.445)	-0.009 (-0.163)	-0.043 (-0.745)	-0.045 (-1.665)	-0.044 (-0.956)	-0.053 (-0.671)	-0.153 (-2.044)
φ	0.669 (17.261)	0.735 (15.785)	0.771 (18.259)	0.746 (36.567)	0.815 (28.158)	0.648 (9.138)	0.710 (12.107)
R^2_{Adj}	0.324	0.335	0.346	0.329	0.356	0.255	0.228
Q-stat.	0.933	0.375	0.885	0.944	0.850	0.631	0.499
sample size	628	422	500	2133	614	321	305

Table 7: Estimation results for Disposition effect in the Second Phase

I estimate by least squares the ARMA(1,1) model in Equation (1) for the Second Phase, with data for the period that runs from 08 April 2008 to 07 August 2009, including all together 32,997 observations. For each parameter estimate, the figures within parenthesis refer to the White's (1980) robust t-statistics. The row Q-stat. reports Q-statistics of Ljung-Box's test (1979) for autocorrelation in the residuals up to order 13. The row sample size reports the number of observations.

	Panel A	Panel B	Panel C	Panel D
	April-Dec '08	Jan-Feb '09	Mar-Apr '09	May-Aug '09
α	9.499 (6.693)	3.492 (3.492)	5.686 (4.023)	7.511 (4.579)
ϕ	-0.072 (-3.829)	-0.017 (-0.851)	-0.033 (-1.389)	-0.062 (-3.068)
φ	0.847 (102.828)	0.913 (169.302)	0.871 (96.261)	0.873 (105.969)
R_{Adj}^2	0.376	0.444	0.411	0.396
Q-stat.	0.920	0.745	0.885470	0.894
sample size	9,543	6,394	6,722	10,388

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